Predictability of Share Price Returns on the JSE

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Abstract

This study addresses the issue of share price predictability on the JSE Securities Exchange (JSE) over the 1989 to 2009 period. The overall predictability of the JSE in terms of market indices and individual share prices is examined. The predictability in prices of portfolios formed by ranking shares according to a number of easily observable benchmarks is also investigated. Finally, the study identifies leading indicators of the returns of these ranked portfolios.

Using a variance ratio test, the study finds little evidence to reject the hypothesis of uncorrelated increments in the JSE All Share Index or in the returns of individual shares. The study does, however, reject the hypothesis that returns of portfolios ranked according to market capitalisation, dividend yield, earnings yield, industry and trading volume are serially uncorrelated. Furthermore, the strong rejections of these hypotheses retain their statistical significance in the presence of heteroskedasticity in portfolio returns.

In line with the results of previous research, the study finds that serial correlation in portfolios increases as the market capitalisation and average trading volume of its constituents decrease. Portfolios containing high dividend and earnings yielding shares are also found to have a high degree of serial correlation. When ranked according to the industry in which their constituents are classified, portfolios of industrial and retail shares show significant levels of serial correlation. Analyses of the lead and lag characteristics of portfolios show that the returns of portfolios consisting of large capitalisation and well traded shares lead those consisting of small capitalisation and thinly traded shares.

The economic and statistical significance of the results show a significant deviation from the commonly held view that the JSE is an efficient market. From the point of view of an investor seeking a potential avenue of excess return, the challenge lies in constructing a trading strategy and a portfolio with sufficient serial correlation to be robust to the costs incurred from frequent trading.

Declaration

I, Ryan Mark Lishman, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

(Ryan Mark Lishman)

Signed at Johannesburg, on the 15th day of December 2009

The Lover of my soul – All riches come from You

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Chapter 1

Introduction

"THE DIFFICULTY LIES NOT SO MUCH IN DEVELOPING NEW IDEAS AS IN ESCAPING FROM OLD ONES." – JOHN MAYNARD KEYNES

1.1 Overview

It is a generally held view amongst finance academics that share prices on major stock exchanges fully reflect all available information. Consequently, in terms of the pioneering definition of Eugene Fama (1970), markets are efficient, share price increments follow unforecastable random trajectories and, in the context of stock market trading, investment advisors have an equivalent standing with fortune tellers (or dart throwing chimpanzees, depending on the malevolence of the claimant).

A consequence of the unpredictability of markets is that it is impossible to beat the market using publicly available information. This includes any active investment strategy based on fundamental or technical analyses. Efficient market theorists advocate that investors should rather save themselves the fees associated with active portfolio management and invest in a market tracking index fund, i.e. they should buy and hold the market portfolio.

This research report is aimed at testing the validity of this view by determining whether share prices on the JSE Securities Exchange (JSE) are predictable to any degree and exploring the relationship between this predictability and a number of easily observable market factors. As well as casting more light on the nature of share price formation on the JSE, it is the hope of this author that this predictability may be used to derive profitable share trading strategies.

1.2 Background

The bulk of the research into market efficiency, particularly research conducted in the 1970s, supports the assertion that financial markets are efficient. Surveys of the evidence related to market efficiency (Fama 1970, 1991, 1998; Lo 2007) conclude that markets are efficient and that all claimed predictability in share prices arises as a result of peculiarity of the study method and data set used.

Despite the popularity of this view, particularly amongst academics, irrefutable evidence exists to its contrary. Campbell and Shiller (1988) find that share prices exhibit significant excess volatility that cannot be explained by the arrival of new information. By employing a powerful variance ratio test, Lo and MacKinlay (1988) find significant predictability in weekly portfolio returns, particularly those composed of the shares of smaller firms. They attribute this predictability to the fact that share prices of larger firms lead those of smaller firms. Jegadeesh and Titman (1993, 2001) find that investors who employed medium term momentum investing strategies on the New York Stock Exchange (NYSE) in the 1965 to 1998 period earned significant and consistent excess returns relative to the market. George and Hwang (2004) show significant excess profits by employing a strategy that buys shares on the basis of the nearness of their price to the highest price of the share in the previous 52 weeks.

Instead of share prices being almost instantaneously traded back to fundamental value by rational investors as the hypothesis of efficient markets requires, much of the evidence suggests that share prices wander above, below, and at times far from a share's fundamental value, showing mean reversion and momentum effects at various times. In describing this characteristic of share prices, Fischer Black (1986) proposes a looser, but somewhat more believable, version of the theory of efficient markets. Black (1986) suggests that most markets are efficient 90% of the time, where efficiency is defined as the characteristic that price and fundamental value are within a factor of two from one another.

Being a major financial market, the JSE has not escaped the scrutiny of economists and has been the subject of many studies related to market efficiency. A survey of the research conducted by Thompson and Ward (1995) concludes that the JSE is largely efficient and where inefficiencies exist, they are unable to yield significant profit for the investor.

Thompson and Ward (1995) provide a detailed review of the research into market efficiency on the JSE. Though most of their review is devoted to research related to event studies, they do provide a comprehensive summary of the research on the JSE related to predictability in share price returns. In the research related to share price predictability on the JSE, there does not appear to be much research that uses newer methods for testing the efficiency of prices, such as the variance ratio test used by Lo and MacKinlay (1988). There is a similar lack of research into the profitability of trading strategies on the JSE that derive their gains from the types of inefficiencies discovered in international markets. In international markets, this gap has been filled by the pioneering research of Jegadeesh and Titman (1993, 2001) and Rouwenhorst (1998) into the profitability of short and medium term momentum trading strategies on major financial markets around the world.

Curiously, on the JSE, there has been significant research effort exerted into long term negative serial correlation in index prices (Bhana 1989) and the profitability of long term contrarian trading strategies (Page and Way 1992; Muller 1999; Cubbin, Eidne, Firer and Gilbert 2006) that rely on investor overreaction of the type popularized by De Bondt and Thaler (1985, 1989). This research lacks credibility because it relies on an effect that has a duration of three to five years, while only typically using 20 years' worth of JSE market data. This yields an extremely small sample size, compromising the external validity of the research. Indeed, even research into mean reversion trading strategies conducted on the NYSE, with over 65 years' worth of market data has been criticised for having an insufficient sample size (Poterba and Summers 1988; Campbell, Lo and MacKinlay 1997).

Existence of the more irrefutable manifestations of return predictability, such as the strong positive serial correlation in market and portfolio prices documented by Lo and MacKinlay (1988) and the significant and sustained profitability of the momentum strategies of Jegadeesh and Titman (1993, 2001) have not received much attention on the JSE. The research of Jammine and Hawkins (1974), who find significant positive serial correlation in index prices over a seven year period, as well as that of Muller (1999), who finds that momentum trading strategies earn excess returns in the short term, are two isolated exceptions to the dearth of research into short to medium term returns predictability on the JSE.

1.3 Research problem

1.3.1 Problem statement

The aim of this research is to establish the degree of predictability of share prices on the JSE and the nature of this predictability.

1.3.2 Sub-problems

1. The first sub-problem is to ascertain the overall degree of predictability of JSE shares prices, when examined individually and collectively.

2. The second sub-problem is to relate the predictability in portfolio prices to a number of easily observable market characteristics or benchmarks.

3. The third sub-problem is to identify any lead or lag relationships in the prices of portfolios grouped according to these benchmarks.

1.4 Importance of the research

Any research into rationally formed, efficient share prices is of value. The reason for this is the pivotal role that the assumption of rationally formed prices plays in modern finance. Every major financial theory, from Markowitz's portfolio selection theory to Sharpe and Lintner's Capital Asset Pricing Model to the Black-Scholes equations for options pricing, assumes rationally formed prices. The way in which the finance profession views risk synonymously with the volatility in share prices is inextricably linked to the assumption that price is a rational reflection of a share's fundamental value. Consequently, this assumption should be tested rigorously.

The study is made particularly relevant by the fact that the existing research into share price predictability on the JSE in the short to medium term is lacking. Equivalent research performed on other major stock exchanges round the world have generated a large degree of insight and subsequent investigation into the predictability of returns, ultimately adding significantly to the understanding of the behaviour of share prices on those exchanges.

Finally, this research attempts to go beyond the usual question of whether or not the JSE is efficient by attempting to relate price inefficiency to observed market factors. As such, it offers more insight into the price formation process and uptake of information in share prices on the JSE than simply testing for market efficiency in its weak form.

Investors are, and always will be, interested in finding sources of excess return or 'out-performance'. Any study that is able to demonstrate the existence of potential for excess return is of relevance to investors. From a practical perspective, this research offers a potential additional tool in the arsenal of technical analysts. A significant degree of market inefficiency will hopefully, though fleetingly, be able to yield a degree of excess return to investors.

Since demonstrated market inefficiencies frequently disappear after they are exposed through the actions of traders seeking to exploit them (Fama 1970, 1998), this research is significant from an economic perspective in that, by exposing inefficiencies, it will tend to make the JSE more efficient. The more efficient a market is, the more prices reflect fundamental values and the more the theories upon which the finance profession so relies better approximate the actual workings of markets.

1.5 Definitions and terms

Event study – An event study is a statistical investigation into the effect of a particular event, such as a merger or issue of shares, on the value of a firm.

Bid-ask bounce – Bid-ask bounce refers to the tendency of share prices to oscillate between the higher value that sellers ask for a share and the lower price that buyers bid when they wish to buy a share. The actual transaction price tends to 'bounce' between these two prices, causing spurious negative serial correlation

1.6 Assumptions and delimitations

The research utilises weekly closing price data of 467 shares on the JSE from the period March 1989 to March 2009. Market microstructure effects such as the bid-offer spreads and weekly high and lows of the shares price moves do not appear in the data set.

Other effects on the share price such as new share issues, share splits, etc, have not been corrected for, however, owing to the complexity in correcting for these effects for 467 shares over a period of twenty years.

Also not reflected in the raw closing price is the effect of dividends issued by the company. To address this, for each share that traded on the JSE in the 1989 to 2009 period, a price series that includes the effect of dividend reinvestment was formed. This dividend inclusive price series is used in variance ratio and lead-lag calculations.

Another market microstructure effect neglected in this study is that of non-synchronous trading. While this will be discussed in detail in section 2.2.2, non-synchronous trading is related to the effect that occurs when, in the absence of a recent trade, the historical price of thinly traded shares is thought to be the current price. In order to mitigate this effect in this research, shares which did not trade at least 90% of the time were excluded from calculation of variance ratios and lead lag effects.

Finally, while lead-lag relationships among the factors linked to serial correlation will be determined in the third sub-problem, no attempt will be made to answer the question of causality among the factors. This is a significant additional research problem which is suggested for future research. Similarly, no analysis of trading based on identified inefficiency and leading indicators using actual market data will be performed. Again, this is a significant research problem in itself.

Chapter 2

Literature Review

"I'D BE A BUM ON THE STREET WITH A TIN CUP IF THE MARKETS WERE ALWAYS EFFICIENT." - WARREN BUFFET

The literature review is organised broadly into two parts. The first, sections 2.1 and 2.2, is a background treatment of the theory related to the share price formation process and the popular concepts related to stock market efficiency and predictability. In this part, theoretical forms of the random walk hypothesis and the martingale model of the efficient markets hypothesis are put forward. Practical limitations to the assumptions underlying the hypothesis of market efficiency are discussed. The second part of the literature review, sections 2.3 and 2.4, discusses the various ways in which prices are predictable and their relative merits and criticisms. Section 2.5 concludes the literature review, giving a summary of how the literature relates to the research conducted in this study.

Since the research into share price predictability is abundant and broad, certain areas are necessarily omitted from the literature review. Anomalies such as seasonality effects, the effect of certain firm specific events on share prices, market crashes and other similar findings related to events are neglected in this review. These are by no means insignificant, however, and the interested reader is referred to several excellent reviews on market efficiency, such as those of Fama (1991, 1998) and Lo (2007).

2.1 Background discussion

2.1.1 Towards Efficient Markets: The Random Walk Hypothesis

The literature relating to the modelling of share prices as random walks dates back to the dawn of the 20th century, when a French mathematician, Louis Bachelier, postulated that share prices follow random walks. Bachelier also described the mathematics of continuous time Brownian motion five years before Einstein published similar results which he applied to the physical sciences fields. Unfortunately, this work was only rediscovered in the 1950s, after other economists, such as Cowles (1933, 1944, 1960), Working (1949, 1958) and Kendall (1953) had arrived at similar conclusions through empirical analysis.

A random walk can be described as a trajectory that is made up of successive random steps (Fu and Madan 2007). In the limit, where the step size is taken to be infinitesimally small, Brownian motion results. Fama (1965) describes the statistical properties of a random walk as follows:

1. Successive price changes are independent of one another
2. Price changes are randomly distributed according to some probability distribution.

Fama argues that a random walk arises from the random arrival of new information which is 'instantaneously' incorporated into a company's share prices. If this were the case, it would be impossible to anticipate its value from known information, since any information would already have been instantaneously incorporated into the price as it occurred. Although Samuelson (1965) mathematically demonstrates this fact, he is quick to caution that his proof offers no indication as to the workings of actual markets.

Fama (1965), however, argues that in a market that has a number of 'superior analysts' (those who are able to better judge the intrinsic value of shares than other traders), any inefficiencies that exist in share prices represent arbitrage opportunities for these analysts. Such superior analysts will quickly take advantage of these opportunities, bringing the share price back to its intrinsic value. Thus, claims Fama (1965), even when the actions of traders are correlated and not dependant on new information, 'arbitrage capital' is able to keep prices at fundamental levels. In support of his reasoning, Fama (1965) analyses serial correlation in 30 shares over a period of just less than five years and finds that though weakly negatively serially correlated, share prices are not predictable enough to be of any benefit to traders. He claims that this will give rise to an 'efficient market', which he describes as *"a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values."* (Fama 1965, pg. 90).

Campbell, Lo and MacKinlay (1997) characterise the Random Walk Hypothesis in terms of three testable forms which are commonly found in the literature researching share prices. These are as follows:

2.1.1.1 ***IID increments***

The most restrictive form of the hypothesis that prices follow random walks is that the increments of price process are independent and identically distributed (IID) according to some distribution. The distribution commonly assumed is the normal distribution, which simplifies many calculations related to tests of the hypothesis under this assumption. The processes which result from the assumption of normally IID increments in price are Arithmetic Brownian Motion (in the case of untransformed increments of price) and Geometric Brownian Motion (in the case of increments in the logarithm of price).

2.1.1.2 ***Independent increments***

The assumption of identically distributed price changes is unrealistic over long period of time. Allowing the parameters of the distribution of price changes to vary over time yields a more general expression of the random walk hypothesis; price increments are independent but not identically distributed (INID). This is equivalent to Fama's 1965 characterisation.

2.1.1.3 ***Uncorrelated increments***

The least restrictive form of the random walk hypothesis and the one most frequently tested in the literature researching predictability in share prices is obtained by relaxing the requirement of independence in price changes. In this form of random walk process, increments in price are merely uncorrelated with one another at all values of lag and lead.

An example of these types of process is the family of prices whose increments are uncorrelated, but whose variances are correlated. Many share price series observed in practice have this property. Large price movements tend to be followed by large price movements of either sign (Fama 1965). Modelling the variance of such a process using autoregressive conditional heteroskedasticity (ARCH) models is an attempt at capturing this dependence in variance.

2.1.2 The Efficient Markets Hypothesis

Arguably the most controversial assertion made by modern finance is that of the hypothesis that markets, and in particular, financial markets are efficient. The formalisation of this hypothesis can be jointly attributed to Eugene Fama (1965) and Paul Samuelson (1965), who, independently, yet at similar times, published research which supported the notion of efficient financial markets.

There exists little consensus as to the definition of an efficient market. At its loosest, the hypothesis that markets are efficient indicates a belief that investors participating in a market act rationally (Le Roy 1989). In a practical sense, the efficient markets hypothesis (EMH) is the belief that it is impossible to make economic profits (risk adjusted returns, after costs) by trading on the basis of publically available information (Jensen 1978). In its purest form, however, the EMH is the hypothesis that *"security prices at any point in time 'fully reflect' all available information."* (Fama 1970, pg. 388). Another way of looking at the EMH is, as highlighted by Jensen (1978) and Le Roy (1989), as a competitive equilibrium condition applied to stock markets. Competitive equilibrium in this sense, means that it is impossible to make arbitrage profits (Grossman and Stiglitz 1980).

Although statements of the EMH as mentioned above offer much understanding, they are too broad to provide a model against which to test the hypothesis of efficient markets (Fama 1970). When expressed merely as a statement, such as Fama's *"security prices at any point in time 'fully reflect' all available information"*, the EMH is an incomplete hypothesis. Indeed, as Le Roy (1989), Fama (1991) and Lo (2007) highlight, any test of market efficiency is the test of a joint hypothesis. Trying to narrow down efficiency with respect to different information sets (i.e. weak form, semi-strong form, etc.) doesn't complete the hypothesis. In order to be testable, the EMH needs an assumption of an equilibrium model by which share prices are said to be efficient. If the EMH is rejected, this could be because markets are indeed inefficient, or because the equilibrium model chosen is inadequate. This implies that the EMH can never truly be rejected.

While Fama attempts to describe the EMH in terms of equilibrium expected return pricing model, his mathematical derivation aims too broadly. As Le Roy (1989) points out, Fama's mathematical derivation is tautologous.

2.1.2.1 ***The martingale model of the EMH***

Samuelson derived a mathematical equilibrium model for futures contract prices (1965), which he later extended to share prices (1973). In his model, Samuelson shows that, assuming zero transaction costs and a risk neutral expectation, the present value of a share price will behave as a martingale process[1], as follows:

[1] In so doing, though it seems deceptively obvious, Samuelson (1965) was the first to rigorously prove the link between the EMH and the martingale process.

$$\mathrm{E}\big(\tilde{\mathrm{p}}_{j,t+1}\big|\Phi_t\big) = \mathrm{p}_{j,t} \tag{2.1}$$

In (2.1), $\mathrm{p}_{j,t}$ is the price[2] of share j at time t, $\tilde{\mathrm{p}}_{j,t+1}$ is a random variable describing its price at time t + 1, Φ_t is the information set that is assumed to be "fully reflected" in $\tilde{\mathrm{p}}_{j,t+1}$ and $\mathrm{E}(\cdot)$ is the expected value operator. According to (2.1), the best estimate of tomorrow's price, given the information known today, is today's price.

Closely related to the concept of a martingale is that of a fair game, which is simply the difference between successive value of a martingale process. Probability theory holds that $\mathrm{p}_{j,t}$ follows a martingale process if and only if $\mathrm{y}_{j,t}$, defined as $\mathrm{p}_{j,t+1} - \mathrm{p}_{j,t}$, follows a fair game process. The expected outcome of a fair game process has the following property:

$$\mathrm{E}(\tilde{\mathrm{y}}_{t+1}|\Phi_t) = 0 \tag{2.2}$$

According to (2.2), tomorrow's expected economic profit from utilising information known today is zero. The martingale model, although it implies some addition assumptions, provides a mathematically rigorous model by which the EMH may be empirically tested. Le Roy (1989) points out that the most widely used pricing model in tests of market efficiency, whether explicitly stated or merely implied, is the martingale model.

The martingale model of price increments is analogous to the least restrictive form of the random walk model, where price increments are uncorrelated. As Le Roy (1989) points out, in a martingale process, there can be no dependence of the conditional expectation of $\mathrm{y}_{j,t+1}$ on information available at time *t*.

2.1.2.2 ***Forms of market efficiency***

Fama (1970) described three forms of market efficiency, which are dependent upon the information set with which prices are said to be efficient. These are as follows:

[2] By price, it is implied that this is the present value of the price of stock j, with dividends re-invested. This is the common view held by the literature (Le Roy 1989), and proved by Samuelson (1973).

- Weak-form efficiency – Prices are efficient with respect to an information set that includes historical. Consequently, there exists no trading strategy based on historical prices that can consistently outperform the market.

- Semi-strong form efficiency – Prices are efficient with respect to an information set that includes all publically available information. Consequently, there exists no trading strategy based on public information that can consistently outperform the market.

- Strong form efficiency – Prices are efficient with respect to all available information, whether publically known or not. Under this form of efficiency, no trading strategy can outperform the market whether inside information is known or not.

Fama (1991) proposes a new categorisation of the forms of market efficiency, as follows:

- Tests for returns predictability – This broadens the prior category of weak form efficiency to include information such as dividend yields, price-earnings ratios and interest rates (information that is continually observable).

- Event studies – This includes tests concerning the adjustment of prices to public announcements (information that is an event).

- Tests for private information – This is equivalent to the Fama's prior category of strong form efficiency.

2.1.2.3 ***Assumptions underlying the EMH***

The martingale model is the least restrictive, yet empirically testable, model of the EMH. In addition, most empirical tests of the EMH assume, either implicitly or explicitly, a martingale model of the market with rational expectation in its agents (Le Roy 1989). The following is an attempt to highlight the assumptions underlying this model of the EMH. These assumptions are highlighted in Samuelson (1973), Le Roy (1989) and Fama (1970).

1. Agents have rational expectations – The theory of rational expectations claims that economic agents will always make decisions using all information available. Individually, rational expectations theory allows that economic agents may make decisions which differ only randomly in a normally distributed sense from 'perfect foresight' (Muth 1961). This implies

that, taken collectively (such as in a market), decisions of agents with rational expectations have no systematic error in their predictions, i.e. the market as a whole estimates the intrinsic value of shares perfectly.

2. Agents evaluate and act on new information instantaneously – Under efficient markets, if investors did not have this property, then investors would act on new information over a finite time window, inducing serial correlation in share prices over that time window, and predictability in prices.

3. Markets are frictionless – Transaction costs alter the equilibrium point in markets, implying that share prices may not reflect intrinsic values.

4. New information and the processing of information has zero cost – Under a perfectly efficient market, the cost of acquiring information and the processing of it must be zero. If it were not, investors would have different sets of information. This would cause the aggregate result of agents' decisions to differ systematically from intrinsic value.

5. Agents have neutral risk preferences – Le Roy (1989) indicates that risk neutrality is needed for efficient markets. If agents were risk averse, they would be unwilling to reverse the effects of irrational trades. These irrational trades may arise out of the random error in agents' decisions, as explained above[3].

6. Agents have equal endowment – In an efficient market, economic agents must have equal endowment (funds to invest). If this were not the case, then an economic agent with superior endowment will be able to make a trade that other agents may not be able to reverse

2.2 The nature of price inefficiency in real world markets

A review of the assumptions underlying the EMH indicates that it is unlikely to hold under actual market conditions. Indeed, even staunch proponents of the EMH acknowledge that the EMH, in its purest form, is impossible to hold in practice (Fama 1991).

Central to the assumptions underlying market efficiency is the theme that the market must have sufficient rational potential to counteract irrational trading. By rational potential, it is implied the

[3] Additionally, the EMH can only be expressed as a martingale model under risk neutrality. With risk-averse investors, the martingale model of efficient markets does not hold (Le Roy 1973; Lucas 1978).

potential to trade in order to bring prices back to fundamental levels. With this in mind, markets will be efficient to the extent that rational capital outweighs irrational capital.

In the following sections, the assumptions underlying market efficiency are discussed and the likely implications on market efficiency are identified if the assumptions are relaxed so that they are more reflective of the real world.

2.2.1 Limits to rational trading

The rational expectations hypothesis requires that the aggregate of investors' decisions represents 'perfect foresight'. Though individual investors may err, their errors are not systematic and thus, collectively represent the best guess of the future (Muth 1961). In reality, however, 'perfect foresight' is not possible. In many situations, the future is unpredictable, and no view can be considered rational. In addition, forecasting the future value of share prices is an exceedingly complex task, involving the optimization of systems of complex stochastic differential equations. As Shiller (2003) claims, it is absurd to expect that investors' aggregate decisions will correctly assess the implication of each new piece of information, arriving at the optimal price for an share all of the time. It is much more likely, as proposed by Black (1986), that price represents a very noisy estimate of value, which wanders back and forth over its intrinsic value. Its wanderings may sometimes take it far from its intrinsic value for extended periods of time.

A strong criticism to investor's rationality comes from the growing field of behavioural finance. Though it is impossible to cover comprehensibly in the scope of this report, the arguments against rationality posed by advocates of behavioural finance are highlighted in the sections below.

2.2.1.1 Feedback theory

Feedback theory relates to the way in which investors will trade in response to word-of-mouth claims of gains by other investors, which creates enthusiasm and an unfounded expectation that prices will rise (or, alternatively, claims of impending losses, creating unfounded fear that prices will fall). This causes buying resulting in prices going up, creating a reinforcing feedback loop that, unless dampened, causes the formation of price bubbles (Shiller 2003). Shiller (2003) cites evidence of feedback in laboratory tests where subjects were shown real sequences of share prices and in natural experiments such as Ponzi schemes.

2.2.1.2 ***Prospect theory***

Prospect theory is a model proposed by Kahneman and Tversky (1979; 1986) of decision making under risk. Prospect theory shows that, when faced with a number of risky prospects, investors exhibit deviations in their decision making from expected utility theory, which underlies assumptions of their rationality. One of these deviations includes the overweighting of certain outcomes when compared with merely probable outcomes. This causes investors to be risk averse when weighing up prospects involving sure gains (they will tend to choose a sure gain over a higher expected probable gain) and risk seeking when weighing up decisions involving loss (they will tend to choose a higher expected probable loss compared to a lower certain loss). Another deviation relates to the tendency of investors to disregard common components of several prospects. As an example, consider an investor who has a 25% chance of succeeding in a venture. If he does succeed, he either makes R3m with certainty or R4m with an 80% probability. Which should he choose? Most investors would choose the R3m option. However, in an equivalent restatement of the problem, when asked to choose between the options of R3m with 25% probability or R4m with 20% probability, the R4m option is chosen. Kahneman and Tversky (1979) demonstrate that, in the initial statement of the problem, investors disregarded the initial probability that was common to both options.

2.2.1.3 ***Representativeness heuristic***

Tversky and Kahneman (1974) argue that when faced with decisions about the uncertainty of how two events or objects are linked, people evaluate the probability of an outcome based on how representative the one is of the other. Such decisions are often framed in terms of "Does A originate from B?", "Does A belong to B?" or "Does A generate B?" Tversky and Kahneman (1974) use the following example to illustrate their point. Consider a person, shy and withdrawn, meek and tidy, with a passion for detail. Is the person a farmer, salesman, pilot, librarian or physician? In assessing the answer to this question, people will judge the probability that the person follows the occupations listed by how representative the description of the person is of the occupation. Most will state that the person is a librarian or physician. This is erroneous because it pays no attention to prior probabilities as Bayes' Rule requires. There are many more salesman and farmers than librarians or physicists, but this fact is usually ignored. The probability implied by the degree of representativeness of the person to the occupation also tends to outweigh the reliability of the description. Thus, people will still judge the person to be a librarian or physicist, even if they are aware that the description of the person is unreliable or outdated.

2.2.1.4 Availability heuristic

Tversky and Kahneman (1974) also present evidence that, faced with a range of uncertain events or objects, people adopt a heuristic principle that assigns to each a probability consistent with the ease with which they are brought to mind. If events or objects are more memorable, emotive or more imaginable, they will be assigned a higher probability than those which are less memorable, emotive or imaginable. For example, one may assess probability of a successful investment in a particular venture by how many of one's acquaintances have made successful investments in such a venture. One may overestimate the importance of recent earnings announcements to a share's value because it is more easily brought to mind than other information relating to the share. In both cases, prior probabilities and base data are ignored. This gives rise, as De Bondt and Thaler (1985) claim, to investor overreaction to new data. This introduces short term momentum and medium term mean-reverting effects in prices (De Bondt and Thaler 1985, 1989).

Other deviations from rationality besides the ones listed above have been postulated in the literature. Kahneman and Riepe (1998) propose several other 'cognitive biases' that investors exhibit, such as overconfidence, optimism, hindsight and regret avoidance. All of these deviations from rationality act to erode the rational potential of the market and tend to cause prices to move away from intrinsic value.

2.2.2 Limits to instantaneous trading

In real markets, propagation and processing of information and corresponding action takes place over finite time intervals. In real markets, the same item of information is incorporated into a share's price at different rates. The rate at which information is incorporated is dependent on the on how actively that particular share is traded. Thinly traded shares may take some time to incorporate the available information into their price.

The share dependent uptake of information gives rise to a problem called non-synchronous trading (Cohen, Hawawini, Maier, Schwartz and Whitcomb 1983; Campbell, Lo and MacKinlay 1997). Non-synchronous trading is the effect that results when share prices are thought to be sampled at equivalent times, but in reality are sampled at different times. This effect is pronounced when comparing the prices of highly liquid stocks to thinly traded illiquid stocks. Liquid stock prices rapidly respond to new information, while thinly traded stocks respond slowly to new information. This causes positive serial cross-correlation between their returns.

2.2.3 Costs to information

Grossman and Stiglitz (1980) show that in a market where information is costly, prices can never 'fully reflect' all available information, since those who gathered that information would not be compensated. Similarly, they show that trade will only take place when the cost of information lies within a certain range. In the limit, if the cost of information is zero, as required by the EMH, or very high, trade tends not to take place, since all traders have homogenous beliefs[4].

Fama (1991) argues that costly information will imply that, in practice, markets are efficient to the point where the marginal benefits of acting on the information equals its marginal cost. This statement almost implies that prices will track fundamental values less a small constant offset. This is not so, however. The marginal benefit of information is not deterministic, but depends (under the rational expectations model) on the random errors made by other traders. This implies that investors will be willing to pay for information to the extent that it allows them to take advantage of the expected benefit created by traders' errors. However, this implies that the benefit created by a certain proportion of traders' errors will be unknown and thus uncompensated for by the market. Prices will become a noisy estimate of fundamental values. In summary, costly information erodes the rational potential of the market to bring prices back to fundamental levels.

2.2.4 Risk aversion

An assumption central to efficient markets is that prices that are not at fundamental levels represent arbitrage[5] opportunities to informed traders. Risk neutral traders will take as large a position as they are able to reduce the discrepancy between price and fundamental value. In a world of uncertainty, however, risk averse traders will be unwilling to take large positions in risky investments (Black 1986; Le Roy 1989). Black posits that risk-averse information traders will not take large enough positions to eliminate irrational trades because, although the information that the trader has will give him an advantage, it does not guarantee a profit. In an uncertain world, a trader may lose his investment despite having superior information, simply because the future is uncertain. In addition to this, risk-averse traders face uncertainty as to what the fundamental level of the price is.

[4] The latter argument, however, neglects the uncertainty generated by rational expectations theory. Under rational expectations theory with appreciable uncertainty, trades will still take place between traders with homogenous beliefs dues to errors in their individual predictions.

[5] The more correct term is 'risk arbitrage', since, in an uncertain world, discrepancies between price and value do not represent 'riskless profit', as arbitrage implies.

While many researchers express similar views, the research of Slezak (2003) offers proof of this fact. Slezak demonstrates in theory that, if rational traders are risk-averse and trades are subject to risk, rational agents are unable to undo the effects of irrational traders. Building on the findings of Grossman and Stiglitz (1980) that semi-strong from efficiency is theoretically impossible, Slezak shows that weak form efficient markets are also impossible in theory.

