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Firm-Specific Attributes and the Cross-Section of JSE Securities Exchange Returns

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DOCTOR OF PHILOSOPHY

Abstract

The empirical counterpart of a theory of asset prices is a model of the cross-section of security returns. Empirical tests of the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), Mossin (1966) and Black (1972) using cross-sectional methodologies have identified numerous cases where variables apart from beta explain expected returns. Initially termed 'anomalies', these empirical violations of the theory are frequently associated with firm-specific attribute data. Traditional views of market efficiency however rule out the ability to predict risk-adjusted asset returns and the source and exploitability of these anomalies remains controversial. This thesis empirically investigates the cross-sectional relationship between twenty-four firm-specific attributes and stock returns on the JSE Securities Exchange (JSE). The results are evaluated to determine whether they conform to the predictions of the CAPM and a two factor Arbitrage Pricing Theory (APT) model suggested by prior research.

In monthly univariate tests similar to Fama and MacBeth (1973), price-to-NAV, dividend yield, price-to-earnings, cashflow-to-price, price-to-profit and size are found to have statistically significant predictive power in the cross-section of returns using monthly data from July 1990 to June 2000. After conducting risk-adjustments using both the CAPM and a two factor APT model these effects are found to persist. Multivariate testing suggests a two factor model with the size and price-to-earnings attributes as explanatory variables. When the cross-sectional tests are compared across the broad industry sectors of the JSE, value effects are observed as being stronger in the financial-industrial sector than in the resource sector, the small size effect is roughly the same across sectors while the premium earned by higher debt levels is negative across all sectors except the financial sector. The results are not reconcilable with the predictions of the CAPM.

Simulated portfolios constructed using a methodology similar to Fama and French (1992) reveal that beta, if anything, is inversely related to average returns on the JSE. Contrary to the international evidence, greater average returns accruing to small and low price-to-earnings firms are not commensurate with higher betas. Controlling for the small size and low price-to-earnings effects does not improve the explanatory power of beta. An application of the Daniel and Titman (1997) methodology suggests that average returns on the JSE are not compensation for factor risk, but instead are associated with the exposure to the attributes themselves. The findings of this study present a serious empirical challenge for covariance-based asset pricing models on the JSE.

Declaration

I, Michael Robertson, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other University. I empower the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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Introduction

“...the main implication of the CAPM is that in a market equilibrium, the value weighted market portfolio, M , is mean-variance efficient. The mean-variance efficiency of M , in turn, says that:

(i) β , the slope in the regression of a security's return on the market return, is the only risk needed to explain expected return;

(ii) There is a positive expected premium for β risk.

Our main point is that evidence of (ii)...is only support for the CAPM if (i) also holds”.

- Fama and French (1996:1948)

1.1 Introduction

For several decades the Capital Asset Pricing Model (CAPM) has played an important role in financial economics. Accredited to Sharpe (1964), Lintner (1965), Mossin (1966) and Black (1972), the model embodies a theory of what can be inferred about asset returns when markets are in equilibrium and when all investors pursue a mean-variance optimising objective. Using equilibrium arguments extending from mean-variance analysis, the CAPM derives market beta as the single priced risk factor linking expected excess returns proportionally to their covariation with the return of the market portfolio.

In contrast, the Arbitrage Pricing Theory (APT) proposed by Ross (1976) integrates a multiple factor return generating process with arbitrage principles to derive a multifactor asset pricing relationship. Unlike the important role bestowed on the market portfolio in the CAPM, the APT is not explicit about the identity of the factors themselves. While it is possible for the CAPM and APT to be consistent with one another even if the market portfolio is not one of the factors in the APT, it is often argued that the APT is a more testable alternative to the CAPM.

Cross-sectional models, the empirical counterpart of asset pricing models, are germane to evaluating the predictions of asset pricing theory. Attempts to empirically verify the CAPM using cross-sectional methodologies have identified numerous inconsistencies. Most notable is the evidence that other variables are able to predict security returns beyond that explained by the risk factor beta. Yet an empirical evaluation of a model of asset prices is inseparable from an appraisal of market efficiency. Asset pricing theory and the Efficient Market Hypothesis (EMH) thus form a joint hypothesis and it never possible to know for certain exactly what the empirical tests imply about the validity of the CAPM itself. While tests may provide evidence against the CAPM, they do not necessarily constitute evidence in support of any alternative model such as the APT. Until a priori theoretical support is offered for one set of variables rather than another, an alternative specification to beta is tentative. Nevertheless, studies that investigate the relationships between asset returns and variables such as firm-specific attributes have done much to increase the understanding of how pricing occurs in the financial markets.

This thesis empirically investigates the cross-sectional relationship between firm-specific attributes and stock returns on the JSE Securities Exchange (JSE). The results are evaluated to determine whether they conform to the predictions of the CAPM and a two factor APT model suggested by prior research¹. The remainder of the chapter is set out as follows. Section 1.2 outlines the motivation for this research and the research objectives, Section 1.3 discusses the contribution and Section 1.4 provides details on the structure of this thesis together with a brief overview of each chapter.

1.2 Motivation for this research

South Africa is an emerging market. The volume of asset pricing research conducted on emerging markets is disproportionately thin compared with the developed markets of Western Europe, Japan and particularly the United States. Emerging market research therefore lags behind the developed market research and several areas remain largely unexplored. As such, any research on emerging markets that addresses this lag and enhances our understanding of their workings is generally well motivated. Further research is also

¹ Throughout this thesis the term 'firm-specific attribute' is often shortened to simply 'attribute'.

required to address some of the peculiarities of emerging markets such as the often-pervasive thin trading problem and market segmentation.

The attributes investigated in this thesis, most of which are financial ratios, are an important source of information for investors. The return on assets, return on equity and price-to-profit ratios provide useful information on the profitability of a firm. Indicators such as the current and quick ratios provide investors with information on short-term liquidity while financial ratios such as debt-to-assets, debt-to-equity and long term loans-to-assets measure the ability of a firm to meet its longer-term financial commitments. Much research in developed markets is directed towards investigating the cross-sectional relationships between stock returns and firm-specific attributes. While there is some preliminary evidence in the literature to suggest the attributes that are related to stock returns in emerging markets are: "...at least qualitatively similar to those documented for developed markets." (Rouwenhorst, 1999:1439), no exhaustive cross-sectional analysis has yet been conducted in South Africa². The first objective of this research is therefore to investigate the cross-sectional relationship between a broad set of attributes and stock returns on the JSE. Once a short-list of individual candidate attributes has been identified, a multi-attribute cross-sectional model for the JSE will be sought.

Whether the same attributes that explain the cross-section of all stock returns also explain the cross-section of returns within the broad sectors of the market is another well-motivated area for further research on the JSE. This is of particular relevance due to evidence, reviewed in Chapter Three, showing that the return generating processes of the financial-industrial and resource sectors of the JSE are not the same. The second objective of this research is therefore to evaluate the robustness of the relationships between attributes and stock returns across the broad market sectors of the JSE. This line of inquiry has not previously appeared in any published research.

Whether the cross-sectional explanatory power of the attributes arises from their role as instruments for risk, as predicted by existing asset pricing theory, or whether the attributes represent a source of risk-adjusted performance (mispricing) has received much attention in

² The Rouwenhorst (1999) study incorporates thirty-three emerging markets but excludes South Africa.

the international literature but remains largely unexplored on the JSE. The third objective of this research is to determine the role of the risk factor beta in describing average stock returns on the JSE. The fourth and final objective seeks to establish more generally whether it is risk factor loadings, measuring the sensitivity of a stock or portfolio to a risk factor, or the attributes themselves that explain returns.

1.3 Contribution

The descriptive statistics section of this thesis provides new evidence detailing the distributional properties of a broad range of firm-specific attributes on the JSE. The results are compared across the major industry sectors to highlight the possibility that differences in the distributional properties may be linked to differing economic interpretation of the attributes across sectors. These findings are relevant to financial research in a number of ways and not only to the ensuing asset pricing research.

In addition to analysing a more comprehensive set of attributes than any previous South African study, this research also represents the first extensive application of an attribute-based cross-sectional methodology on the JSE. This enhances the literature by presenting previously undocumented evidence on the individual cross-sectional relationships between a broad set of attributes and stock returns. The results facilitate the specification of a new empirically motivated multi-attribute cross-sectional model for the JSE. Furthermore, by extending the methodology to the sectors of the JSE, new evidence is presented of the degree to which the relationships between the attributes and stock returns are similar across major industry groupings.

This research also examines how attributes in the multi-attribute model interact with each other and with beta. This provides new evidence on the role of beta in explaining average stock return on the JSE. A further contribution is made by conducting new analysis that investigates whether risk factor loadings determine cross-sectional returns or whether it is the attributes themselves that should be used in the specification of the multi-attribute model. This allows several important theoretical questions regarding the source of the explanatory power of the attributes to be considered for the first time on the JSE. Finally, new empirical

work demonstrates to the investment practitioner how the contributions made elsewhere in this thesis are relevant for the performance analysis of professionally managed equity portfolios.

1.4 Thesis organisation

Chapter Two provides an overview of the investment theory that is relevant to the research conducted in this thesis. The concept of informational efficiency is introduced by linking the random walk model with the EMH. An overview of the theory of asset pricing ensues with an introduction to portfolio selection with a mean-variance optimising objective. The integration of the mean-variance framework with informational efficiency is discussed as a precursor to a theoretical overview of the CAPM. The chapter concludes by relating the principles of arbitrage to the formulation of the APT.

Chapter Three contains a review of the prior literature that is relevant to the empirical work conducted in subsequent chapters. The sections of the literature review are arranged to allow comparisons to be drawn between the international literature and the literature that is specific to the JSE. The chapter begins by reviewing the literature that has sought to empirically evaluate the predictions of the CAPM and offers several explanations for documented CAPM anomalies. A debate on whether attributes or risk factor loadings determine average return is then introduced. The chapter concludes by reviewing the literature relating to the APT.

Chapter Four presents the stock returns and attribute data sets that are analysed in the empirical work in Chapters Five to Eight. Several adjustments to the data sets are discussed and implemented. Descriptive statistics are presented to compare the distributional properties of the attributes across the major sectors of the JSE and economic reasons are suggested to explain any observed differences.

