Non-Linear Dynamics and Stock Return Predictability on the JSE Securities Exchange of South Africa

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to austin khama

Declaration

I declare that this thesis is my own unaided work. It is being submitted for the degree of Doctor of Philosophy in the University of Cape Town. It has not been submitted before for any degree or examination in any other university.

Signed by candidate

Ronald Dadi Mangani

Acknowledgements

On Eagle's wings we plot our course, guided by what lies within our hearts.
Onward; farther distances we soar, gaining wisdom more and more.
Into our future we slowly pass, leaving our memories in our past.
Rising, falling, twisting, turning – always reaching, always learning.
Rising as the winds lift us; plotting our course as we go. *(Unknown)*

Memories of the path I travelled to this destination make me realise that I am much more indebted, now than ever before, to many who, in person or institutionally, inspired and propelled me as the winds on my Eagle's wings. I can only attempt to express my gratitude.

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Joyce, Zak, Kene and Undo, for whom I chose to endure, claim my appreciation and a fair share of the outcomes of this effort; they were always there for me to lean on, and survived the long days of my absence from home. The Senior Chief and his wife in the village, whose parentage I proudly cherish, always remind me that complacency is the assassin of progress.

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Abstract

Recent South African asset pricing research has generally established a preference for the arbitrage pricing theory of Ross (1976) over the capital asset pricing model of Sharpe (1964) and others. However, both the APT and the CAPM are single-period linear models based on the assumption that security prices follow a normal strong random walk process or, equivalently, that security returns are normally and linearly distributed. A crucial implication of this assumption is that the prices and returns are unpredictable, hence it is not possible to earn excess returns on the market through the innovative use of relevant information.

Using time series data on forty-four individual stocks from the JSE Securities Exchange, the FTSE/JSE All Share index and an equally weighted portfolio of the forty-four stocks, this research contributes to the literature by empirically disputing the normal strong random walk assumption, and suggesting a non-linear stochastic model for the JSE return generating process. In particular, the research found that a low-order generalised autoregressive conditional heteroscedasticity model due to Bollerslev (1986) could describe the JSE dynamics, and account for the non-linearities in returns. Within this ARCH-type modelling framework, the study established that there were symmetric effects of shocks on volatility, and that volatility was not commonly priced on the market. The latter finding could indicate that JSE investors sought compensation for other forms of perceived risk than volatility.

By invoking Granger-causality tests and innovation accounting within the environment of vector error correction modelling to establish the nature of the interrelationships among South African monetary, financial and real sectors, the evidence indicated that the discount rate (i.e., Bank/repo rate) and mining production had predictive power for JSE security prices. Thus, monetary policy and mining sector activity were potential sources of priced factors on the market. The research considered the price of gold to be a surrogate for mining sector activity. Further, augmentations of the preferred GARCH(1,1) model to include the discount rate and the price of gold showed that contractionary monetary policy could lower expected returns but scarcely impacted on return volatility. In contrast, gold price changes had largely volatility-increasing effects on resources stocks, and volatility dampening effects on non-resources stocks. However, gold price changes also impacted on expected returns. The study also found that the effects of the two exogenous macroeconomic factors were largely asymmetric. Importantly, positive discount rate changes inversely impacted on mean returns but negative changes did not, while it was mostly negative changes in the price of gold that tended to impact on volatility. Finally, the model with exogenous factors could account for the non-linearities remaining after the GARCH filter.

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Chapter 1

Introduction

1.1 Research Context

The foundation of this research is the random walk hypothesis of security prices, which is an important attribute of most general equilibrium asset pricing models. Prior empirical research into the return generating process on the JSE Securities Exchange of South Africa (hereafter JSE) has been dominated by an enquiry into the relevance of the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966), as well as the arbitrage pricing theory (APT) of Ross (1976). Both of these models are linear relationships whose statistical implementation assumes that security prices follow a normal strong random walk process (or that security returns are normally and linearly distributed) and are, hence unpredictable over time. Because this assumption is generally inconsistent with the time series behaviour of security returns in most markets including the JSE, better insights into the return generating process could arguably be obtained by shifting the scope of enquiry to a non-linear dynamic modelling framework that allows for the profitable predictability of returns over time. The present research pursued this line of enquiry on the JSE.

1.2 Justification and Objectives

The primary objective of portfolio theory and investment analysis is to provide advice to investors on the appropriate securities to choose as constituents of their portfolios. Because investments are generally uncertain undertakings, rational investors will seek to maximise their expected returns while minimising the risks associated with them, through their choice of portfolios and portfolio constituents. The aggregation of the behaviour of all investors in the market permits a determination of the equilibrium prices at which securities should trade, and the returns that investors should expect for holding them. The justification and objectives of the present study fall within the domain of this primary objective.

1.2.1 Justification

The characterisation of the return generating process in the financial market has far-reaching consequences for the investment decision-making process; a correct characterisation means that investors will be well-guided. At one extreme, if a random walk model of security prices is correct and returns are unpredictable, investors should follow a passive portfolio management strategy and not attempt to 'beat the market', since the use of new or privileged information will not result in higher returns than those predicted by the general equilibrium model. On the other hand, if security prices do not follow a random walk process, the correct asset pricing model should take cognisance of the fact that higher than average market returns can be earned through the shrewd gathering and use of information about the future.

Of the two linear asset pricing models widely investigated on the JSE, the APT "appears to potentially offer considerable advantages in its explanation of the pricing of risky assets", Page (1993). Although this subject remains unresolved due to contradictory evidence from various studies, most of the later empirical evidence would appear to support Page's proposition[1]. On the other hand, the CAPM remains the most popular model in practical applications. Irrespective of whether the CAPM or the APT is the preferred general equilibrium model, a violation of the random walk (or linearity) assumption in these models implies that they may not be optimal descriptions of the return generating process. Therefore, in order to properly guide the investment decision-making process among JSE investors, hence to ensure that the potential to earn more that average returns can be exploited, the need to investigate the relevance of a non-linear dynamic characterisation of the JSE return generating process cannot be overemphasised.

Although this subject has been widely investigated in other emerging and developed financial markets, indeed with varied tools being used and generally inconclusive results being obtained, the present study markedly lacked comparators from the South African literature. This is not particularly surprising when one considers how enduring the random walk hypothesis has been as a description of asset returns, and how recent any meaningful debate on the random walk hypothesis is, as is evident in the following:

> ... when we first presented our rejection of the Random Walk Hypothesis at an academic conference in 1986, our discussant – a distinguished economist and senior member of the profession – asserted with great confidence that we had made a programming error, for if our results were correct, this would imply tremendous profit opportunities in the stock market (Lo & MacKinlay, 1999:4).

[1] See Section 2.7.

By addressing the objectives outlined below, it is hoped that this research will contribute to the on-going debate on the security return generating process, provide valuable insights into the dynamic behaviour and predictability of JSE security returns, and stimulate an appetite for further local investigations of an analogous nature.

1.2.2 Research Objectives

This research addresses three main objectives. The first objective is to update and validate, using JSE data, the evidence regarding the statistical properties of security prices and returns documented for most other markets. Specifically, the stationarity property is investigated for both prices and returns, while the normality and linearity properties are investigated for security returns. If security prices are non-stationary processes while returns are stationary, this provides statistical justification for using returns as opposed to prices in analysing stock market behaviour over time. Moreover, if returns are non-normal and non-linear, this violation of the normal strong random walk property implies that return changes are profitably predictable, and renders suspicious the appropriateness of static linear asset pricing models. Because the problem of non-normalities on the JSE seems to have been extensively studied by Page (1993), who noted inconsequential effects of non-normalities on the APT, most of our research in this respect is concerned with addressing the subject of non-linearities.

The second objective of the study is to investigate the structure of the non-linearities in the return series. After validating the potential of volatility clustering in the returns, the study investigates the appropriateness of ARCH-type models in describing JSE return dynamics and in accounting for the observed non-linearities. Evidence in support of the validity of such models in linearly filtered and stationary returns data indicates the presence of stochastic non-linearities rather than deterministic non-linearities or low-dimensional chaos.

The final objective of the study is to link the JSE return dynamics to South African economy-wide dynamics. This enquiry seeks to identify, within a multivariate time series modelling framework, the macroeconomic variables that drive JSE returns over time and, by reverting to the ARCH-type modelling framework, to investigate the effects of such variables on both expected returns and return volatility.

1.3 Limitations and Contributions

The subject of the dynamic modelling of security returns is quite broad and evolving at a fast pace. As such, it is not practically possible to apply every single innovation, particularly when working in an emerging market characterised by non-synchronous trading, non-trading and information asymmetries. In such a market, the tools available at one's disposal are constrained by data and other resource limitations. Further, while other sophisticated and computationally costly methodologies could be attempted, academic research in the context of developing economies ought to address practical issues of eventual usability of research output, in the light of financial products actually being traded or potentially tradable. Such a virtue usually means than the degree of technical and computational sophistication may not necessarily be unconstrained.

The above limitations notwithstanding, this research contributes to the broad subject of non-linear dynamics and security return predictability by providing new insights from the South African[2] environment. By investigating the dynamics of the return generating process and linking such dynamics to the wider macroeconomy, the study develops a potentially usable tool for guiding JSE investors in their insatiable pursuit of self-interest. Because macroeconomic dynamics in South Africa are unique in view of the country's distinctive socio-economic history, this investigation attempts to capture these attributes adequately. Further, because, in a dynamic framework, investors are concerned with not only the expected returns of their investments but also the volatility of such returns, this investigation models both aspects of the investment decision-making process.

1.4 General Methodological Issues

The specific methodologies used in this study are contextually presented in Chapters 3 to 6. This section presents the main sampling procedures and data used in the study. The section also discusses the computer software resources used in the analysis of the data. The research was based on both individual stocks and market aggregates.

1.4.1 Sampling Design

The JSE has existed as an organised stock market since 1887 and, as at June 2002, had a listing of four hundred and fifty-seven stocks[3] that could potentially be included in the study. However, the determination and choice of sample size (in terms of the number of securities

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[2] In some instances, the abbreviation for South Africa, RSA, is used in this report.
[3] Source: Profile Media (2002). This figure was obtained by physically counting the stocks in the source.

included in the sample) and study period was based on two major considerations. The first consideration was the trade-off between a long study period and a reasonably large number of securities to be included. Of the four hundred and fifty-seven stocks, continuous weekly data from 23 February 1973 were available for one hundred and one stocks. An analysis of the gains in stocks achievable as the sample period became shorter revealed that such gains remained minimal until the sample period was significantly reduced. Therefore, the sample period of 23 February 1973 to 5 April 2002 was chosen and, at this stage, the potential number of stocks in the sample was restricted to all the one hundred and one.

The second consideration in the sampling design was based on recent developments at the JSE. On 24 June 2002, the JSE implemented the FTSE global classification system, and introduced the free float criterion which recognises that equity held for control purposes does not trade and, put crudely, "may as well not be listed" (Profile Media, 2002). As a result of these developments, the new FTSE/JSE All Share index represents 99 percent of the unweighted market capitalisation (i.e., full market capitalisation before the application of any 'investibility weightings', a term explained below) of all ordinary securities listed on the JSE that qualified for inclusion in the FTSE/JSE Africa Index Series in accordance with the Ground Rules governing the series. The remaining one percent of the unweighted market capitalisation constitutes a Fledgling index of ordinary securities that are considered too small to be included in the All Share index. Other indices in the FTSE/JSE Africa Index Series are the Top 40 index of the forty largest companies, the Mid Capitalisation index of the next sixty companies after the largest forty, and the Small Capitalisation index of companies in the All Share index but outside the group of the largest one hundred companies. In the determination of constituents, companies are ranked by their unweighted market capitalisations. However, the free float concept only includes, in the calculation of indices, the portion of each company's market capitalisation that has a chance of being traded, or that 'floats freely'. Each share's free float, as a proportion of the share's market capitalisation, is defined in terms of the so-called 'investibility factor' (or 'investibility weighting') whose calculation excludes components of each company's quoted equity not available to the general public for trading purposes.

These developments resulted in major changes to JSE sectors, the most notable being a significant decline in the number of stocks in the JSE All Share index from over four hundred and fifty to only one hundred and sixty as at 4 June 2002, and one hundred and fourteen of the one hundred and sixty stocks constituted 98.83 percent of the weighted All Share index.

In addition, some major blue-chip stocks became underweight in the new index because of free-float problems. Moreover, since a non-zero investibility factor is not an eligibility requirement for a security's inclusion in the FTSE/JSE Africa Index Series, quite a few of the one hundred and sixty constituents of the weighted All Share index had a zero investibility factor, hence did not contribute anything to the index series. All other JSE indices had been equally affected and appropriately re-classified in accordance with the new criteria. Therefore, by studying only a few appropriately selected companies in the new All Share index, it became possible to capture a significant proportion of the freely floating (hence, truly trading) segment of the JSE. Of the one hundred and one stocks selected on the basis of satisfying the requirement of continuous trading and data availability since February 1973, as discussed in the preceding paragraph, forty-four stocks were among the one hundred and fourteen companies that constituted 98.83 percent of the weighted All Share index, and were selected to constitute our final sample.

Concern for thin-trading or illiquidity of some listed securities is well-documented in the literature. Although researchers may correct for the presence of thin-trading through the trade-to-trade approach as suggested by Bowie and Bradfield (1993), some JSE studies have addressed the problem by subjectively omitting the thinly traded stocks and focusing only on well-traded ones (Page, 1993; van Rensburg, 1999). It is noted that the new JSE classification system partly provides a solution to the problems associated with non-synchronous trading and non-trading. Specifically, the Ground Rules that govern the FTSE/JSE Africa Index Series make a provision to ensure that illiquid securities will be excluded from the indices. At the time of this sampling, the (draft) key principal generally guiding the exclusion of illiquid securities was spelt out as follows (see Rule 4.10):

> Securities which do not turnover at least 0.25% of their shares in issue, after application of any free float restrictions, per month in at least ten of the twelve months prior to an annual review ... will not be eligible for inclusion in the indices (except FTSE/JSE Fledgling). An existing constituent failing to trade at least 0.25% of its shares in issue, after the application of any free float restrictions, per month for more than four of the twelve months prior to the quarterly review will be removed... (FTSE, 2003a)[4].

[4] In an updated version of the Ground Rules (see FTSE (2003b), the wording was changed and the minimum required turnover was increased from 0.25 percent to 0.5 percent. Most of the provision remained the same. The updated version was available after we had already sampled the stocks to be included in the study.

Since none of the constituents of the FTSE/JSE Fledgling index were included in our final sample, arguably, most of the forty-four securities chosen for inclusion were relatively well-traded and liquid, at least at the time of the construction of the series. The chosen sample was, therefore, consistent with the observation by some commentators that key financial institutions investing on the JSE tended to concentrate their buying activities on a narrow range of reasonably marketable shares of a blue-chip status (Economist Focus, 1990). However, it is noted that the data could still exhibit some thin trading, particularly since they extended back to the 1970s. In the literature, it is recognised that a major effect of non-synchronous trading is to induce spurious autocorrelation in the series (Atchison, Butler & Simonds, 1987), necessitating that corrective measures be employed to purify the data of linear dependencies. The present study applied such corrective measures to account for the effects of any remaining non-synchronous trading.

The forty-four stocks constituting the study sample are shown in Appendix 1A, which also shows their distribution across the so-called Tradable (Safex) indices of the JSE, based on the new classification system. It is noteworthy that, in addition to capturing a good proportion of the entire JSE (about 46 percent of the FTSE/JSE All Share index), the selected stocks were fairly well distributed across the Safex indices. Specifically, the sample captured over 48 percent of the Top 40 index, and about 52 percent of the Resi index of the top twenty companies in the resources sector. Further, the sample respectively captured about 48 percent, 38 percent and 43 percent of the Indi, Fini and Findi indices in the Safex class[5]. It is also worthwhile noting that, on account of the criteria discussed above, five of the stocks in the final sample had zero investibility factors, hence a zero weighting in all the indices.

Appendix 1B provides further details of the selected stocks, focusing on their distribution in the three broad JSE sectors, namely resources, industrial and financial sectors. Although relatively more stocks were drawn from the resources and industrial sectors than would be suggested by the actual distribution of the stocks on the market, the proportion of the market share captured by the resources stocks did not depart too far from that actually obtaining on the market. The dominance of few blue-chip resources stocks, as well as the insignificance of too many industrial stocks, was quite well captured by the sample. However, the under-representation of the financial stocks observed in Appendix 1A was also evident in Appendix

[5] The Indi index is that of top twenty-five securities in the industrial sector, the Fini index is the index of fifteen securities in the financial sector, and Findi index is that of thirty securities in the financial and industrial sector. Index constituents are selected on the basis of each security's unweighted market capitalisation. For further details, see Appendix 1A.

1B, in which industrial stocks also appeared to be relatively over-represented even in terms of market share. These departures from a desired distributional outcome for the sample stocks are not unexpected in random sampling. Therefore, by and large, it may be safely argued that the results of the analysis based on the selected sample could provide meaningful insights into the behaviour of the JSE as a whole. The sample also provided a rich basis for making meaningful comparisons on the dynamics of security prices and returns across sectors, especially in terms of sectoral relationships with the macroeconomy.

In addition to the forty-four individual stocks described above, two market aggregates (or stock portfolios) were used to capture the aggregate behaviour of the market. The first was the FTSE JSE All Share index whose data, as explained in Section 3.2, were spliced back to 1983 at source. This is denoted ALSI in the ensuing analysis. In addition, we constructed an equally weighted portfolio of the forty-four stocks described above, denoted PORT hereafter, in order to mitigate the effects of value-weighting in ALSI. Because ALSI is dominated by resources (principally mining) stocks as appreciated in the foregoing, the use of the equally-weighted portfolio provided a measure of aggregate market dynamics that was not significantly influenced by the dynamics of the resources stocks *per se*.

Additional variables used in the research are contextually introduced in the investigation of the interrelationships between the stock market and the macroeconomy.

1.4.2 Data

Except for the investigation of the interrelationships between the financial sector and the macroeconomy, the rest of the investigation in this research was based on weekly data. Weekly data were preferred because they generally provide a richer framework for analysing return dynamics, and generally give more degrees of freedom necessary in investigating complex relationships. As noted by Brock, Hsieh and LeBaron (1993), data collected at much higher frequencies (such as daily, hourly or even minutely) tend to be contaminated by the dynamics of market microstructure, which may disguise the dynamics of interest to the researcher. In the case of the JSE, the advantage of a long time series that would be associated with high frequency data is compromised by the fact that such data do not extend backwards in time over long enough periods. On the other hand, when the sampling frequency is too low (e.g., monthly or quarterly), on account of the resultant need to sample over long periods in order to obtain adequate degrees of freedom for estimations based on asymptotic theory, one runs the risk of encountering non-stationarity problems. Kariya (1993) also noted that the time series properties of interest were more prevalent in high frequency rather than low frequency data. We considered weekly data to strike a reasonable balance.

Despite the above preference for weekly data, the interrelationships between the stock market and the macroeconomy were captured using monthly data, because this frequency was the highest for most published macroeconomic variables. This is also consistent with standard practice for the VAR/VEC models that we applied in this particular investigation.

The nature and sources of all the data used in the study are contextually cited and acknowledged, and the raw data are provided as Microsoft Excel files in the accompanying CD-ROM. Further, unless otherwise indicated, all the figures, tables and appendices in this report were generated in the study. Where such entries were extracted, adapted or otherwise sourced from other works, this has been duly acknowledged with appreciation.

1.4.3 Computer Software Resources

Except in conducting BDS linearity tests, all the econometric and graphical analysis in this investigation was conducted using the Econometric Views commercial software, version 3.1 (hereafter EViews 3.1), which is registered to the Institute of Economics, McGill University. Two other resources were used in the BDS linearity tests. These are Econometric Views, version 4.0 (hereafter EViews 4.0), registered to the same institution as EViews 3.1 and, with gratitude, LeBaron's (1991) non-commercial C Source code[6].

1.5 Organisation of the Thesis

The present introductory chapter has provided the rationale for and the broad objectives of the research project, and has discussed general methodological issues. It is indicated in the foregoing that the specific methodologies adopted to address the three major objectives are contextually presented in the relevant chapters. The rest of this report proceeds as follows:

Chapter 2 discusses the general theoretical framework and reviews selected empirical literature. Specifically, the chapter critically discusses the theory and evidence on static asset pricing models, security return predictability and the dynamic modelling of returns. While the selected international evidence is briefly presented within the context of each theoretical framework, a relatively extensive review of the South African evidence is provided in a separate section of the chapter in order to locate the study properly. However, as stated in

[6] I am grateful to Kgabo Sepuru for compiling the C Source code to facilitate my usage in MS-DOS.

the preceding section, theoretical aspects and some selected empirical evidence very directly linked to the objectives of the research are presented in Chapters 3 to 6 where the objectives are addressed. This approach was adopted to make those chapters as self-contained as possible, while still permitting chapter linkages.

The three main objectives of study are investigated from Chapter 3 to Chapter 6, which report on and discuss the results of the research. In Chapter 3 the random walk properties in JSE security prices and returns are investigated. Therefore, the chapter provides new evidence regarding the unit root, normality and linearity properties in the data, and hence an empirical justification for investigating the dynamics of the return generating process within a non-linear modelling framework.

The possibility that stochastic non-linearities could characterise JSE security returns is investigated using ARCH-type models in Chapter 4. Apart from enquiring whether such models are appropriate for the market and whether they can account for the evident non-linearities, the chapter also investigates whether there are asymmetric effects of shocks on volatility, and whether volatility is a commonly priced factor on the JSE.

The last two empirical chapters are concerned with linking the return dynamics to the South African macroeconomy. In Chapter 5, a vector error correction framework is used to identify potentially priced factors on the JSE. These are hypothesised to originate from monetary policy and real sector activities. Therefore, the chapter conducts an investigation, using multivariate Granger-causality tests and innovation accounting, of the causal and predictive interrelationships among the monetary, financial and real sectors of the domestic economy.

In Chapter 6, proxies for the potentially priced factors identified in the preceding chapter are introduced in the appropriate ARCH-type model identified in Chapter 4, in order to parameterise the effects of such factors on security returns. This augmentation of the ARCH-type process is necessary in view of the fact that the VEC model used in Chapter 5 is an atheoretic characterisation of the dynamics, and does not account for the evident non-linearities in the data. The analysis also investigates the possibility of asymmetric effects of the factors on both expected returns and return volatility.

The main findings and conclusions of the research are summarised in Chapter 7, which also shows their relation with prior South African and, mostly, international studies. The potential for further research on the subject is also identified.

Chapter 2

Theoretical Framework and Literature Review

> *Experimental evidence and casual introspection suggest that investors' attitudes towards risk and expected return are nonlinear. The terms of many financial contracts … are nonlinear. And the strategic interactions among market participants, the process by which information is incorporated into security prices, and the dynamics of economy-wide fluctuations are all inherently nonlinear. Therefore, a natural frontier for financial econometrics is the modeling of nonlinear phenomena (Campbell, Lo & MacKinlay, 1997:467).*

2.1 Introduction

Building on the propositions of modern portfolio theory, it is noteworthy that the most widely used asset pricing models are single-period (static) and linear models whose tests implicitly assume that financial markets are informationally efficient. However, the time series properties of data from most financial markets have shown that returns are generally non-normally and non-linearly distributed, hence profitably predictable over time. Therefore, single-period linear asset pricing may not provide an adequate framework for investment decision-making. This chapter seeks to motivate the current research by arguing, through a review of the relevant literature, that a dynamic non-linear framework for modelling and predicting stock returns could offer greater potential for profitable asset allocation decisions, and that this line of enquiry has not received deserving attention from scholars investigating the behaviour of security returns on the JSE.

The scope of this chapter covers the theoretical framework and empirical evidence in a rather generic manner; further reviews of the theoretical and empirical literature are contextually presented in the four successive chapters that discuss the results of the research. In Section 2.2, we briefly review the mean-variance optimisation theory that lays the groundwork for most asset pricing models, notably the capital asset pricing model (CAPM) presented in Section 2.3, and the arbitrage pricing theory (APT). Both the APT and the consumption-based intertemporal CAPM (ICAPM) are reviewed in Section 2.4, which is followed by a formal discussion of the predictability of security returns in Section 2.5. Section 2.6 briefly discusses the dynamic modelling of asset prices and returns, a matter that is pursued later in the study. While the international evidence is briefly and selectively presented contextually within the next five sections of this chapter, a review of selected South African literature is presented in Section 2.7. The chapter ends with a summary and conclusion in Section 2.8.

2.2 Portfolio Theory

Modern portfolio theory is founded on the work of Markowitz (1959) and addresses the question of how a rational investor wishing to maximise the expected utility of his[1] wealth chooses an optimal portfolio from a set of securities. The theory concludes that, under conditions of uncertainty and subject to the available set of all assets, a rational investor chooses a mean-variance efficient portfolio: one that maximises the expected return of his portfolio, while minimising the variance or standard deviation (i.e., the risk) associated with the return on the portfolio. When a risk-free asset is available, the investor chooses a point on the capital market line (CML), defined in expected return-standard deviation space as the positively sloped straight line with a vertical intercept equal to the risk-free rate. The line's slope is determined by its point of tangency with the concave efficient frontier of the available risky assets, a point that characterises the market portfolio of risky assets. The exact location of a given investor on the CML is defined by the point of tangency between the CML and his highest attainable indifference curve, which characterises the investor's attitude to risk.

The most important result of Markowitz' mean-variance optimisation theory is the following so-called two-fund separation principle: given frictionless capital markets and homogeneous expectations, all investors, irrespective of their degree of risk aversion, will hold some combination of the risk-free asset and the market portfolio of risky assets. The separation principle permits the investor to realise benefits from diversification, and to invest in a portfolio commensurate with his attitude to risk. In addition, the theory provides a framework for describing a general equilibrium in the capital market. General equilibrium models allow us to determine the market price of risk, the appropriate measure of risk for a single asset, and the relationship between risk and return for many assets. Together with the conclusions postulated by Tobin's (1958) liquidity preference theory, mean-variance efficiency permits the development of such a model for pricing and Pareto-efficiently allocating risky assets among investors, as demonstrated by the CAPM. However, the theory of general equilibrium asset

[1] The use of masculine pronouns in this thesis is necessitated by the desire to improve readability, and should not be misunderstood as a compromise to our non-sexist intent. However, any incorrect use of pronouns in reference to specific individuals is far from being deliberate, and is very deeply regretted.

pricing is neither harmonious nor conclusive, and the CAPM remains challenged by alternative multifactor descriptions of the equilibrium, notably the APT.

2.3 The Capital Asset Pricing Model

The standard CAPM is a general equilibrium model of asset returns developed separately by Sharpe (1964), Lintner (1965) and Mossin (1966), by utilising the groundwork of Markowitz (1959). The CAPM shows that if markets are frictionless, investors' expectations are homogeneous, and investment portfolios are mean-variance efficient, then the market portfolio of all risky assets will also be mean-variance efficient. Further, assuming the existence of risk-free lending and borrowing opportunities, the model shows that the required rate of return for any given security , say i, is equal to the risk-free rate plus a premium that compensates the investor for taking on risk. Thus, the standard CAPM is:

$$\mu_i = r_f + \left[\frac{\mu_m - r_f}{\sigma_m^2}\right]\sigma_{im} = r_f + \beta_i(\mu_m - r_f), \tag{2.1}$$

where μ_i is the expected return on asset i, μ_m is the expected return on the market portfolio, r_f is the return on the risk-free asset, σ_m^2 is the variance of return on the market portfolio, and σ_{im} is the covariance between return on the market portfolio and return on asset i. A plot of (2.1) gives the security market line (SML), analogous to Markowitz' CML.

The CAPM risk premium is measured as a product of the price of risk (represented by the slope of the security market line, $\mu_m - r_f$), and the quantity of risk, given by the beta of the security, $\beta_i = \sigma_{im}/\sigma_m^2$. The risk-free asset ($f$) and the market portfolio (M) have $\beta_f = 0$ and $\beta_m = 1$ respectively, since $\sigma_{fm} = 0$, and $\sigma_{mm} = \sigma_m^2$.

The CAPM postulates that expected return is a linearly increasing function of beta, and that beta is the sole determinant of expected returns. As an important implication for investment policy, the CAPM shows that the total risk of an asset can be decomposed into idiosyncratic and systematic risk, and that the market will not compensate an investor for taking on idiosyncratic risk, which can be completely eliminated by holding a well-diversified portfolio.

Therefore, in order to determine the riskiness of an individual asset, it is important to look at its contribution towards the risk of the market portfolio, as measured by the beta of the asset.

Like most models derived by abstracting from reality, many of the CAPM assumptions are maintained apprehensively in the real world. In order to establish whether the CAPM is nonetheless a good model, researchers have examined the effects of relaxing some of its assumptions, resulting in the evolution of various non-standard forms of the CAPM. For instance, Lintner (1969) and Williams (1977) examined the effect of the absence of homogeneous beliefs; Brennan (1971) investigated the effects of allowing for other lending and borrowing assumptions; Black (1972) investigated the effect of the absence of a risk-free asset[2]; Mayers (1972) explored the effect of relaxing the assumption that assets were marketable and divisible; while Merton (1973) derived a continuous time version of the CAPM. Also noteworthy is the multi-period, consumption-based ICAPM of Breeden (1979), derived using representative agent assumptions. With the exception of Breeden's model, most of the aforementioned modifications do not seem to yield consequential effects on the key implications of the CAPM (Elton and Gruber, 1995).

The CAPM is a two-date (single-period, or static) model of expected returns, since:

> An investor with perfect information at time 0 is ... assumed to make an investment decision for time 1 at which not only the investor but also the firms in the theory close their whole positions and all the profits obtained by the firms are distributed (Kariya, 1993:10).

The direct implication of the model's key testable derivational assumption of mean-variance efficiency is that it necessitates making further assumptions concerning the time-series behaviour of returns. In keeping with the single-period theoretical characteristic, econometric analysis of the model generally makes the statistical assumption that return series are independently and identically distributed (iid), and are jointly multivariate normal. Compactly, this assumption implies that security prices follow a normal strong random walk process, or that returns are normally and linearly distributed. It is important to mention that the joint normality of asset returns is not a necessary but sufficient condition for deriving the CAPM,

[2] In Black's (1972) more general version of the CAPM, the expected return on asset *i* in excess of the return on a zero-beta (but still risky) asset is linearly related to beta.

although a violation of the iid (strong random walk, or linearity) property would make the model unlikely to hold theoretically (Campbell, Lo & MacKinlay, 1997:208).

The international literature is replete with conflicting evidence on the CAPM[3]. What is considered to be the early supportive evidence provided by Black, Jensen and Scholes (1972), Fama and MacBeth (1973), and Blume and Friend (1973) confirmed that the relationship was linear in beta and that beta explained a significant proportion of asset returns. But the evidence also generally found that the estimated slope of the security market line was smaller than that predicted by the CAPM. In addition, the tests generally obtained an implied estimate of r_f that was too high to be associated with any meaningful risk-free rate. The empirical validity of the model remains suspect, particularly with the appearance of a vast amount of evidence on the so-called CAPM anomalies. Illustratively, the usefulness of factors other than beta in explaining asset returns was confirmed by Black and Scholes (1974), Basu (1977), Litzenberger and Ramaswamy (1979), Banz (1981), Reinganum (1981), as well as Lakonishok and Shapiro (1986), among many others. The extra explanatory variables documented in the literature include price-earnings ratio, firm size, firm growth rate, dividend yield and market-to-book equity. In further studies, Fama and French (1992, 1993) also concluded that size and book-to-market equity better explained stock and bond returns in cross-sectional regressions. An important contribution to the testability of the CAPM was made by Roll (1977), who argued that the model was not acquiescent to testing, or that the tests performed provided little basis for evaluating it.

Although no compelling evidence suggesting that the CAPM beta is an inadequate measure of risk might be said to exist, and although the current evidence does not conclusively show that more sophisticated models might fully address the problems associated with the CAPM, many researchers believe that a multifactor formulation explains the CAPM anomalies better and captures the equilibrium risk-return relationship more appropriately.

2.4 Multifactor Asset Pricing Models

Multifactor asset pricing models are founded on the argument that the asset return generating process should involve multiple factors rather than the single factor postulated by the CAPM. Among the various variations of and extensions to the original formulation of the CAPM, probably the most significant is the consumption-based intertemporal CAPM of

Merton (1973) and Breeden (1979), which relates asset returns to a stochastic discount factor. The ICAPM is based on equilibrium arguments and provides a linear multifactor model of asset returns in which the factors include the market portfolio and state variables for the investor's consumption-investment decision. By invoking representative agent assumptions, the model permits the use of aggregate consumption in place of individual consumption. The state variables, which generally include current wealth and variables that describe the conditional distribution of future asset returns (or shifts in the investment opportunity set) explain optimal aggregate consumption, and arise from the typical investor's demand to hedge against uncertainty about future investment opportunities. Breeden (1979) illustrated that exact factor pricing would hold in the ICAMP framework with mimicking portfolios, which were jointly maximally correlated with the true multiple factors of the model. However, empirical estimations of the model, using the generalised method of moments and invoking simple power utility assumptions to represent investor preferences, provide strong statistical evidence against it. This finding has motivated researchers to suspect effects on model validity from market restrictions and from weaknesses in some of the model's assumptions, especially those describing investors' preferences (Campbell *et al*, 1997).

The most commonly used multifactor model, the arbitrage pricing theory, was suggested by Ross (1976). It is based on the law of one price and permits the derivation of a testable alternative to the CAPM that does not require some of the strong assumptions of the CAPM. In addition to standard competitive market assumptions, one key assumption of the model is that investors have homogeneous beliefs that the random returns for the set of assets under consideration are a linear function of N factors (or indices), say F_j (for all $j = 1,2,...,N$)[4]. Ross's version of the model shows that, in the absence of arbitrage opportunities, the risky asset i is expected to earn a premium that is approximately a linear function of b_{ij}, the sensitivity of the asset's rate of return to each corresponding factor, F_j:[5]

$$\mu_i \approx r_f + \sum_{j=1}^{N} \lambda_j b_{ij} , \tag{2.2}$$

[3] The empirical evidence is too voluminous to be exhaustively presented here. The reader is referred to Elton and Gruber (1995) and Campbell *et al* (1997:211) for excellent summaries of this literature.
[4] One of the *n* factors could (but need not necessarily) be the CAPM beta.
[5] For a comprehensive discussion, see Elton and Gruber (1995:368:374) and Blake (2000:501-504) in addition to the seminal paper by Ross (1976).

where μ_i is the expected return on asset i, r_f is the model's zero-beta parameter, usually assumed to be equal to the risk-free rate of return, and the λ_j's are constants, representing risk premia associated with each risk factor, F_j. Thus, λ_j represents the extra expected return on security i because of a security's sensitivity to the j th attribute of the security due to F_j. For each factor and security, the sensitivity, b_{ij}, also called a factor loading or response amplitude, retains the same interpretation as the CAPM beta coefficient. It is noteworthy that, while the b_{ij}'s are unique to each security and represent an attribute of the security, the F_j's assume the same value for all securities: the factors affect the returns on more than one security and are the sources of co-variances between securities.

By assuming that the market portfolio was well-diversified, Connor (1984) derived an exact factor pricing version of the model that is consistent with a competitive equilibrium. Grinblatt and Titman (1985) and Dybvig (1985) also confirmed that the theoretical deviations from the Ross version to an exact factor pricing model were negligible. Collectively, these results provide justification for empirical work based on the exact-pricing model:

$$\mu_i = r_f + \sum_{j=1}^{n} \lambda_j b_{ij} . \tag{2.3}$$

A complete specification of the APT requires that all the risk factors (the F_j's), as well as all the sensitivities (the b_{ij}'s) be identified, so that the covariance between any residual terms is reduced to zero. Thus, if a sufficiently well-diversified portfolio can be formed that the idiosyncratic risk of the APT equation vanishes, then the model will hold as an equality. This is analogous to the CAPM result that the market will not compensate an investor for taking on idiosyncratic risk. However, the APT is more robust than the CAPM for several reasons. Firstly, the model makes no strong assumptions about individuals' utility functions, other than greed and risk aversion. Secondly, it allows equilibrium asset returns to be dependent on more factors than one, and attributes no special role for the market portfolio, and for mean-variance efficiency *per se*. Thirdly, it yields a statement about the relative pricing of any subset of assets, hence it is unnecessary to measure the entire universe of assets in order to test the theory. Because the model is based on arbitrage conditions, which should hold for all risky assets, it becomes unnecessary to identify all such assets (or even the market portfolio) to test the model. Finally, the APT is extendable to a multi-period framework.

Unlike the CAPM, however, the APT does not specify how many risk factors should be chosen and what those factors are. Researchers generally use the factor analysis model[6], given pre-specified macroeconomic variables, to extract common factors and test their ability to explain variability in asset returns. While most of the earlier factor-analytic applications used common factor analysis, more recent applications have tended to use principal components analysis (PCA), primarily because the latter procedure can help in identifying the economic meaning and significance of the factors derived.

In general, most empirical tests of the APT provide evidence in support of a multifactor model of asset returns (e.g., Roll & Ross, 1980; Dhrymes, Friend & Gultekin, 1984; Chen, Roll & Ross, 1986), and show that the APT can be used to explain the CAPM anomalies (Connor & Korajczyk, 1986, 1988; Lehman & Modest, 1988; Fama & French, 1996). The usefulness of a multifactor model in return prediction was documented by Elton and Gruber (1988, 1989), while a more direct comparison between the CAPM and the APT was made by Burmeister and McElroy (1988), who also found the APT superior. Ferson and Harvey (1991) found that the risk premium associated with a stock market index captured the largest component of the predictable variation in the stock returns, while Fama and French (1993) showed that a portfolio model was successful in explaining stock returns. The latter asserted that a minimum of five factors did "a good job explaining both the common variations in bond and stock returns and the cross section of average returns".

In relatively recent work, Ferson and Korajczyk (1995) derived their own multifactor return predictability models and showed that they performed very well. They also showed that the principal components and pre-specified factor approaches produced broadly similar results. Daniel and Titman (1997) investigated the presence of pervasive factors and risk premia associated with size and book-to-market equity ratio. Their analysis demonstrated that there was no evidence of a separate distress factor, and that characteristics other than factor loadings determined expected returns. Merville, Hayes-Yelken and Xu (2001) examined further the question of the number of fundamental factors that influenced stock returns, but also attempted to bridge the gap between latent principal components and the underlying

[6] Researchers have also used other less popular tools, such as fundamental variables analysis and covariance bi-plot.

economic factors. Their results indicated that there were most likely three factors for size-and-beta- sorted portfolios, namely market return, market capitalisation, and the investment opportunity set. In general, the number of priced factors confirmed by most studies has varied from three (e.g., Fama & French, 1996; Merville *et al*, 2001) to five (e.g., Elton & Gruber, 1988, 1989; Fama & French, 1993), but this generalisation is rudimentary.

The CAPM and the APT share several common characteristics, one of which being that both are one-period (static) models. This framework does not address the intertemporal aspects of asset returns, an issue which the ICAPM attempts to address. However, aside from the already stated testability problems associated with the ICAPM, empirical applications of both the APT and the ICAPM carry with them the disputed CAPM assumptions that returns are iid and multivariate normal processes. An area of growing research interest is that of investigating the predictitability of security prices and returns, by taking into account the time series features of financial market data. This is probably the essence of investment decision-making, as noted by Kariya (1993:7):

> Investments ... are(,) in general(,) commitments to (the) future and need necessarily (be based on) prediction(s). Furthermore, the economic behaviours [*sic*] of pursuing profits and avoiding risks in future cannot be free from prediction. In (the) prediction of financial investments(,) analysis on price variations is the most important...

2.5 The Predictability of Security Returns

2.5.1 Introduction

The most common methodologies for investigating the predictability of returns involve tests of various forms of the random walk hypothesis. Although this hypothesis is frequently confused with the efficient market hypothesis (EMH), the two are different, albeit being quite closely related. The random walk hypothesis addresses the question of whether future stock prices can be predicted from past prices. On the other hand, the EMH is concerned with investigating how well relevant information is incorporated in the price-formation process for securities, in order that security prices should correctly reflect what they are 'worth'. We first critic the appropriateness of the EMH in the context of security return predictability, and later formalise a discussion of the random walk hypothesis. Our focus finally centres on the form of the random walk hypothesis that entails the linearity property of security returns.

2.5.2 The Efficient Market Hypothesis

Although the genesis of the EMH can be traced to the genius of names such as Bachelier, Einstein, Levy, Kolmogorov and Weiner, recent interest in the subject is largely associated with Samuelson (1965) and Fama (1965,1970). Definitionally, an efficient capital market is perceived to be a perfectly competitive market where all relevant information is instantaneously and unbiasedly incorporated in the determination of prices. In such a market, the current stock price, P_t, already incorporates all relevant information. Price changes between two time periods are only due to unforeseeable new information and are entirely unpredictable. This is consistent with the age-old characterisation of a 'fair game' (Cardano, 1565, as quoted in Campbell, Lo & MacKinlay, 1997:30:) and, technically, is equivalent to arguing that prices can be modelled as a martingale process:

$$E\left(P_{t+1} \middle| \Omega_t\right) = P_t, \tag{2.4}$$

where Ω_t is a set of all relevant information available at or before time t, generally contained in the price history, P_t, P_{t-1}, ... Therefore, at time $t+1$, the actual price, P_{t+1}, must equal the expected price conditional on information available at time t, plus a prediction error that is independent of the information available at t. Such an informationally efficient market presents no possibilities for earning abnormal returns. If R_{t+1} denotes the actual return realised at time $t+1$ and R^*_{t+1} is the required return on the market, then the martingale property also holds for returns, implying that expected abnormal return conditional on Ω_t, say $E\left(y_{t+1} \middle| \Omega_t\right)$, will be equal to zero, or will be a fair game (Cuthbertson, 1996:103), i.e.:

$$E\left(y_{t+1} \middle| \Omega_t\right) = E\left(R_{t+1} - R^*_{t+1} \middle| \Omega_t\right) = 0. \tag{2.5}$$

Expression (2.5) is called the rational valuation formula (RVF), and states that, on average, an efficient market will be in continuous stochastic equilibrium[7]. The fair game property for expected abnormal returns also implies that the current market price of a stock equals its fundamental value, given by the discounted present value of expected future dividends:

$$P_t = \sum_{T=1}^{\infty} \delta^T E_t D_{t+T} \ . \tag{2.6}$$

Expression (2.6) is another version of the RFV, where $\delta^T = 1/(1+r)^T$ is the value of the discount factor at time T; and $E_t D_{t+T}$ is the expected level of dividends at time $t+T$, conditional on the information set available at time t.

In order to provide a practical definition of 'relevant information' for the purpose of testing the EMH, preliminary work on the subject (Fama, 1965, 1970) distinguished between three forms of market efficiency: weak-form (how well past prices predict future prices); semi-strong form (how quickly security prices reflect publicly available information); and strong form (how well prices reflect all information that can possibly be known). A pre-condition for the strong version of market efficiency is that information and trading costs be equal to zero (Grossman and Stiglitz, 1980). A weaker and economically more sensible form of the EMH is that prices reflect information to the point where the marginal benefits of acting on information do not exceed the marginal costs (Jensen, 1978).

The EMH has strong implications for the analysis of capital markets, since its validity would imply that the value of such analysis is shady. If financial markets are efficient, passive portfolio management becomes the most feasible strategy, and the role of the investment analyst becomes very limited, since it is not possible 'to beat the market' by exploiting opportunities arising from access to information. In investment decision-making, an efficient market disputes any justification for delaying a physical investment project in the hope that financing conditions will improve, because the current price correctly reflects expected future earnings from the project. Also, under the EMH, the Modigliani-Miller theorem holds: the firm's cost of capital is independent of its debt-equity ratio (Cuthbertson, 1996).

Cox and Ross (1976) and Lucas (1978) have shown that the martingale model of security returns will only hold as a necessary condition for the EMH if returns are properly adjusted for risk. This implies that the validity of the EMH is dependent on all investors' knowledge of a general equilibrium asset pricing model on the basis of which risk-adjusted returns can be derived to characterise 'normal returns' on the market. In addition, the hypothesis will hold if

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[7] A departure from the implication that efficient markets will be in continuous stochastic equilibrium occurs when there are rational bubbles in the market, which arise because of the indeterminate aspect of solutions to

all investors are able to process the relevant information equally. Under the EMH, therefore, investors cannot earn returns in excess of such risk-adjusted returns. In fact, the martingale condition as presented above, which captures Samuelson's version of the EMH, does not necessarily account for risk and investor heterogeneity.

If we assume that all agents in an efficient market know the true equilibrium asset pricing model and are homogeneous in their processing of information, their uniform forecasts of returns based on such a model will be the best possible given the available relevant information, even though, *ex post*, they might make forecast errors involving profits or losses. Therefore, once risk-adjusted expected returns and investor homogeneity are introduced, the return on a security can be modelled as:

$$R_{t+1} = E(R_{t+1}|\Omega_t) + \varepsilon_{t+1}, \qquad (2.7)$$

where the residual, ε_{t+1}, satisfies the properties of unbiasedness, orthogonality and efficiency necessary in the formulation of mathematical expectations. (2.7) is called the rational expectations (RE) element of the EMH, and implies that forecast errors should be equal to zero and be uncorrelated with Ω_t. Clearly, the expectations and forecast errors will be conditional on the equilibrium model of returns used, so that the expected return, $E(R_{t+1}|\Omega_t)$, will include the given equilibrium model's valuation of the appropriate compensation to each investor for taking on (systematic) risk, hence enabling investors to earn normal profits[8].

Given that securities markets will be in continuous stochastic equilibrium under the EMH, the only change in the fair or fundamental value of the security, which should instantaneously be reflected in the security price, will arise from new, unpredictable, and random information. Therefore, the return on a security should also change in response to such information rather unpredictably, implying that the best estimate of future return should be the current level of return. Substituting $E(R_{t+1}|\Omega_t) = R_t$ into (2.7), then the version of the EMH with risk-adjusted returns implies that security returns (and particularly security prices) should follow a random walk in the sense described in subsection 2.5.2 below (Blake, 2000:391).

rational expectations models (Flood and Barber, 1980).

[8] In this context, 'profitable predictability' or simply 'predictability' means that a return different from (in fact generally higher than) that predicted by the equilibrium asset pricing model is attainable.

The above relation between equilibrium asset pricing and the formation of expectations in the EMH poses the problem of what is referred to as the joint hypothesis (Fama, 1991): tests of the EMH are, jointly, tests of such an asset pricing model. Hence a rejection of the hypothesis will be ambiguous as to the validity of the model or the hypothesis itself. In addition, the requirement that agents are homogeneous in their processing of information is unattainable because, in any market, there will always be noise traders acting on improper information, or indeed others willing to trade for reasons other than information. Because such traders permit smart money to earn excess profits, innovative investors in any well-functioning market will be compensated for accessing and using information, irrespective of the degree of market efficiency (Lo & MacKinlay, 1999:6).

To clearly distinguish between the EMH and the random walk hypothesis, it will be noted from the foregoing that the two become equivalent only when expected returns are risk-adjusted (or when risk-neutrality is assumed), and when investor homogeneity is assumed. However, if the two were exactly identical, a violation of the random walk hypothesis should always entail a violation of the EMH. But Leroy (1973) and Lucas (1978) illustrated that the EMH could holds even if prices did not follow a random walk, and argued that the random walk hypothesis was neither a necessary nor a sufficient condition for rationally determined security prices. Lo and MacKinlay (1999:5) argued in this context that "unforecastable prices need not imply a well-functioning financial market with rational investors, and forecastable prices need not imply the opposite...", and also that "...the random walk hypothesis – a purely statistical model of returns, need not be satisfied even if prices do fully reflect all available information" as required by the EMH. These arguments imply that a violation of the random walk hypothesis is not necessarily in conflict with the EMH, or *vice versa*.

Consistent with the above arguments, the work of Grossman (1976) and Grossman and Stiglitz (1980) suggests that the practical usefulness of the EMH is quite limited. In the arguments of the two, the EMH is an unattainable ideal situation: a perfectly efficient market is an impossibility because its existence would lead to the collapse of markets as a result of zero returns being earned for trading on information.

The foregoing does not purport that the EMH is unimportant, but rather that it is inappropriate in the context of the objectives of the current research. Clearly also, most researchers could actually be testing the random walk hypothesis when they claim investigations of the EMH, and most of the so-called CAPM anomalies discussed in Section 2.2 should be considered as evidence of the predictability of returns rather than evidence against the EMH. In this spirit, even the so-called tests of the 'informational efficiency' of the market would be of interest to the random walk hypothesis, since they capture the idea that innovative and informed traders will be rewarded at the expense of noise traders, although this need not entail a violation of the EMH. Therefore, it is still meriting to cautiously review the empirical evidence on how markets are perceived to process information.

In developed equity markets, prior research on the EHM focused on investigating the effectiveness of specific trading rules in earning abnormal returns after adjustments for transaction costs and systematic risk (Alexander, 1961; Fama & Blume, 1966) and testing the independence between excess returns and the information set, Ω_t (Ball & Brown, 1968; Dann, Mayers & Raab, 1977). The prior research generally yielded what was considered as overwhelming evidence in support of the weak and semi-strong forms of the EMH. However, later evidence confirmed the presence of profitable trading rules, (Sweeney, 1986; Brock, Lakonishok and LeBaron, 1992; Taylor, 1992) and anomalies such as calendar effects (Gibbons & Hess, 1981; Harris, 1986,1989; Ariel, 1987, 1990; Lakonishok & Smidt, 1988), and firm size effects (Banz, 1981; Keim, 1983; Fama and French, 1992).

More focus in purportedly testing the semi-strong form of the hypothesis has been directed towards explaining the (excess) volatility of asset returns. In order to operationalise a test based on the RVF, Shiller (1981) proposed the use of actual other than expected dividends to obtain a perfect foresight stock price, $P_t^* = \sum \delta^T D_{t+T}$. In particular, the RE/EMH implies that[9] $P_t^* = P_t + \varepsilon_t$, and simple algebraic manipulations yield $VR = \sigma^2(P_t^*)/\sigma^2(P_t) \geq 1$, where VR is the variance ratio and $\sigma^2(x)$ denotes the variance of x. More commonly, in terms of standard deviations, it is easy to see that $\sigma(P_t^*) \geq \sigma(P_t)$, and the corresponding standard deviation ratio (SDR) will obviously also assume a value of greater than (or equal to) unity. This gives an upper bound for the volatility of P_t, given the volatility of P_t^*. By assuming that share prices were stationary, Shiller also demonstrated that the variance bounds could be investigated by putting a limit on the standard deviation of the price change in terms of the standard deviation of dividends, or in terms of the standard deviation of the change in dividends:

[9] An alternative derivation of the variance inequality is in Blake (2000:4000-401).

$$\sigma(\Delta P) \leq \sigma(d)/\sqrt{2r}, \text{ and} \quad (2.8)$$

$$\sigma(\Delta P) \leq \sigma(\Delta d)/\sqrt{2r^2/(1+2r)}. \quad (2.9)$$

These inequalities were the basis of early volatility tests conducted by Shiller (1981) as well as LeRoy and Porter (1981), who confirmed that there was excess volatility on the market (i.e., asset prices overreacted to news and were more volatile than would be implied by the EMH), but not without criticism. One general criticism made against variance bounds tests is that they do not provide explicit forecasting relations for future dividends, but only assume that forecasts are unbiased and that prediction errors are independent of available information. In consequence, non-stationarity of stock prices in this type of tests has the effect of biasing test results (Marsh & Merton, 1986), and creating problems associated with the need to de-trend P_t and P_t^*. Furthermore, some researchers, such as Flavin (1983), have argued that the Shiller-type tests are biased in small samples. Mankiw, Romer and Shapiro (1985) proposed inequality tests that were unbiased in small samples and did not require the assumptions of statitionarity, but the results of their work were in conformity with those of Shiller as well as LeRoy and Porter regarding the predictability of prices.

Instead of using variance bound inequalities, further developments in the literature assert providing a framework for testing the EMH using variance equalities (Cuthbertson, 1996). These tests use the VAR methodology, which seeks to provide explicit forecasting schemes for D_{t+T} in (2.6) and, therefore, the fundamental value of stock. Assuming that the true forecasting model for dividends is the first order autoregressive process $D_{t+1} = \alpha D_t + \varepsilon_{t+1}$, the chain rule of forecasting yields $E_t D_{t+T} = \alpha^T D_t$, and the best estimate for the discounted present value of future dividends, $P_t^{'}$, called the theoretical price, becomes:

$$P_t^{'} = \sum_{T=1}^{\infty} (\delta\alpha)^T D_t = \delta\alpha D_t / (1 - \delta\alpha). \quad (2.10)$$

If both the RVF and the AR(1) model of dividend forecasts are approximately true, then P_t and $P_t^{'}$ will approximately be equal and will move together. Consequently, the variance ratio

$VR = \mathrm{var}(P_t)/\mathrm{var}(P_t^{'})$ will equal unity and, in a regression of P_t on $P_t^{'}$, we would expect a zero intercept and a slope coefficient equal to unity.

The VAR methodology presents some advantages over the variance bounds approach. First, the methodology provides a simple, regression-based framework for evaluating the RE/EMH, in which parameter restrictions are clear. Second, the approach pays great attention to the use of stationary variables, thereby resolving problems associated with non-stationarity encountered in variance inequality tests. Finally, together with the linearisation of the RVF, the VAR methodology permits an investigation of the relationship between one-period returns, multi-period returns and the volatility of stock prices. Applications of the VAR methodology also provide strong and apparently more conclusive evidence of excess volatility, hence potentially profitable return predictability, as documented by Campbell and Shiller (1988, 1989), Campbell (1991), Shiller and Belratti (1992), Bulkley and Taylor (1992), and Cuthbertson and Hayes (1995), among many others investigating in developed markets.

Further notably important contributions to this literature were made by De Bondt and Thaler (1985, 1987), the genesis of whose research was in experimental psychology. Generally, they found that the stock market tended to overreact to unexpected and dramatic news. In their first study, they found that loser portfolios outperformed the market by 19.6 percent on average, while winner portfolios earned about 5.0 percent less than the market. In total, thus, loser portfolios outperformed winner portfolios by 24.6 percent. Their second study supported these results, and also found evidence of calendar effects, questioned the relevance of the CAPM beta, and noted that the small firm effect was partly a losing firm effect.

As already indicated, most of the above tests could, in fact, be tests of the random walk hypothesis rather than the EHM.

2.5.3 The Random Walk Hypothesis

Although various forms of the random walk hypothesis are presented in the literature, this review discusses four, namely the normal strong, strong, semi-strong and weak forms.

The notation adopted in this discussion is as follows. In Section 2.3 we introduced the iid (i.e., 'independently and identically distributed') notation for a time series process. To formalise and extend, if a time series variable, say X_t, is iid with a mean of μ and a variance of σ^2, where t denotes time, we compactly write: $X_t \sim \text{iid}(\mu, \sigma^2)$. Moreover, if the variable is also normally distributed, we denote the process as $X_t \sim \text{iid}\, N(\mu, \sigma^2)$. Now, let $\log P_t$ be the natural logarithm of the stock price at time t, and assume that its dynamics are:

$$\log P_t = \alpha + \log P_{t-1} + \varepsilon_t, \tag{2.11}$$

where α is an arbitrary drift parameter or the expected price change, and ε_t is a random error term. Trivially, continuously compounded returns, R_t, in this process are given by:

$$R_t = \log P_t - \log P_{t-1} = \alpha + \varepsilon_t, \tag{2.12}$$

and will clearly follow the distribution of ε_t. The four forms of the random walk hypothesis for the logarithmic security prices are as follows (Kariya, 1993:20):

RW1: $\log P_t$ is a normal strong random walk process (or arithmetic Brownian motion) if $\varepsilon_t \sim \text{iid}\, N(0, \sigma^2)$;

RW2: $\log P_t$ is a strong random walk process if $\varepsilon_t \sim \text{iid}(0, \sigma^2)$;

RW3: $\log P_t$ is a semi-strong random walk process if ε_t is an independently distributed process; and

RW4: $\log P_t$ is a weak random walk process if ε_t is an uncorrelated process, i.e., if $cor(\varepsilon_t, \varepsilon_{t-s}) = 0$ for $s \neq 0$.

The independence property in RW1, RW2 and RW3 makes the random walk hypothesis yield a fair game in a much stronger sense than the martingale model. This property means that present prices as well as their linear functions are uncorrelated. For all the four forms above, it can be shown that the random walk is a non-stationary process, and that its conditional mean and variance are linear in time (Campbell *et al*, 1997:32). In the literature, it is common to refer to the RW2 model as the linearity property of security returns (Brock, Hsieh & LeBaron, 1993). Notice also the nestedness of the four forms: the weakest and most general RW4 is in all the other three; RW2 also contains RW3; and RW2 is in RW1.

As stated in Section 2.3 and Section 2.4, both the CAPM and the APT assume that RW1 holds. However, because of the non-normalities prevalent in returns data from most markets, RW2 attracts most attention from scholar since, if the linearity property can be satisfied, alternative distributions to the normal could still be used to characterise security returns. On the other hand, as noted by Kariya (1993:20), and Campbell *et al* (1997), RW3 is not particularly plausible and not practically testable without making further restrictive assumptions. Because they are not strictly relevant to static asset pricing, RW3 and RW4 were not of particular interest in this research.

Testing for RW1 typically involves separately testing for the normality and the linearity assumptions. Page (1993) provided a rich survey of the methodologies available to test for normality. For rich surveys of some of the tools available to test for linearity in data, see BrocK, Hsieh and LeBaron (1993), Dechert (1996), Heij, Schumacher, Hanzon and Praagman (1997), as well as Dunis and Zhou (1998), among others[10].

Observations made in most financial markets generally provide universal evidence that return series, particularly in high-frequency data, exhibit the features of non-normality (particularly leptokurtosis), and non-linearity: the evidence provided by the pioneering work of Mandelbrot, (1963), Fama (1965) and Taylor (1986) is now overwhelmingly supported by others, too numerous to be cited, from both emerging and developed markets. From the discussion of the preceding subsection, it should also be clear that most of the purported evidence against the EMH therein cited may, in fact, be evidence against the random walk hypothesis. Further, observations made in developed markets over the past couple of decades have shown that a large positive return on one day is likely to be followed by a large positive return the following day, and *vice versa*. This suggests what is commonly referred to as volatility clustering: squares of returns on securities are highly serially correlated, such that high return volatility periods are generally followed by low volatility periods (Bollerslev, Engel & Nelson, 1994; Pagan, 1996; Blake, 2000:678). In addition, the presence of noise traders in markets could yield cumulative effects, resulting in asset prices overshooting their long-run fundamental values before returning to equilibrium. This situation is known as mean-reversion. These observations, which typically characterise most financial markets, are obviously inconsistent with the random walk hypothesis, since they imply that returns are correlated over time and, hence, potentially profitably predictable through disciplined active portfolio management: "In much the same way as innovations in biotechnology can garner superior returns for venture capitalists, innovations in financial technology can garner equally superior returns for investors" (Lo & MacKinlay, 1999:8). Most relevant to our research, these patterns could entail the presence of non-linearities in security returns.

To summarise, most financial time series exhibit the variational features of non-normality and non-linearity. These distributional features are not consistent with the assumptions of static, iid-based asset pricing models. Although the features are generally more pronounced in high-frequency returns, they also show up, albeit weakly, in low-frequency data (Kariya, 1993). In general, returns on securities tend to be correlated over time, excessively volatile, mean reverting and predictable, in contrast with the speculations of the random walk hypothesis (but not necessarily in conflict with the EMH). Therefore, security returns may best be modelled by employing a dynamic framework that takes these features into account.

2.6 The Dynamic Modelling of Asset Prices and Returns

A broad range of both parametric and non-parametric techniques is available to model the dynamic behaviour of asset returns. The most common non-parametric estimators are the smoothing estimators derived by such methods as kernel regression, orthogonal series expansion, projection pursuit, nearest neighbour-estimators and average derivative estimation[11]. Artificial neural networks is another non-parametric regression method receiving growing attention. Non-parametric methods have the advantage that they can characterise a general equilibrium without strict distributional assumptions of asset returns, and are capable of capturing some of the complex dynamics which parametric models are not able to. One major disadvantage with non-parametric models, however, is that their data requirements are generally much higher than those of parametric models, and may not be easily satisfied in an emerging, thinly traded market such as the JSE.

In terms of parametric models, many time series models available in the literature can be adapted to describe a dynamic multidimensional return generating process. For instance, Schwert (1989) employed a time-varying risk premium framework and used the VAR model to investigate the nature of the causal relationships between key economic variables and the

[10] Some of these tools are used in the present study and contextually discussed in the empirical chapters.
[11] For details, see Campbell, *et al* (1997); Kariya, 1993.

persistent volatility of stock returns. The study did not provide evidence that movements in stock return volatility could be explained by fundamental economic variables, but showed some evidence of the reverse causal relationship. Pena and Box (1987) proposed an extension of the common factor analysis model to capture the time series properties in the data by assuming (primarily) that the common factors describing asset returns followed a VARMA process. However, the model attracted the criticism that the process by which factors and the associated error terms were distinguished led to a situation where the total variance of the error terms dominated the total variance of the systematic parts represented by the factors and, consequently, the factors themselves yielded small variances and could not be easily modelled. Similarly, VAR specifications have not been very effective in the multivariate analyses of stock markets because of associated statistical problems, such as losses in degrees of freedom, the excessive responsiveness of results to variable transformations, additions or omissions, and the non-identifiability of insignificant parameters likely to dominate the model's coefficient matrix, especially when the number of variables is large. Also, VAR methodologies are generally atheoretic, and yield parameter estimates that do not have structural interpretability. In general, model identification in VAR and VARMA processes is not easy to carry out (Tiao and Tsay, 1989). Moreover, the models do not account for the evident non-linearities in returns. Nonetheless, a framework comparable to this, the vector error correction (VEC) model, was found suitable in Chapter 5 of the current research.

Many researchers (e.g., Dockner, Prskawetz and Feichtinger, 1997)[12], have shown that most of the non-linearities in stock returns could be accounted for by the classical ARCH-type models, of which there is a multiplicity. This implies that linearly filtered series could be used to model the dynamics of asset returns within a multivariate framework. The ARCH-type model framework presents the additional advantage that it permits an augmentation that incorporates exogenous factors, such as macroeconomic variables, hypothesised or known to impact on returns over time (Gulley & Sultan, 2003). In addition, the framework permits a direct augmentation of asset-pricing relationships to capture non-linear dynamics (Cuthbertson, 1996:44). The success of ARCH-type models in capturing non-linear security return dynamics in both developed and emerging markets is quite well documented. A brief review of this literature is presented in Section 4.2, and the relevance of this class of

[12] Dockner *et al* used Vienna Stock Exchange data in their study, and showed that the data exhibited the stylised characteristics of excess kurtosis, volatility clustering and high first-order autocorrelations.

univariate models in describing the dynamics of JSE stock returns was extensively explored in this study, in view of the evidence for non-linearities provided in Chapter 3 of this report.

There also exist multivariate ARCH-type models capable of capturing the complex non-linear relationships, such as the VECH model of Bollerslev, Engel and Wooldridge (1988), and the BEKK model of Engel and Kroner (1995), but these tend to become unmanageable very quickly[13]. Given data limitations and the desire for potential practical applicability, the univariate models were considered appropriate in addressing the objectives of this research.

2.7 A Review of the South African Literature

2.7.1. Introduction

The South African research in the field of finance has generally been driven by theoretical and empirical innovations in developed markets. Relative to developed markets, however, Sandler and Firer (1998) submitted that published finance research in South Africa was very limited and dominated by the output of very few active scholars[14]. We review some of the research in this section, and note that there is an overwhelming need to model the dynamical nature of asset returns, taking into account the emerging market characteristic and risk profile of the South Africa environment.

In the spirit of the empirical review presented in subsection 2.5.2, the review of South African studies includes selected studies purportedly testing the EMH on the JSE, in order to capture the evidence on the predictability of JSE security prices and returns. We reiterate that these could potentially be testing the random walk hypothesis rather than the EHM.

2.7.2 Static Asset Pricing and Return Predictability Research in South Africa

The South African research has generally addressed the asset-pricing question by employing the static CAPM and APT. For instance, Bradfied, Barr and Affleck-Graves (1988) employed weekly JSE data for the period from 1 January 1973 to 31 December 1984, and adopted the methodologies of Black and Scholes (1974) and Fama and MacBeth (1973). In keeping with

[13] An excellent survey is in Kroner and Ng (1993).

[14] Based on a review of work published in a comprehensive selection of relevant South Africa journals, Sandler and Firer (1998) noted that a total of only 503 finance (including accounting) articles were published over the period from 1949 to 1997. Of these, only about 15 percent were in the areas of asset pricing, anomalies and market efficiency put together. The fact that research in the field was dominated by very few scholars could compromise scholarly debate and present limited choice to users of the research output.

the market segmentation hypothesis documented in the South African literature[15], the All-Gold index was used as the market portfolio for gold shares, and the JSE Actuaries Overall index for the JSE as a whole[16]. The study showed that the one-parameter CAPM was a reasonable model for the JSE as a whole. For gold shares, however, betas did not seem to perform equally well as predictors of return. The results for gold shares also showed an improvement in the predictability of beta when measured in dollar terms, implying the possible dominance of US investors on the JSE gold market. Finally, the study did not show evidence of the effects of dividend yield, size or liquidity.

The work of Bradfield (1989) addressed the implications of the statistical problem of thin-trading that characterised most emerging capital markets, including the JSE. They used the methodology of Dimson (1979), but adopted the beta estimation adjustment in Cohen *et al* (1983). Using a sample of weekly data for three hundred and sixty shares collected over the period from 1 January 1978 to 31 August 1987, they concluded that the effect of thin-trading on the estimation of beta coefficients was substantial on the JSE[17]. Although the estimator proposed by Cohen *et al* yielded considerable improvements in beta estimation, a more satisfactory improvement was achievable by either using the JSE Actuaries Overall index with at least one lagged and matching coefficient included in the beta estimator, or when the equally weighted index was used.

The question of thin-trading on the JSE was pursued further by Bowie and Bradfield (1993). They investigated the usefulness of a simulation-based beta estimation procedure known as trade-to-trade, and assessed its performance comparatively with the Cohen *et al* technique as well as the traditional ordinary least squares (OLS) technique. Using data for the period from September 1978 to December 1990, the study concluded that the trade-to-trade approach to beta estimation was both more efficient and more consistent than the other procedures. This notwithstanding, the extensive data requirements of the procedure tended to limit its application. Nonetheless, the trade-to-trade procedure has been adopted for use in the Financial Risk Service, a quarterly investor guide incorporating betas for the JSE published by the University of Cape Town.

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[15] See, for a review of this literature, van Rensburg, 1998:16-18.
[16] To capture the dichotomous nature of the return generating process on the JSE, later studies have used the Industrial index as the market portfolio for non-mining shares (e.g., van Rensburg, 2000).

The work of de Villiers *et al* (1986), who used weekly data on two hundred and eight continuously listed industrial shares over the period from January 1973 to December 1982, provided early evidence against the small firm effect on the JSE. The relationship between excess returns, firm size and earnings on the JSE was further investigated by Page and Palmer (1993). In this study, an *ex-post* version of the CAPM, as in Fama and MacBeth (1973), was used on a sample of one hundred and sixty-four firms for the period from 1978 to 1988. Two methods were used in the estimation of beta, namely the OLS technique using the market model, and the technique developed by Dimson (1979) and enhanced by Cohen *et al* (1983). While confirming the results of de Villiers *et al* regarding the size effect, the investigation by Page and Palmer showed that, during the study period, investors could have earned 6.5 percent more per annum by holding high rather than low earnings-to-price ratio securities. This confirmed the results of Basu (1983). The fact that the excess returns reported in the study were generally higher than those reported for other markets purportedly provided evidence that the JSE was less efficient, and did not have similar excess return characteristics as advanced markets.

Firer (1993) conducted an investigation of the estimation of the risk-free rate and the market risk premium for use in CAPM tests within the South African context. While concluding that the problems of estimating these parameters still remained unresolved, he recommended the use of the Treasury bill rate as a proxy for the risk-free rate, and a value of the order of 9 percent for the market risk premium.

Recently, Graham and Uliana (2001) used the methodology in the celebrated study of Fama and French (1992) to examine monthly excess returns on value and growth portfolios selected from industrial companies listed on the JSE over the period from January 1987 to December 1996. The market-to-book equity measure was used to distinguish between value and growth shares for a sample of fifty-eight companies. The study showed that growth shares out-performed value shares in the period up to and including 1992, while in the post-1992 period, the converse was true. This finding raised further doubt about the validity of the CAPM, and suggested that returns were predictable.