2.2.5 Real world market dynamics

After surveying the research on excess variance share market prices, Shiller (2003) concludes that the market contains substantial levels of noise. He states that the aggregate movements in share markets are dominated by noise.

Black (1986) gives insight into the practical workings of markets, estimating that, in an efficient market, price is within a factor of two (less than double or more than half) of fundamental value 90% of the time. Black also argues that noise traders (traders who trade in the absence of new information) provide the liquidity necessary for financial markets to function. He claims that without noise traders, trades would tend not to take place, since equally informed traders would not trade with one another because they have similar information and don't see any value in the trade. Noise traders, on the other hand, compensate informed traders for gathering information. Most of the time, claims Black, noise traders on average will lose money, while informed traders on average will gain money.

Black also points out, however, that while noise traders provide the necessary liquidity for a market, they also influence its prices, giving rise to inefficiencies. He posits that information traders will not take large enough positions to eliminate noise because they are risk averse. The noise in prices is cumulative, causing prices to wander at times far from intrinsic values. He paradoxically summarises his position by claiming that *"noise creates the opportunity to trade profitably, but at the same time makes it difficult to trade profitably"* (Black 1986, pg. 534).

2.3 Testing for predictability in share prices

Share price predictability and market efficiency are inextricably linked. Efficient prices must, by definition, be unpredictable. Unpredictable prices, however, are not necessarily efficient. The claim that because prices are unpredictable, they must represent intrinsic value is, as Shiller puts it, *"one of the most remarkable errors in the history of economic thought"* (Shiller 1984, pg. 459). Unpredictable prices do not imply informational efficiency (Summers 1986; Bodie, Kane and Marcus 2005). Price series may be highly inefficient yet sufficiently unpredictable as to deny an investor the opportunity of making significant profits. Lack of predictability in price series is simply a lack of evidence that markets are inefficient. It is not evidence that they are efficient. As Shiller (2003, pg. 102) claims, *"It would seem peculiar to argue that irrational markets should display regular and lasting patterns!"*

While unpredictability does not necessarily imply efficiency, as the previous paragraph explains, predictability in share prices is an indication of inefficiency of the market. Many tests of efficient markets, therefore, are tests of various forms of predictability in the price series.

2.3.1 Excess variance

One of the first deviations from market efficiency to be explored was that of excess variance. Shiller (1981) and Le Roy and Porter (1981) first noted that share prices showed too much volatility to be an efficient estimate of the present value of future dividends. The variance bound on share prices is derived from the fact that, in an efficient market, the price of a share is a forecast of the present value of future dividends accruing to shareholders. Mathematically stated, if p_t^* represents the present value of all future dividends arising from a share (assuming perfect foresight) at time *t*, then a forecast for p_t^* can be stated as:

$$\mathrm{p}_t = \mathrm{p}_t^* + x_t \tag{2.3}$$

In (2.3), p_t is the price of a share, or, equivalently, a forecast of p_t^* and x_t is the forecast error. Under the assumption of rationality, p_t is an optimal forecast of p_t^*, which implies that p_t (forecast) and x_t (forecast error) are uncorrelated. Since the variances of two uncorrelated random variables may simply be added, one obtains the following, where Var() denotes the variance,

$$\mathrm{Var}(\mathrm{p}_t) = \mathrm{Var}(\mathrm{p}_t^*) + \mathrm{Var}(x_t) \tag{2.4}$$

Since variances are always positive, the following inequality may be expressed:

$$\mathrm{Var}(\mathrm{p}_t) \leq \mathrm{Var}(\mathrm{p}_t^*) \tag{2.5}$$

Equation (2.5) reflects the essence of the variance bound tests performed by Shiller (1981), Le Roy and Porter (1981) and others. If markets are efficient forecasters of future dividends, then the variance of the observed price at time *t* should be no greater than the variance of the value of future dividends discounted to time *t*.

Shiller (1981) and Le Roy and Porter (1981) found significant excess volatility in share prices and concluded that this evidence represented an anomaly in the efficient markets research at the time. After criticisms of these findings, new refined tests of variance bounds were developed by researchers, most notably Campbell and Shiller (1988). These improved tests again showed significant excess volatility in share prices, which remains unexplained (Shiller 2003).

2.3.2 Serial correlation in prices

As discussed in section 2.1.2.1, evidence of serial correlation in share prices provides sufficient evidence to reject the theory of random walk hypothesis in its least restrictive form and, therefore, the efficient markets hypothesis in its weak form.

2.3.2.1 Serial correlation in portfolio and index prices

Lo and MacKinlay (1988) use a variance ratio test to demonstrate significant serial correlation in weekly index and portfolio prices. They find serial correlation coefficients in weekly equal-weighted index prices of 30% with a high degree of statistical reliability, suggesting economically significant predictability of equal-weighted index prices. For monthly data, Lo and MacKinlay (1988) show serial correlation coefficients of 15%.

Poterba and Summers (1988) conduct variance ratio tests on US and international markets and conclude that over short horizons, equal and value weighted indices are positively serially correlated, supporting conclusions made by Lo and MacKinlay (1988).

On the JSE, Jammine and Hawkins (1974), using data gathered over a seven year period, find that weekly index prices on the JSE exhibit statistically significant serial correlation. They conclude that profits can be earned by technical analysts on the basis of this serial correlation. Their finding is consistent with the findings of significant serial correlation in weekly index prices (Lo and MacKinlay, 1988).

2.3.2.2 ***Serial correlation in individual share prices***

Evidence of the serial correlation in share prices dates back to as early as 1965, when Fama detected negative serial correlation in the prices of individual shares (Fama 1965). He deemed this correlation too insignificant to be of an economic value. Later research into individual share price predictability in the 1980s (French and Roll 1987; Lo and MacKinlay 1988) corroborates these results.

Lo and MacKinlay (1990) go on to argue that the positive cross-correlation in share prices far outweighs this weak individual negative serial autocorrelation, yielding an overall positive serial correlation in the prices of portfolios of shares and index values.

On the JSE, Affleck-Graves and Money (1975) test the serial correlation of fifty individual industrial shares over a five year period and find no significant serial correlation. In contrast to this finding, Hadassin (1976), using JSE prices gathered over a 20 year time period, finds evidence of share price predictability in 30 industrial shares. Gilbertson and Roux (1978), however, study the daily returns of 24 industrial and mining sector shares on the JSE and conclude that any serial correlation in individual share price returns is too small to be of any economic significance. Corroborating their findings, Brümmer and Jacobs (1981) find that, although they are able to observe serial correlation in monthly share prices, any derived profits are economically insignificant.

2.3.2.3 ***Longer term serial correlation in index prices***

Fama and French (1988a) find that index returns over longer time horizons are negatively serially correlated, suggesting that index prices follow a mean reverting process over three to five year periods. Specifically, they find serial correlations in the order of -35% for 3-5 year index prices. They find a similar size effect to Lo and MacKinlay (1988), with a serial correlation of -40% for small firms and -25% for large firms.

Over long time horizons, Poterba and Summers (1988) find evidence of negative serial correlation in index prices, supporting the findings of Fama and French (1988a). Poterba and Summers attribute the short and long term correlation in index prices to noise traders, rather than investor overreaction.

On the JSE, Bhana (1989), using monthly price data finds evidence of a reversal approximately one year after a negative excursion in the share price. He observes no corresponding reversal effect for positive excursions in the share price. This is in contrast to the results of De Bondt and Thaler (1985), who find symmetrical reversals over a 3-5 year period.

2.3.3 Profitability of momentum and contrarian investment strategies

Closely related to research into the degree of the serial correlation present in share prices is that which shows excess profits through the adoption of contrarian and momentum investment strategies. These strategies loosely advocate the following:

1. Create a portfolio of shares at time *t* by weighting them in accordance with the return observed over a period from time *t-b-a* to time *t-b*. Here, *a* is denoted the formation period and *b* the waiting period.

2. Hold this portfolio of shares until *t+c*, where *c* is denoted the holding period.

Contrarian strategies advocate holding a portfolio of shares based on poor returns over the formation period, while momentum strategies advocate holding a portfolio of shares based on high returns over the formation period. Where short sales are included in portfolios, momentum strategies advocate short positions in shares with poor returns over the formation period, while contrarian strategies advocate short positions in shares with high returns over the formation period (Jegadeesh and Titman, 1993, 2001).

The consensus in the literature is that with short to medium term holding periods (3 to 12 months), momentum trading strategies earn profits in excess of the market. Over long term holding periods (three to five years), contrarian strategies earn excess profits. Given the findings of research into serial correlation in share and portfolio prices, these results are to be expected. As discussed in section 2.3.2, the research on correlation in share prices finds that over short horizons, portfolio prices show positive serial correlation, while over longer periods, negative serial correlation.

2.3.3.1 Very short term contrarian trading strategies

Evidence of the profitability of very short term contrarian strategies is offered by Lehmann (1990). He finds that based on a contrarian strategy with a formation period of one week and a holding period of one week, well-diversified portfolios earn excess profits that are robust to trading costs and concerns over the effect of illiquidity on share prices. Lehmann attributes the excess profits to short term liquidity induced inefficiency in the prices of heavily traded shares.

The substantial profits generated by short term contrarian strategies have been criticised by Conrad, Gultekin and Kaul (1997), who show that these profits arise almost entirely from bid-ask bounce. By using the bid price in Lehmann's portfolios, Conrad et al. (1997) claim that the excess profits earned disappear under the assumption of modest trading costs.

Lo and MacKinlay (1990) offer an alternative explanation for short-term reversals than the liquidity induced inefficiency proposed by Lehmann, claiming that negative serial correlation need not be the cause of short term contrarian profits. They demonstrate that positive serial cross-correlation between share prices in Lehmann's portfolios is the more likely source of excess profits in short term contrarian strategies.

2.3.3.2 ***Short to medium term momentum trading strategies***

Jegadeesh and Titman (1993), using market data from the 1965 to 1989 period, show that a momentum investment strategy with a formation period of three to 12 months and a holding period of 12 months a return in excess of the market by 1% per month. They also show that these excess returns do not derive from excess risk in their portfolio. Upon criticisms that these excess returns were the result of data mining, Jegadeesh and Titman (2001) demonstrate higher excess returns earned by identical momentum strategies using market data from the 1990 to 1998 period. Employing the Fama and French three-factor model, they also show that these momentum profits are robust even when risk is taken into account. Lastly, Jegadeesh and Titman (2002) examine the returns of their momentum portfolios after the holding period is complete. They find that their momentum portfolios earn negative returns in the post-holding period, consistent with the literature on negative serial correlation in long period prices.

In support of Jegadeesh and Titman (1993), Grundy and Martin (2001) find that individual share returns account for a large degree of the profits attributed to momentum strategies. They find that momentum profits cannot be explained as the reward for bearing additional risk, nor by cross-sectional variation in expected returns, nor by industry specific factors. The portfolios of Grundy and Martin earn a risk adjusted excess return of 1.3% per month. They do mention, however, that trading costs will diminish these momentum profits.

Conrad and Kaul (1998) claim that the profits generated by momentum strategies are not due to any correlation or other patterns in time series returns, but rather attributed to the momentum trading strategy itself. They argue that the repeated purchase of high return shares from the sale of low return shares biases a portfolio towards an above average return. The greater the cross sectional dispersion of mean returns in shares traded in the market, the greater this effect will tend to be. Conrad and Kaul

(1998) argue that the converse is true for contrarian strategies; any contrarian profits are offset by the fact that the portfolio will be biased towards a below average return. In response to this, Jegadeesh and Titman (2002) claim that the contribution of cross-sectional variation in mean returns is insignificant due to the fact that this cross-sectional variation in returns is small compared to the variation in realized returns over the holding period. They further point to a sampling bias in the methodology of Conrad and Kaul (1998) which overemphasises the contribution of cross sectional return variation to momentum profits.

On the JSE, Muller (1999) analyses the profitability of momentum and contrarian investment strategies on the JSE over 12 year study period from 1985 to 1997. He finds that a momentum strategy with a formation period of 16 months and a holding period of three months yields an annualised return of 15% in excess of the market.

2.3.3.3 ***Longer term contrarian trading strategies***

De Bondt and Thaler (1985) argue that a contrarian investment strategy with a formation and holding period of three to five years will earn excess profits. They attribute these excess profits to investor overreaction, which causes prices to have a mean reverting component in the long term. Alternative explanations to these excess returns have been offered, however, which attribute them to increased risk in the portfolios, or to seasonality and size effects.

De Bondt and Thaler (1985, 1987) attribute the profitability of their long term contrarian strategies to investor overreaction which induces mean reversion in share prices. As Lo and MacKinlay (1990) point out, however, since almost all of the return earned by De Bondt and Thaler's portfolios occur in January, one cannot conclusively attribute the profits to investor overreaction. Conrad and Kaul (1998) also point out that returns arising from long term contrarian strategies are only statistically significant over the 1926 to 1947 period.

Despite statistically significant evidence of long term negative serial correlation in share prices documented by Fama and French (1988a) and Poterba and Summers (1988), Campbell et al. (1997) caution that these results are subject to sample biases. Fama and French's data set contains only 12 non-overlapping five year periods. The use of overlapping periods provides little statistical support to their tests.

A number of studies have been conducted on the JSE to determine whether the long term reversals documented by De Bondt and Thaler (1985, 1989). Page and Way (1992) construct long term contrarian portfolios using market data over a period of 15 years. They measure excess profits of 10% to 20% per annum of the prior loser relative to the prior winner portfolio, using a formation period of two to three years and a holding period of three years.

Muller (1999) finds that a contrarian strategy with a formation period of three to five years and a holding period of one to two years yields a return of 20% in excess of the market. His finding of one year reversals on the JSE ties in with the findings of Bhana (1989).

In perhaps the most conclusive study of long term reversal on the JSE, Cubbin et al. (2006) analyse 1320 shares over a period of 22 years. Using price earnings ratios to rank the shares and by holding the shares for a period of five years, they find that prior losers outperform prior winners by 62% over the five year period, giving a compound annual excess return relative to the market portfolio of 11%.

Similar to the criticism levelled at the research of De Bondt and Thaler (1985, 1989), the significant excess profit observed on the JSE has questionable value outside of the sample period, however, given the insufficient sample size used. The studies of Page and Way (1992), Muller (1999) and Cubbin et al. (2006) use overlapping data to improve their sample size, which, as shown by Poterba and Summers (1988), does little to support the results.

2.4 Factors correlated with predictability in share prices

As Black (1986) states, a consistent error made by researchers is, when observing that two effects happen together, to assume that one causes the other. The truth, however, is that correlation is no indicator of causality. It would be wise to keep this caution in mind when considering the factors correlated with predictability in share prices. To claim that any of these factors causes share price predictability is to fall into the correlation equals causality trap.

Since short to medium term positive serial correlation in index and portfolio prices and the corresponding profitability of momentum strategies are two of the more robust forms of inefficiency found in financial markets, this section is mostly related to the factors correlated with these types of share price effects.

While most researchers agree on the significance of serial correlation in index and portfolio prices, there exists little consensus as to its root causes. The findings of Lo and MacKinlay (1990), however, do shed light on the nature of this strong positive serial correlation in index and portfolio prices as arising from strong serial cross-correlation between the prices of shares making up the index or portfolio.

2.4.1 Firm size

Lo and MacKinlay (1988) note that the degree of positive serial correlation is higher in equal-weighted index prices than value-weighted index prices. In other words, the degree of serial correlation found in portfolio prices is firm size dependant. To verify this, Lo and MacKinlay (1988) calculate the serial correlation in quintile portfolios sorted by the size of the firm. They find serial correlations of 42% for the smallest firm size quintile, 28% for the middle quintile and 14% for the largest firm size quintile. This indicates that the degree of predictability of share prices decreases as firm size increases. In addition to their earlier findings of serial correlation in portfolio returns becomes more pronounced with diminishing market capitalisation, Lo and MacKinlay (1990) find that returns of larger shares tend to lead those of smaller shares.

Conrad and Kaul (1988) find similar results. By forming 10 equal weighted portfolios sorted by firm size, they observe a significant amount of serial correlation for portfolio containing the smallest firms. They observe weekly serial correlation in portfolio returns of 41%, decaying to values of 10% for monthly returns. All portfolios with the exception of the portfolio of the largest firms exhibit weekly serial correlation coefficients of above 18%, which persist for up to four weeks.

Analogous to this, Badrinath, Kale and Noe (1995) find that serial cross-correlation in portfolio returns is dependent on the degree of institutional ownership of the firms comprising the portfolio. They demonstrate that the prices of portfolios of firms with less institutional ownership exhibit stronger serial correlation than those having greater institutional ownership. Arbel, Carvell and Strebel (1983) describe this as a 'neglect effect', where the universe of shares in which institutional investors may invest is limited by legal restrictions. They claim that this neglect by industry analysts leads to greater predictability in the share prices of smaller firms. Badrinath et al. (1995) also claim that shares with a high degree of institutional ownership tend to lead those with little or no institutional ownership.

An obvious explanation to the positive serial cross-correlation in share returns is that it is the result of the result of non-synchronous trading or thinly traded shares of smaller firms (Sentana 1992; Chan 1993). Lo and MacKinlay (1990), however, show that this effect is negligible when compared to the degree of cross correlation in their findings. Another reason offered for the existence of positive serial cross-correlation is the 'speed of adjustments hypothesis' (Brennan, Jegadeesh and Swaminathan 1993). They claim that share prices with a large analyst following adjust more quickly to information with common implications across firms than firms with fewer analysts.

2.4.2 Current price relative to historical price

George and Hwang (2004) propose that a superior momentum investment strategy may be obtained by selecting shares based on the nearness of their price to its 52-week high level. They find that the closer a share's price is to the highest level attained in the previous 52 weeks, the more momentum it exhibits. They claim that the returns earned improve upon the returns earned by Jegadeesh and Titman's 1993 and 2001 momentum strategies and, additionally, that these returns are present when risk is taken into consideration. Unlike Jegadeesh and Titman's momentum portfolios, however, they find no evidence that their portfolios earn negative returns after the holding period is complete. This leads them to conclude that short term momentum and long term reversals are a separate phenomenon.

2.4.3 Industry

Moskowitz and Grinblatt (1999) find that the industry return is a better predictor of portfolio momentum than individual share returns. They find that momentum strategies which buy shares from industries exhibiting high returns in the formation period and sells shares from industries having a low return in the formation period perform are highly profitable and appear independent of size, book-to-market, individual momentum and market microstructure influences. In contrast to momentum strategies based on individual share returns which derive significant profit from the short sales of poor performing shares, industry based momentum strategies generate more profits on the long side of the portfolio. Moskowitz and Grinblatt (1999) attribute the success of industry based momentum strategies to behavioural biases in investors.

2.4.4 Dividend yield

Fama and French (1988b) regress stock returns on lagged dividend yields and find that lagged dividend yields are able to explain more than 25% of the variability in the 2-4 year returns of value and equal weighted portfolios of shares.

While this correlation is strong for long term returns, they claim that only 5% of the variability of short term returns is explained by dividend yield.

2.4.5 Earnings yield

Fama and French (1988b) also regress stock returns on lagged earnings yields. They claim that earnings yield is a reliable forecaster of returns, but that it provides lesser explanatory power for future returns compared to dividend yield. The reason, claim Fama and French (1988b) is that earnings are up to three times more variable than dividends and that this noise, obscures the forecasting ability of the earnings yield.

Lamont (1998) contradicts this, claiming that the variability in the earnings yield is not noise but is actually related to the expected return. He recommends using a combination of dividend and earnings yield ratios to forecast future returns, claiming both offer unique predictive ability.

2.4.6 Volume

Many researchers have attempted to relate serial correlation to trading volume of shares. Possibly the first to attempt such an exercise was Campbell, Grossman and Wang (1993) who examine the relationship between daily serial correlation in returns and trading volume. They find that first order serial correlation (i.e. having a one period lag) for index and large share returns is lower on high volume days than on low volume days. They argue that trading volume can distinguish between price movements caused by the arrival of new information and price movements caused by noise traders. Consequently, they claim that price changes accompanied by high trading volume will tend to be reversed, while those with low volume will not.

Conrad, Hameed and Niden (1994) analyse the relationship between returns and lagged trading volumes. Their findings support those of Campbell et al. (1993). They find that the weekly returns of individual shares are negatively serially correlated when the previous week's volume is high, yet positively serially correlated when the volume is low. They also find that trading volume is a significant predictor of share returns.

Lee and Swaminathan (2000) analyse the relationship between volume and momentum over longer periods. They find that volume is a significant predictor of the extent and persistence of momentum in future returns. Consistent with the Campbell et al. (1993), they also find that portfolios exhibiting high volume are more likely to undergo reversals, while portfolios with low volumes tend to show momentum in their returns.

2.5 Summary of the literature

2.5.1 Predictability of the market as a whole

In reviewing the literature, some anomalies in the price formation process are quickly explained away by further research. Others, however, remain unexplained, despite the passage of over two decades since their discovery. These include the findings of excess variance in share prices by Campbell and Shiller (1988), the findings of excess serial correlation in weekly portfolio prices by Lo and MacKinlay (1988) and the consistent excess profitability earned by momentum investors over a period in excess of forty years (Jegadeesh and Titman 1993) which persisted for ten years after its initial documentation (Jegadeesh and Titman 2001).

Despite their popularity in the literature, particularly that related to the JSE, long term return reversals of the type documented by De Bondt and Thaler (1985, 1987) are less of an unexplained phenomenon than the three highlighted above. Common criticisms are a small sample size (Campbell et al. 1997), even when using a study period in excess of sixty years, seasonality (most of the excess return accrues in January) and inconsistency of the degree of overreaction over the study period (most of the excess return is earned on the NYSE in the decade following the Great Depression) (Fama 1998, Poterba and Summers 1988).

Little research has been conducted into the more unexplained phenomena of excess serial correlation in weekly portfolio returns and the consequent excess profitability of short to medium term momentum trading strategies on the JSE. Specifically, to this author's knowledge, no research has been conducted regarding the serial correlation in share prices on the JSE using heteroskedastically consistent standard error estimates, of the kind employed by Lo and MacKinlay (1988). Past research into tests of serial correlation in the prices of JSE shares and portfolios demonstrate that share prices are not log-normally distributed. In other words, these tests demonstrated that prices do not follow a random walk with IID increments. Consequently, price increments are not distributed according to a log-normal random process with stationary mean and variance. Since the work of Engle (1982) in modelling the volatility of a price series as a time varying autoregressive process, the fact that the variance of a time series is non-stationary has been widely accepted.

The variance ratio tests of Lo and MacKinlay (1988), however, are able to demonstrate that price increments are not uncorrelated with one another, regardless of whether price increments are independent or identical. As Poterba and Summers (1988) demonstrate, this is a much more general and powerful test of the random walk nature of a price series. Because very little is assumed about the price formation process, violations of this form of the random walk model provide strong evidence against the efficiency of markets.

2.5.2 Predictability in share prices related to a number of easily observable factors

As Conrad et al. (1994) and Lo and MacKinlay (1988) point out, serial correlation in portfolios can only arise out of positive cross serial correlation between share prices. They show that the degree of serial correlation in the prices of portfolios of shares decreases as the size of the firm increases.

It is logical to extend these tests based on firm size to other easily observable factors that occur in the literature as being linked to price predictability or excess portfolio profits. These factors include market capitalisation (Lo and MacKinlay 1988), trading volume (Campbell et al. 1993; Conrad et al. 1994; Lee and Swaminathan 2000), dividend yield (Fama and French 1989b), earnings yield (Fama and French 1988b; Lamont 1998) and industry return (Moskowitz and Grinblatt 1999).

2.5.3 The determination of leading indicators of portfolio price movements

Lo and MacKinlay (1990) show that the returns of portfolios comprising small firms are serially correlated with the returns of portfolios of larger firms. This indicates that prices of larger firms tend to lead the prices of smaller firms. To better identify the nature of share price predictability on the JSE, it is logical to test these types of lead lag relationships with firm size sorted portfolios, as well as portfolios ranked by the other factors highlighted above.

Chapter 3

Hypotheses

"THE GREAT TRAGEDY OF SCIENCE - THE SLAYING OF A BEAUTIFUL HYPOTHESIS BY AN UGLY FACT." – THOMAS HUXLEY

This chapter contains a formal statement of the hypotheses tested in this study. Sections 3.1, 3.2 and 3.3 state the hypotheses related to the first, second and third sub-problems, respectively.

3.1 Sub-problem 1: Overall predictability of JSE share prices

Variance ratios and their test statistics are calculated to determine whether various price series on the JSE are correlated at any lag. The following price series will be analysed:

1. The JSE all share index (J203) series will be used as a proxy for the market portfolio.

2. An equal weighted portfolio consisting of all the shares that have traded on the JSE for the study period.

3. The prices series' of individual shares that traded on the JSE for the study period.

The following null hypotheses will be tested in order to address the first sub-problem:

Hypothesis 1: The variance ratio, $\overline{\mathrm{VR}}(q)$, of price increments of the J203 for the study period is unity for variance ratio period $q = 2, 4, 8$ and 16.

Hypothesis 2: The variance ratio, $\overline{\mathrm{VR}}(q)$, of price increments of an equal weighed portfolio of JSE shares for the study period is unity for variance ratio period $q = 2, 4, 8$ and 16.

Hypothesis 3: The average variance ratio, $\overline{\mathrm{VR}}(q)$, of price increments of individual JSE shares for the study period is unity for variance ratio period $q = 2, 4, 8$ and 16.

3.2 Sub-problem 2: Share price predictability related to market benchmarks

In order to relate share price predictability to market benchmarks, variance ratios and their test statistics are calculated for portfolios of shares ranked according to each benchmark. For each benchmark to be tested, five, equal sized (in terms of number of shares per portfolio) and equal weighted portfolios, termed quintiles, are formed.

The following benchmarks are used to rank the shares into portfolios:

1. Market capitalisation
2. Dividend yield
3. Earnings yield
4. Industry
5. Trading volume

The following null hypotheses will be tested in order to address this sub-problem:

Hypothesis 4: The variance ratios, $\overline{\mathrm{VR}}(q)$, of price increments of portfolios of shares ranked by their average market capitalisation for the study period are unity for variance ratio period $q = 2, 4, 8$ and 16.

Hypothesis 5: The variance ratios, $\overline{\mathrm{VR}}(q)$, of price increments of portfolios of shares ranked by their average dividend yield for the study period are unity for variance ratio period $q = 2, 4, 8$ and 16.

Hypothesis 6: The variance ratios, $\overline{\mathrm{VR}}(q)$, of price increments of portfolios of shares ranked by their average earnings yield for the study period are unity for variance ratio period $q = 2, 4, 8$ and 16.

Hypothesis 7: The variance ratios, $\overline{\mathrm{VR}}(q)$, of price increments of portfolios of shares ranked by industry for the study period are unity for variance ratio period $q = 2, 4, 8$ and 16.

Hypothesis 8: The variance ratios, $\overline{\mathrm{VR}}(q)$, of price increments of portfolios of shares ranked by their average trading volume for the study period are unity for variance ratio period $q = 2, 4, 8$ and 16.

3.3 Sub-problem 3: Lead-lag relationships of portfolios sorted by a market benchmark

Cross autocorrelation matrices of the factor sorted portfolios are constructed to analyse the lead-lag relation between portfolio price increments and their lagged counterparts. As in the second sub-problem, quintile portfolios are formed based on rankings in the following market benchmarks:

1. Market capitalisation
2. Dividend yield
3. Earnings yield
4. Industry
5. Trading volume

The cross autocorrelation matrices for quintile portfolios are formed to identify lead-lag trends between high ranking and low ranking portfolios.

The following null hypotheses will be tested in order to address this sub-problem:

Hypothesis 9: There is no significant difference between the cross serial correlation of portfolios of shares ranked by their average market capitalisation for the study period and their leading/lagging counterparts at lags 1, 2 and 3.

Hypothesis 10: There is no significant difference between the cross serial correlation of portfolios of shares ranked by their average dividend yield for the study period and their leading/lagging counterparts at lags 1, 2 and 3.

Hypothesis 11: There is no significant difference between the cross serial correlation of portfolios of shares ranked by their average earnings yield for the study period and their leading/lagging counterparts at lags 1, 2 and 3.

Hypothesis 12: There is no significant difference between the cross serial correlation of portfolios of shares ranked by industry for the study period and their leading/lagging counterparts at lags 1, 2 and 3.

Hypothesis 13: There is no significant difference between the cross serial correlation of portfolios of shares ranked by their average trading volume for the study period and their leading/lagging counterparts at lags 1, 2 and 3.

Chapter 4

Research Methodology

"RESEARCH IS FORMALIZED CURIOSITY. IT IS POKING AND PRYING WITH A PURPOSE." – ZORA NEALE HURSTON

This chapter describes the research methodology used in this study. Section 4.1 gives a mathematical background to the statistical tests used. Section 4.2 describes the data set used as well as any adjustments made to the data. Section 4.3 analyses the statistical power of the variance ratio tests to determine serial correlation using simulated price series. Section 4.4 addresses the dimensional redundancy in the benchmarks used to form portfolios. Finally, section 4.5 discusses the validity of the results, with reference to their applicability to other time periods and markets.

4.1 Background

The research method adopted to deal with the first two sub-problems is to conduct variance ratio tests of the type used in Lo and MacKinlay (1988) and Campbell et al. (1997) on the price series of interest. For reasons highlighted in section 2.5, the variance ratio test is one of the most powerful tests available for determining correlation in share price series.

For purposes of determining lead-lag effects between price series and their lagged counterparts, cross autocorrelation matrices of the factor sorted portfolios are constructed. While this is an oft used approach for determining lead-lag relationships, the mathematical symbols used follows that of Lo and MacKinlay (1990) and Campbell et al. (1997).

4.1.1 The variance ratio test

Mathematically stated, if X_t represents the natural logarithm of the price of a portfolio at time t, and the single period return, r_t evolves according to:

$$r_t \equiv \mathrm{X}_t - \mathrm{X}_{t-1} = \mu + \epsilon_t \tag{4.1}$$

then the null hypothesis is the hypothesis that the random disturbance term, ϵ_t is uncorrelated at any lag, stated as:

$$\mathrm{H}_0\colon \mathrm{E}[\epsilon_t] = 0 \text{ and } \mathrm{E}[\epsilon_t \epsilon_{t-k}] = 0 \qquad \text{for all } t \text{ and for all } k \neq 0 \tag{4.2}$$

Equation (4.2) is actually one component of a compound null hypothesis, the form of which is described in Lo and MacKinlay (1988) and Campbell et al. (1997). The other components of this hypothesis place broad restrictions on the degree of heteroskedasticity that may be present in the price increments. The restrictions on the heteroskedasticity of ϵ_t, are quite general and allow deterministic changes in variance over time (ARCH processes are one example of this).