Chapter Five employs the cross-sectional technique of Fama and MacBeth (1973) to investigate which individual attributes are significantly able to predict monthly stock returns on the JSE. The relationship between each attribute and stock returns is then evaluated after

risk adjusting the stock returns data set using first the CAPM and then a two factor APT model suggested by prior research. All possible permutations of significant attributes are then tested jointly using multivariate regressions for the purpose of deriving a multi-attribute cross-sectional model for the first time on the JSE.

Chapter Six investigates whether the attributes associated with stock returns in the financial, industrial, financial and industrial and resource sectors of the JSE are similar to those documented in Chapter Five for the entire market. Dummy variables are added to the cross-sectional regressions to code individual stocks for sector membership. Explanations for the results are considered in tandem with the descriptive statistics of the attributes presented in Chapter Four. The applicability of the multi-attribute cross-sectional model derived in Chapter Five is then compared across the sectors of the JSE.

Chapter Seven replaces the Fama and MacBeth (1973) methodology with the portfolio approach of Fama and French (1992). The objectives are to evaluate the role of beta on the JSE and assess the interaction between beta and the explanatory roles of the attributes in the multi-attribute model. Simulated portfolios are constructed monthly by ranking stocks on their attribute values and then evaluating whether the average returns of the resulting test portfolios are commensurate with their beta. Additional two-dimensional stock ranking techniques are also employed to study the interaction between the constituents of the multi-attribute model.

Chapter Eight follows a methodology similar to Daniel and Titman (1997) and explicitly investigates whether risk factor loadings or the attributes themselves explain average stock returns on the JSE. For all stocks, risk factor loadings are estimated to represent the sensitivity to the return premiums associated with each of the attributes in the multi-attribute model. Using the same two-dimensional stock sorting procedures as in Chapter Seven, simulated portfolios are constructed with independent variation in the attributes and in the risk factor loadings.

Chapter Nine provides a concise summary of the results from Chapters Five to Eight. In a practical application of the findings of this research, simulated portfolio data is replaced with

a data set of General Equity unit trust returns. An adaptation of the returns-based style analysis technique of Sharpe (1992) is then employed to decompose the return patterns of the unit trusts. The final section concludes the thesis with discussions that consider the findings of previous chapters in the context of the theory outlined in Chapter Two and suggests some areas for further research.

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2

Theoretical Overview

2.1 Introduction

The extent to which asset returns are predictable is an area of great interest to practitioners and academics. For practitioners, the objective is to exploit the information to achieve an improved rate of risk-adjusted return. For academics, the objectives are to develop an understanding of price determination in the asset markets and evaluate the degree of asset market efficiency.

The degree of efficiency depends on the extent to which asset prices fully reflect available information, as Fama (1970:288) notes: *"All the empirical research on the theory of efficient markets has been concerned with whether prices 'fully reflect' particular subsets of available information"*. No insight regarding asset market efficiency can therefore be gained without being explicit about the information set in the context of which efficiency is being judged. Evaluations of asset market efficiency must however also take place within a theoretical framework of asset price determination, as Fama (1991, 1575-6) further explains: *"...market efficiency per se is not testable. It must be tested jointly with some model of equilibrium, an asset-pricing model"*. Tests of asset market efficiency therefore cannot be separated from the asset pricing models and the information sets on which their predictions are conditioned

This chapter provides a theoretical overview of informational efficiency and asset pricing theory as a precursor to the empirical chapters of this thesis. The remainder of the chapter is set out as follows. Section 2.2 introduces the random walk model and the EMH under the heading of informational efficiency. Section 2.3 provides an overview of asset pricing theory by introducing mean-variance analysis followed by a discussion on deriving the CAPM and the APT.

2.2 Informational efficiency

The idea that the information held by market participants has a role in setting the price levels of securities is first noted in the early work of Bachelier (1900). In the opening paragraph of his acclaimed dissertation *‘Theorie de la Spéculation’*, he proposes that: “...*past, present and even discounted future events are reflected in market prices*”. The insights of Bachelier (1900) however remained largely ignored for several decades until Cootner (1964) published and circulated a full translation of the work. In modern financial economics, informational efficiency is more concisely defined as: “*A capital market is said to be informationally efficiency if it fully and correctly reflects all relevant information in determining security prices*”. (The New Palgrave Dictionary of Money and Finance, 1, 730). While this definition seems innocuous at first, there are two important distinct components. The first relates to the question of what constitutes ‘all relevant information’ while the second relates to what is meant by ‘fully and correctly reflects’ in respect of the information set concerned.

Conclusions about asset market efficiency invariably depend on what elements of information are assumed to be available to market participants. It is therefore important to be explicit about what information is available when making inferences about asset market efficiency. The information set assumed to be available in this thesis is a set of publicly available firm-specific attributes. Whether asset prices on the JSE ‘fully and correctly reflect’ this information set requires a model to translate the information into predictions of asset prices against which realised returns may be compared. Two such models, the CAPM and the APT are reviewed later in this chapter and form an important component of the empirical work conducted in later chapters.

2.2.1 The random walk model

In finance the term ‘random walk’ is used to describe a series of asset returns, $r_t, r_{t-1}, \dots, r_{t-n}$, that are serially independent such that¹:

$$\text{cov}(r_t, r_{t-n}) = 0 \quad \text{for} \quad n \neq 0 \quad (2.1)$$

¹ The first reference to the term ‘random walk’ appears to be in Pearson and Rayleigh (1905) although this study is unrelated to finance.

Kendall (1953) provides the first evidence that security prices move randomly by demonstrating that weekly changes in security prices can not be predicted from their own past price behaviour or that of other securities. He concludes that: *"...in series of prices which are observed at fairly close intervals the random changes from one term to the next are so large as to swamp any systematic effect which may be present. The data behave almost like wandering series"*. Subsequent findings by Osborne (1959) and Cowles (1960) add further support to Kendall's (1953) conclusions regarding the randomness in the movement of asset prices.

Following the arrival of greater computing power, more rigorous testing of the data began to produce new evidence that security prices are mildly predictable. This first emerges in the results of a technical trading strategy published by Alexander (1961). His results show evidence of a slight predictability in security returns, but conclude no opportunity for trading profits exists after accounting for transaction costs². Fama (1965) subsequently makes a similar observation that the slight serial correlation in security prices is sufficiently small to render it unexploitable: *"Thus, strictly speaking, the random-walk theory cannot be a completely accurate description of reality. For practical purposes, however, we may be willing to accept the independence assumption of the model as long as the dependence in the series of successive price changes is not above some 'minimum acceptable' level"*. He is however unable to judge whether his findings are legitimate autocorrelations or the by-product of limitations of the statistical techniques employed.

2.2.2 The EMH

The random walk model represents a set of observations that are consistent with the EMH. The first formal conceptualisation of the EMH is given by Samuelson (1965). He notes: *"...in competitive markets there is a buyer for every seller. If one could be sure that a price would rise, it would have already risen...arguments like this are used to deduce that competitive prices must display price changes... that perform a random walk with no predictable bias"*. In a summary of the empirical evidence and a review of the theory, Fama (1970) outlines three forms of market efficiency. The three forms are the weak-form, the semi-strong form and the strong-form. The weak-form of market efficiency is characterised by a random change in asset prices and past asset

² In response to subsequent criticisms of a bias in his results, updated findings are presented in Alexander (1964) although the conclusions remain the same.

prices that contain no information about future changes. Testing for weak-form efficiency requires formulating a hypothesis to evaluate whether expected successive price prediction errors $\varepsilon_{i,t+1}$, and hence stock returns, are serially independent in the random walk sense given an information set Ω_t at time t :

$$E(\varepsilon_{i,t+1}, \varepsilon_{i,t} | \Omega_t) = 0 \quad (2.2)$$

Semi-strong form market efficiency says that asset prices reflect all public information contained in published financial reports such as the attribute data investigated in this study. To evaluate informational efficiency in the semi-strong form requires a hypothesis that asks whether the error in stock price prediction $\varepsilon_{i,t+1}$ is expected given the information set Ω_t at time t :

$$E(\varepsilon_{i,t+1} | \Omega_t) = 0 \quad (2.3)$$

Strong-form market efficiency says that, in addition to public information, all private information is incorporated in asset prices and only privileged or inside information can lead to trading profit. This means that even the most astute forecaster can not uncover any information that could result in profit. To evaluate this form of market efficiency requires a hypothesis that the prediction errors are independent of any forecasts made:

$$E(\varepsilon_{i,t+1} | E(\varepsilon_{i,t+1} | \Omega_t)) = 0 \quad (2.4)$$

Fama (1970) concludes: *"the results are strongly in support of the weak-form of market efficiency"*. He then proceeds with a review of several semi-strong and strong-form tests, and further concludes: *"in short, the evidence in support of the efficient markets model is extensive, and (somewhat uniquely in economics) contradictory evidence is sparse"*. More support for the weak and semi-strong forms of market efficiency is later presented by Treynor (1981) who observes: *"...that the securities market will not always be either quick or accurate in processing new information. On the other hand, it is not easy to transform the resulting opportunities to trade profitably against the market consensus into superior portfolio performance"*.

The EMH has however not pleased all researchers. Most notable are the arguments by Grossman and Stiglitz (1980) that present a paradox of reasoning. The basis of their

argument is that the distribution of the information set among market participants is determined separately from the mechanism of price determination. If information is free and equally shared in the market then an information symmetry among participants will arise. The implication of the EMH is that prices will then fully reflect the information common to all investors. However, if some market participants with superior information are able to generate greater return, then there will be a strong incentive to acquire further information. Since information in reality is costly to acquire, investors would only collect information up to the level that the marginal cost equals the marginal benefit of acquiring it. If the activities of market participants are fully reflected in asset prices as the EMH postulates, then investors could infer the information from observing market prices thereby saving on the cost of acquiring it. If every investor is in the same position then no one investor has an incentive to bear the cost of obtaining the information. Yet paradoxically, asset prices then reflect the information that has not been collected. This is known as the Grossman and Stiglitz (1980:405) paradox: “...because information is costly, prices cannot perfectly reflect the information which is available, since if it did, those who spent resources to obtain it would receive no compensation”. The implication of the paradox is that strong-form efficiency is unlikely to occur other than when all information is free and symmetrically distributed among market participants.