Notably early research on the APT was conducted by Page (1986) using both weekly and monthly data for one hundred and twenty companies quoted on the JSE. Allocating shares to

[17] It is generally argued, unsurprisingly, that thin-trading is more prevalent in high-frequency data (such as weekly data) other than low-frequency data. This has prompted some researchers to use monthly other than

four groups, he used a stepped factor analytic approach to identify priced factors for inclusion in the APT. His study led to the conclusion that a two-factor model could explain security returns on the JSE. Moreover, his comparison of the APT and the CAPM showed that the former performed substantially better than the latter. While the question of factor identification was not fully addressed, the findings provided evidence of the market segmentation hypothesis: the macroeconomic variables that determined the return generating process could be divided into those that influenced the mining sector and those that influenced the industrial sector.

In a follow-up study, Page (1989) used a bootstrapping routine to compare the efficiencies of four benchmarks that could be used for measuring security price performance on the JSE. Three of these were CAPM-based (a mean-adjusted returns model, a market-adjusted returns model and a market-and-risk-adjusted returns model) while the fourth was based on the APT (a two-factor returns model). The models were evaluated and compared on the basis of four ex-post forecasting statistics, namely the root-mean-square simulation error, the mean simulation error, the mean-absolute simulation error and the Theil's inequality coefficient. The research was based on weekly excess returns on thirty securities quoted on the JSE over the period from January 1981 to December 1984. His results showed that the two-factor model was the best on the basis of three of the four statistics. Generally, the mean-adjusted returns model and market-adjusted returns model performed most poorly compared to the other two, with the former producing the poorest results.

Barr (1990) addressed the question of the macroeconomic identification of priced factors for twenty-six non-gold JSE securities over the period from 1979 to 1987. He used both the covariance biplot technique as well as factor analysis. Guided by Page (1986), Barr confined the analysis to the identification of two factors, and identified the five most important indices in each of the two factors. The analysis showed that the first factor predominantly comprised industrial-oriented indices, while the second factor predominantly comprised financial-oriented indices. Barr used thirty-five macroeconomic variables to identify the economic forces driving the two factors. His conclusion was that the first factor was driven by gold and interest rates, while the second was driven by foreign share markets and local property effects. Breaking down the study period into several sub-periods permitted an investigation of which of the two factors dominated in each sub-period. This, in turn, facilitated an investigation of when the various sectors of the market performed best, and which economic

weekly data.

forces were driving these sectors over each sub-period. Generalisation of the results to the entire JSE, however, could be compromised by the omission of gold shares from the sample.

Further evidence of the firm size and earnings anomalies on the JSE was provided by Page (1996) within the framework of the APT. He outlined a methodology for establishing alternative APT-based benchmarks for use in tests of market efficiency. The selection of priced factors was based on Page (1986) and Gilbertson and Goldberg (1981), both of whom had concluded that security returns on the JSE could be explained by at least a two-factor model. The tests for size and earnings anomalies were based on a sample of one hundred and forty-five industrial companies. Estimates of parameters for both the CAPM and APT regressions were obtained, and the methodology for portfolio construction was generally as in Fama and French (1992). The analysis showed that using the APT-based benchmarks had no significant impact on the results found when using the CAPM-based benchmark. The implication of this result was that any model mis-specification within the CAPM framework could not be removed by adopting the APT approach. The addition of up to five factors did not lead to a decline in the size and earnings anomalies. On the contrary, model efficiency tended to decline as more explanatory variables were added. The authors admitted, however, that their results could have been influenced by the limited size of the sample used, which directly impacted on their portfolio construction procedure. Further, the procedure for constructing factor-mimicking portfolios questionably assumed stationarity in the time series. This assumption was not formally established in the study.

In a relatively recent study, van Rensburg and Slaney (1997) applied factor analytic methods on monthly JSE data for the period from January 1985 to December 1995 to test the APT. They used observable macroeconomic proxies to explain the extracted latent factors, in order to achieve economic interpretability of their results as well as to resolve the power problems associated with factor analysis, as recorded in Page (1993). Using principal factor analysis, principal components analysis as well as the maximum likelihood method, van Rensburg and Slaney, provided further evidence for the market segmentation hypothesis, but argued that a two-factor APT model using both mining and industrial indices as factors, captured the relationship better than the 'two security market line approach' proposed by Campbell (1979) and Venter, Bradfield and Bowie (1992). The study also addressed the problem of non-linearities in data by adopting the non-linear seemingly unrelated regression technique of Gibbons (1982), and Burmeister and McElroy (1988). This technique was also employed in the pre-specified variables approach to factor identification in van Rensburg

(1996), based on the work of Chen *et al* (1986) and Burmeister and Wall (1986). The sample used in the latter study constituted seventy-two non-thinly traded and continuously listed JSE securities for the period from January 1980 to December 1989. The study concluded that variability in JSE security returns was significantly explained by unexpected movements in the Dow-Jones Industrial index, short-term interest rates, the term structure of interest rates and a residual market factor.

Apart from the research already reviewed in the context of asset pricing, limited extra work has been done to test for return predictability in the South African environment. A relatively early investigation of the impact of dividend signalling announcements on JSE share pricing was documented by Knight and Affleck-Graves (1987). Using weekly share price data and related variables for about two hundred listed companies over the period from February 1973 to November 1980, their empirical results based on both the abnormal performance index (API) and the cumulative average residuals (CAR) methods showed that dividend announcements conveyed little or no information to the market in excess of the information contained in earnings announcements. The study concluded, therefore, that the JSE was 'dividend-information efficient'. The dividend signalling effects were further investigated in the more recent studies of Bhana (1997, 1998). In both studies, contrary to the conclusion by Knight and Affleck-Graves, it was established that dividend announcements significantly led to increases in company share prices and returns in a manner that strongly ruled out the possibility of effects arising from other contemporaneous announcements.

The Monday effect on the JSE was studied by Bhana (1985) and Davidson and Meyer (1993). Using both parametric and non-parametric techniques, Davidson and Meyer were unable to confirm the result of Bhana that the Monday effect was present on the JSE. In yet another study, Bhana (1989) investigated the reaction of JSE listed security returns to the arrival of new information. Using monthly data of all JSE listed companies for the period from 1970 to 1984, Bhana showed that JSE listed companies overreacted to both unfavourable company-specific news events and earnings announcements, and that the magnitude of the overreaction to unfavourable news events could potentially enable astute investors to outperform the market. On the other hand, the study noted that the JSE did not overreact to unexpected favourable news.

Page and Way (1992) replicated the studies of De Bondt and Thaler (1985, 1987) within the South African environment, and concluded that loser portfolios outperformed winner portfolios by 15 percent on the JSE. The semi-strong form of the EMH was tested using JSE data by Glass and Smith (1995) by investigating the relationship between monetary policy and changes in share prices. By regressing the JSE All Share index on anticipated and unanticipated monetary growth variables, the study showed that share price movements were partially predictable, because they could be partially explained by lagged changes in anticipated monetary growth, but not unanticipated monetary growth. The results were, however, only interpretable with caution on account of a low coefficient of determination.

Hattingh and Smit (1993) examined the existence of various seasonal effects in the price movements of South Africa's three frequently traded bonds (i.e., Post Office, Eskom 168 and RSA) as well as three major JSE equity indices (i.e., Gold, Industrial and All Share). The study found that both the bond and share indices displayed seasonal patterns, and that these patterns were somewhat similar in the two markets. In particular, the study established that the patterns were most significant for Eskom 168 and RSA bonds, as well as for the Industrial and All Share indices, but were weak or non-existent in Post Office bonds and the Gold index. The similarity in the seasonal patterns displayed by the two markets was in contrast with documented evidence from other markets (e.g., Jordan and Jordan, 1991). In a study comparable to the foregoing, Watson and Smit (1994) investigated the existence of seasonal patterns in three South African share near futures contracts, as well as their underlying share indices. The underlying indices were exactly those studied in Hattingh and Smit. The study concluded that the seasonal patterns in the futures market and the spot market were similar, contrary to the results documented by Johnson, Kracaw and McConnell (1991) for the relation between spot and futures markets of American Treasury bills.

Bhana (1995) tested a modified version of the EMH called the uncertain information hypothesis (UIH) to investigate further the reaction of the JSE equity market to the arrival of unanticipated information. The UIH was employed "in order to explain the response of rational, risk-averse investors to news of a dramatic financial nature". The study used data on the JSE All Shares index as well as the largest two hundred companies listed on the JSE to model the effects of both market-wide and company-specific surprises (unanticipated price changes) during the period from 1975 to 1995. By being unable to support the hypothesis that investors consistently over-reacted to new information, the study contradicted the overreaction hypothesis of De Bondt and Thaler (1985, 1987), and actually found evidence in favour of market efficiency.

The question of whether South African financial time series exhibited long-term persistence was investigated by Bendel, Smit and Hamman (1996), using the non-parametric technique of rescaled range analysis. The study established unequivocal evidence of long-term persistence in the All Share, Gold and Industrial indices. This observation was in conflict with the weak form version of the EMH, since it implied that future JSE share returns depended on past returns. On the other hand, the evidence for persistence in gold prices, interest rate series and the exchange rate was either very weak or non-existent.

In another study, Smit and Smit (1998) investigated the presence of a holiday effect on daily returns of the three near futures contracts treated in the Watson and Smit (1994) study already discussed. Distinguishing clearly between pre-holidays, post-holidays and non-holidays, the study concluded that there was no significant and exploitable evidence of holiday effects in any of the three near futures contracts, and that holidays did not influence the documented month-end effect prevalent in the market. Nonetheless, based on the evidence, the study noted that sellers could benefit from higher mean pre-holiday returns, while buyers could take advantage of lower prices during post-holidays.

The prior evidence of seasonal patterns on the JSE was updated by Roux and Smit (2001), who re-examined the existence of calendar effects already examined by Hattingh and Smit (1993) and Watson and Smit (1994), among others. In addition to the indices treated in the said prior studies, Roux and Smit also included the Financial index. In order to assess the persistence of the anomalies, the study period of 1978 to 1998 was divided into two sub-periods, the second sub-period beginning with the calendar year in 1990. In the first sub-period, the study found evidence of significant Monday effects as well as some evidence of turn-of-the-year effects. However, these effects did not seem to persist in the second sub-period, during which week-of-the-month and turn-of-the-month effects were evident. Thus, the study concluded that the Monday effect was no longer present on the JSE (except for the case of the Financial index), and validated the observation by Wang, Li and Erickson (1997) that the Monday effect could largely be due to Monday returns in the latter part of the month. Further, there was evidence that the week-of-the-month effect could be considered a manifestation of the turn-of-the-month effect.

Coutts and Sheikh (2002) recently re-investigated the existence of the weekend, January and pre-holiday effects in the JSE All Gold index using data for the period from 1987 to 1997, and found no evidence of any such calendar effects. The results, notably in contrast with stylised facts regarding the existence of such calendar effects in most other markets, were attributed to the microstructure of the JSE or the construct of the All Gold index used.

The foregoing studies would seem to indicate, albeit inconclusively, that there was less empirical evidence in support of the EMH is South African financial markets.

2.7.3 South African Dynamic Asset Pricing and Return Predictability Research

Very limited work has attempted to investigate the statistical properties of JSE stock prices and returns, as well as the dynamic nature of asset returns in pricing relationships. Among the first relevant observations were those made by Page (1993) who, using a wide range of tests for normality, confirmed the presence of non-normalities in two hundred and forty-four JSE equity returns traded over the period from February 1973 to March 1992. Forty-five of the securities in his sample were quite frequently traded. Using non-parametric runs tests, he also found evidence suggesting that the security returns were non-stationary processes. This suspicious result could have been influenced by the test methodology employed, and would need to be validated using the now popularised, relatively more reliable, unit root testing methodologies in the literature (Dickey and Fuller, 1979, 1981; Perron, 1989, 1994). In addition to the foregoing, while confirming the superiority of the APT over the CAPM further, Page noted that non-normalities had no significant effect on his APT estimation results. One major conclusion of the study was that most empirical procedures employed in the determination and pricing of factors lacked power, a result that could also explain the irrelevance of non-normalities in improving the pricing relationship.

The SUR procedures invoked by van Rensburg (1996) as well as van Rensburg and Slaney (1997) to account for non-linearities within the APT framework were already discussed in the preceding subsection. One point worth noting, however, is that the actual structure of non-linearities being modelled remained uncovered in the studies. More recently, Craig and Bendixen (1998) investigated whether transfer function or multivariate autoregressive integrated moving average (MARIMA) modelling could improve the estimation of the systematic risk component on the JSE. The data used were weekly closing prices of industrial shares for the period from 1 January 1988 to 31 December 1995. The results of the study did not provide compelling evidence against the use of the conventional OLS regression technique, and showed situations where OLS produced better beta estimates. However, the study focused on the estimation of the CAPM beta, and did not address the potential multifactor characterisation of the return generating process. It is also already noted that such models do not account for non-linearities in data. Since the sample used constituted industrial shares only, the results might not be generalised to the entire JSE.

The question of linking variability in security returns to macroeconomic factors was pursued further by van Rensburg (1999) who, in the process, also addressed some dynamic issues in asset pricing. The study sample period of 1965 to 1995 was chosen such as to accommodate the turbulence associated with democratisation in South Africa and, therefore, the socio-economic and institutional effects that bear historical significance. The study addressed the problems associated with stationarity by taking first differences in otherwise non-stationary time series, including returns. The study confirmed that equity returns were 'forward-looking', anticipating and responding to future economic activities as proxied by growths in such macro-level variables as expenditure, building plans, the current account balance, and savings. To explore the predictability of candidate factors, van Rensburg employed Granger-causality tests within a VAR model framework using quarterly data, and noted that the dynamic nature of the system contained statistically significant predictive power regarding the business cycle, short term interest rates, the current account balance and, mildly, returns on the All-Gold index. It is noted that, although the data were generally non-stationary, the study did not investigate the possibility that they could be cointegrated. Moreover, because the times-series behaviour of asset returns is generally more pronounced in high-frequency data, it is likely that the results were affected by the use of quarterly data. Nonetheless, the study found that returns on the All-Gold index were mildly predictable, and that the driving forces could be growth rates in gold sector earnings, rand gold returns and the balance on the current account. van Rensburg submitted that "Whether this is an exploitable example of informational efficiency or the manifestation of time-varying expected returns is a relevant area of future research".

2.7.4 Remarks

From the foregoing review of the South African empirical literature, at least three general observations can be made. Firstly, the evidence suggests that a multifactor model, particularly the APT, could be the preferred general equilibrium model on the market, in spite of the support for the CAPM documented in the earlier literature. Secondly, the evidence for or against the EMH (or return predictability) remained quite inconclusive on the market, although it tended to be chiefly on the less supportive side for the hypothesis than the converse. Thirdly and most importantly for the current research, it is strongly evident that the dynamic behaviour of JSE equity returns has not received adequate attention, especially in terms of attempting to provide a comprehensive link with asset pricing and return predictability.

Being an emerging capital market, the volatility of JSE equity returns is likely to be quite high, and the profile of risk potentially different from that observed in developed markets, due to domestic market characteristics. This would impact on the predictability of asset prices and returns, and the characterisation of the equilibrium asset pricing model that should be used in asset allocation decisions by investors. Prior research has attempted to address the asset pricing question within the static CAPM and APT frameworks, implicitly assuming the normal strong random walk property in security prices, and employing linear regression or, to a much less extent, non-linear SUR techniques. In general, the statistical time series properties of JSE data have not been extensively studied: while compelling evidence for non-normalities was available (although from only one study that we could access), the linearity assumption seemed inadequately explored, if at all. An investigation of the dynamic characterisation of the JSE equity pricing relationship, taking into account the time series properties of equity prices and/or returns and the socio-economic environment in which the JSE operates, could inform further economic research as well as portfolio management.

2.8 Summary and Conclusion

This chapter reviewed modern portfolio theory as well as the theories of asset pricing and return predictability. A review of selected international and South African empirical literature was also made. While most asset pricing models based on modern portfolio theory are static (single-period) and linear, the time series features of financial data observed in most markets tended to contradict the normal strong random walk hypothesis of asset prices and returns, necessitating a dynamic framework for modelling and predicting asset prices and returns. A review of the relevant selected literature showed that this issue does not seem to have been sufficiently addressed in prior South African research.

Because the random walk assumptions of security prices and returns do not seem to have been fully investigated using JSE data, and in order to contextualise the dynamic modelling of JSE returns properly, a natural take-off point in an investigation of this nature would be a validation of the statistical properties of the JSE price and return series. This matter is addressed in the chapter that follows.

3.2 Research Methodologies

This section builds on the general methodological framework of Section 1.4, and focuses on the data used and specific methodologies adopted to investigate the stated hypotheses of the current chapter. The investigations were conducted using the two stock portfolios as well as the forty-four individual stocks.

3.2.1 Data

The primary data used in the analysis conducted in this chapter were weekly close prices for the forty-four selected stocks and the two aggregates. The stocks and aggregates are described in Section 1.4. The study period extended from 23 February 1973 to 5 April 2002 for the individual stocks and PORT, and from 23 December 1983 to 5 April 2002 for ALSI. For the period up to 22 September 2001, close price data on the individual stocks were obtained from an online database maintained by the Statistical Sciences Department of the University of Cape Town, while the rest of the data up to April 2002 were obtained from the Inet-Bridge online database, courtesy of the Department of Accounting at the University of Cape Town. The close price data on ALSI, spliced back to 1983, were also sourced from the Inet-Bridge. Where necessary, the security price data were adjusted at source for stock splits and market capitalisation issues.

Using the close prices, and ignoring dividends due to the unavailability of reliable data, continuously compounded returns were computed as logarithmic price differences, i.e.:

$$R_t = \log P_t - \log P_{t-1} \quad , \tag{3.1}$$

where R_t was continuously compounded return at time t, P_t was the close price at time t; and $\log$ denotes the natural logarithm. Since the computation of returns required that the start date for observations of the return series necessarily be one week after the first close price observation, the start dates for the price series were also adjusted, through the elimination of the first observations for each price series, to coincide with that of the return series. As such, the final sample had 1519 observations of price and return series for each individual stock and PORT, and 954 observations for ALSI[1].

[1] To be precise, the weekly sample of 1519 observations was for the period from 3 March 1973, while that of 954 observations started on 30 December 1983. Both samples extended to 5 April 2002.

3.2.2 Testing for Stationarity

In order to test for stationarity in each of the variables in our sample, we used the Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) tests, as well as the Perron test for stationarity in the presence of structural change.

The various DF test equations that could be used are expressed as in (3.2) to (3.4), while the ADF test equations extend each of the DF equations by including lagged dependent variable terms in order to correct for serially correlated residuals. Thus, for the DF test equation (3.4), the corresponding ADF equation is expressed as (3.5), with equivalently corresponding formulations for (3.2) and (3.3):

$$\Delta x_t = \delta x_{t-1} + \varepsilon_t ; \tag{3.2}$$

$$\Delta x_t = \alpha_1 + \delta x_{t-1} + \varepsilon_t ; \tag{3.3}$$

$$\Delta x_t = \alpha_1 + \alpha_2 T + \delta x_{t-1} + \varepsilon_t ; \tag{3.4}$$

$$\Delta x_t = \alpha_1 + \alpha_2 T + \delta x_{t-1} + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \varepsilon_t . \tag{3.5}$$

In (3.2) to (3.5), x_t is the logarithmic price or return series being tested for stationarity, T is a trend variable, α_1, α_2, δ and β_i are coefficients, while the ε_t terms are (white noise) residuals. Subscript t denotes time. In all the equations, the null hypothesis of non-stationarity is that $\delta = 0$, and the test is resolved by comparing the t-statistic for δ with the appropriate MacKinnon critical values at conventional levels of significance, rejecting the hypothesis whenever the test statistic is in excess of the critical value. Note that the presence of a unit root in the series could imply that the series are martingale, or even random walk processes, and unpredictable (Fama, 1991; Kariya, 1993; Kasch-Haroutounian & Price, 2002).

In order to establish the appropriate ADF autoregressive structure for each variable, the following procedure was adopted. Firstly, (3.4) was run, and the presence of up to tenth order serial correlation in the residual estimates was investigated using the Breusch-Godfrey Lagrange Multiplier test. For series that did not exhibit any such correlation, it was concluded that the residuals from (3.4) were not serially correlated, and that the DF test results were adequate for resolving the unit root hypothesis. For each model with serially correlated errors, we followed Charemza and Deadman (1997:104-105) by seeking the highest in this regard was as follows. For each of the series, the least restrictive (3.4) or, where appropriate, (3.5) was initially estimated. For those series where the unit root hypothesis could not be rejected using the least restrictive model, we then used three statistics denoted ϕ_1, ϕ_2 and ϕ_3, provided by Dickey and Fuller (1981), to test some joint hypotheses on the coefficients and, hence, investigate the effects of including trend and/or intercept terms on the test results. Specifically, ϕ_1 was used to test the null hypothesis that $\alpha_1 = \delta = 0$; ϕ_2 was used to test the null hypothesis that $\alpha_1 = \alpha_2 = \delta = 0$; whereas ϕ_3 was used to test the null hypothesis that $\alpha_2 = \delta = 0$. Under each appropriate null hypothesis, the ϕ_i-statistics were computed as in the standard subset *F*-test for linear restrictions, i.e.:

$$\phi_i = \frac{R_{UR}^2 - R_{RR}^2}{1 - R_{UR}^2} \cdot \frac{n-k}{r}, \qquad (3.6)$$

where R_{UR}^2 and R_{RR}^2 were, respectively, the coefficients of determination in the unrestricted and restricted models; n was the sample size; k was the number of parameters, including intercept and augmentation coefficients, in the unrestricted model; and r was the number of linear restrictions imposed to move from the unrestricted to the restricted model. Because the three test statistics have a distribution that is different from the standard *F*-distribution, the appropriate critical values for resolving the tests have been provided by Dickey and Fuller (1981) and are reported in Appendix 3A.

Following Enders (1995), however, the foregoing procedure for resolving whether trend and intercept terms should be included was only applied where the hypothesis of a unit root could not be rejected in the appropriate least restrictive model used (i.e., either (3.4) or (3.5)). Since these tests are generally associated with low power to reject the null hypothesis of a unit root, Enders advises against proceeding to test for the hypothesis in restricted models if the hypothesis may be rejected in the least restrictive of the plausible models.

Eyeball inspections of the security price series generally provided some evidence for the presence of unit roots, and the typical pattern for logarithmic prices is depicted for PORT and ALSI in Panel I of Figure 3.1. Moreover, these inspections also provided some *prima facie* evidence that our formal test results could have been affected by the presence of structural breaks during the study period. Evidence that South African econometric models could exhibit structural instability due to changes in the economic and political environment was documented by Smit and Wesso (1988). As argued by Perron (1989) and others, unit root tests that do not allow for the presence of structural breaks, such as the DF and ADF tests, are likely to have low power for rejecting the null hypothesis of a unit root. In order to address this concern, we invoked Perron's (1989, 1994) procedure to test for stationarity in the presence of structural change. Among the available options, the following so-called innovational outlier model was used, in order to allow both the intercept and trend terms to change simultaneously:

$$x_t = \alpha_1 + \alpha_2 T + \theta_1 DU_t + \theta_2 DT_t^* + \theta_3 D(T_b)_t + \gamma x_{t-1} + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \varepsilon_t \,. \qquad (3.7)$$

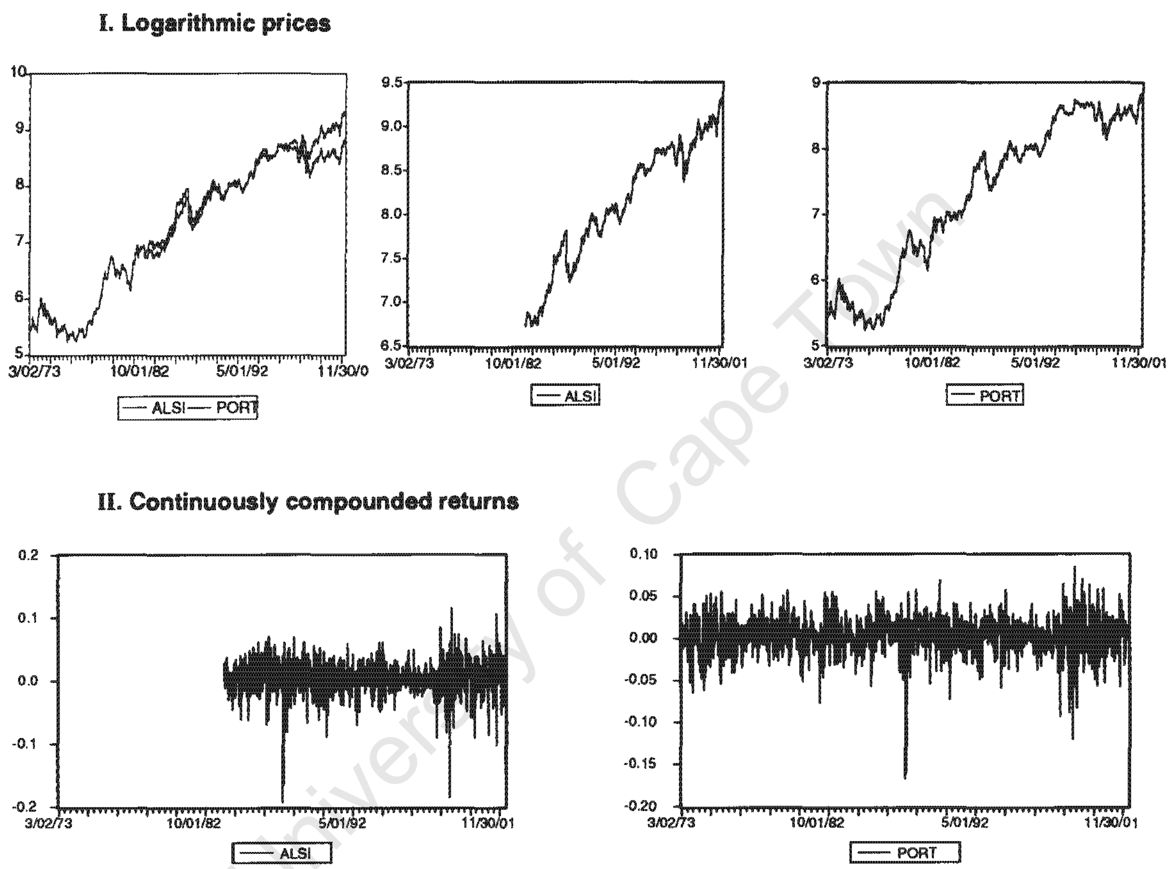
In (3.7), x, T, t and ε are as defined in (3.2) to (3.5), and the break date is identified as T_b. For all $t > T_b$, we set $DU_t = 1$ and $DT_t^* = t - T_b$, but zero otherwise. Lastly, we set $D(T_b)_t = 1$ if $t = T_b$ but zero otherwise. The hypothesis of a unit root was resolved using the *t*-statistic for testing the null hypothesis that $\gamma = 1$, using appropriate critical values as described latter in this subsection. Since, for each series, the autocorrelation structure in this framework must be identical with that of the ADF model, the ADF augmentation structures were used.[2].

The identification of potential permanent shocks, and hence the selection of potential values for T_b within our sample period, was first guided by the turbulent political history of South Africa, which had significantly influenced the country's economic policies and the pattern of its business cycle. In addition to these internal shocks, we also considered the likelihood of contagion effects from other international financial markets, in particular the Asian Crisis of 1997-98. Therefore, weeks inclusive of the following dates were considered as possible break points: 16 June 1976 (Soweto Uprising), 21 July 1985 (State of Emergency), 10 May 1994 (Majority Rule) and 17 August 1998 (Asian Crisis). The political and economic motivations for the selection of these potential break points are summarised in Appendix 3B, and reverted to in Chapter 5. In Panel I of Figure 3.1, the somewhat negative effects on the market of the shocks of July 1985 and August 1998, as well as the optimism associated with the run-up to majority rule, are quite apparent. From the first graph of Panel I, notice also that

[2] Our attempts to re-work out the augmentation structures for the Perron test using the procedure described under the ADF test yielded the same structures as those achieved for the ADF test.

the dynamics of PORT very closely approximated those of ALSI during the entire period where data were available, except around the period of the Asian Crisis.

Figure 3.1 - Behaviour of the JSE during the study period



Because the foregoing framework for resolving the unit root hypothesis in the presence of structural breaks does not involve the simultaneous investigation of multiple break points, the optimal value for T_b was selected endogenously for each series, following Christiano (1992). In particular, the optimal T_b was selected as the value that maximised the (absolute) value of the *t*-statistic for testing the null hypothesis that $\theta_2 = 0$ in (3.7). Compared with the alternative method of selecting T_b as the value that would minimise the *t*-statistic for testing the null hypothesis that $\gamma = 1$ (Zivot & Andrews, 1992; Banerjee, Lumsdaine & Stock, 1992), the Christiano approach was chosen because it generally allows greater power (Rao, 1994:136). Moreover, in order to avoid making the assumption of a one-sided change, the break date was selected by maximising the absolute value of the *t*-statistic constructed under the null hypothesis of $\theta_2 = 0$. The appropriate asymptotic critical values for resolving the unit root hypothesis under these conditions are provided by Perron and Vogelsang (1993, in Rao, 1994), and were accordingly used in the ensuing two-sided tests.

By way of digression, note that if the unit root hypothesis is rejected, (3.7) can be used to analyse the behaviour of the market during the periods of the political and economic turbulences. This tool is available as one realises that θ_1 and θ_2 in (3.7) respectively measure the change in the intercept and slope of the trend function. Therefore, the hypothesis of a one-time change in the regression equation (against the alternative of a permanent structural break) could be resolved by testing for the statistical significance of θ_1 and θ_2, since then T_b is a consistent estimate of the break point, and the *t*-statistics for θ_1 and θ_2 are asymptotically normally distributed. However, these properties will not hold for T_b and the *t*-statistics for θ_1 and θ_2 if the unit root hypothesis is not rejected, because of the usual problems associated with non-stationarity. In such circumstances, the above framework might not be useful in studying further the behaviour of the JSE during the described turbulent periods.

Since the calculation of continuously compounded returns inherently involved data de-trending (and the integration of typically non-stationary series), the test for stationarity in the presence of structural change was only applied to the logarithmic price series. A graphical inspection of the return series showed that it would be overly presumptuous to suspect permanent structural breaks: the series generally displayed a non-trending pattern with a constant mean of about zero throughout the study period, despite few instances of mean-reverting outlier observations. These patterns are illustrated for PORT and ALSI in Panel II of Figure 3.1.

3.2.3 Testing for Random Walk Properties

In addition to the unit root hypothesis, two further aspects of random walk properties in stock market data have generally attracted the attention of researchers, namely normality and linearity. In general, data are said to satisfy the normality property if their probability density function is consistent with that of a normally distributed random variate: generally a symmetric (i.e., skewness equals zero) distribution with a kurtosis parameter of three. Further, a series is said to satisfy the linearity property if it is an independently and identically distributed (iid) process. When both the normality and linearity properties are satisfied in the return series, the underlying price series is said to follow a normal strong random walk process. On the other hand, when the return series is non-normal but iid, it follows a strong random walk process (see Section 2.5). As discussed in the previous chapter, our interest in these properties derives directly from traditional asset pricing theory, which assumes joint multivariate normality and linearity as characterising the distributions of asset returns.

3.2.3.1 Normality Tests

Page (1993) provides compelling evidence that JSE security returns are not normally distributed, and this point did not belabour the present research beyond seeking to buttress the available evidence. The present study examined the descriptive statistics (such as mean, standard deviation, skewness and kurtosis) of the returns for each of the selected stocks and stock portfolios, in order to assess their conformity with the normal distribution. The normality hypothesis was more formally resolved by using the Jarque-Bera test. Following Page, joint multivariate normality was evaluated on the basis that it should arise if the variables were individually normally distributed.

In order to use the basic descriptive statistics for the purpose of resolving the normality hypothesis, note that skewness and kurtosis are the normalised third and forth moments of a random variable[3]. Therefore, when computed for a normal variable, their estimates based on a large sample of size n have means of 0 and 3, and variances of $6/n$ and $24/n$, respectively (Stuart and Ord, 1987). Further, under the null hypothesis of normality and given that our sample sizes were large, the resulting asymptotically standard normally distributed statistics for the sample skewness and sample kurtosis of each return series, respectively denoted $z_{\hat{S}}$ and $z_{\hat{K}}$, were computed in the study as:

$$z_{\hat{S}} = \frac{\sqrt{n}\hat{S}}{\sqrt{6}}, \text{ and} \tag{3.8}$$

$$z_{\hat{K}} = \frac{\sqrt{n}\left(\hat{K}-3\right)}{\sqrt{24}}, \tag{3.9}$$

[3] Formulae for skewness and kurtosis are provided in standard statistics and financial econometrics textbooks. See, for instance, Campbell *et al* (1997:17).

where $\hat{S}$ was sample skewness, $\hat{K}$ was sample kurtosis, and n = 1519 for all series but ALSI, for which n = 954.

The Jarque-Bera test statistic (JB) is also based on a measure of the difference of the skewness and kurtosis of the series with those from the normal distribution. Under the null hypothesis that the series is normally distributed, the statistic is computed as:

$$JB = \left[\hat{S}^2 + \tfrac{1}{4}\left(\hat{K} - 3\right)^2\right]\frac{n-k}{6}, \qquad (3.10)$$

where $\hat{S}$, $\hat{K}$ and n are as defined, and k is the number of estimated coefficients used to create the series.[4] The JB statistic has a χ^2-distribution with 2 degrees of freedom.

3.2.3.2 Linearity Tests

In order to investigate whether the variables satisfied the linearity assumption, we first used a simple test due to Engle (1982), but attached greater reliance on the test results based on the procedure due to Brock, Dechert and Scheinkman (1987), commonly referred to as the BDS test. Although other tests are proposed in the literature (see, for instance, Tsay, 1986; Hsieh, 1989), these two were chosen because they are known to have power against most non-linear models. For instance, while the Engel test was originally intended to detect the autoregressive conditional heteroscedasticity (ARCH) process, McLeod and Li (1983) as well as Brock, Hsieh and LeBaron (1993) showed that this test was quite robust and could be used to identify many types of non-linearities. On the other hand, Hsieh (1991) also argued that the BDS test had power to detect many forms of chaotic and stochastic non-linearities in a random variable, including non-stationary and non-egordic processes, non-linear moving average (NMA) and threshold autoregressive (TAR) processes, as well as ARCH-type models, of which there are many formulations. Brock *et al* (1993) further demonstrated that both the BDS test and the Engle test had power against the tent map, NMA, TAR and some ARCH-type models. They also showed that the BDS test had power against the generalised ARCH (GARCH) of Bollerslev (1986), but that the Engel test was not equally reliable in testing for this process. In contrast, the Tsay test exhibited lower power against Engle's (1982) original ARCH model in the Brock *et al* (1993) illustration. The Tsay test is related to

[4] Refer to the EViews 3.1 Help System

the Hsieh test, since both are based on higher moments of the data, and both have not been found useful in detecting complex non-linearities in time series.

The easier, but comparably powerful Lagrange Multiplier linearity test proposed by Engel is generally conducted as follows. Firstly, a linear model is fitted to the data, in order to obtain residual estimates. Secondly, a *k*th order autoregression (with an intercept term) of the squared residuals from the linear model is estimated, to obtain the coefficient of determination, R^2, hence to computed the χ^2_k-distributed Lagrange Multiplier test statistic, nR^2, where n is the sample size of the original series.

To implement the Engle test in this study, the following autoregression was fitted to each return series:

$$R_t = \alpha + \sum_{i=1}^{p} \rho_i R_{t-i} + e_t \,, \tag{3.11}$$

where t was the current period, α was an intercept term, ρ_i were coefficients, e_t was an uncorrelated error term, and the AR structure was chosen such as to remove any autocorrelation that could arise from non-synchronous trading or otherwise. The exact procedure used to choose the AR terms and to filter autocorrelation from the data is described below in the context of the BDS test, since the same procedure was used in both tests. Where serial correlation could not be detected it was assumed that $\rho_i = 0$ for all i in (3.11), and the actual linear model used was simply $R_t = \alpha + e_t$. Finally, the autoregressive structure fitted to squared residual terms followed a specific-to-general modelling approach. Thus, if the null hypothesis of linearity could be rejected in the simple AR(1) process for the squared residuals, we investigated no further. However, if the null hypothesis could not be rejected in all autoregressions up to the tenth order, it was concluded that there was no evidence of non-linear dynamics in the data.

The more reliable BDS test procedure culminates into the computation of an asymptotically standard normally distributed test statistic for resolving the iid hypothesis. As illustrated by Hsieh (1989, 1991) and others[5], the test is conducted as follows. Firstly the series are pre-

[5] See also Scheinkman and LeBaron (1989), Brock *et al* (1993), as well as Campbell *et al* (1997).

filtered with an autoregression in order to remove autocorrelation, if it is detected. Secondly, the (pre-filtered) data are organised into non-overlapping m-histories, say x_t^m, defined as:

$$x_t^m = \{x_{t-m+1},\dots,x_t\}, \tag{3.12}$$

where the parameter m is called the embedding dimension[6]. The third step involves the calculation of correlation integrals, each of which is the limit, as the sample size increases, of the fraction of pairs of m-histories close to each other. Specifically, for a given number, l, the pair of m-histories, x_s^m and x_t^m, is said to be close to one another if the greatest absolute distance between the corresponding members of the pair is smaller than l; i.e.:

$$\max_{i=0,\dots,m}\left|\hat{x}_{s-i} - \hat{x}_{t-i}\right| \le l. \tag{3.13}$$

Thus, l measures the closeness of the pair of m-histories. Further, a categorical variable, L_{st}, based on l, is defined to equal one if (3.13) holds, and zero otherwise. The correlation integral is, therefore, defined as:

$$C_m(l) \equiv \lim_{n\to\infty} \frac{2}{n(n-1)} \sum_{s<t} L_{st}, \tag{3.14}$$

where n is the sample size. Accordingly, the sample correlation integral becomes:

$$C_{m,n}(l) \equiv \frac{2}{n_m(n_m - 1)} \sum_{s<t} L_{st}, \tag{3.15}$$

where $n_m = n - m + 1$.

The final step involves the calculation of the BDS test statistic. Brock *et al* (1987) showed that, under the null hypothesis that a given series is iid, even when l is finite, we have:

$$C_m(l) = [C_1(l)]^m \tag{3.16}$$

[6] It should not be confusing that the same notation, x_t, was adopted for both the raw data and the filtered data.

for a given n and for fixed m and l. Furthermore, they showed that the following test statistic:

$$W_{m,n}(l) = \sqrt{n}\,\frac{C_{m,n}(l) - [C_{1,n}(l)]^m}{\hat{\sigma}_{m,n}(l)} \tag{3.17}$$

is asymptotically standard normally distributed. In (3.17), $C_{m,n}(l)$ and $C_{1,n}(l)$ are sample correlation integrals defined as in (3.15), and $\hat{\sigma}_{m,n}(l)$ is an estimator of the asymptotic standard deviation under the null hypothesis. A formula for the population variance, $\sigma_m^2(l)$, is provided in Hsieh (1989) as:

$$\sigma_m^2(l) = 4\left[K^m + 2\sum_{i=1}^{m-1} K^{m-i}C^{2i} + (m-1)^2 C^{2m} - m^2 K C^{2m-2}\right], \tag{3.18}$$

where

$$C = C(l) = \int [F(z+l) - F(z-l)]\,dF(z), \text{ and} \tag{3.19}$$

$$K = K(l) = \int\int [F(z+l) - F(z-l)]^2\,dF(z). \tag{3.20}$$

Also, note that $C_{1,n}(l)$ is a consistent estimate of $C(l)$, and

$$K_n(l) = \frac{6}{n_m(n_m - 1)(n_m - 2)} \sum_{s<t<r} L_{st} L_{tr} \tag{3.21}$$

is a consistent estimate of $K(l)$. Therefore, it follows that $\hat{\sigma}_{m,n}(l)$, the consistent estimate of $\sigma_m(l)$, will be obtained by using $C_{1,n}(l)$ and $K_n(l)$.

The calculation of the BDS test statistics in this chapter was facilitated by the use of a program developed by LeBaron (1991)[7]. However, three issues had to be addressed in the

[7] Note that when the test is applied on return series, the asymptotic distribution of the test statistics are quite well approximated by the standard normal distribution, and it is not necessary to bootstrap probability values. This is,

implementation of the test, namely potential serial correlation in the return series (which could arise from non-synchronous trading or non-trading), the choice of values for the embedding dimension, m, and the choice of values for the closeness gauge, l. The procedures followed in the study to address these issues are explained below.

Removing autocorrelation in the return series, if detected, was necessary because the presence of linear dependencies could potentially affect some tests for non-linearities. Therefore, this step was necessary in both the Engel test and the BDS test. In order to detect autocorrelation, we examined the autocorrelation functions (ACFs), partial autocorrelation functions (PACFs) and Ljung-Box *Q*-statistics for each of the series. A series was considered as exhibiting some linear dependencies if the null hypothesis of no autocorrelation could not be accepted at the 10 percent significance level[8]. This was established if the probability value for the *Q*-statistic was less than 10 percent, provided the lag length for the *Q*-statistic was ten or less. The order of autocorrelation was precisely established as the lag length for the first significant *Q*-statistic. Thus, in consistency with the procedure adopted for the ADF test discussed in subsection 3.2.2, the study sought to investigate the presence of autocorrelation of up to the tenth order. If the presence of such autocorrelation could not be established, the BDS test was applied to the raw return data, whereas the Engel test was based on squared residuals from a regression of return on a constant term, as already stated.

In order to filter autocorrelation if it was detected in a given series, say x_t, autoregression (3.11) was fitted to the data. The p autoregressive terms used were identified as the significant spikes in the PACFs of the series, and the filtered data, which were precisely the sequence of estimates of e_t in (3.11), were tested for autocorrelation of up to the tenth order using the Breusch-Godfrey LM test[9]. As in the ADF test, therefore, the final autoregression for each series was chosen on the basis of its ability to filter autocorrelation of up to the desired order of ten. This procedure implies that the analysis focused on the linearly

however, not true when the test is used as a specification test for ARCH-type models, in which case the standard normal distribution tables become inappropriate. Since the LeBaron programme is unable to bootstrap probability values for the test statistics, subsequent applications of the BDS test as a specification test used the EViews 4.0 software.

[8] Although statistical significance was generally evaluated at the 5 percent level in this study, a level of 10 percent for this and related investigations was preferred, in order to increase reliability.

[9] Although the Ljung-Box *Q*-statistic could also be used in testing for serial correlation in the filtered series provided the degrees of freedom for the chi-square-distributed critical values would be adjusted to equal the lag length for Q less the number of AR terms, its use generally yielded parsimonious models that could not filter autocorrelation up to the desired order. This observation is comparable to the problem of using information-based criteria in the ADF test.

unpredictable components of the security returns only, since the predictable part would have been removed using the autoregressive scheme, unless correlation could not be detected in the first place.

Although there are no strict *a priori* values for the embedding dimension, m, the BDS test is known to be quite sensitive to the values chosen. Due to the limitations of data in applied work, the best that researchers can do is to detect low-dimensional chaos by setting $m = 2,3,4,5$ (Scheinkman and LeBaron, 1989; Hsieh, 1991), or $2 \le m \le 10$ (Hsieh, 1989; Dockner, Prskawetz & Feichtinger, 1997). More informatively, Monte Carlo experiments reported in Brock *et al* (1993) suggested that m should be chosen such that the number of non-overlapping data points (i.e., n/m for a series of sample size n) should be in excess of 200 in order for the asymptotic distributional properties of the test to remain reliable. The current study, therefore, set $m = 2,3,4,5$ in this and all subsequent applications of the test.

As with the chosen values for m, the test results will also be sensitive to the choice of l. This choice is quite related to that of m, since the number of points captured by the correlation integral will increase with l for given m. The common procedure is to set l within the interval $0.5\sigma \le l \le 2.0\sigma$, where σ is the standard deviation of the data (Hsieh, 1989,1991; Scheinkman & LeBaron, 1989; Brock *et al*, 1993). The present study chose $l = 0.5\sigma, 1.0\sigma, 1.5\sigma$ throughout all applications of the BDS test.

3.2.4 Summary of the Methodologies

A summary of the methodologies pursued in this chapter is as follows. Firstly, the logarithmic stock prices and returns for the sample of forty-four individual stocks as well as the two stock portfolios were tested for stationarity using the DF/ADF and the Perron tests, while paying due attention to the inclusion of trend and intercept terms as well as the potential effects of structural breaks. Secondly, by examining descriptive statistics and, more formally, invoking the Jarque-Bera test, the study investigated the normality property in the return series. Finally, the validity of the hypothesis that the returns were linearly distributed was assessed using both the Engel (1982) LM test and, more decisively, the BDS test due to Brock *et al* (1987). The next section presents and discusses the key results of the investigations.

3.3 Results and Discussions

3.3.1 Stationarity and Structural Change

Using (3.4), the patterns of autocorrelation and ADF lag structure for each of the logarithmic stock price series are reported in Table 3.1. The table also shows the calculated absolute DF or ADF statistics from the appropriate unrestricted models[10]. Notice that in one-half of the forty-four stocks (i.e., those marked 'U' in column 2), no serial correlation could be detected in the error terms of the DF test equations. Therefore, the unit root hypothesis was initially investigated using (3.4) for such stocks, and (3.5) for the remaining twenty-two stocks in the sample, as well as the two aggregates. Thus, the reported *t*-statistics were from the DF tests in the case of the one-half of the individual stocks already mentioned, and from the ADF tests for the rest. At the significance level of 5 percent, the hypothesis of a unit root could only be rejected for ALSI as well as two of the forty-four individual stocks, namely CHE and SBK[11]. Presumably, the unit root test results for ALSI were affected by the sample size, and potentially different results could have been achieved had the sample size been larger.

Further, in Table 3.2, we report the computed ϕ_i-statistics ($i = 1,2,3$) for the logarithmic price series for which the unit root hypothesis could not be rejected using the least restrictive model, in order to verify the appropriateness of the inclusion of intercept and trend terms. The ϕ_i-statistics were computed using (3.6). Comparing the computed ϕ_3-statistics with the appropriate critical values given in Appendix 3A, it was noted that none of the calculated values was statistically significant. Hence, at the 5 percent significance level, we were unable to reject the null hypothesis of a unit root and/or a deterministic time trend in virtually all the cases[12]. In terms of the ϕ_1-statistic, we were unable to reject the null hypothesis of a unit root and/or an intercept term for PORT as well as all the forty-one individual stocks but three, namely REM, TBS and VNF. Finally, based on the calculated values for ϕ_2, we could not reject the null hypothesis that the data contained an intercept and/or a unit root and/or a deterministic time trend, except for the case of stock REM. Even after controlling for the effects of intercept and trend terms, therefore, we could not reject the null hypothesis of a unit root in the logarithmic security price series.

[10] Note that models 3.4 and 3.5 are herein said to be unrestricted, or least restrictive, because they contain both intercept and trend terms.
[11] When the significance level was increased to 10 percent, OCE became the only other security for which the hypothesis could be rejected.
[12] Note that increasing the significance level to 10 percent changed this result not at all.

Table 3.1 – DF and ADF tests for unit roots in logarithmic stock prices

*This table reports the DF and ADF unit root test results for the logarithmic price series. Column 2 reports the lowest order of serial correlation detected using the Breusch-Godfrey test, where "p" is the probability of accepting the null hypothesis of no serial correlation. "U" implies that no serial correlation of up to the tenth order could be detected. Column 3 shows the significant augmentations included in the ADF test equation, chosen such as to filter serial correlation up to the tenth order. Column 4 gives the absolute DF and ADF test statistics. Both intercept and trend terms were included in the DF and ADF test equations. The absolute MacKinnon critical values for the rejection of the null hypothesis of a unit root were 3.969 and 3.415 at 1% and 5% respectively. * denotes a rejection of the null hypothesis at 1%, while ** denotes a rejection at 5%.*

(a) Stock portfolios

#	1 Portfolio	2 Corr. Order (p)	3 ADF Lag Structure	4 DF/ADF Stat
1	ALSI	1 (0.000)	1,2,5,7,13,25	3.800**
2	PORT	1 (0.000)	1,2,9	2.066

(b) Individual stocks

#	1 Security	2 Corr. Order (p)	3 ADF Lag Structure	4 DF/ADF Stat
1	AFE	2 (0.001)	2,6,9,11,14,18	2.460
2	AFX	U (0.900)	n.a.	1.637
3	AGL	U (0.116)	n.a.	2.557
4	ALT	1 (0.000)	1,10,14,17,20	1.576
5	ANG	U (0.881)	n.a.	2.223
6	ASR	U (0.997)	n.a.	1.648
7	AVI	1 (0.001)	1,5,6,13,17,22,24,25	1.100
8	BAW	U (0.145)	n.a.	2.393
9	BVT	U (0.427)	n.a.	2.824
10	CHE	1 (0.000)	1,3,5,14,21	4.099*
11	CRH	1 (0.008)	1	1.507
12	CTP	U (0.502)	n.a.	2.615
13	DEL	U (0.248)	n.a.	3.011
14	DUR	1 (0.000)	1,22	2.929
15	ECO	1 (0.000)	1,2,4,7,8,9,10,16,19,20,21	1.048
16	ELH	1 (0.000)	1,4,5,6,7,8,18	2.835
17	FOS	1 (0.000)	1,2,3,19,24	0.271
18	GMF	U (0.410)	n.a.	2.812
19	HAR	2 (0.018)	1,2,8	2.991
20	HLH	U (0.559)	n.a.	1.957
21	HVL	U (0.354)	n.a.	2.457
22	IMP	2 (0.019)	2,14,24	2.715
23	JCM	2 (0.000)	2,4,6,7,8,9,11,14,16,23,25	1.866
24	JNC	1 (0.000)	1 to 9, 12 to 15, 19,20,22,23	1.601
25	LGL	U (0.667)	n.a.	1.186
26	MAF	5 (0.000)	2,5,7,20,23	2.935
27	MLB	U (0.975)	n.a.	1.193
28	NED	U (0.677)	n.a.	2.581
29	NPK	U (0.735)	n.a.	1.671
30	OCE	U (0.173)	n.a.	3.221
31	PAM	U (0.852)	n.a.	2.250
32	PIK	U (0.888)	n.a.	2.085
33	PPC	1 (0.000)	1,2,8	1.909
34	REM	1 (0.000)	1,2,3,18	1.524
35	RLO	1 (0.000)	1,2,3,5,14,18	2.647
36	SAB	U (0.981)	n.a.	1.292
37	SAP	U (0.589)	n.a.	2.167
38	SBK	1 (0.040)	1,2,7,8,9,14,17	4.148*
39	TBS	10 (0.040)	3,9,10	1.378
40	TNT	U (0.972)	n.a.	2.759
41	TRE	U (0.933)	n.a.	1.599
42	VNF	1 (0.000)	1,3,4,11,13,15	0.358
43	WAR	1 (0.006)	1,7,9,22,24	2.567
44	WLO	1 (0.024)	1,8,18,19,20	1.455

Table 3.2- ϕ_i -statistics for intercept and trend terms in unit root test equations

*This table shows the computed ϕ_i -statistics for the logarithmic price series for which the unit root hypothesis could not be rejected using the DF and ADF tests. The Appropriate critical values are given in Appendix 3A. * denotes a rejection of the appropriate joint hypothesis of a unit root and/or intercept and/or trend terms (as the case may be) at 1%, while ** denotes a rejection at 5%.*

a) Stock portfolio

#	Portfolio	ϕ_1	ϕ_2	ϕ_3
2	PORT	3.122	3.285	2.203

b) Individual stocks

#	Security	ϕ_1	ϕ_2	ϕ_3
1	AFE	1.488	2.294	3.080
2	AFX	0.361	0.969	1.453
3	AGL	0.421	2.199	3.299
4	ALT	4.010	2.911	2.000
5	ANG	1.577	1.804	2.707
6	ASR	1.813	1.259	1.888
7	AVI	2.931	2.210	0.687
8	BAW	0.358	1.913	2.869
9	BVT	0.174	3.508	5.263
11	CRH	0.671	1.318	1.449
12	CTP	0.021	2.451	3.677
13	DEL	0.057	3.295	4.943
14	DUR	4.180	2.944	4.372
15	ECO	1.418	1.062	0.958
16	ELH	1.344	3.524	4.089
17	FOS	2.889	1.932	0.706
18	GMF	0.199	2.647	3.971
19	HAR	2.523	3.398	4.521
20	HLH	0.919	1.312	1.968
21	HVL	0.877	2.055	3.082
22	IMP	1.965	4.288	4.498
23	JCM	0.800	1.408	1.823
24	JNC	1.580	1.570	1.532
25	LGL	0.279	0.534	0.801
26	MAF	0.913	3.359	4.433
27	MLB	1.023	0.690	1.035
28	NED	0.007	2.575	3.863
29	NPK	0.553	1.081	1.621
31	PAM	2.535	1.691	2.536
32	PIK	2.357	1.572	2.359
33	PPC	2.445	2.700	1.847
34	REM	6.968*	5.396**	1.176
35	RLO	1.795	3.566	3.637
36	SAB	0.268	0.595	0.892
37	SAP	2.364	1.577	2.365
39	TBS	4.693**	3.629	1.107
40	TNT	0.161	2.596	3.894
41	TRE	0.490	0.902	1.353
42	VNF	4.980**	3.327	0.461
43	WAR	1.900	2.353	3.352
44	WLO	1.610	1.566	1.192

The investigation of the joint structural change-unit root hypothesis in the logarithmic prices provided results very similar to the ones already discussed. As reported in Table 3.3, the joint hypothesis could not be rejected at the 5 percent level of significance in all cases except for PIK alone. Note that by this test, even the ALSI logarithmic prices were a non-stationary process. Further, note that for ALSI and thirteen of the forty-four stocks[13], the absolute *t*-statistics for selecting the break point were less than 1.960, temptingly implying that the concerned series might not have experienced any statistically significant structural breaks during the sample period, and the joint hypothesis was potentially irrelevant. This result ought to be cautiously interpreted, however, since the general presence of a unit root in the series could imply that the selected optimal values for the break points might not have been consistent estimates. Moreover, the results showed that the framework could not be used to study further the behaviour of the JSE in the turbulent times under investigation, since the parameter estimates for the dummy variables might not have the desirable asymptotic properties. Further work could pursue the last matter which, despite our ardent desire to do so, we could not in this context.

In general, therefore, the results provided evidence that JSE logarithmic stock prices were non-stationary processes, even after accounting for unnecessary deterministic regressors or potential structural changes. This observation was consistent with those found in other markets (Pagan, 1996; Kasch-Haroutounian and Price, 2001), as well as the JSE (van Rensburg, 1999). This general observation was also consistent with the hypothesis that logarithmic stock prices followed a random walk process, at least of the weak form. Thus, the results provided *prima facie* evidence that the JSE stock prices were unpredictable.

Table 3.3 – Perron's joint unit root-structural break tests for logarithmic stock prices

*This table shows the results of the Perron test for resolving the unit root hypothesis in the presence of structural breaks (see equation (3.7)). t_{θ_2} are t-statistics under the null hypothesis of $\theta_2 = 0$. The break point dates are described in Appendix 3B. t_γ are test statistics for resolving the unit root hypothesis. The Perron-Vogelsang critical values were -5.57, and -4.91 at 1% and 5% levels, respectively. ** denotes a rejection of the null at 5%.*

a) Stock portfolios

#	Portfolio	Optimal Break Point	t_{θ_2}	t_γ
1	ALSI	1994	-1.790	-4.190
2	PORT	1985	-2.354	-3.420

[13] i.e., BVT, CTP, DUR, GMF, HAR, IMP, MAF, NED, PAM, RLO, SAP, SBK and TNT.

Table 3.3 – Perron's joint unit root-structural break tests for logarithmic stock prices
(continued)

b) Individual stocks

#	*Security*	*Optimal Break Point*	t_{θ_2}	t_{γ}
1	AFE	1985	-2.631	-3.602
2	AFX	1994	-3.090	-3.884
3	AGL	1994	-2.797	-4.035
4	ALT	1985	-4.047	-4.268
5	ANG	1985	-2.263	-3.184
6	ASR	1994	-3.577	-4.101
7	AVI	1985	-2.758	-2.467
8	BAW	1985	2.804	-3.954
9	BVT	1994	-1.665	-2.022
10	CHE	1994	-2.151	-4.559
11	CRH	1976	2.077	-1.719
12	CTP	1994	-1.935	-2.735
13	DEL	1985	3.565	-4.687
14	DUR	1985	-1.509	-3.276
15	ECO	1994	-2.960	-3.343
16	ELH	1994	-2.345	-3.361
17	FOS	1994	-4.374	-4.469
18	GMF	1985	-1.382	-3.322
19	HAR	1976	1.820	-3.092
20	HLH	1985	-2.250	-3.476
21	HVL	1985	-2.072	-3.277
22	IMP	1994	1.936	-3.325
23	JCM	1994	-3.507	-3.576
24	JNC	1985	-3.861	-4.013
25	LGL	1994	-4.396	-4.534
26	MAF	1994	-1.572	-3.157
27	MLB	1994	-2.176	-2.889
28	NED	1998	-1.588	-2.477
29	NPK	1994	-3.372	-3.762
30	OCE	1998	2.336	-3.713
31	PAM	1985	-1.541	-3.471
32	PIK	1985	-4.892	-5.172**
33	PPC	1994	-2.735	-3.888
34	REM	1985	-3.729	-3.640
35	RLO	1994	-0.776	-2.242
36	SAB	1994	-2.617	-3.267
37	SAP	1985	-1.385	-2.708
38	SBK	1994	-1.565	-4.011
39	TBS	1985	-2.875	-2.851
40	TNT	1976	1.164	-2.827
41	TRE	1994	-2.681	-3.551
42	VNF	1985	-4.014	-2.724
43	WAR	1976	2.060	-2.689
44	WLO	1994	-3.613	-3.741

The results of the stationarity tests in the stock return series are reported in Table 3.4, and sharply contrasted with those reported for the logarithmic stock price series: even at the stringent 1 percent level of significance, the unit root hypothesis could be rejected for basically all the return series. It is worthwhile noting that, as with the case of the logarithmic price series, no autocorrelation of up to the tenth order could be detected in twenty-seven of the forty-four individual stocks. As such, the DF test equation was accordingly used to resolve the test for the said twenty-seven securities, while the ADF test equation was invoked in the case of the remaining seventeen securities, as well as the two market aggregates, for which the presence of autocorrelation could be established.

Given the problem of low power inherent in stationarity tests, a rejection of the unit root hypothesis in the less restrictive model was considered sufficient, and it was deemed unnecessary to conduct further investigations regarding included regressors (Enders, 1995), nor was it deemed meriting to investigate whether the test results for the return series were influenced by the presence of structural changes, since the calculation of returns inherently involved a de-trending of the logarithmic price series, as shown in Figure 3.1.

From the reported findings, therefore, it could be concluded that JSE stock returns were stationary processes, or that logarithmic stock prices were integrated of order one (i.e, I(1) processes). As with the result for the logarithmic prices, this result was also consistent with those reported for other markets (e.g., Pagan, 1996; Kasch-Haroutounian and Price, 2001), as well as, recently, the JSE (van Rensburg, 1999). However, the finding was somewhat in conflict with that reported by Page (1993), who found JSE security returns to be non-stationary processes. Because the current study employed methodologies that are different from (but arguably more reliable than) those adopted by Page, the conflicting results could be assessed on this basis[14]. The finding that returns did not contain a unit root could be considered as inconsistent with the random walk hypothesis, but only crudely so (Campbell *et al*, 1997:65). Since logarithmic prices were confirmed to contain a unit root in the foregoing, the *prima facie* evidence against the random walk hypothesis (at least in the weak sense) in the return series could mean that the JSE was not in a continuous stochastic equilibrium, and changes in returns could be profitably predictable.

Because returns were scale-free stationary processes and contained all the necessary information to guide the investment decision-making process, financial analysts generally tended to prefer focusing attention on them as opposed to prices (Campbell *et al*, 1997:9). Therefore, the rest of the discussion in this study followed suit.

[14] The methodology employed by Page (1993) is stated in Chapter 2.

Table 3.4 – DF and ADF unit root tests for stock returns

This table reports the serial correlation structure, augmentation structure as well as absolute Dickey-Fuller (DF) and absolute augmented Dickey-Fuller (ADF) test statistics for the return series. Both intercept and trend terms were included in the DF and ADF test equations. The column entries are as defined in Table 3.1. The absolute MacKinnon critical value for the rejection of the null hypothesis of a unit root at 1% was 3.976 for ALSI and 3.969 for all other series. All test statistics were significant at 1%.

a) Stock portfolios

#	***1*** ***Portfolio***	***2*** ***Corr. Order (p)***	***3*** ***ADF Lag Structure***	***4*** ***DF/ADF Stat***
1	ALSI	1 (0.020)	1,2	16.942
2	PORT	1 (0.000)	1,2,3,9	16.388

b) Individual stocks

#	***1*** ***Security***	***2*** ***Corr. Order (p)***	***3*** ***ADF Lag Structure***	***4*** ***DF/ADF Stat***
1	AFE	1 (0.000)	2	24.009
2	AFX	U (0.883)	n.a.	39.108
3	AGL	U (0.226)	n.a.	38.148
4	ALT	2 (0.063)	25	7.143
5	ANG	U (0.897)	n.a.	38.271
6	ASR	U (0.995)	n.a.	39.089
7	AVI	2 (0.026)	1	26.180
8	BAW	U (0.183)	n.a.	40.314
9	BVT	U (0.776)	n.a.	37.080
10	CHE	5 (0.032)	5	14.385
11	CRH	U (707)	n.a.	36.392
12	CTP	U (0.475)	n.a.	38.965
13	DEL	U (0.176)	n.a.	39.516
14	DUR	U (0.616)	n.a.	32.365
15	ECO	1 (0.000)	1 to 10	10.390
16	ELH	6 (0.073)	1 to 8	11.782
17	FOS	1 (0.024)	1 to 16	8.842
18	GMF	U (0.303)	n.a.	38.934
19	HAR	U (0.210)	n.a.	37.306
20	HLH	U (0.716)	n.a.	37.840
21	HVL	5 (0.071)	1,2,3	20.760
22	IMP	1 (0.039)	1 to 17	8.612
23	JCM	1 (0.000)	1 to 18, 23,24	9.150
24	JNC	2 (0.000)	1 to 13,16,27,28,38,78,79,82,85 to 88,91	4.394
25	LGL	U (0.830)	n.a.	40.301
26	MAF	5 (0.000)	1 to 4,6	14.702
27	MLB	U (0.980)	n.a.	39.701
28	NED	U (0.779)	n.a.	40.328
29	NPK	U (0.828)	n.a.	39.232
30	OCE	U (0.158)	n.a.	39.455
31	PAM	U (0.957)	n.a.	37.865
32	PIK	U (0.854)	n.a.	39.855
33	PPC	8 (0.027)	2,3	18.310
34	REM	1 (0.047)	1,2	26.686
35	RLO	1 (0.004)	1 to 12	10.429
36	SAB	U (0.985)	n.a.	38.941
37	SAP	U (0.565)	n.a.	39.739
38	SBK	1 (0.014)	1 to 16	10.813
39	TBS	10 (0.047)	1,2	23.580
40	TNT	U (0.962)	n.a.	39.552
41	TRE	U (0.707)	n.a.	38.361
42	VNF	U (0.265)	n.a.	45.327
43	WAR	U (0.445)	n.a.	36.400
44	WLO	U (0.710)	n.a.	36.805

3.3.2 Normality of Returns

Table 3.5 presents some selected descriptive statistics for the security return series. The table also shows the Jarque-Bera test statistic for each of the series, as well as the corresponding probability values for accepting the null hypothesis of normality. In conflict with the normality assumption, the standard normally distributed statistics computed using (3.8) and (3.9) showed that the sample skewness parameter was insignificant in only five of the forty-four individual stock return series (i.e., AFX, CHE, CRH, SAP, TNT) and in none of the two market aggregate series, while the sample kurtosis parameter was significantly greater than three in virtually all the cases, and generally enormous. Thus, there was unequivocal evidence of leptokurtosis on the JSE, a feature that is documented for most markets, and that renders no support for the assumption of normality in the distributions of security returns.

More formally, for all the series, the generally enormous Jarque-Bera test statistics led to an unambiguous rejection of the null hypothesis of normality in all the series. This finding provided further evidence that the distribution of JSE security returns was consistent with observations made in developed markets (Mandelbrot, 1963; Fama, 1965). More relevantly, the results of the analysis confirmed the finding of Page (1993) that the JSE stock return series exhibited leptokurtosis. Because the variables were all individually non-normal, they could not be jointly multivariate normally distributed. Therefore, joint multivariate normality could not be a realistic assumption for modelling the JSE returns. As noted by Page, however, non-normalities might not have an impact on the relevance of standard asset pricing models.

Table 3.5 – Descriptive statistics for security returns

*In this table of selected descriptive statistics for security returns, $\hat{S}$ and $\hat{K}$ are sample skewness and sample kurtosis, $z_{\hat{S}}$ and $z_{\hat{K}}$ are z-statistics for skewness and kurtosis computed under the null hypothesis of normality, and JB is the Jarque-Bera test statistic. Prob(JB) is the probability of accepting the null hypothesis of normality in the Jarque-Bera test. For $z_{\hat{S}}$ and $z_{\hat{K}}$, * denotes statistical insignificance at the 5% level.*

a) Stock portfolios

#	Portfolio	$\hat{S}$	$z_{\hat{S}}$	$\hat{K}$	$z_{\hat{K}}$	JB	Prob (JB).
1	ALSI	-1.042	-13.145	9.294	39.681	1747.335	0.000
2	PORT	-0.949	-15.107	8.436	43.245	2098.393	0.000

Table 3.5 – Descriptive statistics for security returns (continued)

b) Individual stocks

#	*Security*	$\hat{S}$	$z_{\hat{S}}$	$\hat{K}$	$z_{\hat{K}}$	*JB*	*Prob (JB).*
1	AFE	-2.414	-38.408	43.571	322.770	105655.50	0.000
2	AFX	0.053	0.847*	6.531	28.091	789.83	0.000
3	AGL	-8.901	-141.618	216.060	1695.022	2893157.00	0.000
4	ALT	0.208	3.315	15.166	96.789	9379.04	0.000
5	ANG	0.222	3.529	4.251	9.949	111.44	0.000
6	ASR	-24.820	-394.910	845.913	6705.882	45124813.00	0.000
7	AVI	-2.408	-38.309	39.697	291.944	86699.02	0.000
8	BAW	-2.637	-41.964	43.189	319.731	103988.60	0.000
9	BVT	-0.305	-4.855	15.829	102.065	10440.79	0.000
10	CHE	0.063	1.000*	10.595	60.423	3651.90	0.000
11	CRH	0.061	0.963*	9.468	51.460	2649.04	0.000
12	CTP	0.222	3.536	12.732	77.427	6007.51	0.000
13	DEL	-5.935	-94.431	134.041	1042.509	1095742.00	0.000
14	DUR	0.342	5.442	7.623	36.780	1382.36	0.000
15	ECO	-0.322	-5.118	13.552	83.946	7073.10	0.000
16	ELH	0.275	4.383	9.882	54.748	3016.55	0.000
17	FOS	0.950	15.110	16.424	106.798	11634.06	0.000
18	GMF	-1.136	-18.077	17.367	114.296	13390.30	0.000
19	HAR	0.383	6.095	6.089	24.574	641.04	0.000
20	HLH	-1.137	-18.092	19.055	127.726	16641.11	0.000
21	HVL	0.156	2.484	6.346	26.619	714.73	0.000
22	IMP	0.187	2.972	6.024	24.062	587.80	0.000
23	JCM	-2.282	-36.317	245.745	1931.187	3730803.00	0.000
24	JNC	0.229	3.641	189.066	1480.270	2191213.00	0.000
25	LGL	-0.725	-11.535	14.740	93.400	8856.69	0.000
26	MAF	-20.658	-328.699	648.104	5132.189	26447408.00	0.000
27	MLB	-4.242	-67.496	80.998	620.519	389599.80	0.000
28	NED	-0.156	-2.476	6.164	25.170	639.64	0.000
29	NPK	-0.467	-7.430	8.993	47.677	2328.33	0.000
30	OCE	-0.286	-4.547	9.896	54.863	3030.67	0.000
31	PAM	0.500	7.963	7.446	35.373	1314.69	0.000
32	PIK	-0.220	-3.499	8.676	45.157	2051.41	0.000
33	PPC	0.142	2.262	10.574	60.253	3635.56	0.000
34	REM	-0.702	-11.170	106.449	822.997	677448.80	0.000
35	RLO	0.421	6.698	18.337	122.018	14933.27	0.000
36	SAB	-1.217	-19.363	20.288	137.534	19290.45	0.000
37	SAP	0.024	0.385*	7.539	36.109	1304.02	0.000
38	SBK	-0.226	-3.589	9.904	54.924	3029.49	0.000
39	TBS	-0.124	-1.974	8.924	47.127	2224.85	0.000
40	TNT	-0.044	-0.703*	5.979	23.702	562.28	0.000
41	TRE	2.683	42.683	348.565	2749.177	7559798.00	0.000
42	VNF	-0.986	-15.692	14.485	91.370	8594.76	0.000
43	WAR	0.315	5.013	5.254	17.935	346.81	0.000
44	WLO	-0.399	-6.343	8.862	46.635	2215.06	0.000

3.3.3 Linearity of Returns

Table 3.6 reports the autocorrelation structures for the raw return series, the autoregressive structures used to filter autocorrelation where detected, as well as the Engel linearity test results. It was noted that no autocorrelation could be detected in nineteen of the forty-four individual stock return series. Thus, the returns were already linearly unpredictable for such stocks, and required no autoregressive filtering. Although ARCH and potentially other non-linear processes could not be detected in eleven of the forty-four individual stocks under investigation, there was strong evidence of the prevalence of non-linearities in the remaining return series, including both of the market aggregates. The failure to reject the hypothesis of linearity in a quarter of the individual stocks could be attributed to the fact that, as appreciated in subsection 3.2.3, the Engel test does not have power against other types of non-linearities. This could provide justification for an investigation based on a more robust test, such as the BDS test. Note that since the Engle test was originally intended as a test for the ARCH process, and is unable to detect a GARCH process among other non-linearities, the results implied that we could not use the original ARCH model of Engel (1982) to explain the return dynamics of the said eleven stocks.