Lo and MacKinlay (1988) define the variance ratio as:

$$\overline{\mathrm{VR}}(q) \equiv \frac{\bar{\sigma}_c^2(q)}{\bar{\sigma}_a^2} \tag{4.3}$$

where $\bar{\sigma}_a^2$ and $\bar{\sigma}_c^2(q)$ are estimators of the variance of r_t, defined as:

$$\bar{\sigma}_c^2(q) = \frac{1}{m} \sum_{k=q}^{nq} \left(\mathrm{X}_k - \mathrm{X}_{k-q} - q\hat{\mu}\right)^2 \tag{4.4}$$

$$\text{where } m \equiv q(nq - q + 1)\left(1 - \frac{q}{nq}\right) \tag{4.5}$$

$$\bar{\sigma}_a^2 = \frac{1}{nq - 1} \sum_{k=1}^{nq} (r_k - \hat{\mu})^2 \tag{4.6}$$

$\hat{\mu}$ is an estimator of the mean of r_t, defined as:

$$\hat{\mu} \equiv \frac{1}{nq}\sum_{k=1}^{nq} r_k = \frac{1}{nq}\ (\mathrm{X}_{nq} - \mathrm{X}_0) \tag{4.7}$$

It can be shown (Campbell et al. 1997) that $\overline{\mathrm{VR}}(2) - 1$ is the first order autocorrelation coefficient of r_t, hence $\overline{\mathrm{VR}}(2)$ greater than one indicates positive first order serial correlation in r_t while $\overline{\mathrm{VR}}(2)$ less than one indicates negative first order serial correlation in r_t. More generally, the variance may be expressed as a weighted sum of the first autocorrelation coefficients, where the weights decline linearly in the serial correlation factors of r_t at lag k, denoted by $\rho(k)$:

$$\overline{\mathrm{VR}}(q) = 1 + 2\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\rho(k) \tag{4.8}$$

Campbell et al. (1997) show that the first order q-period serial correlation is related to the variance ratios $\overline{\mathrm{VR}}(q)$ and $\overline{\mathrm{VR}}(2q)$ as follows:

$$\frac{\overline{VR}(2q)}{\overline{VR}(q)} = 1 + \rho_q(1) \tag{4.9}$$

Under the null hypothesis, Lo and MacKinlay (1988) show that a standardized test statistic, $\psi^*(q)$, is normally distributed with zero mean and unit variance. The test statistic, in the presence of heteroskedasticity in r_t is defined as:

$$\psi^*(q) = \sqrt{\frac{nq}{\hat{\theta}(q)}}\left(\overline{VR}(q) - 1\right), \quad \text{where} \tag{4.10}$$

$$\hat{\theta}(q) = 4\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)^2 \hat{\delta}_k, \quad \text{and} \tag{4.11}$$

$$\hat{\delta}_k = \frac{nq\sum_{j=k+1}^{nq}\left(r_j - \hat{\mu}\right)^2\left(r_{j-k} - \hat{\mu}\right)^2}{\left[\sum_{j=1}^{nq}\left(r_j - \hat{\mu}\right)^2\right]^2} \tag{4.12}$$

The asymptotic standard error implied by (4.10) is given by:

$$\mathrm{ASE} = \sqrt{\frac{\hat{\theta}(q)}{nq}} \tag{4.13}$$

Since $\psi^*(q)$ is standard normal, values of $\psi^*(q)$ outside the interval [-1.96; 1.96] reject the null hypothesis at the 95% confidence level.

As (4.8) demonstrates, if the null hypothesis is rejected for some value of variance ratio period, q, then the serial correlation of the price series is serially correlated at some lag(s) k, where $k < q$.

4.1.2 Cross-autocorrelation matrices between price series

If r_t is a vector of returns for a portfolio at time t and a number, n, of periods before time t, let $\mathrm{V}_t \equiv [r_{1t} \;\; r_{2t} \;\; r_{3t} \;\; r_{4t} \;\; r_{5t}]$ contain the returns vector of each of the portfolio returns to be cross correlated. The cross autocorrelation matrices at a lag of k are obtained from the following relation:

$$\hat{\Upsilon}(k) \equiv \hat{\mathrm{D}}^{-\frac{1}{2}}\hat{\mathrm{C}}(k)\hat{\mathrm{D}}^{-\frac{1}{2}} \tag{4.14}$$

In (4.14), $\hat{\mathrm{D}}$ is an estimator of the diagonal matrix of variances of V_t, $\hat{\mathrm{C}}$ is an estimator of the covariance matrix of V_t and V_{t-k} and $\hat{\mu}$ is an estimator for the means of V_t, as follows:

$$\hat{\mathrm{D}} = \mathrm{diag}(\hat{\sigma}_1, \hat{\sigma}_2, \hat{\sigma}_3, \hat{\sigma}_4, \hat{\sigma}_5) \tag{4.15}$$

$$\hat{\mathrm{C}}(k) = \mathrm{E}[(\mathrm{V}_{t-k} - \hat{\mu})(\mathrm{V}_t - \hat{\mu})'] \tag{4.16}$$

$$\hat{\mu} = [\hat{\mu}_1 \;\; \hat{\mu}_2 \;\; \hat{\mu}_3 \;\; \hat{\mu}_4 \;\; \hat{\mu}_5] \tag{4.17}$$

Estimators of the elements of $\hat{\mathrm{D}}$, $\hat{\mathrm{C}}$ and $\hat{\mu}$ are given as:

$$\hat{\mu}_i = \frac{1}{n}\sum_{j=1}^{n} r_j \tag{4.18}$$

$$\hat{\sigma}_i = \frac{1}{n-1}\sum_{j=1}^{n}(r_j - \hat{\mu}_i)^2 \tag{4.19}$$

$$\hat{C}_{i,j} = \frac{1}{n-1}\sum_{p=1}^{n}\left(r_{i,p-k} - \hat{\mu}_i\right)\left(r_{j,p} - \hat{\mu}_j\right) \tag{4.20}$$

The lead-lag trend may be more easily identified by subtracting the transpose of the autocorrelation matrix from itself as follows:

$$\psi(k) = \hat{\Upsilon}(k) - \hat{\Upsilon}'(k) \tag{4.21}$$

If an entry, $\psi_{i,j}(k)$ is positive, this implies that portfolio r_i potentially leads r_j. If the values above or below the diagonal of $\psi(k)$ are all of a particular sign, a trend could arguable exist between higher and lower order ranking quintile portfolios.

The statistical significance of the cross autocorrelation factors may be determined under the null hypothesis that the cross autocorrelation factors between portfolios and their lagged counterparts are zero. Under this assumption and assuming IID returns, the asymptotic standard error in the sample estimate of the cross autocorrelation factors is simply $1/\sqrt{n}$. Statistical significance is tested using a t-test statistic at the 95% confidence interval.

In order to test for statistical significance in the presence of heteroskedastic returns, the standard error must be adjusted upwards in accordance with a method such as White (1980). Owing to the mathematical complexity of this technique, the calculation of heteroskedastically consistent standard error terms has not been undertaken in this research.

4.2 The data set

4.2.1 The study period

The study period over which the variance ratio and cross autocorrelation matrices are evaluated is the entire 20 year period from 31st March 1989 to the 31st March 2009, as well as on the four 5 year sub-periods within that period. This amounts to a sample size of 1 041 for the entire period and 261 for each five year sub-period.

For tests spanning the entire period 1989 to 2009 period, only shares that traded for this duration were included in the test. For sub-period results, only shares that traded for the entire duration of the five year sub-period were included.

4.2.2 The data source

The data set used is the weekly JSE share prices for 467 shares over the study period. The data set includes closing price, dividend yield, earnings yield, volume, and market capitalisation. This data was sourced from I-NET Bridge, in soft copy format. Industry data was gathered from a number of JSE handbook editions from 1990 to 2009.

4.2.3 The benchmarks

The benchmarks used to sort the shares into portfolios in the second and final sub-problems were primarily chosen because they had been highlighted in the literature as being related to share price predictability. A second reason was the fact that they are easy to observe in the financial press. Consequently, according to EMH, their informational value should already be incorporated in share prices.

This does, however, raise questions as to the degree of overlap in the benchmarks. How unique are the benchmarks compared to one another? Are any of the benchmarks used to form the portfolios related to any of the others or to a combination of the others? Put another way, is there any way to reduce the number of benchmarks, but still retain the variability in the resulting portfolios? Since this relates to the validity of the research method, it is considered in section 4.4.

4.2.4 Data adjustments

The following adjustments were made to the dataset to improve on the accuracy of the results:

4.2.4.1 ***Dividend reinvestment***

One potential problem with using raw closing prices as reported on the JSE is that they do not reflect the effects of dividends issued by the company. If these dividend payouts are not accounted for, they will introduce spurious dips in share price once the share trades ex-dividend, since, *ceteris paribus*, on the ex-dividend date, the share's price will drop by the amount of the dividend. This could arguably introduce artificially high variance in the price series, which is unacceptable in statistical tests that test ratios of variance.

In order to address this, for each share that traded on the JSE in the 1989 to 2009 period, a price series that includes the effect of dividend reinvestment was formed. This dividend inclusive price series is used in variance ratio and lead-lag calculations. The mechanism used to adjust the share price is to adjust the price series upwards by the amount of the dividend relative to the first quoted price that the stock traded ex-dividend. This has the effect of reinvesting dividends back into the share.

4.2.4.2 ***Non-trading shares***

A common explanation for positive serial correlation, as put forward by Cohen et al. (1983), is that it is induced by non-synchronous trading. Shares which trade infrequently are slow to incorporate new information into their price, causing positive serial correlation in portfolios comprising these shares as well as shares that trade frequently.

To address this, shares which did not trade at least 90% of the time were excluded from calculation of variance ratios and lead lag effects. In accordance with the analysis conducted by Lo and MacKinlay (1988), even if all the JSE shares used in this study traded only 90% of the time, the maximum serial correlation that could be induced in a portfolio price series is 10%.

4.2.4.3 ***FTSE/JSE all share index (J203) merging with the old JSE overall index calculation***

The JSE replaced the old overall actuaries' index with the FTSE/JSE all share index in June 1995. The two indices ran concurrently for a number of years, but the old JSE overall index ended on the 24th June 2002. To ensure a continuous 20 year history in the market index for the JSE, the old overall index was adjusted by a factor to ensure that, at the start of the J203 in June 1995, the value of the J203 and the value of the old overall index were equal.

The resulting price series therefore includes these adjusted values for the five year period from 1989 to 1995 and, from the 25th of June 1995, uses the J203 price series.

4.2.5 Numerical processing

All numerical processing is performed in MATLAB, a popular computational maths software package. Algorithms and procedures used to perform the calculations and simulation are available from the author on request.

4.3 Statistical power of the variance ratio tests

In order to determine the power of the variance ratio tests to reject the null hypothesis of no correlation in a price series, Monte Carlo simulations were performed to determine standard errors for sample sizes of 1 041 and 261 samples for various degrees of correlation and heteroskedasticity in the simulated price series.

Central to the simulations was the assumption of a process by which the price evolves. The general form of the log return of the price series was specified in accordance with Hull (2006) as follows, where r_t is the weekly log return at time at week *t*:

$$r_t = \mu - \frac{{\sigma_t}^2}{2} + \sigma_t \epsilon_t \tag{4.22}$$

In (4.22), μ is the mean return of the series of log returns, arbitrarily assigned to 8% per annum, ϵ_t is a random variable and σ_t is the weekly standard deviation of r_t, assumed to be a GARCH(1,1) process of the following form:

$$\sigma_t = \sqrt{a(\sigma_{t-1}\epsilon_{t-1})^2 + b(\sigma_{t-1})^2} \tag{4.23}$$

Values for a and b in (4.23) were varied to adjust the degree of heteroskedasticity in return increments. Various initial values for the standard deviation were used.

To simulate correlation in a price series, ϵ_t was mixed with its previous value and a standard normal random variable, z_t, using a correlation coefficient, ρ, in the following way:

$$\epsilon_t = \rho\epsilon_{t-1} + (1 - \rho^2)z_t \tag{4.24}$$

4.3.1 Variance ratio tests under varying degrees of serial correlation

Table 4-1 shows the results of Monte Carlo simulations for whole period price series. The number iterations performed was 10 000 with a price series length of 1041. Simulated first order serial correlations of 2%, 5%, 10%, 15% and 20% were used. The right most column indicates the confidence interval that may be attained, given the mean standard error and test statistic.

As can be seen in the table, the values for the average variance ratio reported by the test is very nearly equal to one plus the correlation between log returns, as equation (4.8) indicates. The standard error of the variance ratio remains roughly constant for various degrees of serial correlation and, for these particular GARCH(1,1) coefficients, is fairly close to the asymptotic standard error for IID increments. Changing the initial standard deviation has little influence on the final variance ratio reported or on the standard error calculated.

Table 4-2 shows a similar table for five year sub-period simulations. Aside from the smaller price series length of 261, parameters were identical to the whole period tests.

Table 4-1 Monte Carlo simulation of $\overline{\mathrm{VR}}(2)$ and $\psi^*(2)$ for various serial correlation coefficients (10 000 iterations, 1041 data points, a = 0.02, b = 0.98)

Serial correlation	Mean $\overline{\mathrm{VR}}(2)$	Mean standard error	Mean test statistic	Confidence interval possible
0.02	1.0199	0.0330	0.6054	0.4551
0.05	1.0495	0.0330	1.5028	0.8671
0.10	1.0998	0.0332	3.0122	0.9974
0.15	1.1495	0.0336	4.4560	1.0000
0.20	1.1998	0.0343	5.8403	1.0000

Table 4-2 Monte Carlo simulation of $\overline{\mathrm{VR}}(2)$ and $\psi^*(2)$ for various serial correlation coefficients (10 000 iterations, 261 data points, a = 0.02, b = 0.98)

Serial correlation	Mean $\overline{\mathrm{VR}}(2)$	Mean standard error	Mean test statistic	Confidence interval possible
0.02	1.0202	0.0626	0.3203	0.2513
0.05	1.0499	0.0626	0.7956	0.5737
0.10	1.0992	0.0630	1.5709	0.8838
0.15	1.1484	0.0638	2.3221	0.9798
0.20	1.1982	0.0647	3.0563	0.9978

4.3.2 Variance ratio tests under varying degrees of heteroskedasticity

Changing the GARCH(1,1) parameters so that the price increments become more heteroskedastic has the expected effect of increasing the standard error and therefore decreasing the power of the test.

Table 4-3 and Table 4-4 show the results of Monte Carlo simulations on price series with various degrees of heteroskedasticity, generated by changing the GARCH(1,1) coefficients. The results of these simulations show that the power of the variance ratio tests become independent of the number of samples as the degree of heteroskedasticity becomes large. This is to be expected, since the variance of a very heteroskedastic price series changes so significantly over time that adding more samples to the test lends little support to testing the variance of the series.

In the limit as the price series increments become homoskedastic, the standard error approaches its asymptotic value of $1/\sqrt{n}$ for IID price increments.

Table 4-3 Monte Carlo simulation of $\overline{\mathrm{VR}}(2)$ and $\psi^*(2)$ for various degrees of heteroskedasticity (ρ = 0.1, 10 000 iterations, 1041 data points)

GARCH(1,1) coefficients, a & b	Mean $\overline{\mathrm{VR}}(\mathbf{2})$	Mean standard error	Mean test statistic	Confidence interval possible
0; 1	1.0999	0.0312	3.1939	0.9986
0.02; 0.98	1.0996	0.0333	2.9963	0.9973
0.05; 0.95	1.0992	0.0431	2.3846	0.9829
0.1; 0.9	1.0970	0.0696	1.5146	0.8701
0.2; 0.8	1.0844	0.1237	0.7555	0.5500

Table 4-4 Monte Carlo simulation of $\overline{\mathrm{VR}}(2)$ and $\psi^*(2)$ for various degrees of heteroskedasticity (ρ = 0.1, 10 000 iterations, 261 data points)

GARCH(1,1) coefficients, a & b	Mean $\overline{\mathrm{VR}}(\mathbf{2})$	Mean standard error	Mean test statistic	Confidence interval possible
0; 1	1.0986	0.0621	1.5826	0.8865
0.02; 0.98	1.0990	0.0630	1.5688	0.8833
0.05; 0.95	1.0983	0.0677	1.4591	0.8555
0.1; 0.9	1.0964	0.0821	1.2175	0.7766
0.2; 0.8	1.0848	0.1244	0.7436	0.5492

4.4 Dimensional redundancy in the benchmarks

To test the possibility that the benchmarks used to sort the shares into portfolios have some degree of overlap, another Monte Carlo simulation was performed. This simulation involved drawing 13 unique numbers at random five times from a total of 65 numbers[6] and counting how many unique numbers one obtained after the five draws. This is analogous to selecting 13 unique shares according to 5 random benchmarks and counting the degree of overlap in the top ranked portfolio for each benchmark.

The results of 100 000 simulations indicated that the number of unique shares that would be obtained from drawing each of the five benchmark portfolios randomly is 47 with a standard deviation of 2.4. When one creates portfolios in accordance with the benchmarks used in this study and counts the number of unique shares in the top scoring portfolio for each benchmark, however, only 38 unique shares are found. This indicates that there is some dimensional redundancy in the benchmarks. In other words, fewer, differently specified benchmarks could have been chosen that would select shares that have less overlap between them.

To test this supposition, a matrix of the rankings of each share with respect to each benchmark was formed. A principle components analysis was performed on the matrix to determine how much of the variability in rankings of each share was explained by its principle components. Figure 4-1 shows a Pareto chart of the variability in rankings that each principle component calculated can explain. The figure indicates that up to 86% of the variability of the share rankings into portfolios could be obtained by using only three principle (orthogonal) benchmarks.

While it is mathematically more elegant to rank the shares in accordance with these three modified benchmarks which capture almost all of the variability in share selection that the previous five benchmarks did, this reduces the study to a purely mathematical exercise. Much of the physical relevance of the benchmarks would be lost. Doing this would also compromise on the external validity of the research, since one cannot discount the possibility that these new composite benchmarks arise from a peculiarity in the data set.

[6] The number of shares in the data set that met the liquidity requirements and traded over the entire 20 year period from March 1989 to March 2009 is 65. The number of shares per portfolio, therefore, is 13.

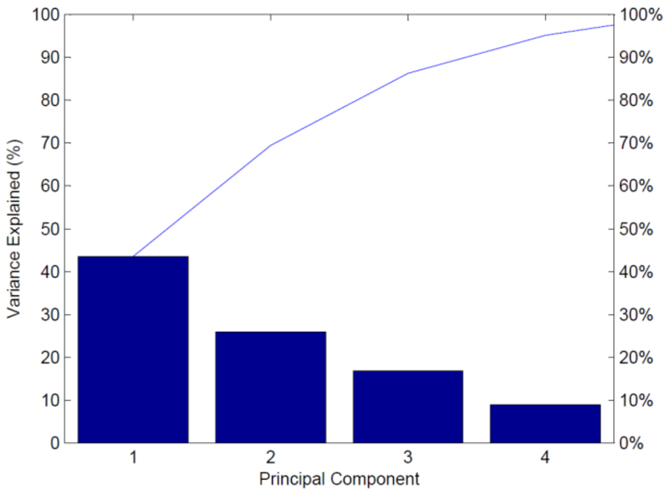

Figure 4-1 Principle components of the rankings obtained by sorting by the set of five benchmarks

For this reason, despite a moderate degree of redundancy, the original benchmarks have been retained when creating portfolios.

4.5 Validity and reliability of the research

4.5.1 Internal validity

Internal validity relates to the degree to which the research method is able to achieve the objectives of the study. In the context of the first and second sub-problems, using a variance ratio test is one of the most statistically powerful methods for determining serial correlation in share prices (Poterba and Summers 1988). In addition, the use of heteroskedastically consistent standard error estimates allows the variance ratio tests to be able to determine statistically significant serial correlations even in the presence of non-identical and dependent price increments. As section 4.3 shows, for common confidence intervals and all but extreme degrees of heteroskedasticity, the variance ratio test is powerful enough to reject the null hypothesis of uncorrelated price increments. The research method therefore answers the first and second sub-problems in one of the most decisive, yet practical ways possible.

The research method used to answer the third sub-problem is a commonly employed statistical tool to determine lead-lag relationships among a collection of factors. While the lagged covariance matrices clearly indicate lead-lag relationships among the factors, these are only tested for statistical significance under the assumption of homoskedastic price increments. The omission of heteroskedastically consistent standard error estimates is a technical shortcoming of the research.

From a data and sampling point of view, a significantly long study period provides the sound foundation that underlies the research methods addressing all three sub-problems. In addition to providing a significant sample size for variance ratio tests, its time diversity incorporates periods of market booms and crashes, allowing one to ensure that correlation trends are valid, regardless of the particular phase of the economic cycle.

4.5.2 External validity

The most common criticism of any study that uses mathematical methods to search and extract conclusions from historical data is that the results arise as a result of a peculiarity of the data set used and the study method (Fama 1998). In other words, rather than extracting generalities from the data, the mathematical methods extract its peculiarities. This is commonly referred to as data mining or data snooping. Essentially, it is a criticism of the external validity of the study.

Though it is never possible to completely discount the possibility of data mining, the likelihood of idiosyncratic results from peculiarities in the data set and study method used may be reduced through the use of a sufficiently long study period. The 20 year study period of the research can be considered a respectable length of study period and should carry some promise of external validity of the findings of the research to other periods in time. In considering the question of what constitutes an acceptable length of study period, one would do well to consider the fact that the EMH was born out of research conducted over a five year period with a population only 30 shares (Fama 1965).

The external validity of the research may also be enhanced by demonstrating that the effects that are observed in the data are present throughout the study period. To facilitate this, the results of the research for the first two sub-problems are quoted for the four five year sub-periods that make up the study period.

Another dimension to the external validity of the research is whether the results obtained can be generalized to other share markets, which may have different dynamics at play. Since market efficiencies should decrease as the size and sophistication of the market increase, one may argue that findings of the research may be extended to other similar and less efficient stock exchanges. One should, however, apply caution when attempting to generalise the results of this study to the world's more sophisticated stock exchanges.

Chapter 5

Presentation and Analysis of Results

"HOWEVER BEAUTIFUL THE STRATEGY, YOU SHOULD OCCASIONALLY LOOK AT THE RESULTS." – WINSTON CHURCHILL

This chapter presents and analyses the results obtained in the study. Sections 5.1 to 5.3 describe the results obtained for each sub-problem of the study. For the second and third sub-problems, the constituents of each portfolio and their rankings according to the relevant benchmark are given in Appendix C to Appendix G. Section 5.4 summarises the results of the study.

5.1 Sub-problem 1: Overall predictability of the JSE

5.1.1 Hypothesis 1: Variance ratio tests of the J203

Table 5-1 shows the results of testing the hypothesis that the FTSE/JSE All Share Index (J203) series is uncorrelated at all lags. The variance ratios, $\overline{\mathrm{VR}}(q)$, for q = 2, 4, 8, 16 are shown in the main rows of the table, with a heteroskedasticity robust test statistic, $\psi^{*}(q)$, shown in parentheses below the main rows. Test statistics shown in bold italics with an asterisk are significant at the 95% confidence level.

Using equation (4.9), the values for overall weekly, two-weekly, four-weekly and eight-weekly serial correlations for the 1989 to 2009 period are 1%, 4%, 8% and 2% respectively. The variance ratios for the 1989 to 2004 sub-periods are all greater than unity, indicating that for lags less than 16 weeks, there is overall weak positive serial correlation in the J203 price series over these sub-periods. In the 2004 to 2009 sub-period, the index exhibited negative serial correlation for weekly and two weekly returns, but overall positive serial correlation for four-weekly and eight-weekly returns.

Table 5-1 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^*(q)$ for the FTSE/JSE All Share Index (J203) from March 1989 to March 2009

Time period	Data points	Variance ratio period q			
		2	4	8	16
1989 to 1994	261	1.02	1.04	1.16	1.22
		(0.38)	(0.35)	(0.82)	(0.77)
1994 to 1999	261	1.18	1.47	1.59	1.48
		(2.48)*	***(3.23)****	***(2.33)****	(1.22)
1999 to 2004	261	1.02	1.01	1.08	1.14
		(0.22)	(0.06)	(0.37)	(0.46)
2004 to 2009	261	0.88	0.82	0.91	1.03
		-(1.07)	-(0.94)	-(0.29)	(0.07)
Whole period (1989 to 2009)	*1041*	*1.01*	*1.05*	*1.13*	*1.15*
		(0.18)	*(0.59)*	*(1.00)*	*(0.80)*

As can be seen from Table 5-1, the variance ratio tests only reject Hypothesis 1 at the 95% confidence level during the period 1994 to 1999 for variance ratio periods 2, 4 and 8. For all other sub-periods and for the overall period, no other statistically significant variance ratios are obtained.

5.1.2 Variance ratio tests of an equal weighted portfolio of all JSE shares

Table 5-2 shows similar variance ratio testing performed for the equal weighted portfolio of stocks on the JSE for the period 1989 to 2009. In contrast to the J203 market capitalisation weighted index, variance ratios of the equal weighted portfolio are positive in all sub-periods, indicating that positive serial correlation is more pronounced than the J203 owing to the equal weighting of shares in the portfolio. The high variance ratios obtained in the 1994 to 1999 sub-period indicate significant positive serial correlation in this period. Using equation (4.9), the values for weekly, 2-weekly, four-weekly and 8-weekly serial correlations for the 1989 to 2009 period are 7%, 9%, 11% and 5% respectively.

Over the entire period, Hypothesis 2 is rejected for variance ratio periods of 4, 8 and 16 weeks at the 95% confidence level, largely supported by strong rejections of the null hypothesis for the 1994 to 1999 sub-period for all variance ratio periods.

Table 5-2 Variance ratio $\overline{\text{VR}}(q)$ and $\psi^{*}(q)$ for an equal weighted JSE portfolio from March 1989 to March 2009

Time period	Data points	Variance ratio period q			
		2	4	8	16
1989 to 1994	261	1.05	1.05	1.17	1.24
		(0.80)	(0.42)	(0.93)	(0.90)
1994 to 1999	261	1.24	1.59	1.75	1.76
		(3.59)*	***(4.12)****	***(3.13)****	***(2.06)****
1999 to 2004	261	1.09	1.17	1.32	1.31
		(1.48)	(1.56)	(1.80)	(1.16)
2004 to 2009	261	1.04	1.19	1.40	1.60
		(0.40)	(0.96)	(1.33)	(1.39)
Whole period (1989 to 2009)	*1041*	*1.07*	*1.17*	*1.30*	*1.36*
		(1.81)	***(2.30)****	***(2.56)****	***(2.07)****

5.1.3 Variance ratio test of individual JSE shares

Table 5-3 shows the average values obtained from variance ratio tests conducted on all JSE shares individually over the 20 year study period. Values on the main rows of the table show the average variance ratios obtained for all JSE shares over the four sub-periods, as well as the whole period results. Values in parentheses below the main rows show the cross sectional standard deviation of the variance ratios across all shares tested. Also of interest is the fact that, on average, the individual share price increments were weakly positively correlated over the 1989 to 1999 sub-periods, and weakly negatively correlated in the 1999 to 2009 sub-periods. Detailed results for each individual share for the 1989 to 2009 period are given in Appendix A.

While the results of Table 5-3 show a significant degree of spread in their variance ratio values, on average, share prices show very little deviation from the assumption of uncorrelated increments. There exists no evidence, therefore, to reject Hypothesis 3 at the 95% confidence level for any period tested.

Table 5-3 Average values of variance ratio $\overline{\text{VR}}(q)$ and its cross sectional standard deviation for all JSE shares between March 1989 and March 2009

Time period	Data points	Shares tested	Variance ratio period q			
			2	4	8	16
1989 to 1994	261	72	1.03	1.04	1.08	1.09
			(0.13)	(0.26)	(0.38)	(0.46)
1994 to 1999	261	131	1.03	1.07	1.08	1.08
			(0.12)	(0.22)	(0.28)	(0.37)
1999 to 2004	261	153	0.95	0.90	0.89	0.89
			(0.10)	(0.18)	(0.26)	(0.34)
2004 to 2009	261	149	0.95	0.92	0.97	1.05
			(0.10)	(0.18)	(0.25)	(0.39)
Whole period (1989 to 2009)	1041	65	1.00	1.00	1.01	1.02
			(0.08)	(0.14)	(0.18)	(0.22)

5.1.4 Comparison with the results of previous research

Comparison of variance ratios and serial correlation coefficients for value weighted and equal weighted market on the JSE are in broad agreement with results obtained for the value and equal weighted CRSP NYSE-AMEX indices reported in Lo and MacKinlay (1988) and Campbell et al. (1997). Both Lo and MacKinlay (1988) and Campbell et al. (1997) show little serial correlation in the value weighted CRSP NYSE-AMEX index. Their sub-period results show a similar trend of decreasing values of serial correlation as those obtained for sub-periods of the J203.

Comparisons of Lo and MacKinlay (1988) and Campbell et al. (1997) results for the equal weighted CRSP NYSE-AMEX index with those of the equal weighted JSE portfolio show higher variance ratios and therefore more serial correlation on the US indices than in the JSE portfolio. Typical values of weekly and 2-weekly serial correlation in the 1978 to 1994 period documented in Campbell et al. (1997) are 19% and 13% respectively. This is much higher than values of 5% and 0% obtained during the 1989 to 1994 sub-period on the JSE, or 7% and 9% obtained for the whole 1989 to 2009 sub-period.

This is a surprising result, given that one would expect the stock exchange of an emerging market to be more predictable and therefore less efficient than that of a first world market, particularly a market such as the NYSE, where the annual value of shares traded is roughly one hundred times that of the JSE in dollar terms (WFE 2008).

One potential explanation for this may be related to the time frame of the analysis. Perhaps, if one were to compare the variance ratios of the US markets over the full 1989 to 2009 period, one might see similar results, given observed fall-off in variance ratios over time in Lo and MacKinlay (1988) and Campbell et al. (1997). Unfortunately, the only overlapping period between this study and the US studies in the literature is the 1989 to 1994 period.

Another potential explanation for the lower variance ratios reported for equal weighted portfolios is that the number of shares used to derive an equal weighted portfolio is far lower (73) than those that make up the equal weighted CRSP NYSE-AMEX index (625). This higher number shares reduces the amount of idiosyncratic, share-specific noise present in the index, which allows trends in variance to be better detected by the variance ratio tests.

Comparison of the variance ratios for individual shares with individual shares on the NYSE are more in line with what one would expect from an emerging market exchange. Though the cross-sectional mean of variance ratios is very nearly unity, the cross sectional variance is much higher than that of the NYSE results. This indicates that, though on average, JSE shares have no serial correlation, there is a much higher spread of the serial correlation values obtained for individual shares than that observed on the NYSE. In contrast to the equal weighted portfolio results, in the context of market efficiency, these results indicate that the JSE is less efficient than the NYSE.

The finding of slight negative serial correlation in the returns of individual shares is a phenomenon noted by Fama and French (1988a) and Lehmann (1990). This effect is only observed on the JSE for the latter half of the study period, with a serial correlation value of -5%. The weak positive serial correlation observed on average for the first half of the study is a phenomenon not observed in the literature. The small average values of serial correlation over the study period, however, supports the results of Gilbertson and Roux (1978) and Brümmer and Jacobs (1981) who find economically insignificant serial correlation in the prices of individual JSE shares.