After much pessimism in the literature about the EMH, Fama (1991) proposes revised classifications of asset market efficiency. In place of the weak, semi-strong and strong forms, he identifies the areas of return predictability, event studies and private information as being more succinct classifications. Under return predictability, he notes a change in empirical focus from testing short-run relationships based on past returns to tests that use longer horizons. Event studies, akin to the former semi-strong tests, involve assessments of the impact of a well-defined incident such as a takeover bid, listing or stock split on subsequent stock prices. Efficient markets theory predicts that the market would react to information about such events quickly and prices would adjust accordingly. Tests of the role of private information measure the extent to which insiders, or professional investment managers, are able to earn abnormal returns. Fama (1991) reports that some researchers conclude that insiders do profit from trading on the basis of their inside knowledge, but outsiders can not profit from public information about this insider trading.

An important implication of market efficiency is that it is consistent with modern neoclassical views of economic efficiency. Economic theory says that if altering the allocation of resources makes one participant worse off then the economy is pareto efficient. A securities market that is pareto efficient would also have to be informationally efficient otherwise market participants with superior information could profit at the expense of others. The notion that securities markets are informationally efficient is central to the theory of asset pricing discussed in the next section.

2.3 The theory of asset pricing

The EMH in the previous section defines an efficient market as one in which information is unrelated to abnormal rates of return. This is in agreement with the contemporary definition that: "...efficiency with respect to an information set, ϕ , implies that it is impossible to make economic profits by trading on the basis of ϕ ." (New Palgrave Dictionary of Money and Finance, 1, 739). Where ϕ is the information set indicated previously as Ω . However, only in the presence of a reliable model of asset prices can the efficiency of an asset market be assessed. It is at this juncture that an evaluation of market efficiency is synonymous with a simultaneous evaluation of asset price behaviour and, by implication, of asset pricing models. Known as the joint efficient market hypothesis, a model of asset prices is inseparable from an appraisal of asset market efficiency, as stated clearly by Fama (1970, 413-4): "*The Theory [of asset market efficiency] only has empirical content . . . within the context of a . . . specific model of market equilibrium, that is, a model that specifies the nature of market equilibrium when prices 'fully reflect' available information*". This section therefore provides an overview of the theory of asset pricing under which mean-variance analysis, the CAPM and the APT are reviewed.

2.3.1 Portfolio selection: Mean-variance analysis

Mean-variance analysis is concerned with the study of individual investor behaviour regardless of whether the market, as a whole, is in equilibrium³. Based on the seminal work of Markowitz (1952), it defines the practical method by which investors select their

³ The concept of market equilibrium is described later in the chapter.

individual portfolios and provides the foundation of the CAPM discussed in the next section. Investors acting according to a mean-variance objective are assumed to select a portfolio that maximises the objective function G :

$$G = G(\mu_p, \sigma_p^2) \quad (2.5)$$

Where μ_p is the expected return on portfolio p and σ_p^2 is the variance of return. Pairs of μ_p and σ_p^2 for which the function is constant can be used to construct a set of indifference curves. The selection of an optimal portfolio by a mean-variance investor has two steps. In the first step, a portfolio frontier is constructed consisting of portfolios for which σ_p^2 is minimised for each μ_p . If the objective function is characterised by an increasing μ_p with a decreasing σ_p^2 only a segment of the portfolio frontier is relevant in the second step. In the second step, a portfolio is chosen from the portfolio frontier that satisfies the expressed individual preferences of an investor regarding μ_p and σ_p^2 . The set of efficient portfolios depends only on expressions of means and variances, not on preferences with regard to expected return. Investors with different risk preferences select different portfolios but will always select a portfolio from the efficient set.

The practical relevance of the mean-variance model arises from means and variances of return that can easily be estimated based on historical observations. A difficulty may however arise when individual investors differ in their beliefs on the best techniques to apply in the estimation of the means and variances. The economic implication is that while investors may be assumed to act in a mean-variance manner, no reason exists to suppose that they should be consciously aware of means and variances per se. Conversely, if all investors have access to identical historical information they should theoretically all arrive at the same estimates of means and variances.

2.3.2 The CAPM

The CAPM is a model of asset prices. As discussed previously, it would be difficult to make the EMH empirically operational without such a model. The CAPM extends the mean-

variance model of portfolio selection for an individual investor to the entire market⁴. The model describes the implications of investors behaving according to a mean-variance optimising objective when they all have the same beliefs about the means and variances of asset returns. The full development of the model, with some variation in structure, is accredited to Sharpe (1964), Lintner (1965), Mossin (1966) and Black (1972). The static version of the CAPM in the presence of a risk-free asset is sometimes referred to as the Sharpe-Lintner model. Where there is no risk-free rate the model is referred to as the Black (1972) version.

While many theoretical expositions of the CAPM discuss at length the assumptions that underlie the predictions of the model, only a brief summary is given here. The assumptions can be grouped into those relating to market equilibrium and those relating to mean-variance portfolio selection. In terms of market equilibrium, the CAPM assumes that asset markets are frictionless with zero transaction costs and no trading restrictions. Investors are able to borrow or lend unlimited amounts at the risk-free rate of interest. Assets are divisible into any units of any size and no indivisible assets exist that consume a large proportion of each investor's initial wealth. All assets in the market are considered to be tradable at observed market prices. Investors are assumed to be price-takers in a competitive market with no investor having monopoly power. Taxes are either zero or the same of all investors and for all sources of income. In terms of assumptions regarding mean-variance portfolio selection, all investors are assumed to behave according to a single period investment horizon. Their individual objectives are concerned only with the value of terminal wealth at a static future date. Portfolios can not be rebalanced or reconstituted during the period. Finally, all investors are assumed to use the same estimates of the variances and covariances of asset returns.

Importantly, the CAPM accounts for investors who hold different portfolios according to their individual risk preferences. Depending on the amount of the risk-free asset held, assuming it exists, a continuation of risk-return efficient portfolios is defined along a straight line called the Capital Markets Line (CML). The CML is a theoretical construct drawn from

⁴ Portfolio theory itself does not require that the markets operate according to equilibrium asset pricing theories, nor does it require that the conditions of an efficient asset market be met in order to be useful. The CAPM and the APT are thus special cases in portfolio theory.

the risk-free intercept to a point on a frontier of mean-variance efficient portfolios that is the same for all homogenous investors. The portfolios along the CML differ only by their dilution with the risk-free asset:

$$E(r_p) = r_f + \frac{E(r_m) - r_f}{\sigma_m} \sigma_p \quad (2.6)$$

Where $E(r_p)$ is the expected return of the risk-return efficient portfolio p , r_f is the risk-free rate of return, $E(r_m)$ is the expected return of the market portfolio, σ_m is the standard deviation of return of the market portfolio and σ_p is the standard deviation of the efficient portfolio p .

Arguably the most well known implication of the CAPM is the Security Market Line (SML). While the CML describes the equilibrium relationship between the systematic risk and expected return of efficient portfolios, the SML describes the relationship between the systematic risk of *any* asset and its expected return in equilibrium. The CAPM implies that the expected return and beta coefficients for all assets and portfolios of assets lie on the SML. When realised rates of return on assets or portfolios are plotted against their estimated beta coefficients, the CAPM predicts that the resulting graph will trace out the SML. The SML is defined as a line with an intercept given by the risk-free rate and a slope equal to the excess of return on the market portfolio over the risk-free rate:

$$E(r_i) = r_f + \beta_i [E(r_m) - r_f] \quad (2.7)$$

Where β_i is the systematic risk of asset i and is estimated as the sensitivity of the return of the asset to the return of the market portfolio using a regression consistent with CAPM known as the market model:

$$r_{it} = a_i + \beta_i r_{mt} + e_{it} \quad (2.8)$$

Where r_{it} is the realised return on stock i and r_{mt} is the realised return on the market portfolio in period t .

The important role of the market portfolio m in the CAPM warrants further attention. Since the CAPM assumes that all investors hold the same information set, there can not

theoretically be a situation where one investor wants to buy a stock that another wants to sell. It is also not possible that some assets in the market would not be bought and held by some investors, since the price of the asset would fall low enough until other investors bought it. This leads to 'market-clearing' prices for all securities⁵.

Therefore if all investors hold the same portfolio of risky assets, and if all assets must be held by somebody so that markets clear, then the tangency portfolio on the efficient set must be a portfolio containing all risky assets in the market. This portfolio is the market portfolio m and is thus composed of all assets held by investors. Each asset is weighted by the proportion of its market value relative to the market value of all assets. Under conditions of equilibrium, every security must therefore be included in the market portfolio otherwise no investor would own it and its equilibrium market price and market value would be zero. For the empirical work in this thesis, the JSE All Share index is used as the proxy for the market portfolio. For practical applications, this index reasonably satisfies the market clearing requirements that all assets be included in the market portfolio and that assets are weighted proportionally to their market value.

The host of restrictive assumptions underlying the CAPM theory presents several practical difficulties. For instance, the reliance on covariance by the CAPM requires that all asset returns are linearly dependent. This rules out the inclusion of synthetic assets in the market portfolio such as options or futures that usually have non-linear pay-off profiles. Another difficulty is the restriction that specifies the CAPM is a static model where the investment horizon is assumed to be a single period. This removes the possibility of portfolio rebalancing due to price changes even if expectations do not change. Some difficulties have however been addressed through variations on the CAPM. The Conditional-CAPM for instance circumvents the reliance on unconditional expectations about means, variances and covariances and allows investors to condition their beliefs on an information set. Alternatively, the Consumption-CAPM overcomes the restriction that the wealth an investor wants to invest in risky assets is exogenously determined by incorporating decisions on

⁵ The CAPM does not describe the actual process by which equilibrium is achieved through investors trading securities in their attempts to hold efficient portfolios. Instead, it describes the situation after the trading process has occurred and investors are assumed to be optimising using prevailing prices.

whether to consume today or to consume in the future. These variations on the CAPM do not feature in this thesis are therefore are not reviewed further in any detail.