The BDS test statistics for resolving the linearity assumption are reported in Appendix 3C. Given the four values for m and the three values for l as described in the methodology, the test was conducted twelve times for each of the forty-six unpredictable return series, giving a total of 552 estimates of the BDS statistic. Clearly, the iid assumption could not be accepted in 543 (i.e., 98 percent) of the 552 experiments. Security ASR showed a linear deterministic distribution for all embedding dimensions when $l = 1.0\sigma$ and $l = 1.5\sigma$, but did not show linearity when $l = 0.5\sigma$. Thus, linearity could be confirmed in eight of the twelve test statistics for this single stock. Linearity was also detected for the lowest embedding dimension for security CHE, but only so when $l = 1.0\sigma$. Apart from these nine outlier cases, there was evidence of varying degrees that the stock returns did not follow an iid process. It is worth noting that all the BDS statistics fell on the positive tail of the normal distribution.

Table 3.6 – Autocorrelation structures and Engel tests for linearity of stock returns

*This table reports the autocorrelation and autoregressive structures of the stock returns, as well as the Engle test results. The order of serial correlation is given in Column 2, where 'U' indicates that no correlation could be detected. The autoregressive structure used to filter correlation is given in Column 3. Column 4 gives the lowest lag length for squared residuals at which the null of linearity could be rejected, 'U' implies that non- linearity could not be detected. The corresponding LM test statistics are given in Column 5. Probability values (p) under the appropriate null hypotheses are indicated in parentheses, and relate to the 10th order for all 'U'. In the Engel test, the null could be rejected if p < 0.05. * and ** imply a rejection of the null at 1% and 5%, respectively.*

a) Stock portfolios

#	1 Portfolio	2 Corr. Order (p)	3 AR Structure	4 AR order	5 nR^2 (p)
1	ALSI	1 (0.000)	1,2,3,5,7	1	13.327 (0.000)*
2	PORT	1 (0.000)	1,2,3,4	1	21.128 (0.000)*

Table 3.6 – Autocorrelation structures and Engel tests for linearity of stock returns
(continued)

b) Individual stocks

#	1 Security	2 Corr. Order (p)	3 AR Structure	4 AR order	5 nR^2 (p)	
1	AFE	2 (0.001)	2	2	6.673	(0.036)**
2	AFX	U (0.883)	n.a.	1	23.078	(0.000)*
3	AGL	U (0.219)	n.a.	U	0.102	(1.000)
4	ALT	1 (0.000)	1,2,3	1	13.430	(0.000)*
5	ANG	U (0.873)	n.a.	1	15.242	(0.000)*
6	ASR	U (0.995)	n.a.	U	0.013	(1.000)
7	AVI	1 (0.002)	1,5	U	5.604	(0.847)
8	BAW	6 (0.049)	6	U	1.498	(0.999)
9	BVT	1 (0.052)	1	3	18.898	(0.000)*
10	CHE	1 (0.000)	1,3,5	2	18.857	(0.000)*
11	CRH	1 (0.008)	1	2	18.930	(0.000)*
12	CTP	U (0.412)	n.a.	1	8.140	(0.004)*
13	DEL	U (0.164)	n.a.	U	4.497	(0.922)
14	DUR	1 (0.000)	1	1	17.242	(0.000)*
15	ECO	1 (0.000)	1,2,4,7,8,9,10,14	1	5.511	(0.019)**
16	ELH	1 (0.000)	1,4,5,7	1	48.230	(0.000)*
17	FOS	1 (0.000)	1,2,3	1	6.666	(0.010)*
18	GMF	U (0.320)	n.a.	U	4.587	(0.917)
19	HAR	2 (0.035)	1,2	1	17.040	(0.000)*
20	HLH	U (0.594)	n.a.	U	7.759	(0.652)
21	HVL	5 (0.033)	5	1	10.061	(0.002)**
22	IMP	2 (0.027)	2	1	11.046	(0.001)*
23	JCM	2 (0.000)	2,4,9,11	2	60.013	(0.000)*
24	JNC	1 (0.000)	1-24, 26,29,30,33	1	36.119	(0.000)*
25	LGL	U (0.676)	n.a.	1	8.123	(0.004)*
26	MAF	5 (0.000)	5,7	U	2.151	(0.995)
27	MLB	U (0.969)	n.a.	U	0.135	(1.000)
28	NED	U (0.686)	n.a.	1	38.018	(0.000)*
29	NPK	U (0.824)	n.a.	1	82.248	(0.000)*
30	OCE	U (0.203)	n.a.	1	6.155	(0.013)**
31	PAM	U (0.898)	n.a.	1	52.888	(0.000)*
32	PIK	U (0.883)	n.a.	6	35.560	(0.000)*
33	PPC	1 (0.000)	1,2,6	1	10.566	(0.001)*
34	REM	1 (0.000)	1,2,3	1	177.336	(0.000)*
35	RLO	1 (0.000)	1,2,3,5	1	10.392	(0.001)*
36	SAB	U (0.986)	n.a.	U	5.955	(0.819)
37	SAP	U (0.654)	n.a.	1	12.324	(0.000)*
38	SBK	1 (0.050)	1,2,7,8,9,17	1	54.832	(0.000)*
39	TBS	10 (0.035)	3,9,10	1	11.579	(0.001)*
40	TNT	U (0.956)	n.a.	1	45.721	(0.000)*
41	TRE	U (0.939)	n.a.	U	0.103	(1.000)
42	VNF	1 (0.000)	1	1	19.651	(0.000)*
43	WAR	1 (0.009)	1	1	5.730	(0.017)**
44	WLO	1 (0.029)	1	1	15.743	(0.000)*

As expected, it was noted that the evidence provided by the more robust BDS test against the random iid assumption was unambiguously stronger than that provided by the Engle test. Finally, as stated earlier in this chapter, the combined effects of the rejection of normality and iid implies that JSE logarithmic security prices did not follows a normal strong random walk process. This evidence would imply that JSE stock returns were profitably predictable over time, and would render suspicious the appropriateness of static asset pricing models in analysing stock price movements on this emerging market.

Since the BDS approach tests for the null hypothesis of a random iid system, and since the test was applied on the linearly unpredictable return series which were also confirmed to be stationary, the results obtained in this section ruled out the possibility that the rejection of the iid hypothesis could be attributable to linear dependencies or to a linear stochastic return generating process. This further implies that the return generating process could be characterised by either non-linear stochastic dynamics or low complexity chaotic (i.e., non-linear deterministic) dynamics. The latter implies the presence of non-linearities in the conditional mean while, for the former, non-linearities would manifest in the conditional variance. Most of the evidence in the literature does not seem to support the presence of chaotic dynamics as accounting for non-linearities in financial time series (e.g., White, 1988; Prescott & Stengos, 1988; Hsieh, 1991; Barkoulas & Travlos, 1998). If the iid hypothesis were rejected because returns were non-linear in variance, as would be the case if volatility clustering were evident, it would imply that JSE equity returns could be modelled as ARCH-type processes, an issue that we pursue in the next chapter.

3.4 Summary and Conclusion

This chapter investigated the stationarity, normality and linearity properties for the logarithmic prices and returns of individual JSE stocks as well as stock portfolios. The sample consisted of weekly data on the forty-four individual stocks as well as the two aggregates described in Section 1.4. In order to investigate the unit root hypothesis, Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) tests were initially used, and the effects of the inclusion of intercept and trend terms were investigated by computing ϕ-statistics as proposed by Dickey and Fuller (1981). Further, the innovational outlier model proposed by Perron (1994) was used to investigate the joint unit root-structural change hypothesis, where the selection of potential break dates was guided by South Africa's largely interrelated social, political and economic developments, but the optimal break point for each series was chosen following Christiano (1992). Secondly, by examining relevant descriptive statistics and invoking the Jarque-Bera test, the study investigated the normality property in the returns. Joint multivariate normality was evaluated by noting that it should arise if the variables were individually normally distributed. Finally, the hypothesis of linearity was resolved by using both the Engel (1982) Lagrange Multiplier test and, more decisively, the BDS test due to Brock *et al* (1987). In both linearity tests, due attention was paid to the problem of autocorrelation which could arise from non-synchronous trading or non-trading. If detected, such autocorrelation was filtered using autoregressive schemes. Therefore, the linearity tests focused on the linearly unpredictable components of returns.

The major findings of this analysis were consistent with stylised facts documented in the literature. Specifically, the results validated the use of returns as opposed to prices as the basis for the analysis of JSE stock price behaviour, because returns were confirmed to be stationary processes, while logarithmic prices were largely non-stationary. Further, the results of the investigations of the normal strong random walk properties in the return series also showed that both the assumptions of normality and linearity were inapt: return distributions were highly leptokurtic, generally displayed excess skewness, and were far from being iid. These findings disputed the applicability of standard two-date asset pricing models in characterising the return generating process on this market. Importantly, they showed that changes in JSE returns could be predictable over time.

Since the procedures pursued in the investigation effectively ruled out the possibility that linear dependencies or stationarity could have accounted for the non-linearities in the stock returns, and because the evidence in the literature was less supportive of the presence of chaotic non-linear dynamics in financial time series, we were persuaded to suspect that the non-linearities were stochastic. Accordingly, therefore, the relevance of ARCH-type models in explaining the non-linear dynamics was hypothesised, and this investigation constitutes the substance of the chapter that follows.

Chapter 4

Modelling Stock Return Volatility on the JSE

We established that the effects of shocks on JSE stock return volatility were symmetric, and that volatility was not a commonly priced factor. Hence, the standard GARCH(1,1) model provided the best description of return dynamics relative to its complex augmentations. Further, the model significantly, but less than fully, accounted for the observed non-linearities in the series.

4.1 Introduction

The previous chapter provided further evidence on stylised statistical properties of stock prices and returns from the JSE. Specifically, it was shown that although JSE logarithmic stock prices were non-stationary processes, continuously compounded returns did not seem to contain a unit root. Secondly, the distributions of returns on the market were not consistent with normality, and showed very strong evidence of leptokurtosis as well as excess skewness. Finally, the distributions of the return series showed strong departures from the iid assumption, implying that stochastic or deterministic non-linearities could characterise the return generating process. These results pointed to the possibility that the parameters of the model governing the return generating process on the JSE might not be constant over time, but rather dynamic. Consequently, static (unconditional) and iid-based asset pricing investigations, which dominated the previous limited work conducted on the JSE, could be improved upon by recasting them to a dynamic framework. Autoregressive conditional heteroscedasticity (ARCH) type of models, which assume that the dynamical behaviour is characterised by a time-dependent variance, provide one possible such framework.

This chapter, therefore, discusses whether ARCH-type models could be used to explain stock return dynamics on the JSE. The motivation for this investigation is the common observation documented in the literature that, even when the return series are themselves linearly unpredictable, their squares usually exhibit some linear dependencies over time. This observation provides evidence that the variance of return (i.e., risk) is not constant over time, but exhibits temporal dependence and predictability. Specifically, the observation suggests that high volatility periods would, most likely, be followed by low volatility periods, a stylised phenomenon termed volatility clustering and usually traced back to the seminal work of Mandelbrot (1963). The key implication of these patterns and observations is that the conditional variance (i.e., volatility) of return, rather than the unconditional variance, is an important determinant in the investment decision-making process.

Most previous studies addressing this subject have focused on very well-developed capital markets: Engle (1982), Engle and Kraft (1983), Bollerslev (1986), French, Schwert, and Stambaugh (1987), Baillie and DeGennaro (1990), Poon and Taylor (1992), Glosten, Jagannathan and Runkle (1993), and McMillan, Speight and apGwilym (2000) is by no means any close to an exhaustive list. Although the importance of understanding the risk profiles of emerging capital markets is well-documented (Siourounis, 2002), the fact that very limited work in this area is reported for emerging markets is also equally well acknowledged (Kasch-Haroutounian & Price, 2001). One notable feature of the limited emerging markets literature on the relevance of ARCH-type models is its surge over the last few years[1]. The models' increasing popularity appears to be premised on the fact that most of the emerging market studies seem to find them potentially capable of describing the unique features of the risk-return relationships that characterise such markets. But of more relevance to this study is the discernible absence, in the emerging markets literature, of work on the JSE and other African stock markets, of which the JSE is the most dominant and active. The present study attempts to fill this gap.

The class of ARCH-type models that could be explored to investigate the risk-return dynamics on the JSE is wide and growing, but attention in this study was specifically to identify an appropriate model consistent with the market under investigation. Specifically, the search for an appropriate ARCH-type specification was guided by the desire to investigate:

a) whether volatility was priced;
b) whether there existed volatility asymmetry; i.e., whether positive and negative shocks impacted on volatility rather differently; and
c) whether an ARCH-type model could account for the non-linearities in the returns.

[1] Notable examples include Kim and Mei (2001), Alles and Murry (2001), Koutmos and Said (2001) Al-Loughani and Cappell (2001), Poshakwale and Murinde (2001) and Solibakke (2001, 2002).

In subsequent chapters, the study used the framework developed in this chapter to investigate further the question of the predictability of JSE stock returns.

The rest of this chapter is organised as follows. Section 4.2 provides a brief overview of ARCH-type models, focusing on the models tested in the present study. Section 4.3 describes the methodologies followed, while the results of the investigation are presented and discussed in Section 4.4. Section 4.5 summarises and concludes the chapter.

4.2 ARCH-Type Models: an Overview

The theoretical framework for modelling volatility and investigating its relationship with returns is usually traced to the original ARCH model developed by Engel (1982), but has received enormous attention, particularly in modelling the dynamics of financial and macroeconomic data in developed economies. Engel's ARCH model for returns recognises that there is a distinction between the unconditional second moment (i.e., variance) and conditional second moment (i.e., volatility) of the return series, in the sense that the latter can change over time even if its corresponding variance measure is homoscedastic. Therefore, in order to capture this time-variability, the ARCH framework imposes an autoregressive structure on the conditional second moment. Thus, if R_t denotes the linearly unpredictable (either uncorrelated or linearly filtered) continuously compounded return series in period t for a given security, and if a structural relationship is not assumed, R_t could be modelled as:

$$R_t = \alpha + \mu_t , \tag{4.1}$$

$$\mu_t | \Omega_{t-1} \sim N(0, h_t), \tag{4.2}$$

$$h_t = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 . \tag{4.3}$$

Equation (4.1), which was already introduced in Section 2.5, gives the mean (expected) return equation. It shows that the expected return does not differ from its long-run average value, α, except by a random error term. Since both positive and negative returns have sensible interpretations, no strong a priori expectations may be held for α. Using linearly filtered returns implies a two-stage procedure in the estimation of (4.1), where the first stage involves fitting an appropriate autoregressive structure[2]. The requirement that R_t are filtered of linear dependencies could be relaxed, so that the autoregressive structure used to remove serial correlation could be included in (4.1), a preferred procedure for other ARCH-type models discussed later in this section. Equation (4.2) states that, conditional upon the set of information, denoted Ω_{t-1}, available in the preceding period, the error term is normally distributed with a mean of zero and a conditionally heteroscedastic variance, h_t. The error term is also serially uncorrelated by definition. As discussed in Section 4.3, the normality assumption could be relaxed in favour of more realistic distributions for μ_t, most commonly Student's *t*-distribution. Finally, by noting that $h_t = E(\mu_t^2 | \Omega_{t-1})$, it becomes clear that (4.3) models volatility as an AR(q) process, where the regressors denote shocks that impact on volatility. Specifically, the constant, ϕ, represents a weighted average of long-term volatility, while the lagged squared errors capture information about volatility observed in previous periods. Equations (4.1) to (4.3) describe the standard ARCH(q) model, which has been found successful in describing the dynamics of various macroeconomic and financial variables. Among other applications of the model, see Engle and Kraft (1983) and Coulson and Robins (1985) on inflation, Weiss (1984) on macroeconomic variables, and Domowitz and Hakkio (1985) on foreign exchange markets.

Bollerslev (1986) observed that, in order to avoid a violation of the non-negativity constraints in view of the long memory typically found in empirical work, the original ARCH model requires that an arbitrary, and usually long, linear declining lag structure be imposed in the conditional variance equation. The result is that the value of q can usually not be small. In order to permit a parsimonious description of the process, he introduced the generalised ARCH (GARCH) model which extends (4.3) by including p lagged conditional variance terms as extra regressors. The volatility equation in the GARCH(p,q) model, therefore, becomes:

$$h_t = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 + \sum_{j=1}^{p} \theta_j h_{t-j} . \tag{4.4}$$

[2] Some studies suggest the use of a moving average structure to filter autocorrelation (see, for instance, French, Schwert & Stambaugh, 1987).

The parsimony achievable through the use of the GARCH model implies that the dynamics of h_t that would best be described by a high-order ARCH process could just as well, and sometimes even better, be described by a low-order GARCH process[3]. Therefore, although higher order GARCH models feature in some studies,[4] the GARCH(1,1) process has demonstrated adequacy in modelling many time series, and is the most commonly featured formulation in applied work[5]. Note that the ARCH model is nested in the GARCH model by setting $p = 0$, while $p = q = 0$ implies that the variance is a white noise process. Further, the quantity $\sum \lambda_i + \sum \theta_j$ measures the persistence of volatility. If $\sum \lambda_i + \sum \theta_j = 1$, then shocks on volatility die off very slowly, and this is called an integrated GARCH (IGARCH) process. This process has the additional implication that the unconditional distribution of μ_t has an infinite variance. The formulation of the GARCH model assumes that $\sum \lambda_i + \sum \theta_j < 1$ and, in most empirical applications, it is the presence of a near-integrated GARCH (i.e., where the sum is less than, but very close to, unity) that has been established (Bollerslev, 1987; Baillie & Bollerslev, 1989). Finally, by expressing (4.4) in terms of the squared errors, we have:

$$\mu_t^2 = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 + \sum_{j=1}^{p} \theta_j \mu_{t-j}^2 + \sum_{j=1}^{p} \theta_j \varepsilon_{t-j} + \varepsilon_t \,, \qquad (4.5)$$

where ε_t is uncorrelated with zero mean. In (4.5), the conditional variance equation is expressed as an ARMA(m, p) process, where $m = \max\{p, q\}$. Therefore, the ARMA order identified by applying the Box-Jenkins approach to the squared errors also identifies the GARCH order. While risking the loss of clarity, hereafter, we shall refer to the p and q terms as GARCH and ARCH terms, respectively.

The ARCH-type models discussed in the foregoing assume that positive and negative shocks of equal magnitude impact on volatility equally. Nelson (1991), Glosten, Jaganathan and Runkle (1993), and Zakoian (1994) suggested formulations that are useful in modelling the differential impact of positive and negative shocks, a phenomenon called volatility

[3] For instance, Bollerslev (1986) demonstrated that the GARCH(1,1) model could explain US inflation better than an ARCH(8) model.
[4] For instance, Mills (1999:152) found that the MA-GARCH(1,2) model provided a better description of S&P 500 daily returns than the MA-GARCH(1,1) process. Also, Yu (2002) found that a GARCH(3,2) specification was preferred to the GARCH(1,1) alternative in a study of volatility on the New Zealand Stock Market.
[5] See, among others, Chou (1988), Baillie and DeGennaro (1990), Bollerslev, Chou and Kroner (1992), Ding, Granger and Engle (1993), as well as Blake (2000:681).

asymmetry. In particular, a leverage effect would be said to exist if bad news would increase volatility more than good news of the same magnitude. These so-called asymmetric ARCH-type models are also useful in describing volatility spillovers (contagion effects) across markets. Nelson's model is referred to as the exponential GARCH (EGARCH) model, while Glosten *et al* developed the dummy GARCH (DGARCH) model, also called the GJR model in the literature. Zakoian developed a formulation comparable with the GJR model[6].

Nelson (1991) proposed a logarithmic conditional variance model in order to achieve exponential leverage effects, and to allow the model's coefficients to become negative without the variance itself becoming negative. Moreover, standardised lagged errors, as well as their moduli, enter the volatility equation as extra regressors, in order to allow for differential effects of positive and negative shocks. The EGARCH(p,q) model is, therefore:

$$\ln h_t = \phi + \sum_{i=1}^{q}\left(\lambda_i \frac{|\mu_{t-i}|}{\sqrt{h_{t-i}}} + \gamma_i \frac{\mu_{t-i}}{\sqrt{h_{t-i}}}\right) + \sum_{j=1}^{p}\theta_j \ln h_{t-j}\,, \tag{4.6}$$

where γ_i are the leverage effect terms. A leverage effect is said to exist if $\sum \gamma_i > 0$, and asymmetric volatility in the EGARCH model is generally established if $\sum \gamma_i \neq 0$.

A simpler approach to modelling asymmetric effects on volatility is to introduce a dummy variable, D_t, into the conditional variance equation. Specifically, D_t assumes a value of unity for bad news (i.e., $D_t = 1$ if $\mu_t < 0$), and a value of zero otherwise. This yields the DGARCH model whose conditional variance equation is, therefore, of the form:

$$h_t = \phi + \sum_{i=1}^{q}\lambda_i \mu_{t-i}^2 + \gamma D_{t-1}\mu_{t-1}^2 + \sum_{j}^{p}\theta_j h_{t-j}\,. \tag{4.7}$$

[6] Zakoian (1994) developed an equivalent of the GJR model, usually called the threshold ARCH (TARCH) model, within the ARCH (other than GARCH) framework, and also expressed the leverage parameter in terms of the conditional standard deviation other than the conditional variance. Nonetheless, the two models are comparable and, consequently, only the GJR model is discussed here. Note that EViews 3.1 estimates the GJR model in its definition of TARCH.

In (4.7) the impact of good news on volatility is $\sum \lambda_i$, while that of bad news is $\sum \lambda_i + \gamma$. As in the EGARCH model, a leverage effect exists if $\gamma > 0$, and the news effects are asymmetric if $\gamma \neq 0$. Apart from its simplicity and the relative ease of interpretability of its parameter estimates, this formulation has been found useful in modelling volatility spillover effects from other markets (see Bae and Cheung, 1993). For compactness of notation, we shall refer to the class of asymmetric volatility models as AGARCH models.

The application of AGARCH models to data from various markets has produced conflicting conclusions. For instance, significant leverage effects were documented by Glosten *et al* (1993) for the US market, and by Siourounis (2002) for the Athens Stock Exchange, while Kasch-Haroutounian and Price (2001) found weak evidence in four emerging markets of Central Europe. Solibakke (2001) noted that asymmetric volatility was more significant in well traded than in thinly traded stocks in the Norwegian market.

Although the above models are useful in describing stochastic non-linear dynamics, they do not explain explicitly the relationship between volatility and the expected return on an asset. In order to address the central question of pricing risk, it is vital that the model should provide an estimate of the premium that an investor would expect for taking on each unit quantity of risk, as measured by the conditional variance or the conditional standard deviation. A very useful extension of the above models is the ARCH-in-mean or the GARCH-in-mean models proposed by Engel, Lilien and Robins (1987) and Bollerslev, Engel and Wooldridge (1988). These formulations introduce the conditional variance (or the conditional standard deviation) as an extra regressor in the mean equation. If R_t denotes uncorrelated (but not necessarily linearly-filtered) return series, then (4.1) may be modified to:

$$R_t = \alpha + \beta h_t + \mu_t \text{, or} \tag{4.8}$$

$$R_t = \alpha + \beta \sqrt{h_t} + \mu_t . \tag{4.8'}$$

In (4.8) or (4.8'), α may be comparable to the rate of return on a risk-free asset[7], while β is the price of risk. The quantity of risk is estimated by the conditional variance or the conditional standard deviation. For the purpose of estimation, (4.8) and (4.8') assume that the return series are uncorrelated. If the series exhibits autocorrelation, then the two-stage

[7] If R_t denotes excess return, the *a priori* expectation for α will be a value of zero.

procedure of fitting the model on already linearly filtered data would not yield consistent estimators. Instead, the mean equation would be estimated as an autoregression (Brock *et al*, 1993:101). Thus, assuming a maximum finite lag length of K required to filter evident linear dependencies, the corresponding autoregression for (4.8) will be:

$$R_t = \alpha + \beta h_t + \sum_{k=1}^{K} \rho_k R_{t-k} + \mu_t , \tag{4.9}$$

with an analogous specification for (4.8'), and the autoregressive structures reported in Table 3.6 of Section 3.3 will apply. Finally, it is straightforward to see that when volatility is modelled as AGARCH (i.e., DGARCH or EGARCH) and the conditional variance (or standard deviation) term is also included in the mean equation, we obtain AGARCH-in-mean (AGARCH-M) models (i.e., DGARCH-M or EGARCH-M processes).

In recent applications of ARCH-type models, the GARCH-M and AGARCH-M processes are probably the most frequently used, and have been found to provide conflicting but generally unsuccessful results regarding the pricing of volatility. Specifically, the results from emerging markets have not been particularly above board. For instance, Alles and Murray (2001) found that the GARCH-M model was unsuitable for Irish equity markets, while Poshakwale and Murinde (2001) found that volatility was not priced in the stock markets of Poland and Hungary. These results are in agreement with those documented by Solibakke (2002) for the thinly traded Norwegian equity market. A similarly weak relation between returns and volatility was documented by Baillie and DeGennaro (1990) for the US market, and by Poon and Taylor (1992) for the UK market, but support for a negative relation between the two was provided by Glosten *et al* (1993) within the US environment.

Many other ARCH-type variants with equally witty acronyms have been proposed in the literature to capture various types of dynamics. An important extension, which nests most of the ARCH-type models, was made by Ding, Granger and Engle (1993), who recognised that if the distribution of the return series' error was non-normal, then moments higher than (or different from) the second could best describe the dynamics. Therefore, they proposed the power ARCH model, which permits an estimation of the optimal power term rather than imposing the second moment to the data. Finally, extensions of the ARCH-type models to multivariate frameworks, as well as to models that could explain deterministic chaos, have been accomplished[8]. Thus, it is not possible to provide an exhaustive account in this very dynamic field within the context of this overview. However, this brief overview is adequate for the purpose of explaining the methodologies pursued in this chapter, to which we turn.

4.3 Research Methodologies

4.3.1 Volatility Clustering

In Section 3.3, recall that an autoregressive structure was used to filter linear dependencies in the raw return series. Where no such dependencies could be established, the logical insinuation was that the series required no filtering. The autoregressive structures in the correlated return series were chosen such as to filter autocorrelation up to the tenth order, as confirmed by the Breusch-Godfrey serial correlation LM test. The series used in the linearity tests conducted in that section, therefore, represented linearly unpredictable returns. As a basis for an investigation of the relevance of ARCH-type models in the present study, we examined the ACFs and PACFs up to lag 6, as well as the Ljung-Box Q(6)-statistics[9] for the squares of each of these linearly independent return series, and the results (excluding the PACFs) are presented in Table 4.1. Two major observations could be made, as follows:

Firstly, all the eleven series for which the Engel test could not detect departures from linearity, as reported in Section 3.3, did not show evidence of volatility clustering. The typical pattern exhibited by these stocks is illustrated in Figure 4.1(a) for stock AGL. Note that the squared unpredictable returns for AGL did not show any discernible cyclical pattern, implying that no volatility clustering was evident. Recollecting that the BDS test led to a universal rejection of linearity in the preceding chapter, it is possible that the Engel test might not have picked some types of stochastic non-linearities. Alternatively, it could be imaginable that some of the non-linearities picked by the BDS test in the previous chapter were deterministic rather than stochastic, and could not be completely filtered using an ARCH-type model.

The second observation made is that the remaining thirty-three of the forty-four individual stocks, as well as both of the portfolios, showed evidence of positive linear dependencies in the squares of unpredictable returns. In Figure 4.1(b), stock TNT is used to illustrate the typical pattern exhibited by most of the stocks in the sample, and the cyclicality in volatility is

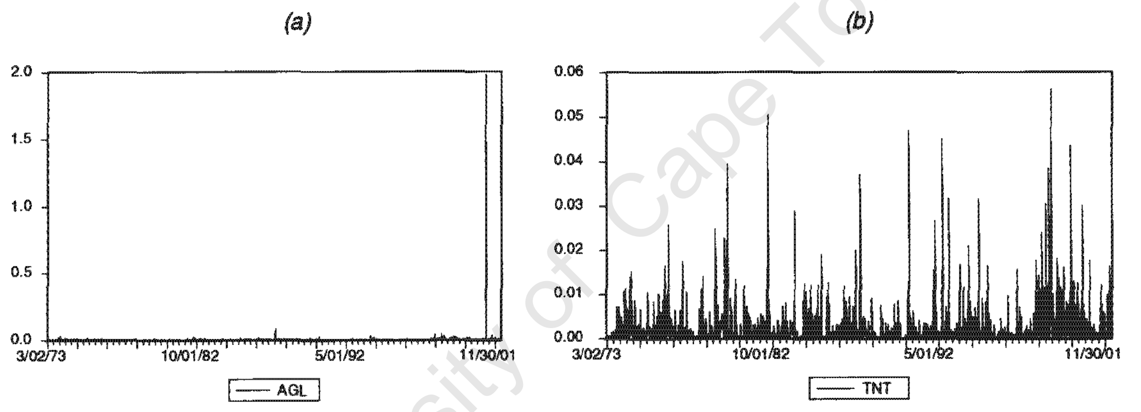
[8] Examples of multivariate ARCH-type models include the VECH form of Bollerslev (1988) and the BEKK model of Engle and Kroner (1995).

[9] The conclusions drawn from this examination did not change when longer lags were considered.

quite clear. For most such series, the ACFs at lag one were significant, and the PACFs showed that autocorrelations at subsequent lags generally contributed relatively less to the patterns of the linear dependence. For these series, the $Q(6)$ statistic was significant at 1 percent in all but one case (i.e., CTP), where significance could not be rejected at the 5 percent level. These findings provided evidence of volatility clustering, and supported the use of ARCH-type models to describe return dynamics on the JSE.

Figure 4.1 – Volatility clustering

This figure shows plots of squared linearly unpredictable returns on AGL and TNT against time.



The observation that both deterministic and stochastic non-linearities might exist on the JSE, if confirmed in further tests, could suggest that a single modelling framework might not fully account for all the return dynamics on this market. Note that this dichotomy in the return generating process would usually not be uncovered when indices alone, other than individual securities as well, were the focus of attention. Therefore, an analysis based on indices alone, while being important in understanding the behaviour of the whole market and/or its key sectors, could be of limited usefulness in active portfolio management, where investors seek to beat the market through the selection of appropriate portfolio constituents from amongst those available on the market. This point is buttressed by the fact that no patterns were clearly perceptible in the eleven securities that provided no evidence of volatility clustering: the list consisted of both large and small stocks distributed across the tradable indices and major JSE sectors as presented in Appendix 1A and Appendix 1B. Further, since it is quite uncommon in the literature to reject volatility clustering in stock returns, the high rejection level recorded in the present study (25 percent of the individual stocks) could signify an atypical feature of the JSE relative to other markets.

Table 4.1 – Autocorrelation structures of squared unpredictable returns

*This table shows the ACFs up to lag 6 (i.e., ρ_i for i = 1, ..., 6) and Ljung-Box Q-statistic at lag 6 (i.e., Q(6)) for the squared linearly unpredictable return series. Under the null hypothesis of no serial correlation, the χ^2_6 critical values at 1% and 5% significance levels were 16.81 and 12.59, respectively. * implies that the null hypothesis may be rejected at 1%, and ** at 5%.*

(a) Stock portfolios

Portfolio	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	Q(6)
ALSI	0.117	0.221	0.049	0.030	0.071	0.009	67.760*
PORT	0.118	0.261	0.063	0.023	0.066	0.030	139.44*

(b) Individual stocks

Security	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	Q(6)
AFE	0.021	0.063	0.068	0.041	0.018	0.047	20.338*
AFX	0.013	0.060	0.043	0.054	0.074	0.048	47.717*
AGL	0.004	-0.001	0.000	0.002	-0.001	-0.002	0.040
ALT	0.094	0.017	0.033	0.082	0.008	0.002	25.954*
ANG	0.100	0.105	0.121	0.042	0.070	0.050	68.148*
ASR	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.008
AVI	0.016	0.002	0.003	0.011	0.008	-0.003	0.706
BAW	0.005	0.018	0.005	0.015	0.012	0.006	1.179
BVT	0.027	0.037	0.104	0.070	0.010	0.024	28.097*
CHE	0.029	0.109	0.103	0.086	0.073	0.070	62.090*
CRH	0.047	0.104	0.049	0.085	0.052	0.072	46.357*
CTP	0.072	0.053	0.020	0.038	0.012	0.015	15.575**
DEL	0.017	-0.002	0.001	-0.002	-0.002	-0.002	0.459
DUR	0.107	0.006	0.030	0.040	-0.006	-0.008	21.266*
ECO	0.061	0.110	0.111	0.139	0.050	0.051	79.382*
ELH	0.179	0.058	0.072	0.065	0.114	0.080	97.132*
FOS	0.066	0.043	0.023	0.008	0.043	0.053	17.468*
GMF	0.032	0.002	0.002	0.016	0.019	-0.008	2.563
HAR	0.106	0.087	0.027	0.013	0.050	0.020	34.410*
HLH	0.013	0.020	0.015	0.063	0.005	0.016	7.717
HVL	0.082	0.048	0.055	0.022	0.085	0.051	33.889*
IMP	0.085	0.047	0.002	0.052	0.037	0.000	20.681*
JCM	-0.002	0.200	-0.001	0.006	-0.001	-0.001	60.321*
JNC	0.154	0.013	0.243	0.267	0.031	0.020	228.90*
LGL	0.074	0.067	0.019	0.050	0.012	0.004	19.751*
MAF	-0.001	0.000	0.000	-0.001	0.038	-0.001	2.150
MLB	0.000	0.005	0.005	-0.002	0.004	-0.001	0.110
NED	0.157	0.132	0.071	0.059	0.086	0.156	125.53*
NPK	0.237	0.118	0.220	0.194	0.125	0.240	350.27*
OCE	0.060	0.099	0.022	0.014	0.032	0.019	23.753*
PAM	0.184	0.031	0.029	0.019	0.024	0.037	57.984*
PIK	0.039	0.041	-0.015	0.003	0.027	0.143	37.742*
PPC	0.084	0.049	0.040	0.029	0.026	0.062	24.806*
REM	0.342	0.008	0.019	0.019	0.002	0.001	179.01*
RLO	0.083	0.051	0.050	0.057	0.011	0.042	26.176*
SAB	0.014	0.044	0.018	0.005	0.026	-0.005	4.860
SAP	0.091	0.098	0.028	0.051	0.086	0.012	43.844*
SBK	0.191	0.376	0.319	0.154	0.293	0.156	624.64*
TBS	0.088	0.027	0.063	0.058	0.101	-0.002	39.425*
TNT	0.172	0.081	0.077	0.031	0.058	0.055	75.001*
TRE	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	0.044
VNF	0.114	0.076	0.036	0.004	-0.019	0.008	31.212*
WAR	0.061	0.104	0.164	0.090	0.088	0.157	125.15*
WLO	0.102	0.054	0.030	0.023	0.036	0.024	25.252*

4.3.2 ARCH-Type Model Identification, Estimation and Appraisal

The general procedure followed to address the key objectives of this chapter was to identify the appropriate ARCH-type model for each of the market aggregates and individual stocks. Rather than impose the GARCH(1,1) specification on the basis of its popularity, the values of p and q were empirically confirmed in the study. First, note that the patterns of the ACFs and Q-statistics of squared linearly unpredictable returns reported in Table 4.1 were comparable with those for squared residual estimates from an OLS estimation of model (4.1), where R_t denoted linearly unpredictable returns[10]. Although the results presented in Table 4.1 apparently suggested the GARCH(1,1) model for most of the series, there were some possible indications of relatively higher order GARCH processes. Therefore, following Solibakke (2001), low-order ARMA models[11] were fitted to the squared residual estimates themselves[12], and the optimal lag structure was initially chosen on the basis of the SBC and the AIC. The use of the information-based criteria in this context was supported by the fact that they usually suggest parsimonious models, which are generally preferred in the GARCH procedure. For the identification of the appropriate ARMA(p,q) specification, the two statistics are given by:

$$SBC(p,q) = \log(\sigma^2) + (p+q)n^{-1}.\log(n), \text{ and} \tag{4.10}$$

$$AIC(p,q) = \log(\sigma^2) + 2(p+q)n^{-1}, \tag{4.11}$$

where σ^2 is the estimated variance of the error term in the estimated model, and n is the sample size. While both statistics reward good fit by a small $\log(\sigma^2)$, they differ in their penalisation for a spurious improvement in fit resulting from excessive parameterisations. The penalties applied by the statistics constitute the rest of the right hand sides in (4.10) and (4.11). Of the two, the SBC is more conservative, since it selects sparser parametisations than the AIC. The ARMA model that yielded the lowest values of the two statistics (which could actually be negative) was chosen for each stock. It is not unusual for the two statistics

[10] In our investigation with squared LS residuals from equation (4.1), the figures in Table 4.1 could be replicated, except in a few inconsequential incidences. In order to avoid an obvious duplication, Table 4.1 was used to provide a preliminary determination of the ARMA structure in the squared residuals.

[11] To be specific, both p and q assumed the value of 1 or 2 in this investigation. Therefore, for each series, the ARMA models fitted to the squared residuals were ARMA(1,1), ARMA(1,2), ARMA(2,1) and ARMA(2,2), and included intercept terms.

[12] In the case of return series for which serial correlation was filtered through an autoregression, this was equivalent to fitting an ARMA model on the squared unpredictable returns.

to suggest the same models, but where they yielded conflicting results, model selection was based on the conservative SBC.

In order to validate the appropriateness of the foregoing identification procedure where higher order GARCH processes were suggested, the statistical performance of such models and that of the GARCH(1,1) process were compared. Specifically, this comparison was based on the statistical significance of parameter estimates derived from the two models, as well as the values of log-likelihood functions.

Engel (1982), and Sumel and Engel (1994), among others, argued that the ARCH model was capable of accounting for volatility clustering in uncorrelated error terms with fat-tailed (leptokurtic) distributions[13]. In order to capture leptokurtosis, the normality assumption in (4.2) is sometimes relaxed in favour of fat-tailed alternatives, usually the Student's *t*-density with v degrees of freedom. Therefore, a common surrogate for (4.2) is (4.2'):

$$\mu_t|\Omega_{t-1} \sim t(0, h_t, v). \qquad (4.2')$$

This modification is sometimes useful when the maximum likelihood parameters of the variance equation are estimated using the traditional BHHH algorithm due to Berndt, Hall, Hall and Hausman (1974). This notwithstanding, ARCH-type models are generally estimated using the maximum likelihood technique under the assumption that the error terms are conditionally normally distributed, so that the model's parameter estimates are asymptotically efficient. Moreover, even if the error terms are not normally distributed, the estimates of the model are still consistent under quasi-maximum likelihood (QML) assumptions. In order to improve the convergence rate of the iterative process, a modification of the BHHH algorithm, known as the Marquardt algorithm, is preferred. This algorithm adds a correction matrix to the BHHH Hessian approximation, although, unless a correction is made, asymptotic standard errors are still computed from the unmodified BHHH Hessian approximation once convergence is achieved (EViews 3.1). In order to correct the standard errors for the effects of departures from the conditional normality assumption, heteroscedasticity-consistent QML standard errors are usually computed using the methods described by Bollerslev and Wooldridge (1992). Therefore, in this study, the maximum likelihood estimation of the models

[13] See also Baillie and DeGennaro, 1990, as well as Poon and Taylor, 1992.

employed the Marquardt algorithm. Throughout, Bollerslev-Wooldridge robust standard errors (and hence robust *z*-statistics) were obtained by utilising the QML method.

A specific-to-general modelling procedure was pursued in the investigation. Thus, the suggested GARCH models were first fitted to each of the series, and these were subsequently generalised in an attempt to capture some of the salient issues discussed in the previous section. In order to investigate the presence of asymmetric effects of shocks on volatility, both the EGARCH and the DGARCH models were attempted. Following Mills (1999), the choice between EGARCH and DGARCH was initially based on simple comparisons of the values of log-likelihood functions generated by the models for each series, a higher value being preferred. This simple model selection procedure is premised on the fact that the maximum likelihood estimates of ARCH-type models are precisely chosen such as to maximise this function[14]. In order to confirm the appropriateness of this procedure, the DGARCH model was also used on all stocks for which the EGARCH model achieved a higher log-likelihood function, and the performance of the models was compared on the basis of standard diagnostic tests. Thus, by examining the signs and statistical significance of the estimated values for the γ coefficients in the AGARCH models, the study assessed the possible asymmetric effects of positive and negative shocks on volatility.

In order to investigate whether volatility was priced on the JSE, a conditional variance term[15] was introduced in the mean equation, and the statistical significance of the associated coefficient, denoted β, was evaluated. Finally, a general AGARCH-M model was fitted to each of the series, in an attempt to capture all the effects simultaneously. Ward tests were then applied to investigate whether the leverage effect variable and the in-mean variable were jointly statistically significant in this most general model. Under the null hypothesis that $\gamma = \beta = 0$, the Ward test statistic has a χ_2^2 distribution[16].

An additional comparison made across the models was to assess the degree of persistence implied by each model. Noting the non-nestedness feature of the models, we adopted the procedure of Glosten *et al* (1993), where the following first order autoregressive scheme:

[14] Solibakke (2001) alludes to the use of a Lagrange (?) Ratio test in the choice between the two models, and documents preference for the DGARCH model. Suspecting that this might have been a Likelihood Ratio test, it is difficult to imagine how the test was conducted, considering the non-nestedness of the two models.
[15] Using the conditional standard deviation did not change the results materially, so the analysis is based on the results of using the conditional variance in pricing risk.
[16] For details, see Davidson and MacKinnon (1993).

$$h_t = \psi + \rho h_{t-1} + \nu_t, \tag{4.12}$$

was fitted to the estimated volatility series from each model, and the magnitude and significance of the autoregressive parameter were assessed and compared across models. In addition, the volatility persistence implied by the standard GARCH model was calculated as a simple summation of the ARCH and GARCH terms, and appraised.

4.3.3 Post-Estimation Diagnostic Checking

Finally, we were particularly interested in establishing whether the successful model for each series was capable of explaining the observed non-linearities in the data. Therefore, we applied the BDS test on the standardised residuals from the model. The test was introduced in Section 3.2, and was herein applied as therein described[17]. Because the distribution of such standardised residuals was known to be inconsistent with the standard normal, the test was conducted using the EViews 4.0 software, rather than the LeBaron programme used in Chapter 3. This facilitated the bootstrapping of probability values for accepting the null hypothesis of linearity, which was done using 1000 iterative repetitions. If the model was capable of capturing all the non-linearities, the test should not reject the iid null hypothesis when thus applied. In this context, the BDS test was a test for correct model specification.

Respecting the work of Chapter 3, two issues ought to be clarified at this point. Firstly, we could not be enticed to conduct the Engel test in addition to the BDS test to resolve the specification hypothesis. To buttress this resolution, Brock *et al* (1993:96) plainly dispute the use of the Engel test as a specification test, by noting that:

> Since (the Tsay and Engel) statistics are not designed to be used on residuals of fitted models, their use here as a residual diagnostic cannot be totally trusted. Also, the Engel statistic is looking for just the ARCH-GARCH type of structure, exactly the structure that is removed by fitting a GARCH model to the data.

Secondly, notice that there was no theoretical motivation to suggest that the structure of non-normalities documented in Chapter 3 could have been affected by fitting ARCH-type models,

[17] In particular, the choice of values for embedding dimension and closeness gauge made in Chapter 3 were maintained in this chapter, i.e., $m = 2,3,4,5$ and $l = 0.5\sigma, 1.0\sigma, 1.5\sigma$, where σ was the standard deviation of the data.

since the models are not designed to account for non-normalities. Although this matter was formally investigated, it was deemed immaterial in the overall objectives of the study at this stage, and the investigation results were omitted[18].

4.3.4 Summary of the Methodologies

To summarise, four ARCH-type processes (i.e., GARCH, GARCH-M, AGARCH and AGARCH-M) were fitted to each of the series, and the appropriate specification was selected on the basis of various diagnostic tests. The successful specification was then assessed in terms of its ability to explain the acknowledged non-linear structures of the series. The results of the investigation are presented and discussed in the next section.

4.4 Results and Discussions

4.4.1 GARCH Model Identification

The information-based criteria generated by low-order ARMA models fitted to the squared residual estimates from the least squares estimation of (4.1) are reported in Table 4.2. Panel I of the table presents the main results, including log likelihood functions from the estimations. For the individual stocks, the main results are further summarised in Panel II. It should be noted that the SBC and AIC measures yielded negative values in virtually all the models estimated, such that the preferred models were those for which the statistics were the largest in absolute value terms. In general, these results confirmed the documented popularity of the GARCH(1,1) model, which was clearly suggested for thirty-two of the forty-four individual stocks, in view of its direct analogy to the ARMA(1,1) model of squared residual estimates. In addition, there was some support for the GARCH(2,1) model, which was apparently appropriate in modelling the dynamics of both aggregates as well as ten stocks. Finally, both the GARCH(1,2) and the GARCH(2,2) processes could each be used to describe volatility in one stock only, namely SBK and JNC, respectively. The fact that the GARCH(2,2) process was almost consistently the least preferred among the four models rendered further evidence for the claim that GARCH models are generally parsimonious. It is also worth mentioning that almost two-thirds of the final GARCH specifications were mutually suggested by the SBC and the AIC, as indicated in the table.

[18] It should suffice to confirm that fitting an ARCH-type model changed the structure of non-normality not at all: the standardised residuals from the GARCH model, which was eventually preferred for all securities, remained asymmetric and highly leptokurtic, and the Jarque-Bera statistics were enormous with zero probability values across all the securities.

In order to validate the findings of the preceding analysis as far as the choice of higher order GARCH formulations was concerned, the results of estimating the suggested models as well as the GARCH(1,1) model for the two aggregates and twelve stocks are reported in Table 4.3. It is clear that the GARCH(1,1) specification would be a significant improvement in modelling volatility for these variables. While only six of the twenty-seven GARCH coefficients were statistically significant in the higher order models at 5 percent, all such coefficients were very significantly positive in the low-order specification. In addition, the low-order model yielded improvements in the statistical significance of ARCH coefficients (and intercepts) for quite a few securities, although there were some declines in the log likelihood functions for PORT and eight stocks. Notice also that only three of the fifteen higher order parameters were themselves significant. These results generally suggested that the GARCH(1,1) model was the most appropriate for the JSE[19] and, unlike in Solibakke (2001), rendered limited support for the use of the information-based criteria in the model selection procedures of the type pursued here.[20]

Given the above identification procedure, the augmentation of the model to capture asymmetric volatility effects and the pricing of volatility was a straightforward exercise. As presented in Table 4.4, an examination of the log likelihood functions generated by the various models provided *prima facie* justification for such extensions, since the extensions yielded higher log likelihood functions than those derived from the standard GARCH model, except for stocks AGL and WLO. It should be noted that, even after a great deal of re-specification efforts for the mean equation, the parameters of the in-mean models could not converge in the case of seven stocks (i.e., AGL, ASR, AVI, BAW, DEL, DUR and MLB)[21]. Further, note that on the basis of the log likelihood function, the DGARCH-M model could be most preferred among the four models, since it was suggested for sixteen of the thirty-seven stocks that encountered no parameter convergence problems during model estimation, as well as the market aggregates. In the sequel, we discuss findings regarding the choice between DGARCH and EGARCH processes.

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[19] A possible outlier to this generalisation is the stock WAR, for which all coefficients but the mean equation intercept were clearly significant in the GARCH(2,1) model, which was also supported by the higher log likelihood function. However, for this particular stock, there was also a marked weakening in the otherwise very strong significance of the coefficient for the first GARCH term as the order increased.

[20] Notice, however, that the SBC suggested the GARCH(1,1) specification in all cases in Solibakke (2001). It is the fact that the criterion could also suggest higher order, yet sub-optimal, models in our case that constitutes a departure from Solibakke.

[21] This non-convergence problem is typical (see Glosten *et al*, 1993), and is acknowledged by the authorship of EViews.

Table 4.2 – GARCH model identification

This table summarises the results of the GARCH model identification procedure. Low-order ARMA models were fitted to the squared residual estimates from the OLS estimation of (4.1). The SBC-preferred GARCH order is presented in the last column. ♦ indicates that the order was mutually preferred by both SBC and AIC. Log L is the log likelihood function. The main results are in Panel I, while a summary for the individual stocks is in Panel II.

I. Main results

(a) Stock portfolios

	ARMA(1,1)			ARMA(1,2)			ARMA(2,1)			ARMA(2,2)			Order
Portfolio	AIC	SBC	Log L	AIC	SBC	Log L	AIC	SBC	Log L	AIC	SBC	Log L	p,q
ALSI	-9.512	-9.497	4502.2	-9.527	-9.507	4510.5	-9.527	-9.506	4505.4	-9.525	-9.499	4505.6	2,1♦
PORT	-10.73	-10.72	8126.6	-10.76	-10.75	8150.1	-10.76	-10.74	8142.3	-10.76	-10.74	8144.4	2,1♦

(b) Individual stocks

	ARMA(1,1)			ARMA(1,2)			ARMA(2,1)			ARMA(2,2)			Order
Security	AIC	SBC	Log L	AIC	SBC	Log L	AIC	SBC	Log L	AIC	SBC	Log L	p,q
AFE	-5.147	-5.137	3904.7	-5.146	-5.132	3905.0	-5.146	-5.132	3902.0	-5.145	-5.127	3902.1	1,1♦
AFX	-7.981	-7.971	6060.8	-7.984	-7.970	6063.8	-7.984	-7.970	6059.8	-7.983	-7.965	6059.8	1,1
AGL	-3.113	-3.102	2365.7	-3.120	-3.106	2372.3	-3.119	-3.105	2369.5	-3.117	-3.099	2369.1	2,1♦
ALT	-6.525	-6.514	4945.6	-6.534	-6.520	4953.9	-6.534	-6.520	4950.3	-6.533	-6.515	4950.2	2,1♦
ANG	-7.462	-7.452	5667.0	-7.461	-7.447	5667.0	-7.461	-7.446	5662.8	-7.459	-7.442	5662.9	1,1♦
ASR	-0.127	-0.117	99.7	-0.126	-0.112	99.7	-0.125	-0.111	99.2	-0.132	-0.114	77.3	1,1
AVI	-5.427	-5.416	4108.5	-5.426	-5.412	4109.0	-5.426	-5.412	4105.8	-5.431	-5.413	4110.5	1,1
BAW	-5.616	-5.606	4248.0	-5.615	-5.601	4249.0	-5.614	-5.600	4245.7	-5.613	-5.596	4245.8	1,1♦
BVT	-6.834	-6.823	5186.4	-6.834	-6.820	5187.9	-6.834	-6.820	5183.8	-6.834	-6.816	5184.9	1,1
CHE	-7.625	-7.621	5776.4	-7.637	-7.623	5781.5	-7.636	-7.622	5777.1	-7.635	-7.618	5777.4	2,1
CRH	-5.156	-5.145	3913.5	-5.155	-5.141	3914.3	-5.154	-5.141	3911.3	-5.155	-5.137	3912.5	1,1♦
CTP	-6.314	-6.304	4795.4	-6.315	-6.300	4796.7	-6.314	-6.300	4793.4	-6.311	-6.294	4792.1	1,1
DEL	-3.547	-3.536	2695.2	-3.546	-3.532	2695.2	-3.545	-3.531	2692.9	-3.544	-3.527	2693.2	1,1♦
DUR	-5.135	-5.124	3897.7	-5.136	-5.122	3899.4	-5.133	-5.119	3894.7	-5.134	-5.116	3896.4	1,1
ECO	-7.226	-7.215	5436.8	-7.227	-7.213	5439.1	-7.227	-7.213	5434.9	-7.225	-7.208	5434.9	1,1
ELH	-6.944	-6.933	5248.9	-6.950	-6.936	5254.8	-6.949	-6.935	5250.3	-6.949	-6.931	5251.3	2,1♦
FOS	-6.738	-6.727	5107.0	-6.738	-6.723	5107.7	-6.737	-6.723	5103.8	-6.736	-6.718	5103.9	1,1♦
GMF	-6.054	-6.044	4598.1	-6.060	-6.046	4603.6	-6.059	-6.045	4600.1	-6.058	-6.041	4600.1	2,1♦
HAR	-6.302	-6.392	4780.2	-6.303	-6.289	4781.5	-6.302	-6.288	4778.0	-6.301	-6.284	4778.2	1,1
HLH	-5.978	-5.967	4540.1	-5.976	-5.962	4540.1	-5.975	-5.962	4536.7	-5.975	-5.957	4536.9	1,1♦
HVL	-7.151	-7.140	5412.5	-7.151	-7.137	5414.0	-7.151	-7.137	5410.0	-7.149	-7.132	5409.8	1,1
IMP	-6.849	-6.838	5194.6	-6.839	-6.825	5188.1	-6.840	-6.826	5185.3	-6.847	-6.829	5191.4	1,1♦
JCM	-0.058	-0.047	46.8	-0.091	-0.076	72.2	-0.089	-0.075	70.7	-0.089	-0.071	71.7	2,1♦
JNC	-0.441	-0.430	325.1	-0.440	-0.425	325.1	-0.439	-0.424	324.4	-0.502	-0.484	371.6	2,2♦
LGL	-7.008	-6.998	5322.2	-7.008	-6.994	5322.7	-7.007	-6.993	5318.8	-7.005	-6.988	5318.6	1,1♦
MAF	-1.346	-1.335	1019.5	-1.344	-1.330	1019.5	-1.344	-1.329	1018.4	-1.343	-1.325	1018.6	1,1♦
MLB	-3.962	-3.952	3010.5	-3.962	-3.948	3011.4	-3.963	-3.949	3010.0	-3.960	-3.942	3008.4	1,1
NED	-7.986	-7.975	6064.2	-7.986	-7.971	6065.0	-7.985	-7.971	6060.6	-7.983	-7.966	6060.4	1,1♦
NPK	-7.822	-7.811	5939.7	-7.822	-7.808	5941.2	-7.821	-7.807	5936.5	-7.826	-7.808	5940.9	1,1
OCE	-7.195	-7.184	5463.7	-7.194	-7.180	5464.5	-7.194	-7.180	5460.6	-7.193	-7.175	5460.7	1,1♦
PAM	-7.504	-7.493	5698.5	-7.508	-7.494	5702.3	-7.502	-7.488	5694.4	-7.506	-7.488	5698.2	2,1♦
PIK	-6.829	-6.818	5185.9	-6.819	-6.805	5179.9	-6.819	-6.805	5176.1	-6.835	-6.817	5187.2	1,1
PPC	-8.102	-8.091	6127.8	-8.101	-8.087	6126.6	-8.101	-8.087	???	-8.099	-8.082	6124.1	1,1♦
REM	-4.054	-4.044	3074.2	-4.053	-4.039	3074.4	-4.052	-4.038	3071.7	-4.051	-4.034	3071.9	1,1♦
RLO	-6.162	-6.152	4664.7	-6.162	-6.148	4665.5	-6.161	-6.147	4662.1	-6.162	-6.144	4663.1	1,1♦
SAB	-6.768	-6.757	5139.6	-6.766	-6.752	5139.6	-6.766	-6.752	5135.8	-6.765	-6.747	5135.9	1,1♦
SAP	-6.986	-6.976	5305.4	-6.986	-6.972	5306.5	-6.986	-6.972	5302.7	-6.983	-6.966	5301.7	1,1
SBK	-7.819	-7.808	5871.0	-7.866	-7.852	5907.7	-7.867	-7.853	5904.1	-7.867	-7.850	5905.6	1,2
TBS	-7.892	-7.882	5953.7	-7.892	-7.877	5954.3	-7.891	-7.877	5949.8	-7.891	-7.874	5951.1	1,1♦
TNT	-7.748	-7.738	5883.9	-7.752	-7.738	5887.9	-7.752	-7.738	5883.8	-7.751	-7.733	5884.0	2,1♦
TRE	-0.678	-0.668	518.0	-0.677	-0.663	518.0	-0.677	-0.663	517.2	-0.675	-0.658	517.2	1,1♦
VNF	-5.921	-5.910	4493.9	-5.920	-5.905	4494.3	-5.919	-5.905	4490.8	-5.919	-5.901	4491.6	1,1♦
WAR	-5.950	-5.940	4516.3	-5.954	-5.940	4520.4	-5.953	-5.939	4516.6	-5.953	-5.935	4517.1	2,1♦
WLO	-7.230	-7.289	5539.9	-7.310	-7.296	5548.5	-7.309	-7.295	5544.5	-7.308	-7.291	5544.5	2,1♦

Table 4.2 – GARCH model identification (continued)

II. Summary: individual stocks

Row	*GARCH Order*	*Stocks*	*No. of Stocks*
#1	1,1	All stocks but those specified in rows #2, #3, and #4	32
#2	2,1	AGL, ALT, CHE, ELF, GMF, JCM, PAM, TNT, WAR, WLO	10
#3	1,2	SBK	1
#4	2,2	JNC	1
		Total	*44*

Table 4.3 ML estimation of standard GARCH models: selected securities

*This table shows the results of estimating the GARCH(1,1) model and the alternative higher order GARCH model suggested by the SBC for each of the two portfolios and twelve individual stocks. The parameters are defined in equations (4.1) and (4.4). Figures in parentheses are robust z-statistics. * and ** denote significance at 1% and at 5%, respectively. Log L is the log likelihood function.*

(a) Stock portfolios

Portfolio	*p,q*	α	ϕ	λ_1	λ_2	θ_1	θ_2	*Log L*
	2,1	0.000 (0.590)	0.000 (2.213)**	0.122 (3.154)*		1.007 (2.797)*	-0.208 (-0.612)	2094.6
ALSI	1,1	0.000 (0.469)	0.000 (1.76)	0.124 (2.843)*		0.795 (11.26)*		2093.8
	2,1	0.000 (0.797)	0.000 (2.800)*	0.114 (3.169)*		0.607 (1.77)	0.212 (0.695)	3774.4
PORT	1,1	0.000 (0.860)	0.000 (3.388)*	0.090 (3.879)*		0.856 (29.37)*		3774.0

(b) Individual stocks

Security	*p,q*	α	ϕ	λ_1	λ_2	θ_1	θ_2	*Log L*
AGL	2,1	0.002 (1.419)	-0.000 (-0.119)	0.027 (0.621)		0.643 (0.275)	0.340 (0.146)	2242.9
	1,1	0.002 (1.477)	-0.000 (-0.166)	0.016 (4.642)*		0.993 (30.89)*		2265.7
ALT	2,1	-0.000 (-0.297)	0.000 (1.450)	0.060 (1.385)		0.303 (0.724)	0.577 (1,482)	2460.3
	1,1	-0.000 (-0.243)	0.000 (0.817)	0.015 (1.592)		0.978 (59.06)*		2477.6
CHE	2,1	0.001 (0.783)	0.000 (1.234)	0.056 (1.83)		0.699 (0.895)	0.104 (0.152)	2698.8
	1,1	0.001 (0.806)	0.000 (1.610)	0.005 (2.025)**		0.830 (9.859)*		2699.8
ELH	2,1	0.001 (1.122)	0.000 (1.83)	0.058 (2.068)**		0.392 (0.999)	0.495 (1.379)	2440.4
	1,1	0.001 (0.958)	0.000 (2.097)**	0.040 (2.601)*		0.924 (31.44)*		2437.4
GMF	2,1	0.004 (2.831)*	0.000 (0.715)	0.047 (1.221)		0.075 (1.070)	0.811 (5.238)*	2319.7
	1,1	0.003 (2.270)**	0.000 (0.718)	0.016 (1.67)		0.968 (30.40)*		2322.7
JCM	2,1	0.005 (2.114)**	0.000 (1.351)	0.886 (1.594)		0.814 (1.906)	-0.133 (-0.402)	2128.0
	1,1	0.005 (1.998)**	0.000 (1.295)	1.069 (1.375)		0.823 (5.237)*		2123.0
JNC	2,2	0.005 (2.210)**	0.000 (1.428)	0.596 (1.329)	-0.236 (-0.483)	0.477 (0.919)	0.255 (0.837)	1867.1
	1,1	0.003 (1.515)	0.000 (0.838)	0.399 (1.87)		0.738 (8.816)*		1853.8
PAM	2,1	0.001 (0.848)	0.000 (2.131)**	0.030 (2.318)**		0.579 (1.362)	0.103 (0.313)	2513.7
	1,1	0.001 (0.857)	0.000 (2.565)**	0.122 (2.996)*		0.697 (7.388)*		2513.5
SBK	1,2	0.000 (0.375)	0.000 (2.873)*	0.154 (3.278)*	-0.042 (-0.835)	0.817 (16.53)*		2738.8
	1,1	0.000 (0.370)	0.000 (3.406)*	0.134 (4.086)*		0.770 (15.85)*		2738.2
TNT	2,1	0.003 (2.634)*	0.000 (2.876)*	0.133 (3.568)*		0.295 (1.435)	0.442 (2.348)*	2514.5
	1,1	0.003 (2.530)**	0.000 (2.769)*	0.086 (3.542)*		0.829 (17.13)*		2511.1
WAR	2,1	0.000 (0.429)	0.000 (2.585)*	0.051 (2.807)*		1.452 (7.175)*	-0.527 (-2.92)*	1797.2
	1,1	0.000 (0.195)	0.000 (2.857)*	0.100 (4.893)*		0.858 (30.41)*		1794.8
WLO	2,1	0.001 (0.539)	0.000 (0.882)	0.035 (0.862)		0.679 (0.505)	0.251 (0.197)	2523.6
	1,1	0.001 (0.509)	0.000 (2.088)**	0.024 (2.090)**		0.951 (47.69)*		2522.6

Table 4.4 – Log likelihood functions of the estimated ARCH-type models

This table presents the log likelihood functions for the various ARCH-type models fitted to the return series. ♦ identifies the log likelihood function-preferred model among all models. The log likelihood function for the preferred AGARCH model is grey-shaded. NC indicates parameter non-convergence.

(a) Stock portfolios

Portfolio	GARCH	DGARCH	EGARCH	GARCH-M	DGARCH-M
ALSI	2093.781	2094.239	2096.955	2096.569	2096.977♦
PORT	3774.011	3776.795	3777.181	3775.024	3777.510♦

(b) Individual stocks

Security	GARCH	DGARCH	EGARCH	GARCH-M	DGARCH-M
AFE	2424.357	2424.388	2410.140	2425.127	2425.040♦
AFX	2652.717	2653.400	2635.509	2653.012	2654.544♦
AGL	2265.717♦	2174.754	2202.770	NC	NC
ALT	2477.569	2478.599♦	2425.509	2473.249	2442.856
ANG	2232.505	2233.111♦	2232.187	2231.545	2232.259
ASR	1473.714	1481.040	1550.606♦	NC	NC
AVI	2511.434	2511.666♦	2400.071	NC	NC
BAW	2526.944	2543.911	2553.706♦	NC	NC
BVT	2592.865	2608.105♦	2548.039	2591.797	2606.626
CHE	2699.758	2713.322	2667.800	2701.811	2718.101♦
CRH	1733.839	1734.656♦	1701.928	1733.462	1734.325
CTP	2354.497	2376.305	2376.675	2366.893	2377.737♦
DEL	2351.470	2362.415♦	2202.939	NC	NC
DUR	1572.637	1572.745	1571.002	1579.237♦	NC
ECO	2681.322	2686.619♦	2680.154	2678.268	2684.024
ELH	2437.374	2449.065	2419.634	2438.810	2449.819♦
FOS	2548.144	2557.856	2541.984	2548.977	2558.890♦
GMF	2322.592	2322.953♦	2304.764	2321.013	2321.025
HAR	1962.282	1963.745	1963.038	1964.117	1965.997♦
HLH	2391.601	2392.184	2398.420♦	2383.253	2384.087
HVL	2289.434	2291.965	2293.894♦	2287.854	2288.530
IMP	2158.371	2162.014♦	2160.772	2156.852	2160.741
JCM	2123.012	2124.983	2036.970	2155.436	2163.069♦
JNC	1853.832	1862.793	1320.556	2029.186	2042.138♦
LGL	2671.537	2678.816	2617.860	2672.847	2679.458♦
MAF	2439.468	2528.479♦	1989.186	2406.177	2500.892
MLB	2030.714	2038.777	2102.796♦	NC	NC
NED	2635.625	2648.688	2651.377♦	2636.679	2649.106
NPK	2751.847	2752.966	2761.473♦	2750.201	2752.885
OCE	2526.558	2526.721	2537.319♦	2528.553	2528.579
PAM	2513.450	2516.898	2512.783	2514.367	2517.623♦
PIK	2312.804	2315.272	2320.891	2315.308	2315.526♦
PPC	2889.467	2890.253	2901.100♦	2890.260	2890.846
REM	2175.333	2186.547	2177.824	2224.578	2238.670♦
RLO	2415.841	2416.101♦	2412.714	2413.922	2413.983
SAB	2682.258	2682.727	2662.638	2686.976	2686.989♦
SAP	2346.042	2347.170	2352.433♦	2347.279	2348.555
SBK	2738.245	2738.455	2731.274	2745.576	2745.767♦
TBS	2745.423	2754.858♦	2703.367	2744.775	2754.464
TNT	2511.125	2513.875	2519.795♦	2509.110	2511.955
TRE	1337.815	1344.081	1434.371♦	1387.529	1328.187
VNF	2219.484	2222.408♦	2184.496	2221.226	2221.727
WAR	1794.835	1795.882	1794.778	1795.587	1796.637♦
WLO	2522.632♦	2514.562	2512.309	2514.530	2514.559

4.4.2 Asymmetric GARCH Model Selection

Limiting the comparison to that between the DGARCH and EGARCH models, Table 4.4 shows that the DGRACH model was suggested for thirty securities, while the remaining sixteen (including the aggregates) could be modelled as EGARCH processes. In an attempt to substantiate this observation, a comparison between the estimation results of the EGARCH and DGARCH models for the sixteen securities was made. The estimation results are summarised in Table 4.5.

Focusing on the statistical significance of the ARCH and GARCH terms, it was noted that the EGARCH model performed at least as well as the DGARCH model for both aggregates as well as eleven of the fourteen stocks. The notable exceptions were ASR, MBL and TRE, where the DGARCH model was somewhat a better fit. More importantly, it was further noted that the coefficient for the leverage effect term was negative in the EGARCH model for virtually all but one stock (i.e., BAW), while all but two stocks (i.e., BAW and MLB) and both aggregates yielded positive leverage effect coefficients in the DGARCH model. Since a positive coefficient was consistent with *a priori* expectations, there was no compelling theoretical reason to suggest that the EGARCH model was a better fit. Hence, we chose to model all the securities as DGARCH processes.