5.2 Sub-problem 2: Market inefficiency in terms of market benchmarks

The graphs in the following sections present results obtained for the entire 1989 to 2009 period. Detailed graphs of sub-period variance ratios and test statistics may be found in Appendix B.

5.2.1 Firm size

Table 5-4 shows the results of variance ratio tests conducted on the prices of portfolios ranked in terms of firm size. Once again, test statistics, $\psi^*(q)$, are shown in parentheses below the main rows with results significant at the 95 % confidence level being highlighted in bold italics with an asterisk.

Figure 5-1 shows these results graphically for the entire 1989 to 2009 period, with each subfigure representing the results obtained from a different variance ratio calculation period, q. The broad blue bars in the graph indicate the variance ratio calculated, which can be read off the graph using the left hand axis, while the narrow red or green bar indicates the test statistic, $\psi^*(q)$, which can be read off the graph on the right hand axis. A red bar for the test statistic indicates results significant at the 95% confidence level and, therefore, rejections of the null hypothesis for that particular quintile and variance ratio calculation period, q.

Table 5-4 Variance ratio $\overline{\text{VR}}(q)$ and $\psi^{*}(q)$ for firm size sorted portfolios from March 1989 to March 2009

Time period	Data points	Shares per portfolio	Variance ratio period q 2	4	8	16
Quintile 1 - Portfolio containing the highest ranked companies by capitalisation						
1989 to 1994	261	14	0.97	0.89	0.91	1.01
			-(0.40)	-(0.92)	-(0.46)	(0.03)
1994 to 1999	261	20	1.06	1.20	1.15	1.06
			(0.86)	(1.57)	(0.71)	(0.18)
1999 to 2004	261	29	1.00	1.02	1.07	1.10
			(0.04)	(0.15)	(0.40)	(0.36)
2004 to 2009	261	29	0.93	0.98	1.09	1.24
			-(0.74)	-(0.13)	(0.34)	(0.61)
Whole period (1989 to 2009)	1041	13	0.95	0.95	0.97	1.01
			-(1.21)	-(0.70)	-(0.26)	(0.07)
Quintile 2 - Portfolio containing the second highest ranked companies by capitalisation						
1989 to 1994	261	14	1.14	1.20	1.43	1.44
			(1.89)	(1.56)	***(2.13)****	(1.49)
1994 to 1999	261	20	1.26	1.60	1.77	1.81
			(2.80)*	***(3.25)****	***(2.61)****	(1.83)
1999 to 2004	261	29	1.10	1.30	1.62	1.61
			(1.41)	***(2.15)****	***(2.93)****	***(2.02)****
2004 to 2009	261	29	1.15	1.40	1.70	1.95
			(1.56)	***(2.07)****	***(2.38)****	***(2.38)****
Whole period (1989 to 2009)	1041	13	1.16	1.40	1.62	1.63
			(3.56)*	***(4.49)****	***(4.37)****	***(3.05)****
Quintile 3 - Portfolio containing the median ranked companies by capitalisation						
1989 to 1994	261	14	1.17	1.30	1.62	1.78
			(2.48)*	***(2.30)****	***(3.05)****	***(2.64)****
1994 to 1999	261	20	1.37	1.91	2.27	2.55
			(4.43)*	***(5.71)****	***(5.04)****	***(4.13)****
1999 to 2004	261	29	1.23	1.45	1.69	1.69
			(3.49)*	***(3.69)****	***(3.55)****	***(2.36)****
2004 to 2009	261	29	1.16	1.32	1.51	1.59
			(1.61)	(1.70)	(1.81)	(1.47)
Whole period (1989 to 2009)	1041	13	1.21	1.35	1.46	1.52
			(4.70)*	***(4.00)****	***(3.51)****	***(2.80)****
Quintile 4 - Portfolio containing the second smallest ranked companies by capitalisation						
1989 to 1994	261	14	1.23	1.61	2.13	2.21
			(3.90)*	***(5.32)****	***(6.01)****	***(4.41)****
1994 to 1999	261	20	1.37	1.75	2.16	2.07
			(2.32)*	***(2.96)****	***(3.42)****	***(2.41)****
1999 to 2004	261	29	1.28	1.72	2.25	2.35
			(4.20)*	***(5.75)****	***(6.21)****	***(4.56)****
2004 to 2009	261	29	1.23	1.73	2.26	2.61
			(2.62)*	***(4.27)****	***(4.90)****	***(4.49)****
Whole period (1989 to 2009)	1041	13	1.17	1.35	1.59	1.67
			(3.87)*	***(4.43)****	***(4.74)****	***(3.65)****
Quintile 5 - Portfolio containing the smallest ranked companies by capitalisation						
1989 to 1994	261	14	1.25	1.46	1.76	1.71
			(3.41)*	***(3.70)****	***(3.89)****	***(2.45)****
1994 to 1999	261	20	1.32	1.61	1.87	2.03
			(2.08)*	***(2.56)****	***(2.65)****	***(2.47)****
1999 to 2004	261	29	1.12	1.30	1.62	2.49
			(1.72)	***(2.34)****	***(3.14)****	***(5.10)****
2004 to 2009	261	29	1.23	1.50	1.89	2.28
			(3.17)*	***(3.57)****	***(4.10)****	***(4.09)****
Whole period (1989 to 2009)	1041	13	1.23	1.47	1.74	1.90
			(3.37)*	***(4.23)****	***(4.95)****	***(4.56)****

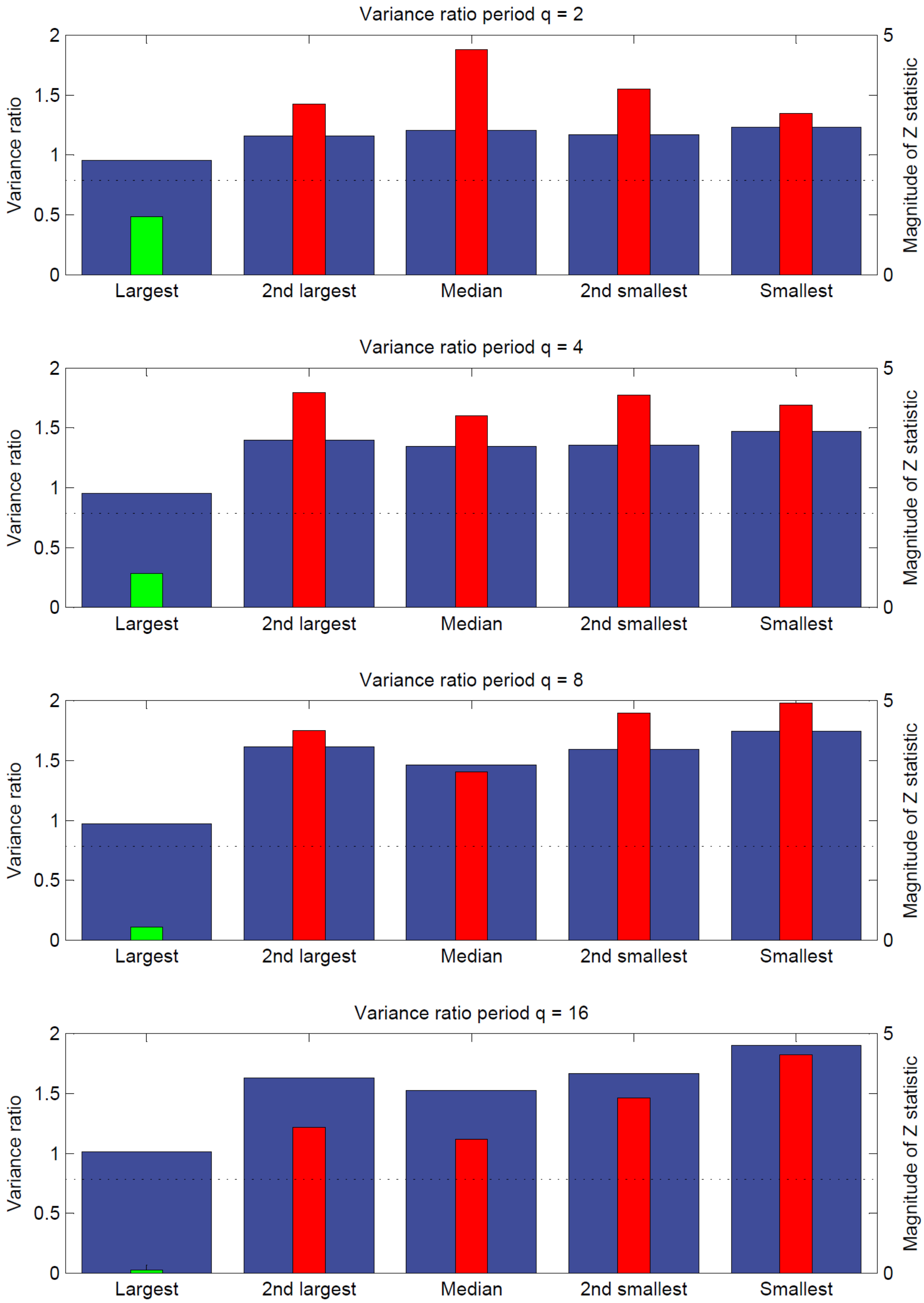

Figure 5-1 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^{*}(q)$ for firm size sorted portfolios from March 1989 to March 2009

Table 5-5 Serial correlation for firm size sorted portfolios from March 1989 to March 2009

Quintile	Serial correlation			
	Weekly	2 weekly	4 weekly	8 weekly
Largest	-0.05	0.00	0.02	0.04
2nd largest	0.16	0.20	0.16	0.01
Median	0.21	0.12	0.08	0.04
2nd smallest	0.17	0.16	0.18	0.05
Smallest	0.23	0.19	0.19	0.09

The results in Table 5-4 and Figure 5-1 show that Hypothesis 4 is strongly rejected at the 95% confidence level for the entire period tested at all lags for all quintiles with the exception of the quintile containing the largest capitalisation shares. The highest variance ratio obtained is 1.23 in the smallest firm size quintile, indicating a single lag serial correlation coefficient of 23% over the entire period. The largest sub-period correlation of 37% is obtained in the third and fourth quintiles during the 1994 to 1999 sub-periods.

Table 5-5 shows the serial correlation coefficients calculated using equation (4.9). The results indicate that this serial correlation persists for up to four weeks in all of the smallest capitalisation portfolios.

5.2.2 Dividend yield

Table 5-6 and Figure 5-2 show variance ratio test results for portfolios containing the shares of companies ranked by their mean dividend yield over the period.

The results show a strong rejection of Hypothesis 5 at the 95% confidence level for the quintile containing the highest dividend yielding stocks, with a reasonably strong rejection of the null hypothesis for the quintile containing the lowest dividend yielding stocks. The central three quintiles show no significant rejection of Hypothesis 5.

Table 5-7 shows the serial correlation coefficients for each quintile over the entire period. The results indicate that this serial correlation persists even up until eight weeks in the quintile containing the highest dividend yield. Moderate serial correlation is observed for the lowest dividend yield quintile which persists for four weeks. For all other quintiles, the serial correlation is negligible. While the test statistics obtained for the portfolio of high dividend yielding stocks are comparable to those obtained for portfolios of small firms, the values of serial correlation obtained are not as high, with weekly serial correlation coefficients of 20% for the portfolio of high dividend yielding stocks compared with 23% for the smallest firm size portfolio.

Table 5-6 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^{*}(q)$ for dividend yield sorted portfolios from March 1989 to March 2009

Time period	Data points	Shares per portfolio	Variance ratio period q 2	4	8	16
Quintile 1 - Portfolio containing the highest ranked companies by dividend yield						
1989 to 1994	261	14	1.17	1.29	1.54	1.56
			(2.42)*	***(2.24)****	***(2.65)****	(1.91)
1994 to 1999	261	25	1.09	1.16	1.09	1.12
			(1.10)	(1.06)	(0.37)	(0.32)
1999 to 2004	261	30	1.16	1.36	1.55	1.37
			(2.46)*	***(3.18)****	***(2.92)****	(1.31)
2004 to 2009	261	29	1.25	1.69	2.16	2.49
			(1.91)	***(3.02)****	***(3.54)****	***(3.36)****
Whole period (1989 to 2009)	1041	13	1.20	1.39	1.58	1.78
			(4.53)*	***(4.91)****	***(4.82)****	***(4.51)****
Quintile 2 - Portfolio containing the second highest ranked companies by dividend yield						
1989 to 1994	261	14	0.92	0.84	0.95	1.17
			-(0.62)	-(0.77)	-(0.20)	(0.52)
1994 to 1999	261	25	1.24	1.60	1.87	2.01
			(2.68)*	***(3.55)****	***(3.37)****	***(2.66)****
1999 to 2004	261	30	0.96	0.95	0.97	0.92
			-(0.66)	-(0.44)	-(0.15)	-(0.29)
2004 to 2009	261	29	1.04	1.16	1.29	1.46
			(0.39)	(0.93)	(1.09)	(1.21)
Whole period (1989 to 2009)	1041	13	0.98	1.00	1.04	1.08
			-(0.50)	(0.00)	(0.39)	(0.47)
Quintile 3 - Portfolio containing the median ranked companies by dividend yield						
1989 to 1994	261	14	1.02	0.98	1.03	0.99
			(0.39)	-(0.16)	(0.14)	-(0.05)
1994 to 1999	261	25	1.15	1.41	1.52	1.43
			(2.03)*	***(2.89)****	***(2.26)****	(1.22)
1999 to 2004	261	30	1.09	1.14	1.29	1.28
			(1.29)	(1.13)	(1.51)	(0.98)
2004 to 2009	261	29	0.97	0.96	1.09	1.21
			-(0.28)	-(0.25)	(0.33)	(0.55)
Whole period (1989 to 2009)	1041	13	1.06	1.15	1.24	1.12
			(1.08)	(1.56)	(1.66)	(0.57)
Quintile 4 - Portfolio containing the second lowest ranked companies by dividend yield						
1989 to 1994	261	14	1.16	1.24	1.30	1.06
			(2.84)*	***(2.27)****	(1.67)	(0.21)
1994 to 1999	261	25	1.23	1.49	1.69	1.61
			(2.36)*	***(2.65)****	***(2.22)****	(1.32)
1999 to 2004	261	30	1.12	1.18	1.28	1.31
			(1.92)	(1.56)	(1.57)	(1.15)
2004 to 2009	261	29	0.95	1.00	1.18	1.42
			-(0.41)	(0.02)	(0.60)	(0.97)
Whole period (1989 to 2009)	1041	13	1.00	1.00	1.06	1.16
			(0.04)	-(0.06)	(0.54)	(0.96)
Quintile 5 - Portfolio containing the lowest ranked companies by dividend yield						
1989 to 1994	261	14	1.13	1.29	1.52	1.44
			(1.84)	***(2.13)****	***(2.35)****	(1.32)
1994 to 1999	261	25	1.31	1.64	1.84	1.68
			(2.65)*	***(3.13)****	***(2.74)****	(1.58)
1999 to 2004	261	30	1.16	1.42	1.74	1.80
			(2.19)*	***(2.96)****	***(3.49)****	***(2.63)****
2004 to 2009	261	29	0.96	0.95	0.96	0.97
			-(0.44)	-(0.29)	-(0.16)	-(0.08)
Whole period (1989 to 2009)	1041	13	1.10	1.19	1.29	1.25
			(2.64)*	***(2.67)****	***(2.63)****	(1.52)

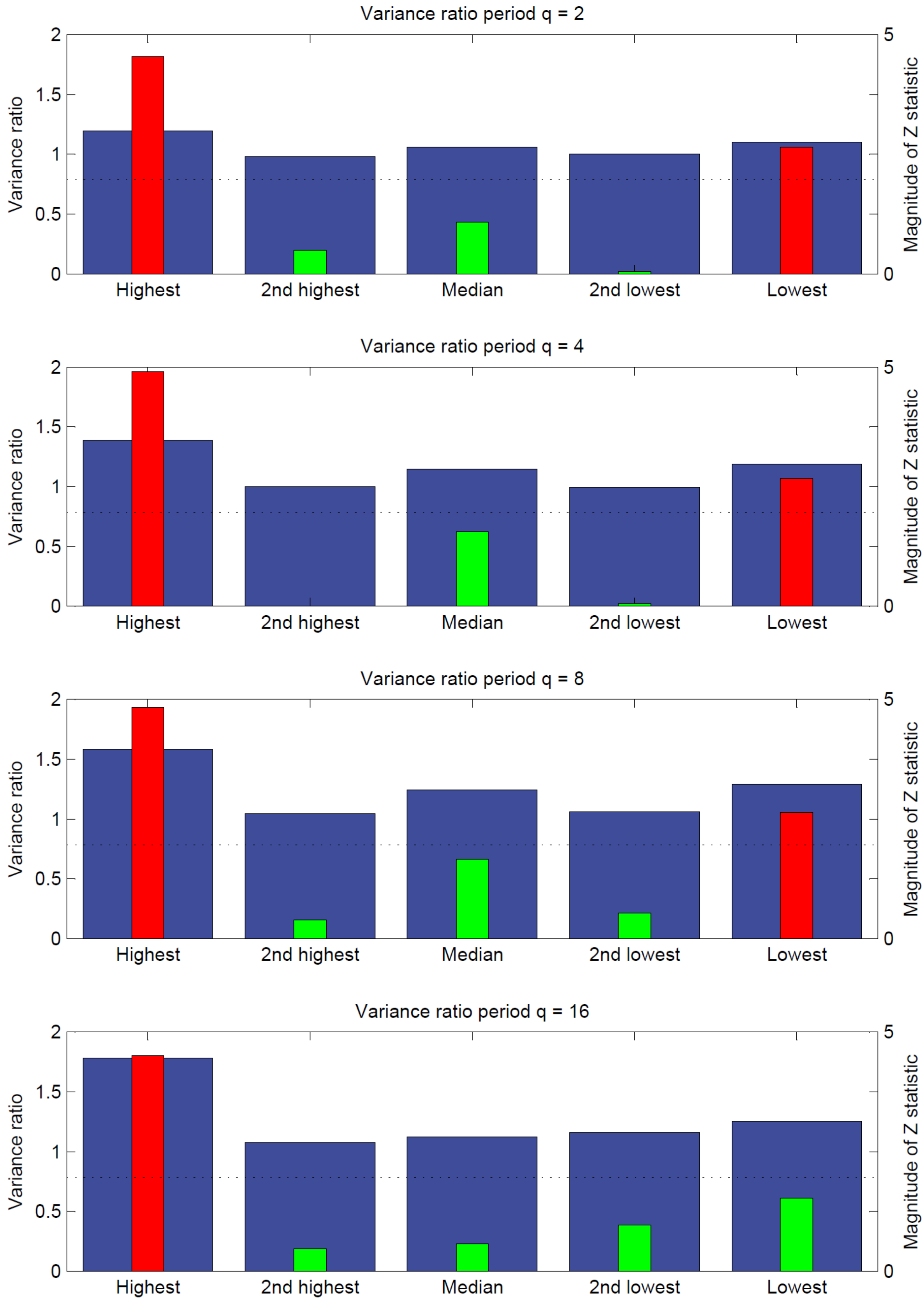

Figure 5-2 Variance ratio $\overline{\text{VR}}(q)$ and $\psi^*(q)$ for dividend yield sorted portfolios from March 1989 to March 2009

Table 5-7 Serial correlation for dividend yield sorted portfolios from March 1989 to March 2009

Quintile	Serial correlation			
	Weekly	2 weekly	4 weekly	8 weekly
Highest	0.20	0.16	0.14	0.13
2nd highest	-0.02	0.02	0.04	0.03
Median	0.06	0.09	0.08	-0.10
2nd lowest	0.00	-0.01	0.07	0.09
Lowest	0.10	0.08	0.09	-0.03

5.2.3 Earnings yield

Variance ratios and test statistics obtained for portfolios of companies ranked by their mean earnings yield are shown in Table 5-9 and Figure 5-3. Strong rejections of Hypothesis 6 at the 95% confidence level can be observed for the quintile containing the highest earnings yielding shares, with other quintiles showing no statistically significant test statistics.

Table 5-8 shows the serial correlation coefficients for each quintile over the entire period. The results indicate that this serial correlation persists strongly until four weeks in the quintile containing the highest earnings yield. No other significant serial correlation is seen for other quintiles.

5.2.4 Industry

Table 5-10 and Figure 5-4 show variance ratio and test statistic results for portfolios containing companies of a particular industry. Strong rejections Hypothesis 7 at the 95% confidence level are seen for portfolios of industrial and retail companies. These occur for almost all sub-periods, as well as for all variance ratio sampling periods. Rejections of Hypothesis 7 at the 95% confidence level are also observed for portfolios containing financial and technology stocks are obtained in some periods for certain values of variance ratio sample period, *q*, but these are by no means as strong as those obtained from portfolios of industrial and retail stocks. The portfolio containing resources stocks shows no rejection of Hypothesis 7 for any sub-period tested or for any variance ratio sampling period and, consequently, very little serial correlation.

Table 5-8 Serial correlation for earnings yield sorted portfolios from March 1989 to March 2009

Quintile	Serial correlation			
	Weekly	2 weekly	4 weekly	8 weekly
Highest	0.20	0.19	0.18	0.10
2nd highest	0.05	0.05	0.10	0.00
Median	0.05	0.05	0.09	-0.02
2nd lowest	0.00	0.06	0.05	0.01
Lowest	-0.02	-0.06	-0.01	0.03

Table 5-9 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^{*}(q)$ for earnings yield sorted portfolios from March 1989 to March 2009

Time period	Data points	Shares per portfolio	Variance ratio period q 2	4	8	16
Quintile 1 - Portfolio containing the highest ranked companies by earnings yield						
1989 to 1994	261	14	1.36	1.83	2.38	2.72
			(5.48)*	***(6.38)****	***(6.89)****	***(6.08)****
1994 to 1999	261	26	1.19	1.44	1.73	2.19
			(2.59)*	***(2.96)****	***(2.92)****	***(3.13)****
1999 to 2004	261	30	1.19	1.36	1.50	1.70
			(2.68)*	***(2.78)****	***(2.45)****	***(2.33)****
2004 to 2009	261	29	1.17	1.46	1.83	2.21
			(1.83)	***(2.40)****	***(2.87)****	***(3.01)****
Whole period (1989 to 2009)	1041	13	1.20	1.43	1.69	1.86
			(4.62)*	***(5.29)****	***(5.56)****	***(4.78)****
Quintile 2 - Portfolio containing the second highest ranked companies by earnings yield						
1989 to 1994	261	14	1.14	1.18	1.46	1.60
			(1.85)	(1.33)	***(2.28)****	***(2.14)****
1994 to 1999	261	26	1.29	1.66	1.88	2.04
			(3.18)*	***(3.93)****	***(3.36)****	***(2.69)****
1999 to 2004	261	30	1.12	1.21	1.43	1.24
			(1.60)	(1.63)	***(2.15)****	(0.83)
2004 to 2009	261	29	1.13	1.29	1.64	2.01
			(1.70)	***(2.07)****	***(2.79)****	***(3.01)****
Whole period (1989 to 2009)	1041	13	1.05	1.11	1.22	1.23
			(1.11)	(1.13)	(1.48)	(1.03)
Quintile 3 - Portfolio containing the median ranked companies by earnings yield						
1989 to 1994	261	14	1.14	1.20	1.40	1.45
			(2.39)*	(1.84)	***(2.16)****	(1.64)
1994 to 1999	261	26	1.24	1.64	1.91	1.88
			(3.34)*	***(4.37)****	***(3.71)****	***(2.29)****
1999 to 2004	261	30	1.00	1.00	1.07	0.93
			(0.03)	-(0.02)	(0.33)	-(0.24)
2004 to 2009	261	29	0.94	0.90	1.00	1.06
			-(0.62)	-(0.59)	-(0.01)	(0.14)
Whole period (1989 to 2009)	1041	13	1.05	1.10	1.20	1.17
			(0.99)	(1.15)	(1.51)	(0.87)
Quintile 4 - Portfolio containing the second lowest ranked companies by earnings yield						
1989 to 1994	261	14	1.09	1.17	1.36	1.20
			(1.28)	(1.40)	(1.87)	(0.71)
1994 to 1999	261	26	1.06	1.12	1.08	1.04
			(0.82)	(0.86)	(0.37)	(0.14)
1999 to 2004	261	30	1.02	1.07	1.15	1.18
			(0.30)	(0.70)	(0.86)	(0.66)
2004 to 2009	261	29	1.04	1.10	1.25	1.43
			(0.35)	(0.55)	(0.88)	(1.05)
Whole period (1989 to 2009)	1041	13	1.00	1.05	1.11	1.12
			-(0.05)	(0.71)	(0.89)	(0.64)
Quintile 5 - Portfolio containing the lowest ranked companies by earnings yield						
1989 to 1994	261	14	1.00	0.95	1.05	1.18
			(0.01)	-(0.36)	(0.27)	(0.63)
1994 to 1999	261	26	1.22	1.40	1.43	1.26
			(2.32)*	***(2.41)****	(1.70)	(0.70)
1999 to 2004	261	30	1.00	0.92	1.01	0.96
			(0.01)	-(0.69)	(0.08)	-(0.15)
2004 to 2009	261	29	0.96	1.05	1.17	1.31
			-(0.44)	(0.29)	(0.67)	(0.83)
Whole period (1989 to 2009)	1041	13	0.98	0.92	0.91	0.94
			-(0.42)	-(1.08)	-(0.80)	-(0.41)

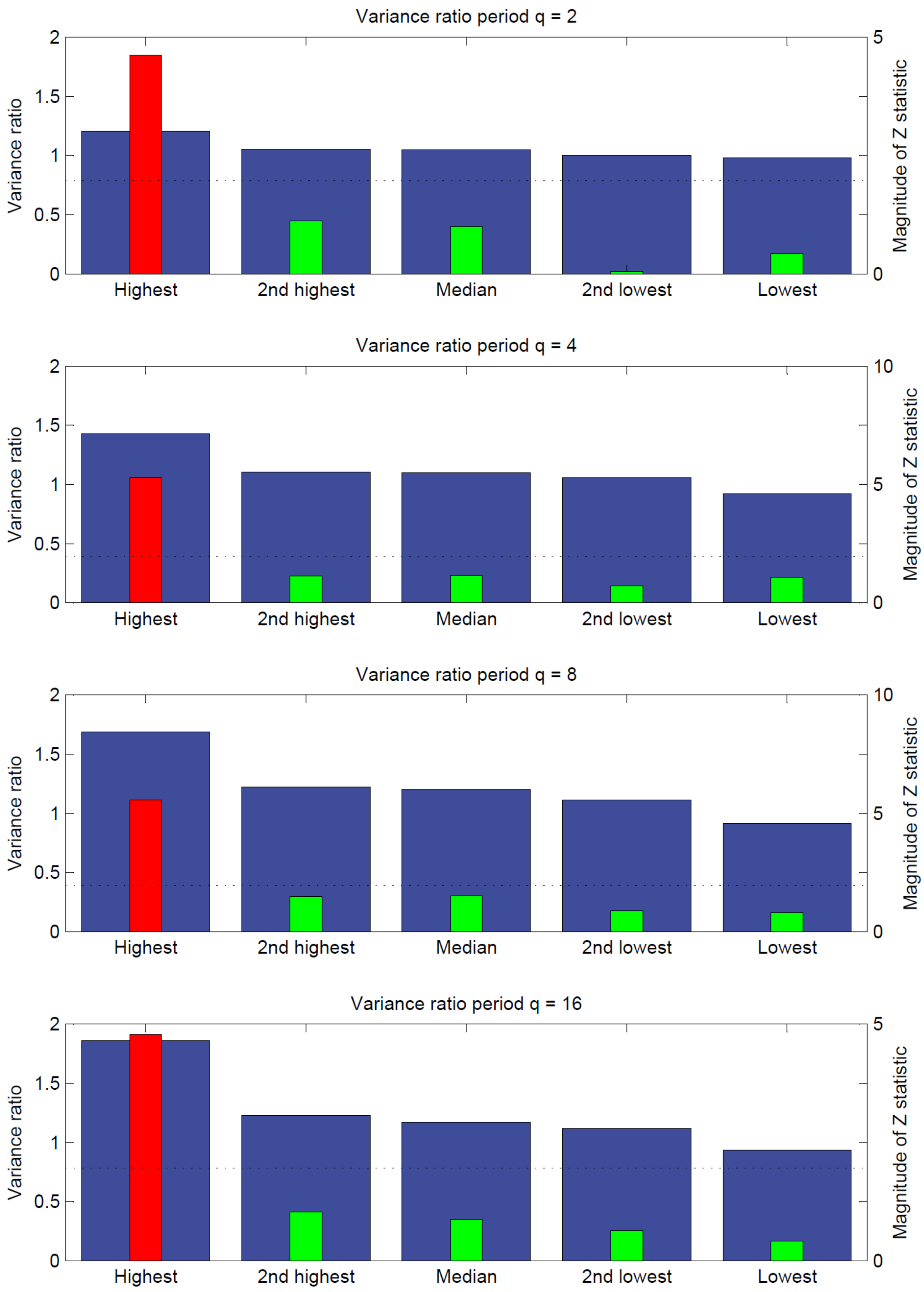

Figure 5-3 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^{*}(q)$ for earnings yield sorted portfolios from March 1989 to March 2009

Table 5-10 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^{*}(q)$ for industry sorted portfolios from March 1989 to March 2009