2.3.3 The APT

Arbitrage can be described as a mechanical process by which investors seek to earn risk-free profits with no amount of initial wealth. This is achieved in theory using an arbitrage portfolio. To illustrate two important characteristics of an arbitrage portfolio, let x_i be the holding in asset $i = 1, 2, \dots, n$ with a price p_i , and let r_{si} be the payoff of asset i in state s . The zero outlay of the arbitrage portfolio can be expressed as:

$$p_1x_1 + p_2x_2 + \dots + p_nx_n = 0 \quad (2.9)$$

Where not all $x_i = 0$. The payoff, r , to arbitrage portfolio x in state s is therefore given by:

$$r(x, s) \equiv r_{s1}x_1 + r_{s2}x_2 + \dots + r_{sn}x_n \quad (2.10)$$

The risk-free characteristic of an arbitrage portfolio can be expressed for every possible state s , as:

$$r_{s1}x_1 + r_{s2}x_2 + \dots + r_{sn}x_n \geq 0 \quad (2.11)$$

Arbitrage theory does not explicitly require that a zero-cost portfolio always have a zero payoff under all s states. Depending on the state, a zero-cost portfolio can earn a negative, positive or zero payoff. For an arbitrage portfolio to exist however requires the complete absence of transaction costs and other market frictions.

By appending these principles of arbitrage with the multifactor return-generating process described below, Ross (1976) derives the APT as an alternative to the CAPM. From a theoretical perspective, the APT is less restrictive than the CAPM. There are no short selling restrictions and no assumptions about the utility functions of investors or the probability distribution of returns. While the CAPM finds equilibrium through optimal portfolios as implied by portfolio theory, the APT finds equilibrium by ruling out arbitrage possibilities.

The return-generating process is assumed to be governed by the following multifactor model:

$$r_{it} = E(r_{it}) + \sum_{k=1}^K b_{ik} f_{kt} + \varepsilon_{it} \quad (2.12)$$

Where r_{it} is the realised return earned by asset i in time t . $E(r_{it})$ is the expected rate of return at the beginning of period t for asset i . f_{kt} is the k_{th} risk factor that impacts on the return of asset i , where $k=1,2,..K$. All risk factors represent unexpected movements in pervasive economic forces and have an expected value of zero. b_{ik} is the coefficient that measures the sensitivity of r_i to movements in f_{kt} . ε_{it} is a normally distributed random error term measuring the unexplained residual return of asset i in period t , where $E(\varepsilon_{it})=0$, $E(\varepsilon_{it}\varepsilon_{jt})=0$ for all $i \neq j$ and $E(\varepsilon_{it}f_{kt})=0$.

The intercept and slope parameters of the multifactor model may take on positive or negative values and may differ across assets. If the return of all assets is determined according to the multifactor model then, in an absence of arbitrage opportunities, the rates of return are linked. This principle is central to the APT. These links enable the calculation of risk premia associated with the factors. It is possible that certain factors will be relevant in the determination of the returns of some assets but irrelevant for others such that some of the b_{ik} parameters may be zero.

There are two components in the ex post return of asset i , the expected return $E(r_{it})$ and the unexpected return U_{it} such that:

$$r_{it} = E(r_{it}) + U_{it} \quad (2.13)$$

The unexpected return can be decomposed into a component that is generated by systematic risk factors S_{it} and a component that is generated by unsystematic risk factors ε_{it} :

$$r_{it} = E(r_{it}) + S_{it} + \varepsilon_{it} \quad (2.14)$$

It is assumed that the systematic component of unexpected returns, S_{it} , can be decomposed into a number of significant risk factors:

$$S_{it} = \sum_{k=1}^K k_{ik} f_{kt} \quad (2.15)$$

Combining the two previous equations gives an ex post expression of expected returns:

$$r_{it} = E(r_{it}) + \sum_{k=1}^K k_{ik} f_{kt} + \varepsilon_{it} \quad (2.16)$$

An important feature of this equation is that it does not represent an equilibrium pricing relationship as no restrictions are placed on the constant $E(r_{it})$. This allows assets with identical factor sensitivities to have different expected returns.

The identity of the k risk factors in the APT is however unknown. The central assumption of the model is that several non-diversifiable economic factors exist that determine security returns and that these factors are priced in equilibrium. The factors are hypothesised to introduce non-diversifiable risk into a portfolio of invested wealth and investors are assumed to price these factors in a precise manner. The factors can be determined either through theoretical considerations or statistical methods. Widely used statistical methods include factor analysis and principal component methods. The assumption of a linear relationship between the assets in the CAPM is replaced in the APT by the assumption of a linear relationship between risk factors. As discussed in the previous section, this assumption rules out nonlinear assets such as derivatives. The advantage of the APT however is that there is no requirement to form a market portfolio that includes these assets.

2.4 Summary and conclusion

Appraisals of asset market efficiency frequently rely on random walk models. Yet most recent evidence from empirical studies on the behaviour of asset prices suggest that prices are to some extent predictable, as Fama (1991:1616) observes: *"Overall it appears the market is quite efficient but not perfectly so. There appears to be some predictability and some mean reversion in long-run returns, but not so much in the short-run tests. Often at times the apparent market inefficiencies are just that, apparent as they are due to measurement or modeling errors"*. Exactly what inferences about asset market efficiency may be drawn from these observations is certain as Samuelson (1994:17) notes: *"We only have one history of capitalism. Inferences based on a sample of one must never be accorded sure-thing interpretations"*.

A necessary requirement in an evaluation of asset market efficiency is an a priori model of asset prices on which the test hypotheses are conditional. The model serves as conduit for linking the information set with predictions of asset prices. A test of market efficiency therefore implies a test of the asset pricing model meaning that, in a theoretical sense, the two are indistinguishable, as explained by Fama (1991:1589): “...empirical research on asset-pricing models ...does not place itself in the realm of tests of market efficiency, but this just means that efficiency is a maintained hypothesis. Depending on the emphasis desired, one can say that efficiency must be tested conditional on an asset-pricing model or that asset-pricing models are tested conditional on efficiency. ...Moreover, many of the front-line empirical anomalies in finance (like the size effect) come out of tests directed at asset-pricing models. Given the joint hypothesis problem, one can't tell whether such anomalies result from misspecified asset-pricing models or market inefficiency”.

The issues discussed in this chapter outline several important theoretical considerations that are relevant to the empirical work conducted in this thesis. The specific implication of the theory is that any judgment regarding the efficiency of the JSE in respect of a certain information set is only as reliable as the underlying model of asset prices. The CAPM and a two factor APT model are employed in later chapters as the benchmark asset pricing models against which the explanatory power of a set of firm-specific attributes is assessed. As outlined in the previous chapter, the objective is to provide new insight into price determination on the JSE.

3

Literature Review

3.1 Introduction

The investment theory introduced in the previous chapter provides a framework for empirical asset pricing research. Empirical research evaluates the extent to which the ex ante predictions of the theory are aligned with ex post realisations. The objective of this chapter is to provide an appraisal of the investment literature as a reference for the empirical work conducted in the subsequent chapters of this thesis.

In each section of this chapter the international literature is reviewed separately to the literature that is specific to the JSE. This allows the South African case to be contrasted with the international evidence. The remainder of the chapter is set out as follows. Section 3.2 surveys the literature that empirically evaluates the predictions of the CAPM, followed by an overview of CAPM anomalies and the closely related area of style analysis. Section 3.3 presents arguments for several competing explanations for the CAPM anomalies and style effects. Section 3.4 introduces an important debate that challenges the theoretical assertion that return premiums are associated with factor risk. Section 3.5 reviews the literature that is concerned primarily with the different approaches to APT factor identification and Section 3.6 summarises and concludes.

3.2 Empirical evaluations of the CAPM

The CAPM-related literature is reviewed in three sections. The first section provides an overview of the early classical tests that are primarily concerned with evaluating the structure of the SML and the relationship between beta and expected returns. The second section surveys the subsequent empirical contradictions of the CAPM known as anomalies. The third section introduces the concept of style, an area of empirical asset pricing research that

is closely related to the CAPM anomalies and often used by practitioners in general terms for describing the characteristic orientation of an investment portfolio.

3.2.1 Evaluations of the SML and beta

Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) conduct the first extensive tests on the predictions of the CAPM. The specific focus of their tests is on estimating and testing the form of the SML, the theoretical construct that says the relationship between expected return and beta is the same for all assets in a perfect market¹. Often referred to as the classical tests, they represent a major innovation in providing more powerful empirical tests of the theory. The innovation lies in the development of a methodology called the two-step regression. The first step is an ordinary least squares (OLS) regression used to estimate the market beta for each asset over subsets in the time series. The second step estimates the regression coefficients as a cross-sectional relationship over all securities at a point in time. The dependent variable in the second step is the actual return of the security while the independent variable is the estimated beta of the asset from the first step.

Using a US sample from 1926 to 1966, Black, Jensen, and Scholes (1972) sort stocks into portfolio deciles based on individual stock betas calculated from the previous five years. The results from thirty-five years of monthly returns show that the intercept terms are consistently negative for portfolios with betas greater than one, and consistently positively for portfolios with betas less than one². Importantly, the cross-sectional tests reveal that, while the relationship between the average return and beta is almost linear, the estimated slope of the SML is too flat and the intercept is too high. The overall assessment lends support to the Black (1972) zero-beta version of the CAPM mentioned in Chapter Two, which appears to fit the data better.

The Fama and MacBeth (1973) tests conducted from 1926 to 1968 also on a US sample differ slightly. Whereas Black, Jensen, and Scholes (1972) perform the cross-sectional

¹ The basis of their test hypothesis is that when expected returns are plotted against betas, all assets should theoretically plot on the SML.

² An analysis of the sub-periods shows a strong positive relationship between beta and return from 1931 to 1939, a smaller but still positive relationship from 1939 to 1949 and a small *negative* relationship from 1957 to 1965.

regressions over all time periods used in estimating the portfolio betas, Fama and MacBeth (1973) do not use any of the time periods in the cross-sectional regressions that are used to compute the set of portfolio betas. The exact reasons for not estimating the cross-sectional equation out of the same sample used for calculating the beta estimates is not clearly explained by Fama and MacBeth (1973:618) other than: “...*the model only has content if there is some relationship between future returns and estimates of risk that can be made on the basis of current information*”.³ Similar to the findings of Black, Jensen, and Scholes (1972) their results show that the empirical CAPM has an intercept higher than the risk-free with a slope lower than implied by the theory.