Finally, both the GARCH and DGARCH models selected as described above were extended further by including the conditional variance term in the mean equation, such that four ARCH-type models were estimated for each security as described in the methodologies. The estimation results for the portfolios are contextually presented in this chapter, while those for the individual stocks are contained in Appendix 4A. Therefore, Table 4.6 to Table 4.9, which summarise the results for individual stocks, merely seek to facilitate the analysis and do not purport to substitute the appendix. The appendix duly deserves full attention.

Two points ought to be mentioned regarding the ensuing analysis. Firstly, it is trivial, yet of necessity, to note that a parameter estimate that is statistically significant at 10 percent is equivalently significantly positive or negative at the 5 percent level, the latter being a one-tail test. That is to say, once statistical significance is established at any given conventional level, the one-tail test alternative hypothesis that the concerned coefficient is significantly positive or negative can always not be rejected. As such, we evaluated two-tail statistical significance at 10 percent in the succeeding analysis, to achieve the aforesaid 5 percent one-tail equivalence. Secondly, since no strict structural model was assumed for the mean equation, there was no motivation for a statistical evaluation of this equation, except in terms of the worth of the in-mean variable. Generally, it was the slope coefficients that mattered.

Table 4.5 – ML estimation of AGARCH models: selected securities

*This table shows the maximum likelihood estimates (with robust z-statistics in parentheses) of the DGARCH and EGARCH models for the sixteen securities for which the EGARCH model was preferred to the DGARCH model on the basis of the log likelihood function (see Table 4.4). For both models, the conditional mean equation was (4.1). The conditional variance equations were (4.6) for EGARCH and (4.7) for DGARCH. * denotes statistical significance at 1%, while ** denotes significance at 5%.*

(a) Stock portfolios

Portfolio	*Model*	α	ϕ	λ_1	γ	θ_1
ALSI	DGARCH	0.000 (0.320)	0.000 (1.806)	0.102 (1.567)	0.041 (0.544)	0.786 (10.363)*
	EGARCH	0.000 (0.350)	-0.000 (-2.515)**	0.248 (3.755)*	-0.051 (-1.167)	0.897 (18.695)*
PORT	DGARCH	0.000 (0.411)	0.000 (3.759)*	0.053 (2.152)**	0.060 (1.624)	0.857 (31.952)*
	EGARCH	0.000 (0.157)	-0.000 (-3.971)*	0.212 (3.855)*	-0.051 (-1.71)	0.917 (38.880)*

(b) Individual stocks

Security	*Model*	α	ϕ	λ_1	γ	θ_1
AGL	DGARCH	0.006 (2.160)**	0.002 (6.999)*	0.049 (0.751)	1.461 (0.867)	0.006 (0.375)
	EGARCH	0.004 (2.433)**	-5.958 (-6.308)*	0.585 (3.560)*	-0.357 (-1.292)	0.047 (0.248)
ASR	DGARCH	-0.000 (-0.269)	0.005 (1.097)	-0.053 (-1.978)**	0.052 (1.982)**	0.612 (1.126)
	EGARCH	0.000 (0.000)	-4.876 (-0.900)	-0.268 (-0.579)	-0.188 (-0.608)	0.010 (0.008)
BAW	DGARCH	-0.000 (-0.044)	0.000 (4.301)*	0.228 (1.353)	-0.167 (-0.841)	0.814 (24.476)*
	EGARCH	-0.000 (-0.021)	-0.524 (-4.013)*	0.214 (2.666)*	0.080 (0.703)	0.940 (56.198)*
CTP	DGARCH	0.003 (2.532)**	0.000 (1.754)	0.025 (0.992)	0.068 (1.979)**	0.923 (23.549)*
	EGARCH	0.005 (4.021)*	-0.345 (-2.253)**	0.151 (2.333)**	-0.092 (-3.434)*	0.958 (48.102)*
HLH	DGARCH	0.002 (2.426)**	0.000 (2.454)**	0.085 (1.883)	0.024 (0.725)	0.894 (29.203)*
	EGARCH	0.003 (2.552)**	-0.421 (-2.650)**	0.208 (2.506)**	-0.045 (-1.510)	0.952 (47.083)*
HVL	DGARCH	-0.000 (-0.338)	0.000 (1.413)	-0.001 (-0.089)	0.029 (2.477)**	0.979 (88.855)*
	EGARCH	-0.001 (-0.832)	-0.011 (-2.165)**	0.211 (3.934)*	-0.015 (-0.416)	0.852 (11.330)*
MLB	DGARCH	0.001 (0.442)	0.002 (1.701)	0.073 (1.527)	-0.077 (-1.607)	0.568 (2.446)**
	EGARCH	0.001 (1.049)	-4.692 (-1.93)	0.155 (1.423)	-0.120 (-1.285)	0.180 (0.384)
NED	DGARCH	0.003 (2.758)*	0.000 (3.103)*	0.013 (0.702)	0.106 (3.118)*	0.874 (27.401)*
	EGARCH	0.003 (2.808)*	-0.309 (-3.490)*	0.108 (2.949)*	-0.080 (-3.645)*	0.964 (81.731)*
NPK	DGARCH	0.003 (2.881)*	0.000 (2.740)*	0.036 (2.102)**	0.032 (1.314)	0.914 (41.473)*
	EGARCH	0.003 (3.189)*	-0.333 (-3.256)*	0.131 (3.722)*	-0.034 (-1.575)	0.963 (70.706)*
OCE	DGARCH	0.003 (2.954)*	0.000 (1.277)	0.048 (2.408)**	-0.002 (-0.038)	0.928 (24.469)*
	EGARCH	0.003 (2.807)*	-0.353 (-2.120)**	0.130 (3.348)*	-0.006 (-0.103)	0.956 (41.206)*
PPC	DGARCH	0.000 (0.191)	0.000 (1.741)	0.029 (1.730)	0.017 (0.854)	0.936 (39.675)*
	EGARCH	-0.000 (-0.177)	-0.850 (-2.146)**	0.084 (2.955)*	-0.014 (-0.575)	0.981 (87.930)*
SAP	DGARCH	0.003 (2.084)**	0.000 (1.646)	0.031 (2.498)**	0.019 (0.931)	0.947 (63.035)*
	EGARCH	0.003 (2.371)**	-0.109 (-2.578)*	0.073 (3.353)*	-0.034 (-2.450)*	0.991 (162.819)*
TNT	DGARCH	0.002 (2.133)**	0.000 (3.041)*	0.062 (1.966)**	0.059 (1.195)	0.816 (16.958)*
	EGARCH	0.002 (2.019)**	-0.784 (-3.284)*	0.205 (3.729)*	-0.057 (-1.401)	0.896 (25.618)*
TRE	DGARCH	0.004 (1.721)	0.006 (1.721)	-0.003 (-3.217)*	-0.000 (-1.87)	0.596 (1.884)
	EGARCH	-0.000 (-0.662)	-4.530 (-4.528)*	-0.101 (-0.757)	-0.372 (-1.964)**	0.047 (0.311)

4.4.3 GARCH Model Estimation

The results of estimating the GARCH(1,1) model are comprehensively presented in Appendix 4A for the individual stocks, and summarised in Table 4.6. For the two market aggregates, reversion to Table 4.3(a) for reference is in order. The estimation results indicated that the standard GARCH process was a successful univariate model of volatility on the JSE. Firstly, the coefficient for the GARCH term, θ_1, was significantly positive in all but two cases (ASR and MLB), and remained positive but insignificant for those two stocks. In most cases, the level of significance was exceedingly high, implying strong evidence that volatility in the previous week sturdily explained current volatility. The estimated values for the coefficient were also quite high (generally close to, but less than unity). This had an implication for the structure of volatility persistence, a matter pursued in subsection 4.4.7.

Table 4.6 - GARCH model estimation results: summary for individual stocks

This table provides a summary of the estimation results for the standard GARCH model for individual stocks. The conditional mean and volatility equations are given by (4.1) and (4.4) above, respectively. C in the first column is the estimated coefficient in the model, and could take any of the values indicated in the third column. For each such value, the stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in columns four and five, respectively. A comprehensive presentation of these findings is in Appendix 4A.

C	*Row*	*Value of C*	*Securities*	*No.*
	#1	Positive	All stocks but those in Row #3	37
	#2	Significantly positive	AFX, ANG, CTP, GMF, HLH, JCM, NED, NPK, OCE, PIK, SAB, SAP, TNT	13
α	#3	Negative	ALT, BAW, DUR, HAR, HVL MLB, REM,	7
	#4	Significantly negative	None	0
	#5	Not significant	All but those in Row #2	31
	#6	Positive	All stocks	44
	#7	Significantly positive	ANG, BAW, BVT, DUR, ECO, ELH, HAR, HLH, HVL, IMP, MAF, NED, NPK, PAM, PPC, REM, SBK, TBS, TNT, VNF, WAR	21
ϕ	#8	Negative	None	0
	#9	Significantly negative	None	0
	#10	Not significant	All stocks but those in Row #7	23
	#11	Positive	All stocks but those in Row #13	41
	#12	Significantly positive	All stocks but those in Row #13 and Row #15	35
λ_1	#13	Negative	ASR, MLB, TRE	3
	#14	Significantly negative	ASR, MLB, TRE	3
	#15	Not significant	AFE, ALT, JCM, MAF, REM, VNF	6
	#16	Positive	All stocks	44
	#17	Significantly positive	All stocks but those in Row #20	42
θ_1	#18	Negative	None	0
	#19	Significantly negative	None	0
	#20	Not significant	ASR, MLB	2

Secondly, the ARCH term also yielded a commonly positive coefficient ($\lambda_1 > 0$ in forty-three of the forty-six cases), which was significant in forty instances. For three stocks (ASR, MLB and TRE), it is interesting to note that λ_1 was actually significantly negative, showing an inverse relationship between shocks and volatility. Although the estimated values for λ_1 in these three stocks were very low in absolute value terms (0.001, 0.005 and 0.003, respectively), the effects of the term might not be ignored, particularly considering that the concerned stocks also yielded relatively low and practically insignificant estimates for θ_1. All in all, the empirical findings indicated that strong GARCH effects were apparent on the JSE[22], and that individual stock dynamics could be approximated well by the dynamics for the market aggregates.

4.4.4 Dummy GARCH Model Estimation

In Table 4.7, a summary of the results of estimating the DGARCH model is presented to supplement the relevant parts of Appendix 4A. For the results relating to the aggregates, refer once more to Table 4.5(a). It was noted that the asymmetric effect term was positive for both portfolios and twenty-eight of the individual stocks, but significantly so for only nine stocks. For the said nine stocks, therefore, a negative shock apparently tended to increase volatility more than a positive shock of similar magnitude (i.e., there were seemingly significant leverage effects). Although the remaining stocks showed that a negative shock could reduce volatility by more than a positive shock of equal magnitude ($\gamma < 0$), the parameter was only significant for two of the sixteen stocks involved (i.e., TRE and VNF). Therefore, the *prima facie* evidence was that asymmetric effects could be observed in one-quarter of the stocks under investigation, but not in any of the aggregates, and that most of these observed asymmetries were consistent with the supposition of a leverage effect. This observation notwithstanding, it was further noted that the ARCH term parameter became statistically insignificant in virtually all stocks that showed evidence of significant asymmetric effects. This could imply that the ARCH term and the asymmetric effect term were highly collinear, and hence that the significance of the asymmetric effect parameter was spurious. Collinearity also potentially spanned other stocks and ALSI, such that only twenty stocks and PORT had significant ARCH term coefficients in the DGARCH model, compared with thirty-eight stocks and both aggregates in the GARCH model. This led us to suspect that the asymmetric effect term was 'detrimental' to the estimation of the model, and to conclude that genuine asymmetric effects were not discernible on the market.

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[22] When the GARCH(2,1) model was estimated for WAR as apparently suggested by prior diagnostics, it was noted that the coefficient for the second GARCH term was significantly negative, while that for the first remained significantly positive. This tendency could support the phenomenon of mean reversion for volatility: while volatility in the immediate previous week tended to increase current volatility rather strongly, an overly excessive departure from the mean level was thwarted by the effect of volatility in the previous fortnight, which tended to exert a countering force towards the mean.

Except for the above observations, the results of fitting the DGARCH model were quite comparable with those of the standard GARCH specification. Specifically, it was noted that the first order GARCH term was not affected by the inclusion of the asymmetric effect term. Since the 'detrimental' variable was clearly collinear with only one other variable, namely the ARCH term, its omission was deemed appropriate in improving parameter estimation, in the spirit of Frisch's confluence analysis (Koutsoyiannis, 1988).

Table 4.7 - DGARCH model estimation results: summary for individual stocks

This table provides a summary of the estimation results for the DGARCH model for individual stocks. The specific conditional mean and volatility equations are given by (4.1) and (4.7), respectively. C in the first column is the estimated coefficient in the model, and could take any of the values indicated in the third column. For each such value, the stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in columns four and five, respectively. Appendix 4A gives a comprehensive presentation of these findings.

C	Row	Value of C	Stocks	No.
	#1	Positive	All stocks but those in Row #3	34
α	#2	Significantly positive	AFX, AGL, CTP, DEL, GMF, HLH, JCM, JNC, LGL, MAF, NED, NPK, OCE, PIK, SAB, SAP, TNT, TRE	18
	#3	Negative	ALT, ASR, BAW, BVT, CHE, CRH, DUR, HAR, HVL, REM	10
	#4	Significantly negative	None	0
	#5	Not significant	All stocks in Row #3 as well as AFE, ANG, AVI, ECO, ELH, FOS, IMP, MLB, PAM, PPC, RLO, SBK, TBS, VNF, WLO	25
	#6	Positive	All stocks	44
ϕ	#7	Significantly positive	AGL, ANG, BAW, BVT, CHE, CTP, DUR, ECO, ELH, HAR, HLH, IMP, MAF, MLB, NED, NPK, PAM, PPC, REM, SAP, SBK, TBS, TNT, TRE, WAR, WLO	21
	#8	Negative	None	0
	#9	Significantly negative	None	0
	#10	Not significant	All stocks but those in Row #7	23
	#11	Positive	All stocks but those in Row #13	41
λ_1	#12	Significantly positive	AFX, ANG, AVI, DEL, DUR, HAR, HLH, NPK, OCE, PAM, PPC, SAB, SAP, SBK, TNT, VNF, WAR, WLO	18
	#13	Negative	ASR, CHE, HVL, TRE	4
	#14	Significantly negative	ASR, TRE	2
	#15	Not significant	All stocks but those in Row #12 and Row #14	24
	#16	Positive	All stocks but those in Row #18	28
	#17	Significantly positive	ASR, BVT, CHE, CTP, ELH, HVL, LGL, NED, TBS,	9
γ	#18	Negative	AFE, ALT, BAW, DEL, DUR, GMF, JCM, JNC, MAF, MLB, OCE, REM, SBK, TRE, VNF, WLO	16
	#19	Significantly negative	TRE, VNF	2
	#20	Not significant	All stocks but those in Row #17 and Row #19	33
	#21	Positive	All stocks	44
	#22	Significantly positive	All stocks but those in Row #25	41
θ_1	#23	Negative	None	0
	#24	Significantly negative	None	0
	#25	Not significant	AGL, ASR, REM,	3

4.4.5 GARCH-in-Mean Model Estimation

The results of estimating the GARCH-M model are presented in Table 4.8, where part (a) presents the results for the portfolios, and part (b) summarises the relevant part of Appendix 4A. As alluded to in subsection 4.4.1, convergence could not be achieved in the estimation of the parameters of the model for six stocks, namely AGL, ASR, AVI, BAW, DEL, and MLB, such that the analysis was based on the remaining forty assets. It will be noted from the table that the volatility coefficient in the mean equation was negative for PORT and twenty-seven of the stocks, but only significantly so for PORT and JNC. Further, only DUR and HAR among the forty-four individual stocks showed that volatility was positively priced in their return dynamics. For these, an increase in volatility was, on average, associated with higher expected returns. Since the general requirement for a priced factor is that it should be common across the stocks in the market, volatility could be perceived as representing idiosyncratic, other than systematic, risk for the few assets where it was priced. This could suggest that volatility did not meet the criterion of a priced factor, and that we could look for priced factors elsewhere. The behaviour of PORT in this model rendered suspicious the use of aggregates in determining the empirical nature of the risk-return relationship for stocks: the highly statistically significant return-dampening effect of volatility observed in PORT did not seem to be characteristic of individual stock dynamics, nor of the market index. It could, therefore, be a construct of the particular portfolio under consideration.

Except for the apparent lack of success of the GARCH-M model documented above, the model retained the desirable attributes of the standard GARCH process: generally significant ARCH and GARCH coefficients in the volatility equation. This contrasted sharply with the results obtained from the DGARCH process already discussed, and pointed to the possibility of reformulating the mean equation such as to provide a pricing relationship for stocks. One way by which this could be done is to introduce priced factors, which could be macroeconomic-based or otherwise, as extra explanatory variables. This crucial matter belabours subsequent chapters.

4.4.6 Dummy GARCH-in-Mean Model Estimation

Fitting the most general DGARCH-M process to the individual stock return series yielded the results reported in Appendix 4A alongside those for the rest of the models, which have been summarised in part (b) of Table 4.9. Part (a) of the table focuses on the results for the two aggregates. As was the case with the GARCH-M model, convergence could not be achieved in the estimation of the parameters of the model for seven stocks, namely AGL, ASR, AVI,

Table 4.8 – GARCH-M model estimation results: summary of findings

*This table provides a summary of the estimation results for the GARCH-M model. For uncorrelated returns, the specific conditional mean and volatility equations are given by (4.8) and (4.4), respectively. For correlated returns, the mean equation used was (4.9). In part (a), robust z-statistics are in parentheses, while *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively. In part (b), C in the first column is the estimated coefficient, and could take any of the values indicated in the third column. The stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in columns four and five, respectively. Because of parameter non-convergence, six stocks (i.e., AGL, ASR, AVI, BAW, DEL, and MLB) were excluded from the analysis. A comprehensive presentation of the findings in part (b) is in Appendix 4A.*

(a) Stock portfolios

Portfolio	α	β	ϕ	λ_1	θ_1
ALSI	0.003 (1.949)***	0.064 (0.029)	0.000 (1.806)***	0.152 (2.734)*	0.765 (9.376)*
PORT	0.005 (3.870)*	-5.400 (-1.706)***	0.000 (3.631)*	0.117 (3.881)*	0.806 (21.781)*

(b) Individual stocks

C	*Row*	*Value of C*	*Stocks*	*No.*
	#1	Positive	All stocks but those in Row #3	31
	#2	Significantly positive	AFX, HLH, ELH, JCM, JNC, LGL, MAF, REM, SAB, SBK, TBS, TNT, VNF	13
α	#3	Negative	ANG, CRH, DUR, GMF, PAM, SAP, WAR	7
	#4	Significantly negative	DUR	1
	#5	Not significant	All stocks but those in Row #2 and in Row # 4	24
	#6	Positive	ALT, ANG, BVT, CRH, CTP, DUR, GMF, HAR, HVL, PAM, PIK, SAP, WAR	13
	#7	Significantly positive	DUR, HAR	2
β	#8	Negative	All stocks but those in Row #6	25
	#9	Significantly negative	JNC	1
	#10	Not significant	All stocks but those in Row #7 and Row #9	35
	#11	Positive	All stocks	38
	#12	Significantly positive	All stocks but those in Row #15	24
ϕ	#13	Negative	None	0
	#14	Significantly negative	None	0
	#15	Not significant	AFX, CRH, CTP, GMF, IMP, JNC, LGL, OCE, PIK, RLO, SAB, SAP, TRE, VNF	14
	#16	Positive	All stocks but that in Row #18	37
	#17	Significantly positive	All stocks but those in Row #18 and Row #20	33
λ_1	#18	Negative	TRE	1
	#19	Significantly negative	TRE	1
	#20	Not significant	GMF, MAF, REM, VNF,	4
	#21	Positive	All stocks	38
	#22	Significantly positive	All stocks	38
θ_1	#23	Negative	None	0
	#24	Significantly negative	None	0
	#25	Not significant	None	0

Table 4.9 – DGARCH-M model estimation results: summary of findings

*This table provides a summary of the estimation results for the DGARCH-M model. For uncorrelated stock returns, the specific conditional mean and volatility equations are given by (4.8) and (4.7), respectively. For correlated returns, the mean equation used was (4.9). In part (a), robust z-statistics are in parentheses, while *, ** and *** denote statistical significance at 1%, 5% and 10% levels, respectively. In part (b), C in the first column is the estimated coefficient, and could take any of the values indicated in the third column. The stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in columns four and five, respectively. Because of parameter non-convergence, seven stocks (i.e., AGL, ASR, AVI, BAW, DEL, DUR and MLB) were excluded from the analysis. For a comprehensive presentation of the findings in part (b), see Appendix 4A.*

(a) Stock portfolios

Portfolio	α	β	ϕ	λ_1	γ	θ_1
ALSI	0.003 (1.997)**	-0.211 (-0.097)	0.000 (1.890)***	0.130 (1.615)	0.044 (0.545)	0.755 (8.798)*
PORT	0.005 (3.732)*	-5.949 (-1.90)***	0.000 (3.960)*	0.082 (2.558)**	0.075 (1.745)***	0.792 (21.927)*

(b) Individual stocks

C	Row	Value of C	Stocks	No.
	#1	Positive	All stocks but those in Row #3	26
	#2	Significantly positive	AFX, CTP, JCM, ELH, JCM, JNC, LGL, NED, OCE, REM, SAB, SBK, TNT, TRE, VNF	15
α	#3	Negative	ALT, ANG, CHE, CRH, GMF, HAR, HVL, PAM, PIK, SAP, WAR	11
	#4	Significantly negative	HAR, REM, WAR	3
	#5	Not significant	All stocks but those in Row #2 and in Row # 4	19
	#6	Positive	ALT, ANG, BVT, CHE, CRH, ECO, GMF, HAR, HVL, JCM, PAM, PIK, SAP, TBS, WAR	15
	#7	Significantly positive	HAR, WAR	2
β	#8	Negative	All stocks but those in Row #6	22
	#9	Significantly negative	None	0
	#10	Not significant	All stocks but those in Row #7	35
	#11	Positive	All stocks	37
	#12	Significantly positive	All stocks but those in Row #15	22
ϕ	#13	Negative	None	0
	#14	Significantly negative	None	0
	#15	Not significant	AFX, CRH, FOS, GMF, IMP, JNC, MAF, LGL, PIK, RLO, SAP, VNF	12
	#16	Positive	All stocks but that in Row #18	36
	#17	Significantly positive	ANG, CTP, HAR, HLH, HVL, NKP, OCE, PAM, PPC, SAB, SAP, SBK, TNT, VNF, WAR, WLO	16
λ_1	#18	Negative	CHE	1
	#19	Significantly negative	None	0
	#20	Not significant	All stocks but those in Row #17	21
	#21	Positive	All stocks but those in Row #23	27
	#22	Significantly positive	BVT, CHE, CTP, ELH, HLH, NED, NPK, PAM, PPC, TBS, TNT	11
γ	#23	Negative	AFE, JCM, JNC, MAF, OCE, REM, SBK, TRE, VNF, WLO	10
	#24	Significantly negative	None	0
	#25	Not significant	All stocks but those in Row #22	26
	#26	Positive	All stocks	37
	#27	Significantly positive	All stocks but that in Row #30	36
θ_1	#28	Negative	None	0
	#29	Significantly negative	None	0
	#30	Not significant	REM	1

BAW, DEL, DUR and MLB [23]. Therefore, the results of this analysis were based on the remaining thirty-nine assets. These results, summarised in Table 4.9, showed that the more general DGARCH-M model retained the combined weaknesses of both the DGARCH and GARCH-M models. Specifically, volatility was only prices in PORT, DUR, HAR and WAR, while only PORT and eleven stocks showed evidence of symmetric effects. The significant leverage effect parameters were positive, which was consistent with prior belief. Finally, the consequences of potential collinearity observed in the DGARCH model were also present.

As a further diagnostic checking of the DGARCH-M model, we conducted Ward tests for the joint significance of β and γ in the model. The null hypothesis was that $\beta = \gamma = 0$, and the resultant χ^2_2-distributed test statistics are presented in Table 4.10.

Table 4.10 – Ward tests for the DGARCH-M model

*This table shows the χ^2_2-distributed Ward test statistics (W) for the null hypothesis of $\beta = \gamma = 0$ in the DGARCH-M model. Figures in parentheses are the probabilities of accepting the null. NC indicates non-convergence in parameter estimation. * and ** imply that the null could be rejected at 1% and 5% significance levels, respectively.*

(a) Stock portfolios

Portfolio	*W*	*Security*	*W*
ALSI	0.309 (0.857)	PORT	7.286 (0.026)**

(b) Individual stocks

Security	*W*	*Security*	*W*
AFE	1.168 (0.558)	JCM	3.443 (0.179)
AFX	1.118 (0.572)	JNC	8.828 (0.012)**
AGL	NC	LGL	3.334 (0.189)
ALT	1.937 (0.380)	MAF	1.749 (0.417)
ANG	2.221 (0.329)	MLB	NC
ASR	NC	NED	10.139 (0.006)*
AVI	NC	NPK	1.844 (0.398)
BAW	NC	OCE	2.031 (0.362)
BVT	4.284 (0.117)	PAM	3.722 (0.156)
CHE	4.648 (0.098)	PIK	0.572 (0.751)
CRH	1.177 (0.555)	PPC	0.794 (0.672)
CTP	4.264 (0.119)	REM	0.774 (0.679)
DEL	NC	RLO	0.125 (0.940)
DUR	NC	SAB	0.824 (0.662)
ECO	3.255 (0.196)	SAP	3.100 (0.212)
ELH	5.929 (0.052)	SBK	0.548 (0.760)
FOS	4.744 (0.093)	TBS	5.415 (0.067)
GMF	1.005 (0.605)	TNT	3.215 (0.200)
HAR	4.861 (0.088)	TRE	10.222 (0.006)*
HLH	1.079 (0.583)	VNF	4.486 (0.106)
HVL	0.886 (0.642)	WAR	2.236 (0.327)
IMP	1.602 (0.449)	WLO	0.883 (0.643)

[23] Note that, with the exception of DUR, all the remaining stocks were the same ones that could not converge in the GARCH-M model.

The Wald test results showed that, at a significance level of 5 percent, the null hypothesis could only be rejected for PORT, JNC, NED and TRE, in keeping with the observation that at least one of the two coefficients was significant for these series. This notwithstanding, and despite being the most log likelihood-preferred of the four models, there was no adequate motivation to choose the general DGARCH-M model as a description of univariate JSE equity returns. The stipulated evidence of collinearity and the fact that volatility was not commonly priced among the stocks rendered the model less useful.

4.4.7 Volatility Persistence

Following Glosten *et al* (1993), the volatility persistence implied by each of the four ARCH-type models was estimated using a first-order autoregressive function of estimated volatility. The estimated autoregressive parameters and their corresponding *t*-statistics[24] are shown in Table 4.11. In addition, the table shows the persistence measure given by the standard GARCH model, being the simple summation of the estimated ARCH and GARCH coefficients. In general, it was clearly evident that all the models exhibited very high volatility persistence. The estimated volatility measure implied by the standard GARCH model coefficients averaged 0.933 for the portfolios, and very closely approximated that of 0.935 for the individual stocks [25]. The averages of the estimated autoregressive parameters for individual stocks ranged from a minimum of 0.869 in the DGARCH process to a maximum of 0.897 in the GARCH-M process. Therefore, by the autoregression gauge, the standard GARCH model exhibited a persistence pattern in the region of the median of the persistence implied by all the models. A near-IGARCH process was generally suggested. Once again, the dynamics of individual stocks were quite well approximated by those of the aggregates.

Aside from the general conclusion that a near-IGARCH process seemed to describe the JSE, and notwithstanding few other cases in which the estimated autoregressive parameters were relatively low, it is noteworthy that the DGARCH model for AGL displayed 'outlier' behaviour, yielding a very low and statistically insignificant value. This was not particularly surprising, considering that the security showed the unique characteristic that even the GARCH term, let alone the ARCH term, yielded an insignificant parameter. The calculation of the mean autoregressive parameter estimate for individual stocks in the DGARCH formulation excluded this value.

[24] Note that the standard error of the autoregressive parameter is necessarily equal to one over the square root of the sample size.

[25] Note that quite a few stocks (i.e., AGL, DEL, JCM, JNC) yielded $\lambda_1 + \theta_1 > 1$ in the standard GARCH model, although the sum remained very close to unity and still suggested an IGARCH formulation.

Table 4.11 – Volatility persistence in ARCH-type models

*This table shows the degrees of volatility persistence implied by the ARCH-type models. ρ was estimated using the first order autoregression given in (4.12). Figures in parentheses are t-statistics. NC denotes parameter non-convergence in model estimation. * indicates that the parameter was not significantly different from zero at all conventional levels.*

(a) Market aggregates

		ρ							
Portfolio	$\lambda_1 + \theta_1$	*GARCH*		*DGARCH*		*GARCH-M*		*DGARCH-M*	
ALSI	0.919	0.888	(27.327)	0.879	(27.050)	0.870	(26.773)	0.861	(26.496)
PORT	0.946	0.935	(36.393)	0.931	(36.237)	0.904	(35.186)	0.884	(34.408)
Mean	0.933	0.912		0.905		0.887		0.873	

(b) Individual stocks

		ρ							
Security	$\lambda_1 + \theta_1$	*GARCH*		*DGARCH*		*GARCH-M*		*DGARCH-M*	
AFE	0.939	0.903	(35.171)	0.903	(35.171)	0.859	(33.457)	0.857	(33.379)
AFX	0.931	0.911	(35.506)	0.918	(35.778)	0.934	(36.402)	0.949	(36.987)
AGL	1.009	0.996	(38.818)	0.006	(0.234)*	NC	-	NC	-
ALT	0.993	0.991	(38.585)	0.990	(38.546)	0.991	(38.585)	0.684	(26.632)
ANG	0.927	0.919	(35.817)	0.910	(35.467)	0.925	(36.051)	0.916	(35.701)
ASR	0.606	0.606	(23.618)	0.608	(23.696)	NC	-	NC	-
AVI	0.988	0.944	(36.731)	0.947	(36.848)	NC	-	0.949	(36.926)
BAW	0.954	0.831	(32.324)	0.855	(33.257)	NC	-	NC	-
BVT	0.873	0.838	(32.650)	0.813	(31.676)	0.829	(32.299)	0.805	(31.364)
CHE	0.881	0.902	(35.097)	0.952	(37.042)	0.932	(36.264)	0.968	(37.665)
CRH	0.942	0.857	(33.390)	0.945	(36.819)	0.945	(36.819)	0.943	(36.741)
CTP	0.985	0.964	(37.571)	0.952	(37.104)	0.972	(37.883)	0.959	(37.376)
DEL	1.012	0.924	(36.012)	0.936	(36.480)	NC	-	NC	-
DUR	0.553	0.485	(18.896)	0.438	(17.065)	0.505	(19.676)	NC	-
ECO	0.957	0.964	(37.398)	0.960	(37.243)	0.963	(37.359)	0.959	(37.204)
ELH	0.964	0.970	(37.718)	0.968	(37.640)	0.976	(37.951)	0.969	(37.679)
FOS	0.861	0.860	(33.485)	0.886	(34.497)	0.854	(33.251)	0.876	(34.108)
GMF	0.984	0.983	(38.312)	0.984	(38.351)	0.988	(38.507)	0.988	(38.507)
HAR	0.964	0.951	(37.040)	0.956	(37.235)	0.954	(37.157)	0.960	(37.391)
HLH	0.992	0.922	(35.934)	0.916	(35.701)	0.913	(35.584)	0.905	(35.272)
HVL	0.943	0.942	(36.653)	0.988	(38.443)	0.864	(33.618)	0.874	(34.007)
IMP	0.946	0.948	(36.923)	0.952	(37.079)	0.953	(37.118)	0.962	(37.469)
JCM	1.692	0.692	(26.872)	0.696	(27.028)	0.746	(28.969)	0.895	(34.756)
JNC	1.137	0.869	(33.227)	0.883	(33.762)	0.886	(33.877)	0.877	(33.533)
LGL	0.989	0.984	(38.351)	0.980	(38.195)	0.986	(38.429)	0.982	(38.273)
MAF	1.037	0.810	(31.496)	0.888	(34.529)	0.841	(32.702)	0.916	(35.618)
MLB	0.495	0.501	(19.526)	0.566	(22.059)	NC	-	NC	-
NED	0.942	0.948	(36.948)	0.940	(36.636)	0.952	(37.104)	0.950	(37.026)
NPK	0.979	0.986	(38.429)	0.977	(38.078)	0.963	(37.532)	0.976	(38.039)
OCE	0.977	0.960	(37.415)	0.958	(37.337)	0.968	(37.727)	0.968	(37.727)
PAM	0.819	0.792	(30.868)	0.825	(32.154)	0.798	(31.102)	0.827	(32.232)
PIK	0.942	0.939	(36.597)	0.911	(35.506)	0.975	(38.000)	0.969	(37.766)
PPC	0.972	0.969	(37.691)	0.973	(37.847)	0.969	(37.691)	0.973	(37.847)
REM	0.800	0.709	(27.606)	0.428	(16.665)	0.723	(28.151)	0.392	(15.263)
RLO	0.893	0.863	(33.579)	0.869	(33.813)	0.841	(32.723)	0.842	(32.762)
SAB	0.984	0.962	(37.493)	0.963	(37.532)	0.969	(37.766)	0.969	(37.766)
SAP	0.987	0.980	(38.195)	0.979	(38.156)	0.982	(38.273)	0.981	(38.234)
SBK	0.904	0.930	(36.043)	0.931	(36.082)	0.940	(36.430)	0.939	(36.392)
TBS	0.954	0.939	(36.476)	0.904	(35.117)	0.939	(36.476)	0.900	(34.961)
TNT	0.915	0.908	(35.389)	0.896	(34.921)	0.872	(33.986)	0.860	(33.518)
TRE	0.591	0.591	(23.034)	0.592	(23.073)	0.920	(35.856)	0.757	(29.504)
VNF	0.988	0.985	(38.377)	0.986	(38.416)	0.988	(38.494)	0.984	(38.338)
WAR	0.976	0.939	(36.585)	0.937	(36.507)	0.977	(38.065)	0.970	(37.793)
WLO	0.975	0.979	(38.143)	0.488	(19.013)	0.472	(18.390)	0.473	(18.429)
Mean	0.935	0.883		0.869[26]		0.897		0.891	

[26] Note that the calculation of this mean excluded the estimated ρ from the 'outlier' case, AGL. When this was included, the mean declined to 0.849

The results of the analyses reported in subsection 4.4.1 though 4.4.7 indicated that the standard GARCH model was the preferred description for the dynamics of JSE returns. Based on this empirical evidence, we proceeded to assess the model's ability to account for the non-linear structures established in Chapter 3. The results of this investigation follow.

4.4.8 Linearity in the GARCH Model

In order to investigate whether the GARCH(1,1) process could account for the non-linearities, we applied the BDS test to the standardised residual estimates from the model. The resulting BDS test statistics are reported in Appendix 4B, while Table 4.12 provides a summary for the individual stocks. Compared with the results for the linearly filtered return series reported in Appendix 3C, there was strong evidence that the GARCH model filtered most of the non-linearities in the return series. Specifically, no remaining non-linear structures could be observed in both portfolios and in seven individual stocks, and the magnitudes of the BDS statistics were drastically reduced in virtually all the cases. Moreover, of the forty-four stocks, at least one BDS statistic was insignificant in thirty-one. The results were quite similar to those obtained by Dockner *et al* (1997), who concluded that the DGARCH process accounted for most non-linearities on the Vienna Stock Exchange. The GARCH(1,1) model, therefore, showed promise in accounting for the non-linearities on the JSE.

Table 4.12 – BDS tests for standardised GARCH(1,1) residuals: summary of findings for individual stocks

This tables summarises the BDS test results, presented in Appendix 4B, for the standardised GARCH(1,1) residuals. Results are for individual stocks. The stocks and numbers of stocks with significant BDS test statistics equal to the number in Column 1 are presented in Column 2 and Column 3, respectively. Column 4 and Column 5 give cumulative figures.

1 *# of Sig. Stat.*	*2* *Stocks*	*3* *# of Stocks*	*4* *# of Sig. Stat.*	*5* *# of Stocks*
0	ANG, ASR, BAW, NED, SBK, TBS, WAR	7	0	7
1	-	0	≤ 1	7
2	IMP, MAF	2	≤ 2	9
3	CHE, CRH, JNC	3	≤ 3	12
4	AFX, HLH	2	≤ 4	14
5	DUR, REM	2	≤ 5	16
6	AFE, HAR, PIK	3	≤ 6	19
7	-	0	≤ 7	19
8	BVT, PAM, TNT	3	≤ 8	22
9	DEL, ECO, JCM, OCE, PPC	5	≤ 9	27
10	GMF, RLO	2	≤ 10	29
11	CTP, FOS	2	≤ 11	31
12	AGL, ALT, AVI, ELH, HVL, LGL, MLB, NPK, SAB, SAP, TRE, VNF, WLO	13	≤ 12	44

The foregoing observation notwithstanding, it could still be noted from these results that some non-linear structures were existent in the standardised residuals from the GARCH model for the individual stocks. Therefore, the model with a time-varying conditional variance could account for most, but apparently not all, of the non-linearities. The remaining non-linear structures could indicate the presence of noise, low-order deterministic chaos, or additional linear dependencies not fully filtered through autoregression. Such linear dependencies could, for instance, be those associated with asset pricing anomalies, such as calendar, firm balance sheet and macroeconomic effects on stock returns.

4.5 Summary and Conclusion

This chapter investigated the usefulness of ARCH-type models in describing the return dynamics on the JSE. The investigation was premised on the validated evidence of volatility clustering prevalent on the market. A specific-to-general modelling procedure was adopted in which the standard GARCH model was initially fitted to the return series, and eventually augmented in an attempt to capture the salient issues of interest. The GARCH(1,1) formulation was preferred relative to higher order GARCH specifications for all forty-six securities, of which two were stock portfolios and the rest were individual stocks. In order to investigate the presence of asymmetric effects of shocks on volatility, the dummy GARCH (DGARCH) model was preferred to the exponential GARCH (EGARCH) model on the basis of a statistical evaluation. Further, the GARCH-in-mean (GARCH-M) process was tested to investigate if volatility was priced on the market. Finally, to capture all the salient issues within one modelling framework, the more general dummy GARCH-in-mean (DGARCH-M) specification was invoked. The models were evaluated on the basis of statistical diagnostics. Several key conclusions can be drawn from the analysis, as follows:

Firstly, the inclusion of the asymmetric effects term was detrimental to the estimation of the standard GARCH model, to the extent that the term was highly collinear with the ARCH term. Thus, the parameters of the DGARCH model were imprecisely estimated, and there was no compelling evidence for leverage or even asymmetric effects of shocks on volatility.

Secondly, there was no evidence that volatility was a commonly priced factor on the market. Thus, although volatility was prevalent, JSE investors sought a premium for taking on other forms of perceived risk than volatility. Macroeconomic activities could provide effective surrogates for such priced factors.

Thirdly, and implicitly from the above two points, augmentations of the standard GARCH process did not improve the model's ability to explain the dynamics of the market. The standard GARCH model provided the best fit among the models, and showed potential as a framework for investigating further the stock return dynamics.

Finally, although the standard GARCH model performed relatively better than more complex formulations, it could only partially account for the evident non-linearities whose presence on the market was validated in Chapter 3. Specifically, although the standardised residuals from the model showed that it was capable of accounting for a significant part of the non-linearities, it was evident that non-iid structures still remained in the series. This could imply that the remaining non-linear structures were deterministic (chaotic) rather than stochastic, or that additional linear dependencies existed in the data. Such dependencies could, for instance, be of the type associated with calendar effects, seasonalities or structural breaks, and could be a manifestation of the impact of broader macroeconomic activities on the JSE.

The subsequent two chapters are motivated by the observation that volatility was not priced on the JSE, and that the standard GARCH model could not fully account for the non-linear structures. They report on an investigation of the relevance of macroeconomic activities in explaining the non-linear JSE stock return dynamics. In particular, Chapter 5 seeks to establish whether monetary policy and real sector activity could predict stock returns in a general, Granger-causal and innovation accounting sense, and to identify the appropriate measures of policy and real activity for this purpose. In Chapter 6, the frameworks developed in Chapter 4 and Chapter 5 are used to parameterise the dynamic relationship between the stock market and the macroeconomy. In this particular investigation, the GARCH(1,1) model is augmented by introducing macroeconomic variables in the mean and volatility equations, as guided by the investigation reported in Chapter 5.

Chapter 5

Monetary, Financial and Real Sector Interrelationships in South Africa

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Using Granger-causality tests and innovation accounting within the environment of vector error correction modelling, we established important dynamic interrelationships among real, financial and monetary variables in the South African economy. Most relevant to our study, we found evidence that the discount rate and mining sector activity could predict JSE stock prices.

5.1 Introduction

The preceding chapter examined the relevance of various ARCH-type models in explaining the dynamics of JSE stock returns. The main conclusions of the analysis were threefold. Firstly, the standard GARCH(1,1) model performed relatively better than its more complex alternatives in explaining the dynamics: there appeared to be no compelling motivation to invoke higher order GARCH processes, and extensions of the standard low-order model to include asymmetric effects of shocks on volatility were virtually unrewarding. Secondly, there was no evidence that volatility was priced on the JSE, since its inclusion as an extra regressor in the conditional mean return equation showed that it had no impact on the return series. Finally, the GARCH formulation appreciably, but less than fully, explained the non-linear structures in stock returns. The present chapter pursues the second observation, regarding the identification of the determinants of stock returns, by examining the interrelationships among macroeconomic variables and the JSE. By extending the framework developed in the preceding chapter to include a structural mean equation model, the next chapter (Chapter 6) examines the dynamic impacts, on stock returns and return volatilities, of the macroeconomic variables identified in the present chapter. Chapter 6 also addresses the question of additional linear structures remaining after the GARCH (1,1) filter.

The observation that volatility was not priced on the JSE implied that volatility did not constitute a source of risk which investors on the market could be compensation for taking on. Even if volatility were priced, this would not preclude the need for an economic explanation of such a conditional risk factor. Moreover, to the extent that no structural model of returns was assumed for the conditional mean equations of the volatility models explored in Chapter 4, the econometric information set remained unspecified. At that stage, our decision not to specify a structural model for the mean equation was made to avoid an arbitrary choice of variables, since such variables ought to be empirically determined. This chapter extends the analysis by linking JSE stock return dynamics to the South African macroeconomy. Although the main objective of the chapter in the context of our study is to establish the role of monetary policy interventions and real sector activity in explaining JSE stock prices over time, the analysis provides a detailed account of the nature of the interrelationships among the variables, including the effectiveness of South African monetary policy. Therefore, we may state the broad hypothesis of this chapter as follows:

> There existed causal interrelationships among monetary, financial and real variables in the South African economy.

Clearly, many specific hypotheses could be developed from this broad hypothesis, and most of these received due attention in the study. However, to remain focused on the main objectives of the study, the following precise hypothesis deserved particular attention:

> Monetary and real variables caused JSE stock prices.

As appreciated in Chapter 2, very limited work has been done to establish the dynamic interrelationships among South African macro-economic variables and the JSE, noteworthy being the work of van Rensburg (1999). However, the approach pursued in our study was different from that of van Rensburg in several ways. Firstly, while van Rensburg used annual and quarterly data, the present analysis used monthly data, since very low frequency data is usually not capable of depicting the dynamics accurately (Brock *et al*, 1993). Although this implies that we could not use some of the macroeconomic time series only available at low frequencies, there is a wide range of alternative measures of real and monetary sector activities, and the monthly frequency made our results comparable with those documented for other markets. In addition, monthly data generally provides the desired degrees of freedom that are quickly lost in procedures of the type herein pursued. Secondly, this study established that the chosen macroeconomic variables were generally integrated of order one, but also cointegrated. Therefore, Granger causality tests were appropriately conducted within the environment of vector error correction (VEC) models, as opposed to the vector autoregression (VAR) framework adopted in van Rensburg. As noted by Enders (1995:367-368), if I(1) variables are cointegrated, using VAR in first differences is inappropriate, since the omission of the error correction term(s) entails model misspecification. Thirdly, the study invoked innovation accounting to trace the effects of a shock to any one variable on the predictability of all other variables in the system, a tool not previously applied for this kind of investigation on the JSE. Finally, while van Rensburg also included 'international effects' which do not directly enter the present value formula for asset prices (see Section 2.5), this study adopted the approach of a typical monetary policy transmission mechanism, and restricted the choice of macroeconomic variables to 'numerator' and 'denominator' effects, to borrow from van Rensburg's own terminology. Our assumption was that the effects of international variables such as exchange rates, which are important and have been used in some VAR studies of the effectiveness of monetary policy (see, for instance, Sims, 1992), would nonetheless be picked by most of the macroeconomic variables included in the system, as buttressed in Section 5.3. Our choice of variables was, therefore, more focused and guided by Darrat and Dickens (1999) among others, but mostly by the historical macroeconomic developments in South Africa.

The rest of Chapter 5 proceeds in the following manner. An overview of recent South African macroeconomic developments is provided in Section 5.2, in order to put the analysis in the proper context. Section 5.3, discusses the methodologies pursued, including a justification for the choice of variables, while Section 5.4 reports and discusses the results of the analysis. Section 5.5 summarises the investigation and concludes the chapter.

5.2 An Overview of South African Economic Developments

Although this overview merely seeks to locate our enquiry, it is not possible to provide such an historical account without considerable reliance on the work of others. The overview does not purport to substitute the informative summary of the socio-economic and institutional framework for the evolution of the South African economy provided by van Rensburg (1999), or the detailed accounts on the same and the conduct of policy in Nattrass, Wakeford and Muradzikwa (2002) and Roux (2002), among others. For our reliance on these and other works as cited, we remain greatly indebted.

5.2.1 South African Business Cycles

Recent economic developments in South Africa have been influenced by several factors, notably international economic trends, national resource endowments and policies, as well as the social-political developments already alluded to in Chapter 3 (see Appendix 3B). In general, records show that the country registered an average growth rate of 3.4 percent per annum in the post World War II period, but that most of the growth was realised during the period ending in the late 1960s. For the rest of the period thereafter, a gradual decline in economic growth was registered.

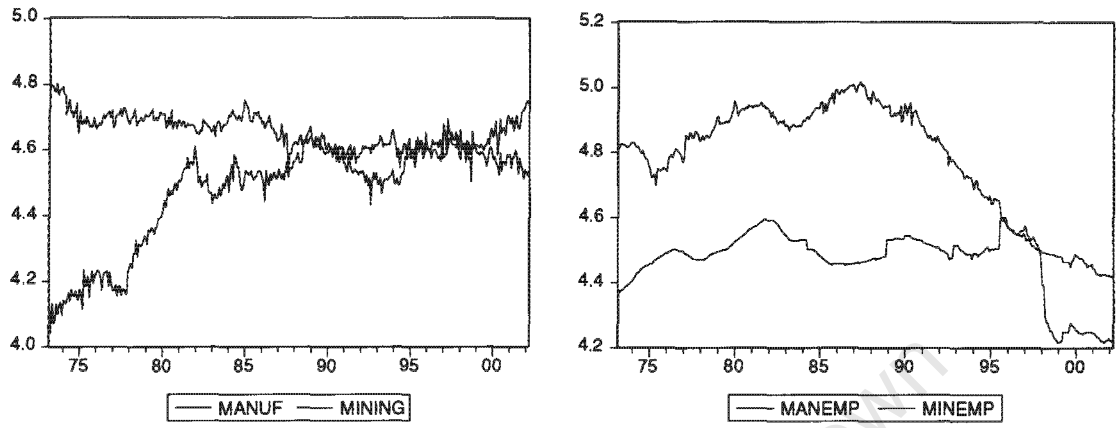
The high economic growth in the period up to the late 1960s was largely attributed to increased manufacturing sector activity, which augmented the already established mining and agricultural sectors, coupled with increases in international demand for the output from such a booming manufacturing industry. The period was, therefore, associated with massive inflows of foreign capital and a strong balance of payments position, notwithstanding the 1961-62 downturn occasioned by the Sharpeville massacre and related events. The economy, therefore, registered a mean annual growth rate of 6 percent in the 1960's (Roux, 2002).

Unfavourable factors emerged in the 1970s and 1980s, which resulted in a failure of the economy to sustain the gains registered in the previous decades. One major cause for the lacklustre performance in this period was deterioration in the terms of trade for South Africa resulting from declining world prices and demand for primary exports, especially agricultural products. This was exacerbated by the capital intensity of the country's economic activities, which implied increased demand for imported technology, but was somewhat eased by the continued inflows of foreign capital. As van Rensburg (1999) noted, therefore, the balance of payments constraint had been pivotal in the design of South African macroeconomic policy. In this respect, it is noted that the balance of payments gains recorded during the boom period extending to the late 1960s, as well as continued foreign capital inflows, permitted the country to run current account deficits without a depletion of reserves. Therefore, policies in the early 1970s were aimed at stimulating economic activity to achieve growth, despite the prevalence of unfavourable terms of trade.

Trade and economic relations between South Africa and the international community have not been independent of the socio-political developments already cited. As such, selective economic sanctions were imposed in the 1960s and 1970s in reaction to governance issues largely occasioned by racial tensions. For instance, a sharp drop in net foreign capital inflows followed the 1976 Soweto Uprising, and the country could no longer afford stimulatory economic policies. Instead, restrictive policies aimed at achieving a balance of payments equilibrium and controlling a worrisome inflation trend were pursued. Such policies were further necessitated by domestic currency depreciation, liquidity shortages and the foreign debt crisis of 1985. Although the measures were useful in containing inflation, they also accounted for the unimpressive economic growth rates recorded in the period. The late 1980s saw a worsening of the balance of payments position as the country run low on foreign reserves. However, this deteriorating position was saved by the availability of foreign capital in reaction to the introduction of pluralistic politics in 1994, permitting the country to revert to expansionary policies.

In analysing the economic performance of South Africa, it is of the essence to distinguish between the contributions of the manufacturing and mining sectors and, particularly, to take cognisance of the crucial role that the mining sector plays in economic growth. South Africa is among the three largest producers of a wide range of minerals, notably gold, manganese, platinum, chromium, vanadium and diamonds, and the mining sector accounts for over one half of the country's export earnings (Roux, 2002:40). More specifically, gold plays a key role in determining South Africa's balance of payments position, since all the gold produced is sold to the South African Reserve Bank (SARB) and directly beefs up the country's reserve position. In fact, the gold price increases recorded in the 1970s and 1980s were crucial in mitigating some of the effects of the capital flights stipulated above, as well as the oil price hikes experienced during the turbulent periods (van Rensburg, 1999). This notwithstanding, the mining and agricultural sectors jointly currently contribute only 10 percent of GDP (Roux, 2002:40), and the increasingly important role of the manufacturing sector cannot be overemphasised. Customarily, therefore, real sector activity in South Africa is distinguished in terms of output and employment in the two sectors. Figure 5.1 shows trends in the levels of manufacturing output (*MANUF*), manufacturing employment (*MANEMP*), mining output (*MINING*) and mining employment (*MINEMP*) from 1973 to 2002. The data used were natural logarithms of monthly indexes obtained from the International Financial Statistics (IFS) of the International Monetary Fund (IMF). The trends clearly show increasing manufacturing sector output and declining mining sector output, while a closely synchronised trend in employment from the two sectors is noticeable up to the early 1990s. However, the more contemporary trend in employment is strongly consistent with the declining role of mining relative to manufacturing. Notice that the effects of the economic shocks of the 1970s and, especially, the 1980s are quite perceptible in the figure.

Figure 5.1 –Trends in RSA manufacturing and mining sector activities: 1973-2002



5.2.2 South African Monetary Policy

From the foregoing, it is clear that the conduct of monetary policy by the SARB could be crucial in the performance of the macroeconomy. As with the nature and causes of the business cycle, the historical account of the conduct of monetary policy in South Africa is well documented, and only an overview should suffice here.

In keeping with the global trend, South African monetary policy in the 1960s was largely influenced by Keynesian theories of demand management. However, the collapse of the Bretton Woods' fixed exchange rate system in 1971, a phenomenon associated with rising inflation and unemployment, produced an increased worldwide reliance on monetarist arguments. Coupled with South Africa's own largely politically induced experiences, these worldwide economic developments resulted in paradigm shifts by the SARB that culminated into a systematic withdrawal of direct controls in favour of interest rate controls. Thus, by the early 1980s, South African monetary policy was characterised by a mix of Keynesian and monetarist theories, with the attainment of macroeconomic stability and balance of payments management as the primary objectives. The latter objective was largely induced by a debt crisis and the elaborate imposition of sanctions in 1985. Since December 1983, the interest rate has been the operational tool of monetary policy, and money supply has been endogenous. By the early 1990s, SARB policy became more monetarist, initially utilising a money supply targeting framework adopted in 1986. More recently[1], an inflation-targeting regime has been adopted.

As aforementioned, December 1983 is noteworthy in the history of South African monetary policy because, following a recommendation of the Commission of Enquiry into the Monetary System and Monetary Policy in South Africa[2], the SARB implemented the so-called "classical cash reserve system" which, officially until March 1998 (but arguably even to date), characterised the conduct of monetary policy. The system involved the normalisation of accommodation[3] whose interest rate, set by the SARB, varied depending on how much of it was required by each commercial bank. Initial accommodation sought was provided at the Bank rate[4], and any subsequent accommodation attracted a penalty. By ensuring a positive money market shortage and calculatedly altering the Bank rate, the SARB could influence the entire structure of interest rates. Nattrass *et al* (2002:221) put it succinctly that:

> In short, the SARB acted as a wholesaler of money (at the Bank rate) to commercial banks, which retailed money to consumers at market rates, which were spread in a relatively fixed structure around the Bank rate.

Indeed, van Rensburg (1999) noted that SARB's control of interest rates was perceived as a tool for managing the business cycle, the money market liquidity, the money supply, the external value of the rand, the level of gold and foreign reserves, and the balance of payments, *inter alia*. Several avenues were available to the SARB to induce a positive money market shortage in the system, in order to facilitate the control of interest rates. Primarily among these were open market operations (OMO) involving the sell (or purchase) of government securities to the general public, thereby inducing a reduction (or an increase) in bank deposits and reserves. Other tools included transfers of government funds between Tax and Loan Accounts at private banks and the Exchequer Account at the SARB, alterations of the cash reserve requirement, and foreign currency swaps with commercial banks. In all circumstances, a positive money market shortage could be induced by creating circumstances under which commercial bank reserves fell short of required reserves.

[1] Inflation targeting was adopted in January 2000. The control of domestic inflation is currently perceived to be the primary objective of the SARB.
[2] This so-called De Kock Commission in respect of its head, was appointed by the Prime Minister of South Africa at the time for an objective explicit it its name.
[3] Accommodation is SARB overnight lending to commercial banks in order to meet reserve requirements.
[4] The Bank rate is the rate at which the SARB discounts bills.

The SARB changed from the accommodation system to the so-called flexible repurchase system in March 1998, in order to address problems associated with the former[5]. Under this so-called repo system, the SARB fixed the amount of liquidity it desired to supply on the market, and invited commercial banks to indicate how much interest they were willing to pay for desired accommodation in a tender bid. The interest rate was necessarily the rate of discount on the financial assets each bidding bank sought to surrender in return for cash. The tender bid included an undertaking by the commercial bank to repurchase from the central bank any financial assets surrendered in return for liquidity. The average of the tender bid rates (which varied across bids from various banks), called the repo rate, replaced the Bank rate of the accommodation system. At its introduction, therefore, the repo system implied that the discount rate would be market determined, purportedly rendering more transparency in the policy intentions of the SARB, as reflected in the amount of liquidity it offered for tender on a daily basis. As with the Bank rate, the repo rate generally set the basis for most other interest rates in the economy. Of course, under the repo system, the central bank would restrict the amount of liquidity offered in order to contain inflationary pressures, since this could in turn trigger interest rate increases and credit contractions in the economy. If deemed appropriate, the SARB continued to invoke OMO and variations in cash reserve requirements.

In practical terms, it was observed that the repo rate was much more stable than the envisaged flexibility of the system would have implied, even when liquidity was restricted by the authorities. Between 1999 and 2000, the SARB explicitly fixed the repo rate several times, and provided full accommodation, as in the cash reserve system. Although the variable repo rate was formally reinstate in January 2000, the Monetary Policy Committee (MPC) of the SARB continued to make announcements regarding the rate, which remained fixed between meetings of the said committee. Finally, in October 2001, the SARB formally adopted the fixed repo system, which is not substantially different from the previous accommodation system, "in order to eliminate any ambiguity in the bank's monetary policy signals" (Nattrass *et al* 2002:232). In the current fixed repo system, commercial banks are able to acquire any amount of accommodation sought from the central bank as under the old system. As such, after a very short break, the central bank re-gained its debatably clear control over interest rates in the economy. Arguably, therefore, the Bank/repo rate could be considered as a single series and as a potential measure of the stance of South African

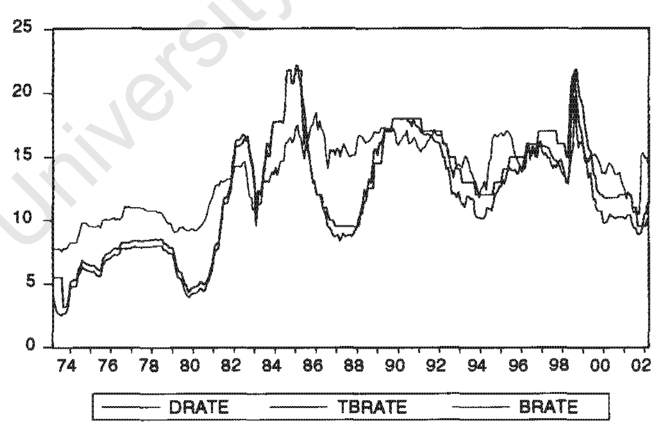
[5] An account of these problems is in Nattrass *et al* (2002:224-225).

monetary policy. Hereafter, we shall refer to the Bank/repo rate as the discount rate, to adopt the language of the IMF[6].

Although the foregoing would seem to imply that the SARB, rather than the market, generally set interest rates, this matter is complicated by the fact that market indicators, such as the Treasury bill rate, are considered influential in the central bank's determination of the discount rate. One plausible argument of the central bank in this respect is that if the financial markets pushed the Treasury bill rate significantly above the discount rate, the central bank would be stirred to increase the discount rate in order to prevent commercial banks from borrowing at a low rate and investing in Treasury bills. However, experience has shown that the SARB could also influence the market for Treasury bills to curb such an unmatched rise[7].

Figure 5.2 shows the relationship between the discount rate (*DRATE*), the Treasury bill rate (*TBRATE*) and the rate on a ten year Government bond (*BRATE*) over the period from March 1973 to March 2002. The data used were monthly series in percentages per annum. The close

Figure 5.2 –Trends in RSA interest rates: 1973-2002



synchronisation between the discount rate and the Treasury bill rate is very evident in the figure, with *TBRATE* leading *DRATE* in some periods. In addition, the long-term bond rate also shows co-movement with the short-term rates, albeit relatively weakly. As expected, the

[6] The 'discount rate' variable recorded in line 60 of the IMF's International Financial Statistics for South Africa is necessarily the Bank rate up to February 1998, and the repo rate thereafter.

[7] A May 1986 case in point is cited as a reference (see Nattrass *et al*, 2002:223).

long-term rate is generally above the short-term rates to compensate for risk. Notice, however, that the turbulent period of the early to mid 1980s (which period also reflects the introduction of the cash reserve system), as well as the Asian crisis period (1997-1998), show anomalous behaviour in which the short-term rates shot above the long-term rate.

5.3 Research Methodologies

5.3.1 Selection of Variables

The so-called monetary policy transmission mechanism provides a theoretical guide to the nature of the interrelationships among monetary and real variables. Specifically, within the South African context, a discount rate increase could induce an increase in market interest rates and reduce the level of borrowing by the private sector. In turn, this could have a contractionary effect on money supply, a phenomenon called the 'liquidity effect', hence a reduction in aggregate spending on goods and assets (including financial assets such as stocks) and a reduction in prices. This price reduction (or inflation dampening effect) would discourage production, resulting in a decline in real activity. Moreover, the low prices and low real output imply that even nominal output should decline as a result of contractionary monetary policy. Expansionary policy should have the converse effect (Tobin, 1969). From the foregoing discussion of the South African business cycle, it would appear plausible that the measures of real activity should distinguish between the manufacturing and mining sectors. This study, therefore, measured real activity in terms of both manufacturing production and mining production.

Albeit being a debatable issue, the relevant literature generally establishes that the effects of monetary policy fall almost entirely on prices, with little or no impact on the real sector (Sims, 1998; Walsh, 2003:15). This phenomenon is referred to as the 'neutrality of money'[8]. It is, therefore, vital that inflation, being the obvious policy target in the transmission mechanism, should be included in tracing the macroeconomic interrelationships.

It is also generally established in the literature that "most variation in monetary policy instruments are accounted for by responses of policy to the state of the economy, not by random disturbances to policy" (Sims 1998:933). This poses a problem in the sense that

[8] As stated by Walsh (2003:52), "... any change in the nominal quantity of money that is matched by a proportional change in the price level, leaving *m* (real money balances) unchanged, has no effect on the economy's real equilibrium. This is described by saying that the model exhibits the *neutrality of money*".

measured reactions of macroeconomic variables to a supposedly monetary policy intervention could potentially be a reaction to some other underlying condition to which the authorities could be responding in setting policy. The approach pursued in the literature is to assess the interrelationships within a VAR framework, where fitted values associated with the monetary policy variable represent the effects of endogenous policy actions, while the residuals represent those of exogenous policy actions (Bernanke and Blinder, 1992; Rudebusch, 1998). It is the exogenous effects that are generally of interest. Moreover, even if the monetary authority's policy instrument were apparently clear, this dissection of exogenous from endogenous policy could imply that another variable closely related to the instrument could better capture the policy effects. This is buttressed by the illustration made earlier that, in setting the discount rate, the SARB could potentially be responding to movements in market rates rather than pursuing interventionist macroeconomic policy. This, as well as the fact that monetary aggregates have traditionally been perceived as measures of policy, necessitates a thorough investigation of the information contents of various potential measures. The important point to make within the South African context is that the policy regimes discussed in the preceding subsection did not necessarily guarantee that the discount rate was exogenous from a macroeconomic viewpoint, nor that it was an unequivocal measure of monetary policy. Such a fact ought to be empirically determined. Therefore, this study considered the discount rate, the Treasury bill rate and the broad measure of money supply (M3) as potential measures of monetary policy. While Tan and Baharumshah (1999), in a similar investigation for Malaysia, included narrower measures of money supply in addition to M3, the choice of the broader aggregate might not be contentious in the South African context where policy explicitly focuses on the growth rate in M3 (Nattrass *et al*, 2002:240).

The relation between stock prices and the macroeconomy is founded on the fact that, as stated in Section 2.5, the current stock price can be equated to the present value of expected future dividends. Putting $\delta^T = 1/(1+r)^T$ in (2.6) gives:

$$P_{it} = \sum_{T=1}^{\infty} \frac{E(D_{i,t+T})}{(1+r_i)^T}, \qquad (5.1)$$

where, as before, P_{it} is the price of stock i in period t, $E(D_{i,t+T})$ is the expected dividend receipt of the stock in period $t+T$, and r_i is the required rate of return on the stock. In view of the discussion in Section 2.5, it is assumed that r_i is accordingly adjusted for risk. Expression (5.1) is consistent with the hypothesised inverse relation between stock prices and interest rates preached in macroeconomics lectures, which should also imply a direct relation between stock prices and nominal money supply. Also, since future dividends are funded from earnings, a direct relation should exist between stock prices and 'earnings effects', such as growth in real output and broad measures of the macroeconomy (van Rensburg, 1999). As measures of JSE stock price behaviour, this study considered the close prices for ALSI (the variable is denoted *ALSI*) and PORT (denoted *PORT*), the market aggregates already described in previous chapters.

While it is recognised that many other important variables could have been omitted from this selection[9], our approach took cognisance of the fact that the VAR or VEC models herein invoked tend to be quickly over-parameterised, particularly when longer lags are also suggested by the lag-length selection criteria. This analysis is, therefore, comparable with Darrat and Dickens (1999), whose methodologies, as well as those pursued by Tan and Baharumshah (1999), were followed, *mutatis mutandi*.

We summarise the selection of variables and formally introduce the notation used for new variables (indicated in braces) as follows. On the basis of the monetary policy transmission mechanism and the South African macroeconomic experience, this study investigated the dynamic interrelationships by using both manufacturing production (*MANUF*) and mining production (*MINING*) to measure real output. The Treasury bill rate (*TBRATE*), the discount rate (*DRATE*) as well as the M3 monetary aggregate (*M3*) were selected as potential measures of monetary policy, while the inflation rate (*INFL*) was the chosen intermediate target. The close prices for ALSI (*ALSI*) and for PORT (*PORT*) were the financial variables.

5.3.2 Data

The data characteristics and sources for the variables chosen as discussed in the preceding subsection are described in Appendix 5A. *MANUF* and *MINING* were both seasonally adjusted indexes. *DRATE* and *TBRATE* were end-of-period percentages per annum, while *INFL* was the annualised monthly rate of inflation, based on the consumer price index (CPI), which was specifically the index of prices of all consumer goods and services for metropolitan areas. Note that with the exception of the interest rate variables, all other

[9] Many researchers are guided by Chen *et al* (1986) in the selection of a very wide range of macroeconomic variables impacting on the stock market.

variables were in natural logarithmic levels, and annualised monthly inflation was computed in the study as:

$$INFL_t = \log CPI_t - \log CPI_{t-12} \quad , \tag{5.2}$$

where $\log$ denotes the natural logarithm. It is noteworthy that, in order to resolve the so-called 'price puzzle', (i.e., the observation that contractionary monetary policy was, in the short-run, inflationary) [10], the SARB currently targets CPIX inflation, where the CPIX is the CPI excluding the interest cost of mortgage bonds (SARB, 2003:23). By using CPI in (5.2), rather than CPIX for which adequate time series were not yet available, the study could validate the presence of the price puzzle in South Africa.

Monthly data for the period from December 1983 to March 2002 were used in the analysis, to coincide with the period of the adoption of the cash reserve system[11]. Thus, the realisation constituted 220 observations of each variable. For *ALSI* and *PORT*, the logarithmic close price for each month was estimated as the last weekly observation in that particular month.

5.3.3 Variable Permutations

In order to avoid unnecessary model over-parameterisation, in order to minimise the problem of collinearity among the variables, and in order to assess the robustness of our findings, no two financial and interest rate variables were entered simultaneously in the ensuing models. Specifically, only *MANUF* and *MINING*, which arguably captured akin effects, were the two variables entered simultaneously, with the intention of gauging any interrelationships between the two real sectors[12]. Therefore, by substituting *TBRATE* for *DRATE* and *ALSI* for *PORT* in the ensuing estimations, four variable permutations were achieved. As such, the four models investigated in the study were distinguished by the variable permutations presented in Table 5.1. It is noteworthy that each of these permutations could yield six-variable VAR or VEC models. In the subsequent discussions, therefore, Model p ($p = 1,2,3,4$) reflects a specific variable permutation as indicated in the table.

[10] See Walsh (2003).
[11] The computation of *INFL*, therefore, accordingly used CPI observations of the previous twelve months.
[12] While an earlier version of this analysis did not allow *MANUF* and *MINING* to enter the models simultaneously, we took the advice given at one of our UCT School of Economics Seminar presentations that causal interrelationships might exist between the two real sectors. It turned out that this was somewhat correct.

Table 5.1 – Variable permutations in the dynamic models

Model	*Variables*
Model 1	*TBRATE M3 ALSI INFL MANUF MINING*
Model 2	*DRATE M3 ALSI INFL MANUF MINING*
Model 3	*TBRATE M3 PORT INFL MANUF MINING*
Model 4	*DRATE M3 PORT INFL MANUFMINING*

5.3.4 Seasonality and Stationarity Tests

In order to ensure that the variables were appropriately modelled, we first established their time series properties. Seasonality in the series was tested by using the following unrestricted autoregressive model:

$$x_t = \sum_{l=1}^{L} \pi_l x_{t-l} + \sum_{m=1}^{12} \eta_m D_{mt} + \mu_t \qquad , \tag{5.3}$$

where t denotes time, x is the variable being tested for seasonality, D_m ($m = 1,2,...,12$) are dummy variables for each of the twelve months, while π_l and η_m are coefficients to be estimated. Thus, we set D_{1t} = 1 for t = *January*, and zero for $t \neq$ *January*, *et cetera*. As described in Section 3.2, the autoregressive terms in (5.3) were generally identified as the significant spikes in the series' partial autocorrelation functions, and the Breusch-Godfrey LM test was used to confirm the absence of autocorrelation of up to the tenth order in the resultant linearly filtered series, where necessary. Under the null hypothesis of no seasonality, Wald tests for the joint significance of the dummy variables were carried out.