Time period	Data points	Shares per portfolio	Variance ratio period q			
			2	4	8	16
Quintile 1 - Portfolio containing companies in the resources sector						
1989 to 1994	261	14	1.01	0.97	1.05	1.20
			(0.19)	-(0.26)	(0.29)	(0.75)
1994 to 1999	261	23	1.10	1.19	1.05	1.06
			(1.37)	(1.34)	(0.23)	(0.17)
1999 to 2004	261	20	1.02	1.07	1.09	1.21
			(0.30)	(0.65)	(0.52)	(0.79)
2004 to 2009	261	21	0.95	1.05	1.20	1.39
			-(0.44)	(0.26)	(0.71)	(0.98)
Whole period (1989 to 2009)	1041	13	0.99	1.02	1.06	1.18
			-(0.18)	(0.25)	(0.52)	(1.02)
Quintile 2 - Portfolio containing companies in the financial sector						
1989 to 1994	261	13	1.13	1.26	1.28	1.06
			(2.64)*	(2.63)*	(1.57)	(0.21)
1994 to 1999	261	22	1.28	1.61	1.83	1.67
			(1.81)	(2.33)*	(2.14)*	(1.23)
1999 to 2004	261	27	1.04	1.05	1.11	0.92
			(0.54)	(0.33)	(0.54)	-(0.26)
2004 to 2009	261	37	1.10	1.28	1.70	1.99
			(1.47)	(2.06)*	(3.17)*	(3.08)*
Whole period (1989 to 2009)	1041	13	1.13	1.27	1.45	1.37
			(1.89)	(2.26)*	(2.51)*	(1.41)
Quintile 3 - Portfolio containing companies in the retail sector						
1989 to 1994	261	17	1.02	1.04	1.29	1.25
			(0.27)	(0.30)	(1.34)	(0.83)
1994 to 1999	261	37	1.40	1.99	2.60	2.91
			(4.24)*	(5.32)*	(5.27)*	(4.23)*
1999 to 2004	261	42	1.25	1.38	1.65	1.61
			(3.21)*	(2.61)*	(3.02)*	(2.00)*
2004 to 2009	261	38	1.12	1.35	1.67	1.96
			(1.44)	(2.31)*	(2.85)*	(2.95)*
Whole period (1989 to 2009)	1041	15	1.17	1.38	1.63	1.67
			(4.09)*	(4.87)*	(5.20)*	(3.74)*
Quintile 4 - Portfolio containing companies in the technology sector						
1989 to 1994	261	5	1.24	1.29	1.43	1.48
			(3.14)*	(1.94)	(1.98)*	(1.63)
1994 to 1999	261	7	1.09	1.20	1.15	1.13
			(1.18)	(1.44)	(0.71)	(0.41)
1999 to 2004	261	17	1.12	1.36	1.75	1.89
			(1.56)	(2.66)*	(3.58)*	(2.93)*
2004 to 2009	261	14	0.91	0.83	0.88	1.00
			-(0.80)	-(0.87)	-(0.41)	(0.00)
Whole period (1989 to 2009)	1041	3	1.16	1.27	1.27	1.22
			(2.71)*	(2.77)*	(1.92)	(1.11)
Quintile 5 - Portfolio containing companies in the industrial sector						
1989 to 1994	261	23	1.21	1.41	1.86	2.07
			(3.18)*	(3.50)*	(4.63)*	(3.98)*
1994 to 1999	261	35	1.33	1.71	1.99	2.16
			(4.09)*	(4.41)*	(3.71)*	(2.90)*
1999 to 2004	261	43	1.12	1.25	1.43	1.34
			(1.43)	(1.71)	(2.06)*	(1.16)
2004 to 2009	261	39	1.20	1.53	1.92	2.11
			(1.67)	(2.54)*	(2.94)*	(2.52)*
Whole period (1989 to 2009)	1041	22	1.25	1.52	1.84	2.01
			(5.24)*	(5.94)*	(6.37)*	(5.23)*

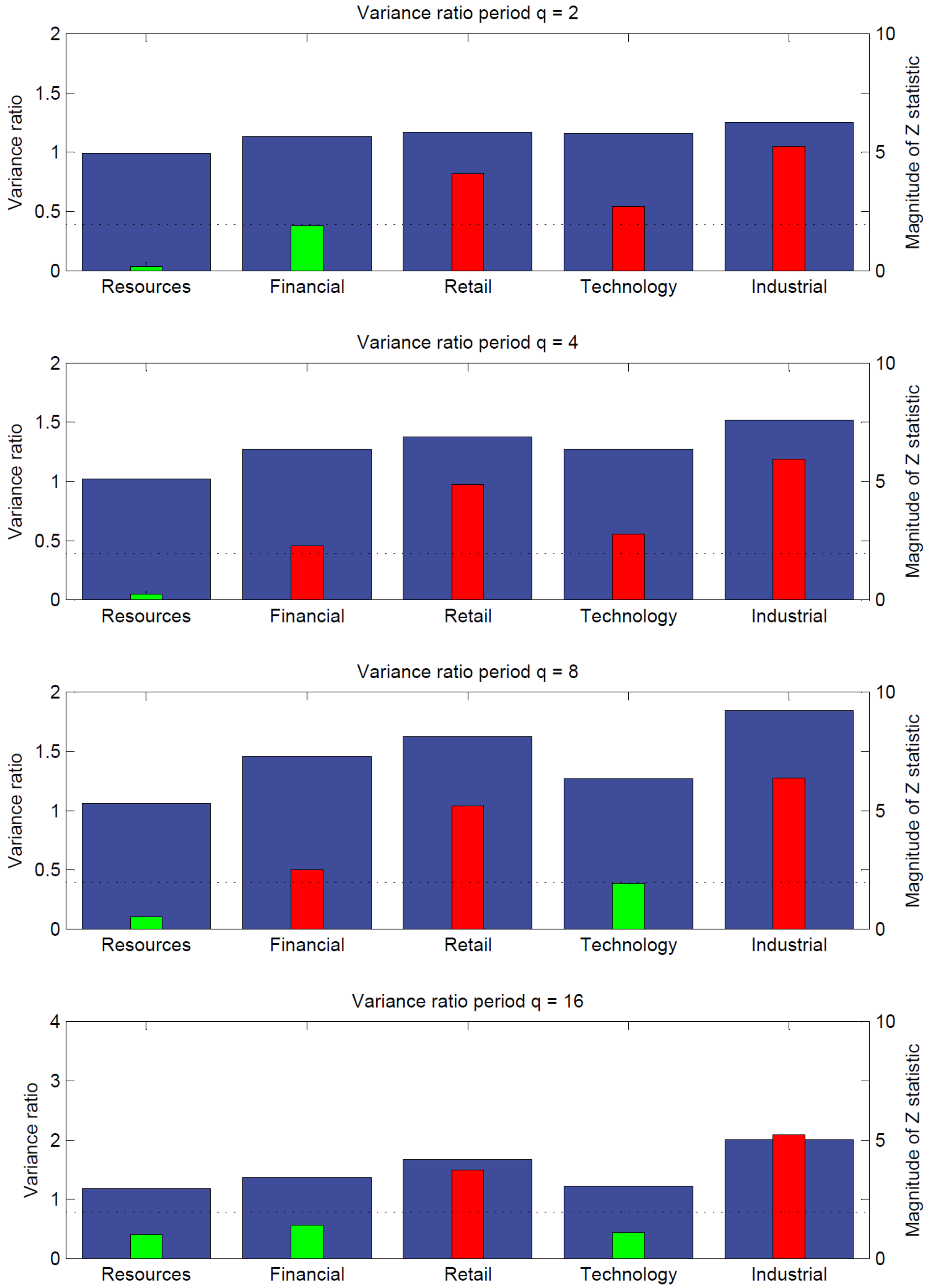

Figure 5-4 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^*(q)$ for industry sorted portfolios from March 1989 to March 2009

Table 5-11 Serial correlation for industry sorted portfolios from March 1989 to March 2009

Quintile	Serial correlation Weekly	2 weekly	4 weekly	8 weekly
Resources	-0.01	0.03	0.04	0.11
Financial	0.13	0.13	0.14	-0.06
Retail	0.17	0.18	0.18	0.03
Technology	0.16	0.10	0.00	-0.04
Industrial	0.25	0.21	0.21	0.09

Table 5-11 shows the serial correlation coefficients for industry sorted portfolios. Correlation is strongest in the industrial (25%) and retail (17%) portfolios, persisting for up to four weeks. Moderate serial correlation in the financial portfolio that persists for up to four weeks is also seen.

5.2.5 Volume

Variance ratios and test statistics for volume sorted portfolios are shown in Table 5-13 and Figure 5-5. In the quintile containing the least traded shares, very strong rejections of Hypothesis 8 at the 95% confidence level are seen over the entire 1989 to 2009 period for all variance ratio periods, *q*. In the second least traded quintile, rejections of Hypothesis 8 at the 95% confidence level are seen for the entire 1989 to 2009 period for all variance ratio sampling periods. In the central quintile, some rejections of Hypothesis 8 are seen in the 1989 to 2004 sub-period for variance ratio sampling periods of 2, 4 and 8 weeks, while no rejections of Hypothesis 8 are seen for the two most heavily traded quintiles.

Table 5-12 shows the serial correlation coefficients for portfolios sorted by trading volume. Correlation is strongest in the least traded portfolio, at 26% and persists strongly for 4 weeks, dropping to 11% serial correlation for eight weeks. In the second least traded quintile, lower values of serial correlation are observed, which persist for a shorter time period. Very little serial correlation is seen in the higher order portfolios.

Table 5-12 Serial correlation for trading volume sorted portfolios from March 1989 to March 2009

Quintile	Serial correlation Weekly	2 weekly	4 weekly	8 weekly
Highest	-0.03	0.00	0.04	0.01
2nd highest	-0.04	-0.05	0.01	0.02
Median	-0.01	0.03	0.03	0.00
2nd lowest	0.20	0.22	0.08	-0.06
Lowest	0.26	0.19	0.19	0.11

Table 5-13 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^{*}(q)$ for trading volume sorted portfolios from March 1989 to March 2009

Time period	Data points	Shares per portfolio	Variance ratio period q 2	4	8	16
Quintile 1 - Portfolio containing the highest ranked companies by number of shares traded						
1989 to 1994	261	1	0.99	0.97	1.01	0.90
			-(0.14)	-(0.23)	(0.06)	-(0.32)
1994 to 1999	261	26	1.16	1.44	1.54	1.48
			(2.35)*	***(2.99)****	***(2.14)****	(1.24)
1999 to 2004	261	30	1.04	1.04	1.07	1.10
			(0.53)	(0.28)	(0.34)	(0.35)
2004 to 2009	261	29	0.85	0.78	0.85	0.92
			-(1.42)	-(1.14)	-(0.52)	-(0.20)
Whole period (1989 to 2009)	1041	13	0.97	0.98	1.02	1.02
			-(0.58)	-(0.29)	(0.13)	(0.13)
Quintile 2 - Portfolio containing the second highest ranked companies by number of shares traded						
1989 to 1994	261	1	1.01	0.94	0.93	0.95
			(0.13)	-(0.47)	-(0.38)	-(0.16)
1994 to 1999	261	26	1.04	1.18	1.19	1.16
			(0.59)	(1.32)	(0.84)	(0.48)
1999 to 2004	261	30	0.96	0.95	1.02	0.96
			-(0.83)	-(0.46)	(0.09)	-(0.17)
2004 to 2009	261	29	0.95	0.96	1.04	1.11
			-(0.55)	-(0.22)	(0.18)	(0.31)
Whole period (1989 to 2009)	1041	13	0.96	0.91	0.92	0.94
			-(0.83)	-(1.11)	-(0.68)	-(0.36)
Quintile 3 - Portfolio containing the median ranked companies by number of shares traded						
1989 to 1994	261	1	1.18	1.52	1.78	1.52
			(2.81)*	***(3.75)****	***(3.48)****	(1.69)
1994 to 1999	261	26	1.22	1.53	1.66	1.57
			(2.96)*	***(3.73)****	***(2.85)****	(1.55)
1999 to 2004	261	30	1.15	1.28	1.53	1.55
			(2.16)*	***(2.16)****	***(2.54)****	(1.83)
2004 to 2009	261	29	1.00	1.12	1.24	1.41
			-(0.01)	(0.68)	(0.90)	(1.05)
Whole period (1989 to 2009)	1041	13	0.99	1.02	1.06	1.05
			-(0.18)	(0.29)	(0.47)	(0.30)
Quintile 4 - Portfolio containing the second lowest ranked companies by number of shares traded						
1989 to 1994	261	1	1.01	1.02	1.14	1.39
			(0.09)	(0.12)	(0.59)	(1.08)
1994 to 1999	261	26	1.43	1.97	2.28	2.25
			(3.65)*	***(4.79)****	***(4.47)***	***(3.17)***
1999 to 2004	261	30	1.15	1.35	1.61	1.62
			(1.75)	***(2.42)****	***(2.80)****	***(1.99)****
2004 to 2009	261	29	1.15	1.52	1.87	2.25
			(1.65)	***(2.51)****	***(2.74)****	***(2.86)****
Whole period (1989 to 2009)	1041	13	1.20	1.46	1.58	1.49
			(3.08)*	***(4.00)****	***(3.63)****	***(2.25)****
Quintile 5 - Portfolio containing the lowest ranked companies by number of shares traded						
1989 to 1994	261	1	0.91	0.79	0.78	0.70
			-(1.15)	-(1.53)	-(1.02)	-(0.99)
1994 to 1999	261	26	1.15	1.33	1.35	1.43
			(2.18)*	***(2.20)****	(1.33)	(1.10)
1999 to 2004	261	30	1.16	1.43	1.72	1.67
			(2.63)	***(3.65)***	***(3.81)***	***(2.37)***
2004 to 2009	261	29	1.25	1.52	1.77	1.93
			(2.41)	***(2.88)***	***(2.87)***	***(2.44)****
Whole period (1989 to 2009)	1041	13	1.26	1.50	1.79	1.99
			(6.03)*	***(6.67)****	***(6.81)****	***(5.91)****

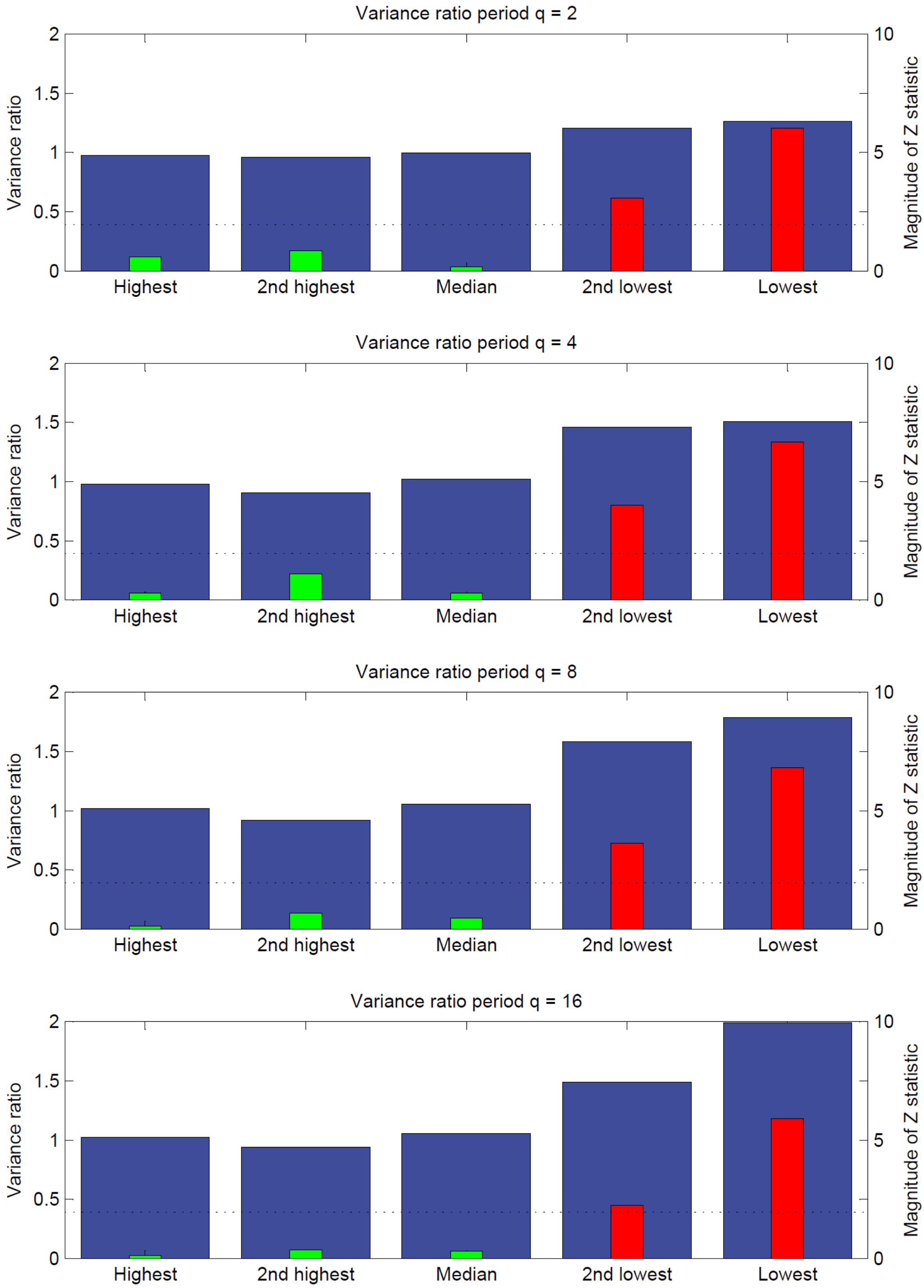

Figure 5-5 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^*(q)$ for trading volume sorted portfolios from March 1989 to March 2009

5.2.6 Comparison with the results of previous research

The finding of significant serial correlation in portfolios that are comprised of small capitalisation shares on the JSE is in agreement with the literature on international markets. The significant positive serial correlation observed in small firm portfolios is an effect described by Conrad and Kaul (1988), Lo and MacKinlay (1988) and Campbell et al. (1997). Although, the values of serial correlation seen for firm size sorted portfolios on the JSE are smaller than those observed on the NYSE, the persistence in serial correlation to periods of up to 8 weeks matches the trend seen in the research of Campbell et al. (1997).

Considering the results obtained from firm size sorted portfolios on the JSE, it is difficult to resolve the question of whether or not the excess serial correlation observed for portfolios of small firms is as a result of size, institutional ownership (Badrinath et al. 1995; Arbel et al. 1983) or 'speed of adjustments' hypothesis (Brennan et al. 1993). This topic will be revisited when the broader, trading process of the JSE and its comparison to other markets is discussed in 6.2.

The findings of strong serial correlation observed for the weekly returns of a portfolio of high dividend and high earnings yielding shares supports the position taken by Lamont (1998) who claims, in contradiction to Fama and French (1988b), that both earnings and dividend yields have significant forecasting ability.

While the finding of high serial correlation among portfolios of firms having a high dividend yield is, of itself, not an indicator of high returns, it does indicate that the returns of these portfolios are likely to persist over time. This is supported by the notion that a firm's dividend policy, which indicates the managerial outlook for future business and contributes to the *"permanent component of stock prices"* (Lamont 1998, p. 1564), thus, decreasing the variability of future returns.

The stark difference in the serial correlation of various industry sorted portfolios is curious. The low serial correlation observed in the resources portfolio may arise from the fact that resources and the companies which mine and distribute them are subject to far greater international investor scrutiny than industrial and retail companies, whose portfolios exhibited the highest serial correlations. Resources companies deal in globally traded commodities, are large capitalisation companies and are sometimes dual listed and/or headquartered outside of South Africa. In addition, to a certain extent, traders trade in resources companies as a proxy for the underlying resource, using the shares of resources companies to speculate on the resource or, from a local point of view, to hedge against exchange rate risk. Consequently, one would expect the shares of resources companies to be more heavily traded than the shares of predominantly local, mid-capitalisation industrial and retail companies.

The strong serial correlation in certain industry based portfolios lends support to the assertion of Moskowitz and Grinblatt (1999) that industry return is a strong predictor of portfolio return. This could only be true if there exists significant correlation between the price increments of companies in the same industry. Interestingly, the findings of significant serial correlation in the portfolio prices of industrial shares is supported by the work of Haddasin (1976), who finds that industrial shares exhibit share price predictability over the previous 20 year period.

The serial correlation results obtained for trading volume sorted portfolios is in agreement with the findings of Campbell et al. (1993), who claim that serial correlation of large stocks declines with volume. They also agree with the results of Conrad et al. (1994), who find that high volume shares are associated with a successful contrarian investment strategy (which requires negative serial correlation) and that low volume shares are associated with a successful momentum strategy (which requires positive serial correlation).

5.3 Sub-problem 3: Lead-lag relationships of portfolios sorted by a market benchmark

5.3.1 Firm size

Table 5-14 shows a table of cross autocorrelation matrices of firm size sorted portfolios. Cross autocorrelation matrices for lags of zero, one, two and three weeks are shown on the left of the table. Values highlighted in yellow in the cross autocorrelation matrices show statistically significant values at the 95% confidence level. Values in the asymmetry matrices highlighted in the darker pink or green indicate rejections of Hypothesis 9 at the 95% confidence level.

Table 5-14 Cross autocorrelation matrices $\hat{\Upsilon}(k)$ for k = 0, 1, 2 and 3 for firm size sorted portfolios. Cross-autocorrelation matrix asymmetry, $\hat{\Upsilon}(k) - \hat{\Upsilon}(k)'$, highlighting lead-lag effects is also included for k = 1, 2 and 3.

Cross-autocorrelation matrix - No lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t}	1	0.41	0.45	0.42	0.24
R_{2t}	0.41	1	0.64	0.42	0.52
R_{3t}	0.45	0.64	1	0.46	0.49
R_{4t}	0.42	0.42	0.46	1	0.33
R_{5t}	0.24	0.52	0.49	0.33	1

Key

R1	Largest capitalisation portfolio
R2	Second largest capitalisation portfolio
R3	Median capitalisation portfolio
R4	Second smallest capitalisation portfolio
R5	Smallest capitalisation portfolio

Cross-autocorrelation matrix - Single period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-1}	-0.05	0.06	0.14	0.16	0.13
R_{2t-1}	0.01	0.15	0.21	0.20	0.28
R_{3t-1}	0.00	0.17	0.20	0.18	0.23
R_{4t-1}	0.01	0.09	0.16	0.16	0.21
R_{5t-1}	0.02	0.18	0.16	0.16	0.22

Asymmetry of cross-autocorrelation matrix - Single period lag

	R1	R2	R3	R4	R5
R1	0.00	0.04	0.14	0.15	0.11
R2	-0.04	0.00	0.04	0.11	0.10
R3	-0.14	-0.04	0.00	0.02	0.08
R4	-0.15	-0.11	-0.02	0.00	0.05
R5	-0.11	-0.10	-0.08	-0.05	0.00

Cross-autocorrelation matrix - Two period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-2}	0.01	0.04	0.08	0.04	0.05
R_{2t-2}	0.02	0.10	0.11	0.11	0.16
R_{3t-2}	0.01	0.06	0.04	0.09	0.13
R_{4t-2}	0.03	0.09	0.08	0.06	0.08
R_{5t-2}	-0.01	0.03	0.05	0.10	0.07

Asymmetry of cross-autocorrelation matrix - Two period lag

	R1	R2	R3	R4	R5
R1	0.00	0.02	0.07	0.02	0.06
R2	-0.02	0.00	0.05	0.01	0.13
R3	-0.07	-0.05	0.00	0.02	0.08
R4	-0.02	-0.01	-0.02	0.00	-0.01
R5	-0.06	-0.13	-0.08	0.01	0.00

Cross-autocorrelation matrix - Three period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-3}	0.00	0.03	-0.01	0.04	0.06
R_{2t-3}	-0.04	0.09	0.05	0.06	0.16
R_{3t-3}	-0.04	0.03	-0.03	0.04	0.12
R_{4t-3}	-0.03	-0.03	0.00	0.07	0.08
R_{5t-3}	-0.06	0.03	0.03	0.04	0.11

Asymmetry of cross-autocorrelation matrix - Three period lag

	R1	R2	R3	R4	R5
R1	0.00	0.07	0.04	0.07	0.13
R2	-0.07	0.00	0.02	0.09	0.13
R3	-0.04	-0.02	0.00	0.04	0.10
R4	-0.07	-0.09	-0.04	0.00	0.04
R5	-0.13	-0.13	-0.10	-0.04	0.00

The cross-autocorrelation matrices for single period lag in Table 5-14 shows a clear pattern of asymmetry, since all the values above the diagonal are positive, while all those below the diagonal are negative. Further, in general, the further from the diagonal, the greater the asymmetry becomes. This asymmetrical pattern in $\psi(k)$ shows a tendency for the returns of large capitalisation portfolios to lead those of small capitalisation portfolios.

While the cross-autocorrelation values themselves seem to diminish in significance as the lag increases, the asymmetry seems to remain roughly constant for $\psi(k)$, for lags of k = 1, 2 and 3.

5.3.2 Dividend yield

Table 5-15 shows a table of cross autocorrelation and asymmetry matrices of dividend yield sorted portfolios. Values in the asymmetry matrices highlighted in the darker pink or green indicate rejections of Hypothesis 10 at the 95% confidence level.

The lead and lag pattern for dividend yield sorted portfolios is not as clear as the result obtained for firm size sorted portfolios. There does appear to be a trend, however, for the highest dividend yield portfolio to lag the other portfolios by a single week.

Table 5-15 Cross autocorrelation matrices $\hat{\Upsilon}(k)$ for k = 0, 1, 2 and 3 for dividend yield sorted portfolios. Cross-autocorrelation matrix asymmetry, $\hat{\Upsilon}(k) - \hat{\Upsilon}(k)'$, highlighting lead-lag effects is also included for k = 1, 2 and 3

Cross-autocorrelation matrix - No lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t}	1	0.38	0.40	0.44	0.30
R_{2t}	0.38	1	0.45	0.72	0.58
R_{3t}	0.40	0.45	1	0.57	0.45
R_{4t}	0.44	0.72	0.57	1	0.62
R_{5t}	0.30	0.58	0.45	0.62	1

Key

R1	Largest dividend yield portfolio
R2	Second largest dividend yield portfolio
R3	Median dividend yield portfolio
R4	Second smallest dividend yield portfolio
R5	Smallest dividend yield portfolio

Cross-autocorrelation matrix - Single period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-1}	0.19	0.04	0.07	0.02	0.03
R_{2t-1}	0.13	-0.02	0.02	-0.01	0.06
R_{3t-1}	0.16	0.01	0.05	0.00	0.05
R_{4t-1}	0.17	0.05	0.08	0.00	0.10
R_{5t-1}	0.10	0.03	0.06	0.01	0.10

Asymmetry of cross-autocorrelation matrix - Single period lag

	R1	R2	R3	R4	R5
R1	0.00	-0.09	-0.10	-0.15	-0.07
R2	0.09	0.00	0.01	-0.06	0.03
R3	0.10	-0.01	0.00	-0.09	-0.01
R4	0.15	0.06	0.09	0.00	0.09
R5	0.07	-0.03	0.01	-0.09	0.00

Cross-autocorrelation matrix - Two period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-2}	0.07	0.04	0.02	0.01	0.03
R_{2t-2}	0.02	0.00	0.05	0.01	0.06
R_{3t-2}	0.05	0.03	0.05	0.04	0.07
R_{4t-2}	0.07	0.03	0.05	0.00	0.06
R_{5t-2}	0.00	0.00	0.05	-0.03	0.03

Asymmetry of cross-autocorrelation matrix - Two period lag

	R1	R2	R3	R4	R5
R1	0.00	0.02	-0.03	-0.06	0.03
R2	-0.02	0.00	0.02	-0.01	0.06
R3	0.03	-0.02	0.00	0.00	0.02
R4	0.06	0.01	0.00	0.00	0.09
R5	-0.03	-0.06	-0.02	-0.09	0.00

Cross-autocorrelation matrix - Three period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-3}	0.04	0.01	-0.04	-0.01	0.00
R_{2t-3}	0.01	0.04	-0.02	-0.03	0.03
R_{3t-3}	0.04	-0.04	0.02	-0.05	-0.01
R_{4t-3}	0.03	0.00	-0.03	-0.04	0.02
R_{5t-3}	0.00	-0.02	0.07	-0.05	0.02

Asymmetry of cross-autocorrelation matrix - Three period lag

	R1	R2	R3	R4	R5
R1	0.00	0.00	-0.08	-0.04	0.00
R2	0.00	0.00	0.02	-0.03	0.05
R3	0.08	-0.02	0.00	-0.02	-0.08
R4	0.04	0.03	0.02	0.00	0.07
R5	0.00	-0.05	0.08	-0.07	0.00

5.3.3 Earnings yield

Table 5-16 shows a table of cross autocorrelation and asymmetry matrices of earnings yield sorted portfolios. Values in the asymmetry matrices highlighted in the darker pink or green indicate rejections of Hypothesis 11 at the 95% confidence level.

Similar to the results for dividend yield portfolios, the lead and lag pattern for earnings yield sorted portfolios shows a slight trend for the highest earnings yield portfolio to lag the other portfolios by a single week.

Table 5-16 Cross autocorrelation matrices $\widehat{\Upsilon}(k)$ for k = 0, 1, 2 and 3 for earnings yield sorted portfolios. Cross-autocorrelation matrix asymmetry, $\widehat{\Upsilon}(k) - \widehat{\Upsilon}(k)'$, highlighting lead-lag effects is also included for k = 1, 2 and 3

Cross-autocorrelation matrix - No lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t}	1	0.54	0.51	0.44	0.23
R_{2t}	0.54	1	0.66	0.53	0.25
R_{3t}	0.51	0.66	1	0.65	0.28
R_{4t}	0.44	0.53	0.65	1	0.45
R_{5t}	0.23	0.25	0.28	0.45	1

Key

R1	Largest earnings yield portfolio
R2	Second largest earnings yield portfolio
R3	Median earnings yield portfolio
R4	Second smallest earnings yield portfolio
R5	Smallest earnings yield portfolio

Cross-autocorrelation matrix - Single period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-1}	0.20	0.10	0.11	0.07	-0.02
R_{2t-1}	0.21	0.04	0.12	0.05	0.03
R_{3t-1}	0.19	0.06	0.04	0.03	0.00
R_{4t-1}	0.17	0.08	0.05	-0.01	-0.01
R_{5t-1}	0.03	0.04	-0.01	-0.03	-0.01

Asymmetry of cross-autocorrelation matrix - Single period lag

	R1	R2	R3	R4	R5
R1	0.00	-0.10	-0.07	-0.10	-0.05
R2	0.10	0.00	0.05	-0.03	0.00
R3	0.07	-0.05	0.00	-0.02	0.01
R4	0.10	0.03	0.02	0.00	0.02
R5	0.05	0.00	-0.01	-0.02	0.00

Cross-autocorrelation matrix - Two period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-2}	0.09	0.08	0.07	0.05	0.03
R_{2t-2}	0.05	0.02	0.02	0.03	0.05
R_{3t-2}	0.04	0.05	0.00	0.04	0.02
R_{4t-2}	0.05	0.07	0.03	0.02	0.03
R_{5t-2}	0.00	0.06	0.01	0.00	-0.05

Asymmetry of cross-autocorrelation matrix - Two period lag

	R1	R2	R3	R4	R5
R1	0.00	0.04	0.03	0.00	0.03
R2	-0.04	0.00	-0.03	-0.04	-0.01
R3	-0.03	0.03	0.00	0.01	0.01
R4	0.00	0.04	-0.01	0.00	0.03
R5	-0.03	0.01	-0.01	-0.03	0.00

Cross-autocorrelation matrix - Three period lag

	R_{1t}	R_{2t}	R_{3t}	R_{4t}	R_{5t}
R_{1t-3}	0.06	0.00	0.00	-0.01	-0.03
R_{2t-3}	0.04	0.01	0.03	0.00	-0.06
R_{3t-3}	0.07	-0.01	0.02	0.01	-0.03
R_{4t-3}	0.08	0.01	0.05	0.07	-0.01
R_{5t-3}	-0.03	-0.07	0.00	-0.01	-0.01

Asymmetry of cross-autocorrelation matrix - Three period lag

	R1	R2	R3	R4	R5
R1	0.00	-0.03	-0.07	-0.09	0.00
R2	0.03	0.00	0.04	-0.01	0.02
R3	0.07	-0.04	0.00	-0.04	-0.02
R4	0.09	0.01	0.04	0.00	0.00
R5	0.00	-0.02	0.02	0.00	0.00

5.3.4 Industry sorted portfolios

Table 5-17 shows a table of cross autocorrelation and asymmetry matrices of industry sorted portfolios. Values in the asymmetry matrices highlighted in the darker pink or green indicate rejections of Hypothesis 12 at the 95% confidence level.