The two-step regression procedure can be interpreted as a joint test of two hypotheses, both of which are implications of the CAPM. The first is the hypothesis that there is a systematic relationship between beta and return, while the second is the hypothesis that the average risk premium is positive. Using simulations, Affleck-Graves and Bradfield (1992) show that the power of the traditional two-step procedure is rather low. They conclude that a sample period of at least thirty years is required to obtain sufficient power. In addition to the errors-variables-problem that arises when the explanatory variables in a regression model are estimates of population parameters, a further problem with the two-step procedure is the likelihood that, over time, the error terms are heteroskedastic and cross-sectionally correlated.

Apart from the statistical considerations, a further problem exists in that the CAPM is a static one-period model where ex post returns are not necessarily reconcilable with ex ante expectations. The issue arises because the relationship between expected return and beta is ex ante whereas the observed set of time series returns is ex post. The viability of the CAPM therefore rests partly on whether a framework can be designed to reconcile the relationship between ex post returns and ex ante beliefs. Fama and MacBeth (1973) argue the easiest way to accomplish this is to assume strong homogeneity of individual investor beliefs. However, as Ross (1978) points out, the reality is that investors: “...*do not show the homogeneity of beliefs*”

³ It appears that Fama and MacBeth (1973) believe predicting the betas out-of-sample reduces the chance that in-sample measurements will influence the slope estimates in the cross-sectional regressions.

that characterise our theories. To the contrary, it is widely believed that it is differences in beliefs and disparate changes in these beliefs which occasionally trade..."

While there are other assumptions that govern the empirical testing of the CAPM, such as the distributional properties of returns and the structure of investor utility curves, the Roll (1977:129) critique of the validity of the tests is perhaps best known: "*No correct and unambiguous test of the theory has appeared in the literature, and there is practically no possibility that such a test can be accomplished in the future*". When test portfolios are constructed to include a subset of assets intended to be an observable and representative proxy for the true market portfolio, the basis of the Roll (1977) argument is that the CAPM is not really being tested⁴. He argues that substituting proxies for the true market portfolio is unacceptable because the proxy may be efficient when the true market portfolio is inefficient, thereby leading to false acceptance of the CAPM. Conversely, if the proxy is inefficient when the true market portfolio is efficient, this may lead to a false rejection of the CAPM.

3.2.1.1 Evaluations of the SML and beta on the JSE

In surveying the literature that is specific to the JSE, much of the research that evaluates the form of the SML and the explanatory role of beta is considered in tandem with a general observation that the market appears segmented. Widely attributed to the prevalence of mining-related firms on the JSE, the issue of a mining-industrial dichotomy has become largely inseparable from the debate over the suitability of the market portfolio and beta. With the segmentation issue in mind, the majority of researchers on the JSE consider sector-related alternatives to the market portfolio and, as such, the texts could arguably be reviewed alongside the APT literature later in this chapter.

In an early study of the explanatory power of the market portfolio on the JSE, Affleck-Graves (1977) finds evidence that a broad market index can only explain more than ten percent of the variation in less than one-third of the stocks tested. While not a critique of the CAPM itself, the results initiated further a debate over the suitability of the market portfolio as an explanatory factor on the JSE.

⁴ This does not constitute a rejection of the CAPM itself, only its empirical testability.

Campbell (1979) shows that market betas decline for the industrial stock index from 1974 to 1978 compared with 1964 to 1968, but increase for the gold stock index over the same periods. Although not expressed at the time, this is the first indication of market segmentation on the JSE that relates to the anecdotal distinction in the character of a firm depending on whether its core business is mining-related or not. Campbell (1979) goes further and proposes that a different SML exists for each sector of the JSE. While this may be empirically correct, the idea does not have great theoretical appeal since it is unlikely the sectors represent mean-variance efficient portfolios.

Gilbertson and Goldberg (1981:41) are the first to consider the asset pricing implications of the apparent characteristic division between mining and non-mining firms on the JSE. They suggest that the presence of a large number of mining companies whose price is affected by: *"...international political and economic events that are frequently quite divorced from the developments in the local South African economy."* is the cause of the apparent lack of power of the market portfolio. Using a modified market model to test a sample of just three stocks and then a portfolio comprising all three, Gilbertson and Goldberg (1981:42) conclude that *"...at least two factors"* are required to capture the dichotomy that exists between mining and non-mining companies on the JSE. The results reveal that a two factor model has a higher explanatory power than the market model.

While the Gilbertson and Goldberg (1981) study is not a rigorous test of the CAPM or an exposition of single factor beta, the results provide the first serious challenge to beta on the JSE. The narrow focus of the study does not allow the results to be generalised with any confidence. They also do not consider what influence the use of other indices may have in the decomposition of risk on the JSE. In an explicit test of the validity of the CAPM on the JSE, Bradfield, Barr and Affleck-Graves (1988:19) test a sample of one hundred continually listed stocks from 1973 to 1984. By contrast they conclude that, although beta is a better ex ante predictor of return for industrial stocks than for gold stocks, the: *"...one parameter CAPM is a reasonable model for the JSE as a whole"*.

An explanation for the apparent division in the JSE is offered by Bowie and Bradfield (1993) who posit that the segmentation is linked to exchange control regulations that cause

investors to perceive the mining sector of the JSE to be an alternative to investing abroad. Expanding on the idea of Gilbertson and Goldberg (1981), they support the use of a two-SML model. Bowie and Bradfield (1993) also suggest several approaches to improving beta estimation including, but not limited to, an adjustment for thin trading and more careful consideration of the market portfolio⁵.

The notion that risk on the JSE is multidimensional is further endorsed in Venter, Bradfield and Bowie (1992), reviewed in Bowie and Bradfield (1993), who evaluate the difference in betas calculated using the broad market index and those calculated with indices consisting of mining stocks and financial and industrial stocks. Their results, intuitively similar to Gilbertson and Goldberg (1981), are supportive of market segmentation on the JSE and reveal that a single broad market index has less predictive power than the sector-based indices.

In a direct evaluation of a two index model and the market model from 1985 to 1995, van Rensburg and Slaney (1997) find further confirmatory evidence that the return generating process on the JSE is segmented. They show that a two index model consisting of the gold and industrial indices captures the central intuition behind the two-SML model and, in addition, is more easily applied in practice. They propose that the two factor model should take the form of the theoretically more appealing APT rather than the two-SML. In addition, the van Rensburg and Slaney (1997:20) results have far reaching implications for future asset pricing research on the JSE because of the important observation that: *"...the two factor APT model has the pricing implications not compatible with the CAPM employing the JSE All Share Index as the market proxy"*. The segmentation of the JSE has important implications for the structure of several tests designs employed later in this thesis.

3.2.2 CAPM anomalies

Following the early classical tests of the CAPM, several empirical contradictions of the theory emerged when researchers observed that stocks of firms with similar attributes appeared to move together in a manner that is suggestive of a common factor. Since these

⁵ The thin trading problem is reviewed in the next chapter.

observations cannot be explained by the CAPM or related versions of asset pricing models, they have often been termed anomalies or *effects*⁶. The existence of such anomalies plays an important role in the later empirical work of this thesis. It would not be possible to survey the many thousands of published studies into CAPM anomalies. The following reviews therefore are limited to the seminal papers that led the development of research in this area.

The Banz (1981) study into the role of the firm size in the cross-section of US stock returns is widely regarded as among the first serious empirical challenges to the CAPM. He shows that when an indicator of firm size is appended to a beta-based model, the cross-sectional explanatory power of the model is improved. Using the total market value of listed equity as an indicator of firm size, Banz (1981) forms twenty-five test portfolios from two-way quintile sorts on size and market beta⁷. The research design specifies a model where stock returns are a function of firm size in addition to risk, as measured by market beta. If size has no explanatory power then the model is reduced to the CAPM. Using risk-adjusted returns, he shows that the average return on the quintile of small capitalisation stocks in the US exceeds the average return on the quintile of large capitalisation stocks from 1926 to 1980. In addition, the results of the two-way sorts show that the average returns of small capitalisation stocks are too high to be explained by their beta estimates, and vice versa. Although the findings contradict both the CAPM and by implication the EMH, Banz (1981) does not offer any theoretical explanation for the observed effect⁸. A subsequent study by Reinganum (1983) reveals a monotonic relationship between firm size and stock returns over a shorter period from 1963 to 1977. His results show that portfolios formed from the smallest firms generate average annual returns that are greater than the average return, while portfolios formed from the largest firms generate average annual returns that are lower than the average return⁹.

⁶ The terms *anomalies* and *effects* are used interchangeable throughout the remainder of this thesis.

⁷ The methodology and theoretical considerations for creating test portfolios using stock sorting procedures is discussed later in this chapter.

⁸ The theoretical link between the CAPM and the EMH, the efficient market joint hypothesis, is outlined in the previous chapter.

⁹ The average annual returns are measured from a portfolio constructed to represent all stocks in the sample.

In a study to determine whether these observed size effects might be seasonal, Keim (1983) finds that roughly one-half of the annual US small firm premium observed by Banz (1981) occurs during the month of January and tends to be concentrated in the first five days. In a related study, Haugen and Lakonishok (1988) also find evidence of upward price pressure on small capitalisation stocks at year-end, although the effect appears to be absent for large capitalisation US stocks. Similarly Blume and Stambaugh (1983) report evidence that is consistent with the conclusion that the size effect in the US is concentrated in January. Roll (1983) proposes that the higher volatility of small stocks causes them to experience greater short-term capital losses that investors may want to realise for income tax purposes before the end of the tax year. Known as the tax-loss selling hypothesis, it creates downward pressure on the prices of small cap stocks in December, leading to a rebound in early January as investors repurchase their stocks.

The importance of the Banz (1981) and Reinganum (1983) results above is that they prove the existence of differences in the average returns that can not be explained by the estimated beta coefficients in the CAPM. Around the same time, Basu (1977, 1983) reports that both earnings-to-price and firm size are significant factors in determining average returns among US listed firms. He also shows that market beta is positively related to stock returns, thereby still giving support to the theoretical underpinning of the CAPM that the market factor is a component of expected returns. Basu (1983) argues that the size effect is a proxy for his earnings-to-price effect thereby implying that the Banz (1981) model is incorrectly specified. Ball (1978) describes this relationship as a proxy arrangement whereby the earnings-to-price ratios are likely to be higher for high risk stocks that have greater expected returns regardless of the true source of risk.