In addition, tests for stationarity of the series were conducted using the DF and ADF procedures described in Section 3.2. Because the evidence regarding deterministic trends was scanty (see, for instance, Figure 5.2), the test equations with intercept terms only as well as those with both trend and intercept terms were applied in all cases, and up to tenth order serial correlation was filtered, where detected, using significant augmentations.

5.3.5 Testing for Cointegration

Although a regression in levels of non-stationary variables is generally considered spurious, this might not be the case if the variables are synchronised or trend together over time. Such synchrony suggests that a linear combination of the non-stationary variables is itself stationary, and the regression in levels represents a long-run equilibrium relationship. Such variables are said to be cointegrated, and their regression in levels is termed a cointegrating regression (Gujarati, 1995). Therefore, once non-stationarity is confirmed among variables, it is of the essence to establish if the variables are also cointegrated, especially if they are integrated of the same order.

In order to investigate whether the variables in each of the four models were cointegrated when the possibility was suggested in the data, we used the Johansen (1988) maximum likelihood approach, as opposed to such alternatives as the two-step procedure suggested by Engle and Granger (1987) [13], or the cointegrating regression Durbin-Watson (CRDW) test[14]. The CRDW test is a quick and crude tool whose results invariably invite validation by a more powerful test. Further, DeJong (1992), and Gonzalo (1994) established that the Johansen procedure was superior to the Engle-Granger procedure, an observation also noted by Rao (1994) and confirmed by Enders (1995). In an investigation analogous to the present one, Darrat and Dickens (1999) claimed that their results were more acceptable than those obtained by Malliaris and Urrutia (1991) because of their application of the Johansen procedure as opposed to the Engle-Granger procedure[15], among other reasons.

The Johansen test generalises the ADF test to a multivariate framework. To illustrate the concept using matrix notation, suppose that $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})'$ is an ($n \times 1$) vector each of whose elements, say x_{jt} (for all $j = 1,2,\ldots,n$) is an I(1) variable. A VAR of order p in the levels of the variables is:

$$x_t = Ay_t + \Omega_1 x_{t-1} + \ldots + \Omega_i x_{t-i} + \ldots + \Omega_p x_{t-p} + e_t \qquad (5.4)$$

where y_t is a vector of deterministic variables such as constant, trend and seasonal terms, Ω_i and A are matrices of coefficients to be estimated, and e_t is an ($n \times 1$) vector of error

[13] Since an error term from a regression equation in the levels of the non-stationary series is in fact a linear combination of the series, application of the DF or ADF tests on residuals from such a regression is a test for cointegration. If stationary cannot be rejected, it would indicate that the original variables are cointegrated. Critical values for resolving such a test have been provided by Engle and Granger (1987), hence the Engle-Granger Test.

[14] The CRDW test uses the Durbin-Watson statistic obtained from the potentially cointegrating regression, but the absence of cointegration entails a null hypothesis that the statistic is not different from zero. Critical values for the test have been provided by Sargan and Bhargava (1983).

[15] For more on the weaknesses associated with the Engle-Granger procedure, see Enders (1995:385).

terms, e_{jt}, which may be contemporaneously correlated across equations. As illustrated in Enders (1995:390), we may write (5.4) as:

$$\Delta x_t = Ay_t + \pi x_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta x_{t-i} + e_t, \quad \text{where} \tag{5.5}$$

$$\pi = \sum_{i=1}^{p} \Omega_i - I, \text{ and } \beta_i = -\sum_{j=i+1}^{p} \Omega_j .$$

Compared with (3.4) of Section 3.2, (5.5) is clearly a multivariate generalisation of the ADF equation. If the I(1) variables in x_t are cointegrated, then there exists at least one linear combination of x_t which is an I(0) process. Such a combination could be represented by πx_{t-1} in (5.5), where π is a matrix with elements Ω_{ji}, at least one of which is non-zero. Each row of π is, therefore, a cointegrating vector of x_t. Testing for cointegration entails testing for the number of such cointegrating vectors, called the cointegrating rank of π, in the same way that we test for unit roots. If the rank of π (denoted r) is equal to zero, there are no cointegrating equations, and (5.5) is a VAR in first differences of the non-stationary variables. Moreover, $r = n$ would imply that the variables are stationary, whereas the maximum number of cointegrating relations obtainable for non-stationary variables is $n-1$.

The Johansen test recognises that the number of cointegrating vectors is based on the significance of the characteristic roots of π. Using estimates of π to obtain the estimated characteristic roots (also called eigenvalues), two statistics for resolving the test are computed as:

$$Q_{trace} = -N \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \qquad \text{for} \quad r = 0,1,\ldots,n-1, \text{ and} \tag{5.6}$$

$$Q_{\max} = -N \ln\left(1 - \hat{\lambda}_{r+1}\right), \tag{5.7}$$

where $\hat{\lambda}_i$ is the largest eigenvalue and N is the number of usable observations. Q_{trace} is called the trace statistic, and tests the null hypothesis of r or less cointegrating vectors against a general alternative. Note that $Q_{trace} = 0$ for $\lambda_i = 0$, and is an increasing function of λ_i. On the other hand, $Q_{\max}$ tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ vectors, and is also an increasing function of λ_i. Note also that $Q^r_{\max} = Q^r_{trace} - Q^{r+1}_{trace}$.

The critical values for the two test statistics, provided by Johansen and Juselius (1990) and Osterwald-Lenum (1992), are quite sensitive to assumptions made regarding drift and intercept terms in the cointegrating vectors. In this study it was assumed that the original sets of series had linear deterministic trends, while the cointegrating equations only contained intercept terms. In all cases, the appropriate null hypothesis would not be rejected for test statistics smaller than the critical values at a given significance level. This study used the Osterwald-Lenum critical values, which are reproduced in Appendix 5B for reference.[16]

Part of the Johansen test output in EViews includes maximum-likelihood-efficient normalised cointegrating coefficient estimates, which are useful in charactering error correction terms and, hence, in specifying VEC models. These were accordingly used in the study.

In order to select the appropriate order of the cointegration test VARs, the study applied likelihood ratio (LR) tests based on the VAR models in levels of the variables as described by Enders (1995:313-314), while paying due attention to serial correlation. Starting with a uniform lag length of twelve, we investigated whether the lag length in all equations for each VAR could be reduced, in multiples of three or six. To implement these cross-equation restrictions, both the standard LR statistic and the correction suggested by Sims (1980) were applied. Using subscript S to distinguish between the test statistic suggested by Sims and the standard test statistic, the two statistics are computed as follows, under the null hypothesis that the restrictions are not binding (i.e., that the VAR order could be reduced):

$$LR = (n)(\ln|\Sigma_{RR}| - \ln|\Sigma_{UR}|), \quad \text{and} \qquad (5.8)$$

$$LR_S = (n-c)(\ln|\Sigma_{RR}| - \ln|\Sigma_{UR}|). \qquad (5.9)$$

In (5.8) and/or (5.9), n is the number of usable observations, c is the number of parameters estimated in each equation of the unrestricted VAR, while $\ln|\Sigma_{RR}|$ and $\ln|\Sigma_{UR}|$ are natural logarithms of the determinants of the variance/covariance matrices of the residuals in the

[16] Notice that for the trace test version, the Osterwald-Lenum critical values reported in Appendix 5B were also readily generated by the EViews program.

restricted and unrestricted VARs, respectively. Both statistics follow a χ_v^2 distribution, where v, the degrees of freedom, equals the number of restrictions in the system. Low values for the test statistics show that the restrictions are not binding.

As noted by Charemza and Deadman (1997:159-160), it is advisable that the lag length in a VAR model be chosen such as to yield residuals without significant autocorrelation. This is because serial correlation is a potentially serious problem in VAR models, and can lead to inconsistent least squares estimates. Therefore, to bolster the above choice of lag length, the VAR orders suggested by the LR tests were tested for serial correlation on an equation-by-equation basis. As in preceding chapters, the Breusch-Godfrey test was used.

5.3.6 VEC Model Specifications

For any model where cointegration could not be rejected in the study, it followed that (5.5) was necessarily a vector error correction (VEC) model, where πx_{t-1} were error correction terms (ECTs). The ECTs measure the amount of the discrepancy between the short-run and long-run equilibriums that is corrected in each period, and their omission in first-difference VARs of cointegrated variables constitutes a misspecification. Therefore, the VEC model was the appropriate framework for conducting Granger causality tests and innovation accounting procedures in such circumstances.

The procedure pursued in the specification of the VEC models was as follows. Firstly, time series of error correction variables (denoted *EC*) were distilled using the normalised cointegrating equations generated in the cointegration tests reported above, since these were efficiently estimated using the Johansen maximum likelihood method. Secondly, the procedure for the determination of VAR orders described in the preceding subsection, including paying due attention to potential serial correlation in individual equations, was followed to establish VEC orders. Thus, uniform lag lengths that yielded approximately white noise error terms were used. The deterministic trend assumptions made in the VEC models were identical to those made under the cointegration tests[17]. Further, it should be noted that the error correction variables were introduced with a one-period lag, in consistency with (5.5).

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[17] Notice that, based on the empirical results, we also investigated the implications of extending the maximum lag length in the VEC order LR tests to twenty-four, with commensurate increases in the multiples of lag length restrictions.

5.3.7 Multivariate Granger-Causality Tests

In order to conduct Granger-causality tests within the VEC model framework, the individual equations in the VEC models were estimated using the least squares method. Under the null hypothesis that a given variable did not Granger-cause the dependent variable, Wald test statistics for the joint significance of all the lags of each variable in a given VEC model were sequentially computed using the standard procedure. Further, the study evaluated the statistical significance of the coefficients of the *EC* variables in the dynamic systems.

5.3.8 Innovation Accounting

In addition to establishing the directions of causality, the dynamic interrelations were investigated by examining impulse response functions as well as variance decompositions as described by Charemza and Deadman (1997) and Enders (1995). From the viewpoint of monetary policy, this became necessary considering the distinction between endogenous and exogenous policy changes already described.

To understand impulse response functions, it should be noted that the contemporaneous shock (or innovation) denoted e_{jt} in (5.5) will impact on contemporaneous and future values of x_j, as well as future values of all other variables in the system. Tracing such effects facilitates an understanding of the interactions among the constituent variables in x_t. Specifically, by recasting the VEC model into its moving average representation, impulse response functions, which trace the effects of a one standard deviation change in e_t on the x_t sequences over time, are necessarily the coefficients of the moving average terms. In a given period, say p ($p = 0,1,2,...$), of or after the shock, the impact of a t-period shock to variable j on another variable k may be denoted by the moving average term e^k_{jt}, and could be measured by the coefficient of e^k_{jt}, say ϕ^k_{jp}. A plot of ϕ^k_{jp} against p, therefore, provides a visual depiction of the reactions of the variables in the system to various shocks over time.

If the innovations were uncorrelated across equations, it would be easy to interpret e_{jt} as the innovation for x_j, so that its impulse response function would measure the effect on the whole system of a shock in x_j occurring at time t. However, correlation in innovations across the equations implies that some component of the shock would commonly be attributable to more than one variable. A procedure called Cholesky decomposition, which attributes the common component to the variable that appears first in the model, is frequently used to resolve this problem. As its drawback, this procedure implies that impulse response functions are sensitive to the order in which variables are presented in the computation of the functions. This study computed the functions using several orderings, and reports findings based on two orderings that were perceived as summarily producing the most divergent results. The first ordering placed interest rates before output in each of the four models, while the second ordering was a reversal of the first. Thus, to illustrate with Model 1 in Table 5.1, the first ordering was (*TBRATE M3 ALSI INFL MINING MANUF*), while the second ordering was (*MANUF MINING INFL ALSI M3 TBRATE*). Note that, in an analysis based on impulse response functions, the first ordering corresponds to the typical monetary policy transmission mechanism described in subsection 5.3.1: an interest rate shock could impact on money supply which, in turn, could impact on the price system (asset and commodity prices) which, in turn, could impact on real activity. This ordering was consistent with Bernanke and Blinder (1992), and Bacchetta and Ballabriga (2000). It could, however, be meriting to investigate the behaviour with other assumptions, such as the second ordering. This latter ordering could be premised on the fact that monetary policy is hardly exogenous, as described by Sims (1998).

As already indicated, the study also examined variance decompositions. A forecast error variance decomposition for a given variable shows the relative importance of a random innovation to each endogenous variable in the prediction of the dependent variable. It measures the proportion of the total variability in a left-hand endogenous variable due to shocks in the variable itself relative to shocks in all other endogenous variables in the VEC model, at various forecasting horizons. If shocks to all other variables in the system explain none of the forecast error variance in x_{jt} at all forecasting horizons, then the x_{jt} sequence is exogenous. Conversely, if the forecast error variance in x_{jt} can entirely be explained in terms of shocks to other variables in the system but its own shocks, then x_{jt} is perfectly endogenous. It is usually the case that the proportion of the variance attributable to the variable itself is high at short forecasting horizons, and declines as the horizon increases, implying that most of the contemporaneous effects on a variable are due to its own shocks, while other variables impacted on it with a lag. Tracing these effects over long enough horizons is, therefore, usually recommended. In this study, both the variance decompositions and impulse responses were traced over a forecasting horizon of four years. No significant differences occurred beyond forty-eight months to warrant an extension of the horizon.

5.3.9 Summary of the Methodologies and Relation with Prior Studies

A summary of the methodologies of this chapter is as follows. Firstly, the monetary, financial and real sector variables selected as discussed in subsection 5.3.1 were tested for seasonality, stationarity and cointegration. When evidence of cointegration was found, uniform-lag VEC models carefully specified such as to achieve approximately white noise error terms were estimated using OLS, and Wald tests were used to resolve Granger-causality hypotheses. In order to validate the conclusions established in the Granger-causality tests, impulse response functions and variance decompositions were traced over a forecasting horizon of four years, and examined.

Darrat and Dickens (1999) applied methodologies somewhat similar to those adopted in this chapter to investigate the Granger-causal interrelationships among real, monetary and financial variables, and found that the stock market was a leading indicator of both monetary policy and real activity, that the money stock could not cause either real activity or stock returns, and that interest rates caused all variables in the systems including stock returns. No other variable, however, had an impact on stock prices. Because they did not include stock prices in their analysis, the results of Tan and Baharumshah were less appealing. However, their methodologies were comparable to the foregoing, and included innovation accounting.

The results of the entire analysis are presented and discussed in the next section.

5.4 Results and Discussions

5.4.1 Seasonality Tests

The results of identifying and estimating equation (5.3), and testing for the joint significance of the coefficients for the monthly dummy variables, are presented in Table 5.2. Note that the presence of seasonal effects could not be confirmed in any of the variables, and the high adjusted coefficients of determination indicated that the autoregressive terms significantly explained movements in all the variables.

5.4.2 Unit Root Tests

The DF and ADF unit root test results for the variables are presented in Table 5.3. Because the evidence for deterministic trends was scanty, the tests were conducted both with and without trend terms, but always included intercept terms. For the tests in levels, the null hypothesis of a unit root could not be rejected for all variables except *TBRATE*, *INFL* and

Table 5.2 - Seasonality tests

This table shows Wald test results for the null hypothesis of no seasonal patterns, against the alternative of some seasonal patterns. The Test equation is given in (5.3). The second column gives the autoregressive structure[18]. $\overline{R}^2$ is the adjusted coefficient of determination. The fourth column gives the chi-square statistic and, in parentheses, the probability values for accepting the null. Virtually all variables showed no seasonal patterns.

Variable	*Lag Structure*	$\overline{R}^2$	χ^2_{12} (p)
TBRATE	1,2	0.964	18.211 (0.109)
DRATE	1,2	0.969	8.566 (0.739)
ALSI	1	0.991	11.136 (0.517)
PORT	1	0.984	9.566 (0.654)
INFL	1,2,3	0.974	2.198 (0.999)
M3	1,2,3,4	1.000	4.296 (0.977)
MANUF	1,2,3,4	0.858	12.419 (0.413)
MINING	1,2,3,4,6	0.697	16.637 (0.164)

Table 5.3 – DF and ADF tests for unit roots in the variables

*This table reports the serial correlation structure, augmentation structure as well as absolute Dickey-Fuller (DF) and absolute augmented Dickey-Fuller (ADF) test statistics for the variables. Except for ALSI and PORT which showed no evidence of tenth order correlation or lower, all variables showed first order serial correlation, which was filtered using the lag structures indicated in column 3. Column 4 indicates the DF and ADF test statistics for the test equation with both trend (T) and intercept (c) terms. Column 5 indicates the test statistics for the equation with c only. For column 4 statistics, the absolute MacKinnon critical values for the rejection of the null of a unit root were 4.006, 3.433 and 3.140 at 1%, 5% and 10% respectively[19]. The corresponding values for column 5 statistics were 3.464, 2.876 and. 2.574. * denotes a rejection of the null at 1% and ** denotes a rejection at 5%.*

		4 ***DF/ADF Test Stat (T and c)***		***5*** ***DF/ADF Test Stat (c only)***	
1 ***Variable***	***3*** ***ADF Lag Structure***	***Levels***	***1st Differences***	***Levels***	***1st Differences***
TBRATE	1, 2, 3, 4, 7, 11, 15	4.316*	5.425*	4.341*	5.417*
DRATE	1, 5, 8, 9	3.000	7.225*	3.057**	7.511*
M3	1, 3	1.656	9.731*	0.863	9.710*
INFL	1, 2	4.332*	6.565*	1.597	6.520*
ALSI	n.a.	3.114	14.003*	0.982	14.029*
PORT	n.a.	2.343	15.224*	1.672	15.213*
MANUF	1, 2, 9	1.609	10.915*	0.408	10.911*
MINING	1, 2, 3, 11, 12	3.854**	10.095*	2.323	10.107*

[18] For *M3*, although AR(1) was suggested by the PACFs, the additional AR terms were necessary to filter autocorrelation. Further, while 6th order serial correlation was somewhat still present in the AR(4) model for *MANUF*, this was considered tolerable since we were unable to eliminate it through further augmentation.

[19] These critical values correspond to the DF test and should, ideally, be equivalent to those for the ADF test. We, however, noted a sight difference, such that the ADF test absolute critical values were 3.981, 3.428 and 3.1352, respectively.

MINING, when both intercept and trend terms are included. However, when only intercept terms are included, the hypothesis could not be rejected for all variables but *TBRATE* and *DRATE*. The tests in the first differences of the variables showed practically non-conflicting results: the null hypothesis was strongly rejected for all the variables irrespective of assumptions made regarding deterministic trends. Therefore, the results suggested that the variables were, generally, I(1) processes, and were potentially cointegrated.

5.4.3 Cointegration Tests

5.4.3.1 VAR Order Determination

In Table 5.4, we present the LR test results for the selection of the lag length for each of the models described in Table 5.1. The standard LR test results showed that restrictions to nine or six lags were binding in virtually all the systems, therefore suggesting unrestricted twelfth order VARs. On the other hand, using the Sims approach, nine lags were suggested for all the four models, since further reduction of the lag length from nine to six could be rejected. However, the use of six or lower lags in these models could not be rejected when direct cross restrictions from a lag length of twelve to six were applied, in contradiction with the results achieved using the standard test. In addition, the Sims test suggested that the lowest lag length of three was plausible for Model 1. Based on these rather inconclusive results, and since longer lags given degrees of freedom are generally preferred, a uniform lag length of nine appeared reasonable for all the models[20].

To reinforce this choice of lag length, we investigated the nature of serial correlation in each suggested equation. Given the four VARs of six variables each, this entailed estimating twenty-four equations. The results, presented in Table 5.5, showed no galling signs of serial correlation in the individual equations. Note that the hypothesis of correlation could be rejected up to the tenth order in 21 of the 24 equations. Except for the first order correlation detected in the *M3* equation in VAR Model 2, only less bothersome high-order correlation could be detected in the two real sector variable equations of Model 1. Moreover, the inclusion of *M3*, *MANUF* and *MINING* in all the models could somewhat mitigate the effects of the detected correlation in terms of the overall interpretability of the results. Therefore, the selected uniform lag length of nine for all the four systems seemed permissible.

[20] We attempted to invoke multivariate generalisations of the information-based criteria (i.e., AIC and SBC) in the lag length selection procedure. These mutually suggested VARs of order three in virtually all cases. There was no motivation to consider this finding compelling.

Table 5.4 - LR tests for VAR order determination

*This table shows standard likelihood ratio (LR) and Sim's likelihood ratio (LR_S) test statistics for null hypotheses of restricted VAR models (H_0) against alternatives of unrestricted VAR models (H_1). The z-statistics indicated in parentheses were computed using $\sqrt{2\chi^2} - \sqrt{(2k-1)} = z \sim N(0,1)$, where χ^2 was LR or LR_S. *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively.*

Model	Hypotheses	LR	(z)	LR_S	(z)
Model 1	H_0: p = 9; H_1: p = 12	150.034	(2.660)*	97.378	(-0.707)
	H_0: p = 6; H_1: p = 9	170.908	(3.825)*	125.716	(1.194)
	H_0: p = 3; H_1: p = 6	131.068	(1.528)	107.753	(0.017)
	H_0: p = 6; H_1: p = 12	320.943	(4.575)*	208.304	(-0.350)
Model 2	H_0: p = 9; H_1: p = 12	164.555	(3.478)*	106.802	(0.048)
	H_0: p = 6; H_1: p = 9	183.741	(4.507)*	135.156	(1.778)***
	H_0: p = 3; H_1: p = 6	131.948	(1.582)	108.477	(0.066)
	H_0: p = 6; H_1: p = 12	348.296	(5.633)*	226.058	(0.502)
Model 3	H_0: p = 9; H_1: p = 12	175.174	(4.055)*	113.695	(0.417)
	H_0: p = 6; H_1: p = 9	189.626	(4.812)*	139.485	(2.039)**
	H_0: p = 3; H_1: p = 6	131.926	(1.581)	108.458	(0.065)
	H_0: p = 6; H_1: p = 12	364.800	(6.251)*	236.769	(1.000)
Model 4	H_0: p = 9; H_1: p = 12	180.090	(4.316)*	116.886	(0.627)
	H_0: p = 6; H_1: p = 9	201.635	(5.419)*	148.318	(2.560)**
	H_0: p = 3; H_1: p = 6	123.231	(1.036)	101.310	(-0.428)
	H_0: p = 6; H_1: p = 12	381.726	(6.870)*	247.755	(1.499)

Table 5.5 - Serial correlation structures in the VAR(9) models

This table shows Breusch-Godfrey serial correlation test results for the VAR(9) processes. Models 1 to 4 are described in Table 5.1. Entries are the orders of detected serial correlation, with probability values for accepting the null hypothesis of no serial correlation in parentheses. U implies that serial correlation of up to the tenth order could not be detected, and associated p-values are for the tenth order correlation test statistic.

Dependent Variable	VAR Model			
	1	2	3	4
BILL	U (0.693)		U (0.624)	
DRATE		U (0.296)		U (0.358)
M3	U (0.489)	1 (0.039)	U (0.499)	U (0.177)
ALSI	U (0.958)	U (0.712)		
PORT			U (0.395)	U (0.087)
INFL	U (0.668)	U (0.526)	U (0.858)	U (0.731)
MANUF	10 (0.044)	U (0.152)	U (0.061)	U (0.178)
MINING	6 (0.050)	U (0.550)	U (0.232)	U (0.806)

5.4.3.2 Cointegration Test Results

Utilising the uniform lag length of nine selected as above[21], The Johansen cointegration test procedure yielded the results presented in Table 5.6, which were evaluated using the critical

[21] Notice that this corresponded to a lag length of 8 in first differences, in the EViews environment.

values in Appendix 5B. The results from both the maximum eigenvalue and trace versions of the test provided strong evidence that the variables were cointegrated, with two cointegrating equations in virtually all the processes. This finding confirmed that the dynamic causal relationships among the variables should be investigated using Granger-causality tests and innovation accounting within the environment of VEC models.

5.4.4 Specification of VEC Models

5.4.4.1 Error Correction Terms

For each of the four systems, the expressions for the ECTs using the normalised cointegrating relations are given in Table 5.7[22]. From these equations, distillation of the time series for each of the *EC* variables was trivial.

Table 5.6 - Cointegration tests

*In this table, $Q_{\max}$ and Q_{trace} are the respective test statistics for the maximum eigenvalue and trace versions of the Johansen test. Models 1 to 4 are described in Table 5.1. Critical values are provided in Appendix 5B. * and ** denote statistical significance at 1% and 5% levels, respectively.*

(a) Maximum eigenvalue test statistics

H_0	H_1	$Q_{\max}$			
		Model 1	Model 2	Model 3	Model 4
r = 0	r = 1	40.495**	49.078*	42.737**	51.428*
r ≤ 1	r = 2	34.586**	38.127**	36.643**	40.349*
r ≤ 2	r = 3	18.906	19.366	19.428	19.633
r ≤ 3	r = 4	14.612	15.258	13.557	14.591
r ≤ 4	r = 5	6.389	6.982	5.196	5.343
r ≤ 5	r = 6	0.006	0.119	0.077	0.271

(b) Trace test statistics

H_0	H_1	Q_{trace}			
		Model 1	Model 2	Model 3	Model 4
r = 0	r ≥ 1	114.995*	128.930*	117.639*	131.615*
r ≤ 1	r ≥ 2	74.499**	79.852*	74.902**	80.186*
r ≤ 2	r ≥ 3	39.913	41.725	38.259	39.837
r ≤ 3	r ≥ 4	21.007	22.359	18.831	20.204
r ≤ 4	r ≥ 5	6.396	7.101	5.273	5.614
r ≤ 5	r =6	0.006	0.119	0.077	0.271

[22] Time subscripts are omitted in the expressions for the error correction terms to simplify notation. Although figures are rounded to three decimals for presentation purposes, actual computations of the terms used all decimals provided by the EViews software, which ranged from four to six for the various figures.

Table 5.7 - Normalised cointegrating relations

This table shows the equations used to distil observations of the EC variables for each of the VEC models, as suggested by the Johansen procedure. The j th ECT for model i is denoted ECT_{ij} for i = 1,2,3,4; and j = 1,2. Models 1 to 4 are described in Table 5.1.

Model 1	$ECT_{1,1}$ = *BILL* – 20.587*ALSI* – 232.543*INFL* + 10.615*MANUF* – 129.692*MINING* + 727.742 $ECT_{1,2}$ = *M3* + 0.348*ALSI* +16.296*INFL* – 0.621*MANUF* + 9.826*MINING* – 59.203
Model 2	$ECT_{2,1}$ = *DRATE* – 28.034*ALSI* – 317.111*INFL* + 7.649*MANUF* – 166.900*MINING* + 981.468 $ECT_{2,2}$ = *M3* + 0.800*ALSI* + 22.161*INFL* - 0.592*MANUF* + 12.106*MINING* – 74.144
Model 3	$ECT_{3,1}$ = *BILL* – 10.252*PORT* – 97.115*INFL* – 12.260*MANUF* – 51.392*MINING* +327.665 $ECT_{3,2}$ = *M3* + 0.098*PORT* + 13.264*INFL* – 0.443*MANUF* + 8.113*MINING* – 49.761
Model 4	$ECT_{4,1}$ = *DRATE* – 10.914*PORT* – 89.048*INFL* – 13.532*MANUF* – 49.931*MINING* + 375.346 $ECT_{4,2}$ = *M3* + 0.204*PORT* + 14.570*INFL* – 0.228*MANUF* + 8.278*MINING* – 52.505

5.4.4.2 VEC Order Determination

The likelihood ratio test results for the determination of the appropriate VEC model orders are reported in Table 5.8, and seemed to suggest that the lag length could not be reduced from twelve. Indeed, these findings suggested that the distributed-lag relationships among the variables spanned over a longer period than one year[23]. However, extending the lag length beyond twelve months seemed less attractive in view of its costs on degrees of freedom. Most importantly, an investigation of the serial correlation structures implied by various uniform lag lengths showed that lower lags than twelve were preferred in virtually all cases, yielding models that significantly minimised the worrisome serial correlation evidently prevalent when a lag length of twelve was used. These results are shown in Table 5.9, and suggested an order of eight for all the models, notwithstanding minor concern for high-order correlation evident in the equations for *MANUF* and *MINING* in Model 2, as well as that for *PORT* in Model 4. As noted in subsection 5.4.3, the inclusion of the real sector variables in all the models, and *PORT* in Model 3 as well, could mitigate the effects of this limitedly annoying serial correlation. Also, the suggestion for VEC models of order eight was consistent with that documented in subsection 5.4.3 since, in the environment of EViews 3.1, a lag length of nine in levels is equivalent to that of eight in first differences.

[23] When we applied the likelihood ratio tests for cross-equation restrictions to models with a maximum lag of 24, the standard test always preferred the longest lag, while the Sims test suggested models with a lag of between 18 and 21. We considered such models to be overly parameterised and too costly in terms of degrees of freedom.

Table 5.8 – LR tests for VEC order determination

This table shows standard likelihood ratio (LR) and Sim's likelihood ratio (LR_S) test statistics for null hypotheses of restricted VEC models (H_0) against alternatives of unrestricted VEC models (H_1). Entries are as described in Table 5.4.

Model	*Hypotheses*	*LR*	*(z)*	*LR_S*	*(z)*
Model 1	H_0: p = 9; H_1: p = 12	228.325	(6.706)*	145.598	(2.402)**
	H_0: p = 6; H_1: p = 9	188.302	(4.743)*	136.451	(1.857)
	H_0: p = 3; H_1: p = 6	131.542	(1.557)	106.759	(-0.051)
	H_0: p = 6; H_1: p = 12	416.628	(8.106)*	265.676	(2.291)*
Model 2	H_0: p = 9; H_1: p = 12	247.570	(7.589)*	157.891	(3.106)*
	H_0: p = 6; H_1: p = 9	191.258	(4.895)*	138.593	(1.986)**
	H_0: p = 3; H_1: p = 6	111.967	(0.302)	90.872	(-1.182)
	H_0: p = 6; H_1: p = 12	438.829	(8.865)*	279.833	(2.897)*
Model 3	H_0: p = 9; H_1: p = 12	225.827	(6.589)*	144.005	(2.308)**
	H_0: p = 6; H_1: p = 9	211.163	(5.888)*	153.017	(2.831)*
	H_0: p = 3; H_1: p = 6	140.591	(2.106)**	114.103	(0.444)
	H_0: p = 6; H_1: p = 12	436.990	(8.803)*	278.660	(2.847)*
Model 4	H_0: p = 9; H_1: p = 12	255.148	(7.927)*	162.703	(3.376)*
	H_0: p = 6; H_1: p = 9	209.501	(5.807)*	151.812	(2.762)*
	H_0: p = 3; H_1: p = 6	117.878	(0.691)	95.669	(-0.830)
	H_0: p = 6; H_1: p = 12	464.649	(9.724)*	296.298	(3.583)*

Table 5.9 - Serial correlation structures at various lag lengths in the VEC models

This table shows Breusch-Godfrey serial correlation test results for the VEC processes of various orders. Models 1 to 4 are described in Table 5.1. Entries are as described in Table 5.5, and those for the preferred lag length are in the shaded column.

(a) Model 1

Dependent Variable	*Uniform Lag Length*					
	3	4	6	8	9	12
BILL	4 (0.003)	U (0.587)	U (0.491)	U (0.546)	U (0.187)	U (0.138)
M3	U (0.651)	U (0.317)	U (0.233)	U (0.210)	1 (0.037)	3 (0.009)
ALSI	U (0.977)	U (0.627)	4 (0.024)	U (0.910)	U (0.092)	9 (0.006)
INFL	4 (0.025)	4 (0.020)	1 (0.027)	U (0.777)	U (0.211)	8 (0.047)
MANUF	2 (0.053)	6 (0.028)	6 (0.042)	10 (0.039)	1 (0.031)	U (0.715)
MINING	U (0.334)	7 (0.053)	1 (0.002)	6 (0.037)	U (0.057)	10 (0.019)

(b) Model 2

Dependent Variable	*Uniform Lag Length*					
	3	4	6	8	9	12
DRATF	U (0.155)	U (0.212)	U (0.417)	U (0.160)	U (0.060)	2 (0.047)
M3	U (0.602)	U (0.257)	U (0.147)	U (0.168)	U (0.853)	U (0.281)
ALSI	U (0.909)	U (0.451)	U (0.403)	U (0.719)	9 (0.003)	2 (0.014)
INFL	U (0.123)	5 (0.027)	5 (0.007)	U (0.671)	1 (0.013)	6 (0.001)
MANUF	3 (0.018)	5 (0.023)	6 (0.025)	U (0.146)	1 (0.003)	U (0.821)
MINING	U (0.354)	1 (0.013)	1 (0.005)	U (0.444)	U (0.407)	U (0.084)

Table 5.9 - Serial correlation structures at various lag lengths in the VEC models (continued)

(c) Model 3

Dependent Variable	*Uniform Lag Length*					
	3	4	6	8	9	12
BILL	4 (0.004)	U (0.743)	U (0.796)	U (0.432)	U (0.205)	1 (0.036)
M3	U (0.674)	U (0.388)	U (0.207)	U (0.255)	1 (0.013)	3 (0.018)
PORT	U (0.887)	U (0.418)	4 (0.037)	U (0.415)	U (0.104)	9 (0.002)
INFL	8 (0.054)	4 (0.028)	1 (0.009)	U (0.885)	1 (0.028)	7 (0.031)
MANUF	3 (0.015)	3 (0.017)	1 (0.054)	U (0.064)	U (0.088)	1 (0.042)
MINING	U (0.336)	U (0.069)	1 (0.002)	U (0.147)	U (0.100)	U (0.072)

(d) Model 4

Dependent Variable	*Uniform Lag Length*					
	3	4	6	8	9	12
DRATE	U (0.145)	U (0.242)	U (0.673)	U (242)	8 (0.052)	7 (0.033)
M3	U (0.700)	U (0.380)	U (0.155)	U (186)	U (0.545)	3 (0.053)
PORT	U (0.800)	U (0.191)	5 (0.046)	5 (0.053	U (0.120)	10 (0.019)
INFL	U (0.130)	5 (0.025	5 (0.001)	U (0.786)	1 (0.008)	6 (0.001)
MANUF	3 (0.016)	3 (0.028)	1 (0.052)	U (0.215)	1 (0.054)	U (0.728)
MINING	U (0.204)	1 (0.009)	1 (0.008)	U (0.669)	U (0.568)	U (0.143)

5.4.5 Granger-Causality Tests

The Granger-causality test results obtained in the context of the four VEC systems are presented in Table 5.10. Although the results were quite sensitive to model specification, several key observations were palpable, and these are discussed in the sequel[24]. As a precursor to this discussion, it must be noted that the coefficients for error correction variables were individually as well as jointly statistically significant in three of the six equations for each of the four systems. This result buttresses our prior cointegration test results, and shows that the VEC models might have been correctly specified.

Our discussion of the Granger-causality test results centres on three main issues, namely the effectiveness of monetary policy, the macroeconomic effects of stock market activity, and real sector cause-effect dynamics.

[24] Note that diagonal entries were omitted, since they did not have causal implications.

Table 5.10 - Granger-causality tests

*This table shows the Granger-causality test results conducted within the VEC model environment. Models 1 to 4 are described in Table 5.1. Except for those under ECs, all entries show the probabilities of accepting the null hypothesis that the corresponding group of column variables did not Granger-cause the row variable, based on the χ^2-statistics for Wald tests. For ECs, entries are t-statistics under the null that they were individually insignificant. *, ** and *** denote statistical significance at 1%, 5% and 10% levels, respectively. ♦ implies that the EC coefficients were (jointly) significant at 5%.*

(a) Model 1

	ΣΔTBRATE	ΣΔM3	ΣΔALSI	ΣΔINFL	ΣΔMANUF	ΣΔMINING	$EC_{1,1}$	$EC_{1,2}$	
ΔTBRATE		0.250	0.257	0.502	0.144	0.521	-3.585*	-3.246*	♦
ΔM3	0.177		0.417	0.621	0.608	0.680	0.068	-0.449	
ΔALSI	0.522	0.488		0.721	0.937	0.775	1.011	0.162	
ΔINFL	0.000*	0.054***	0.106		0.400	0.226	2.230**	-1.345	♦
ΔMANUF	0.763	0.309	0.558	0.357		0.242	-3.341*	-3.837*	♦
ΔMINING	0.600	0.322	0.869	0.225	0.168		1.444	-0.154	

(b) Model 2

	ΣΔDRATE	ΣΔM3	ΣΔALSI	ΣΔINFL	ΣΔMANUF	ΣΔMINING	$ECT_{1,1}$	$ECT_{1,2}$	
ΔDRATE		0.039**	0.065***	0.063***	0.200	0.173	-4.763*	-3.836*	♦
ΔM3	0.066***		0.185	0.703	0.695	0.718	-0.508	-0.898	
ΔALSI	0.088***	0.419		0.630	0.950	0.582	0.738	0.001	
ΔINFL	0.176	0.080***	0.319		0.732	0.066***	1.095	-1.670***	♦
ΔMANUF	0.220	0.225	0.509	0.380		0.236	-4.022*	-4.512*	♦
ΔMINING	0.159	0.340	0.863	0.220	0.062***		1.410	0.256	

(c) Model 3

	ΣΔTBRATE	ΣΔM3	ΣΔPORT	ΣΔINFL	ΣΔMANUF	ΣΔMINING	$ECT_{1,1}$	$ECT_{1,2}$	
ΔTBRATE		0.213	0.374	0.519	0.098***	0.423	-3.828*	-3.089*	♦
ΔM3	0.209		0.588	0.512	0.558	0.685	-0.227	-0.689	
ΔPORT	0.778	0.501		0.472	0.881	0.059***	0.771	0.058	
ΔINFL	0.000*	0.145	0.027**		0.131	0.214	3.072*	-2.210**	♦
ΔMANUF	0.908	0.297	0.918	0.503		0.245	-2.914*	-3.420*	♦
ΔMINING	0.473	0.254	0.781	0.271	0.109		1.450	-0.559	

(d) Model 4

	ΣΔDRATE	ΣΔM3	ΣΔPORT	ΣΔINFL	ΣΔMANUF	ΣΔMINING	$ECT_{1,1}$	$ECT_{1,2}$	
ΔDRATE		0.031**	0.189	0.110	0.177	0.249	-4.872*	-2.842*	♦
ΔM3	0.112		0.379	0.631	0.602	0.734	-0.661	-1.043	
ΔPORT	0.023**	0.368		0.389	0.821	0.009*	0.410	-0.408	
ΔINFL	0.204	0.150	0.084***		0.428	0.063***	2.216**	-3.000*	♦
ΔMANUF	0.435	0.267	0.944	0.415		0.248	-3.601*	-4.078*	♦
ΔMINING	0.075***	0.240	0.618	0.239	0.033**		1.533	-0.446	

Regarding the impact of monetary policy in the South African economy, it was first noted that, in both of the relevant models, unidirectional causality was suggested from the Treasury bill rate to inflation, while some unidirectional causal relationship from money supply to inflation was evident only in Model 1. Further, when *TBRATE* was used, the neutrality of money tended to emerge clearly: neither *TBRATE* nor *M3* influenced real output, regardless of how the latter was measured. However, the superiority of *DRATE* over both *TBRATE* and *M3* as a measure of monetary policy was confirmed whenever this variable replaced *TBRATE*. The discount rate was influential in the forecasting of stock prices, yielding a strongly significant causal effect whenever *PORT* was used instead of *ALSI*. A somewhat bilateral causal relationship also existed between the discount rate and money supply, although the direction of causality was stronger from *M3* to *DRATE* than in the converse direction, rendering support for the argument that policy was largely reactionary to the state of the economy rather than being exogenous. It is notewothy, however, that despite being a better measure of policy, *DRATE* did not evocatively influence real output. Further, as opposed to the strong unidirectional causality from the Treasury bill rate to inflation already noted, the discount rate and inflation were largely independent of each other. A related point is that apart from its aforementioned causal association with *TBRATE*, inflation was otherwise inconsequential in the systems, influencing neither the stock market nor real activity. Indeed, the evidence seemed to suggest that real activity in South Africa was generally unaffected by monetary policy, rendering support to real business cycle theories of the macroeconomy. This result was only partially in tandem with that documented by Darrat and Dickens (1999) who found no impact of policy even on the stock market. But the result was in conflict with Tan and Habarumshah (1999), who found policy to be effective. Importantly in our context, the findings rendered support for the use of the discount rate not only as a better measure of monetary policy, but also as a potential source for a priced factor on the JSE. The fact that the significance of the causal effect of *DRATE* on the stock market was more pronounced when *PORT* (rather than *ALSI*) was used suggested that the impact of policy on individual stock returns might not be accurately characterised by the dynamics of a value-weighted market index.

To address the second issue of relevance, it could be noted that the stock market had important causal implications for monetary policy. Specifically, bilateral causality was evident between *ALSI* and *DRATE* (Model 2), albeit being weak in terms of statistical significance. In addition, unidirectional causality was evident from *PORT* to *INFL* in Model 3 and Model 4. These findings were consistent with the argument that the stock market was a leading indicator of monetary policy. We could not find any evidence, however, to suggest that the stock market could also lead real activity, as documented by Darrat and Dickens (1999).

Finally, a clear distinction in the dynamics of the two real sectors emerged from the analysis. Clearly, the pattern of statistical significance of the error correction coefficients intimated that any causal macroeconomic effects on the real sectors occurred only in the long-run in the manufacturing sector, and only in the short-run in the mining sector. To verify this finding, notice that in all the four models, only the *EC* coefficients were significant in all equations for *MANUF*. On the other hand, none of the *EC* coefficients were significant in the equations for *MINING*. Further, unidirectional causality was evident from *MANUF* to *MINING* (see Model 2 and Model 4). Thus, we could confirm that activity in the manufacturing sector caused activity in the mining sector, but that the converse did not hold. This observation was consistent with the prior account regarding the increasing role of the manufacturing sector in South Africa, which could entail a substitution effect of manufacturing output for mining output. Apart from this observation, there did not seem to be any other significant effect on the macroeconomy emanating from activity in the manufacturing sector. On the other hand, unidirectional Granger-causality was evident from *MINING* to *INFL* (Model 2 and Model 4) and, more importantly, from *MINING* to *PORT* whenever *PORT* was used instead of *ALSI*. These findings were consistent with the market segmentation hypothesis well-documented for the JSE (Page 1986, van Rensburg and Slaney, 1997): if the return generating process for JSE mining stocks was indeed different from that for industrial stocks, then the underlying real sectors should also display heterogeneous dynamics. Moreover, the implication of the important finding that *MINING* caused *PORT* is that some measure of mining sector activity could be included as a potential priced factor for individual JSE stocks. Evidently, similar justification could not be made for MANUF, nor could the justification have surfaced had the stock market index alone been used to capture these dynamics. Arguably, since *MINING* had a significant causal effect on an *equally-weighted* portfolio of the stocks in the sample, the proxy for mining sector activity could potentially enter the asset pricing relationships for all individual stocks in the sample, including those from the non-mining sectors. This is because the ability of *MINING* to predict such a portfolio could imply that the priced factor derived from mining had a crosscutting impact on all stocks. Such is the desirable characteristic of a priced factor in the context of the multifactor asset pricing literature.

5.4.6 Innovation Accounting

Variance decompositions and impulse response functions were generated over a four-year forecasting horizon for each of the four models, based on the two orderings described in the methodologies. However, to illustrate prudently without being overly simplistic, the variance decompositions are presented in Table 5.11 for Model 1 and Model 4 only. Similarly, Figure

5.3 illustrates the results of tracing the impulse responses implied by Model 1 and Model 4. Results for Model 2 and Model 3, which were generally intermediate to the two extreme cases shown, are not reported herein merely and inconsequentially to conserve space.

5.4.6.1 Variance Decomposition Analysis

The first observation relating to Table 5.11 was that the impact of a monetary policy innovation on the stock market was, in the long-term, negligible. At long horizons, own variability in both *ALSI* and *PORT* tended to firmly explain most of the total variability, regardless of variable ordering. Of the modest remaining variability in *ALSI* and *PORT* after accounting for that due to the variable itself, however, the interest rate variables accounted for some of it, especially when they were placed first in the ordering. Moreover, as opposed to the results documented in subsection 5.4.5, there was no evidence that *DRATE* was a better measure of policy than *TBRATE* by the variance decomposition metric. Therefore, *DRATE* had a significant impact on the stock market only in the short term.

Secondly, the effects of monetary policy on inflation did not seem to be significant at long horizons. Instead, mining sector production tended to account for most of the variability in inflation. A third observation was that while evidence of the neutrality of monetary policy was firm in the Granger-causality framework, the short-term interest rates tended to explain quite a momentous proportion of the variability in *MANUF* at long horizons. This result could imply that manufacturing production tended to respond to policy shocks with a long lag. Except for some relatively weak impact of inflationary pressures, however, it was noted that *MINING* still remained largely irresponsive to policy, even in the long run.

Table 5.11 – Sample variance decompositions

This tables shows variance decompositions at a 48-month forecasting horizon for Model 1 and Model 4 described in Table 5.1, computed from the VEC models. Orderings are described in subsection 5.3.8. Entries are percentages of the forecast error variance of the row variable due to each corresponding column variable.

(a) Model 1; 1st variable ordering

Endogenous Variable	***Percentage of Forecast Error Variance: Distribution Across Innovations***					
	TBRATE	*M3*	*ALSI*	*INFL*	*MANUF*	*MINING*
TBRATE	23.462	8.376	58.129	6.575	0.894	2.564
M3	3.074	76.967	7.822	0.841	0.728	10.568
ALSI	4.667	1.336	90.104	3.277	0.461	0.155
INFL	4.760	6.016	1.960	36.769	0.310	50.185
MANUF	39.018	6.027	7.989	4.704	40.980	1.282
MINING	7.542	1.699	8.760	11.477	1.255	69.266

Table 5.11 – Sample variance decompositions (continued)

(b) Model 1; 2nd variable ordering

Endogenous Variable	*Percentage of Forecast Error Variance: Distribution Across Innovations*					
	MINING	*MANUF*	*INFL*	*ALSI*	*M3*	*TBRATE*
MINING	76.122	1.378	8.105	10.723	2.205	1.486
MANUF	1.664	48.117	1.055	10.340	10.945	27.879
INFL	57.734	0.338	34.255	2.448	2.542	2.683
ALSI	0.091	3.655	3.131	89.987	1.509	1.627
M3	8.213	4.481	4.067	5.462	75.074	2.703
TBRATE	0.763	1.524	10.736	54.020	9.388	23.569

(c) Model 4; 1st variable ordering

Endogenous Variable	*Percentage of Forecast Error Variance: Distribution Across Innovations*					
	DRATE	*M3*	*PORT*	*INFL*	*MANUF*	*MINING*
DRATE	26.869	6.435	59.549	3.768	2.866	0.513
M3	0.894	71.136	5.792	1.113	1.817	11.202
PORT	4.804	0.565	92.458	1.186	0.738	0.249
INFL	1.483	5.455	3.074	39.577	1.183	49.228
MANUF	35.816	4.866	1.461	7.309	47.846	2.702
MINING	5.537	1.832	6.193	11.182	1.778	73.478

(d) Model 4; 2nd variable ordering

Endogenous Variable	*Percentage of Forecast Error Variance: Distribution Across Innovations*					
	MINING	*MANUF*	*INFL*	*PORT*	*M3*	*DRATE*
MINING	77.757	1.589	6.221	9.255	2.078	3.100
MANUF	1.756	47.518	3.880	2.536	13.409	30.901
INFL	55.514	1.005	36.343	3.251	2.183	1.704
PORT	0.779	0.900	0.915	94.916	0.772	1.718
M3	8.210	6.371	5.149	5.599	64.765	9.906
DRATE	0.720	4.359	3.650	58.155	8.651	24.466

Fourthly, the stock market was very influential in the long-term predictability of interest rates and, to a lesser extent, of money supply. Thus, the stock market was a leading indicator of the stance of monetary policy in both the short term and the long term. However, in tandem with the Granger-causality test results, the stock market did not lead real activity at all.

Finally, the distinct role of the mining sector *vis-à-vis* the manufacturing sector remained firm over the passage of time. Further to the observation that *MANUF* was generally more endogenous that *MINING*, the latter had more important predictive implications in the systems. In addition to accounting for the dynamics of inflation, *MINING* also explained a proportion of the variability in the monetary aggregate. On the other hand, *MANUF* did not seem to be similarly useful in the predictability of monetary variables, and no longer contributed to the prediction of *MINING* as documented in subsection 5.4.5. As with the discount rate, however, the already documented causal effect of *MINING* on the stock market was not observable in the long run.

It is worth noting that Table 5.11 provides point estimates of the variance decompositions occurring four years after a shock, and does not show how these changed over the four-year horizon. We preferred to trace such time-path dynamics using impulse response functions.

5.4.6.2 Impulse Response Analysis

The impulse response functions depicted in Figure 5.3 also revealed important interrelationships among the variables, major among which are herein discussed. As a precursor to the major discussions, it should be noted that the impulse responses generally tended to converge towards zero, implying that the models depicted stability over time. This observation was consistent with the fact that the first differenced variables in the systems were stationary.

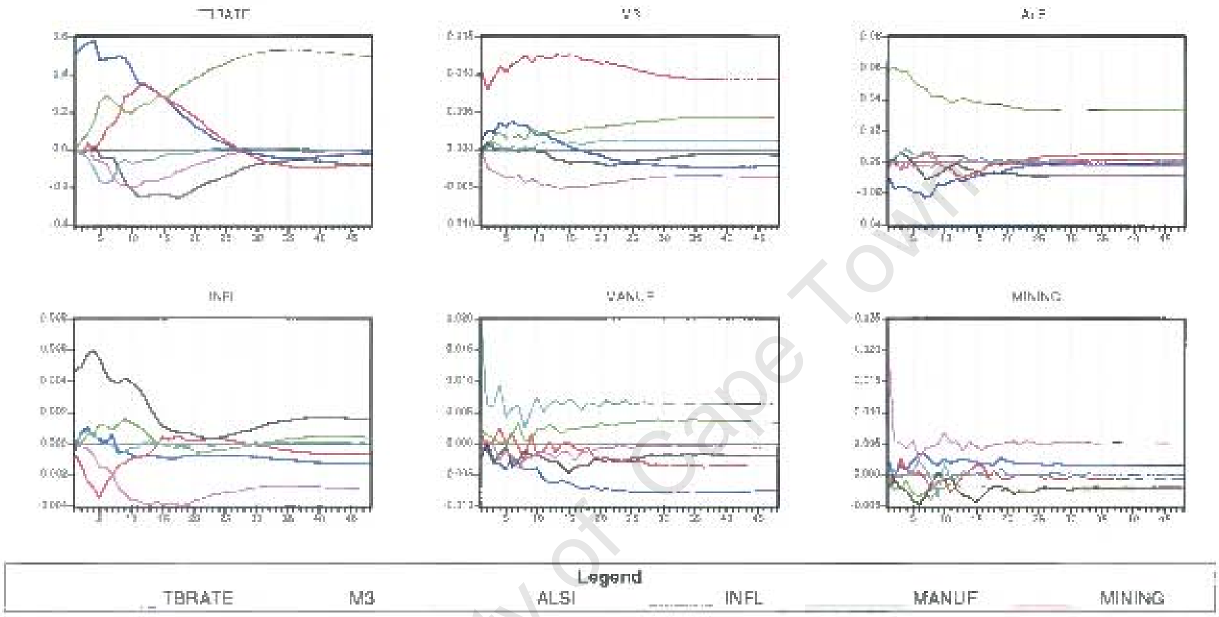
The first major observation made on the impulse responses was that the stock market, irrespective of how it was measured, responded strongly to short-term interest rate shocks than it did to shocks from any other variable in the system, and that the impact of such shocks was almost entirely exhausted within two years. Moreover, the theoretical inverse relation between stock prices and interest rates was evident, and the impact of a *DRATE* shock on *PORT* was clearly much stronger than that of a *TBRATE* shock on *ALSI*[25]. These findings rendered further support for the use of *DRATE* in capturing the short-term dynamics, and were not particularly inconsistent with those reported under the variance decomposition analysis, where point estimates obtained four years later were the basis. The observation that the impacts of interest rates on the stock market died off within two years could imply that variance decompositions reported after two years, such as those in Table 5.11, would not depict important effects occurring at shorter horizons.

[25] In other permutations not recorded here, it was also evident that *DRATE* innovations impacted more on *ALSI* than did *TBRATE* innovations on *PORT*.

Figure 5.3 - Sample impulse response functions

This figure shows the impulse response functions from the VEC models identified as Model 1 and Model 4 in Table 5.1, using the two orderings presented in subsection 5.3.8. Each graph shows the time path of the subject variable as a result of a one standard deviation shock in the relevant variable as identified in the legend. Time, in months, is recorded on the horizontal axes.

(a) Model 1; 1st variable ordering



(b) Model 1; 2nd variable ordering

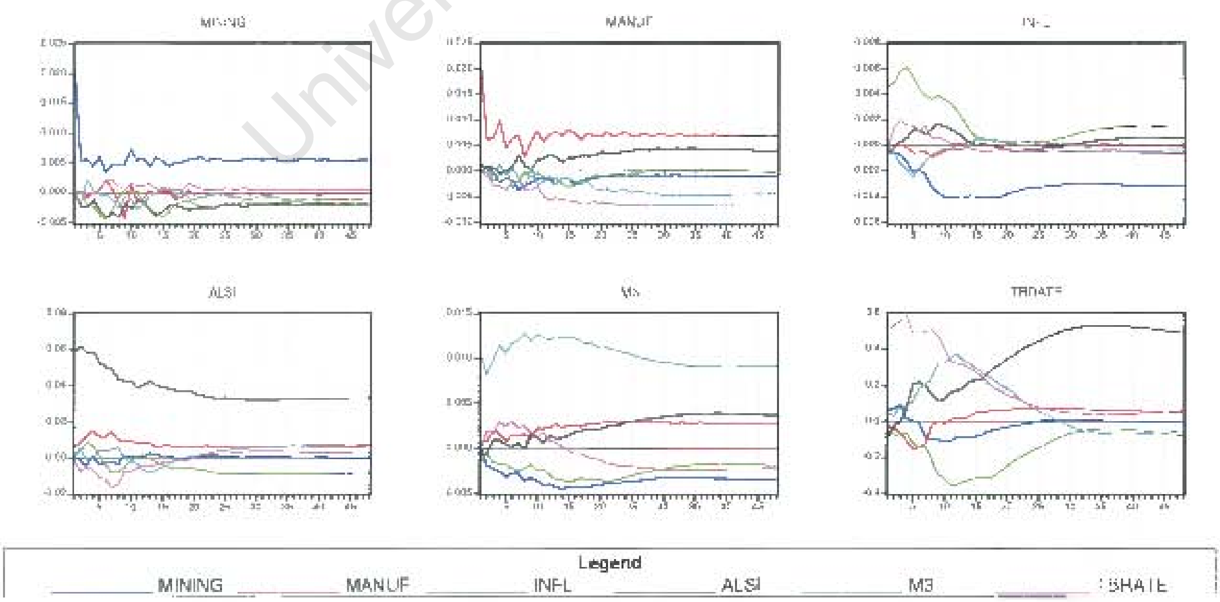
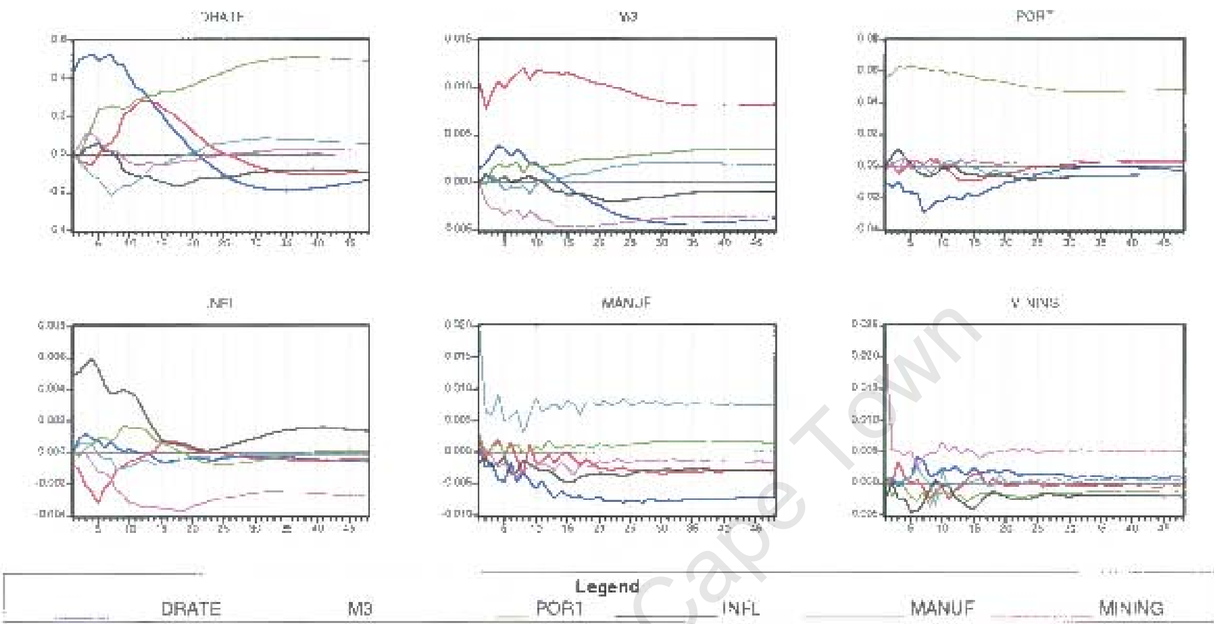
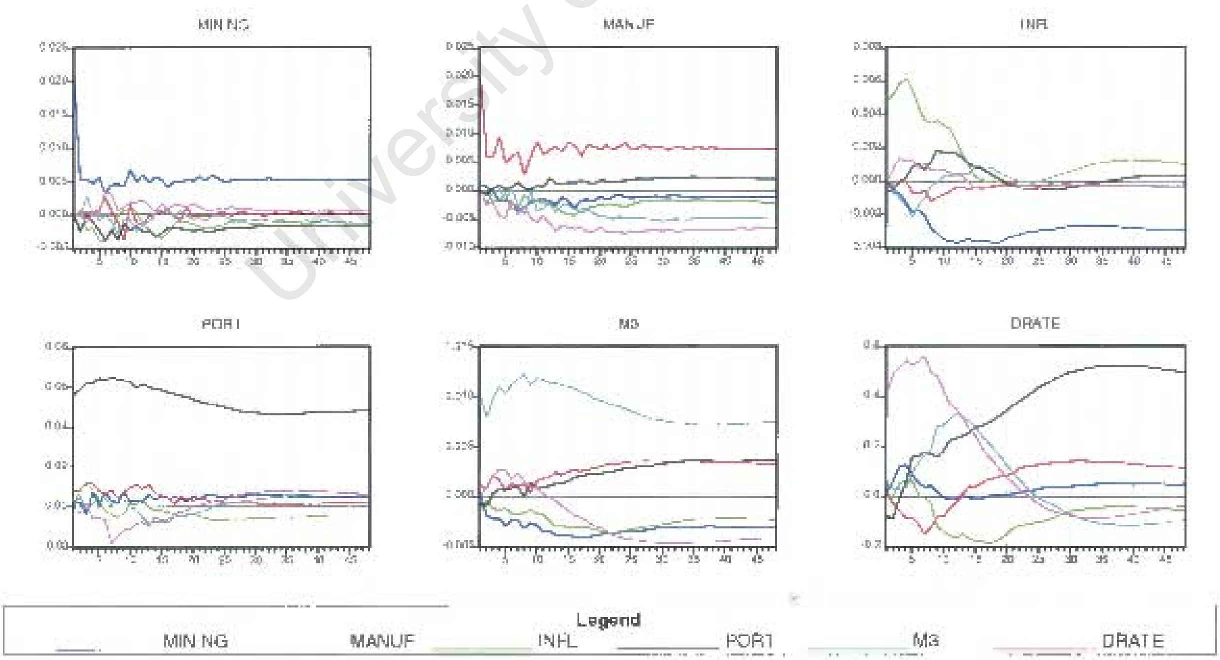


Figure 5.3 - Sample impulse response functions *(continued)*

(c) Model 4; 1st variable ordering



(d) Model 4; 2nd variable ordering



Secondly, it was observed that although *MANUF* appeared to exhibit neutrality of money in the initial periods, it responded to interest rate shocks quite strongly after about nine months, and such a reaction tended to be sustained beyond the four-year horizon. On the other hand, *MINING* seemed to respond to such innovations relatively weakly, and the responses were fully realised within twelve to eighteen months. These findings were consistent with those observed in the Granger-causality tests (notice the pattern of significance of the error correction terms) as well as the variance decompositions. On its part, *MINING* also tended to impact on monetary policy by strongly influencing *TBRATE*, *M3* and *INFL*, largely irrespective of variable ordering. In keeping with the market segmentation hypothesis, no similar impacts could be associated with *MANUF*. As with the variance decomposition analysis, we could not find further strong evidence of the Granger-causality test result that *MINING* could predict stock market prices. On the other hand, there appeared to be a significant impact of a *MANUF* shock on *MINING*, but one that was completely realised within eighteen months of the shock and understandably could not show in the variance decompositions.

Further to the above observations, it was interesting to note the significant impact of the stock market on both *TBRATE* and *DRATE*, as well as on *M3*. As already stated, these findings were consistent with the view that the stock market was a leading indicator of monetary policy. We continued to observe, however, that, the stock market did not lead real activity, irrespective of the manner in which the latter was measured. Inflation was itself also responsive to a monetary shock almost instantaneously, but the price puzzle showed quite strongly in all the models: a positive shock to money supply tended to display a dampening effect on inflation, rather than increasing the general price level. Of course, this could be accounted for by including a commodity price variable in the system, in order to minimise model misspecification resulting from the omission of key information variables (Walsh 2002:29). However, arguing that the price puzzle reflected an effect called the 'cost channel of monetary policy', Barth and Ramey (2001) showed that the puzzle had an economic interpretation and did not necessarily indicate model misspecification. As noted in subsection 5.3.2, the SARB's current solution to the price puzzle is to target CPIX inflation.

5.5 Summary and Conclusion

This chapter investigated the dynamic interrelationships among monetary, financial and real variables in South Africa. Within the overall context of our study, the primary objective of the analysis was to identify potentially priced macroeconomics variables on the JSE, in view of the observation made in Chapter 4 that volatility was not one such a priced factor. However, the chapter also established important interrelationships among the sectors, and examined the effectiveness of monetary policy. Real activity was measured by manufacturing and mining production, while the Bank/repo rate (i.e., the discount rate), the Treasury bill rate and M3 were the potential measures of monetary policy. Further, close prices on the JSE All Share Index as well as those on the equally-weighted portfolio of the forty-four stocks introduced in Chapter 3 were used as measures of JSE activity. Monthly data were used in the analysis, and the sample period of 1983 to 2002 was chosen such as to coincide with the introduction of the classical cash reserve system of monetary policy in South Africa. In order to assess the robustness of our results, and in order to minimise model over-parameterisation and variable collinearity, four six-variable models were used in tracing the dynamics. Model specifications were guided by the alternate introduction of the two interest rate variables as well as the two measures of stock market activity, but all the models included the inflation, money supply and real output variables. Because the investigation established cointegration among the variables in each of the systems, Granger-causality tests were conducted in the environment of vector error correction models. In addition, the dynamics were traced by computing variance decompositions and impulse response functions over a four-year forecasting horizon. The key conclusions of the analysis are as follows:

Firstly, although monetary policy had predictive power for inflation, there was no strong evidence that the effects of policy also impacted on the real sector in the short-run. While the Granger-causality tests showed no traces for the effects of policy on the real sector at all, innovation accounting revealed that the mining sector could respond to monetary shocks after long periods. The evidence, therefore, confirmed the short-run neutrality of money.

Secondly, there was evidence that the discount rate had a causal effect on stock prices, particularly when the equally-weighted portfolio was used. Although the Treasury bill rate also showed forecasting power on stock prices in innovation accounting, the discount rate was less sensitive to variables orderings in such analyses, and its impacts were generally stronger. Therefore, we concluded that the discount rate contained unique information that could be used to capture the effects of monetary policy on the stock market.

Thirdly, the stock market was consistently a leading indicator of monetary policy but, in general, did not lead real activity irrespective of the manner in which the latter was measured.

Fourthly, there was a clear distinction between the dynamics of the mining and manufacturing sectors. Mining production showed that it had long-run interrelationships with policy variables, and could predict both inflation and stock prices. No similar effects seemed to derive from manufacturing production. On the other hand, there was strong evidence that manufacturing production had predictive power for mining production, both in the short-run and the long-run. These findings were consistent with the market segmentation hypothesis for which there was strong evidence in previous JSE studies.

Finally, the study confirmed the presence of the price puzzle in the South African economy, in the sense that the initial effect of contractionary monetary policy was to induce inflation. Over time, it would be necessary to analyse whether the price puzzle could disappear as a result of targeting CPIX inflation as opposed to CPI inflation.

For the rest of this research, the most important result was the observation that the discount rate and mining sector activity had predictive power for the stock market. This finding provided justification for the inclusion of the discount rate and some measure of mining sector activity in the characterisation of the return generating process for JSE equities. Reverting to the GARCH(1,1) framework developed in Chapter 4, Chapter 6 pursues this issue.

Chapter 6

Modelling Macroeconomic Effects on the JSE

When the GARCH(1,1) model was extended to incorporate exogenous factors, both the discount rate and the gold price became important determinants of expected returns and return volatility, especially when the variables were decomposed to capture asymmetric effects. Moreover, the effects of news on mean returns and return volatility were largely asymmetric for both the discount rate and the gold price. Finally, the extended GARCH model could account for most of the non-linearities remaining after the GARCH(1,1) filter.

6.1 Introduction

Chapter 5 used vector error correction (VEC) modelling to establish the nature of the dynamic interrelationships among monetary, financial and real sector variables. One of the key observations made in the chapter was that both monetary policy (through the discount rate) and mining sector production had explanatory power for stock prices. However, although the procedure of Chapter 5 was useful in identifying potentially priced macroeconomic variables on the JSE, the actual parameter estimates were not of particular interest, since VEC models are atheoretic by nature. In addition, the models do not account for non-linearities. In order to derive parameters that would describe the nature of the relationship between the stock market and the macroeconomic variables while taking into account the non-linearities in returns, it was necessary to recast the analysis to a structural modelling framework whose parameter estimates could yield meaningful interpretations. This chapter investigates these dynamic structural interrelationships by extending the GARCH(1,1) model discussed in Chapter 4. Therefore, the specific objectives of the chapter are as follows:

a) to investigate the contemporaneous effects of monetary policy and mining sector activity on stock return dynamics;
b) to investigate possible asymmetric effects of news about monetary policy stance as well as mining sector activity on stock return dynamics; and

c) to investigate whether the inclusion of the macroeconomic variables could account for the remaining non-linearities in the GARCH(1,1) model.

In order to address these objectives, the chapter proceeds as follows. The next section recalls the theoretical framework for investigating the effects of the macroeconomic variables on the stock market, and presents selected literature on the subject. The methodologies pursued in the investigation are discussed in Section 6.3, and largely build on the work of the preceding chapters. The results of the analysis are presented and discussed in Section 6.4, while Section 6.5 presents a summary of the investigation, including its main conclusions.

6.2 Theoretical Framework and the Literature

The main theoretical basis for this investigation was already presented in Section 5.3. To recapitulate, macroeconomic theory postulates an inverse relationship between stock prices and interest rates, as reflected in the present value formula of stock prices. This formula also implies that there should be a positive relationship between "earnings" or "numerator" factors and stock prices. Therefore, given the evidence of the preceding chapters that security returns are predictable, it is expected that contractionary monetary policy should induce a decline in stock prices and returns, while increased real sector activity should increase prices and returns. For instance, a gold price increase implies increased returns from investments in the gold sector, which should in turn increase stock prices.

While prior research investigating the effects of policy on the level of asset returns is extensive, it is argued that monetary policy shocks should also affect the volatility of returns (Tarhan, 1993). Moreover, "if positive and negative changes (in monetary policy) are perceived to be conveying either a pessimistic or an optimistic outlook on the economy, then the market's reaction to the information flows should be asymmetric" (Gulley & Sultan, 2003). We contend that similar arguments could be made with respect to a measure of activity in the real sector, if such a measure contains important information in predicting asset returns.