While statistically significant cross correlation values are reported for $\widehat{\Upsilon}(k)$, there exists little asymmetry in the values of $\psi(k)$. Isolated statistically significant values are obtained indicate that financial portfolio returns lead technology portfolios returns for a single week lag and financial portfolio returns lead industrial portfolio returns for a two weekly lag. Aside from these isolated cases, there exists little lead-lag effect between portfolios containing shares based on industry.

Table 5-17 Cross autocorrelation matrices $\widehat{\Upsilon}(k)$ for k = 0, 1, 2 and 3 for industry sorted portfolios. Cross-autocorrelation matrix asymmetry, $\widehat{\Upsilon}(k) - \widehat{\Upsilon}(k)'$, highlighting lead-lag effects is also included for k = 1, 2 and 3.

Cross-autocorrelation matrix - No lag

	R_t	F_t	E_t	T_t	I_t
R_t	1	0.21	0.30	0.18	0.40
F_t	0.21	1	0.62	0.44	0.56
E_t	0.30	0.62	1	0.40	0.61
T_t	0.18	0.44	0.40	1	0.40
I_t	0.40	0.56	0.61	0.40	1

Key

R	Resources portfolio
F	Financial portfolio
E	Retail portfolio
T	Technology portfolio
I	Industrial portfolio

Cross-autocorrelation matrix - Single period lag

	R_t	F_t	E_t	T_t	I_t
R_{t-1}	-0.01	0.03	-0.01	0.04	0.07
F_{t-1}	0.01	0.12	0.17	0.16	0.16
E_{t-1}	0.03	0.11	0.14	0.15	0.19
T_{t-1}	0.00	0.07	0.12	0.15	0.13
I_{t-1}	0.04	0.16	0.19	0.16	0.24

Asymmetry of cross-autocorrelation matrix - Single period lag

	R	F	E	T	I
R	0.00	0.02	-0.04	0.04	0.03
F	-0.02	0.00	0.06	0.09	0.01
E	0.04	-0.06	0.00	0.03	0.00
T	-0.04	-0.09	-0.03	0.00	-0.04
I	-0.03	-0.01	0.00	0.04	0.00

Cross-autocorrelation matrix - Two period lag

	R_t	F_t	E_t	T_t	I_t
R_{t-2}	0.02	0.04	0.01	0.03	0.09
F_{t-2}	0.01	0.03	0.08	0.10	0.09
E_{t-2}	0.01	0.06	0.07	0.07	0.13
T_{t-2}	-0.01	0.04	0.04	0.05	0.01
I_{t-2}	0.04	0.00	0.02	0.05	0.11

Asymmetry of cross-autocorrelation matrix - Two period lag

	R	F	E	T	I
R	0.00	0.03	0.01	0.05	0.05
F	-0.03	0.00	0.01	0.06	0.09
E	-0.01	-0.01	0.00	0.03	0.10
T	-0.05	-0.06	-0.03	0.00	-0.04
I	-0.05	-0.09	-0.10	0.04	0.00

Cross-autocorrelation matrix - Three period lag

	R_t	F_t	E_t	T_t	I_t
R_{t-3}	0.01	0.00	-0.01	0.04	-0.01
F_{t-3}	-0.07	0.07	0.05	0.02	0.05
E_{t-3}	-0.05	0.11	0.08	0.05	0.06
T_{t-3}	-0.02	0.00	0.00	-0.04	-0.01
I_{t-3}	-0.03	0.04	0.03	0.00	0.04

Asymmetry of cross-autocorrelation matrix - Three period lag

	R	F	E	T	I
R	0.00	0.07	0.04	0.06	0.01
F	-0.07	0.00	-0.07	0.02	0.01
E	-0.04	0.07	0.00	0.05	0.04
T	-0.06	-0.02	-0.05	0.00	-0.01
I	-0.01	-0.01	-0.04	0.01	0.00

5.3.5 Trading volume

Table 5-18 shows a table of cross autocorrelation and asymmetry matrices of trading volume sorted portfolios. Values in the asymmetry matrices highlighted in the darker pink or green indicate rejections of Hypothesis 13 at the 95% confidence level.

Examination of the asymmetry matrices, $\psi(k)$, shows a pattern of asymmetry between elements above and below the main diagonal. The values indicate that returns of portfolios of stocks that trade thinly lag the returns of portfolios of stocks that trade with high volume. For single period lag, this trend is of a greater strength that that of firm size sorted portfolios, but, for the central three portfolios, seems to diminish for lags, k, of greater than one week.

Table 5-18 Cross autocorrelation matrices $\hat{\Upsilon}(k)$ for k = 0, 1, 2 and 3 for trading volume sorted portfolios. Cross-autocorrelation matrix asymmetry, $\hat{\Upsilon}(k) - \hat{\Upsilon}(k)'$, highlighting lead-lag effects is also included for k = 1, 2 and 3.

Cross-autocorrelation matrix - No lag

	R1t	R2t	R3t	R4t	R5t
R_{1t}	1	0.68	0.64	0.49	0.42
R_{2t}	0.68	1	0.48	0.37	0.31
R_{3t}	0.64	0.48	1	0.29	0.30
R_{4t}	0.49	0.37	0.29	1	0.46
R_{5t}	0.42	0.31	0.30	0.46	1

Key

R1	Highest trade volume portfolio
R2	Second highest trade volume portfolio
R3	Median trade volume portfolio
R4	Second lowest trade volume portfolio
R5	Lowest trade volume portfolio

Cross-autocorrelation matrix - Single period lag

	R1t	R2t	R3t	R4t	R5t
R_{1t-1}	-0.03	0.03	0.03	0.20	0.21
R_{2t-1}	-0.01	-0.04	0.04	0.13	0.13
R_{3t-1}	-0.02	-0.02	-0.01	0.10	0.14
R_{4t-1}	-0.01	-0.02	0.04	0.19	0.21
R_{5t-1}	0.03	0.01	0.06	0.16	0.26

Asymmetry of cross-autocorrelation matrix - Single period lag

	R1	R2	R3	R4	R5
R1	0.00	0.04	0.05	0.21	0.18
R2	-0.04	0.00	0.06	0.16	0.11
R3	-0.05	-0.06	0.00	0.06	0.08
R4	-0.21	-0.16	-0.06	0.00	0.05
R5	-0.18	-0.11	-0.08	-0.05	0.00

Cross-autocorrelation matrix - Two period lag

	R1t	R2t	R3t	R4t	R5t
R_{1t-2}	0.03	0.03	0.06	0.09	0.09
R_{2t-2}	0.02	-0.02	0.04	0.07	0.02
R_{3t-2}	0.01	0.01	-0.01	0.05	0.01
R_{4t-2}	0.05	0.02	0.06	0.13	0.10
R_{5t-2}	-0.01	0.00	0.02	0.04	0.08

Asymmetry of cross-autocorrelation matrix - Two period lag

	R1	R2	R3	R4	R5
R1	0.00	0.02	0.06	0.03	0.10
R2	-0.02	0.00	0.03	0.04	0.02
R3	-0.06	-0.03	0.00	-0.01	-0.01
R4	-0.03	-0.04	0.01	0.00	0.06
R5	-0.10	-0.02	0.01	-0.06	0.00

Cross-autocorrelation matrix - Three period lag

	R1t	R2t	R3t	R4t	R5t
R_{1t-3}	-0.04	-0.03	0.02	0.08	0.07
R_{2t-3}	-0.07	-0.03	-0.03	0.03	0.01
R_{3t-3}	0.02	0.02	0.07	0.02	0.06
R_{4t-3}	-0.08	-0.07	-0.04	0.04	0.06
R_{5t-3}	-0.02	-0.01	0.03	0.05	0.07

Asymmetry of cross-autocorrelation matrix - Three period lag

	R1	R2	R3	R4	R5
R1	0.00	0.04	0.00	0.16	0.09
R2	-0.04	0.00	-0.04	0.09	0.02
R3	0.00	0.04	0.00	0.06	0.03
R4	-0.16	-0.09	-0.06	0.00	0.01
R5	-0.09	-0.02	-0.03	-0.01	0.00

5.3.6 Comparison with the results of previous research

The fact that the prices of portfolios of small firms on the JSE lag those of portfolios consisting of larger firms is consistent with the results of Lo and MacKinlay (1990) on the NYSE. These lag effects, however, are not as clear and pronounced as those of the NYSE, where strong cross serial correlation is observed and persists for up to four weeks. On the JSE, however, though single lag cross serial correlation is large, this dissipates at lags greater than a single week.

A similar effect is observed for volume sorted portfolios, where the returns of high volume portfolios lead those of lower volume portfolios. This gives support to the proposition of Brennan et al. (1993) that firms all adjust to common information at a speed that is proportional to their trading volume. Under this assumption, one would expect a measurable lag in the returns of slowly adjusting stocks against those of quickly adjusting stocks. Such a pattern is observed in the results of section 5.3.5.

5.4 Summary of the results

Table 5-19 shows a table that summarises the results of this study. The table provides a link between the hypothesis tested, the sub-problem the hypothesis relates to, the trend observed and the previous research undertaken that is relevant to this topic.

Table 5-19 Summary of the results

Hypothesis	Related sub-problem	Result	Observed trend	Previous research
1. J203 is uncorrelated	Sub-problem 1	Not rejected	Weak positive serial correlation until 2004, weak negative serial correlation after 2004	Jammine and Hawkins (1974), Lo and MacKinlay (1988), Poterba and Summers (1988)
2. Equal weighted portfolio prices are uncorrelated	Sub-problem 1	Rejected for q = 4, 8, 16	Overall positive serial correlation for all lags	Jammine and Hawkins (1974), Lo and MacKinlay (1988), Poterba and Summers (1988)
3. Individual share prices are uncorrelated	Sub-problem 1	Not rejected	Weak positive serial correlation until 1999, weak negative serial correlation after 1999	Fama (1965), Affleck-Graves and Money (1975), Hadassin (1976), Gilbertson and Roux (1978), Brümmer and Jacobs (1981), French and Roll (1987), Lo and MacKinlay (1988)
4. Firm-size sorted portfolio prices are uncorrelated	Sub-problem 2	Rejected for portfolios 2 to 5	Serial correlation decreases as portfolio firm size increases	Arbel et al. (1983), Lo and MacKinlay (1988), Conrad and Kaul (1988), Badrinath et al. (1995), Brennan et al. (1993)
5. Dividend yield sorted portfolio prices are uncorrelated	Sub-problem 2	Strongly rejected for portfolio 1	Serial correlation is significant for the largest dividend yielding portfolio	Fama and French (1988b)
6. Earnings yield sorted portfolio prices are uncorrelated	Sub-problem 2	Strongly rejected for portfolio 1	Serial correlation is significant for the largest earnings yielding portfolio	Fama and French (1988b), Lamont (1998)
7. Industry sorted portfolio prices are uncorrelated	Sub-problem 2	Strongly rejected for industrial and retail portfolios	Serial correlation is high in industrial and retial portfolios	Moskowitz and Grinblatt (1999)
8. Trading volume sorted portfolio prices are uncorrelated	Sub-problem 2	Strongly rejected for portfolios 4 and 5	Serial correlation decreases as portfolio trading volume increases	Sentana and Wadhwani (1992), Chan (1993), Campbell et al. (1993), Conrad et al. (1994), Badrinath et al. (1995), Lee and Swaminathan (2000)
9. No lead / lag in firm size sorted portfolio prices	Sub-problem 3	Rejected	Large firm size portfolios lead small firm size portfolios	Lo and MacKinlay (1990)
10. No lead / lag in dividend yield sorted portfolio prices	Sub-problem 3	Rejected	Largest dividend yield portfolio lags other portfolios	Fama and French (1988b)
11. No lead / lag in earnings yield sorted portfolio prices	Sub-problem 3	Rejected	Largest earnings yield portfolio lags other portfolios	Fama and French (1988b), Lamont (1998)
12. No lead / lag in industry sorted portfolio prices	Sub-problem 3	Rejected	No apparent trend	None
13. No lead / lag in trading volume sorted portfolio prices	Sub-problem 3	Rejected	Highly traded portfolios lead thinly traded portfolios	Campbell et al. (1993), Conrad et al. (1994), Lee and Swaminathan (2000)

Chapter 6

Conclusion

"REASONING DRAWS A CONCLUSION, BUT DOES NOT MAKE THE CONCLUSION CERTAIN, UNLESS THE MIND DISCOVERS IT BY THE PATH OF EXPERIENCE." – ROGER BACON

6.1 Conclusions of the study

This research tests the assumption by most financial theorists that share prices on the JSE are unpredictable. It draws its significance from the fact that almost all financial theories developed in the latter half of the last century are premised on the assumption of unpredictable, rationally determined prices.

The study examines the overall predictability of the JSE in terms of market indices and individual share prices. It also looks at the predictability of share prices when the shares are grouped according to some common factor or benchmark. Finally, it attempts to identify leading indicators of the returns of commonly grouped shares.

The findings of the study indicate that the assumption of unpredictable prices is true only in the most general case when considering the market as a whole, or when considering a random group of individual shares. The results of the study indicate statistically significant levels of serial correlation in the returns of portfolios grouped, in descending order of significance, according to trading volume, industry, firm size, earnings yield and dividend yield.

Furthermore, the study finds that the returns of small firms tend to lag those of large firms. A similar effect is seen in the tendency of the returns of highly traded firms to lag the returns of lowly traded firms.

The results obtained from this study are in broad agreement with trend in results reported in the literature for the NYSE. One observation the study makes, however is that the values of serial correlation are not as high as those observed for the NYSE. Whether this is as result of a trend for diminishing serial correlation in portfolio prices in more recent times, or the lower number of shares making up the portfolios, or the low comparative liquidity on the JSE remains unanswered.

6.2 Implications of the study for share price formation on the JSE

The comparison of the results of this study to those for the NYSE found in the literature bears further mention. The results of Conrad et al. (1988) for serial correlations of ten size sorted portfolios on the NYSE show clear, consistent trends, with very little noise obscuring the results. Not one of the ten portfolios in the results of Conrad et al. (1988) shows any significant deviation from the trend of decreasing serial correlation with increasing firm size. In contrast, the equivalent JSE results are much noisier, with frequent deviations from the general trend.

Further insight into this difference may be gained from Table 6-1, which shows some summary statistics gathered from the World Federation of Exchanges (2008). In the table, statistics for three first world markets, the NYSE, the NASDAQ and the London Stock Exchange (LSE) are shown. Statistics for the JSE are shown, as well as those of the Korean Stock Exchange (KSE), since it is a similarly sized exchange in a developing nation. All the exchanges shown in the table have a significantly larger number of listed companies than the JSE. This, in itself, is a major factor in the better noise performance of portfolios of shares on the more liquid exchanges. More companies in a portfolio have a powerful averaging effect on its price, causing idiosyncratic noise of individual shares to be effectively removed from portfolio prices.

Another explanation for the noisy results on the JSE arises from the fact that, in comparison with other exchanges, the JSE is rather illiquid. The other exchanges shown in Table 6-1 turn over at least three times their total domestic market capitalisation per year. The JSE, on the other hand, does not turn over its capitalisation once. Similarly, the other exchanges in Table 6-1 effect between 3 and 45 times more trades per unit of share value than the JSE. Additionally, the average value of each trade on all exchanges but the LSE is significantly lower.

Table 6-1 Summary statistics of the JSE compared with other stock exchanges (source: WFE 2008)

Exchange	Total domestic market cap (USD billions)	Listed companies	Value traded (USD billions)	Number of trades (millions)	Average value of trade (USD thousands)	Market Concentration (by market cap)	Market Concentration (by trading value)
NYSE-AMEX	9208	3011	33 639	4 051	8.3	54.8%	30.3%
NASDAQ	2396	2952	36 447	3 779	9.6	69.1%	33.1%
London SE	1868	3096	6 272	201	31.1	88.8%	97.3
Korean SE	471	1793	1 432	641	2.2	63.1%	58.0%
JSE	483	411	395	17	22.7	30.4%	66.0%

Smaller trades imply that, on average, the price of a share adjusts less with each trade than it would with large trades. Were it not for the higher frequency of trading on the more liquid markets, this would result in significantly lower variance. In comparison with the fine-grained, rapid price adjustments of liquid markets, JSE price adjustments are coarse and less rapid. As a result, although their statistical properties may be similar, they have more of a tendency to obscure trends than shares trading in liquid markets.

This argument highlights the unique role that trading volume has in the formation of prices. To draw an analogy from the physical sciences, volume can be thought of as the force which acts on the inertia of a share price. As such, as Conrad et al. (1994) and Lee and Swaminathan (2000) agree, price and volume are inextricably linked; both arise in the equilibrium of the market. In the context of serial correlation in prices, volume cannot be thought of as a separate factor which may or may not be linked to serial correlation. All forms of serial correlation in portfolios should have low aggregate volume as a by-product.

Lo and MacKinlay (1988) consider a model of non-trading to try and explain the serial correlation observed in size sorted portfolio prices. They conclude that, because the probability of non-trading is low, it cannot cause the serial correlation observed in their results. Non-trading is an extreme case, however. Low volume trades are also able to hamper the adjustment of prices to new information. The results of this study indicate that, up to a certain point, serial correlation decreases proportionally as trading volume increases. Considering the question of whether excess serial correlation in firm size sorted portfolios is as a result of size, institutional ownership, or ‘speed of adjustments’; it results from all of them, since they are all linked with reduced trade in the portfolio constituents, which slows the incorporation of common information in their prices.

6.3 Implications of the study for the investor

6.3.1 Sources of returns predictability in JSE market indices and individual shares

The results obtained for overall predictability of the JSE show that, when looking at the JSE from a market capitalisation point of view, there is very little predictability in the market as a whole. Although a small improvement in predictability may be made by looking at the JSE from an equal weighted point of view, the lack of an equal weighted index in which to invest in (through the derivatives market) makes any potential investment in an equal weighted portfolio of JSE shares too expensive to offset the available gains.

Turning to investing in individual shares does not improve the prospects for an average investor. Forming a portfolio from a random group of shares is not likely to lead to any significant measure of predictability, since the average serial correlation of all JSE shares is very close to zero. An investor might, out of luck, create a portfolio where the price increments of the various constituents combine to form some measure of serial correlation in the resulting price series, but this just as likely not to happen.

6.3.2 Sources of predictability of factor sorted portfolios on the JSE

The results of the second sub-problem yield some interesting results from a share price predictability point of view. By ranking the shares on the JSE in terms an easily observable benchmark, portfolios with significant serial correlation can be constructed. The simple way in which these portfolios are formed coupled with the fact that their serial correlation persists across most of the sub-periods of the study indicates that this result does not draw on a peculiarity of the dataset, but rather a generality. This fact is of relevance to the investor.

The significant degree of predictability in returns of the most correlated portfolio raises some obvious questions:

1. How significant is the serial correlation obtained by using the set of benchmarks to sort the shares into portfolios? Could one generate equivalent serial correlations by merely selecting shares at random from all the shares on the JSE?

2. Is it possible to form a super-portfolio that is highly serially correlated by using a combination of the benchmarks, or by any other means?

These uncertainties will be addressed in the following sections.

6.3.2.1 ***Significance of the serial correlation obtained***

The significance of the serial correlation values obtained for the factor sorted portfolios was determined by comparing them to distribution of serial correlation values obtained when equivalent sized portfolios were formed by selecting shares at random from the dataset.

Over the 1989 to 2009 period, there were 65 shares on the JSE which traded for the entire period and met the minimum trading volume requirements for the tests. Five quintile portfolios consisting of 13 shares each were formed out of these 65 shares. Since the theoretical number of combinations in which 13 unique shares may be selected from 65 is very large (1.6×10^{13}), a Monte Carlo simulation was used to determine the distribution of possible serial correlations resulting from randomly forming a portfolio of 13 unique shares from the JSE over this period. Figure 6-1 shows the distribution of weekly serial correlation coefficients obtained from 100 000 iterations of the simulation. While this number is very small in comparison to the total population of potential combinations of shares, the distribution obtained shows no major discontinuities.

As expected, the mean of the distribution in Figure 6-1 at 6.4% is of a very similar value to the serial correlation obtained for an equal weighted portfolio of all the 65 shares in section 5.1.2, which was calculated to be 7.3%.

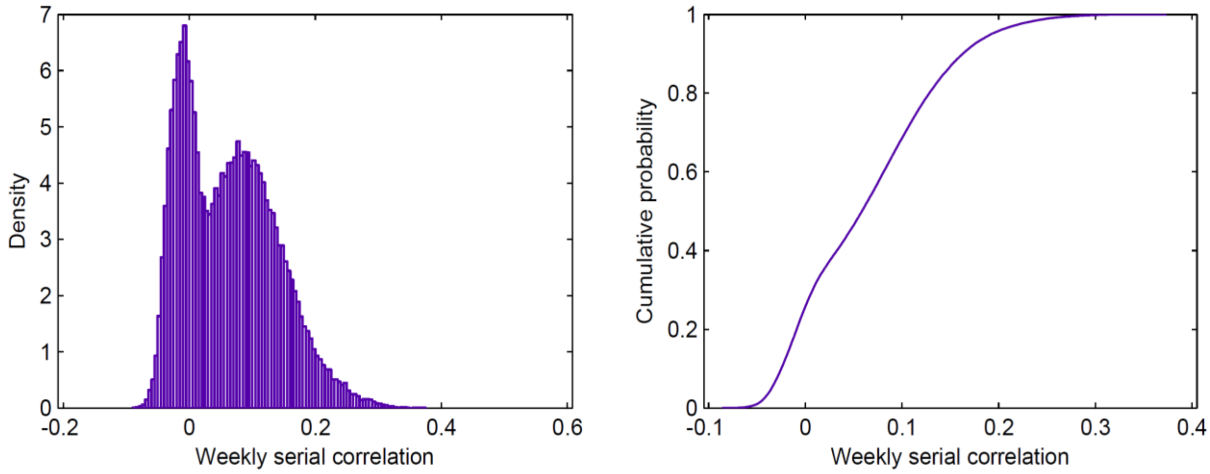

Figure 6-1 Probability density and cumulative distribution function obtained form 100 000 random portfolio formations of 13 shares from a population of 65

Table 6-2 Serial correlation of benchmark portfolios, probability of their random occurrence and their significance

Benchmark	Serial correlation	Probability of random occurrence	Significance
Market capitalisation	0.23	2%	98%
Dividend yield	0.20	4.2%	95.8%
Earnings yield	0.20	4.2%	95.8%
Industry	0.25	1.1%	98.9%
Trading volume	0.26	0.8%	99.2%

Table 6-2 reports the probability of randomly obtaining the serial correlation value for the most correlated quintile portfolios obtained for each benchmark, as well as the significance of the serial correlation obtained. All of the benchmarks used yield significant values of serial correlation at the 95% level. All three of the trading volume, industry and market capitalisation benchmarks are above the 98% level.

6.3.2.2 Finding a better metric

Given that significant serial correlations were obtained using a relatively simple means of sorting shares into portfolios, it is tempting to search for a metric by which to form a portfolio that is better able to isolate the resulting serial correlation. However, since the serial correlation is a complex function of the combination of shares in a portfolio, and since the number of potential combinations is enormous, finding a metric that is better able to group shares into a portfolio in order to maximise their serial correlation is not a simple task.

Modern Portfolio Theory shows that in order to minimize the risk in a portfolio, one should adjust the weightings of its constituents to minimize the variance of the portfolio, for a given return. By adjusting the weightings of the constituent shares, it is possible to arrive at a much lower variance for the portfolio than each constituent has on its own; hence the value of diversification. The degree of minimization of portfolio variance possible is dependent on the covariance matrix of the return of each constituent with every other return.

A similar analogy may be drawn with the serial correlation of a portfolio. By adjusting the weightings of a portfolio, it is possible to arrive at a portfolio having a far higher serial correlation that that of the constituents themselves. This involves the maximisation of the serial correlation of the portfolio, not the minimization of its variance.

Appendix H contains the mathematical details of the maximization performed. For the in-sample period, the results obtained from this maximisation were excellent. Serial correlations of greater than 50% could be obtained by mathematically adjusting the weightings of the portfolio constituents. Out of sample correlations, however were disappointing. The high values of serial correlation experienced in the sample period were quick to disappear when moving out of the sample period.

While one may be tempted to disregard this mathematical means of serial correlation maximisation because of its poor out of sample performance, one should point out that this type of problem is exactly the same as that experienced by practitioners of Markowitz's Modern Portfolio Theory, who seek to minimize the standard deviation of the portfolio by adjustment of the constituent weightings. While it is relatively easy to minimise the standard deviation for a sample of assets, the portfolio standard deviation is quite sensitive to changes in the covariance matrix when moving out of the sample period. An avenue for further research is to find ways of maximising the serial correlation of the portfolio in a way that is robust to covariance matrix changes.

6.3.3 The economic value of serial correlation

Serial correlation in a portfolio allows an investor to better time the market. If one neglects trading costs, the serial correlation in a portfolio that an investor requires to make an excess return is small. In a similar manner to the way in which a casino makes money from the roulette wheel by virtue of the small 'house edge' it enjoys, serial correlation affords the investor a small 'edge' in timing the market.

The economic value of serial correlation in trading is best demonstrated by simulation. This simulation was constructed using a number of fictitious investors, each of which is allowed to invest in a Monte Carlo simulated portfolio. Each investor abides by the following rules:

1. Each has a choice of two assets in which to invest. The first is a risk free asset that yields a return of 8% per annum. The second is a risky asset that yields a return of 12% per annum but with a standard deviation that is a parameter in the simulation. In addition, the risky asset also exhibits a certain amount of serial correlation in its returns which is a second parameter in the simulation.

2. Each starts with the same amount of wealth, with all of it invested in the risky asset.

3. Each follows a simple long-only trading strategy. After each week, if the return achieved by the risky asset is less than its mean and the investor already holds the risky asset, he sells the risky asset and buys the riskless asset. Otherwise, if the last week's return is more than its mean and the investor holds the riskless asset, he sells the riskless asset and buys the risky asset.

For certain values of input parameters, serial correlation and portfolio variance, the simulation was run for 52 periods (a full year) with 100 000 investors, each having their own independent risky asset, the price of which updates according to equation (4.22).

Figure 6-2 shows a contour plot of mean annual return and Sharpe ratios achieved for a given value of serial correlation and portfolio variance input to the model. For comparison purposes, return out-performance and improvement in Sharpe ratio are also shown on the figure. The results of the simulation show some interesting trends:

1. An active investment strategy outperforms a 'buy and hold' strategy as the variance and serial correlation of the portfolio increase.

2. The region in which a 'buy and hold' investment strategy outperforms an active strategy is hyperbolic, i.e. either for very low values of portfolio standard deviation or for very low values of serial correlation. Any significant value in the product of standard deviation and serial correlation advocates an active investment strategy.

3. The return per unit of risk, as measured by the Sharpe ratio, increases as the serial correlation of the portfolio increases. For a given value of serial correlation, however, the Sharpe ratio decreases slightly as the standard deviation of the portfolio returns increases. If one wants to maximise return per unit of risk, the results indicate that a portfolio with minimum standard deviation, but maximum serial correlation should be sought.

Obviously, in the real world, the returns offered by an active investment strategy would be offset by the trading costs associated with the frequent moving into and out of the market that is required to take advantage of the serial correlation in the portfolio. It is conceivable that any gains of an active investment strategy would only happen for unrealistic values of serial correlation and portfolio variance. The robustness of these returns is a study in and of itself and is recommended as a topic for further research.

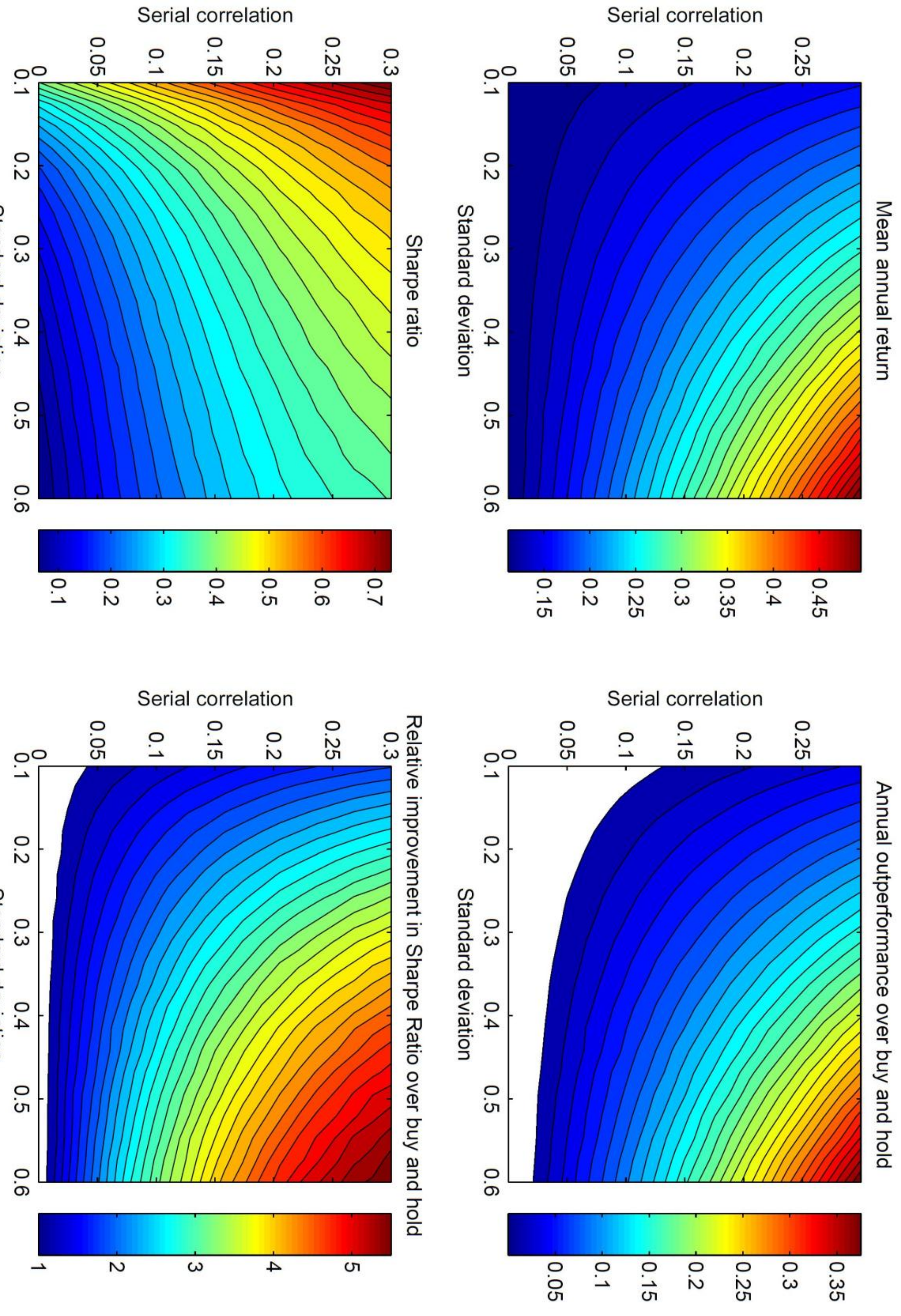

Figure 6-2 Mean annual return and outperformance of an active investment strategy over buy and hold

6.4 Implications of the study for market efficiency

In terms of its strictest definition (Fama 1970), market efficiency on the JSE in its semi strong form is clearly violated by the results of this study. In its weakest form, however, the market efficiency of the JSE is still intact, since the results of the first sub-problem fail to show convincing serial correlation based on price information alone.