Another important finding in the expanding evidence of CAPM anomalies is by Stattman (1980) and Rosenberg, Reid and Lanstein (1985) who present the first empirical evidence showing a positive cross-sectional relationship between average stock returns in the US and the book-to-market ratio. This hybrid ratio of accounting-based valuation and market-based valuation is widely used as a measure of relative *value*, similar to the price-to-earnings and

cashflow-to-price ratios¹⁰. LaPorta (1996) finds that systematic errors in market expectations about long term earnings growth partially explain the book-to-market effect in the US. The source of the premium for value stocks however is an area of much debate in the literature and is discussed in more detail in the next section.

Since the perception exists that geared firms present greater risks to investors, the use of leverage as a pricing factor seems unremarkable at first. Seen in the context of the Fama (1970) argument that a firm's financing decisions ought to have no effect on its market value, the possibility that a leverage effect exists in stock returns has attracted much attention in empirical finance¹¹. Bhandari (1988) presents the first evidence that an indicator of leverage, as measured by the total debt-to-equity ratio, is instrumental in explaining the expected stock returns in the US. Later work by Chan and Chen (1991) and Shumway (1996) also shows that US firms with high measures of leverage, financial distress, or probability of default tend to earn higher returns.

In a widely acclaimed paper, Fama and French (1992) evaluate the role of beta in the presence of the CAPM anomalies associated with the size, leverage, book-to-market and earnings-to-price attributes over the period 1963 to 1990¹². Conducting two-way portfolio sorting procedures on a US sample, their results reveal that when there is variation in market beta that is unrelated to size, there is no longer a relationship between market beta and average return. Even when beta is the only explanatory variable, they still find no reliable relationship with return¹³. Furthermore, they show the relationship between leverage and average stock returns is captured by the book-to-market attribute and the association between earnings-to-price and average return is absorbed by a combination of the size and book-to-market attributes. There is some evidence of a January effect in the book-to-market

¹⁰ Value is a generic term used to indicate the *cheapness* of a stock relative to the accounting valuation of its assets. A more comprehensive explanation of value appears later in the chapter.

¹¹ The Fama (1970) argument relies on the existence of a perfect capital market where firms maximise combined stockholder and bondholder wealth.

¹² The article won the Smith-Breeden prize for best paper in the Journal of Finance by the largest margin ever.

¹³ It is surprising that this result receives so much attention in the literature since Black, Jensen, and Scholes (1972) had *already* reported six instances of negative risk-return relationships over two and eight year periods.

variable but the positive relationship is strong throughout the year¹⁴. The results lead Fama and French (1992:428) to a unified statement of CAPM opposition: *"Our bottom-line results are: (a) beta does not seem to help explain the cross-section of average stock returns, and (b) the combination of size and book-to-market equity seems to absorb the roles of leverage and E/P in average stock returns, at least during our 1963-1990 sample period. If assets are priced rationally, our results suggest that stock risks are multidimensional"*. The role of beta in the presence of CAPM anomalies is an important yet unexplored area of research on the JSE and is the focus of Chapter Seven of this thesis.

3.2.2.1 CAPM anomalies on the JSE

The anomaly-related research on the JSE begins with De Villiers, Lowlings, Pettit and Affleck-Graves (1986) who show that from 1973 to 1982 larger firms, measured by market capitalisation, earn greater returns than smaller firms. Bradfield, Barr and Affleck-Graves (1988) examine the role of firm size, dividend yield and trading liquidity in stock returns from 1973 to 1984 but find no evidence of anomalous behaviour. Using a sample from 1978 to 1987, Page and Palmer (1993) adopt a within-groups portfolio simulation methodology similar to Jaffe, Keim and Westerfield (1989). They find no evidence of a size effect on the JSE but do find evidence that a portfolio of low price-to-earnings securities outperform a portfolio of high price-to-earnings.

Page (1996) investigates whether the outperformance of large capitalisation stocks documented in De Villiers, Lowlings, Pettit and Affleck-Graves (1986) and the earnings effect in Page and Palmer (1993) are a result of market inefficiency or a mispricing. Using a sample of weekly returns of continuously listed stocks from 1973 to 1992, he compares the performance of the Black (1972) version of the CAPM with a three and five factor version of the APT. The results show that the earnings-to-price effect persists across different benchmarks and is robust to risk-adjustment of up to five APT factors¹⁵. Unexpectedly, no significant small size effect is observed and Page (1996) suggests further research in this area.

¹⁴ Fama and French (1992) do not report any details of this January effect.

¹⁵ The factors are *factor analytic* constructs, described in detail later in the chapter.

Finally, in a search for style factors on the JSE from 1983 to 1999, van Rensburg (2001) documents CAPM anomalies associated with earnings yield, past twelve month return, market capitalisation, dividend yield, past six month return, leverage, cashflow-to-debt, turnover and past three month return. These anomalies persist after risk adjustment using the two factor APT model of van Rensburg and Slaney (1997) reviewed later in this chapter.

3.2.3 Style effects

The CAPM anomalies represent the first empirical evidence that securities with certain attributes move together in a way that suggests the attribute has predictive power. It has also emerged that investment portfolios consisting of securities with similar attributes show a clustering of performance (King, 1966; Farrell, 1975), anecdotally termed 'style effects'. The first style classification of investment managers were simply subjective and qualitative assessments of the procedures governing security selection. For practitioners and academics, style has become a catch-all term for describing the strategic or inadvertent positioning of an equity portfolio towards stocks with similar attributes.

Style returns are the premium earned by exposing a portfolio to a particular style and are akin to the premiums documented for the attributes associated with the CAPM anomalies. Investment managers who construct their portfolios using securities with a particular attribute may be said to have a style that is synonymous with the attribute. This is the subtle link between the CAPM anomalies and style effects. It may be said that an individual security displays a particular attribute, while a portfolio of such securities displays a particular style. The link between the security attributes and portfolio style is neatly described in Arnott and Bailey (1986:21): "*A managers' investment style may be characterised by the set of fundamental investment principals the manager uses, on a consistent basis, to construct portfolios*". For the remainder of this thesis, unless otherwise indicated, the term style is used to describe the characteristic orientation of an equity portfolio or investment manager, as opposed to an attribute of an individual stock.

Due to its subjective origins, it is unlikely there will ever be broad consensus on exactly what constitutes an investment style. Assigning style classifications to stocks or investment

portfolios remains largely an ad-hoc task. Amid the plethora of potential styles, *large* and *small* further subdivide into *value*, *growth* and *glamour* appear to dominate the international investment literature. The classification of investment portfolios into small and large styles usually involves an assessment of the weighted aggregation of portfolio holdings based on the logarithmic transformations of the market capitalisation of constituent securities. The orientation of a portfolio towards value and growth styles generally involves evaluating a proportional measure of market valuation relative to accounting valuation such as the book-to-market or earnings-to-price attributes reviewed earlier. A portfolio with a *glamour* style is frequently identified by evaluating the prevalence of stocks that have performed well in the past, similar to the anomalous CAPM momentum effect of Fama and French (1992; 1996) and Jegadeesh and Titman (1993). In this regard, these styles effects could be considered the portfolio-level equivalents of the pervasive size, book-to-market and momentum attributes documented in Fama and French (1992).

The empirical measurement of style effects is conducted either as returns-based analysis or as composition-based analysis. Returns-based style analysis is the time-series assessment of the influence of a set of style returns on portfolio returns. It is less data and computationally intensive than the composition-based approach and holds a greater intuitive appeal because returns are the ultimate goal of the investor. The composition-based approach involves an analysis of the attributes of individual securities in a portfolio at varying points in time. In relation to empirical techniques used in asset pricing studies, the returns-based analysis is mechanically similar to the factor-mimicking portfolio approach, while the composition-based analysis can be considered similar to stock-level cross-sectional research designs. Insofar as the term style is used in a formal asset pricing context, much of the international research has been directed towards explaining the performance of mutual and pension fund returns or classifying investment portfolio according to style.

In returns-based analysis on US mutual fund returns from 1985 to 1989, Sharpe (1988, 1992) pioneers an econometric technique called the 'effective mix'. This technique, based on quadratic programming, involves a constrained linear regression that uses combinations of several style returns to replicate the historical return pattern of a portfolio¹⁶. Two constraints

¹⁶ Among others, Sharpe (1988, 1992) examines small, medium and large value and growth stocks.

are imposed on the regression coefficients. The first constraint forces the coefficients to sum to one giving the coefficients an intuitively similar interpretation to style weights. The second constraint causes the coefficients to be positive to reflect the short-selling constraint most portfolios managers are subject to. A non-linear regression procedure is then followed to arrive at point estimates for the portfolio weights. Placing constraints on the regression parameters however makes it less straightforward for confidence intervals to be calculated for the parameter estimates¹⁷.

Sharpe concludes (1988:16) that: *"...the effective mix will account for a large portion of the month-to-month variation in returns for the typical portfolio"*. Chan, Chen and Lakonishok (1999) apply both the returns-based and composition-based style analysis techniques to evaluate the consistency of styles among US mutual funds from 1976 to 1997. Their results show a consistency in respect of the size style, a drift towards glamour and no movement in the value style¹⁸. In terms of evaluating the compatibility of the two techniques, Chan, Chen and Lakonishok (1999:29-30) report that: *"The two approaches to style identification (portfolio characteristics and factor sensitivities) generally give similar readings of a fund's style...however the approach based on characteristics on average gives more accurate predictions of future fund returns"*. In an earlier sample of US pension funds Lakonishok, Shleifer and Vishny (1992) report similar results. Recently, Hwang and Satchell (2000) use a Markov model to forecast style returns and find that since 1994, US style returns have become less forecastible¹⁹. This finding is consistent with the hypothesis that style returns are the result of anomalies in the CAPM sense, rather than legitimate risk premia. They suggest the most likely reason is that an increasing awareness amongst investors of style effects has translated into strategies that arbitrage away excess style returns.

In composition-based analysis, Brown and Goetzmann (1997) seek to evaluate the empirical style classification of a sample of US mutual fund according to eight investment styles from

¹⁷ A subsequent study by DiBartolomeo and Lobosco (1997) proposes a technique for approximating the confidence intervals for the style coefficients.

¹⁸ They use market capitalisation as a measure of size, book-to-market as an indicator of value and a three-year measure of prior return.

¹⁹ A Markov model is a highly technical statistical methodology that generates a sequence of observable events; in this study the events were style factor returns.