As with most of the investigations conducted in the preceding chapters, the relevant published empirical literature on these issues is scanty, if available, for the South African market. The international literature, on the other hand, presents generally conflicting evidence. For instance, Jensen and Johnson (1993) as well as Gulley and Sultan (2003) documented an inverse relationship between stock prices and the discount rate, while expansionary monetary policy was noted to lower stock prices in Hafer (1986) as well as

Peace and Roley (1983). Kearney and Daly (1998) noted that the volatility of the stock market was determined by the volatilities of inflation and interest rates. Further, Hafer (1983) confirmed the presence of asymmetric effects of policy on stock prices, while Morgan (1993) found that policy had asymmetric effects on output growth, hence possibly on asset prices as well, in view of the present value formula. There also exist many studies that establish that stock return variations can be explained by measures of real activity (e.g., Chen, Roll & Ross, 1986; Barro, 1990; Fama, 1990; Chen, 1991), as well as others that do not find such a relationship to hold, particularly in more recent subperiods of a long investigation period (e.g., Binswanger, 2000). Such a finding is also consistent with a recent observation made by Muradoglu and Metin (2001) that the effects of money and interest rates on stock returns tended to be time-sensitive, disappearing as the market became more mature.

It would appear meriting, therefore, to contribute to this discussion by investigating more closely the effects of South African monetary policy and mining sector earnings on JSE stock returns. The extensions of the GARCH(1,1) model necessary to incorporate these issues, as well as other methodological issues, are discussed in the next section.

6.3 Research Methodologies

6.3.1 Variable Selection, Definitions and Data

From the evidence presented in Chapter 5, this study considered the discount rate to be an appropriate measure of monetary policy in South Africa, and a surrogate for a priced factor on the JSE. In addition, the study chose the gold price as a measure of priced mining sector activity on the JSE, in view of the importance of gold in the South African economy, and given that the gold price was a frequently quoted macroeconomic indicator. Apart from being influenced by the availability of weekly data[1], this choice was also consistent with the discussion of Section 5.2, as well as prior South African asset pricing studies (e.g., van Rensburg, 1999). It should be noted that the price of gold is an "earnings" factor and should, *a priori*, be positively related with stock prices, *ceteris paribus*. As already indicated above, monetary policy and the earnings effects could affect both conditional mean returns as well as return volatility, notwithstanding the evidence that volatility was not priced by the JSE. Indeed, this fact could necessitate that volatility be shrewdly avoided by rational investors, since there would be no compensation for taking it on in this particular market.

[1] One commentator suggested the use of a commodity price index (all commodities or metal) in place of the gold price index. However, data on these variables were only available from year 1989 at the weekly frequency.

To introduce new notation, let *GPRICE* be the natural logarithm of the price of gold. As indicated in Appendix 5A, the original time series, obtained from the Inet-Bridge database, was measured in rand per kilogram. We continue to denote the discount rate as *DRATE*. Weekly data on *GPRICE* and *DRATE* were obtained for the period from 15 December 1983 to 5 April 2002, once again to coincide with the period of the introduction of the classical cash reserve system of monetary policy in South Africa. At the weekly frequency, this gave a total of 957 observations. Thus, the estimation period for individual stocks and PORT coincided with that used in the preceding chapter, but constituted about two-thirds of the data used in Chapter 3 and Chapter 4. It should be noted, however, that ALSI equations were still based on the realisation of 954 observations, as described in Section 3.2.

Questioning the robustness of the GARCH model estimation results reported in Chapter 4 in view of the said reduction in the sampling period, the standard GARCH(1,1) model was estimated using the smaller sample for all the forty-four stocks[2]. The results appear in Table 6.1. As read with Appendix 4A as well as Table 4.6, the results showed that, but for yielding lower log-likelihood functions and few other insignificant deviations, the reduction in sample size left the GARCH model parameter estimates generally unaffected. For instance, as with the larger sample, three stocks (i.e., ASR, MLB and TRE) yielded significantly negative ARCH terms. ARCH term estimates for the rest of the stocks were all positive, with only minor shifts in statistical significance. Further, all GARCH terms remained positive and typically extremely significant. Four GARCH terms were insignificant in the restricted sample, compared with two in the previous results. The persistence of volatility remained close to but less than unity, with the GARCH terms continuing to account for most of such persistence. An exception to this observation was stock JMC which, surprisingly, showed an ARCH term distinctly in excess of unity. This term was, however, insignificant even at the 10 percent level. All in all, the GARCH(1,1) model estimation results were insensitive to changes in sample size.

The models used in this investigation were univariate adaptations of the multivariate models proposed by Gulley and Sultan (2003). The two authors used a multivariate GARCH(1,1) process to model simultaneously the dynamic reactions of bond and stock market returns to changes in the CBOT 30-day federal funds futures rate. Further, they investigated whether positive and negative changes in the rate had asymmetric effects on the stock and bond

[2] Since the GARCH model for ALSI was estimated from February 1984 in Chapter 4, and we already noted there that reducing the sample did not change the estimation results for PORT, we omitted both ALSI and PORT from this sensitivity analysis.

prices as well as their volatilities. In our context, we used the two variables described above within a univariate framework, but also attempted to capture asymmetric effects in a manner similar to Gulley and Sultan. Specifications of the models used in the current study follow.

Table 6.1 – Estimation of GARCH(1,1) model: restricted sample

*This table shows the maximum likelihood estimates (with robust z-statistics in parentheses) of the GARCH(1,1) model for the forty-four stocks. The sample period was from 15 December 1983 to 5 April 2002. The conditional mean equation was (4.1), and the conditional variance equation was (4.5). Log-L is the log likelihood function. * denotes statistical significance at 1%, while ** and *** denote significance at 5% and at 10%, respectively.*

Security	α	ϕ	λ_1	θ_1	Log-L
AFE	-0.001 (-0.348)	0.000 (1.493)	0.113 (1.268)	0.803 (10.124)*	1413.020
AFX	0.004 (3.394)*	0.000 (2.488)**	0.188 (4.122)*	0.666 (8.263)*	1729.016
AGL	0.003 (1.854)***	0.000 (0.034)	0.009 (0.803)	0.994 (82.663)*	1308.825
ALT	-0.002 (-1.493)	0.008 (2.894)*	0.206 (2.008)**	0.417 (2.416)**	1663.917
ANG	0.002 (0.937)	0.000 (1.575)	0.074 (2.751)*	0.867 (14.887)*	1382.944
ASR	-0.000 (-0.119)	0.007 (1.528)	-0.002 (-1.718)***	0.589 (1.307)	753.354
AVI	0.002 (1.509)	0.000 (1.170)	0.076 (4.493)*	0.926 (50.849)*	1587.039
BAW	-0.003 (-0.668)	0.000 (2.735)*	0.140 (1.966)**	0.785 (17.094)*	1483.032
BVT	0.001 (1.020)	0.000 (1.603)	0.094 (1.927)**	0.750 (6.505)*	1622.641
CHE	0.002 (1.717)***	0.000 (1.875)***	0.054 (1.672)***	0.872 (15.113)*	1700.197
CRH	0.002 (0.734)	0.001 (1.206)	0.053 (1.861)***	0.848 (8.938)*	1116.979
CTP	0.004 (3.043)*	0.000 (0.953)	0.038 (1.421)	0.935 (16.897)*	1640.719
DEL	0.003 (1.911)***	0.000 (0.539)	0.127 (2.311)**	0.906 (91.881)*	1476.324
DUR	-0.037 (-1.425)	0.004 (3.788)*	0.204 (2.099)**	0.224 (1.330)	1025.749
ECO	0.001 (0.973)	0.000 (2.503)**	0.055 (2.683)*	0.907 (37.824)*	1601.134
ELH	0.000 (0.324)	0.000 (1.720)***	0.031 (1.780)***	0.936 (28.517)*	1504.106
FOS	0.001 (0.776)	0.000 (1.763)***	0.073 (1.456)	0.774 (6.814)*	1527.439
GMF	0.002 (1.383)	0.000 (1.742)***	0.007 (0.811)	0.985 (85.161)*	1389.536
HAR	-0.001 (-0.592)	0.000 (2.278)**	0.074 (3.816)*	0.899 (35.530)*	1223.750
HLH	0.003 (1.743)***	0.000 (1.288)	0.049 (3.074)*	0.937 (38.195)*	1426.822
HVL	-0.000 (-0.127)	0.001 (1.878)***	0.104 (3.113)*	0.742 (7.079)*	1380.121
IMP	0.001 (0.552)	0.000 (1.770)***	0.027 (1.635)	0.944 (32.749)*	1381.589
JCM	0.006 (2.421)**	0.000 (0.393)	1.506 (1.486)	0.612 (5.934)*	1263.272
JNC	0.004 (1.385)	0.000 (0.542)	0.480 (1.488)	0.736 (7.104)*	1085.566
LGL	0.004 (3.147)*	0.000 (1.111)	0.045 (2.950)*	0.947 (41.943)*	1625.840
MAF	0.002 (1.781)***	0.000 (0.911)	0.356 (1.068)	0.756 (41.568)*	1489.727
MLB	-0.002 (-3.048)*	0.003 (1.630)	-0.006 (-5.128)*	0.555 (1.714)***	1186.472
NED	0.003 (2.443)**	0.000 (2.126)**	0.081 (2.913)*	0.866 (19.336)*	1637.139
NPK	0.003 (2.377)**	0.000 (2.301)**	0.143 (3.464)*	0.706 (8.260)*	1665.187
OCE	0.004 (3.625)*	0.000 (2.635)*	0.127 (4.639)*	0.795 (16.240)*	1687.323
PAM	0.002 (1.608)	0.000 (1.858)***	0.036 (2.542)**	0.945 (44.992)*	1606.568
PIK	0.003 (1.758)***	0.000 (1.322)	0.038 (1.508)	0.881 (13.765)*	1531.564
PPC	0.000 (0.393)	0.000 (1.159)	0.036 (2.094)**	0.920 (18.572)*	1753.695
REM	-0.001 (-0.167)	0.001 (6.132)*	0.988 (1.184)	0.090 (1.225)	1403.385
RLO	0.001 (0.780)	0.000 (1.986)**	0.094 (1.998)**	0.858 (16.257)*	1445.346
SAB	0.003 (2.155)**	0.000 (0.958)	0.047 (3.140)*	0.946 (46.837)*	1648.155)
SAP	0.003 (1.486)	0.000 (1.349)	0.053 (2.834)*	0.931 (30.714)*	1379.123
SBK	0.001 (1.072)	0.000 (3.104)*	0.136 (3.235)*	0.783 (15.505)*	1731.455
TBS	0.001 (0.683)	0.000 (2.056)**	0.040 (2.161)**	0.909 (24.422)*	1691.825
TNT	0.003 (2.198)**	0.000 (1.586)	0.059 (2.525)**	0.879 (15.685)*	1572.480
TRE	0.004 (1.363)	0.008 (1.861)***	-0.004 (-2.884)*	0.595 (1.858)***	683.842
VNF	0.000 (0.100)	0.000 (1.242)	0.015 (0.759)	0.936 (15.507)*	1481.265
WAR	0.000 (0.125)	0.000 (2.510)*	0.126 (4.686)*	0.846 (28.416)*	1111.261
WLO	-0.000 (-0.058)	0.001 (3.022)*	0.220 (3.306)*	0.226 (1.508)	1521.833

6.3.2 Specification of the GARCH Model of Macroeconomic Effects

Using the unit root testing procedures discussed in Section 3.2, it was established that both *DRATE* and *GPRICE* were integrated of order one[3]. As such, first differences of the variables are prefixed with a '*D*' to distinguish them from their equivalents in levels. Therefore, the GARCH(1,1) model discussed in Chapter 4 was extended as follows:

$$R_t = \alpha_0 + \alpha_1 DDRATE_t + \alpha_2 DGPRICE_t + \mu_t, \qquad (6.1)$$

$$\mu_t|\Omega_{t-1} \sim N(0,h_t) \text{ or } \mu_t|\Omega_{t-1} \sim t(0,h_t,v), \qquad (6.2)$$

$$h_t = \phi_0 + \lambda_1\mu_{t-1} + \theta_1 h_{t-1} + \phi_1 DDRATE_t + \phi_2 DGPRICE_t. \qquad (6.3)$$

In model (6.1) to (6.3), R_t were the uncorrelated or linearly filtered return series described in Section 3.2; α_0 and ϕ_0 were intercept terms in the conditional mean and volatility equations corresponding to α and ϕ in (4.1); and (4.4); while α_1, α_2, ϕ_1 and ϕ_2 were coefficients for the new variables. All other terms assumed the unambiguous interpretations of Section 4.2.

While model estimation and appraisal followed the procedures of Chapter 4, the analysis of the present chapter focused on the coefficients for *DDRATE* and *DGPRICE*, since there was general stability in the ARCH and GARCH terms. Specifically, in order to establish the extent to which the exogenous macroeconomic variables impacted on the conditional mean returns and/or the volatility of returns for each of the individual stocks and portfolios, the following hypotheses were tested:

H_0: *DDRATE* and/or *DGPRICE* had no impact on either the mean returns or the return volatility (i.e., $\alpha_i = \phi_j = 0$ for $i = 1,2$ and $j = 1,2$);

H_1: Not H_0;

H_2: *DDRATE* and/or *DGPRICE* impacted on both the mean returns and the return volatility (i.e., at least one $\alpha_i \neq 0$ for some $i = 1,2$, and/or at least one $\phi_j \neq 0$ for some $j = 1,2$);

H_3: *DDRATE* and/or *DGPRICE* only impacted on the mean returns (i.e., $\phi_j = 0$ for both $j = 1,2$, but at least one $\alpha_i \neq 0$ for some $i = 1,2$); and

[3] The unit root tests were conducted again on *DRATE* at the weekly frequency to validate the results obtained in the preceding chapter, where monthly data were used.

H_4: *DDRATE* and/or *DGPRICE* only impacted on the return volatility (i.e., $\alpha_i = 0$ for both $i = 1,2$, but at least one $\phi_j \neq 0$ for some $j = 1,2$).

To resolve this investigation, we initially examined the *t*-statistics for the individual parameters. Since, however, coefficients could be individually insignificant while jointly having an influence on the dependent variable, for all cases where the individual parameters were insignificant based on the *t*-statistics but also as stipulated under any appropriate (null) hypothesis stated above, we sought to confirm their joint insignificance by invoking Wald tests for linear restrictions. Note, however, that the individual *t*-tests were entirely adequate for resolving hypothesis H_2, while a rejection of H_0 implied that we could not reject H_1.

6.3.3 Specification of the GARCH Model of Asymmetric Macroeconomic Effects

In order to investigate the hypothesis that the macroeconomic variables had asymmetric effects on the return dynamics depending on how the market viewed news associated with changes in the variables, we adopted the procedure of Gulley and Sultan (2003). Each of the two variables was decomposed into two new categorical variables. Adopting the notation that *DPOS* and *DNEG* were the categorical variables for *DDRATE* while *GPOS* and *GNEG* were those for *DGPRICE*, these were defined as follows:

$DPOS_t$ $= DDRATE_t$ if $DDRATE_t \geq 0$;
$= 0$ otherwise.

$DNEG_t$ $= DDRATE_t$ if $DDRATE_t < 0$;
$= 0$ otherwise.

$GPOS_t$ $= DGPRICE_t$ if $DGPRICE_t \geq 0$;
$= 0$ otherwise.

$GNEG_t$ $= DGPRICE_t$ if $DGPRICE_t < 0$
$= 0$ otherwise

This procedure was equivalent to the introduction of multiplicative dummy variables into the system. The four new variables, therefore, replaced *DDRATE* and *DGPRICE* in (6.1) and (6.3), and the resultant model was as follows:

$$R_t = \alpha_0 + \eta_1 DPOS_t + \eta_2 DNEG_t + \eta_3 GPOS_t + \eta_4 GNEG_t + \mu_t, \qquad (6.4)$$

$$\mu_t | \Omega_{t-1} \sim N(0, h_t) \text{ or } \mu_t | \Omega_{t-1} \sim t(0, h_t, \nu), \qquad (6.5)$$

$$h_t = \phi_0 + \lambda_1 \mu_{t-1} + \theta_1 h_{t-1} + \varphi_1 DPOS_t + \varphi_2 DNEG_t + \varphi_3 GPOS_t + \varphi_4 GNEG_t. \qquad (6.6)$$

In this model, the effects of positive changes in the discount rate and gold prices were respectively measured by η_1 and η_3 in the conditional mean equation, and by φ_1 and φ_3 in the conditional variance equation. Similarly, the effects of negative changes in the discount rate and gold prices were respectively measured by η_2 and η_4 in the mean equation, and by φ_2 and φ_4 in the volatility equation. Note that, since they measured the effects of negative changes in the exogenous variables, the signs for the estimated values of η_2, η_4, φ_2 and φ_4 had to be reserved for usual interpretation. Apart from an examination of the signs, magnitudes and significance of the relevant individual coefficients, Wald tests for the equality between the coefficients of *DPOS* and *DNEG* were conducted for both the mean and volatility equations where this could be suspected. Similar equality tests were conducted for *GPOS* and *GNEG* coefficients. To be more specific, the following hypotheses were tested:

H_{0A}: There were no exogenous variable effects whatsoever (i.e., $\eta_i = \varphi_j = 0$ for all $i = 1,...,4$ and $j = 1,...,4$);

H_{1A}: Not H_{0A};

H_{0B}: There were no *DDRATE* asymmetric effects on mean returns (i.e., $\eta_1 = \eta_2 = 0$);

H_{1B}: There were some *DDRATE* asymmetric effects on mean returns (i.e., at least one $\eta_i \neq 0$ for some $i = 1,2$);

H_{0C}: There were no *DGPRICE* asymmetric effects on mean returns (i.e., $\eta_3 = \eta_4 = 0$);

H_{1C}: There were some *DGPRICE* asymmetric effects on mean returns (i.e., at least one $\eta_i \neq 0$ for some $i = 3,4$);

H_{0D}: There were no *DDRATE* asymmetric effects on return volatility (i.e., $\varphi_1 = \varphi_2 = 0$);

H_{1D}: There were some *DDRATE* asymmetric effects on return volatility (i.e., at least one $\varphi_j \neq 0$ for some $j = 1,2$);

H_{0E}: There were no *DGPRIPCE* asymmetric effects on return volatility (i.e., $\varphi_3 = \varphi_4 = 0$); and

H_{1E}: There were some *DGPRICE* asymmetric effects on return volatility (i.e., at least one $\varphi_j \neq 0$ for some $j = 3,4$).

6.3.4 Post-Estimation Diagnostic Checking

Finally, we conducted post-estimation diagnostics on the standardised residuals from the extended GARCH(1,1) models. As argued in Chapter 4, our main interest in the diagnostic checking was to investigate whether the extension could account for the remaining non-linearities in the GARCH model. Consistent with the methodologies adopted in Section 4.3, the BDS test was invoked, and a bootstrapping procedure with 1000 repetitions was used to compute probability values for the BDS test statistics, using the EViews 4.0 software. Further, The values for the embedding dimension and the measure of closeness were maintained as in the preceding applications (i.e., $m = 2,3,4,5$, and $l = 0.5\sigma, 1.0\sigma, 1.5\sigma$).

6.3.5 Summary of the Methodologies

The methodologies used in this chapter follow directly from the investigations of the previous chapters. To recollect, Chapter 5 established that we could use the discount rate as a measure of monetary policy. We also noted effects on the stock market from mining sector activity, and chose to use the price of gold to capture such activity. Therefore, the standard GARCH(1,1) model chosen in Chapter 4 was extended to include these macroeconomic variables, whose effects were investigated on the basis of statistical significance. Further, the two variables were decomposed into multiplicative categorical variables to facilitate an investigation of potential asymmetric effects, on the stock market, of news contained in the variables. The possibility of such effects was also investigated on the basis of statistical significance. Finally, a post-estimation diagnostic checking was conducted on the standardised residuals from the extended models, to investigate the linearity assumption further. The investigation was conducted on the two portfolios (ALSI and PORT) as well as each of the forty-four individual stocks. The results of the analysis and discussions follow.

6.4 Results and Discussions

6.4.1 Macroeconomic Effects on JSE Stock Return Dynamics

The estimation results for the GARCH model described by (6.1) to (6.3) for ALSI and PORT are reported in Table 6.2. The inclusion of the two macroeconomic variables did not affect the statistical characteristics of the ARCH and GARCH terms, which remained significantly positive in both cases. Further, the extension somewhat improved log-likelihood functions in both cases. With respect to the effects of monetary policy, the results agreed with those documented by Gulley and Sultan (2003) for the US market: there was a significant inverse relationship between stock returns (especially as measured by PORT) and discount rate changes, but such changes did not significantly impact on the volatility of stock returns. As noted in the theoretical framework, this inverse relationship is consistent with standard macroeconomics theory. In addition, the analysis showed that changes in the price of gold positively influenced stock returns as measured by ALSI, but had no impact on PORT. These findings were congruent with the conclusions reached in the Granger-causality tests reported in Chapter 5, where the dynamics of ALSI and PORT were conspicuously different. The positive relation between ALSI returns and *DGPRICE* was also consistent with *a priori* expectations. As with the discount rate, it was furthermore noted that mining sector activity did not impact on the volatility of the stock market as captured by the two portfolios.

Table 6.2 - Estimation of GARCH(1, 1) model with exogenous factors: stock portfolios

*This table shows the maximum likelihood estimates (with robust z-statistics in parentheses) of the GARCH(1,1) model with exogenous factors for ALSI and PORT. The conditional mean equation was (6.1), and the conditional variance equation was (6.3). *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively.*

Coefficient	*ALSI Estimates*	*PORT Estimates*
α_0	-0.000 (-0.010)	0.001 (1.095)
α_1	-0.006 (-1.609)	-0.006 (-2.619)*
α_2	0.230 (5.303)*	-0.022 (-0.761)
ϕ_0	0.000 (1.684)***	0.000 (3.210)*
λ_1	0.115 (2.830)*	0.100 (3.058)*
θ_1	0.803 (11.538)*	0.857 (30.274)*
ϕ_1	-0.000 (-0.173)	-0.000 (-1.291)
ϕ_2	0.002 (1.275)	0.001 (1.408)
Log likelihood	2117.016	2374.033

If the dynamics of ALSI and/or PORT closely approximated return dynamics for individual JSE stocks, one would expect that *DDRATE* and *DGPRICE* should impact on conditional mean returns, but not also on return volatility, for the individual stocks.

Appendix 6A provides estimation results of the GARCH model described by (6.1) to (6.3) for each of the forty-four stocks in the sample. Compared with the results shown in Table 6.1, there was a general improvement in log-likelihood functions, which declined in only nine cases. Because the robustness of the ARCH and GARCH parameter estimates did not appear to be an issue, our analysis progressed by focusing on the estimated coefficients of *DDRATE* and *DGPRICE*.

The Wald test results in cases where these were appropriate as described in subsection 6.3.2, and as suggested by the results in Appendix 6A, are presented in Table 6.3. These tests showed that an evaluation based on the individual *t*-tests could be adequate in all cases. A broad summary of the significance tests is, therefore, provided in Table 6.4.

Table 6.3 - Wald tests for joint statistical significance: selected individual stocks

This table shows results for the Wald tests conducted in accordance with the hypotheses described in subsection 6.3.2. Entries are χ^2-statistics, with probability values for accepting the null hypothesis of joint statistical insignificance indicated in parentheses. No joint statistical significance could be established at the 5% level.

#	*Security*	H_0	H_3	H_4
1	AFE		2.158 (0.340)	
2	AFX	2.366 (0.669)		
3	AGL			2.465 (0.292)
6	ASR			3.998 (0.135)
7	AVI	0.193 (0.996)		
8	BAW		3.345 (0.188)	
10	CHE			0.063 (0.969)
11	CRH	3.459 (0.484)		
12	CTP			0.535 (0.765)
13	DEL	2.158 (0.707)		
14	DUR		0.729 (0.694)	
15	ECO		2.600 (0.272)	
16	ELH			3.045 (0.218)
17	FOS			0.562 (0.755)
20	HLH		0.326 (0.850)	
21	HVL		0.201 (0.904)	
24	JNC			1.507 (0.471)
25	LGL		1.700 (0.427)	
26	MAF			0.564 (0.754)
28	NED	0.242 (0.993)		
29	NPK	2.588 (0.692)		
30	OCE			1.544 (0.462)
31	PAM	2.895 (0.576)		
33	PPC		1.724 (0.422)	
34	REM	2.365 (0.505)		
35	RLO		1.598 (0.450)	0.896 (0.639)
38	SBK		1.708 (0.426)	
39	TBS			2.349 (0.309)
40	TNT		4.176 (0.124)	
41	TRE	2.813 (0.590)		
42	VNF			0.520 (0.771)
43	WAR		4.325 (0.115)	

Table 6.4 – Statistical significance of coefficients for exogenous factors: individual stocks

This table provides an analysis of the statistical significance of individual and joint parameter estimates for the individual stocks. Tests were based on the hypotheses described in subsection 6.3.2.

Unrejected Hypothesis	*t-Test*	
	Securities	*No.*
H_0	AFX, AVI, CRH, DEL, NED, NPK, PAM, REM, SAP, TRE	10
H_1	All but those in H_0	34
H_2	ALT, ANG, BVT, GMF, HAR, IMP, JCM, MLB, PIK, WLO	10
H_3	AFE, BAW, DUR, ECO, HLH, HVL, LGL, PPC, RLO, SBK, TNT, WAR	12
H_4	AGL, ASR, CHE, CTP, ELH, FOS, JNC, MAF, OCE, SAB, TBS, VNF	12

The summary provided in Table 6.4 shows that the dynamics revealed by using ALSI and PORT might not have been reflective of individual stock return dynamics. Firstly, it was noted that neither *DDRATE* nor *DGPRICE* had any form of influence on ten of the forty-four stocks. Using the classification of stocks presented in Appendix 1B, five of the stocks thus not influenced were in the industrial sector (i.e., AFX, AVI, NPK, SAP and TRE), while four were in the financial sector (i.e., CRH, DEL, NED and REM). Only one, PAM, was in resources[4]. The fact that the macroeconomic variables influenced either the return or volatility dynamics for over three-quarters of the stocks under investigation rendered further support for their usefulness in modelling the JSE stock return generating process, in keeping with the findings reported in Chapter 5. Secondly, it was noted that in another ten stocks, *DDRATE* and/or *DGPRICE* influenced both the mean returns and the volatility of such returns. On the other hand, the variables influenced return volatility alone (but not expected returns) in twelve stocks, and expected returns alone (but not return volatility) in another twelve stocks. These findings were clearly in sharp contrast with those obtained when ALSI and PORT were used, where the macroeconomic variables clearly solely impacted on the expected returns. Evidently, aggregation into portfolios tended to misrepresent individual stock return dynamics, and could potentially ill-guide investment decision-making.

[4] Since the sample largely constituted industrial stocks, it might be informative to indicate that the stocks not influenced by the macroeconomic variables constituted 7 percent of the industrial stocks in the sample, as well as 57 percent and 11 percent of those in the financial and resources sectors, respectively.

To focus more closely on the specifics of how *DDRATE* and *DGPRICE* influenced JSE stock return dynamics, a further summary of the findings detailed in Appendix 6A is provided in Table 6.5. As above, interest was on the estimated coefficients of *DDRATE* and *DGPRICE*. Based on the estimated values of the α_i $(i = 1, 2)$ coefficients, it was noted that the inverse relationship between interest rates and asset prices could be upheld in thirty-five of the forty-four cases, although only fourteen of these showed that this relationship was statistically significant. Moreover, in none of the remaining nine stocks that showed a positive association was this association significant at all. Conversely, no similarly clear pattern emerged regarding the impact of a change in gold prices on the level of returns: there was an equal split between positive and negative coefficients, and an approximately equal split between significantly positive and significantly negative coefficients. As with *DDRATE*, *DGPRICE* was also significant in only fourteen of the forty-four mean equations. Looking closely at the significant coefficients of *DGPRICE*, all resources stocks for which the coefficient was significant, of which there were five, showed that the association was positive. Logically, therefore, a positive change in the price of gold tended to increase returns for these resources stocks. For the industrial sector, the reaction tended to vary, being positive in three stocks and negative in five. Only one financial stock (i.e., SBK) showed a reaction to *DGPRICE* in the mean equation, and this reaction was necessarily negative. These findings could indicate the possibility of substitution effects among the sectors: as mining rector returns increased, investors tended to re-allocate their worth in favour of resources stocks, leading to a reduction in returns on some stocks from other sectors and, potentially, to further increases in returns on resources stocks.

In terms of the impacts of the macroeconomic variables on volatility, it was apparent that *DGPRICE* had relatively higher impacts on stock return volatility than did *DDRATE*, and that changes in gold prices generally had volatility-increasing rather than dampening effects. The ϕ_2 coefficient was positive in thirty-one stocks, and significantly so in eleven of them. All resources and financial stocks that showed a significant impact of *DGPRICE* on volatility[5] also showed that this relationship was positive, while the industrial sector yielded mixed reactions, once again. It was noted that all the six stocks that yielded significantly negative values for ϕ_2 belonged to the industrial sector. However, an additional seven stocks from this sector showed a positive association. On the other hand, *DDRATE* generally showed a (rather weak) dampening effect on volatility, being negative in twenty-nine stocks, but

[5] These were AGL, ANG and IMP for resources; and MAF and VNF for financials.

significantly so in only six of them. Of the fifteen stocks for which this coefficient was positive, statistical significance could be confirmed in five. Apart from the observation that return volatility for a good proportion of resources stocks were significantly influenced by discount rate changes[6], there were no other noteworthy discernible patterns associated with the estimated values of ϕ_1.

Table 6.5 – Estimation results for GARCH(1,1) model with exogenous variables: summary for individual stocks

This table provides a summary of the estimation results for the GARCH(1,1) model with exogenous variables. The conditional mean and volatility equations are given by (6.1) and (6.3) respectively. C in the first column is the estimated coefficient, and could take any of the values indicated in the third column. For each such value, the stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in the forth and fifth columns, respectively. Appendix 6A gives a comprehensive presentation of these findings.

C	Row	Value of C	Stocks	No.
	#1	Positive	AVI, BVT, FOS, JCM, MAF, NED, REM, TRE, VNF	9
	#2	Significantly positive	None	0
α_1	#3	Negative	All stocks but those in Row #1	35
	#4	Significantly negative	AFE, ANG, ALT, BAW, ECO, GMF, HLH, IMP, LGL, MLB, RLO, TNT, WAR, WLO	14
	#5	Not significant	All stocks but those in Row #4	30
	#6	Positive	AGL, ANG, ASR, BAW, CRH, DEL, DUR, ECO, FOS, GMF, HAR, HVL, IMP, JCM, LGL, NED, PAM, PPC, REM, RLO, TRE, WAR	22
	#7	Significantly positive	ANG, DUR, GMF, HAR, HVL, IMP, JCM, PPC,	8
α_2	#8	Negative	All stocks but those in Row #7	22
	#9	Significantly negative	ALT, BVT, HLH, PIK, SBK, WLO	6
	#10	Not significant	All stocks but those in Row #7 and Row #9	30
	#11	Positive	AGL, ANG, BVT, CHE, CRH, DEL, ECO, ELH, JNC, MAF, NPK, TBS, TRE, VNF, WAR	15
	#12	Significantly positive	AGL, ANG, JNC, MAF, TBS	5
ϕ_1	#13	Negative	All stocks but those in Row #11	29
	#14	Significantly negative	ASR, GMF, HAR, JCM, MLB, WLO	6
	#15	Not significant	All stocks but those in Row #12 and Row #14	33
	#16	Positive	All stocks but those in Row #18	31
	#17	Significantly positive	AGL, CTP, ELH, FOS, IMP, JCM, JNC, MAF, PIK, SAB, VNF	11
ϕ_2	#18	Negative	AFE, ALT, AVI, BVT, CHE, HAR, LGL, MLB, OCE, PPC, SBK, WAR, WLO	13
	#19	Significantly negative	ALT, BVT, CHE, MLB, OCE, WLO	6
	#20	Not significant	All stocks but those in Row #17 and Row #19	27

[6] The eleven significant coefficients for *DDRATE* were distributed at the ratio of 5:5:1 among resources, industrial and financial sectors. In terms of proportions of stocks in the sample, this implied that 56 percent of resources stocks were influenced, while the proportions for the other two sectors were 18 percent and 14 percent, respectively.

6.4.2 Asymmetric Macroeconomic Effects on Return Dynamics

The estimation results for the GARCH model represented by (6.4) to (6.6) for ALSI and PORT are presented in Table 6.6. The results showed some departure from those documented for the non-decomposed variables, as well as the conclusions of Gulley and Sultan (2003), since the decomposed variables tended to impact on both expected returns and return volatility.

In terms of expected returns, the coefficients corresponding to *DDRATE* maintained their negative signs for both portfolios, consistent with the hypothesised inverse relationship between stock prices and interest rates. However, the coefficients were significant only for *DPOS* but not for *DNEG*. It could be concluded, therefore, that *DDRATE* had asymmetric effects on the portfolios, with positive changes influencing expected returns but not negative changes. On the other hand, *DGPRICE* tended to show a significantly symmetric influence on ALSI returns, but no impact whatsoever on PORT returns. A Wald test for the equality of η_3 and η_4 in the model for ALSI yielded $\chi^2 = 0.184$ with a probability value of 0.668, thereby providing evidence for a symmetric effect.

Table 6.6 - Estimation of GARCH(1, 1) model with decomposed exogenous variables: stock portfolios

*This table provides a summary of the estimation results for the GARCH(1,1) model with decomposed exogenous variables for ALSI and PORT. The conditional mean and volatility equations are given by (6.4) and (6.6), respectively. Entries are parameter estimates, with corresponding z-statistics under the null of insignificance in parentheses. * implies significance at 1*, while ** and *** imply significance at 5% and at 10%, respectively.*

Coefficient	*ALSI*	*PORT*
α_0	-0.000 (-0.161)	0.001 (0.770)
η_1	-0.007 (-1.696)***	-0.009 (-3.894)*
η_2	-0.006 (-1.155)	-0.001 (-0.237)
η_3	0.258 (3.873)*	0.001 (0.028)
η_4	0.206 (2.517)**	-0.037 (-0.736)
ϕ_0	0.000 (1.190)	0.000 (3.343)*
λ_1	0.144 (2.403)**	0.081 (2.674)*
θ_1	0.737 (7.556)*	0.871 (30.087)*
φ_1	0.000 (0.443)	-0.000 (-0.241)
φ_2	-0.000 (-1.113)	-0.000 (-1.874)***
φ_3	0.003 (1.901)***	-0.000 (-0.069)
φ_4	0.001 (0.282)	0.002 (2.948)*
Log likelihood	2120.451	2381.150

In terms of the volatility equations, asymmetric effects of both *DDRATE* and *DGPRICE* on PORT were apparent, with negative changes yielding significant effects but not positive changes. Specifically, a reduction in the discount rate had a volatility-dampening effect for PORT, implying a positive relationship. This is expected, *a priori*, since it shows that investors consider a discount rate reduction to be 'good news'. On the other hand, a decline in the gold price tended to step up the volatility of PORT returns. In terms of the volatility of ALSI returns, only positive changes in gold prices tended to show a significant volatility-increasing influence, albeit very weakly so. The general indication, therefore, was that there were asymmetric effects of macroeconomic shocks on the volatility of the portfolio returns.

For the individual stocks, the estimation results for the GARCH model with decomposed variables are reported in Appendix 6B. Table 6.7 summarises the results on the basis of the significance of the coefficients associated with the decomposed variables, and hence addresses hypotheses H_{0A} and H_{1A} in some detail[7]. The results showed that the model with decomposed variables significantly improved the explanatory power of the macroeconomic variables for individual stocks, both in terms of expected returns and return volatility. At this point, it is worthwhile mentioning that the model with decomposed variables for *DDRATE* and *DGPRICE* showed that hypothesis H_{0A} could not be rejected for only four of the forty-four stocks (i.e., ASR, HVL, NKP and SAP), compared with nine stocks when non-decomposed variables were used. In particular, the *DDRATE* and *DGPRICE* decompositions were significant in twenty-six and twenty-four mean equations respectively, as opposed to fourteen for both variables in Model 6(1) to 6(3). In addition, the *DDRATE* and *DGPRICE* decompositions were significant in twenty-two and thirty-three volatility equations respectively, as opposed to eleven and seventeen in model 6(1) to 6(3). These findings indicated that the effects of the two macroeconomic variables could better be analysed within the framework of Model 6(4) to 6(6) than otherwise. These findings could be due to the fact that the decomposed variables captured relatively more specific dynamics than the non-decomposed variables, and were less adulterated by opposing dynamics within the variables themselves. The findings were also compatible with the observation that, when the decomposed variables were used, both the conditional mean and volatility equations for ALSI and PORT showed some responsiveness to changes in the macroeconomic variables.

7 In our discussion, we continue to ignore the coefficients for the ARCH and GARCH terms, which were relatively stable across specifications. For the GARCH model with decomposed exogenous variables, these are presented in Appendix 6B.

Table 6.7 - Estimation of GARCH(1,1) model with decomposed exogenous variables: summary for individual stocks

This table provides a summary of the estimation results for the GARCH(1,1) model with decomposed exogenous variables for individual stocks. The conditional mean and volatility equations are given by (6.4) and (6.6) respectively. C in the first column is the estimated coefficient in the model, and could take any of the values indicated in the third column. For each such value, the stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in columns four and five, respectively. A comprehensive presentation of these findings is given in Appendix 6B.

C	*Row*	*Value of C*	*Stocks*	*No.*
η_1	#1	Positive	CTP, JCM, JNC, MAF	4
	#2	Significantly positive	JCM	1
	#3	Negative	All stocks but those in Row #1	40
	#4	Significantly negative	AFE, AGL, ALT, ANG, AVI, BAW, CHE, ECO, ELH, GMF, HLH, IMP, JCM, LGL, MLB, PPC, RLO, SAB, TNT, WAR, WLO	21
	#5	Not significant	All stocks but those in Row #2 and Row #4	22
η_2	#6	Positive	ASR, AVI, BVT, CHE, ELH, FOS, JCM, JNC, LGL, MAF, NED, NPK, SAB, TBS, TRE, VNF	16
	#7	Significantly positive	JCM, JNC	2
	#8	Negative	All stocks but those in Row #6	28
	#9	Significantly negative	ANG, IMP	2
	#10	Not significant	All stocks but those in Row #7 and Row #9	40
η_3	#11	Positive	All stocks but those in Row #13	24
	#12	Significantly positive	ANG, CHE, CRH, DUR, HAR, LGL, REM, VNF	8
	#13	Negative	AFX, AGL, ALT, BVT, CTP, DEL, ELH, FOS, HLH, JNC, NED, NPK, OCE, PIK, PPC, RLO, SBK, TBS, TNT, WLO	20
	#14	Significantly negative	ALT, BVT, HLH, TBS, WLO	5
	#15	Not significant	All stock but those in Row #12 and Row #14	31
η_4	#16	Positive	AFE, AGL, ANG, CTP, DEL, DUR, FOS, GMF, HAR, HVL, IMP, JCM, MAF, NED, OCE, PPC, RLO, SAB, TBS, TNT, TRE, WLO	22
	#17	Significantly positive	AGL, ANG, CTP, DUR, FOS, IMP, PPC, RLO	8
	#18	Negative	All stocks but those in Row #16	22
	#19	Significantly negative	MLB, PIK, VNF	3
	#20	Not significant	All stocks but those in Row #17 and Row #19	33
φ_1	#21	Positive	AFX, ALT, ANG, AVI, BAW, CHE, CRH, DEL, ELH, HLH, HVL, NED, NPK, PAM, PPC, REM, RLO, SAB, SBK, TBS, VNF, WAR	22
	#22	Significantly positive	None	0
	#23	Negative	All stocks but those in Row #21	22
	#24	Significantly negative	AFE, AGL, CTP, DUR, HAR, JCM, LGL, MLB, WLO	9
	#25	Not significant	All stocks but those in Row #24	35
φ_2	#26	Positive	ANG, BVT, CHE, DUR, JCM, JNC, MAF, MLB, TBS, TRE, VNF, WAR	12
	#27	Significantly positive	JNC, TRE	2
	#28	Negative	All stocks but those in Row #26	32
	#29	Significantly negative	AFE, AFX, ALT, BAW, IMP, OCE, PPC, RLO, SBK, TNT, WLO	11
	#30	Not significant	All stocks but those in Row #27 and Row #29	31

Table 6.7 - Estimation of GARCH(1,1) model with decomposed exogenous variables: summary for individual stocks (continued)

C	*Row*	*Value of C*	*Stocks*	*No.*
	#31	Positive	AGL, CTP, DEL, DUR, ELH, FOS, GMF, HVL, IMP, JCM, MAF, NED, NPK, PAM, PIK, PPC, RLO, SAB, SAP, TNT, TRE, VNF	22
φ_3	#32	Significantly positive	IMP, PIK, SAB	3
	#33	Negative	All stocks but those in Row #31	22
	#34	Significantly negative	AFE, ALT, BVT, CHE, HLH, MLB, OCE, WAR, WLO	9
	#35	Not significant	All stocks but those in Row #32 and Row #34	33
	#36	Positive	All stocks but those in Row #38	
φ_4	#37	Significantly positive	AFE, ANG, AVI, CTP, ECO, FOS, JCM, JNC, LGL, MAF, PIK, REM, TNT, VNF	14
	#38	Negative	AGL, ALT, BVT, CHE, DEL, ELH, HVL, NED, OCE, PAM, PPC, RLO, SAB, SAP, SBK, WAR, WLO	18
	#39	Significantly negative	DEL, NED, OCE, PAM, PPC, SBK, WLO	7
	#40	Not significant	All stocks but those in Row #37 and Row #39	23

To focus closely on the significance of the decomposed variables, it was noted that *DPOS* dominated in explaining changes in expected returns, yielding the hypothesised inverse relationship in forty stocks. Moreover, most of the *DPOS* coefficients in the mean equations were significant. The coefficients for *DNEG*, which generally also showed a negative association with expected returns, were significant for as few as four stocks. Respecting the *DDRATE* decomposition, therefore, the mean equation asymmetric effects were quite unambiguous. We revert to this matter later in this subsection.

The blurry influences of *DGPRICE* on expected returns still emerged when the multiplicative dummy variables were used, in the sense that the decomposition showed roughly an equal split between positive and negative coefficients. However, there appeared to be more significantly positive that significantly negative coefficients for this decomposition. Evidence of asymmetric effects of *DGPRICE* on expected returns was less apparent at this stage.

In terms of the volatility equations, the influences of the *DGPRICE* decompositions seemed more significant than those of *DDRATE*. In particular, while *DPOS* and *DNEG* only significantly impacted on the volatility of nine and thirteen stocks respectively, *GNEG* alone was influential in the volatility dynamics of twenty-one stocks. *GPOS* also contributed to the volatility dynamics of twelve stocks. Importantly, the fact that most of the significant values of φ_4 were positive showed that a negative change in the gold price was considered as 'bad news', and tended to increase volatility. However, volatility-dampening effects also tended to emanate from this variable (seven stocks) as well as *GPOS* (nine stocks). Additional important dampening effects could be traced to *DPOS* (nine stocks) and *DNEG* (eleven stocks). The statistics for *DPOS* and *DNEG* potentially indicated symmetric effects of discount rate changes on volatility, an issue discussed in what follows.

Table 6.8 further summarises the results presented in Appendix 6B along the lines of hypotheses H_{0B} through H_{1E} presented in Section 6.3. Specifically, the table shows the numbers of stocks for which the respective hypotheses could not be rejected, in order to address more clearly the question of potential asymmetric effects of news on expected stock returns and return volatility. The analysis excluded stocks ASR, HVL, NKP and SAP for which hypothesis H_{0A} of no effects from the decomposed exogenous variables could not be rejected. As indicated in the methodology, and in order to confirm the possible coefficient equalities suggested by a naïve inspection of the coefficients' values and *t*-statistics, Wald tests were conducted where appropriate. These were also conducted to establish whether positive and negative changes had opposite effects of equal magnitudes, where this was suspected[8]. Panel I of the table presents the relevant Wald test results. Note that only four hypotheses of coefficient equality were rejected by the Wald test, a result that is reflected in the last column of Panel II upon which further conclusions of the asymmetric effects investigation were based.

The results showed strong evidence of asymmetric effects of news on both the conditional mean returns and return volatility. Specifically, positive and negative changes in both *DDRATE* and *DGPRICE* had symmetric effects on the mean returns for only three stocks. Notice that, for stock *ANG*, mean return symmetric effects appeared to emanate from both of the exogenous variables. For all other stocks, of which there were thirty-seven after discounting four stocks that showed no responsiveness to the decomposed variables, the evidence was that the effects were asymmetric in mean and/or volatility. In the case of *DDRATE*, positive changes induced the hypothesised negative relation with expected returns, while negative changes were not that influential, and generally yielded symmetric effects with positive changes whenever they had a significant impact. This finding could imply that JSE investors were, rather rationally, concerned with discount rate increases but not

[8] In general, this was suspected where *DPOS* and *DNEG* were both significant but of different signs in the same equation. A similar condition held for *GPOS* and *GNEG*. Where the magnitudes of the estimated coefficients were clearly unequal, this test was only a formality.

decreases in seeking compensation for interest rate risk. Thus, stock market returns could be sticky in the wake of expansionary monetary policy, but responsive to contractionary policy.

Table 6.8 – Hypothesis tests for GARCH(1,1) model with decomposed ....exogenous variables: individual stocks

*This table shows results for hypothesis tests of asymmetric effects of the exogenous variables. The Wald tests were conducted in accordance with the hypotheses described in subsection 6.3.3, and the entries are χ^2-statistics, with probability values for accepting the null hypothesis of joint statistical insignificance indicated in parentheses. * implies statistical significance at 1%, ** at 5% and *** at 10%. Panel II shows the stocks and numbers of stocks for which the corresponding hypotheses could not be rejected. Details are in Appendix 6B.*

I. Wald tests

Stock	*Null Hypothesis*	χ^2	*(p)*
AFE	$\phi_1 = \phi_2$	3.207	(0.073)***
	$\phi_3 = -\phi_4$	0.096	(0.757)
ANG	$\alpha_1 = \alpha_2$	0.062	(0.803)
	$\alpha_3 = \alpha_4$	0.009	(0.926)
DUR	$\alpha_3 = \alpha_4$	0.063	(0.802)
IMP	$\alpha_1 = \alpha_2$	1.233	(0.267)
JCM	$\alpha_1 = \alpha_2$	3.764	(0.052)
OCE	$\phi_3 = \phi_4$	1.597	(0.206)
PIK	$\phi_3 = \phi_4$	4.559	(0.033)**
REM	$\alpha_3 = -\alpha_4$	0.493	(0.483)
VNF	$\alpha_3 = -\alpha_4$	1.205	(0.272)
WLO	$\phi_1 = \phi_2$	9.098	(0.003)*
	$\phi_3 = \phi_4$	3.324	(0.068)***

II. Overall test results

Unrejected Hypothesis	*t-Test*		*t-Test and Wald test*	
	Stocks	No.	*Stocks*	No.
H_{0B}	ANG, IMP, JCM	3	*ANG, IMP*	2
H_{1B}	AFE, AGL, ALT, AVI, BAW, CHE, ECO, ELH, GMF, HLH, LGL, MLB, PPC, RLO, SAB, TNT, WAR, WLO	18	All stocks selected using *t*-test, as well as *JCM*	19
H_{0C}	ANG, DUR	2	*ANG, DUR*	2
H_{1C}	AGL, BVT, CHE, CRH, CTP, FOS, HAR, HLH, IMP, LGL, MLB, PIK, PPC, REM, RLO, TBS, VNF, WAR, WLO	19	All stocks selected using *t*-test	19
H_{0D}	AFE, WLO	2	None	0
H_{1D}	AFX, AGL, ALT, BAW, CTP, DUR, HAR, IMP, JCM, JNC, LGL, MLB, OCE, PPC, RLO, SBK, TNT, TRE	18	All stocks selected using *t*-test, as well as *AFE, WLO*	20
H_{0E}	OCE, PIK, WLO	3	*OCE*	1
H_{1E}	ALT, ANG, AVI, BVT, CHE, CTP, DEL, ECO, FOS, HLH, IMP, JCM, JNC, LGL, MAF, MLB, NED, PAM, PPC, REM, SAB, SBK, TNT, VNF, WAR	25	All stocks selected using *t*-test, as well as *PIK, WLO*	27

Less unequivocal results than the foregoing were obtained with respect to the *DGPRICE* decomposition in the mean equation. While some significant asymmetric effects emanated from *GPOS* and *GNEG*, the dominance of one over the other was not as plain as the case of *DPOS* versus *DNEG*. Specifically, of the nineteen total asymmetric effects recorded for these variables, seven occurred due to the significance of *GPOS* when *GNEG* was not significant, and eight due to the converse. In the case of two stocks (i.e., REM and VNF), asymmetric effects occurred due to the fact that the coefficient for *GPOS* was positive while that of *GNEG* was negative, but the hypothesis of equality of the impacts in absolute value terms could not be rejected in both cases (see Panel I of Table 6.8). The conclusion regarding the impact of *DGPRICE* on expected returns, even after the decomposition, remained that it varied depending on the particular stocks being investigated. As already stated, the evidence seemed to suggest the presence of substitution effects across sectors in the investment decision-making process.

The effects of the decomposed exogenous variables on return volatility showed even stronger evidence of significant asymmetries than those documented for the mean equations. In fact, *DPOS* and *DNEG* showed asymmetric effects in virtually all cases where their impacts were significant, while only one symmetric effect was confirmed for *GPOS* and *GNEG* (i.e., stock OCE). Of the twenty cases in which *DPOS* and *DNEG* showed asymmetric effects on volatility, seven were on account of the significance of *DPOS* while eleven were on account of the significance of *DNEG*. The actual impacts on volatility were explained in a previous discussion. Although symmetric effects could be suspected for stocks AFE and WLO, the hypothesis was rejected in the Wald tests, implying that the impacts of *DNEG* were greater in absolute terms than those of *DPOS* for both cases. It would continue to appear that *DNEG*, which was unimportant in describing conditional mean returns, was relatively more important that *DPOS* in describing return volatility.

The dominance of *DGPRICE* in accounting for return volatility dynamics continued to show in the hypothesis of asymmetric effects. Of the twenty-seven asymmetric effects recorded for the decomposition of this variable, seventeen were on account of the statistical significance of *GNEG*, and eight on that of *GPOS*. Further, Wald tests rejected coefficient equalities for stocks PIK and WLO, suggesting that the absolute impacts of *GNEG* on the volatility of these stocks were greater than those of *GPOS*. Wald tests also rejected the hypothesis of opposing impacts of equal magnitudes in AFE, suggesting again that the absolute impact of *GNEG* outweighed that of *GPOS*. In a nutshell, it would appear unmistakable to conclude that *GNEG* was a more important variable in describing JSE return volatility than *GPOS*. The actual effects were already described.

6.4.3 Post-Estimation Diagnostic Checking

Detailed results for the BDS test for the standardised residual estimates from the GARCH model represented by (6.1) to (6.3) are presented in Appendix 6C, but a quick summary, focusing on the individual stocks, is presented in Panel I of Table 6.9. Similarly, the BDS test results for the model represented by (6.4) to (6.6) are in Appendix 6D, and summarised in Panel II of Table 6.9.

Compared with the results presented in Appendix 3C, Appendix 4B and Table 4.12, the results recorded in Appendix 6C, Appendix 6D and Table 6.9 showed that the inclusion of the exogenous macroeconomic variables was a significant improvement in filtering non-linearities. As with the standard GARCH model, both ALSI and PORT showed that no additional linear structures remained for all values of the embedding dimension, m, and the closeness gauge, l, both in the model of non-decomposed and decomposed variables. For the individual stocks, only five showed that the hypothesis of linearity could be rejected for all values of m and l using both models, compared with thirteen in the model of Chapter 4; for the remaining thirty-nine stocks in each of these models, there was at least one BDS statistic for which linearity could not be rejected. Moreover, linearity could not be rejected for virtually all values of m and l for twelve and eight stocks respectively in the models with non-decomposed and decomposed exogenous variables, but for only seven stocks in the standard GARCH(1,1) model. The evidence also showed that most stocks had fewer than many significant test statistics in this chapter's models: six or less significant statistics for twenty-eight stocks in the first model and twenty-three in the second, more than nineteen stocks in the model of Chapter 4. Thus, the inclusion of the macroeconomic factors accounted for most of the linear structures that remained after fitting the GARCH(1,1) model.

The foregoing results could indicate that the non-linear dynamics in JSE stock returns were generally stochastic rather than deterministic or chaotic in nature. Further research could, nonetheless, investigate whether the structure could better be modelled by considering the potential presence of deterministic or chaotic non-linearities on the JSE.

Table 6.9 – BDS tests for residuals from GARCH(1,1) model with exogenous variables: summary of findings for individual stocks

This tables summarises the BDS test results presented in Appendix 6C and Appendix 6D. The stocks and numbers of stocks with significant BDS test statistics equal to the number in Column 1 are presented in Column 2 and Column 3, respectively. Column 4 and Column 5 give cumulative numbers. Panel I shows results for Model 6(1) to 6(3), while Panel II shows those for Model 6(4) – 6(6).

I. Results for Model 6(1) – 6(3)

1 ***# of Sig. Stat.***	*2* ***Stocks***	*3* ***# of Stocks***	*4* ***# of Sig. Stat.***	*5* ***# of Stocks***
0	AFX, ALT, ANG, BAW, IMP, MAF, NED, PIK, PPC, SBK, TBS, WAR,	12	0	12
1	-	0	≤ 1	12
2	-	0	≤ 2	12
3	CHE	1	≤ 3	13
4	ASR, CRH, CTP, NPK, VNF	5	≤ 4	18
5	AVI, DEL, HLH, JCM, TNT	5	≤ 5	23
6	AFE, DUR, ELH, GMF, OCE,	5	≤ 6	28
7	RLO	1	≤ 7	29
8	ECO, HVL	2	≤ 8	31
9	BVT, HAR, LGL	3	≤ 9	34
10	SAB, WLO	2	≤ 10	36
11	PAM, SAB, TRE	3	≤ 11	39
12	AGL, FOS, JNC, MLB, REM	5	≤ 12	44

II. Results for Model 6(4) – 6(6)

1 ***# of Sig. Stat.***	*2* ***Stocks***	*3* ***# of Stocks***	*4* ***# of Sig. Stat.***	*5* ***# of Stocks***
0	AFX, ALT, ANG, NED, PPC, SBK, TBS, WAR	8	0	8
1	IMP, PIK	2	≤ 1	10
2	CRH, HLH	2	≤ 2	12
3	AFE, ASR, CHE, DEL	4	≤ 3	16
4	-	0	≤ 4	16
5	GMF, TNT	2	≤ 5	18
6	ELH, HVL, MAF, NPK, OCE	5	≤ 6	23
7	DUR, ECO, JCM, LGL, PAM, RLO	6	≤ 7	29
8	AVI, CTP, FOS, TRE, VNF	5	≤ 8	34
9	AGL, BVT	2	≤ 9	36
10	WLO	1	≤ 10	37
11	HAR, SAP	2	≤ 11	39
12	BAW, JNC, MLB, REM, SAB	5	≤ 12	44

6.5 Summary and Conclusion

Building on the observation, made in Chapter 5, that the discount rate (i.e., the Bank/repo rate) and mining sector activity had predictive power for the stock market, this chapter investigated the interrelationships in a structural framework by extending the GARCH(1,1) model discussed in Chapter 4. Mining sector activity was captured using the price of gold, and weekly data for the period since the introduction of the classical cash reserve system were used. Both stock portfolios as well as individual stocks were used in the investigation. Apart from investigating the effects of the variables on the conditional mean returns and return volatility *per se*, the study also investigated potential asymmetric effects of news about the two macroeconomic variables. This was accomplished by decomposing each of the variables into multiplicative categorical variables reflective of positive and negative changes. Finally, a post-estimation diagnostic checking similar to that of Chapter 4 was conduced on the standardised residual estimates from the extended GARCH models, to investigate whether the inclusion of the exogenous factors could account for the non-linear structures that remained after fitting the GARCH(1,1) model. Several key observations and conclusions could be made from the analysis, as follows:

Firstly, the inclusion of the exogenous factors did not affect the statistical characteristic of the ARCH and GARCH terms, implying that the GARCH(1,1) model was generally robust. The robustness of the GARCH model was further confirmed when the sampling period for individual stocks was reduced to the last two-thirds of that used in Chapter 4.

Secondly, using stock portfolios (i.e., market aggregates) yielded results that were not reflective of individual stock dynamics when non-decomposed variables were used. Specifically, while the two macroeconomic variables only impacted on conditional mean returns for both the All Share index and the equally-weighted portfolio, they impacted on both the expected returns and return volatility in a good proportion of the individual stocks. This revealed that an analysis sorely based on market aggregates could potentially mislead investors. This result was, however, challenged when decomposed variables were used, where both portfolio mean returns and return volatility tended to be affected by the factors.

Thirdly, the model with non-decomposed variables showed that the variables significantly impacted on expected returns and return volatility in only a few individual stocks. However, where the discount rate was an important determinant of expected returns, the evidence showed that the hypothesised inverse relationship between interest rates and stock prices prevailed in South Africa. In particular, contractionary monetary policy could lower stock returns. In addition, changes in the gold price also exhibited some effects on expected returns, and there was possible evidence of substitution effects: increased expected returns from mining sector investments resulting from gold price increases were associated with lower non-mining sector expected returns, possibly as investors switched to resources stocks. In terms of the effects of the non-decomposed variables on volatility, the gold price was a more important determinant than the discount rate. Specifically, the gold price had a largely volatility-increasing effect, particularly for resources stocks. However, some gold price volatility-dampening effects were noted for a few non-resources stocks. In the few cases where the discount rate also impacted on volatility, the effects were generally dampening.

The fourth point to note was that the effects of the exogenous variables became more significant when the variables were decomposed to capture the possibility of their asymmetric effects. Apart from the decomposed variables influencing the expected returns and returns volatility of both market aggregates, their effects were significant in the mean and volatility equations for most individual stocks. Moreover, the hypothesised inverse relationship between interest rates and stock prices was strengthened in this decomposition, as was the observation of possible substitution effects between mining and non-mining investments. If the two exogenous variables were indeed important determinants of JSE return dynamics, it would appear that this decomposition could significantly improve their ability to explain such dynamics and predict returns.

Fifthly, the evidence indicated that the effects of the two exogenous variables were strongly asymmetric. To be specific, positive discount rate changes inversely impacted on expected returns, while negative changes were largely inconsequential on returns. Thus, JSE investors were, rather rationally, more concerned with discount rate increases than decreases. On the other hand, negative discount rate changes had stronger volatility-dampening effects than positive changes, implying that interest rate decreases were correctly perceived as 'good news' by market participants. Further, while both positive and negative discount rate changes impacted on expected returns, the effects varied depending on the stock, but remained asymmetric. In general, these effects tended to bolster the evidence of substitution effects among the sectors. In addition, while both positive and negative changes in the gold price were also influential in describing stock return volatility, most of the influences tended to emanate from negative changes and hand volatility-increasing effects. This implied that gold price decreases were considered 'bad news' by market participants. In general, the effects of the gold price decomposition on volatility were much stronger than those of the discount rate decomposition.

Finally, the evidence strongly indicated that the GARCH model with exogenous variables significantly accounted for most of the non-linearities that remained after the standard GARCH(1,1) model was fitted. This evidence could indicate that the non-linear dynamics in the JSE return generating process were most likely stochastic rather than deterministic or low-dimensionally chaotic. Thus, focus on non-linearities in the error terms of asset pricing relationships has promise in yielding characterisations that would best approximate the true return generating process on the JSE Securities Exchange.

Chapter 7

Conclusions

Four decades after the introduction of the capital asset pricing model (CAPM), and close to three decades after that of the arbitrage pricing theory (APT), both models continue to attract the attention of academics, quantitatively inclined financial analysts, financial engineers and investors alike. Within the South Africa context, many researchers believe that the APT has potential as the best description of the return generating process on the JSE Securities Exchange (JSE), while most investment analysts still report and use CAPM-based betas as measures of risks for individual JSE stocks and stock portfolios. From a theoretical viewpoint, both the CAPM and the APT are linear and static models of security returns, and are based on the assumption that security prices follow a normal strong random walk process. This assumption implies that security prices and returns are not predictable, and that it is not possible to earn excess returns on the market as a reward for the shrewd use of information. However, empirical evidence of the time series properties of security prices documented for most markets shows striking evidence against the normal strong random walk property, suggesting that static linear asset pricing models might not represent the best characterisation of the return generating process. Instead, these observations may indicate that returns are predictable and that excess profits are attainable in stock markets. The observations also imply that non-linear dynamic models can describe the return generating process better. It was noted from our review of the South African literature that the potentially non-linear dynamics of JSE security returns had not been adequately investigated.

The present research makes a contribution to the foregoing debate by showing that a structural non-linear dynamic model can be used to describe the JSE return generating process, and to guide the investment decision-making process better.

The first major result of this research was that the normal strong random walk property was not consistent with the dynamics of JSE data. While establishing that logarithmic stock prices were integrated of order one, thereby confirming the statistical preference for the use of returns as opposed to prices in analysing the dynamics, the research showed that the assumptions of normality and linearity of returns could not be supported. In particular, return distributions were highly leptokurtic, generally displayed excess skewness, and were far from being independently and identically distributed. These findings were consistent with those extensively documented for most other markets as acknowledged by Kasch-Haroutounian and Price (2001) but, except for the documented violation of the normality assumption (Page, 1993), these statistical properties had not been adequately explored for the JSE. The findings disputed the applicability of standard two-date linear asset pricing models in characterising the return generating process on this market. Importantly, they showed that changes in JSE security returns could be profitably predictable over time, conforming to Keynes' argument that "stock prices are not only determined by fundamentals but, in addition, market psychology and investors' animal spirits influence financial markets" (Brock & Hommes, 1997:1).

Because the procedures pursued in investigating the linearity assumption somewhat discounted the possibility that linear dependencies or stationarity could have accounted for the evident non-linearities in the stock returns, and because the evidence in the literature was less supportive of the presence of chaotic non-linear dynamics in financial time series, we were persuaded to suspect that the non-linearities were stochastic. This assumption was confirmed by the evidence of volatility clustering in the returns series also established in the study. Accordingly, therefore, the relevance of models in the class of the autoregressive conditional heteroscedasticity process (i.e., ARCH-type models) was hypothesised. In other markets, these univariate non-linear time series models were known to account for the statistical features already noted (Engel & Sumel, 1994; Engel, 1982), because they are based on the observation that the variance of the error term in a time series regression could be unconditionally homoscedastic but conditionally heteroscedastic. Modelling the conditional variance (i.e., the volatility) of returns could, therefore be a promising avenue for describing these dynamics.

The second major finding of the research was that the standard low-order generalised ARCH (i.e., GARCH(1,1)) model of Bollerslev (1986) provided the best description of the security return dynamics, compared with its relatively more complex extensions. Within this framework, the study could not find compelling evidence that there were asymmetric effects of shocks on volatility, or that volatility was a commonly priced factor on the market. Because prior research findings for the JSE could not be identified for comparison, our results are potentially a marked contribution. Further, the evidence contributed to the generally conflicting results documented in the international literature. For instance, while the popularity of the low-order GARCH model was consistent with Bollerslev (1986), Baillie and DeGennaro (1990), and Ding, Granger and Engel (1993), among many others, the appropriateness of relatively higher order GARCH processes was confirmed in other studies, including Yu (2002) and Mills (1999). In addition, the evidence that the effects of shocks on volatility were symmetric was in conflict with Glosten, Jagannathan and Runkle (1993) for the United States market, and Siourounis (2002) for the Athens Stock Exchange. Weak evidence of asymmetric effects was documented by Kasch-Haroutounian and Price (2001) for the markets of Central Europe, while Solibakke (2001) found that asymmetric effects on volatility were more significant in well-traded than thinly-traded Norwegian stocks. Finally, the result that volatility was not a commonly priced factor on the JSE was consistent with observations made in most emerging markets (Alles & Murry, 2001; Poshakwale & Murrinde, 2001; Solibakke, 2002) as well as developed markets (Baillie & DeGennaro, 1990; Poon & Taylor, 1992). However, this result was not in conformity with Glosten *et al*, who found a negative relation between expected returns and volatility in the United States environment. Equally important in our investigation was the finding that the GARCH(1,1) model could significantly, though less than fully, account for the non-linear structures in the return series. This result was consistent with Dockner, Prskawetz and Fieichtnger (1997), among others. The evidence that some non-linearities still remained after the GARCH filter could suggest the presence of deterministic (chaotic) rather than stochastic non-linearities, or that additional linear dependencies still existed in the data.

The observation that volatility was not priced on the JSE suggested that investors sought compensation for taking on other perceived forms of risk than volatility. Guided by the multifactor asset pricing literature, we hypothesised that monetary policy and real sector dynamics could potentially provide effective surrogates for such priced factors. Further, we suspected that the identification and inclusion of such exogenous macroeconomic variables in a structural non-linear dynamic model could also account for the remaining non-linearities, unless such non-linearities were of a chaotic nature.

The final major finding of the research was that monetary policy and mining sector activity had predictive power for expected returns and return volatility on the JSE. In particular, within the environment of vector error correction (VEC) modelling, the study established that the discount rate (i.e., the Bank/repo rate) and mining production could predict stock prices. This result was partially consistent with Darrat and Dickens (1999), who found that interest rates could Granger-cause stock prices, but not real activity. Further, the result was inconsistent with Malliaris and Urrutia (1991) who found totally no causal interrelationships. Because the predictive power of money supply and the Treasury bill rate were also investigated, the evidence suggested that the discount rate contained unique information for the predictability of stock prices, in tandem with Bernanke and Blinder (1992). In the same vein, the fact that mining production could predict stock prices but manufacturing production could not provided further evidence of the market segmentation hypothesis on the JSE (Page 1986, van Rensburg and Slaney, 1997), but using a different methodology.

The foregoing VEC model results were generally supported when the GARCH(1,1) model was augmented to include exogenous macroeconomic variables. In this framework, the discount rate was found to be an important determinant of expected returns, and the hypothesised inverse relationship between interest rates and stock prices prevailed in South Africa. Therefore, contractionary monetary policy could lower expected stock returns on the JSE, in accord with Gulley and Sultan (2003) and Jensen and Johnson (1993). However, the discount rate only mildly impacted on the volatility of returns, but had volatility dampening effects whenever it did. The fact that the discount rate could not sturdily explain volatility was also consistent with Gulley and Sultan. On the other hand, the price of gold, used in the study as a surrogate for mining sector activity, was an important determinant of security return volatility than the discount rate. Specifically, the gold price had a largely volatility-increasing effect, particularly for resources stocks. However, some gold price volatility-dampening effects were noted for few non-resources stocks. In addition, the gold price could also impact on expected returns, and a possible substitution effect between resources and non-resources stocks was evident: gold price increases tended to increase resources stock returns and lower non-resources stock returns as rational investors possibly re-allocated their portfolio constituents accordingly.

The study also found that the effects of the exogenous variables became more significant when the variables were decomposed to capture the possibility of their asymmetric effects on the stock market. Apart from the observation that decomposed variables influenced both the expected returns and returns volatility of stock portfolios while non-decomposed variables only impacted on the expected returns of such portfolios, the effects of decomposed variables were significant in the mean and volatility equations for most individual stocks. Moreover, the hypothesised inverse relationship between interest rates and stock prices was strengthened in this decomposition, as was the observation of possible substitution effects between mining and non-mining investments. The study submits that this decomposition could significantly improve the predictability of JSE stock returns.

In addition to the foregoing, the research established that the effects of the two exogenous variables on expected returns and return volatility were largely asymmetric. To be specific, positive discount rate changes inversely impacted on expected returns, while negative changes were largely inconsequential on stock returns. Thus, JSE investors were, rather rationally, more concerned with discount rate increases than decreases. This result was also consistent with Gulley and Sultan. In addition, it was actually negative discount rate changes that tended to yield volatility dampening effects on the market, implying that these were correctly perceived as 'good news'. Further, while both positive and negative discount rate changes impacted on expected returns, the effects varied depending on the stock, but remained asymmetric. In general, these effects tended to bolster the evidence of substitution effects among the sectors. In the same vein, while both positive and negative changes in the gold price were also influential in describing stock return volatility, most of the influences tended to emanate from negative changes and had volatility-increasing effects. This implied that gold price decreases were considered 'bad news' by market participants. In general, the effects of the gold price decomposition on volatility were much stronger than those of the discount rate decomposition.