In terms of its practical definition (Jensen 1978), whether the results of this research indicate inefficiency of the JSE is dependent on the trading costs associated with taking advantage of portfolio serial correlation. As such, the answer to this question is one that will be found on the trading floor, rather than in further theorising.

One should bear in mind, however, that the robustness of a theory to practical realities such as costly trading and irrational expectations has never stood in the way of economists' adoption of major economic theories in the past.

6.5 Recommendations for further study

The following topics are recommended for further research in this field:

1. An investigation into an active investment strategy that is robust with respect to trading costs

2. The identification of a benchmark that is better able to predict out-of-sample serial correlation in portfolio returns.

3. The investigation of the role that stock market characteristics such as number of shares, the value of the average trade and the number of trades have on serial correlation in particular, as well as observation of market trends in general.

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Appendix A

Detailed individual share results

Table A-3 Variance ratio $\overline{\mathrm{VR}}(q)$ and $\psi^*(q)$ for individual shares from March 1989 to March 2009

Share code	Share name	Variance ratio period q 2	4	8	16
GRF	GROUP FIVE LTD ORD	1.07	1.10	1.15	1.23
		(1.63)	(1.36)	(1.34)	(1.40)
SFN	SASFIN HOLDINGS LTD	0.98	0.99	1.04	1.13
		-(0.49)	-(0.20)	(0.38)	(0.79)
GND	GRINDROD LTD	0.87	0.80	0.74	0.73
		-(2.04)*	-(1.87)	-(1.67)	-(1.21)
PAM	PALABORA MINING CO ORD	1.08	1.10	1.16	1.30
		(1.83)	(1.33)	(1.34)	(1.69)
SNT	SANTAM LTD	1.02	1.04	1.00	0.96
		(0.29)	(0.37)	-(0.01)	-(0.20)
OMN	OMNIA HOLDINGS LTD	1.04	1.13	1.23	1.26
		(0.81)	(1.66)	***(1.99)****	(1.65)
JDG	JD GROUP LTD	1.07	1.15	1.21	1.18
		(1.71)	***(1.98)****	(1.72)	(1.00)
NWL	NU-WORLD HOLDINGS LTD	0.95	0.98	1.06	1.01
		-(0.87)	-(0.19)	(0.47)	(0.07)
PAP	PANGBOURNE PROP LTD	0.96	0.96	0.97	0.87
		-(0.99)	-(0.56)	-(0.26)	-(0.86)
HDC	HUDACO INDUSTRIES LTD	1.04	1.09	1.19	1.32
		(0.49)	(0.68)	(1.11)	(1.45)
JSC	JASCO ELECTRONICS HLDGS	1.01	1.02	1.03	1.08
		(0.19)	(0.19)	(0.25)	(0.40)
FPT	FOUNTAINHEAD PROP TRST	0.90	0.84	0.83	0.78
		-(2.47)*	***-(2.32)****	-(1.57)	-(1.41)
HVL	HIVELD STEEL AND VANADUM	1.06	1.16	1.09	1.15
		(1.69)	***(2.14)****	(0.81)	(0.90)
DST	DISTELL	1.05	1.03	1.07	1.12
		(1.33)	(0.50)	(0.64)	(0.84)
AFE	A E C I LTD ORD	1.01	0.90	0.92	1.12
		(0.30)	-(1.05)	-(0.47)	(0.51)
BCF	BOWLER METCALF LTD	0.94	0.88	0.87	0.84
		-(1.71)	-(1.65)	-(1.18)	-(0.94)
SYC	SYCOM PROPERTY FUND	1.02	1.07	1.14	1.11
		(0.35)	(0.78)	(1.07)	(0.61)
ASA	ABSA GROUP LIMITED	0.95	0.89	0.90	0.78
		-(1.26)	-(1.29)	-(0.76)	-(1.11)
OCE	OCEANA GROUP LTD	0.96	1.04	1.10	1.08

		-(0.97)	(0.52)	(0.89)	(0.51)
ADR	ADCORP HLDGS LTD ORD	1.03	1.10	1.12	1.19
		(0.56)	(1.06)	(0.99)	(1.16)
MOB	MOBILE	0.98	0.95	0.90	0.77
		-(0.34)	-(0.58)	-(0.71)	-(1.16)
SOL	SASOL LTD	0.92	0.85	0.78	0.78
		-(1.98)*	-(1.89)	-(1.81)	-(1.26)
MAF	MUTUAL & FEDERAL	1.08	1.12	1.16	1.03
		(1.89)	(1.61)	(1.38)	(0.21)
ATN	ALLIED ELECTRONICS CORP	1.03	1.08	1.13	1.17
		(0.65)	(0.91)	(1.07)	(0.96)
CAT	CAXTON CTP PUBLISH PRINT	1.01	1.02	1.14	1.26
		(0.34)	(0.27)	(1.27)	(1.67)
RLO	REUNERT ORD	1.02	1.09	1.18	1.24
		(0.46)	(1.00)	(1.38)	(1.27)
DLV	DORBYL LTD ORD	1.20	1.34	1.43	1.42
		(5.58)*	***(4.89)****	***(3.79)****	***(2.52)****
CSB	CASHBUILD LTD	1.09	1.15	1.24	1.47
		(2.00)*	(1.91)	***(2.00)****	***(2.82)****
MDC	MEDI-CLINIC CORP LTD ORD	0.97	0.95	0.91	0.95
		-(0.51)	-(0.60)	-(0.67)	-(0.27)
TSX	TRANS HEX GROUP LTD	1.03	1.07	1.20	1.30
		(0.65)	(0.83)	(1.62)	(1.74)
SBK	STANDARD BANK GROUP LTD	0.99	0.89	0.89	0.78
		-(0.15)	-(0.98)	-(0.62)	-(0.86)
NED	NEDBANK GROUP LTD	0.94	0.88	0.90	0.82
		-(1.59)	-(1.65)	-(0.90)	-(1.06)
ALT	ALLIED TECHNOLOGIES	1.22	1.33	1.27	1.18
		(4.79)*	***(4.18)****	***(2.29)****	(1.03)
TRE	TRENCOR LTD	1.13	1.25	1.26	1.18
		(2.43)*	***(2.63)****	(1.86)	(0.89)
MET	METROPOLITAN HLDGS LTD	0.99	1.06	1.08	0.95
		-(0.10)	(0.60)	(0.52)	-(0.23)
IMP	IMPALA PLATINUM HLGS LD	0.95	0.93	0.94	0.98
		-(1.15)	-(1.04)	-(0.60)	-(0.11)
MUR	MURRAY AND ROBERTS H ORD	1.02	1.04	1.14	1.21
		(0.39)	(0.50)	(1.05)	(1.12)
SAP	SAPPI LTD	0.99	0.94	0.93	1.02
		-(0.32)	-(0.82)	-(0.60)	(0.10)
DAW	DISTRIBUTION AND WAREHSG	0.90	0.76	0.73	0.76
		-(1.80)	***-(2.21)****	-(1.61)	-(0.98)
APN	ASPEN PHARMACARE HLDGS.	1.02	1.04	0.96	1.04
		(0.33)	(0.36)	-(0.24)	(0.19)
AGL	ANGLO AMERICAN PLC	0.96	0.91	0.91	0.98
		-(0.95)	-(1.11)	-(0.74)	-(0.11)
NPK	NAMPAK LTD ORD	0.92	0.93	0.96	0.97
		-(1.49)	-(0.73)	-(0.28)	-(0.12)
PPC	PRETORIA PORT CEMNT	1.10	1.20	1.26	1.24
		(2.66)*	***(2.79)****	***(2.33)****	(1.51)
SUI	SUN INTERNATIONAL LTD	1.01	1.04	1.05	1.07
		(0.26)	(0.48)	(0.49)	(0.43)
INL	INVESTEC LTD	0.99	0.93	0.96	0.90
		-(0.25)	-(0.88)	-(0.32)	-(0.53)
FOS	FOSCHINI LTD ORD	1.05	1.15	1.23	1.36
		(1.03)	(1.68)	(1.74)	(1.91)
SHP	SHOPRITE HLDGS LTD ORD	1.03	0.91	0.83	0.76
		(0.70)	-(1.25)	-(1.48)	-(1.47)
FSR	FIRSTRAND LTD	0.94	0.89	0.84	0.73

		-(1.17)	-(1.17)	-(1.04)	-(1.27)
BAT	BRAIT S.A.	1.16	1.30	1.36	1.22
		(1.79)	***(2.17)****	***(2.02)****	(0.91)
AFX	AFRICAN OXYGEN LTD ORD	1.00	0.98	0.94	0.93
		-(0.05)	-(0.32)	-(0.51)	-(0.43)
SAB	SABMILLER PLC	0.94	0.85	0.84	0.74
		-(1.56)	***-(2.02)****	-(1.37)	-(1.55)
AMS	ANGLO PLATINUM LTD	0.94	0.93	0.90	0.85
		-(1.45)	-(0.93)	-(0.83)	-(0.84)
PIK	PIK N PAY STORES LTD	0.97	0.97	0.92	0.80
		-(0.89)	-(0.35)	-(0.70)	-(1.13)
PWK	PIKWIK	0.90	0.89	0.80	0.73
		-(2.62)*	-(1.51)	-(1.77)	-(1.61)
DDT	DIMENSION DATA HLDGS PLC	1.04	1.12	1.24	1.40
		(1.03)	(1.55)	***(2.03)****	***(2.25)****
DEL	DELTA ELECRICAL IN	1.04	1.10	1.12	1.01
		(1.09)	(1.54)	(1.10)	(0.06)
SPS	SPESCOM LTD	0.95	0.96	0.98	0.97
		-(0.96)	-(0.40)	-(0.19)	-(0.18)
GFI	GOLD FIELDS LTD	0.97	0.87	0.75	0.77
		-(0.68)	-(1.70)	***-(2.13)****	-(1.34)
NHM	NORTHAM PLATINUM LTD	1.02	0.97	0.98	1.10
		(0.37)	-(0.40)	-(0.16)	(0.61)
ANG	ANGLOGOLD ASHANTI LTD	0.90	0.78	0.74	0.74
		-(1.06)	-(1.48)	-(1.44)	-(1.17)
HAR	HARMONY G M CO LTD	1.03	1.03	0.99	1.06
		(0.92)	(0.49)	-(0.12)	(0.37)
AFO	AFLEASE GOLD LTD	0.92	0.74	0.69	0.62
		-(1.60)	***-(2.97)****	***-(2.50)****	***-(2.28)****
WNH	WINHOLD LTD ORD	0.79	0.63	0.52	0.45
		-(2.24)*	***-(2.53)****	***-(2.60)****	***-(2.47)****
DRD	DRDGOLD LTD	1.09	1.15	1.20	1.20
		(2.28)*	***(2.12)****	(1.95)	(1.36)
BSR	BASIL READ HLDGS LTD	0.91	0.85	0.84	0.98
		-(1.51)	-(1.53)	-(1.14)	-(0.09)

Shares not included because of non-trading

AOO	AF & OVR
ASR	ASSORE
BIC	BICC CAFCA LTD
CKS	CROOKES
CMH	COMBINED MOTOR HLDGS LTD
CPL	CAPITAL PROPERTY FUND
CRG	CARGO CARRIERS LTD
CRW	CORWIL
EUR	EUREKA IND LTD ORD
HWA	HWANGE COLLIERY LD ORD
HYP	HYPROP INVESTMENTS LTD
ITE	ITALTILE
JCD	JCI LIMITED
LNF	LONDON FIN INV GRP PLC
MAS	MASONITE AFRICA LTD ORD
MIP	MERCHANT & IND PROP LTD
MTA	METAIR INVESTMENTS ORD
MTE	MARSHALL MONTEAGLE HD SA
NCS	NICTUS BEPERK
PALX	PALS HOLDINGS LIMITED
PPR	PUTPROP LTD

RTO	REX TRUEFORM CLOTH ORD
SAL	SALLIES LTD
SBL	SABLE HLDGS LTD ORD
SBO	SAAMBOU
SBV	SABVEST LTD
SER	SEARDEL INVEST CORP LTD
SIM	SIMMER AND JACK MINES
SPA	SPANJAARD LTD
STI	STILFONTEIN
TPC	TRANSPACO LTD
VIL	VILLAGE MAIN REEF G M CO
YRK	YORKCOR
ZCI	ZCI
ZSA	ZURICH SA

Appendix B

Detailed variance ratio graphs

Figure B-3 through Figure B-7 describe the detailed variance ratios and z-statistics calculated obtained in the sub-periods 1989 to 1994, 1994 to 1999, 1999 to 2004 and 2004 to 2009.

In the graphs, the thick bars indicate the variance ratio calculated, while the thin bars inside the thick bars indicate the statistical significance of the result. A 5% significance reference line is included to highlight statistically significant results obtained. Additionally, z-statistic scores are highlighted in red if they are significant, or green if they are not.

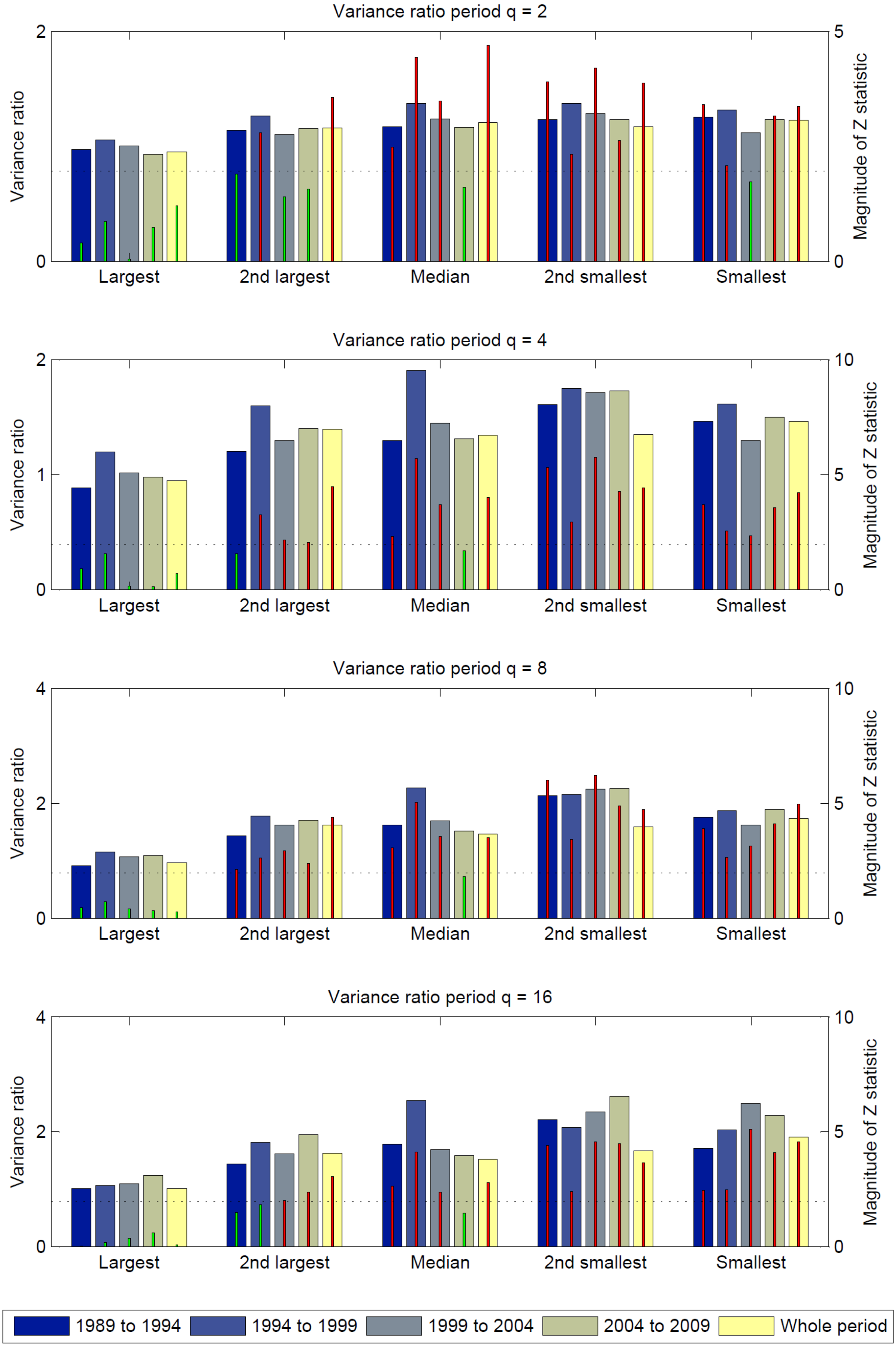

Figure B-3 Detailed variance ratios $\overline{\mathrm{VR}}(q)$ for firm size sorted portfolios from March 1989 to March 2009

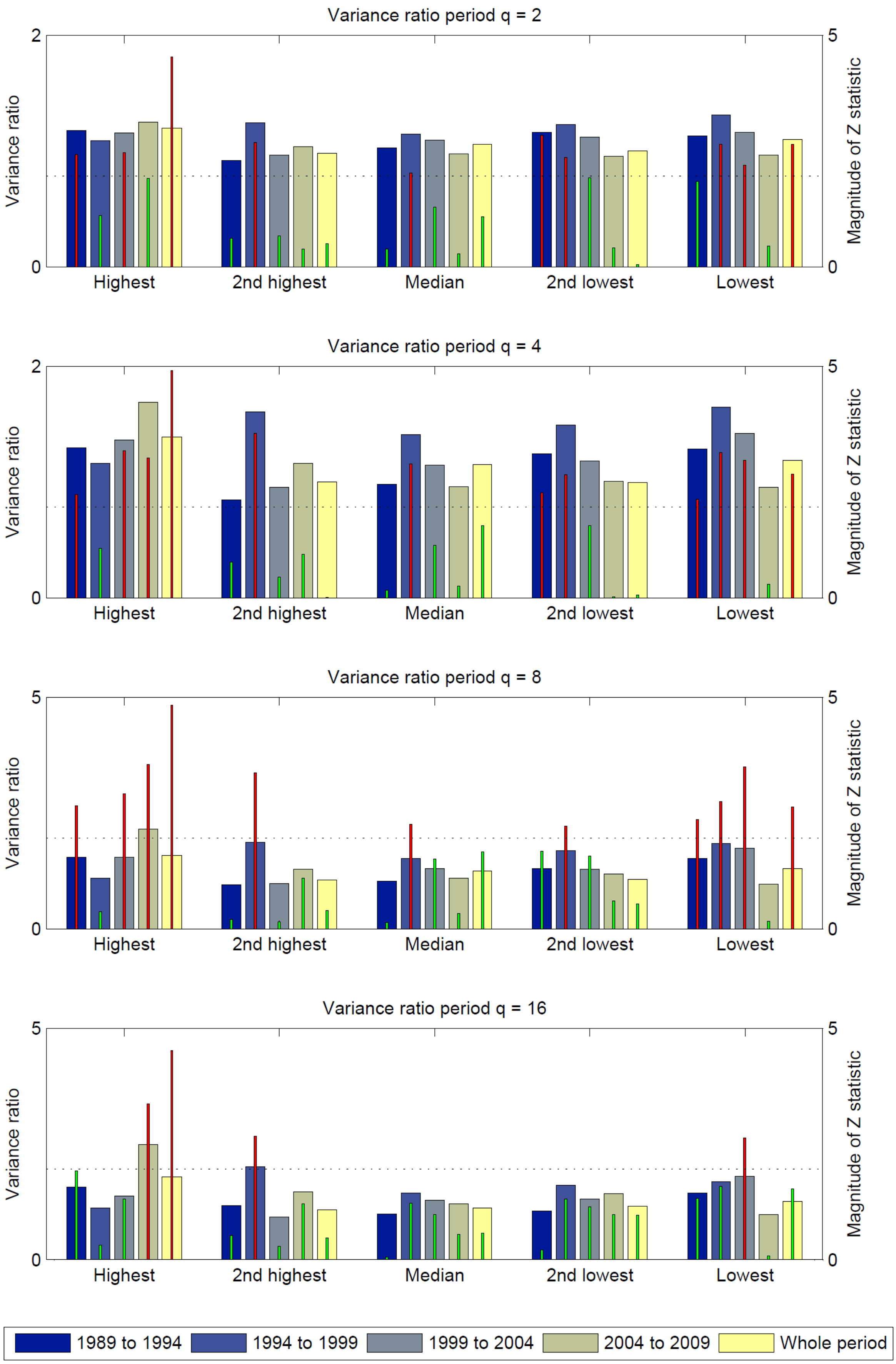

Figure B-4 Detailed variance ratios $\overline{\mathrm{VR}}(q)$ for dividend yield sorted portfolios from March 1989 to March 2009

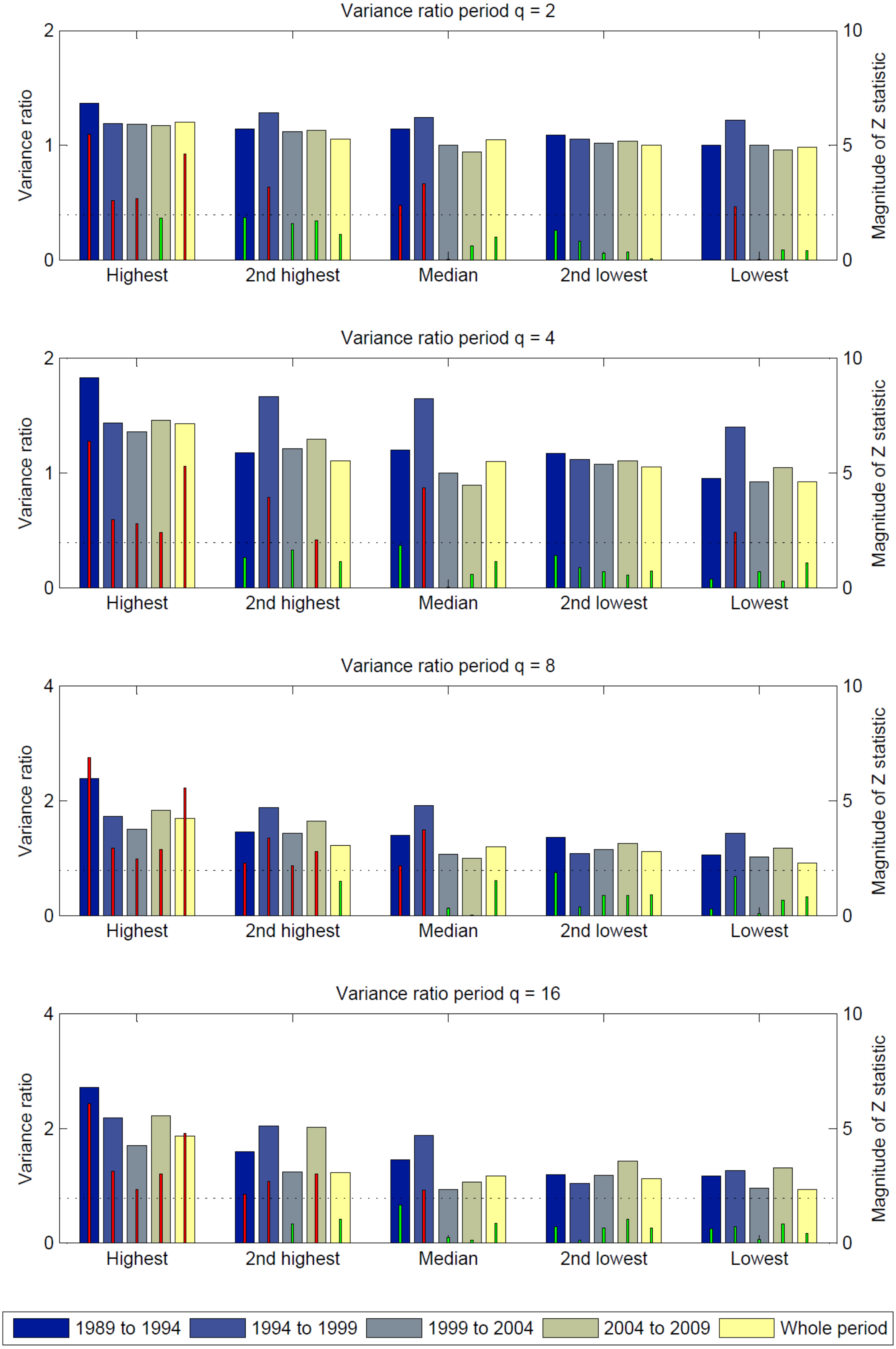

Figure B-5 Detailed variance ratios $\overline{\mathrm{VR}}(q)$ for earnings yield sorted portfolios from March 1989 to March 2009

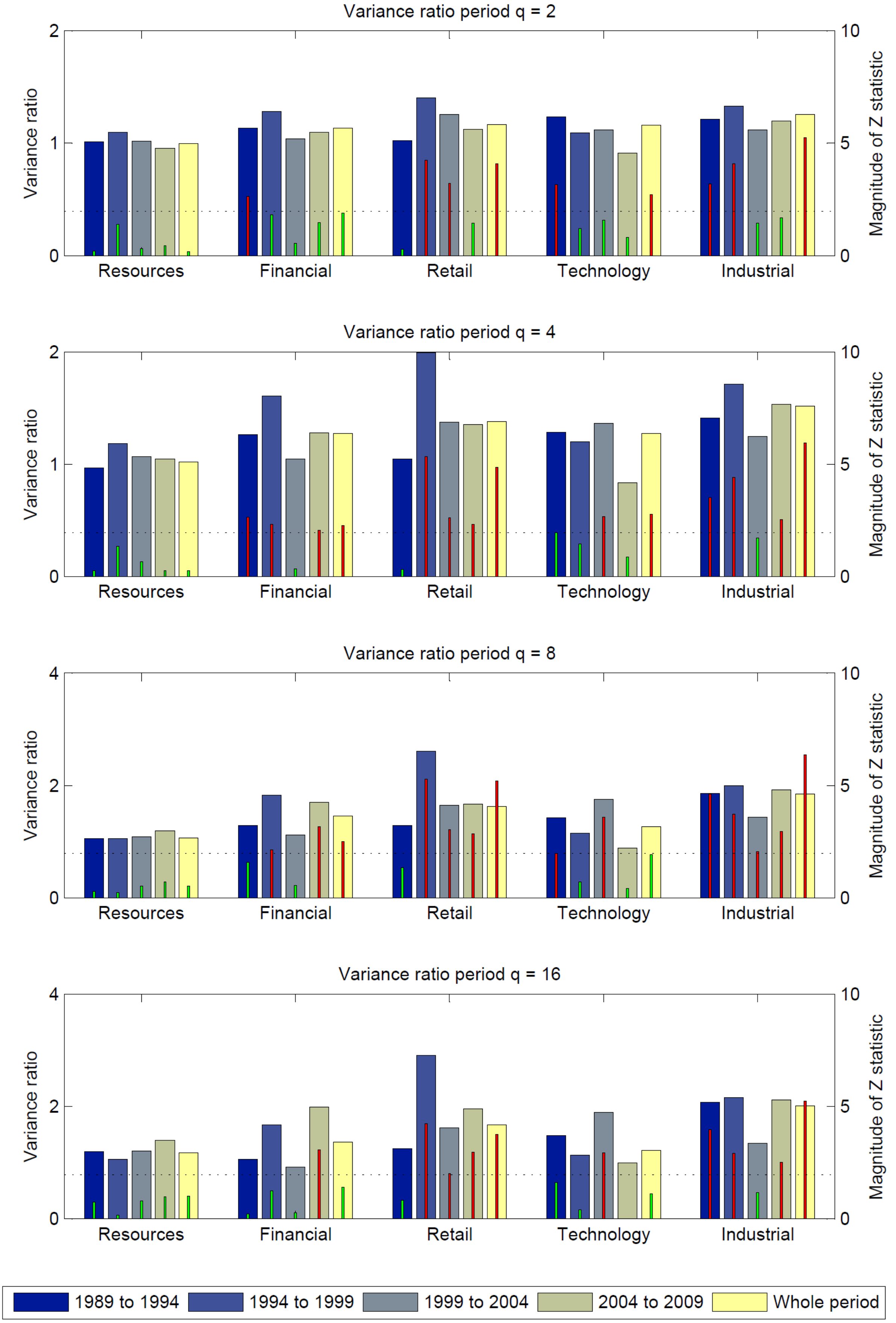

Figure B-6 Detailed variance ratios $\overline{\mathrm{VR}}(q)$ for industry sorted portfolios from March 1989 to March 2009

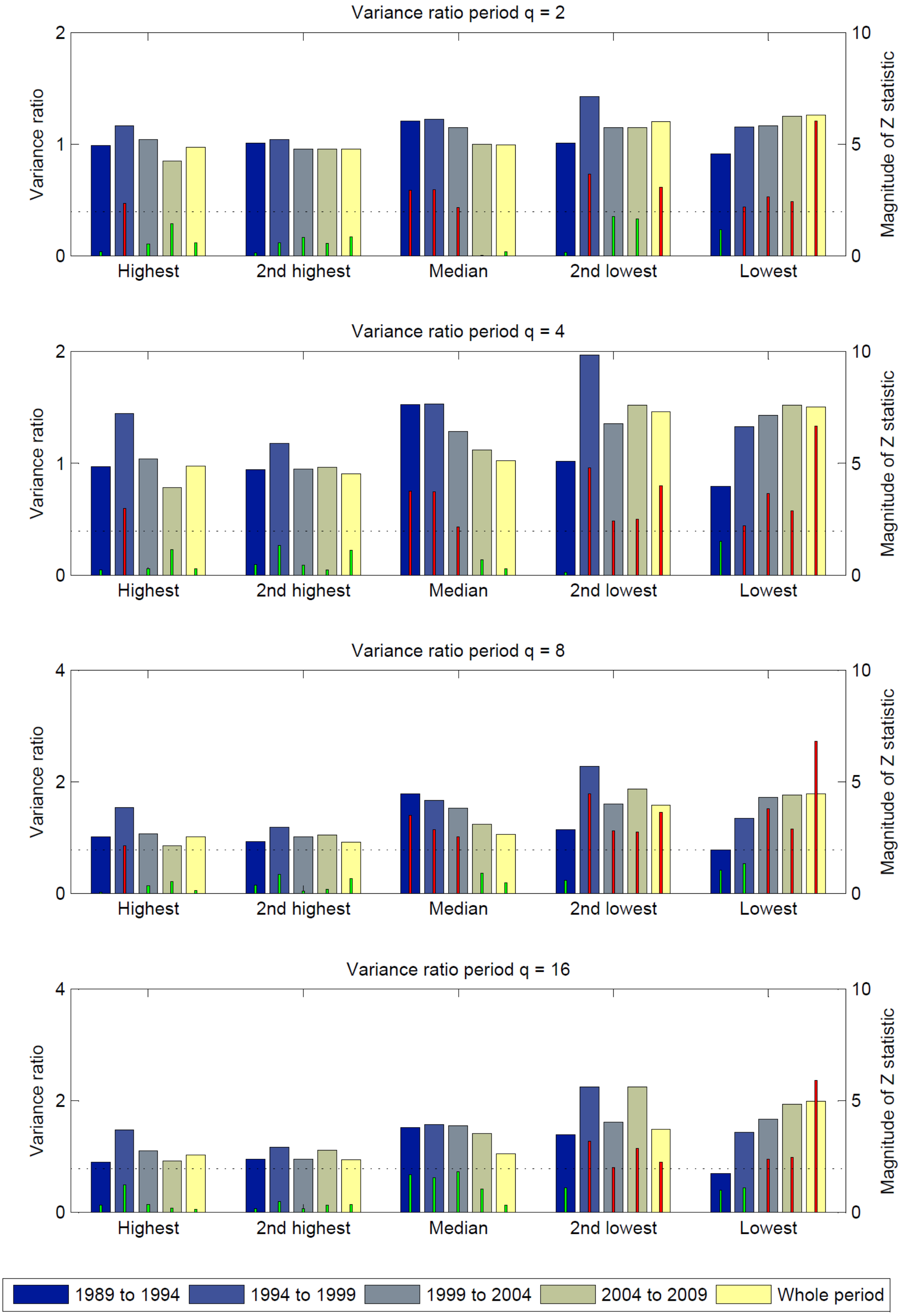

Figure B-7 Detailed variance ratios $\overline{\mathrm{VR}}(q)$ for trading volume sorted portfolios from March 1989 to March 2009