1976 to 1992. Using a switching regression technique to develop a style classification algorithm, they find evidence of a pronounced distinction between value and glamour styles but no monotonic differentiation among size styles.

The use of style analysis has also been extended for the purpose of classifying and verifying the classification of investment portfolios according to style, rather than allowing investment managers to self-declare their styles. This is an important function in light of the findings by DiBartolomeo and Witkowski (1997), Brown and Goetzmann (1997) and Kim, Shukla and Tomas (2000) who all report evidence of serious misclassifications of portfolio if self-reported investment objectives are compared to measured styles.

The increasing interest in detecting investment style and pursuing style investing can also have direct implications for asset prices. If investors allocate funds in the pursuit of certain investment styles they generate coordinated demand shocks across all securities grouped within a particular style. This can invoke covariation in security prices irrespective of whether the securities in a particular style have shared fundamentals. Another implication for asset prices is the negative externalities that can arise from activities such as style rotation or style switching. As the flow of investment funds is drawn towards outperforming styles, the stability of style returns through time can be compromised and any predictive power is eroded. Recent evidence in Chan, Karceski and Lakonishok (2001) is supportive of this based on results that show the returns to the value and size styles become inverted over the period 1990 to 1998.

3.2.3.1 Style effects on the JSE

The influence of style-based effects on the JSE is a rapidly expanding arena of enquiry although the volume of research lags considerable behind the international efforts. While the studies reviewed earlier such as De Villiers, Lowlings, Pettit and Affleck-Graves (1986), Bradfield, Barr and Affleck-Graves (1988) and Page and Palmer (1993) *inter alia* investigate the existence of isolated anomalies within the framework of traditional asset pricing theory, only recently have multivariate studies been specifically designed to determine the identity of pervasive style effects on the JSE.

Although not explicitly pursuant to the topic of style, the results of Plaistowe and Knight (1986) present the first evidence of a value style premium on the JSE from 1973 and 1980. In a methodology related to the composition-based approach, they use book-to-market attributes to sort stocks into two test portfolios. The first portfolio represents stocks that trade at a premium to book value, while the other contains stocks that trade at a discount to book value. Their results show that the discount portfolio of book-to-market firms earn small but persistent abnormal returns. In a style sense, a strategy of investing in value stocks earns a premium.

In another characteristically-orientated study, Fraser and Page (2000) evaluate the rewards associated with value and momentum effects on the JSE. Adopting the methodology of Asness (1997), they use twenty-eight day intervals from 1973 to 1997 and form test portfolios of industrial stocks by ranking on the cross-section of attribute data. Portfolios are formed based on the logarithm of book-to-market, dividend yield and on a technical measure of prior twelve month momentum. Once stocks are ranked, equal-weighted quintile portfolios are formed for each strategy. An analysis of the average return of the portfolios lead Fraser and Page (2000:20) to conclude: *"...among industrial firms on the JSE between January 1973 and October 1997, both value strategies, based on B/M and D/P, and momentum strategies, based on PAST (12), have the power, independently, to predict the return on a share one month into the future and, thereby earn superior returns"*. It remains unclear whether the results from this study would generalise beyond the industrial sector in light of the evidence of market segmentation discussed in previous sections.

In a recent study, Graham and Uliana (2001) search for value and growth style effects on the JSE from 1987 to 1996. Similar to Fraser and Page (2000) they use the book-to-market attributes as the sorting criteria to create test portfolios. High book-to-market portfolios are taken as being representative of a value strategy, while low book-to-market portfolios are used to proxy for a growth strategy. Their results reveal a persistent outperformance of value stocks over their growth counterparts. Like several studies on the JSE, a limitation of the Graham and Uliana (2001) findings is the restriction of the sample to only industrial stocks and the assumption that the inverse of a value style is a growth style.

To empirically investigate the identity of the style factors that explain the expected return of industrial shares on the JSE, van Rensburg (2001) adopts the portfolio approach to search for the presence of style-based effects among a set of twenty-three candidate attributes from 1983 to 1999. Applying a hierarchical cluster analysis procedure to the monthly time series returns of a range of style-based portfolios, the results indicate the presence of value, small size and momentum effects leading van Rensburg (2001:60) to conclude: *"The results support a three factor model as a parsimonious representation of style-based risk for the industrial sector of the JSE"*.

Strictly returns-based approaches on the JSE appears limited to Robertson, Firer and Bradfield (2000) who use an iterative version of Sharpe's (1992) methodology to verify the industry classification of fifty-one equity unit trust funds²⁰. Their results show that almost one-fifth of all equity unit trusts in existence from 1994 to 1998 are misclassified in terms of their existing industry assigned category. Robertson, Firer and Bradfield (2000:13) conjecture that: *"...a style-based reclassification technique reduces the likelihood that investors will be misled by the generalist nature of the current classification system"*. In a follow-on study that re-checks the validity of the classification system using style returns from the BARRA commercial factor model, Robertson, Firer and Bradfield (2001:99) find results that contradict the international evidence of the compatibility of the two techniques: *"...employing composition-based style factor returns within a returns-based style analysis framework does not generate results that are consistent with the returns-based approach (alone) ..."*.

3.3 Explanations for CAPM anomalies and style effects

As discussed in the theoretical overview in Chapter Two, it is uncertain whether the CAPM anomalies or style effects should be interpreted as general violations of market efficiency or whether they are temporary transient distortions. In the absence of a correctly specified model of asset prices the possibility exists that: *"...exceptions to the current body of knowledge may be incorporated into that body of knowledge and become tomorrow's conventional wisdom"* (New Palgrave Dictionary of Money and Finance, 3, 573).

²⁰ The methodology in this study is similar to that employed in DiBartolomeo and Witkowski (1997).

Ball (1978) makes the important observation that empirical contradictions of the CAPM associated with observable stock attributes, and hence style effects, are more likely to be caused by a fault in the pricing model than by a market inefficiency. As such, the general response has been to broaden the search for alternative pricing models. Jagannathan and Wang (1996) disagree with this pursuit based on an argument that the lack of empirical support for the theory is a result of the underlying assumptions made to facilitate empirical analysis. Since there is now general consensus in the investment literature that CAPM anomalies and style effects do indeed exist, the debate has shifted to establishing the economic reasons for the anomalies and style effects and assessing the form of market efficiency. What follows is a discussion of several competing views on the causes of the CAPM anomalies and style effects.

The first view is that the rejection of the CAPM is spurious and related to methodological biases such as data-snooping or the technical design of the tests. In a study to explicitly evaluate the impact of data-snooping on tests of asset pricing models, Lo and MacKinlay (1990) show that the results may be misleading when the properties of the data used in the tests are already familiar to the researcher²¹. Using Monte Carlo simulations and two case studies, they demonstrate that the effects of data-snooping can be substantial²². While Lo and MacKinlay (1990) do not propose any solution for the data-snooping problem, their conclusion is that data-snooping offers a plausible explanation for the CAPM anomalies and style effects. In a test for bias in model structure, MacKinlay (1995) evaluates both risk-based multifactor asset pricing models and non-risk based models. His results show that deviations from the predictions of the CAPM that are related to an omitted risk factor are empirically difficult to detect, whereas deviations caused by non-risk factors associated with many of the anomalies are comparatively easier to detect.

In other studies on the influence of data-related problems, Kothari, Shanken and Sloan (1995) point out that the Fama and French (1992) results are influenced by a combination of

²¹ Black (1993) makes a similar criticism of the Fama and French (1992) results. He claims their conclusions are influenced by data-snooping biases since the size and book-to-market variables under investigation had previously been shown by other researchers to be anomalous and are therefore empirically motivated.

²² Monte Carlo simulation is a procedure of statistical simulations conducted using several sequences of inputs.

survivorship bias in the data set and period-dependant performance issues²³. They further claim that the Fama and French (1992) methodology possesses a low statistical power for testing the legitimacy of a positive market risk premium and that little scope exists for rejecting the null hypothesis. Hawawini and Keim (1995) also put forward the possibility that survivorship bias or sample selection towards certain types of firms may lead to the anomalies. Studies also highlight a methodological bias arising from techniques that plot beta against return. In this regard Roll and Ross (1994) show that a market proxy can be almost mean-variance efficient even though the slope from an OLS regression of expected returns on betas is zero. Conversely, Kandel and Stambaugh (1995) demonstrate it is possible to obtain an almost perfect OLS relationship between return and beta calculated relative to a market proxy that is known to be ex ante inefficient.

A second explanation for the CAPM anomalies and style effects, advocated by Fama and French (1992), is that asset pricing is rational and conforms to a three factor risk-based model and not the CAPM. If this view is correct then any attribute associated with a CAPM anomaly should proxy for a risk factor, meaning the anomaly reflects systematic risks that the single risk factor in the CAPM fails to capture. The attributes in this sense are simply less noisy proxies for beta than the conventional time series estimate. Accepting this explanation is akin to rejecting the semi-strong form of the EMH. This is in agreement with the empirical evidence surveyed in Fama (1991, 1998) that is generally supportive of the idea that markets are weak and semi-strong efficient but not strong-form efficient. Reasonably convincing arguments are made in Fama and French (1993, 1995) that the superior returns of small size portfolios and high book-to-market portfolios represent compensation for factor risk, although Fama and French (1996:76) acknowledge the thin economic interpretation of their results: “...we have simply found three portfolios that absorb most of the anomalies of the CAPM. In other words, without knowing why, we have stumbled on explanatory portfolios that are close to three-factor multi-factor-minimum variance”.

Another view proposed by Amihud and Mendelson (1986) is a liquidity argument that says higher expected returns accrue to illiquid stocks. Their results show a relationship exists

²³ Specifically by low book-to-market past winners and high book-to-market past losers.

between expected returns and stock liquidity that persists after adjusting for risk using the CAPM²⁴. In related work, Brennan and Subrahmanyam (1996) report a relationship between stock return and indicators of liquidity even after conducting risk adjustment using the Fama and French (1992) three factor model. More recently, Brennan, Chordia, and Subrahmanyam (1998) test the interaction between stock returns, risk and a range of non-risk attributes. They find a strong negative relation between average returns and trading volume that is consistent with a liquidity premium. The Brennan, Chordia, and Subrahmanyam (1998) results persist after an APT risk adjustment using several Connor and Korajczyk (1988) type principal component factors²⁵.