Finally, the evidence strongly suggested that the GARCH model with exogenous variables significantly accounted for most of the non-linearities that remained after the standard GARCH(1,1) filter. This evidence could indicate that the non-linear dynamics in the JSE return generating process were, most likely, stochastic rather than deterministic or low-dimensionally chaotic. Thus, focus on non-linearities in the error terms of asset pricing relationships had promise in yielding characterisations that could best approximate the true return generating process on the JSE Securities Exchange.

Apart from the above results, all of which directly addressed the key objectives of the study, the VEC model framework suggested additional important interrelationships among the three sectors of the South African economy. Firstly, although monetary policy had predictive power for inflation, there was no strong evidence that the effects of policy also impacted on the real sector, at least in the short-run. The evidence, therefore, confirmed the short-run neutrality of money, in conformity with Darrat and Dickens (1999) and Sims (1998), among many others. Secondly, the stock market was a leading indicator of monetary policy but, in general, did not lead real activity irrespective of the manner in which the latter was measured. Darrat and Dickens, on the contrary found the stock market as a leading indicator of both policy and real activity. Thirdly, the market segmentation evidence presented above manifested itself in at least two other ways, as follows: (a) mining production had long-run interrelationships with monetary policy variables, and could predict both inflation and stock prices, but no similar effects seemed to emanate from manufacturing production; and (b) there was strong evidence that manufacturing production had predictive power for mining production, both in the short-run and the long-run, but the converse did not hold. Finally, the research confirmed the presence of the price puzzle in the South African economy, in the sense that the initial effect of contractionary monetary policy was to induce inflation. This anomaly is widely documented by monetary economists (see the summary in Walsh, 2002:29). Because the South Africa Reserve Bank's solution to the puzzle is to target CPIX inflation rather than CPI inflation[1], future research could pursue this cursory matter of our research.

To revert to the main objectives of the research, it is worthwhile summarising more explicitly that the present research suggests that a structural GARCH(1,1) model in which the discount rate and the price of gold are included as exogenous factors in both the mean and volatility equations shows promise in describing JSE security return dynamics. Moreover, by decomposing the exogenous variables, the model provides a useful framework for investigating the possibility of asymmetric effects of such variables on expected returns and return volatility.

JSE investors and financial analysts could find the following advice useful. Firstly, the continued application of both the CAPM and the APT, as bases for investment decision-making, was not statistically founded, since these models failed to capture the true characterisation of the return generating process on the market. In particular, the correct measure of risk for each security ought to reflect its time-dependency, as do ARCH-type models rather than models based on the disputed iid assumption.

Secondly, JSE investors would rather avoid risk (as measured by return volatility), since there was no premium for taking own such risk on this market. Thirdly, investors should look around for economy-wide factors that drove returns and that impacted on risk. An examination of the movements in such factors would not only allow investors to maximise their returns, but also minimise the risks of their investments. This study established that two

[1] For definitions of CPI and CPIX inflation, see page 5–12 and page 5-13.

such variables, whose movements investors could benefit from, were the discount rate and the price of gold. In particular, a discount rate increase should be considered as a signal that JSE returns would decline, while a discount rate decrease would signal greater price stability (lower risks) on the market without necessarily affecting expected returns. Further, investors could profit by increasing their holdings of resources stocks (thereby reducing their holdings of non-resources stocks) during periods of increases in gold prices, while generally lowering the proportion of wealth held in stocks when gold prices were decreasing, since such decreases tended to signal higher risks on the stock market.

Several issues remain open to further research. The first is the use of gold prices as a proxy for mining sector activity. This assumption was based on prior research on the JSE and, to the largest extent, by the unavailability of adequate weekly data on other possible measures, such as the commodity price index. Future research could investigate whether a better surrogate could be identified. Related to this is the use of nominal, rather than real, returns. Since such returns may be an overstatement due to the presence of an inflation premium, future research should establish whether similar or different results could be obtained by using real returns[2]. It is probable to imagine, however, that the understatement of returns due to the omission of dividend payments and the overstatement in the nominal measure might somewhat offset each other. The third area regards the assumption of stochastic non-linearities in the JSE security returns made in the current research. Although this assumption was satisfied to a large extent, it could be of interest to investigate whether modelling deterministic chaos could improve the results. The final point relates to the fact that, except where VEC models were used, most of the research was conducted within a univariate time series modelling framework as opposed to a multivariate framework. This preference was motivated by the desire to capture stock-specific dynamics, in addition to the dynamics of the market as a whole, while taking cognisance of the limitations of data. Multivariate frameworks usually require the use of portfolios in order to reduce the number of variables in the system, particularly in view of the fact that such generalisations tend to be quickly over-parameterised and data-intensive. As higher frequency data becomes more and more available over long enough sampling periods, it may become feasible and informative to investigate the dynamics within such a multivariate framework. Such models can capture both the autocorrelations and cross-autocorrelations of security returns, and may improve the modelling of complex dynamics in time series data.

[2] I am indebted to one of my referees for pointing this out.

Appendices

Appendix 1A – Stocks in the study sample and their distribution by Tradable (Safex) indices

The following table shows the 44 stocks selected to constitute the final sample of the study. UMC is the market capitalisation, in million rand, before the application of the investibility factor (denoted IF), while the WMC is the market capitalisation, in million rand, after this application. The proportion of each stock in the new All Share index as well as the distribution of the selected securities by Tradable (Safex) indices are also shown. All indices were weighted, in accordance with the rules of the new FTSE/JSE Africa Index Series. Top 40 index is the index of the 40 largest companies that qualified for inclusion in the index series, ranked by UMC. Resi index is the index of 20 securities in the resources sector; Indi index is that of 25 securities in the industrial sector; Fini index is the index of 15 securities in the financial sector; Findi index is that of 30 securities in the financial and industrial sector. As of June 2002, the Safex indices had 41, 20, 26, 16 and 31 constituents, respectively

JSE Code	Company Name	UMC (Rm)	IF (%)	WMC (Rm)	% of All Share Index	% of Top 40 Index	% of Resi Index	% of Indi Index	% of Fini Index	% of Findi Index
AFE	AECI Ltd	2346	100	2346	0.16					
AFX	African Oxygen Ltd	4558	50	2279	0.15			0.6		
AGL	Anglo American Plc	273677	100	273677	18.11	20.24	37.51			
ALT	Allied Technologies Ltd	2383	50	1191	0.08					
ANG	Anglogold Ltd	74176	50	37088	2.45	2.74	5.08			
ASR	Assore Ltd	1820	0	0	0					
AVI	Anglovaal Industries Ltd	4581	100	4581	0.3			1.21		
BAW	Barloworld Ltd	14680	100	14680	0.97	1.09		3.87		2.27
BVT	The Bidvest Group Ltd	15415	100	15415	1.02	1.14		4.07		2.38
CHE	Chemical Services Ltd	1427	40	571	0.04					
CRH	Coronation Holdings Ltd	1658	50	829	0.05	0.06			0.27	0.13
CTP	CTP Holdings Ltd	1930	30	579	0.04					
DEL	Delta Electrical Industries Ltd	2409	100	2409	0.16					
DUR	Durban Roodepoort Deep Ltd	9724	100	9724	0.64		1.33			
ECO	Edgers Consolidated Stores Ltd	2039	100	2039	0.13					
ELH	Ellerine Holdings Ltd	1255	100	1255	0.08					
FOS	Foschini Ltd	2073	75	1555	0.1					

Appendix 1A – Stocks in the study sample and their distribution by Tradable (Safex) indices (continued)

JSE Code	*Company Name*	*UMC (Rm)*	*IF (%)*	*WMC (Rm)*	*% of All Share Index*	*% of Top 40 Index*	*% of Resi Index*	*% of Indi Index*	*% of Fini Index*	*% of Findi Index*
GMF	Gencor Ltd	16802	0	0						
HAR	Harmony Gold Mining Co Ltd	28572	100	28572	1.89	2.11	3.92			
HLH	Hunt Leuchars & Hepburn Holdings Ltd	1824	0	0	0					
HVL	Highveld Steel Steel & Vanadium Corp. Ltd	1612	30	484	0.03					
IMP	Impala Platinum Holdings Ltd	38649	75	28986	1.92	2.14	3.97			
JCM	Johncom Communications Ltd	1354	0	0	0					
JNC	Johnnic Holdings Ltd	7309	100	7309	0.48	0.54		1.93		1.13
LGL	Liberty Group Ltd	16526	50	8263	0.55	0.61			2.7	1.28
MAF	Mutual & Federal Insurance Co Ltd	4432	0	0	0					
MLB	Malbak Ltd	2333	50	1166	0.08					
NED	Nedcor Ltd	32370	50	16185	1.07	1.2			5.28	2.5
NPK	Nampak Ltd	7405	100	7405	0.49	0.55		1.95		1.14
OCE	Oceana Group Ltd	1536	40	614	0.04					
PAM	Palabora Mining Company Ltd	1699	40	680	0.04		0.09			
PIK	Pik n Pay Stores Ltd	6736	50	3368	0.22	0.25		0.89		
PPC	Pretoria Portland Cement Co Ltd	3918	40	1567	0.1			0.41		
REM	Remgro Ltd	34541	100	34541	2.29	2.55			11.27	5.34
RLO	Reunert Ltd	3999	100	3999	0.26			1.06		
SAB	South African Breweries plc	71864	100	71864	4.76	5.31		18.96		11.11
SAP	Sappi Ltd	34068	100	34068	2.25	2.52		8.99		5.27
SBK	Standard Bank Group Ltd	47001	100	47001	3.11	3.48			15.34	7.27
TBS	Tiger Brands Ltd	12058	100	12058	0.8	0.89		3.18		1.86
TNT	The Tongaat-Hulett Group Ltd	4789	50	2394	0.16	0.18		0.63		0.37

Appendix 1A – Stocks in the Study Sample and their Distribution by Tradable (Safex) Indices (continued)

JSE Code	*Company Name*	*UMC (Rm)*	*IF (%)*	*WMC (Rm)*	*% of All Share Index*	*% of Top 40 Index*	*% of Resi Index*	*% of Indi Index*	*% of Fini Index*	*% of Findi Index*
TRE	Trencor Ltd	1383	0	0	0					
VNF	VenFin Ltd	8708	100	8708	0.58	0.64			2.84	1.35
WAR	Western Areas Ltd	4315	75	3236.25	0.21		0.44			
WLO	Wooltru Ltd	1792	100	1792	0.12			0.47		
	Sample	**813746**		**694478**	**45.93**	**48.24**	**52.34**	**48.22**	**37.70**	**43.40**

(Source: Adapted from Profile Media, 2002).

Appendix 1B - Distribution of sample stocks by broad sectors

This appendix details further characteristics of the stocks in the final study sample as viewed in terms of the three JSE broad sectors. Panel I shows distribution of the sample stocks into each of the sectors, as compared with the actual sectoral distribution for all JSE stocks as of mid 2002. Panel II shows the shares of each of the sectors as implied by the sample, compared with the actual sectoral shares on the JSE by 9 April 2002. Shares are based sectoral aggregates of the weighted market capitalisation (WMC) in Appendix 1A. Appendix 1A is constructed from information contained in various parts of Profile's JSE Handbook Jul 2002 – Dec 2002. Any errors could be ours.

I. *Distribution by numbers of stocks*

		No. of Stocks		Percent of Stocks	
Sector	**Stocks in Sample**	**Sample**	**JSE**	**Sample**	**JSE**
Resources	AGL, ANG, ASR, DUR, GMF, HAR, IMP, PAM, WAR	9	55	20.5	12.0
Industrial	AFE, AFX, ALT, AVI, BAW, BVT, CHE, CTP, DEL, ECO, ELH, FOS, HLH, HVL, JCM, JNC, MLB, NPK, OCE, PIK, PPC, RLO, SAB, SAP, TBS, TNT, TRE, WLO	28	270	63.6	59.1
Financial	CRH, LGL, MAF, NED, REM, SBK, VNF	7	132	15.9	28.9
		44	457	100.0	100.0

II. *Market shares by weighted market capitalisation*

		Sample		FTSE/JSE	
Sector	**Stocks**	**WMC**	**%**	**WMC**	**%**
Resources	AGL, ANG, ASR, DUR, GMF, HAR, IMP, PAM, WAR	382.0	55.0	736	49
Industrial	AFE, AFX, ALT, AVI, BAW, BVT, CHE, CTP, DEL, ECO, ELH, FOS, HLH, HVL, JCM, JNC, MLB, NPK, OCE, PIK, PPC, RLO, SAB, SAP, TBS, TNT, TRE, WLO	197.0	28.4	321	21
Financial	CRH, LGL, MAF, NED, REM, SBK, VNF	115.5	16.4	438	29
		694.5	100.0	1495	100

Appendix 3A – DF critical values for ϕ_i

This appendix gives the empirical distribution of the ϕ_i ($i = 1,2,3$) test statistics for the inclusion of intercept and trend terms in Dickey-Fuller unit root tests. The statistics are described in Section 3.2, and are given by (3.6).

	Probability of Smaller Value							
Sample Size	0.01	0.025	0.05	0.01	0.90	0.95	0.975	0.99
				ϕ_1				
25	0.29	0.38	0.49	0.65	4.41	5.18	6.30	7.88
50	0.29	0.39	0.50	0.66	3.94	4.86	5.80	7.06
100	0.29	0.39	0.50	0.67	3.86	4.71	5.57	6.70
250	0.30	0.39	0.51	0.67	3.81	4.63	5.45	6.52
500	0.30	0.39	0.51	0.67	3.79	4.61	5.41	6.47
∞	0.30	0.40	0.51	0.67	3.78	4.59	5.38	6.43
				ϕ_2				
25	0.61	0.75	0.89	1.10	4.67	5.68	6.75	8.21
50	0.62	0.77	0.91	1.12	4.31	5.13	5.94	7.02
100	0.63	0.77	0.92	1.12	4.16	4.88	5.59	6.50
250	0.63	0.77	0.92	1.13	4.07	4.75	5.40	6.22
500	0.63	0.77	0.92	1.13	4.05	4.71	5.35	6.15
∞	0.63	0.77	0.92	1.13	4.03	4.68	5.31	6.09
				ϕ_3				
25	0.74	0.90	1.08	1.33	5.91	7.24	8.65	10.61
50	0.76	0.93	1.11	1.37	5.61	6.73	7.81	9.31
100	0.76	0.94	1.12	1.38	5.47	6.49	7.44	8.73
250	0.76	0.94	1.13	1.39	5.39	6.34	7.25	8.43
500	0.76	0.94	1.13	1.39	5.36	6.30	7.20	8.34
∞	0.77	0.94	1.13	1.39	5.34	6.25	7.16	8.27

Source: Enders (1995:421).

Appendix 3B – Characterisation of potential break points on the JSE

The table in this appendix summarises the major socio-political and economic characteristics of the four potential break point dates chosen in the study.

Potential Break Point	*Socio-Political Characterisation*	*Economic Characterisation*
16 June 1976: Soweto Uprising	• The death of over 575 and wounding of 2389 people in Soweto Township in protests against the imposition of Africaans in black schools. • The Angolan Conflict, subsequent to the Lisbon coup (April 1974) and the Angolan Independence (November 1975), commenced with direct RSA military involvement.	• There was a significant decline in capital inflows into South Africa, and net foreign capital flows became strongly negative. Inflation rose to double digits. • Restrictive monetary and fiscal policies, aimed at maintaining balance of payments equilibrium and controlling inflation were adopted. • Capital flight and oil price hike effects were cushioned by the gold price decontrol of 1968 and the gold price increases of 1973-74 (to $200 by end 1974) and 1979-80 (to $850 in January 1980). • The South African Reserve Bank adopted a managed float exchange rate system in January 1979, and maintains it to date. Latter in the same year, the bank also adopted a more "market related" interest rate policy; the Bank/repo rate remains the most prominent monetary policy instrument, used to manipulate short-term interest rates as intermediate policy variables.
21 July 1985: State of Emergency	• Government imposed a partial State of Emergency (June 1985) and a full one the following month, due to intensified anti-Apartheid activities. • Prime Minister PW Botha delivered the defiant Rubicon speech, opting to continue with discriminatory Apartheid policies.	• The impact of economic sanctions on RSA was severe from 1985. Each year from 1984 to 1987, the numbers of US firms that disinvested were 7, 49, 58 and almost 80, respectively. 20% of UK firms had withdrawn by 1987. The US Congress passed the Comprehensive Anti-Apartheid Act in September 1986. • There was a restriction on RSA's access to foreign capital. A moratorium on foreign debt payments was forced on 1 September 1985. • The initial State of Emergency was precipitated by an organised black consumer boycott of white-owned shops.
10 May 1994: Majority Rule	• Nelson Mandela was sworn in as first president of democratic South Africa. • Increased bloody political violence, as well as non-political crime such as rapes and motor vehicle thefts.	• Foreign capital became available in the wake of the April 1994 elections, easing prior pressure to maintain a current account surplus.
17 August 1998: Asian Crisis		• The devaluation of the Thai baht in mid 1997 led to the weakening of currencies and markets of the Asian Tigers, other South American economies and Russia. The position sharply worsened on 17 August 1998 when Russia devalued and defaulted on parts of its debt. All major world economies were affected, and emerging markets suffered greatly.

Sources: van Rensburg (1999); miscellaneous articles.

Appendix 3C – BDS tests for returns

*This appendix presents the standard normally distributed BDS test statistics for the returns. The test is described in subsection 3.2.3.2. The statistics, given by (3.17) were generated using the LeBaron (1991) C source code. m is the embedding dimension, while l measures the closeness of a given pair of embedding dimensions, in standard deviations of the data. * implies that the statistic was not significant at the 5% significance level.*

I. Test statistics for $l = 0.5\sigma$

a) Stock portfolios

#	*Portfolio*	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	2.700	4.985	6.678	8.877
2	PORT	5.486	5.951	6.579	6.511

b) Individual stocks

#	*Security*	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	6.848	9.126	11.424	13.239
2	AFX	5.015	5.398	6.079	6.676
3	AGL	3.350	4.497	5.458	6.562
4	ALT	4.045	5.116	6.496	7.787
5	ANG	5.033	6.355	7.160	7.628
6	ASR	3.960	4.878	4.951	5.158
7	AVI	7.829	9.438	11.131	13.640
8	BAW	5.984	6.602	7.393	8.019
9	BVT	6.119	7.572	8.883	10.359
10	CHE	3.316	5.392	6.449	7.437
11	CRH	4.122	5.049	4.782	4.271
12	CTP	8.710	10.750	11.871	13.548
13	DEL	7.677	8.880	9.649	10.991
14	DUR	5.673	7.194	8.582	9.797
15	ECO	4.937	7.123	9.208	11.527
16	ELH	8.869	11.375	13.416	15.466
17	FOS	8.099	8.890	11.060	13.501
18	GMF	4.812	5.512	6.049	6.698
19	HAR	4.830	5.921	6.756	7.992
20	HLH	4.652	7.562	9.579	11.328
21	HVL	7.207	7.086	7.039	7.197
22	IMP	3.444	4.709	5.434	7.364
23	JCM	8.871	12.032	12.907	13.384
24	JNC	16.958	19.590	21.960	24.738
25	LGL	6.894	7.585	7.875	8.729
26	MAF	5.481	6.075	6.481	7.321
27	MLB	6.685	7.243	7.355	7.904
28	NED	4.525	5.636	5.747	5.705
29	NPK	7.972	9.017	9.872	11.087
30	OCE	3.636	5.789	7.053	9.087
31	PAM	5.764	7.930	9.520	11.237
32	PIK	4.248	5.539	6.521	7.526
33	PPC	7.340	8.158	9.200	9.914
34	REM	6.829	6.953	6.244	5.969
35	RLO	9.178	11.071	13.378	15.555
36	SAB	4.575	6.606	7.062	6.893
37	SAP	6.536	8.103	9.310	10.451
38	SBK	4.421	5.923	7.052	8.019
39	TBS	4.240	4.353	5.611	5.784
40	TNT	7.327	8.956	10.143	10.958
41	TRE	7.195	8.271	9.569	10.120
42	VNF	5.234	6.460	7.301	7.886
43	WAR	4.371	6.049	6.682	7.768
44	WLO	8.605	10.281	11.960	14.241

Appendix 3C – BDS tests for returns (continued)

II. Test statistics for $l = 1.0\sigma$

a) Stock portfolios

#	*Portfolio*	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	3.306	5.339	6.742	8.040
2	PORT	6.066	7.277	7.788	7.899

b) Individual stocks

#	*Security*	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	6.095	7.692	8.894	9.417
2	AFX	5.282	6.170	6.802	7.480
3	AGL	4.316	5.096	5.929	6.988
4	ALT	4.990	5.659	6.418	6.723
5	ANG	5.479	6.969	7.635	8.254
6	ASR	0.805*	0.769*	0.761*	1.190*
7	AVI	7.579	8.744	9.467	10.380
8	BAW	6.525	7.261	7.782	8.075
9	BVT	5.539	6.963	7.029	7.437
10	CHE	1.394*	3.001	3.589	4.060
11	CRH	4.132	4.822	5.046	4.983
12	CTP	7.492	9.280	10.403	11.603
13	DEL	7.052	7.210	7.460	7.972
14	DUR	6.058	7.321	7.887	8.211
15	ECO	4.518	6.875	7.892	8.468
16	ELH	8.122	8.839	8.975	9.198
17	FOS	6.805	7.475	7.874	8.404
18	GMF	3.787	4.445	5.038	5.608
19	HAR	5.085	5.610	6.137	6.804
20	HLH	5.391	7.338	8.010	8.955
21	HVL	6.869	6.873	6.989	7.026
22	IMP	2.609	3.693	4.105	4.651
23	JCM	2.210	8.122	10.136	10.900
24	JNC	19.541	21.578	22.865	23.529
25	LGL	7.076	6.772	6.374	6.813
26	MAF	2.695	4.155	4.853	5.348
27	MLB	6.369	7.050	7.261	7.665
28	NED	4.685	6.069	6.363	6.563
29	NPK	8.633	9.053	9.322	9.656
30	OCE	5.252	6.787	8.068	9.403
31	PAM	5.592	7.420	8.464	8.913
32	PIK	2.859	3.405	3.527	3.514
33	PPC	6.364	7.193	7.716	8.062
34	REM	4.428	4.924	4.861	4.847
35	RLO	6.980	8.418	10.043	11.010
36	SAB	4.700	6.898	7.479	7.573
37	SAP	5.276	6.898	7.478	7.900
38	SBK	4.897	6.072	7.421	8.196
39	TBS	4.041	4.403	5.341	5.504
40	TNT	7.007	7.544	7.920	8.084
41	TRE	4.771	5.236	5.541	5.555
42	VNF	4.750	5.424	5.256	5.373
43	WAR	3.927	5.395	6.240	7.190
44	WLO	7.753	8.906	9.533	9.980

Appendix 3C – BDS tests for returns (continued)

III. Test statistics for $l = 1.5\sigma$

a) Stock portfolios

#	*Portfolio*	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	3.785	5.197	6.088	6.813
2	PORT	6.439	7.969	8.438	8.569

b) Individual stocks

#	Security	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	6.716	8.200	9.074	9.161
2	AFX	6.021	6.759	7.366	7.982
3	AGL	6.193	6.508	7.053	7.793
4	ALT	4.955	5.241	5.749	6.189
5	ANG	5.592	6.915	7.454	7.892
6	ASR	1.311*	0.844*	0.475*	1.034*
7	AVI	8.203	8.944	9.167	9.458
8	BAW	6.586	7.520	8.004	8.321
9	BVT	2.958	4.876	5.363	5.876
10	CHE	2.402	3.831	4.190	4.226
11	CRH	3.949	4.884	5.341	5.670
12	CTP	5.927	7.618	8.230	9.045
13	DEL	6.024	6.039	5.981	6.336
14	DUR	5.609	6.431	6.635	6.969
15	ECO	4.203	6.513	7.190	7.473
16	ELH	7.706	8.124	8.064	8.101
17	FOS	5.144	5.911	6.230	6.336
18	GMF	3.578	4.197	4.783	5.295
19	HAR	5.509	6.180	6.484	6.794
20	HLH	4.662	5.986	6.178	6.792
21	HVL	6.314	6.141	6.121	5.778
22	IMP	2.013	2.837	2.974	3.285
23	JCM	2.197	8.530	9.882	10.122
24	JNC	18.194	19.705	21.553	22.215
25	LGL	7.763	7.406	7.134	7.617
26	MAF	1.949	2.965	3.422	3.688
27	MLB	6.049	6.996	7.204	7.440
28	NED	4.910	6.825	7.334	7.602
29	NPK	8.448	9.118	9.494	9.611
30	OCE	4.067	5.206	5.768	6.503
31	PAM	4.829	6.332	7.181	7.365
32	PIK	2.142	3.274	3.393	3.519
33	PPC	6.166	6.859	7.283	7.310
34	REM	3.808	5.003	5.154	5.472
35	RLO	4.385	6.511	7.769	8.449
36	SAB	4.665	6.870	7.665	7.889
37	SAP	5.250	6.449	6.813	6.943
38	SBK	5.128	6.312	7.872	8.723
39	TBS	3.615	4.320	5.307	5.577
40	TNT	6.670	6.917	7.022	7.178
41	TRE	2.818	2.523	2.912	3.356
42	VNF	6.026	6.770	6.539	6.525
43	WAR	3.970	5.341	6.444	7.295
44	WLO	7.047	8.272	8.700	8.725

Appendix 4A - ML estimates for ARCH-type models: individual stocks

This appendix presents the maximum likelihood estimates (with z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses) for the following ARCH-type models described in Section 4.2, where $p = q = 1$*:*

GARCH(1,1): $R_t = \alpha + \mu_t;\ \mu_t|\Omega_{t-1} \sim N(0, h_t);\ h_t = \phi + \lambda_1 \mu_{t-1}^2 + \theta_1 h_{t-1}$.

DGARCH(1,1): $R_t = \alpha + \mu_t;\ \mu_t|\Omega_{t-1} \sim N(0, h_t);\ h_t = \phi + \lambda_1 \mu_{t-1}^2 + \gamma D_{t-1}\mu_{t-1}^2 + \theta_1 h_{t-1}$.

GARCH-M(1,1): $R_t = \alpha + \beta h_t + \sum_{k=1}^{K} \rho_k R_{t-k} + \mu_t;\ \mu_t|\Omega_{t-1} \sim N(0, h_t);\ h_t = \phi + \lambda_1 \mu_{t-1}^2 + \theta_1 h_{t-1}$.

DGARCH-M(1,1): $R_t = \alpha + \beta h_t + \sum_{k=1}^{K} \rho_k R_{t-k} + \mu_t;\ \mu_t|\Omega_{t-1} \sim N(0, h_t);$

$$h_t = \phi + \lambda_1 \mu_{t-1}^2 + \gamma D_{t-1}\mu_{t-1}^2 + \theta_1 h_{t-1}$$

The returns, R_t *were uncorrelated or linearly filtered in GARCH and DGARCH, and correlated but not linearly filtered in GARCH-M and DGARCH-M. In the latter two processes, the mean equation for uncorrelated* R_t *was also* $R_t = \alpha + \mu_t$*. Log-L is the log likelihood function. Tables 4.6 to 4.9 further summarise these results. * denotes statistical significance at 1%, while ** and *** denote significance at 5% and 10%, respectively. Results are for the forty-four individual stocks.*

Model	α	β	ϕ	λ_1	γ	θ_1	Log-L
			AFE				
GARCH	0.000 (0.236)		0.000 (1.573)	0.082 (1.433)		0.857 (14.985)*	2422.357
DGARCH	0.000 (0.280)		0.000 (1.549)	0.086 (1.229)	-0.018 (-0.197)	0.856 (14.721)*	2424.386
GARCH-M	0.004 (1.387)	-0.990 (-0.888)	0.000 (1.724)***	0.108 (1.646)***		0.606 (11.786)*	2425.127
DGARCH-M	0.005 (1.507)	-1.335 (-1.046)	0.000 (1.780)***	0.147 (1.499)	-0.056 (-0.792)	0.761 (10.123)*	2426.040
			AFX				
GARCH	0.004 (3.665)*		0.000 (1.416)	0.065 (3.614)*		0.642 (15.715)*	2652.524
DGARCH	0.003 (3.331)*		0.000 (1.363)	0.070 (1.733)***	0.031 (0.765)	0.646 (10.418)*	2653.400
GARCH-M	0.006 (2.298)**	-1.257 (-0.869)	0.000 (1.422)	0.075 (2.566)*		0.870 (13.912)*	2653.102
DGARCH-M	0.005 (1.756)***	-0.772 (-0.524)	0.000 (1.382)	0.046 (1.751)***	0.034 (1.000)	0.891 (16.395)*	2654.544
			AGL				
GARCH	0.002 (1.477)		-0.000 (-0.166)	0.016 (4.642)*		0.993 (30.893)*	2265.717
DGARCH	0.006 (2.160)**		0.002 (6.999)*	0.049 (0.751)	1.461 (0.867)	0.006 (0.375)	2194.754
Note: Parameter non-convergence was experienced in GARCH-M and DGARCH-M for AGL.							
			ALT				
GARCH	-0.000 (-0.243)		0.000 (0.617)	0.015 (1.592)		0.976 (59.056)*	2477.567
DGARCH	-0.000 (-0.126)		0.000 (0.858)	0.019 (1.442)	-0.009 (-0.716)	0.978 (60.663)*	2478.594
GARCH-M	0.001 (0.387)	0.993 (0.818)	0.000 (0.725)	0.019 (1.773)***		0.976 (56.069)*	2473.249
DGARCH-M	0.001 (0.147)	1.006 (0.556)	0.001 (1.649)***	0.059 (1.456)	0.097 (1.041)	0.585 (3.239)*	2442.656
			ANG				
GARCH	0.002 (1.629)***		0.000 (2.053)**	0.065 (3.614)*		0.642 (15.715)*	2232.507
DGARCH	0.002 (1.562)		0.000 (2.162)**	0.077 (3.255)*	0.030 (0.734)	0.830 (15.389)*	2233.111
GARCH-M	-0.003 (-0.677)	1.610 (1.274)	0.000 (2.045)**	0.083 (3.702)*		0.849 (16.836)*	2231.645
DGARCH-M	-0.003 (-0.662)	1.720 (1.212)	0.000 (2.207)**	0.076 (3.376)*	0.027 (0.697)	0.635 (16.282)*	2232.259

Appendix 4A - Maximum likelihood estimates for ARCH-type models: individual stocks (continued)

Model	α	β	ϕ	λ_1	γ	θ_1	*Log-L*
ASR							
GARCH	0.001 (0.353)		0.005 (1.508)	-0.00 (-1.88)***		0.607 (1.448)	1473.714
DGARCH	-0.000 (-0.269)		0.005 (1.097)	-0.05 (-1.978)**	0.052 (1.982)**	0.812 (1.128)	1481.040
Note: Parameter non-convergence was experienced in GARCH-M and DGARCH-M for ASR.							
AVI							
GARCH	0.001 (0.878)		0.000 (0.815)	0.084 (5.570)*		0.924 (30.138)*	2511.434
DGARCH	0.001 (0.804)		0.000 (0.839)	0.061 (3.004)*	0.004 (0.133)	0.928 (35.728)*	2511.866
Note: Parameter non-convergence was experienced in GARCH-M and DGARCH-M for AVI.							
BAW							
GARCH	-0.002 (-0.709)		0.000 (4.335)*	0.139 (2.031)**		0.815 (22.984)*	2526.944
DGARCH	-0.000 (-0.044)		0.000 (4.301)*	0.228 (1.353)	-0.167 (-0.841)	0.814 (24.478)*	2543.911
Note: Parameter non-convergence was experienced in GARCH-M and DGARCH-M for BAW							
BVT							
GARCH	0.001 (0.594)		0.000 (2.230)**	0.089 (2.296)**		0.784 (11.070)*	2592.865
DGARCH	-0.000 (-0.302)		0.000 (2.803)*	0.017 (0.630)	0.151 (1.991)**	0.773 (11.363)*	2608.105
GARCH-M	0.002 (0.560)	0.957 (0.579)	0.000 (2.182)**	0.095 (2.337)**		0.770 (10.004)*	2591.797
DGARCH-M	0.002 (0.642)	0.346 (0.226)	0.000 (2.516)**	0.019 (0.885)	0.155 (2.034)**	0.780 (10.382)*	2606.626
CHE							
GARCH	0.001 (0.806)		0.000 (1.810)	0.051 (2.028)**		0.830 (9.859)*	2699.8
DGARCH	-0.000 (-0.221)		0.000 (1.830)***	-0.002 (-1.157)	0.061 (1.914)***	0.910 (22.066)*	2713.322
GARCH-M	0.006 (1.088)	-1.129 (-0.359)	0.000 (1.720)***	0.043 (1.789)***		0.870 (13.806)*	2701.811
DGARCH-M	-0.001 (-0.147)	2.163 (0.792)	0.000 (1.901)***	-0.005 (-0.477)	0.054 (1.920)***	0.931 (28.801)*	2718.101
CRH							
GARCH	0.000 (0.174)		0.000 (1.552)	0.044 (2.606)*		0.898 (20.757)*	1733.852
DGARCH	-0.000 (-0.024)		0.000 (1.580)	0.037 (1.495)	0.017 (0.521)	0.899 (21.489)*	1734.657
GARCH-M	-0.004 (-0.560)	1.118 (0.952)	0.000 (1.475)	0.045 (2.822)*		0.896 (19.590)*	1733.482
DGARCH-M	-0.004 (-0.641)	1.108 (0.984)	0.000 (1.511)	0.037 (1.460)	0.018 (0.542)	0.896 (20.031)*	1734.325
CTP							
GARCH	0.004 (2.856)*		0.000 (1.416)	0.057 (1.885)***		0.928 (22.819)*	2364.497
DGARCH	0.003 (2.532)**		0.000 (1.754)***	0.025 (0.992)	0.068 (1.979)**	0.923 (23.549)*	2378.305
GARCH-M	0.003 (1.296)	0.409 (0.495)	0.000 (1.428)	0.050 (2.157)**		0.938 (29.971)*	2366.893
DGARCH-M	0.004 (1.808)	-0.155 (-1.778)	0.000 (1.861)***	0.024 (1.055)	0.060 (1.865)***	0.931 (27.307)*	2377.737
DEL							
GARCH	0.002 (1.593)		0.000 (0.998)	0.097 (2.823)*		0.915 (104.47)*	2351.470
DGARCH	0.003 (2.027)**		0.000 (1.498)	0.136 (1.714)***	-0.089 (-1.087)	0.915 (73.079)*	2362.415
Note: Parameter non-convergence was experienced in GARCH-M and DGARCH-M for DEL.							

Appendix 4A - Maximum likelihood estimates for ARCH-type models: individual stocks (continued)

Model	α	β	ϕ	λ_1	γ	θ_1	*Log-L*
			DUR				
GARCH	-0.002 (-1.060)		0.003 (3.050)*	0.160 (2.419)**		0.393 (2.265)**	1572.637
DGARCH	-0.002 (-0.947)		0.004 (3.020)*	0.170 (1.889)***	-0.025 (-0.263)	0.388 (2.200)**	1572.746
GARCH-M	-0.028 (-2.55)**	3.601 (2.594)*	0.003 (3.562)*	0.156 (2.668)*		0.397 (2.602)*	1579.237
Note: Parameter non0convergence was experienced in DGARCH-M for DUR.							
			ECO				
GARCH	0.001 (1.030)		0.000 (2.542)**	0.052 (3.034)*		0.905 (35.829)*	2661.322
DGARCH	0.001 (0.527)		0.000 (2.442)**	0.027 (1.581)	0.046 (1.601)	0.901 (31.509)*	2666.619
GARCH-M	0.004 (1.504)	-0.428 (-0.261)	0.000 (2.263)**	0.054 (3.071)*		0.902 (32.786)*	2676.268
DGARCH-M	0.002 (0.621)	0.278 (0.156)	0.000 (2.231)**	0.026 (1.519)	0.050 (1.678)***	0.897 (28.423)*	2684.024
			ELH				
GARCH	0.001 (0.958)		0.000 (2.079)**	0.040 (2.601)*		0.924 (31.444)*	2437.374
DGARCH	0.001 (0.553)		0.000 (2.218)**	0.011 (0.525)	0.065 (2.078)**	0.901 (27.679)*	2449.065
GARCH-M	0.007 (1.900)***	-1.362 (-0.885)	0.000 (1.911)***	0.036 (2.594)*		0.936 (37.032)*	2436.810
DGARCH-M	0.007 (1.757)***	-1.577 (-0.953)	0.000 (2.100)**	0.011 (0.560)	0.064 (2.077)**	0.913 (28.037)*	2449.819
			FOS				
GARCH	0.001 (0.675)		0.000 (1.576)	0.049 (1.700)***		0.812 (7.910)*	2548.144
DGARCH	0.000 (0.452)		0.000 (1.462)	0.009 (0.832)	0.084 (1.608)	0.797 (7.046)*	2557.655
GARCH-M	0.011 (1.569)	-3.588 (-1.166)	0.000 (1.650)***	0.051 (1.756)***		0.805 (6.052)*	2546.977
DGARCH-M	0.010 (1.51.0)	-3.466 (-1.139)	0.000 (1.522)	0.011 (0.964)	0.088 (1.657)***	0.791 (7.273)*	2556.690
			GMF				
GARCH	0.003 (2.270)**		0.000 (0.718)	0.018 (1.667)***		0.968 (30.396)*	2322.692
DGARCH	0.003 (2.326)**		0.000 (0.730)	0.019 (1.322)	-0.005 (-0.224)	0.967 (33.509)*	2322.953
GARCH-M	-0.002 (-0.329)	1.617 (0.836)	0.000 (0.511)	0.013 (1.450)		0.974 (29.116)*	2321.013
DGARCH-M	-0.003 (-0.417)	2.065 (0.901)	0.000 (0.548)	0.010 (0.759)	0.003 (0.139)	0.976 (34.004)*	2321.025
			HAR				
GARCH	-0.000 (-0.264)		0.000 (2.348)**	0.064 (4.221)*		0.900 (34.981)*	1962.262
DGARCH	-0.001 (-0.565)		0.000 (2.185)**	0.049 (2.663)*	0.030 (1.082)	0.906 (37.100)*	1963.745
GARCH-M	-0.006 (-1.303)	1.936 (1.806)***	0.000 (2.400)**	0.062 (4.224)*		0.904 (37.633)*	1964.117
DGARCH-M	-0.007 (-1.406)	1.945 (1.768)***	0.000 (2.352)**	0.045 (2.733)*	0.032 (1.201)	0.909 (40.935)*	1965.997
			HLH				
GARCH	0.003 (2.531)**		0.000 (2.383)**	0.094 (2.463)**		0.898 (30.780)*	2391.601
DGARCH	0.002 (2.426)**		0.000 (2.454)**	0.085 (1.863)***	0.024 (0.725)	0.894 (29.203)*	2392.184
GARCH-M	0.003 (1.627)***	-0.207 (-0.325)	0.000 (2.228)**	0.103 (2.570)*		0.866 (26.107)*	2383.253
DGARCH-M	0.003 (1.932)***	-0.298 (-0.493)	0.000 (2.295)**	0.090 (2.055)**	0.034 (0.926)	0.683 (26.374)*	2384.087
			HVL				
GARCH	-0.000 (-0.065)		0.000 (1.717)***	0.046 (3.048)*		0.897 (20.795)*	2289.434
DGARCH	-0.000 (-0.338)		0.000 (1.413)	-0.001 (-0.089)	0.029 (2.477)**	0.979 (88.855)*	2291.965
GARCH-M	0.001 (0.134)	0.371 (0.244)	0.000 (1.937)***	0.081 (3.348)*		0.799 (10.068)*	2287.854
DGARCH-M	-0.001 (-0.180)	0.771 (0.510)	0.000 (1.850)***	0.061 (2.178)**	0.031 (0.621)	0820 (11.118)*	2268.530

Appendix 4A - Maximum likelihood estimates for ARCH-type models: individual stocks (continued)

Model	α	β	ϕ	λ_1	γ	θ_1	*Log-L*
			IMP				
GARCH	0.001 (0.364)		0.000 (1.712)***	0.040 (2.308)**		0.906 (20.307)*	2158.371
DGARCH	0.000 (0.045)		0.000 (1.843)***	0.019 (0.985)	0.040 (1.258)	0.910 (22.787)*	2182.014
GARCH-M	0.007 (0.134)	-0.936 (-0.473)	0.000 (1.380)	0.038 (2.071)**		0.912 (18.023)*	2158.852
DGARCH-M	0.004 (0.570)	-0.042 (-0.023)	0.000 (1.499)	0.017 (0.892)	0.037 (1.262)	0.925 (23.782)*	2180.741
			JCM				
GARCH	0.005 (1.998)**		0.000 (1.295)	1.089 (1.375)		0.623 (5.237)*	2123.007
DGARCH	0.006 (2.301)**		0.000 (1.210)	1.154 (1.099)	-0.216 (-0.178)	0.631 (5.016)*	2124.979
GARCH-M	0.006 (3.575)*	-0.18 (-1.85)***	0.000 (2.064)**	1.318 (1.824)***		0.520 (6.132)*	2155.436
DGARCH-M	0.006 (3.801)*	0.178 (1.842)***	0.000 (1.675)***	1.576 (1.442)	-0.540 (-0.406)	0.543 (4.497)*	2183.069
			JNC				
GARCH	0.003 (1.515)		0.000 (0.838)	0.399 (1.868)***		0.738 (8.818)*	1853.833
DGARCH	0.005 (2.457)**		0.000 (1.028)	0.464 (1.327)	-0.198 (-0.831)	0.752 (10.742)*	1862.794
GARCH-M	0.006 (4.481)*	-0.256 (-2.28)**	0.000 (1.111)	0.487 (1.879)***		0.705 (7.400)*	2029.186
DGARCH-M	0.007 (4.955)*	-0.199 (-1.332)	0.000 (1.186)	0.595 (1.224)	-0.320 (-0.645)	0.726 (9.490)*	2042.138
			LGL				
GARCH	0.004 (3.714)*		0.000 (1.019)	0.033 (2.840)*		0.956 (44.348)*	2671.537
DGARCH	0.003 (3.216)*		0.000 (1.414)	0.010 (0.947)	0.039 (1.743)	0.956 (47.905)*	2678.814
GARCH-M	0.006 (2.723)*	-1.528 (-1.236)	0.000 (0.982)	0.031 (2.499)**		0.959 (48.395)*	2672.847
DGARCH-M	0.004 (2.208)**	-0.708 (-0.691)	0.000 (1.298)	0.010 (0.932)	0.037 (1.843)	0.960 (49.928)*	2679.458
			MAF				
GARCH	0.002 (1.712)***		0.000 (1.800)***	0.232 (0.974)		0.805 (17.657)*	2439.488
DGARCH	0.004 (1.874)***		0.000 (2.835)*	0.308 (1.012)	-0.301 (-1.012)	0.848 (19.384)*	2528.479
GARCH-M	0.004 (2.068)**	-0.282 (-0.436)	0.000 (1.540)	0.150 (0.457)		0.804 (11.238)*	2406.177
DGARCH-M	0.010 (1.061)	-3.495 (-0.890)	0.000 (0.360)	0.089 (0.312)	-0.091 (-0.311)	0.949 (7.257)*	2500.892
			MLB				
GARCH	-0.000 (-0.366)		0.003 (1.558)	-0.005 (-6.677)*		0.500 (1.409)	2030.714
DGARCH	0.001 (0.442)		0.002 (1.701)***	0.073 (1.527)	-0.077 (-1.607)	0.568 (2.446)**	2038.777
Note: Parameter non-convergence was experienced in GARCH-M and DGARCH-M							
			NED				
GARCH	0.004 (3.472)*		0.000 (2.531)**	0.077 (3.360)*		0.865 (23.203)*	2835.625
DGARCH	0.003(2.758)*		0.000 (3.103)*	0.013 (0.702)	0.106 (3.110)*	0.874 (27.401)*	2848.688
GARCH-M	0.004 (1.328)	-0.089 (-0.058)	0.000 (2.547)**	0.074 (3.350)*		0.872 (24.690)*	2635.879
DGARCH-M	0.004 (1.818)	-0.687 (-0.498)	0.000 (3.056)*	0.009 (0.508)	0.100 (3.148)*	0.893 (32.902)*	2649.106
			NPK				
GARCH	0.003 (3.138)*		0.000 (2.369)**	0.047 (3.072)*		0.932 (44.715)*	2751.847
DGARCH	0.003 (2.881)*		0.000 (2.740)*	0.036 (2.102)**	0.032 (1.314)	0.914 (41.473)*	2752.966
GARCH-M	0.004 (1.669)***	-0.598 (-0.394)	0.000 (3.015)*	0.077 (3.848)*		0.866 (27.174)*	2750.201
DGARCH-M	0.003 (1.303)	-0.068 (-0.048)	0.000 (2.747)*	0.036 (2.109)**	0.032 (1.358)	0.912 (40.438)*	2752.885

Appendix 4A - Maximum likelihood estimates for ARCH-type models: individual stocks (continued)

Model	α	β	ϕ	λ_1	γ	θ_1	*Log-L*
				OCE			
GARCH	0.003 (2.439)**		0.000 (1.586)	0.048 (3.044)*		0.929 (29.999)*	2526.558
DGARCH	0.003 (2.954)*		0.000 (1.277)	0.048 (2.408)**	-0.002 (-0.038)	0.928 (24.469)*	2561.898
GARCH-M	0.007 (2.460)**	-1.831 (-1.400)	0.000 (1.417)	0.040 (2.891)*		0.942 (34.187)*	2528.223
DGARCH-M	0.007 (2.576)*	-1.889 (-1.421)	0.000 (1.170)	0.041 (2.231)**	-0.003 (-0.056)	0.941 (30.582)*	2528.579
				PAM			
GARCH	0.001 (0.857)		0.000 (2.565)**	0.122 (2.996)*		0.697 (7.388)*	2513.450
DGARCH	0.001 (0.458)		0.000 (2.311)**	0.073 (2.259)**	0.081 (1.303)	0.727 (7.855)*	2561.696
GARCH-M	-0.004 (-1.139)	2.328 (1.547)	0.000 (2.582)*	0.124 (3.098)*		0.694 (7.365)*	2514.367
DGARCH-M	-0.004 (-1.118)	2.223 (1.362)	0.000 (2.356)**	0.075 (2.310)**	0.079 (1.334)	0.721 (7.754)*	2517.623
				PIK			
GARCH	0.004 (2.653)*		0.000 (1.131)	0.035 (1.650)***		0.907 (14.004)*	2312.604
DGARCH	0.003 (2.098)**		0.000 (1.317)	0.017 (0.568)	0.039 (0.978)	0.888 (12.782)*	2315.272
GARCH-M	0.001 (0.146)	1.014 (0.527)	0.000 (1.376)	0.025 (1.670)***		0.951 (34.824)*	2315.308
DGARCH-M	-0.001 (-0.136)	1.492 (0.724)	0.000 (1.295)	0.020 (0.848)	0.011 (0.457)	0.946 (28.768)*	2315.526
				PPC			
GARCH	0.000 (0.218)		0.000 (1.748)***	0.041 (3.133)*		0.931 (37.858)*	2889.467
DGARCH	0.000(0.191)		0.000 (1.741)***	0.029 (1.730)***	0.017 (0.854)	0.936 (39.675)*	2890.253
GARCH-M	0.004 (1.595)	-0.868 (-0.468)	0.000 (1.760)***	0.041 (3.174)*		0.932 (38.901)*	2890.260
DGARCH-M	0.003 (1.332)	-0.542 (-0.285)	0.000 (1.754)***	0.031 (1.781)***	0.016 (0.775)	0.937 (41.246)*	2890.846
				REM			
GARCH	-0.001 (-0.434)		0.001 (3.127)*	0.281 (1.118)		0.519 (3.946)*	2172.333
DGARCH	-0.001 (-0.701)		0.002 (3.535)*	0.726 (0.891)	-0.612 (-0.775)	0.156 (0.767)	2186.847
GARCH-M	0.004 (2.212)**	-0.193 (-0.465)	0.001 (3.103)*	0.354 (1.035)		0.439 (2.252)**	2224.578
DGARCH-M	0.006 (3.259)*	-0.216 (-0.457)	0.002 (3.580)*	0.680 (0.904)	-0.561 (-0.765)	0.234 (1.171)	2238.670
				RLO			
GARCH	0.000 (0.258)		0.000 (1.348)	0.090 (2.247)**		0.803 (10.547)*	2415.841
DGARCH	0.000 (0.206)		0.000 (1.388)	0.078 (1.310)	0.014 (0.226)	0.807 (10.406)*	2416.101
GARCH-M	0.004 (1.266)	-0.370 (-0.311)	0.000 (1.344)	0.102 (2.451)**		0.775 (8.705)*	2413.922
DGARCH-M	0.004 (1.219)	-0.379 (-0.316)	0.000 (1.347)	0.096 (1.450)	0.007 (0.093)	0.775 (8.418)*	2413.983
				SAB			
GARCH	0.003 (3.141)*		0.000 (1.020)	0.043 (3.431)*		0.941 (35.248)*	2684.488
DGARCH	0.003(3.176)*		0.000 (1.029)	0.041 (2.833)*	0.006 (0.228)	0.943 (41.103)*	2687.743
GARCH-M	0.005 (2.238)**	-1.106 (-0.919)	0.000 (0.961)	0.041 (3.466)*		0.949 (49.753)*	2686.976
DGARCH-M	0.005 (2.203)**	-1.058 (-0.883)	0.000 (0.935)	0.040 (2.667)*	0.002 (0.082)	0.949 (50.199)*	2686.989
				SAP			
GARCH	0.003 (2.279)**		0.000 (1.424)	0.040 (3.370)*		0.947 (49.201)*	2346.042
DGARCH	0.003 (2.084)**		0.000 (1.846)***	0.031 (2.498)**	0.019 (0.931)	0.947 (63.035)*	2347.170
GARCH-M	-0.002 (-0.648)	1.990 (1.836)	0.000 (1.417)	0.038 (3.465)*		0.950 (54.082)*	2347.279
DGARCH-M	-0.002 (-0.758)	2.023 (1.645)***	0.000 (1.633)	0.028 (2.276)**	0.019 (0.931)	0.949 (66.425)*	2348.555

Appendix 4A - Maximum likelihood estimates for ARCH-type models: individual stocks (continued)

Model	α	β	ϕ	λ_1	γ	θ_1	*Log-L*
			SBK				
GARCH	0.000 (0.370)		0.000 (3.406)*	0.134 (4.086)*		0.770 (15.847)*	2738.245
DGARCH	0.000 (0.504)		0.000 (3.423)*	0.143 (3.028)*	-0.018 (-0.343)	0.772 (16.257)*	2738.435
GARCH-M	0.004 (2.134)**	-0.814 (-0.643)	0.000 (3.276)*	0.132 (4.244)*		0.763 (17.420)*	2745.574
DGARCH-M	0.004 (2.191)**	-0.813 (-0.641)	0.000 (3.329)*	0.142 (3.087)*	-0.020 (-0.376)	0.782 (17.579)*	2745.767
			TBS				
GARCH	0.001 (0.916)		0.000 (2.256)**	0.063 (2.641)*		0.891 (23.406)*	2745.432
DGARCH	0.000 (0.104)		0.000 (2.799)*	0.013 (0.776)	0.105 (2.287)**	0.856 (20.040)*	2754.856
GARCH-M	0.005 (1.977)**	-0.730 (-0.459)	0.000 (2.224)**	0.064 (2.697)*		0.889 (23.189)*	2744.775
DGARCH-M	0.003 (1.157)	0.118 (0.071)	0.000 (2.832)*	0.012 (0.743)	0.110 (2.320)**	0.850 (19.216)*	2754.464
			TNT				
GARCH	0.003 (2.530)**		0.000 (2.769)*	0.086 (3.542)*		0.829 (17.125)*	2511.125
DGARCH	0.002 (2.133)**		0.000 (3.041)*	0.062 (1.966)**	0.059 (1.195)	0.816 (16.958)*	2513.878
GARCH-M	0.007 (2.047)**	-1.913 (-1.215)	0.000 (2.851)*	0.101 (3.529)*		0.760 (12.698)*	2509.110
DGARCH-M	0.006 (1.860)***	-1.732 (-1.151)	0.000 (3.198)*	0.071 (2.045)**	0.072 (1.309)	0.770 (13.165)*	2511.965
			TRE				
GARCH	0.003 (1.551)		0.006 (1.545)	-0.003 (-3.292)*		0.594 (1.734)***	1337.615
DGARCH	0.000 (1.721)***		0.006 (1.721)***	-0.003 (-3.217)*	-0.00 (-1.87)***	0.596 (1.684)***	1344.081
GARCH-M	0.018 (1.478)	-1.150 (-0.998)	0.001 (0.981)	-0.002 (-2.653)*		0.922 (11.377)*	1387.529
DGARCH-M	0.037 (5.702)*	-2.194 (-2.764)*	0.004 (2.864)*	0.029 (1.924)***	-0.033 (-2.22)**	0.742 (6.017)*	1328.167
			VNF				
GARCH	0.000 (0.206)		0.000 (1.701)***	0.025 (1.574)		0.963 (40.041)*	2219.484
DGARCH	0.001 (0.580)		0.000 (1.457)	0.047 (2.178)**	-0.03 (-2.072)**	0.956 (34.044)*	2222.408
GARCH-M	0.006 (1.699)***	-0.654 (-0.601)	0.000 (1.602)	0.002 (1.580)		0.976 (43.810)*	2221.226
DGARCH-M	0.006 (1.806)***	-0.486 (-0.438)	0.000 (1.544)	0.051 (2.024)**	-0.03 (-2.089)**	0.951 (29.125)*	2221.727
			WAR				
GARCH	0.000 (0.195)		0.000 (2.857)*	0.100 (4.893)*		0.658 (30.411)*	1794.836
DGARCH	-0.000 (-0.125)		0.000 (2.868)*	0.087 (3.051)*	0.032 (0.790)	0.857 (30.887)*	1795.662
GARCH-M	-0.004 (-0.885)	1.079 (1.450)	0.000 (2.836)*	0.102 (4.883)*		0.856 (29.670)*	1795.687
DGARCH-M	-0.004 (-0.892)	0.967 (1.320)	0.000 (2.865)*	0.089 (3.040)*	0.033 (0.776)	0.852 (29.532)*	1796.637
			WLO				
GARCH	0.001 (0.509)		0.000 (2.088)**	0.024 (2.090)**		0.951 (47.694)*	2522.632
DGARCH	0.000 (0.267)		0.001 (3.336)*	0.169 (3.120)*	-0.014 (-0.177)	0.385 (2.993)*	2514.562
GARCH-M	0.006 (1.487)	-1.765 (-0.932)	0.001 (3.230)*	0.161 (3.372)*		0.380 (2.897)*	2514.530
DGARCH-M	0.006 (1.493)	-1.768 (-0.735)	0.001 (3.255)*	0.168 (3.126)*	-0.012 (-0.162)	0.378 (2.849)*	2514.559

Appendix 4B – BDS tests for standardised GARCH(1,1) residuals

*This appendix presents the BDS test statistics for the standardised residual estimates from the GARCH(1,1) model. The test is described in subsection 3.2.3.2. The statistics, given by (3.17) were generated using the EViews 4.0 software. Probability values for accepting the null hypothesis of linearity, given in parentheses, were bootstrapped using 1000 iterative repetitions. m is the embedding dimension, while l measures the closeness of a given pair of embedding dimensions, in standard deviations of the data. * implies that the statistic was significant at the 1% significance level, and ** at 5%.*

I. Test statistics for $l = 0.5\sigma$

a) Stock portfolios

#	*Portfolio*	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	-0.861 (0.446)	-0.076 (0.974)	0.092 (0.872)	0.477 (0.592)
2	PORT	1.177 (0.258)	1.013 (0.334)	1.060 (0.324)	1.054 (0.324)

b) Individual stocks

#	*Security*	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	2.660 (0.010)**	3.712 (0.000)*	4.806 (0.000)*	5.248 (0.000)*
2	AFX	2.318 (0.020)**	2.032 (0.040)**	1.748 (0.086)	1.668 (0.116)
3	AGL	3.273 (0.002)*	4.401 (0.000)*	5.228 (0.000)*	6.199 (0.000)*
4	ALT	2.752 (0.010)**	3.516 (0.002)*	4.401 (0.000)*	5.228 (0.000)*
5	ANG	0.737 (0.474)	1.038 (0.330)	0.947 (0.384)	0.502 (0.626)
6	ASR	4.577 (0.000)*	5.463 (0.000)*	5.423 (0.000)*	5.568 (0.000)*
7	AVI	5.123 (0.000)*	5.879 (0.000)*	6.165 (0.000)*	6.863 (0.000)*
8	BAW	0.995 (0.282)	0.153 (0.764)	-0.484 (0.720)	-0.657 (0.598)
9	BVT	4.046 (0.000)*	5.193 (0.000)*	6.477 (0.000)*	8.068 (0.000)*
10	CHE	1.693 (0.102)	3.630 (0.000)*	4.663 (0.000)*	5.508 (0.000)*
11	CRH	2.413 (0.016)**	3.014 (0.000)*	2.578 (0.020)**	1.856 (0.072)
12	CTP	4.082 ((0.000)*	5.810 (0.000)*	6.390 (0.000)*	7.355 (0.000)*
13	DEL	4.428 (0.000)*	5.206 (0.000)*	5.351 (0.000)*	6.109 (0.000)*
14	DUR	1.525 (0.112)	2.440 (0.026)**	3.358 (0.006)*	4.122 (0.002)*
15	ECO	2.094 (0.038)**	3.482 (0.002)*	4.911 (0.000)*	6.491 (0.000)*
16	ELH	5.779 (0.000)*	7.595 (0.000)*	8.760 (0.000)*	9.289 (0.000)*
17	FOS	6.731 (0.000)*	6.949 (0.000)*	8.604 (0.000)*	10.311 (0.000)*
18	GMF	3.163 (0.006)*	3.416 (0.004)*	3.774 (0.002)*	4.264 (0.004)*
19	HAR	2.518 (0.018)**	2.363 (0.024)**	2.311 (0.030)**	2.397 (0.044)**
20	HLH	1.276 (0.196)	2.104 (0.054)	2.189 (0.046)**	2.401 (0.044)**
21	HVL	4.996 (0.000)*	4.213 (0.002)*	3.675 (0.004)*	3.248 (0.004)*
22	IMP	1.339 (0.208)	2.110 (0.050)	2.412 (0.024)**	4.027 (0.004)*
23	JCM	-2.441 (0.010)**	-0.777 (0.444)	-0.744 (0.470)	-1.120 (0.274)
24	JNC	3.082 (0.010)**	1.972 (0.070)	1.328 (0.194)	1.467 (0.148)
25	LGL	4.323 (0.000)*	4.054 (0.002)*	3.523 (0.002)*	3.780 (0.004)*
26	MAF	0.362 (0.680)	-0.461 (0.668)	-0.446 (0.662)	-0.294 (0.834)
27	MLB	6.908 (0.000)*	7.605 (0.000)*	7.725 (0.000)*	8.287 (0.000)*
28	NED	0.865 (0.372)	1.157 (0.270)	0.612 (0.530)	0.125 (0.856)
29	NPK	4.874 (0.000)*	5.223 (0.000)*	5.461 (0.000)*	5.891 (0.000)*
30	OCE	1.853 (0.066)	3.312 (0.008)*	4.129 (0.000)*	5.361 (0.000)*
31	PAM	2.290 (0.024)**	3.241 (0.006)*	3.774 (0.002)*	4.225 (0.002)*
32	PIK	3.501 (0.000)*	4.761 (0.000)*	5.907 (0.000)*	6.943 (0.000)*
33	PPC	4.567 (0.000)*	5.027 (0.000)*	5.584 (0.000)*	5.906 (0.000)*
34	REM	1.223 (0.206)	1.072 (0.276)	0.383 (0.634)	0.521 (0.548)
35	RLO	4.973 (0.000)*	5.761 (0.000)*	6.916 (0.000)*	7.424 (0.000)*
36	SAB	2.155 (0.048)**	3.335 (0.008)*	3.491 (0.006)*	2.972 (0.018)**
37	SAP	4.229 (0.000)*	4.551 (0.002)*	5.050 (0.002)*	5.588 (0.000)*
38	SBK	-0.094 (0.980)	0.041 (0.870)	0.223 (0.766)	0.398 (0.618)
39	TBS	1.845 (0.084)	1.207 (0.270)	1.805 (0.100)	1.419 (0.200)
40	TNT	3.476 (0.000)*	4.151 (0.000)*	4.235 (0.000)*	4.152 (0.002)*
41	TRE	7.453 (0.000)*	8.504 (0.000)*	9.792 (0.000)*	10.338 (0.000)*
42	VNF	4.105 (0.002)*	5.631 (0.000)*	7.280 (0.000)*	8.663 (0.000)*
43	WAR	-0.286 (0.776)	-0.405 (0.722)	-0.669 (0.550)	-0.612 (0.624)
44	WLO	6.167 (0.000)*	7.470 (0.000)*	8.473 (0.000)*	9.859 (0.000)*

Appendix 4B – BDS tests for standardised GARCH(1,1) residuals (continued)

II. Test statistics for $l = 1.0\sigma$

a) Stock portfolios

#	*Portfolio*	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	ALSI	-0.850 (0.424)	0.268 (0.754)	0.695 (0.450)	1.045 (0.266)
2	PORT	0.810 (0.388)	0.807 (0.414)	0.646 (0.466)	0.259 (0.734)

b) Individual stocks

#	*Security*	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	AFE	1.265 (0.234)	1.998 (0.064)	2.844 (0.008)*	2.966 (0.010)**
2	AFX	2.108 (0.038)**	2.190 (0.022)**	1.951 (0.050)	1.829 (0.078)
3	AGL	3.610 (0.000)*	4.415 (0.000)*	5.171 (0.000)*	6.110 (0.000)*
4	ALT	2.302 (0.020)**	2.790 (0.008)*	3.369 (0.004)*	3.585 (0.002)*
5	ANG	1.139 (0.288)	1.235 (0.258)	1.109 (0.298)	0.834 (0.410)
6	ASR	1.366 (0.282)	1.282 (0.270)	1.218 (0.262)	1.600 (0.146)
7	AVI	4.069 (0.000)*	4.711 (0.000)*	4.767 (0.000)*	4.858 (0.000)*
8	BAW	1.325 (0.206)	0.409 (0.638)	-0.087 (0.972)	-0.591 (0.592)
9	BVT	2.901 (0.002)*	3.632 (0.002)*	3.317 (0.002)*	3.471 (0.002)*
10	CHE	-0.327 (0.750)	0.899 (0.332)	1.361 (0.150)	1.549 (0.116)
11	CRH	1.799 (0.076)	2.022 (0.042)**	1.848 (0.052)	1.549 (0.116)
12	CTP	2.602 (0.014)**	3.159 (0.002)*	3.026 (0.000)*	3.190 (0.000)*
13	DEL	3.750 (0.000)*	2.920 (0.008)*	2.482 (0.028)**	2.604 (0.016)**
14	DUR	0.893 (0.356)	1.711 (0.074)	2.102 (0.038)**	2.409 (0.020)**
15	ECO	1.501 (0.138)	2.693 (0.010)**	3.346 (0.006)*	3.722 (0.004)*
16	ELH	5.092 (0.000)*	5.413 (0.000)*	5.109 (0.000)*	5.081 (0.000)*
17	FOS	4.277 (0.000)*	4.739 (0.000)*	5.176 (0.000)*	5.612 (0.000)*
18	GMF	2.509 (0.010)**	2.856 (0.002)*	3.060 (0.006)*	3.316 (0.008)*
19	HAR	2.371 (0.012)**	2.070 (0.040)**	1.776 (0.082)	1.663 (0.116)
20	HLH	1.849 (0.046)**	2.275 (0.018)**	1.901 (0.056)	1.851 (0.062)
21	HVL	4.673 (0.000)*	3.999 (0.000)*	3.586 (0.002)*	3.207 (0.004)*
22	IMP	0.626 (0.492)	1.203 (0.224)	1.134 (0.230)	1.367 (0.174)
23	JCM	-2.636 (0.006)*	-2.287 (0.014)**	-2.421 (0.010)**	-2.640 (0.010)**
24	JNC	2.541 (0.006)*	1.483 (0.138)	1.047 (0.258)	0.931 (0.290)
25	LGL	4.262 (0.000)*	3.619 (0.000)*	2.754 (0.010)**	2.772 (0.016)**
26	MAF	-1.104 (0.304)	-1.411 (0.202)	-1.668 (0.114)	-1.585 (0.106)
27	MLB	6.599 (0.000)*	7.412 (0.000)*	7.599 (0.000)*	7.996 (0.000)*
28	NED	0.421 (0.670)	0.554 (0.560)	0.066 (0.948)	-0.356 (0.768)
29	NPK	4.489 (0.000)*	4.052 (0.000)*	3.842 (0.006)*	3.589 (0.008)*
30	OCE	2.711 (0.020)**	3.780 (0.000)*	4.437 (0.006)*	4.904 (0.000)*
31	PAM	2.055 (0.040)**	3.024 (0.002)*	3.408 (0.000)*	3.266 (0.002)*
32	PIK	1.761 (0.098)	2.160 (0.036)**	2.099 (0.040)**	1.942 (0.058)
33	PPC	3.364 (0.000)*	3.305 (0.000)*	3.364 (0.000)*	3.210 (0.004)*
34	REM	-1.516 (0.154)	-1.703 (0.106)	-1.957 (0.068)	-1.949 (0.046)**
35	RLO	2.573 (0.012)**	3.441 (0.000)*	4.541 (0.000)*	5.036 (0.000)*
36	SAB	2.269 (0.024)**	3.520 (0.000)*	3.562 (0.000)*	3.174 (0.004)*
37	SAP	3.171 (0.006)*	3.579 (0.002)*	3.414 (0.002)*	3.191 (0.002)*
38	SBK	-0.135 (0.944)	-0.220 (0.850)	0.026 (0.940)	0.126 (0.834)
39	TBS	1.322 (0.202)	0.953 (0.306)	1.403 (0.146)	1.046 (0.286)
40	TNT	3.008 (0.008)*	2.805 (0.012)**	2.463 (0.024)**	2.037 (0.060)
41	TRE	5.172 (0.000)*	5.594 (0.000)*	5.863 (0.000)*	5.852 (0.000)*
42	VNF	3.631 (0.000)*	4.041 (0.000)*	3.824 (0.000)*	3.961 (0.000)*
43	WAR	-0.570 (0.604)	-0.818 (0.418)	-1.107 (0.280)	-1.202 (0.244)
44	WLO	4.934 (0.000)*	5.555 (0.000)*	5.809 (0.000)*	5.938 (0.000)*

Appendix 4B – BDS tests for standardised GARCH(1,1) residuals (continued)

III. Test statistics for $l = 1.5\sigma$

a) Stock portfolios

#	Security	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	-0.449 (0.656)	0.514 (0.594)	0.671 (0.486)	0.844 (0.386)
2	PORT	0.678 (0.490)	0.807 (0.376)	0.540 (0.546)	0.084 (0.886)

b) Individual stocks

#	Security	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	1.025 (0.350)	1.626 (0.102)	1.977 (0.062)	1.752 (0.090)
2	AFX	1.219 (0.240)	1.865 (0.070)	1.871 (0.062)	1.863 (0.078)
3	AGL	4.857 (0.000)*	5.167 (0.000)*	5.739 (0.000)*	6.476 (0.000)*
4	ALT	2.916 (0.012)**	3.127 (0.006)*	3.335 (0.004)*	3.513 (0.000)*
5	ANG	0.899 (0.388)	0.964 (0.332)	0.828 (0.426)	0.585 (0.560)
6	ASR	1.414 (0.286)	0.942 (0.406)	0.567 (0.578)	1.121 (0.318)
7	AVI	2.844 (0.002)*	3.175 (0.002)*	3.109 (0.000)*	2.935 (0.002)*
8	BAW	1.030 (0.284)	0.181 (0.844)	-0.304 (0.782)	-0.770 (0.432)
9	BVT	1.060 (0.270)	1.685 (0.074)	1.446 (0.120)	1.603 (0.094)
10	CHE	-0.216 (0.842)	1.060 (0.292)	1.263 (0.202)	1.243 (0.212)
11	CRH	1.054 (0.280)	1.443 (0.154)	1.553 (0.106)	1.528 (0.106)
12	CTP	1.910 (0.068)	2.796 (0.002)*	2.621 (0.010)**	2.872 (0.002)*
13	DEL	2.205 (0.036)**	1.321 (0.180)	0.681 (0.462)	0.560 (0.564)
14	DUR	0.097 (0.924)	0.297 (0.752)	0.517 (0.564)	0.980 (0.268)
15	ECO	0.534 (0.582)	1.970 (0.054)	2.355 (0.026)**	2.565 (0.020)**
16	ELH	3.640 (0.000)*	3.633 (0.000)*	3.424 (0.000)*	3.278 (0.000)*
17	FOS	1.997 (0.064)	2.366 (0.030)**	2.278 (0.030)**	2.309 (0.030)**
18	GMF	1.723 (0.070)	1.820 (0.056)	2.022 (0.036)**	2.246 (0.024)**
19	HAR	2.047 (0.050)	1.925 (0.066)	1.541 (0.142)	1.208 (0.230)
20	HLH	0.936 (0.340)	1.297 (0.202)	0.855 (0.376)	0.737 (0.468)
21	HVL	3.975 (0.002)*	3.084 (0.006)*	2.620 (0.016)**	2.014 (0.048)**
22	IMP	0.028 (0.950)	0.411 (0.636)	0.124 (0.854)	0.117 (0.886)
23	JCM	-2.240 (0.004)*	-2.456 (0.000)*	-2.858 (0.004)*	-3.112 (0.002)*
24	JNC	2.076 (0.038)**	1.008 (0.332)	0.709 (0.476)	0.620 (0.524)
25	LGL	3.974 (0.000)*	3.160 (0.002)*	2.160 (0.024)**	2.096 (0.030)*
26	MAF	-1.440 (0.152)	-1.623 (0.104)	-1.883 (0.048)**	-2.079 (0.030)*
27	MLB	6.382 (0.000)*	7.396 (0.000)*	7.581 (0.000)*	7.811 (0.000)*
28	NED	-0.056 (0.986)	0.292 (0.762)	-0.186 (0.864)	-0.567 (0.602)
29	NPK	3.654 (0.000)*	3.122 (0.006)*	3.153 (0.004)**	3.133 (0.004)*
30	OCE	0.909 (0.342)	1.480 (0.134)	1.900 (0.054)	2.170 (0.034)**
31	PAM	1.263 (0.202)	1.931 (0.060)	1.955 (0.052)	1.477 (0.134)
32	PIK	0.914 (0.380)	1.512 (0.142)	1.488 (0.128)	1.420 (0.154)
33	PPC	2.326 (0.030)**	1.996 (0.050)	1.957 (0.064)	1.673 (0.124)
34	REM	-2.436 (0.008)*	-2.523 (0.006)*	-2.688 (0.004)*	-2.485 (0.012)**
35	RLO	0.545 (0.574)	1.527 (0.118)	2.244 (0.034)**	2.401 (0.022)**
36	SAB	2.540 (0.020)**	3.921 (0.000)*	4.133 (0.000)*	3.837 (0.000)*
37	SAP	2.666 (0.008)*	3.125 (0.002)*	2.973 (0.004)*	2.793 (0.008)*
38	SBK	-0.089 (0.972)	-0.624 (0.630)	-0.262 (0.880)	-0.032 (0.984)
39	TBS	1.198 (0.254)	0.939 (0.366)	1.224 (0.266)	0.897 (0.404)
40	TNT	2.277 (0.038)**	1.671 (0.116)	1.190 (0.232)	0.891 (0.344)
41	TRE	3.132 (0.030)**	2.834 (0.034)**	3.097 (0.020)**	3.483 (0.012)**
42	VNF	3.222 (0.000)*	4.178 (0.000)*	3.784 (0.000)*	3.683 (0.000)*
43	WAR	-0.922 (0.410)	-1.138 (0.286)	-1.139 (0.276)	-1.049 (0.324)
44	WLO	4.140 (0.000)*	4.811 (0.000)*	4.948 (0.000)*	4.759 (0.000)*

Appendix 5A – Macroeconomic variable definitions and data sources

*This appendix provides definitions and data sources for the macroeconomic variables used in the study, particularly in Chapter 5 and Chapter 6. Data on all variables marked with * were sourced from the Inet-Bridge online database, while those on variables marked **were sourced from the International Financial Statistics (IFS) CD-Rom and Internet databases[1]. S/A implies that the data were already seasonally adjusted. Unless otherwise stated in this appendix, end-of-period data were used. Interest rates were expressed as annual percentage rates, and all other variables were expressed in logarithmic levels, unless otherwise indicated in the analysis.*

BRATE:	The rate on a ten-year South African Government bond*.
CPI:	The index of prices of all consumer goods and services for metropolitan areas; base = 2000*.
DRATE:	The discount rate (i.e. Bank/repo rate)[2]*.
GPRICE:	The price of gold; rand per kilogram*.
INFL:	The annualised monthly CPI inflation, computed in study.
M3:	The broad (illiquid) money supply measure; million rand, S/A[3]*.
MANEMP:	The index of private manufacturing employment; period averages, S/A[4]**.
MANUF:	The index of manufacturing production; period averages, S/A**.
MINEMP:	The index of mining employment; period averages, S/A[5]**.
MINING:	The index of mining production; period averages, S/A**.
TBRATE:	The three-month Treasury bill tender rate*.