Appendix C

Portfolio rankings by firm size

Table C-1 Portfolio rankings by market capitalisation for the period from March 1989 to March 2009

Share code	Share name	Ranking	Average market capitalisation (Rm)
Quintile 1 - Portfolio containing the highest ranked companies by capitalisation			
AGL	ANGLO AMERICAN PLC	1	197 470
SAB	SABMILLER PLC	2	73 498
SOL	SASOL LTD	3	60 345
AMS	ANGLO PLATINUM LTD	4	58 687
FSR	FIRSTRAND LTD	5	48 130
SBK	STANDARD BANK GROUP LTD	6	43 787
ANG	ANGLOGOLD ASHANTI LTD	7	33 269
IMP	IMPALA PLATINUM HLGS LD	8	31 469
GFI	GOLD FIELDS LTD	9	26 117
ASA	ABSA GROUP LIMITED	10	25 890
NED	NEDBANK GROUP LTD	11	23 735
HAR	HARMONY G M CO LTD	12	14 924
SAP	SAPPI LTD	13	13 140
Quintile 2 - Portfolio containing the second highest ranked companies by capitalisation			
INL	INVESTEC LTD	14	11 443
DDT	DIMENSION DATA HLDGS PLC	15	9 956
NPK	NAMPAK LTD ORD	16	7 400
SHP	SHOPRITE HLDGS LTD ORD	17	6 964
PPC	PRETORIA PORT CEMNT	18	6 576
MUR	MURRAY AND ROBERTS H ORD	19	6 233
PIK	PIK N PAY STORES LTD	20	5 273
SNT	SANTAM LTD	21	4 814
AFX	AFRICAN OXYGEN LTD ORD	22	4 788
APN	ASPEN PHARMACARE HLDGS.	23	4 771
FOS	FOSCHINI LTD ORD	24	4 735
RLO	REUNERT ORD	25	4 720
MET	METROPOLITAN HLDGS LTD	26	4 570
Quintile 3 - Portfolio containing the median ranked companies by capitalisation			
SUI	SUN INTERNATIONAL LTD	27	4 514
JDG	JD GROUP LTD	28	4 291
MAF	MUTUAL & FEDERAL	29	4 041
MDC	MEDI-CLINIC CORP LTD ORD	30	3 766
NHM	NORTHAM PLATINUM LTD	31	3 750
AFE	A E C I LTD ORD	32	3 696
DST	DISTELL	33	3 685
CAT	CAXTON CTP PUBLISH PRINT	34	3 320
HVL	HIVELD STEEL AND VANADUM	35	3 169
PWK	PIKWIK	36	3 119
ALT	ALLIED TECHNOLOGIES	37	2 404
GND	GRINDROD LTD	38	2 361

TRE	TRENCOR LTD	39	2 307
Quintile 4 - Portfolio containing the second smallest ranked companies by capitalisation			
FPT	FOUNTAINHEAD PROP TRST	40	2 007
PAM	PALABORA MINING CO ORD	41	1 919
DRD	DRDGOLD LTD	42	1 899
ATN	ALLIED ELECTRONICS CORP	43	1 506
GRF	GROUP FIVE LTD ORD	44	1 364
BAT	BRAIT S.A.	45	1 286
SYC	SYCOM PROPERTY FUND	46	1 235
OCE	OCEANA GROUP LTD	47	1 183
PAP	PANGBOURNE PROP LTD	48	1 147
OMN	OMNIA HOLDINGS LTD	49	1 096
DEL	DELTA ELECRICAL IN	50	1 045
TSX	TRANS HEX GROUP LTD	51	918
DLV	DORBYL LTD ORD	52	756
Quintile 5 - Portfolio containing the smallest ranked companies by capitalisation			
HDC	HUDACO INDUSTRIES LTD	53	751
DAW	DISTRIBUTION AND WAREHSG	54	679
ADR	ADCORP HLDGS LTD ORD	55	653
MOB	MOBILE	56	580
CSB	CASHBUILD LTD	57	476
NWL	NU-WORLD HOLDINGS LTD	58	389
BSR	BASIL READ HLDGS LTD	59	383
SFN	SASFIN HOLDINGS LTD	60	377
AFO	AFLEASE GOLD LTD	61	267
BCF	BOWLER METCALF LTD	62	220
SPS	SPESCOM LTD	63	167
JSC	JASCO ELECTRONICS HLDGS	64	132
WNH	WINHOLD LTD ORD	65	73
Shares not included because of non-trading			
AOO	AF & OVR		
ASR	ASSORE		
BIC	BICC CAFCA LTD		
CKS	CROOKES		
CMH	COMBINED MOTOR HLDGS LTD		
CPL	CAPITAL PROPERTY FUND		
CRG	CARGO CARRIERS LTD		
CRW	CORWIL		
EUR	EUREKA IND LTD ORD		
HWA	HWANGE COLLIERY LD ORD		
HYP	HYPROP INVESTMENTS LTD		
ITE	ITALTILE		
JCD	JCI LIMITED		
LNF	LONDON FIN INV GRP PLC		
MAS	MASONITE AFRICA LTD ORD		
MIP	MERCHANT & IND PROP LTD		
MTA	METAIR INVESTMENTS ORD		
MTE	MARSHALL MONTEAGLE HD SA		
NCS	NICTUS BEPERK		
PALX	PALS HOLDINGS LIMITED		
PPR	PUTPROP LTD		
RTO	REX TRUEFORM CLOTH ORD		
SAL	SALLIES LTD		
SBL	SABLE HLDGS LTD ORD		
SBO	SAAMBOU		
SBV	SABVEST LTD		
SER	SEARDEL INVEST CORP LTD		
SIM	SIMMER AND JACK MINES		
SPA	SPANJAARD LTD		
STI	STILFONTEIN		
TPC	TRANSPACO LTD		
VIL	VILLAGE MAIN REEF G M CO		
YRK	YORKCOR		
ZCI	ZCI		
ZSA	ZURICH SA		

Appendix D

Portfolio rankings by dividend yield

Table D-1 Portfolio rankings by dividend yield for the period from March 1989 to March 2009

Share code	Share name	Ranking	Average dividend yield
Quintile 1 - Portfolio containing the highest ranked companies by dividend yield			
PAP	PANGBOURNE PROP LTD	1	13.13
FPT	FOUNTAINHEAD PROP TRST	2	11.26
SYC	SYCOM PROPERTY FUND	3	10.76
NHM	NORTHAM PLATINUM LTD	4	9.10
PAM	PALABORA MINING CO ORD	5	6.90
BSR	BASIL READ HLDGS LTD	6	6.57
SFN	SASFIN HOLDINGS LTD	7	6.37
DST	DISTELL	8	5.85
GND	GRINDROD LTD	9	5.43
OCE	OCEANA GROUP LTD	10	5.42
GRF	GROUP FIVE LTD ORD	11	5.42
HVL	HIVELD STEEL AND VANADUM	12	5.38
OMN	OMNIA HOLDINGS LTD	13	5.18
Quintile 2 - Portfolio containing the second highest ranked companies by dividend yield			
SNT	SANTAM LTD	14	4.92
PPC	PRETORIA PORT CEMNT	15	4.82
HDC	HUDACO INDUSTRIES LTD	16	4.76
DLV	DORBYL LTD ORD	17	4.69
AFE	A E C I LTD ORD	18	4.43
RLO	REUNERT ORD	19	4.25
ANG	ANGLOGOLD ASHANTI LTD	20	4.24
IMP	IMPALA PLATINUM HLGS LD	21	4.11
MET	METROPOLITAN HLDGS LTD	22	3.98
MUR	MURRAY AND ROBERTS H ORD	23	3.96
BCF	BOWLER METCALF LTD	24	3.94
AMS	ANGLO PLATINUM LTD	25	3.88
ASA	ABSA GROUP LIMITED	26	3.82
Quintile 3 - Portfolio containing the median ranked companies by dividend yield			
NPK	NAMPAK LTD ORD	27	3.81
PWK	PIKWIK	28	3.79
SUI	SUN INTERNATIONAL LTD	29	3.76
ALT	ALLIED TECHNOLOGIES	30	3.72
INL	INVESTEC LTD	31	3.67
SOL	SASOL LTD	32	3.66
JDG	JD GROUP LTD	33	3.66
JSC	JASCO ELECTRONICS HLDGS	34	3.53
MAF	MUTUAL & FEDERAL	35	3.42
PIK	PIK N PAY STORES LTD	36	3.41
ADR	ADCORP HLDGS LTD ORD	37	3.39
BAT	BRAIT S.A.	38	3.36
NED	NEDBANK GROUP LTD	39	3.33

Quintile 4 - Portfolio containing the second lowest ranked companies by dividend yield			
NWL	NU-WORLD HOLDINGS LTD	40	3.25
MDC	MEDI-CLINIC CORP LTD ORD	41	3.25
ATN	ALLIED ELECTRONICS CORP	42	3.20
APN	ASPEN PHARMACARE HLDGS.	43	3.17
TSX	TRANS HEX GROUP LTD	44	3.12
AFX	AFRICAN OXYGEN LTD ORD	45	3.10
CSB	CASHBUILD LTD	46	3.04
FSR	FIRSTRAND LTD	47	3.02
SAP	SAPPI LTD	48	3.00
WNH	WINHOLD LTD ORD	49	2.99
SBK	STANDARD BANK GROUP LTD	50	2.98
GFI	GOLD FIELDS LTD	51	2.94
AGL	ANGLO AMERICAN PLC	52	2.70
Quintile 5 - Portfolio containing the lowest ranked companies by dividend yield			
DEL	DELTA ELECRICAL IN	53	2.64
SAB	SABMILLER PLC	54	2.59
SHP	SHOPRITE HLDGS LTD ORD	55	2.57
FOS	FOSCHINI LTD ORD	56	2.41
CAT	CAXTON CTP PUBLISH PRINT	57	2.33
DAW	DISTRIBUTION AND WAREHSG	58	1.94
MOB	MOBILE	59	1.88
TRE	TRENCOR LTD	60	1.77
HAR	HARMONY G M CO LTD	61	1.37
SPS	SPESCOM LTD	62	1.23
DDT	DIMENSION DATA HLDGS PLC	63	1.12
DRD	DRDGOLD LTD	64	0.06
AFO	AFLEASE GOLD LTD	65	0.00
Shares not included because of non-trading			
AOO	AF & OVR		
ASR	ASSORE		
BIC	BICC CAFCA LTD		
CKS	CROOKES		
CMH	COMBINED MOTOR HLDGS LTD		
CPL	CAPITAL PROPERTY FUND		
CRG	CARGO CARRIERS LTD		
CRW	CORWIL		
EUR	EUREKA IND LTD ORD		
HWA	HWANGE COLLIERY LD ORD		
HYP	HYPROP INVESTMENTS LTD		
ITE	ITALTILE		
JCD	JCI LIMITED		
LNF	LONDON FIN INV GRP PLC		
MAS	MASONITE AFRICA LTD ORD		
MIP	MERCHANT & IND PROP LTD		
MTA	METAIR INVESTMENTS ORD		
MTE	MARSHALL MONTEAGLE HD SA		
NCS	NICTUS BEPERK		
PALX	PALS HOLDINGS LIMITED		
PPR	PUTPROP LTD		
RTO	REX TRUEFORM CLOTH ORD		
SAL	SALLIES LTD		
SBL	SABLE HLDGS LTD ORD		
SBO	SAAMBOU		
SBV	SABVEST LTD		
SER	SEARDEL INVEST CORP LTD		
SIM	SIMMER AND JACK MINES		
SPA	SPANJAARD LTD		
STI	STILFONTEIN		
TPC	TRANSPACO LTD		
VIL	VILLAGE MAIN REEF G M CO		
YRK	YORKCOR		
ZCI	ZCI		
ZSA	ZURICH SA		

Appendix E

Portfolio rankings by earnings yield

Table E-1 Portfolio rankings by earnings yield for the period from March 1989 to March 2009

Share code	Share name	Ranking	Average earnings yield
Quintile 1 - Portfolio containing the highest ranked companies by earnings yield			
GRF	GROUP FIVE LTD ORD	1	18.93
SFN	SASFIN HOLDINGS LTD	2	15.99
GND	GRINDROD LTD	3	14.72
PAM	PALABORA MINING CO ORD	4	14.12
SNT	SANTAM LTD	5	13.65
OMN	OMNIA HOLDINGS LTD	6	13.55
JDG	JD GROUP LTD	7	13.47
NWL	NU-WORLD HOLDINGS LTD	8	13.30
PAP	PANGBOURNE PROP LTD	9	12.84
HDC	HUDACO INDUSTRIES LTD	10	12.28
JSC	JASCO ELECTRONICS HLDGS	11	12.14
FPT	FOUNTAINHEAD PROP TRST	12	11.31
HVL	HIVELD STEEL AND VANADUM	13	11.25
Quintile 2 - Portfolio containing the second highest ranked companies by earnings yield			
DST	DISTELL	14	11.01
AFE	A E C I LTD ORD	15	10.95
BCF	BOWLER METCALF LTD	16	10.93
SYC	SYCOM PROPERTY FUND	17	10.91
ASA	ABSA GROUP LIMITED	18	10.78
OCE	OCEANA GROUP LTD	19	10.55
ADR	ADCORP HLDGS LTD ORD	20	10.17
MOB	MOBILE	21	10.16
SOL	SASOL LTD	22	10.02
MAF	MUTUAL & FEDERAL	23	9.82
ATN	ALLIED ELECTRONICS CORP	24	9.64
CAT	CAXTON CTP PUBLISH PRINT	25	9.58
RLO	REUNERT ORD	26	9.50
Quintile 3 - Portfolio containing the median ranked companies by earnings yield			
DLV	DORBYL LTD ORD	27	9.40
CSB	CASHBUILD LTD	28	9.21
MDC	MEDI-CLINIC CORP LTD ORD	29	9.16
TSX	TRANS HEX GROUP LTD	30	9.08
SBK	STANDARD BANK GROUP LTD	31	9.04
NED	NEDBANK GROUP LTD	32	8.97
ALT	ALLIED TECHNOLOGIES	33	8.84
TRE	TRENCOR LTD	34	8.75
MET	METROPOLITAN HLDGS LTD	35	8.71
IMP	IMPALA PLATINUM HLGS LD	36	8.59
MUR	MURRAY AND ROBERTS H ORD	37	8.56
SAP	SAPPI LTD	38	8.52
DAW	DISTRIBUTION AND WAREHSG	39	8.50

Quintile 4 - Portfolio containing the second lowest ranked companies by earnings yield			
APN	ASPEN PHARMACARE HLDGS.	40	8.34
AGL	ANGLO AMERICAN PLC	41	8.30
NPK	NAMPAK LTD ORD	42	8.19
PPC	PRETORIA PORT CEMNT	43	7.68
SUI	SUN INTERNATIONAL LTD	44	7.58
INL	INVESTEC LTD	45	7.57
FOS	FOSCHINI LTD ORD	46	7.52
SHP	SHOPRITE HLDGS LTD ORD	47	7.37
FSR	FIRSTRAND LTD	48	6.90
BAT	BRAIT S.A.	49	6.53
AFX	AFRICAN OXYGEN LTD ORD	50	6.03
SAB	SABMILLER PLC	51	5.61
AMS	ANGLO PLATINUM LTD	52	5.56
Quintile 5 - Portfolio containing the lowest ranked companies by earnings yield			
PIK	PIK N PAY STORES LTD	53	5.38
PWK	PIKWIK	54	5.14
DDT	DIMENSION DATA HLDGS PLC	55	4.65
DEL	DELTA ELECRICAL IN	56	4.58
SPS	SPESCOM LTD	57	4.07
GFI	GOLD FIELDS LTD	58	4.05
NHM	NORTHAM PLATINUM LTD	59	3.76
ANG	ANGLOGOLD ASHANTI LTD	60	3.46
HAR	HARMONY G M CO LTD	61	2.58
AFO	AFLEASE GOLD LTD	62	-4.71
WNH	WINHOLD LTD ORD	63	-13.10
DRD	DRDGOLD LTD	64	-13.53
BSR	BASIL READ HLDGS LTD	65	-20.97
Shares not included because of non-trading			
AOO	AF & OVR		
ASR	ASSORE		
BIC	BICC CAFCA LTD		
CKS	CROOKES		
CMH	COMBINED MOTOR HLDGS LTD		
CPL	CAPITAL PROPERTY FUND		
CRG	CARGO CARRIERS LTD		
CRW	CORWIL		
EUR	EUREKA IND LTD ORD		
HWA	HWANGE COLLIERY LD ORD		
HYP	HYPROP INVESTMENTS LTD		
ITE	ITALTILE		
JCD	JCI LIMITED		
LNF	LONDON FIN INV GRP PLC		
MAS	MASONITE AFRICA LTD ORD		
MIP	MERCHANT & IND PROP LTD		
MTA	METAIR INVESTMENTS ORD		
MTE	MARSHALL MONTEAGLE HD SA		
NCS	NICTUS BEPERK		
PALX	PALS HOLDINGS LIMITED		
PPR	PUTPROP LTD		
RTO	REX TRUEFORM CLOTH ORD		
SAL	SALLIES LTD		
SBL	SABLE HLDGS LTD ORD		
SBO	SAAMBOU		
SBV	SABVEST LTD		
SER	SEARDEL INVEST CORP LTD		
SIM	SIMMER AND JACK MINES		
SPA	SPANJAARD LTD		
STI	STILFONTEIN		
TPC	TRANSPACO LTD		
VIL	VILLAGE MAIN REEF G M CO		
YRK	YORKCOR		
ZCI	ZCI		
ZSA	ZURICH SA		

Appendix F

Portfolio rankings by industry

Table F-1 Portfolio rankings by industry for the period from March 1989 to March 2009

Share code	Share name
Quintile 1 - Portfolio containing companies in the resources sector	
AFO	AFLEASE GOLD LTD
AGL	ANGLO AMERICAN PLC
AMS	ANGLO PLATINUM LTD
ANG	ANGLOGOLD ASHANTI LTD
DRD	DRDGOLD LTD
GFI	GOLD FIELDS LTD
HAR	HARMONY G M CO LTD
HVL	HIVELD STEEL AND VANADUM
IMP	IMPALA PLATINUM HLGS LD
NHM	NORTHAM PLATINUM LTD
PAM	PALABORA MINING CO ORD
SOL	SASOL LTD
TSX	TRANS HEX GROUP LTD
Quintile 2 - Portfolio containing companies in the financial sector	
ASA	ABSA GROUP LIMITED
BAT	BRAIT S.A.
FPT	FOUNTAINHEAD PROP TRST
FSR	FIRSTRAND LTD
INL	INVESTEC LTD
MAF	MUTUAL & FEDERAL
MET	METROPOLITAN HLDGS LTD
NED	NEDBANK GROUP LTD
PAP	PANGBOURNE PROP LTD
SBK	STANDARD BANK GROUP LTD
SFN	SASFIN HOLDINGS LTD
SNT	SANTAM LTD
SYC	SYCOM PROPERTY FUND
Quintile 3 - Portfolio containing companies in the retail sector	
APN	ASPEN PHARMACARE HLDGS.
CAT	CAXTON CTP PUBLISH PRINT
CSB	CASHBUILD LTD
DST	DISTELL
FOS	FOSCHINI LTD ORD
JDG	JD GROUP LTD
KWV	KWV BELEGGINGS
MDC	MEDI-CLINIC CORP LTD ORD
NWL	NU-WORLD HOLDINGS LTD
OCE	OCEANA GROUP LTD
PIK	PIK N PAY STORES LTD
PWK	PIKWIK
SAB	SABMILLER PLC

SHP	SHOPRITE HLDGS LTD ORD
SUI	SUN INTERNATIONAL LTD
Quintile 4 - Portfolio containing companies in the technology sector	
ALT	ALLIED TECHNOLOGIES
DDT	DIMENSION DATA HLDGS PLC
SPS	SPESCOM LTD
Quintile 5 - Portfolio containing companies in the industrial sector	
ADR	ADCORP HLDGS LTD ORD
AFE	A E C I LTD ORD
AFX	AFRICAN OXYGEN LTD ORD
ATN	ALLIED ELECTRONICS CORP
BCF	BOWLER METCALF LTD
BSR	BASIL READ HLDGS LTD
DAW	DISTRIBUTION AND WAREHSG
DEL	DELTA ELECRICAL IN
DLV	DORBYL LTD ORD
GND	GRINDROD LTD
GRF	GROUP FIVE LTD ORD
HDC	HUDACO INDUSTRIES LTD
JSC	JASCO ELECTRONICS HLDGS
MOB	MOBILE
MUR	MURRAY AND ROBERTS H ORD
NPK	NAMPAK LTD ORD
OMN	OMNIA HOLDINGS LTD
PPC	PRETORIA PORT CEMNT
RLO	REUNERT ORD
SAP	SAPPI LTD
TRE	TRENCOR LTD
WNH	WINHOLD LTD ORD
Shares not included because of non-trading	
AOO	AF & OVR
ASR	ASSORE
BIC	BICC CAFCA LTD
CKS	CROOKES
CMH	COMBINED MOTOR HLDGS LTD
CPL	CAPITAL PROPERTY FUND
CRG	CARGO CARRIERS LTD
CRW	CORWIL
EUR	EUREKA IND LTD ORD
HWA	HWANGE COLLIERY LD ORD
HYP	HYPROP INVESTMENTS LTD
JCD	JCI LIMITED
LNF	LONDON FIN INV GRP PLC
MAS	MASONITE AFRICA LTD ORD
MIP	MERCHANT & IND PROP LTD
MTA	METAIR INVESTMENTS ORD
MTE	MARSHALL MONTEAGLE HD SA
NCS	NICTUS BEPERK
PALX	PALS HOLDINGS LIMITED
PPR	PUTPROP LTD
RTO	REX TRUEFORM CLOTH ORD
SAL	SALLIES LTD
SBL	SABLE HLDGS LTD ORD
SBO	SAAMBOU
SBV	SABVEST LTD
SER	SEARDEL INVEST CORP LTD
SIM	SIMMER AND JACK MINES
SPA	SPANJAARD LTD
STI	STILFONTEIN
TPC	TRANSPACO LTD
VIL	VILLAGE MAIN REEF G M CO
YRK	YORKCOR
ZCI	ZCI
ZSA	ZURICH SA

Appendix G

Portfolio rankings by trading volume

Table G-1 Portfolio rankings by trading volume for the period from March 1989 to March 2009

Share code	Share name	Ranking	Average trading volume ('000s)
Quintile 1 - Portfolio containing the highest ranked companies by trading volume			
FSR	FIRSTRAND LTD	1	42 468
DDT	DIMENSION DATA HLDGS PLC	2	15 185
SBK	STANDARD BANK GROUP LTD	3	14 247
AGL	ANGLO AMERICAN PLC	4	12 064
IMP	IMPALA PLATINUM HLGS LD	5	8 417
SOL	SASOL LTD	6	8 145
GFI	GOLD FIELDS LTD	7	7 686
SAB	SABMILLER PLC	8	7 498
ASA	ABSA GROUP LIMITED	9	6 924
FPT	FOUNTAINHEAD PROP TRST	10	6 289
MET	METROPOLITAN HLDGS LTD	11	5 590
NPK	NAMPAK LTD ORD	12	5 410
MUR	MURRAY AND ROBERTS H ORD	13	4 594
Quintile 2 - Portfolio containing the second highest ranked companies by trading volume			
HAR	HARMONY G M CO LTD	14	4 417
SAP	SAPPI LTD	15	4 295
SHP	SHOPRITE HLDGS LTD ORD	16	3 780
INL	INVESTEC LTD	17	3 308
PPC	PRETORIA PORT CEMNT	18	3 135
FOS	FOSCHINI LTD ORD	19	3 054
NED	NEDBANK GROUP LTD	20	3 030
PIK	PIK N PAY STORES LTD	21	2 998
APN	ASPEN PHARMACARE HLDGS.	22	2 700
GND	GRINDROD LTD	23	2 654
JDG	JD GROUP LTD	24	2 528
ANG	ANGLOGOLD ASHANTI LTD	25	2 298
RLO	REUNERT ORD	26	1 934
Quintile 3 - Portfolio containing the median ranked companies by trading volume			
DRD	DRDGOLD LTD	27	1 881
MOB	MOBILE	28	1 767
NHM	NORTHAM PLATINUM LTD	29	1 669
AMS	ANGLO PLATINUM LTD	30	1 536
PAP	PANGBOURNE PROP LTD	31	1 389
MDC	MEDI-CLINIC CORP LTD ORD	32	1 368
PWK	PIKWIK	33	1 313
AFO	AFLEASE GOLD LTD	34	1 294
AFX	AFRICAN OXYGEN LTD ORD	35	1 029
AFE	A E C I LTD ORD	36	1 021
SYC	SYCOM PROPERTY FUND	37	1 011
DAW	DISTRIBUTION AND WAREHSG	38	930
GRF	GROUP FIVE LTD ORD	39	759

Quintile 4 - Portfolio containing the second lowest ranked companies by trading volume			
BAT	BRAIT S.A.	40	720
CAT	CAXTON CTP PUBLISH PRINT	41	603
SUI	SUN INTERNATIONAL LTD	42	596
ALT	ALLIED TECHNOLOGIES	43	468
TRE	TRENCOR LTD	44	436
SPS	SPESCOM LTD	45	427
HVL	HIVELD STEEL AND VANADUM	46	400
TSX	TRANS HEX GROUP LTD	47	390
SNT	SANTAM LTD	48	383
BSR	BASIL READ HLDGS LTD	49	373
JSC	JASCO ELECTRONICS HLDGS	50	352
WNH	WINHOLD LTD ORD	51	303
ADR	ADCORP HLDGS LTD ORD	52	289
Quintile 5 - Portfolio containing the lowest ranked companies by trading volume			
MAF	MUTUAL & FEDERAL	53	268
OMN	OMNIA HOLDINGS LTD	54	259
ATN	ALLIED ELECTRONICS CORP	55	255
OCE	OCEANA GROUP LTD	56	245
HDC	HUDACO INDUSTRIES LTD	57	199
DLV	DORBYL LTD ORD	58	192
DEL	DELTA ELECRICAL IN	59	170
NWL	NU-WORLD HOLDINGS LTD	60	155
BCF	BOWLER METCALF LTD	61	146
CSB	CASHBUILD LTD	62	126
PAM	PALABORA MINING CO ORD	63	93
DST	DISTELL	64	91
SFN	SASFIN HOLDINGS LTD	65	80
Shares not included because of non-trading			
AOO	AF & OVR		
ASR	ASSORE		
BIC	BICC CAFCA LTD		
CKS	CROOKES		
CMH	COMBINED MOTOR HLDGS LTD		
CPL	CAPITAL PROPERTY FUND		
CRG	CARGO CARRIERS LTD		
CRW	CORWIL		
EUR	EUREKA IND LTD ORD		
HWA	HWANGE COLLIERY LD ORD		
HYP	HYPROP INVESTMENTS LTD		
ITE	ITALTILE		
JCD	JCI LIMITED		
LNF	LONDON FIN INV GRP PLC		
MAS	MASONITE AFRICA LTD ORD		
MIP	MERCHANT & IND PROP LTD		
MTA	METAIR INVESTMENTS ORD		
MTE	MARSHALL MONTEAGLE HD SA		
NCS	NICTUS BEPERK		
PALX	PALS HOLDINGS LIMITED		
PPR	PUTPROP LTD		
RTO	REX TRUEFORM CLOTH ORD		
SAL	SALLIES LTD		
SBL	SABLE HLDGS LTD ORD		
SBO	SAAMBOU		
SBV	SABVEST LTD		
SER	SEARDEL INVEST CORP LTD		
SIM	SIMMER AND JACK MINES		
SPA	SPANJAARD LTD		
STI	STILFONTEIN		
TPC	TRANSPACO LTD		
VIL	VILLAGE MAIN REEF G M CO		
YRK	YORKCOR		
ZCI	ZCI		
ZSA	ZURICH SA		

Appendix H

Maximisation of the serial correlation by adjustment of a weightings matrix

Mathematically stated, one may maximise ρ_P, the serial correlation of the portfolio, where:

$$\rho_P(k) = \frac{\sum_{i=1}^{n}\left(r_{P,i} - \mu\right)\left(r_{P,i-k} - \mu\right)}{(n-1)\sigma^2} \tag{14.1}$$

where $r_{P,i}$ is the ith portfolio return in the series of length n, calculated in terms of the ith price in the price series of constituent j of m, $X_{j,i}$, and w_j is the weighting given to the jth constituent:

$$r_{P,i} = \ln\left(\sum_{j=1}^{m} w_j \frac{X_{j,i}}{X_{j,i-1}}\right) \cong \sum_{j=1}^{m} w_j r_{j,i} \tag{14.2}$$

This approximation is valid when $r_{j,i}$ is small.

This maximization was performed using a constrained minimization algorithm of $-\rho_P(k)$. The algorithm was made subject to a variance bound on the log return series of the portfolio, r_P, such that the minimization does not try to focus too much on peculiarities in the data which leads to very strong serial correlation for a short portion of the returns series, while neglecting the serial correlation of the rest of the series. Placing a variance bound on the returns series constrains the algorithm to placing too much emphasis at one point on the returns series.