[1] The IMF Malawi Office kindly supplied us with a January 2000 version of the CD-ROM. The required supplementary data for the sample period were downloaded from the Internet version in the Main Library of the University of Cape Town.

[2] This is the rate at which the SARB discounts commercial paper from commercial banks. It is the Bank rate up to February 1998, and the repurchase agreement (repo) rate thereafter. This change is explained in Section 5.2.

[3] M3 aggregates currency in circulation, checking and transmission deposits, other demand deposits with banking institutions, as well as other short-term, medium-term and long-term deposits with banking institutions and building societies.

[4] Monthly mining and manufacturing employment figures were apparently discontinued after December 1997, and the lowest available frequency is currently the quarterly. Therefore, from 1998, the quarterly observations were assigned to the last month of the quarter, and observations for the intra-quarter months were extrapolated. The variations in the figures, even at the quarterly frequency, were so minor that this should be virtually inconsequential, more so given that it only affected a very small proportion of the sample.

Appendix 5B – Critical values for the Johansen cointegration test statistics

This appendix gives quantiles of the asymptotic distribution of the cointegrating rank test statistics derived in the study, based on the assumption that the original sets of series had linear deterministic trends while the cointegrating equations only contained intercept terms. r is the hypothesised number of cointegrating equations.

H_0	Q_{max}		Q_{trace}	
	95%	**99%**	**95%**	**99%**
r ≤ 5	3.76	6.65	3.76	6.65
r ≤ 4	14.07	18.63	15.41	20.04
r ≤ 3	20.97	25.52	29.68	35.65
r ≤ 2	27.07	32.24	47.21	54.46
r ≤1	33.46	38.77	68.52	76.07
r = 0	39.37	45.10	94.15	103.18

Source: Osterwald-Lenum (1992:468)

Appendix 6A - ML estimates for GARCH(1,1) model with exogenous variables: individual stocks

This appendix presents the maximum likelihood estimates (with z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses) for the following GARCH model described in Section 6.3:

$$R_t = \alpha_0 + \alpha_1 DDRATE_t + \alpha_2 DGPRICE_t + \mu_t;\ \mu_t|\Omega_{t-1} \sim N(0, h_t);$$
$$h_t = \phi_0 + \lambda_1 \mu_{t-1} + \theta_1 h_{t-1} + \phi_1 DDRATE_t + \phi_2 DGPRICE_t.$$

*The returns, R_t, were uncorrelated or linearly filtered. Log-L is the log likelihood function. * denotes statistical significance at 1%, while ** and *** denote significance at 5% and 10%, respectively. Results are for the 44 individual stocks.*

α_0	α_1	α_2	ϕ_0	λ_1	θ_1	ϕ_1	ϕ_2
AFE							
-0.001 (-0.431)	-0.014 (-3.17)*	-0.007 (-0.117)	0.000 (1.497)	0.113 (1.164)	0.812 (9.998)*	-0.000 (-1.378)	-0.000 (-0.250)
AFX							
0.004 (3.437)*	-0.004 (-0.669)	-0.018 (-0.287)	0.000 (2.475)**	0.179 (4.128)*	0.882 (8.978)*	-0.000 (-1.285)	0.001 (0.223)
AGL							
-0.000 (-0.181)	-0.009 (-1.083)	0.124 (1.191)	0.002 (3.378)*	0.017 (1.019)	0.821 (24.49)*	0.003 (2.125)**	0.054 (2.994)*
ALT							
-0.002 (-1.7)***	-0.013 (-2.59)*	-0.070 (-2.1)**	0.001 (4.377)*	0.017 (1.019)	0.821 (24.49)*	-0.000 (-1.494)	-0.009 (-5.77)*
ANG							
0.001 (0.474)	-0.019 (-2.74)*	0.254 (3.448)*	0.000 (2.114)**	0.091 (2.989)*	0.835 (14.88)*	0.001 (2.332)**	0.004 (1.303)
ASR							
-0.002 (-0.496)	-0.000 (-0.053)	0.077 (1.094)	0.007 (0.395)	-0.002 (-0.948)	0.566 (0.433)	-0.005 (-7.85)*	0.023 (0.279)
AVI							
0.000 (0.025)	0.002 (0.071)	-0.008 (-0.013)	0.000 (0.835)	0.180 (2.009)**	0.798 (5.242)*	-0.000 (-0.107)	-0.003 (-0.106)
BAW							
-0.001 (-0.306)	-0.01 (-1.95)***	0.015 (0.175)	0.000 (2.557)**	0.085 (3.571)*	0.887 (33.77)*	-0.000 (-0.994)	0.014 (1.801)
BVT							
0.002 (1.579)	0.001 (0.088)	-0.059 (-3.31)*	0.001 (3.522)*	0.134 (2.230)**	0.551 (4.819)*	0.000 (0.093)	-0.013 (-4.75)*
CHE							
0.001 (1.012)	-0.001 (-0.133)	-0.005 (-0.231)	0.001 (2.534)**	0.112 (3.119)*	0.814 (5.184)*	0.000 (1.418)	-0.008 (-3.44)*
CRH							
0.002 (0.821)	-0.012 (-1.355)	0.108 (1.049)	0.001 (1.110)	0.051 (1.93)***	0.853 (8.887)*	0.000 (0.555)	0.049 (0.440)
CTP							
0.004 (2.887)*	-0.002 (-0.373)	-0.029 (-0.570)	0.001 (2.590)*	0.157 (2.892)*	0.525 (5.560)*	-0.000 (-1.148)	0.021 (3.738)*
DEL							
0.004 (2.807)*	-0.017 (-0.856)	0.092 (0.752)	0.000 (0.755)	0.118 (1.293)	0.881 (43.37)*	-0.000 (0.271)	0.003 (0.440)
DUR							
-0.004 (-1.7)***	-0.009 (-1.388)	0.389 (3.474)*	0.004 (3.410)*	0.201 (2.065)**	0.274 (1.528)	-0.001 (-0.813)	0.008 (0.457)
ECO							
0.001 (0.980)	-0.014 (-2.2)**	0.018 (0.234)	0.000 (2.398)**	0.050 (2.448)**	0.917 (43.92)*	0.000 (0.189)	0.005 (1.522)

Appendix 6A - Maximum likelihood estimates for GARCH(1,1) model with exogenous

variables: individual stocks (continued)

α_0	α_1	α_2	ϕ_0	λ_1	θ_1	ϕ_1	ϕ_2
ELH							
0.001 (0.413)	-0.009 (-1.635)	-0.023 (-0.692)	0.001 (2.576)**	0.127 (2.326)**	0.598 (4.935)*	0.000 (0.271)	0.016 (5.431)*
FOS							
0.001 (0.932)	0.001 (0.116)	0.050 (0.750)	0.000 (1.90)***	0.076 (2.591)*	0.837 (21.05)*	-0.000 (-0.719)	0.011 (2.351)**
GMF							
0.003 (1.88)***	-0.025 (-3.63)*	0.160 (1.83)***	0.002 (2.215)**	0.042 (1.128)	0.275 (0.904)	-0.001 (-1.643)	0.016 (1.491)
HAR							
-0.002 (-1.046)	-0.007 (-0.943)	0.389 (4.026)*	0.000 (2.322)**	0.064 (3.636)*	0.914 (40.99)*	-0.001 (-2.4)**	-0.003 (-0.946)
HLH							
0.003 (2.045)**	-0.013 (-2.2)**	-0.140 (-1.9)***	0.000 (1.293)	0.050 (3.002)*	0.935 (35.63)*	-0.000 (-0.070)	0.001 (0.531)
HVL							
-0.000 (-0.363)	-0.012 (-1.556)	0.149 (1.74)***	0.001 (1.84)***	0.102 (3.133)*	0.749 (7.247)*	-0.000 (-0.436)	0.001 (0.165)
IMP							
0.000 (0.129)	-0.02 (-2.35)**	0.197 (2.383)*	0.003 (4.370)*	0.091 (1.76)***	0.030 (0.175)	-0.001 (-1.008)	0.020 (4.127)*
JCM							
0.001 (0.029)	0.014 (1.251)	1.038 (5.047)*	0.010 (3.078)*	1.309 (0.677)	0.365 (1.365)	-0.007 (-2.4)**	0.152 (1.74)***
JNC							
-0.003 (-0.368)	-0.008 (-1.063)	-0.233 (-0.953)	0.008 (2.525)**	0.290 (1.167)	0.565 (4.052)*	0.013 (3.668)*	0.180 (8.583)*
LGL							
0.004 (3.204)*	-0.013 (-3.02)*	0.040 (0.680)	0.000 (1.349)	0.040 (2.678)*	0.951 (45.61)*	-0.000 (-0.558)	-0.002 (-1.282)
MAF							
0.004 (1.200)	0.004 (0.548)	-0.008 (-0.192)	0.003 (2.027)**	0.239 (0.275)	0.595 (3.566)*	0.003 (3.677)*	0.073 (5.358)*
MLB							
-0.000 (-0.002)	-0.017 (-3.58)*	-0.126 (-1.248)	0.003 (1.999)**	-0.005 (-4.1)*	0.580 (2.053)**	-0.001 (-1.97)**	-0.031 (-3.33)*
NED							
0.003 (2.517)**	0.001 (0.181)	0.014 (0.124)	0.000 (2.006)**	0.078 (2.910)*	0.873 (20.12)*	-0.000 (-0.272)	0.002 (0.446)
NPK							
0.003 (2.521)**	-0.001 (-0.106)	-0.066 (-1.026)	0.000 (2.296)**	0.136 (3.505)*	0.727 (9.378)*	0.000 (0.277)	0.004 (1.135)
OCE							
0.004 (3.379)*	-0.003 (-0.762)	-0.064 (-1.043)	0.000 (2.785)*	0.147 (4.216)*	0.738 (10.88)*	-0.000 (-0.414)	-0.005 (-3.04)*
PAM							
0.002 (1.495)	-0.009 (-1.539)	0.029 (0.418)	0.000 (1.75)***	0.037 (2.386)*	0.943 (41.01)*	-0.000 (-0.325)	0.002 (0.765)
PIK							
0.004 (3.010)*	-0.005 (-0.600)	-0.244 (-4.30)*	0.000 (2.536)**	0.071 (2.039)**	0.774 (15.51)*	-0.000 (-0.757)	0.016 (6.068)*
PPC							
0.000 (0.137)	-0.008 (-1.192)	0.11 (1.857)***	0.001 (2.510)**	0.182 (2.503)**	0.446 (2.477)**	-0.000 (-0.516)	-0.006 (-1.254)
REM							
-0.001 (-0.144)	0.000 (0.008)	0.093 (1.239)	0.001 (6.400)*	1.004 (1.203)	0.093 (1.297)	-0.000 (-0.578)	0.006 (0.907)
RLO							
0.001 (0.825)	-0.020 (-3.98)*	0.060 (0.752)	0.000 (1.82)***	0.071 (2.560)**	0.895 (28.15)*	-0.000 (-1.214)	0.001 (0.222)

Appendix 6A - Maximum likelihood estimates for GARCH(1,1) model with exogenous

variables: individual stocks (continued)

α_0	α_1	α_2	ϕ_0	λ_1	θ_1	ϕ_1	ϕ_2
SAB							
0.003 (2.383)**	-0.006 (-0.946)	-0.004 (-0.048)	0.000 (1.114)	0.042 (2.361)**	0.947 (52.98)*	-0.000 (-0.528)	0.004 (2.584)*
SAP							
0.003 (1.591)	-0.006 (-1.362)	-0.013 (-0.144)	0.000 (1.66)***	0.048 (2.539)**	0.932 (31.43)*	-0.000 (-1.018)	0.001 (0.422)
SBK							
0.002 (1.350)	-0.004 (-0.794)	-0.110 (-1.8)***	0.000 (3.259)*	0.138 (3.344)*	0.787 (16.87)*	-0.000 (-0.847)	-0.002 (-0.869)
TBS							
0.001 (0.660)	-0.004 (-0.602)	-0.075 (-1.454)	0.000 (2.299)**	0.032 (2.101)**	0.918 (28.83)*	0.000 (2.055)**	0.000 (0.098)
TNT							
0.003 (2.377)**	-0.017 (-2.88)*	-0.018 (-0.254)	0.000 (1.570)	0.060 (2.661)*	0.884 (18.21)*	-0.000 (-1.099)	0.006 (1.607)
TRE							
0.003 (1.039)	0.004 (1.025)	0.134 (1.592)	0.008 (0.574)	-0.004 (-2.18)**	0.587 (0.830)	0.002 (0.579)	0.078 (0.488)
VNF							
0.001 (0.699)	0.005 (0.713)	-0.003 (-0.058)	0.001 (4.870)*	0.040 (0.998)	0.574 (6.217)*	0.000 (0.641)	0.022 (5.510)*
WAR							
-0.000 (-0.045)	-0.02 (-1.95)***	0.089 (0.835)	0.000 (2.855)*	0.120 (4.811)*	0.851 (29.83)*	0.000 (0.013)	-0.007 (-1.619)
WLO							
0.000 (0.048)	-0.018 (-10.4)*	-0.186 (-3.77)*	0.001 (3.891)*	0.190 (3.347)*	0.309 (3.153)*	-0.00 (-10.86)*	-0.016 (-4.42)*

Appendix 6B - ML estimates for GARCH(1,1) model with decomposed exogenous variables: individual stocks

This appendix presents the maximum likelihood estimates (with z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses) for the following GARCH model described in Section 6.3:

$$R_t = \alpha_0 + \eta_1 DPOS_t + \eta_2 DNEG_t + \eta_3 GPOS_t + \eta_4 GNEG_t + \mu_t;\ \mu_t|\Omega_{t-1} \sim N(0,h_t);$$
$$h_t = \phi_0 + \lambda_1\mu_{t-1} + \theta_1 h_{t-1} + \varphi_1 DPOS_t + \varphi_2 DNEG_t + \varphi_3 GPOS_t + \varphi_4 GNEG_t\ .$$

*The returns, R_t, were uncorrelated or linearly filtered. Log-L is the log likelihood function. * denotes statistical significance at 1%, while ** and *** denote significance at 5% and 10%, respectively. Results are for the 44 individual stocks.*

α_0	η_1	η_2	η_3	η_4	ϕ_0	λ_1	θ_1	φ_1	φ_2	φ_3	φ_4
AFE											
-0.001 (-0.491)	-0.02 (-11.64)*	-0.004 (-0.377)	0.028 (0.303)	0.034 (0.432)	0.000 (2.360)**	0.131 (1.318)	0.775 (14.067)*	-0.001 (-5.239)*	-0.002 (-2.39)**	-0.008 (-1.643)	0.009 (2.417)**
AFX											
0.004 (2.780)*	-0.009 (-1.364)	-0.004 (-0.320)	-0.055 (-0.624)	-0.009 (-0.103)	0.000 (2.557)**	0.177 (4.164)*	0.619 (7.115)*	0.000 (0.709)	-0.002 (-2.53)**	-0.001 (-0.181)	0.003 (0.755)
AGL											
0.007 (3.097)*	-0.027 (-3.118)*	-0.008 (-0.713)	-0.211 (-0.878)	0.332 (2.173)**	0.001 (3.652)*	0.110 (1.440)	0.049 (0.477)	-0.011 (-3.076)*	-0.001 (-0.491)	0.391 (1.048)	-0.253 (-1.318)
ALT											
-0.001 (-0.621)	-0.019 (-3.309)*	-0.005 (-0.491)	-0.059 (-3.540)*	-0.501 (-0.643)	0.001 (8.087)*	0.247 (2.589)*	0.291 (12.975)*	0.000 (0.664)	-0.004 (-2.25)**	-0.011 (-9.302)*	-0.000 (-0.032)
ANG											
0.001 (0.432)	-0.02 (-1.94)***	-0.020 (-2.07)**	0.207 (1.82)***	0.222 (2.578)*	0.000 (3.085)*	0.099 (3.522)*	0.807 (16.102)*	0.001 (0.815)	0.000 (0.822)	-0.002 (-0.813)	0.011 (2.790)*
ASR											
-0.004 (-0.641)	-0.004 (-1.342)	0.031 (1.412)	0.289 (1.483)	-0.166 (-1.251)	0.007 (2.682)*	0.083 (0.326)	0.590 (1.311)	-0.004 (-1.560)	-0.002 (-0.032)	-0.005 (-0.017)	0.043 (0.304)
AVI											
0.000 (0.003)	-0.025 (-2.873)*	0.016 (0.829)	0.086 (0.637)	-0.132 (-1.059)	0.001 (3.189)*	0.159 (4.049)*	0.526 (3.791)*	0.001 (1.198)	-0.007 (-0.559)	-0.009 (-1.237)	0.018 (5.414)*
BAW											
0.000 (0.187)	-0.018 (-2.708)*	-0.005 (-0.530)	0.089 (0.749)	-0.024 (-0.175)	0.000 (0.893)	-0.002 (-0.268)	0.988 (156.90)*	0.000 (0.134)	-0.001 (-2.15)**	-0.001 (-0.665)	0.003 (0.467)
BVT											
0.003 (1.555)	-0.006 (-0.319)	0.007 (1.229)	-0.071 (-2.566)*	-0.007 (-0.049)	0.001 (2.697)*	0.136 (2.204)**	0.563 (4.820)*	-0.000 (-0.004)	0.000 (0.559)	-0.012 (-3.736)*	-0.010 (-0.343)

Appendix 6B - Maximum likelihood estimates for GARCH(1,1) model with decomposed exogenous variables: individual stocks (continued)

α_0	η_1	η_2	η_3	η_4	ϕ_0	λ_1	θ_1	φ_1	φ_2	φ_3	φ_4
CHE											
0.001 (0.640)	-0.012 (-2.29)**	0.003 (0.773)	0.050 (3.162)*	-0.066 (-0.548)	0.000 (1.87)***	0.101 (2.533)**	0.614 (3.730)*	0.001 (1.030)	0.000 (0.212)	-0.007 (-3.639)*	-0.017 (-1.297)
CRH											
-0.003 (-0.936)	-0.005 (-0.551)	-0.021 (-1.378)	0.354 (2.269)*	-0.229 (-1.211)	0.001 (1.386)	0.047 (1.490)	0.877 (11.891)*	0.001 (0.345)	-0.001 (-0.864)	-0.003 (-0.242)	0.016 (1.174)
CTP											
0.005 (3.056)*	0.002 (0.265)	-0.000 (-0.021)	-0.132 (-1.381)	0.030 (2.169)**	0.001 (3.375)*	0.146 (2.281)**	0.526 (5.146)*	-0.003 (-1.9)***	-0.000 (-0.114)	0.016 (1.469)	0.026 (4.952)*
DEL											
0.009 (3.745)*	-0.015 (-0.407)	-0.001 (-0.153)	-0.151 (-1.539)	0.413 (1.370)	0.000 (1.83)***	0.265 (2.116)**	0.360 (1.89)***	0.020 (0.529)	-0.001 (-0.980)	0.004 (0.710)	-0.048 (-2.45)**
DUR											
-0.005 (-1.333)	-0.013 (-1.456)	-0.008 (-0.577)	0.445 (2.471)**	0.368 (1.82)***	0.004 (3.266)*	0.201 (2.089)**	0.280 (1.572)	-0.001 (-2.18)**	0.001 (0.751)	0.021 (0.968)	0.009 (0.292)
ECO											
0.001 (0.616)	-0.025 (-4.471)*	-0.001 (-0.111)	0.021 (0.196)	-0.044 (-0.308)	0.001 (2.689)*	0.121 (2.312)**	0.581 (3.544)*	-0.000 (-1.116)	-0.001 (-0.922)	-0.006 (-1.008)	0.017 (4.056)*
ELH											
0.003 (1.581)	-0.021 (-2.739)*	0.001 (0.148)	-0.153 (-0.916)	-0.028 (-0.218)	0.000 (1.644)	0.098 (2.176)**	0.601 (3.681)*	0.002 (1.188)	-0.000 (-0.704)	0.040 (1.260)	-0.005 (-0.390)
FOS											
0.003 (1.85)***	-0.006 (-1.417)	0.014 (1.474)	-0.072 (-0.714)	0.192 (2.364)*	0.000 (2.908)*	0.094 (2.051)*	0.754 (10.540)*	-0.000 (-0.039)	-0.004 (-1.220)	0.005 (0.592)	0.009 (2.400)**
GMF											
0.004 (1.574)	-0.021 (-2.752)*	-0.029 (-1.7)***	0.147 (1.135)	0.068 (0.621)	0.002 (2.359)**	0.068 (1.71)***	0.362 (2.179)**	-0.000 (-0.767)	-0.011 (-1.318)	0.001 (0.080)	0.008 (0.616)
HAR											
-0.005 (-1.9)***	-0.004 (-0.631)	-0.021 (-1.7)***	0.521 (3.151)*	0.180 (1.074)	0.000 (2.141)**	0.065 (3.733)*	0.913 (41.736)*	-0.001 (-2.18)**	-0.001 (-1.019)	-0.005 (-0.917)	0.003 (0.659)
HLH											
0.004 (1.94)***	-0.015 (-2.00)**	-0.001 (-0.094)	-0.081 (-2.19)**	-0.078 (-0.748)	0.000 (1.88)***	0.048 (3.419)*	0.936 (46.447)*	0.000 (0.642)	-0.000 (-1.127)	-0.004 (-4.096)*	0.005 (1.262)
HVL											
-0.002 (-0.681)	-0.014 (-1.423)	-0.014 (-1.202)	0.197 (1.327)	0.094 (0.652)	0.001 (1.85)***	0.114 (2.787)*	0.626 (4.199)*	0.001 (0.559)	-0.002 (-1.447)	0.011 (0.850)	-0.002 (-0.120)
IMP											
0.001 (0.283)	-0.017 (-2.20)**	-0.036 (-2.42)**	0.196 (1.421)	0.307 (2.426)**	0.003 (7.540)*	0.084 (2.171)*	-0.237 (-3.195)*	-0.000 (-0.927)	-0.009 (-3.159)*	0.031 (2.289)**	0.004 (0.409)

Appendix 6B - Maximum likelihood estimates for GARCH(1,1) model with decomposed exogenous variables: individual stocks (continued)

α_0	η_1	η_2	η_3	η_4	ϕ_0	λ_1	θ_1	φ_1	φ_2	φ_3	φ_4
					JCM						
0.009 (0.450)	0.013 (2.124)**	0.058 (2.723)*	0.074 (0.270)	0.323 (1.395)	0.012 (1.93)***	0.705 (0.656)	0.512 (1.88)***	-0.007 (-2.31)**	0.004 (0.891)	0.013 (0.254)	0.186 (4.353)*
					JNC						
-0.006 (-0.766)	0.008 (0.543)	0.025 (2.086)**	-0.110 (-0.372)	-0.085 (-1.423)	0.016 (1.091)	0.224 (0.959)	0.563 (1.287)	-0.005 (-0.749)	0.010 (2.303)**	-0.005 (-0.063)	0.234 (2.873)*
					LGL						
0.002 (1.231)	-0.018 (-7.175)*	0.008 (0.740)	0.188 (3.091)*	-0.056 (0.141)	0.001 (3.700)*	0.139 (3.718)*	0.580 (4.812)*	-0.001 (-6.301)*	-0.000 (-0.172)	-0.008 (-1.274)	0.015 (1.980)**
					MAF						
0.004 (0.714)	0.000 (0.029)	0.024 (0.849)	0.347 (1.050)	0.208 (0.929)	0.001 (4.821)*	0.171 (0.268)	0.791 (6.563)*	-0.001 (-1.068)	0.001 (0.368)	0.022 (0.785)	0.022 (4.055)*
					MLB						
-0.003 (-1.035)	-0.023 (-3.158)*	-0.019 (-1.280)	0.040 (0.270)	-0.33 (-1.66)***	0.003 (2.387)**	0.046 (1.277)	0.569 (4.509)*	-0.000 (-1.96)**	0.001 (0.663)	-0.03 (-1.75)***	0.017 (0.867)
					NED						
0.005 (2.956)*	-0.007 (-0.843)	0.012 (1.051)	-0.155 (-1.465)	0.116 (0.711)	0.000 (1.091)	0.084 (2.055)**	0.761 (8.228)*	0.001 (1.412)	-0.001 (-1.326)	0.005 (0.952)	-0.019 (-2.07)**
					NPK						
0.004 (1.77)***	-0.011 (-1.631)	0.007 (0.793)	-0.042 (-0.339)	-0.056 (-0.475)	0.000 (1.81)***	0.107 (3.006)*	0.772 (11.613)*	0.000 (1.042)	-0.000 (-0.956)	0.001 (0.256)	0.007 (1.152)
					OCE						
0.005 (2.779)*	-0.001 (-0.193)	-0.007 (-0.864)	-0.056 (-0.768)	0.020 (0.134)	0.000 (1.78)***	0.091 (3.587)*	0.789 (13.557)*	-0.000 (-0.002)	-0.001 (-1.7)***	-0.004 (-2.606)*	-0.02 (-1.78)***
					PAM						
-0.000 (-0.113)	-0.002 (-0.330)	-0.016 (-1.626)	0.110 (1.052)	-0.124 (-0.999)	0.000 (1.069)	0.092 (2.823)*	0.815 (13.753)*	0.000 (0.682)	-0.001 (-1.278)	0.006 (1.072)	-0.01 (-1.86)***
					PIK						
0.002 (1.196)	-0.011 (-1.082)	-0.000 (-0.028)	-0.085 (-0.738)	-0.329 (-3.218)*	0.000 (2.085)**	0.066 (1.88)***	0.775 (9.438)*	-0.000 (-0.160)	-0.001 (-1.403)	0.007 (1.77)***	0.016 (5.645)*
					PPC						
0.002 (1.400)	-0.016 (-2.46)**	-0.001 (-0.136)	-0.005 (-0.062)	0.230 (1.997)**	0.001 (3.488)*	0.155 (2.782)*	0.213 (1.817)**	0.000 (0.999)	-0.004 (-2.12)**	0.001 (0.151)	-0.04 (-1.91)***
					REM						
-0.004 (-0.816)	-0.002 (-0.191)	-0.014 (-1.305)	0.256 (1.69)***	-0.169 (-3.373)*	0.001 (6.820)*	0.831 (1.111)	0.165 (1.70)***	0.000 (0.012)	-0.004 (-1.118)	-0.001 (-0.057)	0.014 (3.092)*
					RLO						
0.004 (2.035)**	-0.025 (-3.002)*	-0.002 (-0.179)	-0.139 (-1.169)	0.352 (2.487)**	0.000 (1.177)	0.075 (2.293)**	0.862 (20.823)*	0.000 (0.612)	-0.002 (-1.8)***	0.000 (0.022)	-0.007 (-1.338)

Appendix 6B - Maximum likelihood estimates for GARCH(1,1) model with decomposed exogenous variables: individual stocks (continued)

α_0	η_1	η_2	η_3	η_4	ϕ_0	λ_1	θ_1	φ_1	φ_2	φ_3	φ_4
SAB											
0.003 (1.88)***	-0.014 (-1.9)***	0.018 (1.529)	0.025 (0.217)	0.025 (0.188)	-0.000 (-3.358)*	-0.001 (-0.191)	0.976 (64.859)*	0.000 (1.630)	-0.000 (-1.589)	0.006 (2.937)*	-0.001 (-0.544)
SAP											
0.000 (0.204)	-0.005 (-0.997)	-0.009 (-0.822)	0.106 (0.747)	-0.173 (-0.956)	0.000 (1.528)	0.046 (2.045)**	0.922 (18.466)*	-0.000 (-0.287)	-0.001 (-0.885)	0.003 (0.684)	-0.002 (-0.253)
SBK											
0.002 (0.991)	-0.008 (-1.434)	-0.000 (-0.029)	-0.116 (-1.129)	-0.118 (-1.120)	0.000 (2.014)**	0.115 (2.525)**	0.789 (14.782)*	0.000 (0.684)	-0.001 (-1.7)***	-0.001 (-0.345)	-0.007 (-1.7)***
TBS											
0.003 (1.427)	-0.010 (-1.449)	0.001 (0.082)	-0.15 (-1.88)***	0.034 (0.346)	0.000 (2.014)**	0.030 (1.94)***	0.905 (22.980)*	0.000 (1.238)	0.000 (0.836)	-0.000 (-0.251)	0.002 (0.785)
TNT											
0.004 (2.115)**	-0.022 (-3.177)*	-0.007 (-0.672)	-0.068 (-0.573)	0.039 (0.373)	0.000 (2.014)**	0.054 (2.220)**	0.867 (13.545)*	-0.001 (-0.458)	-0.001 (-1.7)***	0.004 (0.750)	0.007 (1.66)***
TRE											
0.005 (1.024)	-0.001 (-0.155)	0.008 (1.398)	0.085 (0.347)	0.206 (1.298)	0.008 (5.479)*	0.132 (0.844)	0.599 (3.969)*	-0.003 (-0.683)	0.006 (4.535)*	0.001 (0.007)	0.007 (0.066)
VNF											
-0.002 (-1.054)	-0.004 (-0.473)	0.009 (1.060)	0.228 (1.85)***	-0.101 (-3.937)*	0.001 (4.366)*	0.019 (0.567)	0.580 (4.369)*	0.001 (0.545)	0.001 (1.084)	0.006 (0.958)	0.027 (7.417)*
WAR											
-0.000 (-0.116)	-0.022 (-2.24)**	-0.008 (-1.023)	0.004 (0.086)	-0.042 (-0.166)	0.000 (2.104)**	0.119 (4.303)*	0.851 (29.709)*	0.001 (0.715)	0.000 (0.749)	-0.010 (-3.620)*	-0.014 (-1.092)
WLO											
0.002 (1.118)	-0.018 (-12.60)*	-0.008 (-0.539)	-0.288 (-3.842)*	0.019 (0.137)	0.001 (2.881)*	0.105 (2.512)**	0.342 (2.690)*	-0.000 (-9.148)*	-0.005 (-3.270)*	-0.011 (-3.043)*	-0.055 (-2.17)**

Appendix 6C – BDS tests for standardised residuals from GARCH(1,1) model with exogenous variables

This appendix presents the BDS test statistics for the standardised residual estimates from the GARCH(1,1) model with exogenous variables (see 6.1 to 6.3). Test and entry details are the same as in Appendix 4B.

I. **Test statistics for** $l = 0.5\sigma$

a) Stock portfolios

#	Portfolio	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	-0.305 (0.836)	0.388 (0.644)	0.614 (0.506)	1.464 (0.184)
2	PORT	0.260 (0.730)	0.441 (0.620)	0.817 (0.372)	1.215 (0.254)

b) Individual stocks

#	Security	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	2.149 (0.034)**	2.679 (0.008)*	3.033 (0.004)*	2.596 (0.022)**
2	AFX	1.487 (0.137)	1.077 (0.281)	0.942 (0.346)	1.191 (0.234)
3	AGL	3.317 (0.002)*	4.092 (0.002)*	5.058 (0.004)*	6.028 (0.002)*
4	ALT	0.357 (0.721)	0.420 (0.674)	0.639 (0.523)	0.702 (0.483)
5	ANG	0.192 (0.766)	-0.024 (0.964)	-0.120 (0.970)	-0.165 (0.984)
6	ASR	2.507 (0.030)**	2.992 (0.006)*	2.876 (0.004)*	3.020 (0.002)*
7	AVI	3.299 (0.002)*	3.416 (0.000)*	3.095 (0.010)**	3.066 (0.020)**
8	BAW	1.864 (0.062)	1.476 (0.162)	1.472 (0.154)	1.791 (0.122)
9	BVT	3.199 (0.002)*	4.357 (0.000)*	5.144 (0.000)*	5.942 (0.000)*
10	CHE	1.410 (0.190)	2.582 (0.022)**	3.572 (0.008)*	4.365 (0.000)*
11	CRH	2.832 (0.005)*	2.439 (0.022)**	2.173 (0.040)**	1.257 (0.196)
12	CTP	1.097 (0.278)	2.529 (0.028)**	2.404 (0.040)**	2.621 (0.026)**
13	DEL	2.656 (0.012)**	3.440 (0.002)*	4.234 (0.000)*	5.090 (0.000)*
14	DUR	1.932 (0.058)	2.495 (0.018)**	2.711 (0.020)**	3.336 (0.006)*
15	ECO	1.660 (0.096)	2.751 (0.008)*	3.609 (0.000)*	4.378 (0.000)*
16	ELH	3.212 (0.000)*	3.659 (0.002)*	4.102 (0.000)*	4.037 (0.000)*
17	FOS	5.730 (0.000)*	5.103 (0.000)*	6.167 (0.000)*	7.869 (0.000)*
18	GMF	2.884 (0.014)**	2.654 (0.022)**	2.981 (0.028)**	3.400 (0.026)**
19	HAR	1.952 (0.064)	2.276 (0.030)**	2.461 (0.030)**	2.390 (0.040)**
20	HLH	1.443 (0.000)*	2.567 (0.024)**	2.468 (0.032)**	2.513 (0.032)**
21	HVL	4.172 (0.000)*	3.435 (0.000)*	3.479 (0.000)*	3.092 (0.008)*
22	IMP	0.635 (0.504)	1.314 (0.226)	1.470 (0.182)	2.042 (0.088)
23	JCM	0.942 (0.306)	3.672 (0.000)*	4.713 (0.000)*	5.352 (0.000)*
24	JNC	8.635 (0.000)*	10.297 (0.000)*	12.115 (0.000)*	14.305 (0.000)*
25	LGL	2.604 (0.018)**	2.428 (0.018)**	2.431 (0.020)**	3.193 (0.012)**
26	MAF	1.412 (0.150)	1.158 (0.184)	1.275 (0.140)	1.601 (0.096)
27	MLB	7.828 (0.000)*	9.159 (0.000)*	9.492 (0.000)*	10.275 (0.000)*
28	NED	0.696 (0.462)	0.681 (0.466)	0.124 (0.836)	-0.503 (0.726)
29	NPK	2.942 (0.014)**	2.945 (0.016)**	2.829 (0.018)**	3.569 (0.006)*
30	OCE	1.053 (0.280)	2.438 (0.040)**	3.469 (0.002)*	4.405 (0.000)*
31	PAM	3.299 (0.002)*	4.249 (0.000)*	4.680 (0.000)*	5.199 (0.000)*
32	PIK	2.090 (0.052)	1.854 (0.092)	1.998 (0.080)	2.325 (0.058)
33	PPC	1.608 (0.104)	0.679 (0.446)	0.576 (0.516)	0.507 (0.534)
34	REM	-3.979 (0.000)*	-3.810 (0.002)*	-3.320 (0.008)*	-2.590 (0.032)**
35	RLO	3.126 (0.002)*	4.455 (0.000)*	4.937 (0.000)*	4.914 (0.002)*
36	SAB	2.521 (0.018)**	3.211 (0.004)*	3.735 (0.002)*	3.397 (0.018)**
37	SAP	2.585 (0.008)*	3.154 (0.002)*	3.995 (0.002)*	4.419 (0.002)*
38	SBK	0.382 (0.764)	0.302 (0.756)	-0.087 (0.954)	-0.119 (0.942)
39	TBS	1.402 (0.196)	0.679 (0.508)	0.867 (0.412)	0.040 (0.912)
40	TNT	2.863 (0.004)*	3.043 (0.004)*	3.080 (0.008)*	3.249 (0.008)**
41	TRE	6.892 (0.000)*	7.267 (0.000)*	7.968 (0.000)*	8.083 (0.000)*
42	VNF	1.296 (0.184)	2.177 (0.036)**	2.491 (0.028)**	2.230 (0.058)
43	WAR	0.337 (0.668)	0.762 (0.466)	0.599 (0.552)	0.389 (0.688)
44	WLO	3.178 (0.004)*	4.091 (0.000)*	5.372 (0.000)*	6.365 (0.000)*

Appendix 6C – BDS tests for standardised residuals from GARCH(1,1) model with exogenous variables (continued)

II. Test statistics for $l = 1.0\sigma$

a) Stock portfolios

#	*Portfolio*	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	ALSI	-0.698 (0.502)	0.409 (0.600)	0.475 (0.548)	0.687 (0.446)
2	PORT	-0.195 (0.890)	-0.122 (0.988)	-0.261 (0.880)	-0.501 (0.668)

b) Individual stocks

#	*Security*	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	AFE	1.274 (0.166)	1.844 (0.048)**	2.183 (0.026)**	1.806 (0.078)
2	AFX	0.867 (0.306)	0.744 (0.426)	0.513 (0.560)	0.739 (0.384)
3	AGL	3.918 (0.000)*	4.647 (0.000)*	5.376 (0.000)*	6.135 (0.000)*
4	ALT	-0.533 (0.664)	-0.288 (0.864)	0.131 (0.816)	0.247 (0.740)
5	ANG	0.315 (0.722)	0.236 (0.762)	-0.023 (0.954)	-0.182 (0.920)
6	ASR	0.239 (0.802)	0.457 (0.636)	0.659 (0.522)	1.050 (0.304)
7	AVI	2.350 (0.026)**	1.944 (0.052)	1.722 (0.086)	1.657 (0.100)
8	BAW	1.403 (0.150)	1.486 (0.126)	1.718 (0.076)	1.783 (0.072)
9	BVT	2.901 (0.004)*	3.881 (0.000)*	3.826 (0.000)*	4.503 (0.000)*
10	CHE	0.133 (0.834)	0.829 (0.370)	1.473 (0.126)	1.651 (0.086)
11	CRH	2.166 (0.032)**	1.705 (0.110)	1.443 (0.156)	0.913 (0.340)
12	CTP	0.780 (0.376)	1.704 (0.070)	1.771 (0.066)	1.992 (0.040)**
13	DEL	2.367 (0.014)**	1.509 (0.142)	1.182 (0.248)	1.437 (0.156)
14	DUR	1.322 (0.214)	2.256 (0.018)**	2.352 (0.016)**	2.565 (0.014)**
15	ECO	1.665 (0.108)	2.633 (0.008)*	3.221 (0.002)*	3.426 (0.002)*
16	ELH	2.428 (0.024)**	2.345 (0.024)**	2.083 (0.044)**	1.965 (0.068)
17	FOS	3.625 (0.002)*	3.933 (0.002)*	4.144 (0.000)*	4.734 (0.000)*
18	GMF	1.585 (0.088)	1.561 (0.098)	1.891 (0.052)	2.462 (0.014)**
19	HAR	2.112 (0.040)**	2.381 (0.020)**	2.207 (0.034)**	1.893 (0.070)
20	HLH	1.831 (0.062)	2.378 (0.016)**	1.917 (0.058)	1.989 (0.062)
21	HVL	3.124 (0.002)*	2.432 (0.012)**	2.370 (0.022)**	2.034 (0.052)
22	IMP	-0.177 (0.938)	0.313 (0.692)	0.427 (0.614)	0.759 (0.418)
23	JCM	0.041 (0.936)	1.914 (0.090)	2.719 (0.016)**	2.964 (0.006)*
24	JNC	7.262 (0.000)*	8.120 (0.000)*	9.626 (0.000)*	11.175 (0.000)*
25	LGL	2.905 (0.014)**	2.181 (0.040)**	1.673 (0.106)	2.077 (0.048)**
26	MAF	1.312 (0.238)	1.519 (0.132)	1.645 (0.072)	1.805 (0.052)
27	MLB	7.132 (0.000)*	8.399 (0.000)*	8.523 (0.000)*	8.800 (0.000)*
28	NED	-0.130 (0.940)	-0.007 (0.958)	-0.339 (0.794)	-0.740 (0.518)
29	NPK	1.966 (0.080)	1.816 (0.094)	1.686 (0.098)	1.802 (0.072)
30	OCE	1.178 (0.184)	1.926 (0.046)**	2.377 (0.018)**	2.677 (0.012)**
31	PAM	2.955 (0.010)**	3.954 (0.000)*	4.519 (0.000)*	4.511 (0.000)*
32	PIK	0.755 (0.426)	0.761 (0.422)	0.852 (0.368)	1.101 (0.248)
33	PPC	0.841 (0.418)	0.276 (0.790)	0.105 (0.890)	0.205 (0.770)
34	REM	-4.597 (0.000)*	-4.543 (0.000)*	-4.017 (0.000)*	-3.287 (0.002)*
35	RLO	1.289 (0.186)	2.185 (0.040)**	2.583 (0.018)**	2.473 (0.030)**
36	SAB	1.989 (0.058)	2.901 (0.010)**	3.655 (0.000)*	3.628 (0.002)*
37	SAP	2.148 (0.042)	2.822 (0.006)*	3.154 (0.004)*	3.029 (0.004)*
38	SBK	-0.054 (0.960)	-0.220 (0.862)	-0.314 (0.820)	-0.173 (0.940)
39	TBS	0.931 (0.342)	0.852 (0.368)	0.918 (0.318)	0.541 (0.556)
40	TNT	2.351 (0.022)**	1.584 (0.116)	1.253 (0.212)	1.064 (0.300)
41	TRE	5.440 (0.000)*	5.655 (0.000)*	5.927 (0.000)*	5.930 (0.000)*
42	VNF	1.285 (0.182)	1.951 (0.062)	2.093 (0.032)**	2.430 (0.022)**
43	WAR	-0.032 (0.988)	-0.026 (0.960)	-0.343 (0.820)	-0.343 (0.790)
44	WLO	2.521 (0.012)**	2.947 (0.006)*	3.671 (0.002)*	4.008 (0.000)*

Appendix 6C – BDS tests for standardised residuals from GARCH(1,1) model with exogenous variables (continued)

III. Test statistics for $l = 1.5\sigma$

a) Stock portfolios

#	Portfolio	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	ALSI	-0.303 (0.796)	0.580 (0.512)	0.494 (0.548)	0.602 (0.464)
2	PORT	-0.298 (0.770)	-0.064 (0.998)	-0.319 (0.798)	-0.692 (0.528)

b) Individual stocks

#	Security	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	AFE	0.836 (0.338)	1.305 (0.164)	1.483 (0.108)	0.932 (0.310)
2	AFX	0.334 (0.728)	0.417 (0.662)	0.184 (0.846)	0.349 (0.662)
3	AGL	4.635 (0.000)*	5.337 (0.000)*	6.001 (0.000)*	6.401 (0.000)*
4	ALT	0.079 (0.880)	0.010 (0.942)	-0.004 (0.944)	0.150 (0.806)
5	ANG	0.211 (0.772)	0.135 (0.872)	0.030 (0.936)	-0.063 (0.968)
6	ASR	1.020 (0.406)	0.685 (0.538)	0.420 (0.622)	0.878 (0.442)
7	AVI	1.486 (0.144)	0.962 (0.302)	0.696 (0.442)	0.324 (0.720)
8	BAW	1.160 (0.230)	1.304 (0.176)	1.614 (0.102)	1.568 (0.106)
9	BVT	0.670 (0.488)	2.048 (0.058)	2.013 (0.052)	2.485 (0.018)**
10	CHE	-0.311 (0.796)	0.326 (0.720)	0.648 (0.538)	0.811 (0.422)
11	CRH	1.902 (0.072)	1.732 (0.096)	1.512 (0.144)	1.245 (0.206)
12	CTP	-0.418 (0.762)	0.975 (0.310)	1.362 (0.176)	1.697 (0.094)
13	DEL	1.670 (0.120)	0.766 (0.428)	0.229 (0.778)	0.221 (0.772)
14	DUR	0.697 (0.436)	1.180 (0.214)	1.131 (0.254)	1.509 (0.140)
15	ECO	0.976 (0.318)	1.796 (0.074)	2.236 (0.016)**	2.364 (0.016)**
16	ELH	1.070 (0.254)	1.206 (0.176)	0.923 (0.292)	0.908 (0.298)
17	FOS	2.155 (0.040)**	2.580 (0.016)**	2.482 (0.028)**	2.538 (0.018)**
18	GMF	0.910 (0.372)	0.981 (0.366)	1.538 (0.138)	2.223 (0.038)**
19	HAR	1.941 (0.050)	2.298 (0.024)**	2.172 (0.024)**	1.912 (0.056)
20	HLH	1.739 (0.116)	2.397 (0.024)**	1.973 (0.070)	1.991 (0.068)
21	HVL	2.088 (0.034)**	1.228 (0.202)	0.869 (0.330)	0.320 (0.692)
22	IMP	-0.571 (0.586)	-0.224 (0.846)	-0.164 (0.908)	0.161 (0.786)
23	JCM	-0.003 (0.708)	0.571 (0.494)	0.639 (0.458)	0.767 (0.376)
24	JNC	4.910 (0.000)*	5.124 (0.000)*	6.755 (0.000)*	8.253 (0.000)*
25	LGL	2.083 (0.006)*	1.787 (0.082)	1.126 (0.232)	1.376 (0.150)
26	MAF	0.980 (0.370)	0.656 (0.430)	0.911 (0.318)	0.985 (0.254)
27	MLB	5.611 (0.000)*	6.823 (0.000)*	7.008 (0.000)*	7.239 (0.000)*
28	NED	-0.887 (0.366)	-0.367 (0.716)	-0.600 (0.550)	-0.853 (0.388)
29	NPK	0.953 (0.322)	0.457 (0.562)	0.606 (0.498)	0.862 (0.346)
30	OCE	-0.145 (0.964)	0.339 (0.722)	0.507 (0.592)	0.579 (0.516)
31	PAM	2.032 (0.056)	2.958 (0.010)**	3.233 (0.002)*	2.850 (0.016)**
32	PIK	0.620 (0.524)	0.744 (0.428)	0.801 (0.396)	0.990 (0.300)
33	PPC	0.355 (0.664)	-0.067 (0.964)	-0.145 (0.984)	-0.071 (0.944)
34	REM	-4.380 (0.000)*	-4.277 (0.000)*	-3.887 (0.000)*	-3.245 (0.000)*
35	RLO	0.347 (0.670)	1.252 (0.168)	1.380 (0.166)	1.161 (0.232)
36	SAB	1.998 (0.052)	3.163 (0.002)*	4.068 (0.000)*	4.133 (0.000)*
37	SAP	1.684 (0.100)	2.280 (0.042)**	2.437 (0.022)**	2.325 (0.024)**
38	SBK	0.098 (0.848)	-0.538 (0.630)	-0.520 (0.656)	-0.305 (0.788)
39	TBS	0.284 (0.748)	0.354 (0.718)	0.386 (0.684)	0.135 (0.858)
40	TNT	1.774 (0.072)	1.074 (0.238)	0.615 (0.458)	0.534 (0.536)
41	TRE	4.229 (0.014)**	3.771 (0.120)	3.395 (0.014)**	3.636 (0.010)**
42	VNF	0.631 (0.554)	1.239 (0.220)	1.264 (0.226)	1.576 (0.122)
43	WAR	-0.399 (0.770)	-0.553 (0.654)	-0.682 (0.572)	-0.432 (0.766)
44	WLO	1.299 (0.208)	1.739 (0.088)	2.459 (0.020)**	2.592 (0.014)**

Appendix 6D – BDS tests for standardised residuals from GARCH(1,1) model with decomposed exogenous variables

This appendix presents the BDS test statistics for the standardised residual estimates from the GARCH(1,1) model with decomposed exogenous variables (see 6.4 to 6.6). Test and entry details are the same as in Appendix 4B.

I. Test statistics for $l = 0.5\sigma$

a) Stock portfolios

#	Portfolio	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	-1.013 (0.356)	-0.382 (0.780)	-0.203 (0.910)	0.525 (0.558)
2	PORT	0.376 (0.676)	0.647 (0.576)	0.968 (0.512)	1.400 (0.226)

b) Individual stocks

#	Security	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	2.078 (0.070)	2.466 (0.032)**	2.875 (0.018)**	2.421 (0.050)
2	AFX	1.349 (0.172)	0.951 (0.316)	1.067 (0.260)	1.773 (0.104)
3	AGL	1.419 (0.172)	2.217 (0.044)**	2.825 (0.026)**	3.662 (0.016)
4	ALT	-0.370 (0.766)	-0.158 (0.924)	-0.046 (0.876)	-0.022 (0.902)
5	ANG	0.088 (0.886)	0.233 (0.778)	0.474 (0.598)	0.731 (0.516)
6	ASR	2.132 (0.052)	2.552 (0.020)**	2.482 (0.014)**	2.680 (0.006)*
7	AVI	3.406 (0.004)*	3.906 (0.002)*	4.444 (0.002)*	5.734 (0.002)*
8	BAW	4.478 (0.000)*	4.926 (0.000)*	5.621 (0.000)*	6.619 (0.000)*
9	BVT	3.085 (0.000)*	4.390 (0.000)*	5.142 (0.000)*	5.864 (0.000)*
10	CHE	1.790 (0.078)	2.524 (0.024)**	3.457 (0.004)*	4.415 (0.000)*
11	CRH	2.355 (0.016)**	2.038 (0.048)**	1.617 (0.146)	0.750 (0.470)
12	CTP	1.055 (0.238)	2.448 (0.024)**	2.449 (0.030)**	2.677 (0.028)**
13	DEL	1.753 (0.060)	2.724 (0.010)**	3.177 (0.006)*	4.025 (0.002)*
14	DUR	2.036 (0.046)**	2.522 (0.028)**	2.755 (0.012)**	3.401 (0.008)*
15	ECO	2.010 (0.044)**	3.867 (0.000)*	5.380 (0.000)*	6.933 (0.000)*
16	ELH	3.882 (0.002)*	4.350 (0.000)*	4.771 (0.000)*	5.041 (0.000)*
17	FOS	5.458 (0.000)*	5.034 (0.000)*	6.228 (0.000)*	8.267 (0.000)*
18	GMF	2.797 (0.010)**	2.448 (0.034)**	2.737 (0.020)**	3.540 (0.014)**
19	HAR	2.075 (0.056)	2.376 (0.044)**	2.682 (0.030)**	2.541 (0.040)**
20	HLH	1.132 (0.262)	2.396 (0.032)**	2.322 (0.046)**	2.456 (0.050)
21	HVL	3.763 (0.000)*	3.127 (0.006)*	3.386 (0.004)*	3.063 (0.010)**
22	IMP	0.777 (0.398)	1.709 (0.106)	1.928 (0.086)	2.483 (0.048)**
23	JCM	3.335 (0.000)*	6.313 (0.000)*	7.267 (0.000)*	7.929 (0.000)*
24	JNC	10.963 (0.000)*	13.481 (0.000)*	16.194 (0.000)*	19.113 (0.000)*
25	LGL	3.174 (0.006)*	3.202 (0.002)*	3.613 (0.000)*	5.154 (0.000)*
26	MAF	2.132 (0.040)**	1.722 (0.096)	1.664 (0.128)	1.829 (0.106)
27	MLB	7.209 (0.000)*	8.391 (0.000)*	8.631 (0.000)*	9.313 (0.000)*
28	NED	-0.589 (0.574)	-0.219 (0.838)	-0.778 (0.456)	-1.057 (0.316)
29	NPK	3.187 (0.000)*	3.317 (0.002)*	3.213 (0.010)**	4.099 (0.000)*
30	OCE	1.418 (0.130)	2.948 (0.006)*	3.869 (0.002)*	4.737 (0.000)*
31	PAM	1.900 (0.066)	2.876 (0.004)*	3.120 (0.006)*	3.235 (0.012)**
32	PIK	2.007 (0.042)**	1.759 (0.078)	1.575 (0.122)	1.857 (0.092)
33	PPC	1.134 (0.246)	0.578 (0.524)	0.871 (0.378)	1.175 (0.252)
34	REM	-3.547 (0.000)*	-3.863 (0.000)*	-3.509 (0.002)*	-2.966 (0.014)**
35	RLO	3.097 (0.004)*	4.137 (0.000)*	4.518 (0.000)*	4.519 (0.000)*
36	SAB	3.272 (0.004)*	4.254 (0.000)*	5.132 (0.000)*	5.453 (0.000)*
37	SAP	2.349 (0.048)**	3.048 (0.010)**	3.900 (0.002)*	4.171 (0.004)*
38	SBK	0.198 (0.784)	0.208 (0.804)	0.016 (0.928)	0.060 (0.886)
39	TBS	1.455 (0.122)	0.912 (0.350)	1.145 (0.254)	0.580 (0.566)
40	TNT	2.696 (0.018)**	3.080 (0.010)**	3.221 (0.008)*	3.404 (0.012)**
41	TRE	6.250 (0.000)*	6.499 (0.000)*	6.951 (0.000)*	6.969 (0.000)*
42	VNF	1.755 (0.068)	2.607 (0.016)**	2.927 (0.020)**	2.660 (0.032)**
43	WAR	0.369 (0.654)	0.663 (0.476)	0.448 (0.608)	0.229 (0.740)
44	WLO	3.712 (0.000)*	4.616 (0.000)*	6.215 (0.000)*	7.339 (0.000)*

Appendix 6D – BDS tests for standardised residuals from GARCH(1,1) model with decomposed exogenous variables (continued)

II. Test statistics for $l = 1.0\sigma$

a) Stock portfolios

#	*Portfolio*	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	-1.431 (0.158)	-0.374 (0.756)	-0.345 (0.798)	-0.136 (0.974)
2	PORT	-0.120 (0.958)	0.161 (0.794)	0.009 (0.914)	-0.236 (0.880)

b) Individual stocks

#	*Security*	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	1.602 (0.132)	1.869 (0.072)	2.077 (0.048)**	1.626 (0.098)
2	AFX	0.700 (0.432)	0.717 (0.414)	0.477 (0.520)	0.736 (0.360)
3	AGL	1.669 (0.080)	2.621 (0.014)**	3.226 (0.004)*	3.884 (0.004)*
4	ALT	-0.806 (0.418)	-0.234 (0.872)	0.185 (0.778)	0.388 (0.638)
5	ANG	-0.006 (0.920)	-0.023 (0.944)	-0.202 (0.914)	-0.256 (0.866)
6	ASR	-0.250 (0.952)	0.128 (0.848)	0.390 (0.706)	0.866 (0.424)
7	AVI	2.505 (0.018)**	2.342 (0.030)**	2.584 (0.020)**	3.009 (0.004)*
8	BAW	3.511 (0.000)*	4.235 (0.000)*	4.736 (0.000)*	5.331 (0.000)*
9	BVT	2.761 (0.006)*	3.783 (0.000)*	3.649 (0.000)*	4.356 (0.000)*
10	CHE	-0.021 (0.986)	0.670 (0.504)	1.395 (0.150)	1.623 (0.084)
11	CRH	1.948 (0.052)	1.522 (0.124)	1.055 (0.256)	0.479 (0.598)
12	CTP	1.000 (0.334)	1.919 (0.046)**	2.124 (0.038)**	2.394 (0.018)**
13	DEL	0.798 (0.406)	0.675 (0.498)	0.909 (0.364)	1.446 (0.156)
14	DUR	1.544 (0.118)	2.410 (0.014)**	2.465 (0.016)**	2.638 (0.010)**
15	ECO	0.404 (0.654)	1.818 (0.062)	2.608 (0.008)*	2.972 (0.002)*
16	ELH	2.107 (0.024)**	2.044 (0.040)**	1.709 (0.084)	1.741 (0.074)
17	FOS	3.219 (0.000)*	3.110 (0.002)*	3.334 (0.000)*	4.104 (0.000)*
18	GMF	1.310 (0.196)	1.124 (0.252)	1.481 (0.120)	2.218 (0.042)**
19	HAR	2.157 (0.022)**	2.585 (0.004)*	2.448 (0.014)**	2.147 (0.026)**
20	HLH	1.343 (0.176)	1.954 (0.066)	1.600 (0.132)	1.692 (0.110)
21	HVL	2.805 (0.006)*	2.093 (0.040)*	2.093 (0.050)	1.811 (0.096)
22	IMP	-0.165 (0.908)	0.719 (0.442)	0.950 (0.314)	1.318 (0.188)
23	JCM	1.357 (0.238)	3.445 (0.010)**	4.106 (0.002)*	4.221 (0.000)*
24	JNC	9.682 (0.000)*	11.169 (0.000)*	13.191 (0.000)*	14.882 (0.000)*
25	LGL	2.920 (0.004)*	2.074 (0.050)	1.852 (0.084)	2.776 (0.012)**
26	MAF	1.868 (0.098)	2.410 (0.028)**	2.352 (0.030)**	2.346 (0.030)**
27	MLB	6.335 (0.000)*	7.415 (0.000)*	7.400 (0.000)*	7.635 (0.000)*
28	NED	-1.247 (0.242)	-8.873 (0.462)	-1.102 (0.330)	-1.362 (0.182)
29	NPK	2.179 (0.028)**	2.137 (0.038)**	1.933 (0.064)	1.986 (0.052)
30	OCE	1.524 (0.152)	2.381 (0.030)**	2.834 (0.006)*	3.034 (0.006)*
31	PAM	1.447 (0.134)	2.563 (0.020)**	3.040 (0.004)*	2.821 (0.006)*
32	PIK	0.918 (0.332)	0.948 (0.316)	0.911 (0.334)	1.109 (0.278)
33	PPC	0.483 (0.606)	0.479 (0.594)	0.457 (0.588)	0.634 (0.486)
34	REM	-4.259 (0.000)*	-4.472 (0.000)*	-3.997 (0.000)*	-3.405 (0.000)*
35	RLO	1.613 (0.114)	2.243 (0.030)**	2.607 (0.016)**	2.608 (0.028)**
36	SAB	2.636 (0.010)**	3.997 (0.000)*	4.922 (0.000)*	5.091 (0.000)*
37	SAP	2.215 (0.032)**	2.935 (0.000)*	3.212 (0.002)*	2.988 (0.004)*
38	SBK	-0.252 (0.852)	-0.349 (0.768)	-0.339 (0.774)	-0.088 (0.986)
39	TBS	0.766 (0.410)	0.668 (0.456)	0.782 (0.368)	0.457 (0.578)
40	TNT	2.059 (0.042)**	1.379 (0.168)	1.061 (0.232)	0.866 (0.324)
41	TRE	4.187 (0.000)*	4.103 (0.000)*	4.274 (0.000)*	4.278 (0.000)*
42	VNF	1.725 (0.074)	2.571 (0.012)**	2.754 (0.010)**	3.089 (0.008)*
43	WAR	-0.003 (0.992)	-0.118 (0.954)	-0.455 (0.668)	-0.374 (0.744)
44	WLO	2.726 (0.006)*	3.295 (0.004)*	3.942 (0.000)*	4.174 (0.000)*

Appendix 6D – BDS tests for standardised residuals from GARCH(1,1) model with decomposed exogenous variables (continued)

III. Test statistics for $l = 1.5\sigma$

a) Stock portfolios

#	*Portfolio*	$m=2$	$m=3$	$m=4$	$m=5$
1	ALSI	-1.185 (0.244)	-0.406 (0.714)	-0.485 (0.658)	-0.342 (0.842)
2	PORT	-0.207 (0.856)	0.209 (0.816)	0.016 (0.930)	-0.323 (0.782)

b) Individual stocks

#	*Security*	$m=2$	$m=3$	$m=4$	$m=5$
1	AFE	0.890 (0.344)	1.027 (0.268)	1.131 (0.222)	0.577 (0.482)
2	AFX	0.497 (0.588)	0.690 (0.468)	0.430 (0.642)	0.744 (0.452)
3	AGL	2.123 (0.052)	3.219 (0.000)*	3.976 (0.000)*	3.976 (0.000)*
4	ALT	-0.806 (0.468)	-0.234 (0.906)	0.185 (0.774)	0.388 (0.616)
5	ANG	-0.068 (0.982)	-0.118 (0.970)	-0.246 (0.864)	-0.317 (0.822)
6	ASR	0.833 (0.484)	0.564 (0.550)	0.290 (0.702)	0.722 (0.500)
7	AVI	1.587 (0.100)	1.326 (0.188)	1.596 (0.114)	1.709 (0.072)
8	BAW	3.071 (0.006)*	3.871 (0.000)*	4.303 (0.000)*	4.716 (0.000)*
9	BVT	0.528 (0.558)	1.950 (0.060)	1.959 (0.058)	2.472 (0.018)**
10	CHE	-0.121 (0.954)	0.449 (0.584)	0.774 (0.368)	0.916 (0.294)
11	CRH	1.854 (0.082)	1.631 (0.104)	1.318 (0.174)	0.999 (0.290)
12	CTP	0.407 (0.630)	1.829 (0.064)	2.262 (0.024)**	2.568 (0.008)*
13	DEL	-0.564 (0.542)	-0.582 (0.526)	-0.279 (0.776)	0.057 (0.914)
14	DUR	0.900 (0.348)	1.309 (0.170)	1.206 (0.206)	1.498 (0.120)
15	ECO	-0.234 (0.912)	1.070 (0.258)	1.640 (0.084)	1.955 (0.040)**
16	ELH	0.791 (0.402)	0.786 (0.366)	0.431 (0.606)	0.457 (0.572)
17	FOS	1.525 (0.124)	1.722 (0.090)	1.609 (0.118)	1.793 (0.082)
18	GMF	-0.128 (0.964)	-0.171 (0.924)	0.409 (0.610)	1.186 (0.178)
19	HAR	2.110 (0.036)**	2.526 (0.016)**	2.386 (0.028)**	2.179 (0.042)**
20	HLH	1.341 (0.182)	1.944 (0.054)	1.535 (0.124)	1.576 (0.116)
21	HVL	1.979 (0.070)	1.146 (0.260)	0.856 (0.398)	0.365 (0.678)
22	IMP	-0.498 (0.602)	0.286 (0.726)	0.433 (0.640)	0.718 (0.456)
23	JCM	0.241 (0.680)	0.944 (0.390)	0.935 (0.354)	1.083 (0.288)
24	JNC	7.913 (0.000)*	8.511 (0.000)*	10.593 (0.000)*	13.248 (0.000)*
25	LGL	2.606 (0.028)**	1.618 (0.128)	1.380 (0.166)	2.231 (0.036)**
26	MAF	2.550 (0.032)**	2.376 (0.034)**	2.155 (0.052)	2.043 (0.056)
27	MLB	4.631 (0.000)*	5.913 (0.000)*	5.999 (0.000)*	6.130 (0.000)*
28	NED	-1.697 (0.096)	-1.250 (0.224)	-1.347 (0.182)	-1.527 (0.116)
29	NPK	1.181 (0.214)	0.749 (0.416)	0.919 (0.300)	1.161 (0.214)
30	OCE	0.624 (0.494)	1.121 (0.252)	1.141 (0.234)	1.045 (0.288)
31	PAM	0.682 (0.488)	1.699 (0.098)	2.072 (0.046)**	1.660 (0.112)
32	PIK	0.888 (0.400)	1.077 (0.254)	1.099 (0.254)	1.237 (0.192)
33	PPC	0.428 (0.630)	0.632 (0.474)	0.436 (0.592)	0.568 (0.530)
34	REM	-4.141 (0.000)*	-4.264 (0.000)*	-3.933 (0.000)*	-3.490 (0.000)*
35	RLO	0.547 (0.538)	1.134 (0.268)	1.316 (0.220)	1.118 (0.276)
36	SAB	2.176 (0.030)**	3.970 (0.000)*	4.987 (0.000)*	5.317 (0.000)*
37	SAP	1.858 (0.072)	2.379 (0.028)**	2.463 (0.014)**	2.313 (0.024)**
38	SBK	0.052 (0.882)	-0.721 (0.506)	-0.639 (0.570)	-0.394 (0.758)
39	TBS	0.099 (0.944)	0.067 (0.988)	0.103 (0.454)	-0.087 (0.876)
40	TNT	1.509 (0.168)	0.768 (0.428)	0.304 (0.706)	0.222 (0.746)
41	TRE	2.722 (0.108)	2.280 (0.118)	1.934 (0.140)	2.085 (0.108)
42	VNF	1.253 (0.204)	2.104 (0.052)	2.190 (0.046)**	2.482 (0.024)**
43	WAR	-0.312 (0.832)	-0.535 (0.650)	-0.696 (0.540)	-0.0.465 (0.710)
44	WLO	1.766 (0.096)	1.938 (0.076)	2.287 (0.020)**	2.261 (0.024)**

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