Finally, the possibility that investor behaviour differs from the theoretical norms has motivated a new area of finance research based on hypotheses about investor reaction to market or informational stimuli. Termed behavioural finance, the veracity and legitimacy of this area of research has attracted much skepticism and objection, such as Statman (1999:18) who argues: *"People are rational in standard finance; they are normal in behavioral finance."* and Thaler (1999:16) agrees: *"I predict that in the not-too-distant future, the term behavioral finance will be correctly viewed as a redundant phrase. What other kind of finance is there?"*. Nevertheless, behavioural arguments have entered the mainstream literature as explanations for deviations from the predictions of asset pricing theory and the existence of style effects. This behaviour is however contrary to what the theory discussed in Chapter Two assumes about investors, that they are risk-averse, expected utility maximisers and make rational choices based on rational expectations.

Lakonishok, Shleifer, and Vishny (1994) make an argument that it is investor irrationality that prevents the three factor Fama and French (1993) model from being reduced to the CAPM. The basis of the Lakonishok, Shleifer, and Vishny (1994:1542) argument relies on contrarian investment strategies that pursue a style of investing in value stocks and take advantage of the irrational behavior of investors who pursue a style of investing in growth stocks: *"...some investors tend to get overly excited about stocks that have done very well in the past and buy them up, so that these glamour stocks become overpriced. Similarly, they overreact to stocks that have done very badly, oversell*

²⁴ They do not explicitly propose this is a risk premium.

²⁵ The Connor and Korajczyk (1988) principal component factors are effectively APT factors constructed similar to the Page (1986) factors introduced in a later section.

them, and these out-of-favor value stocks become underpriced. Contrarian investors bet against such naïve investors".²⁶ They conclude with three points in support of their overreaction argument. Firstly, that value styles, in general, outperformed their growth counterparts during the periods from 1968 to 1990. Secondly, investors appear to have been consistently too optimistic about the returns of growth stocks relative to value stocks. Finally, conventional measures of risk show that value styles are not significantly riskier than growth styles.

Recently, a compromise view called bounded rationality has entered the literature. Bounded rationality characterises investor behaviour as consisting of choices that are nearly optimal. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) argue that, in the presence of limits to arbitrage, bounded rationality can reconcile all of the return pattern anomalies and style effects otherwise attributed to irrationality.

3.4 Attributes or risk?

Prior to discussing the relationship between attributes and risk factors, an introduction is required to an important innovation in empirical finance called the *factor portfolio*. The return of a factor portfolio is designed to be highly correlated with that of a risk factor. Huberman, Shmuel and Stambaugh (1987) show that the technique of constructing factor portfolios is particularly useful when the factor is directly observable. Under equilibrium, the expected return to a factor-mimicking portfolio should equate to the corresponding factor premium. The standard construction procedure is to rank stocks according to some criteria and then form portfolios by inserting breakpoints into the ranking. The factor portfolio is created using a zero cost long-short combination of the two extreme portfolios. For this reason, factor-mimicking portfolios are often referred to in the literature as hedged portfolios.

Firm-specific attributes are often used in asset pricing studies as the ranking criteria. If the attribute has explanatory power, the idea is that a long-short attribute-sorted portfolio should mimic the return pattern of the associated although unnamed source of priced risk.

²⁶ This reason is in direct contrast to the Fama and French (1992) view that low book-to-market stocks are fundamentally riskier.

However, not all researchers are in agreement on this, such as Berk (2000:408): *“Assume a researcher has uncovered a variable, γ , that is cross-sectionally correlated with returns. He postulates that he has uncovered an anomaly - that is, he claims that γ is a better predictor of return than a particular risk based asset pricing model...When stocks are first sorted into groups based on a variable like γ that is known to be correlated with returns, the average return of each group will reflect this correlation”*. The basis of this argument is that when stocks are sorted into portfolios based on an attribute that is known to be associated with stock returns, the average returns of the test portfolios reflect this association. The result is a high between-portfolio and low within-portfolio variation in expected return which may lead to false conclusions. This criticism is levied specifically at the methodologies of the Black, Jensen and Scholes (1972) and Fama and MacBeth (1972) design.

Fama and French (1993) provide several tests showing that a firm's size and book-to-market ratio are proxies for the loading on priced risk factors²⁷. They find evidence that the loadings on zero-cost factor-mimicking portfolios formed on market capitalisation, book-to-market ratios and a value-weighted market index are able to explain the excess returns of a complete range of book-to-market and size sorted portfolios in the US. The source of these premiums however remains widely contested in the literature.

Adding to the debate is a subsequent study by Daniel and Titman (1997) that asks whether the return patterns of the characteristic-sorted portfolios observed by Fama and French (1993) are consistent with a risk model at all. Specifically, Daniel and Titman (1997:751) propose that the common variation in the cross-section of stock returns does not arise from loadings on a shared risk factor, but instead from common characteristics: *“...common variation arises because the HML (‘High-Minus-Low’ book-to-market sorted factor) portfolio to consists of ‘similar’ firms that have similar factor loadings whether or not they are distressed...a portfolio of high book-to-market firms would earn a high return because it contains many oil firms, which load on the ‘distressed’ oil factor, which now has a high return premium”*.

²⁷ The loading is the coefficient or sensitivity of a stock to a factor, or in this case to a factor portfolio.

Daniel and Titman (1997) present three models to test their hypothesis. The first model is the null hypothesis and is consistent with the views of Fama and French (1993, 1994, 1996) that a financial distress factor with a positive risk premium exists. In this model, a separate time-varying distress factor is specified to allow firms to move in and out of distress. The second model represents an alternative hypothesis that the expected return of a firm is determined by its risk factor loadings. Although similar to the first model, no separate distress factor is specified. The third model is a framework designed to conclude whether it is firm attributes rather than factor loadings that determine expected returns. The mechanics of constructing the test portfolios involve sorting stocks into portfolios with cross-sectional variation in both attributes and factor loadings. The result is a set of test portfolios with high book-to-market attributes but with return covariances that resemble low book-to-market portfolios and vice-versa.

An analysis of the returns of the test portfolios does not produce any evidence that a separate risk factor is associated with either high or low book-to-market attributes. They find that while high book-to-market stocks do covary with one another, their covariances are equally strong before the firms become financially distressed²⁸. Importantly, no return premium is found to be associated with any of the three factors identified by Fama and French (1993). Daniel and Titman (1997) interpret this to mean that the high returns associated with small and high book-to-market firms cannot be seen as compensation for factor risk. They further document, similar to the results reported by Fama and French (1992) and Jegadeesh (1992), that after controlling for size, there is a slightly negative relationship with beta.

Daniel and Titman (1997) offer three explanations for the findings. Firstly, they argue that in a rational world attributes and factor loadings should be correlated since stocks with a high loading on a priced risk factor will tend to have lower prices because their future cash flows are discounted at higher rates. Secondly, characteristically similar firms are likely to become mispriced at the same time thereby inducing a relationship between the risk factor structure and the attributes. Thirdly, the information content of the attributes is more up-to-date than risk factor loadings that are simply historic estimators of sensitivity.

²⁸ A firm under financial distress is assumed to have a high book-to-market ratio.

The important conclusion of the Daniel and Titman (1997) findings are that the variables commonly used to predict future covariance do not predict future returns. The implication is that traditional measures of risk do not determine expected returns. This presents a problem in that traditional asset pricing models rely on the covariance structure of returns to determine expected returns. Not all researchers are however convinced, such as Berk (2000:423) who argues: “...*simply by sorting into enough groups, it is possible for a researcher to reduce the explanatory power of even an economically correct asset pricing model to zero*”. The basis of the Berk (2000) criticism is that if a second sort on estimated factor loadings is conducted, the possibility exists that stocks are divided into groups according to measurement error, and may thus produce no real variation in average returns or in the true factor loadings. This could lead to a conclusion that incorrectly rejects an asset pricing model that may in fact be correct.

Although the primary focus of the Daniel and Titman (1997) analysis is on the factor portfolios suggested by Fama and French (1993), they predict their findings will have implications for other studies that employ portfolio sorting methodologies. It is also suggested that risk factor loadings measured with respect to the various macroeconomic factors used by Chan, Chen, and Hsieh (1985), Chen, Roll, and Ross (1986), Jagannathan and Wang (1996) and others will similarly fail to explain stock returns once attributes are controlled for. No attempts have been made to determine whether the attribute versus factor issue would have any impact on the factor loadings estimated on a factor portfolio of JSE stocks. The empirical work in Chapter Eight of this thesis initiates this line of enquiry on the JSE.

3.5 Empirical evaluations of the APT

Tests of the APT are constructed in a similar way to those for the CAPM. The primary difference is that when evaluating the APT, there is freedom to choose any set of variables to represent the factors in the model. Consequently, anomalies do not generally exist in the CAPM sense. If an anomaly is detectable under the APT, an additional factor could simply be added, or any unexplained variation can be rolled up in the residual of the model.

Consequently, the majority of empirical studies of the APT have been directed towards the search for factors and the evaluation of the pricing accuracy of the resulting model.

Since the theory does not specify the relevant factor structure of the APT, there will always be uncertainty over the general empirical validity of the model. Like the CAPM, the APT says that the return of a security is a function of its systematic risk. An important theoretical difference between the factor in the CAPM and those in the APT is that the CAPM uses an equilibrium argument to identify the market as being the single systematic risk factor. Conversely, the APT is not based on an equilibrium argument and hence there is no need to be explicit about the factors in the model.

Factors can be derived through factor analytic techniques or prespecified based on economic theory. Factor analytic techniques derive factors that are statistical constructs extracted from the covariance or correlation matrix of asset returns. Factors that are prespecified can either be directly observable, such as the inflation rate or interest rates or indirectly observable, as is the case with the market portfolio or proxy thereof in the CAPM.

3.5.1 Factor-analytic methodologies

The factor analytic approach is a rigorous technique of factor extraction using statistical methods. Although the factors accurately capture the variation in security returns, they have no economic identity. The lack of economic meaning in the factors is noted in Fama's (1991) general criticism of the use of this technique in asset pricing: *"The approach leaves one hungry for economic insights about how the factors relate to uncertainties about consumption and portfolio opportunities that are of concern to investors"*.

Among the first studies to apply a factor analytic procedure in APT estimation is Roll and Ross (1980). They extract successive factors from the covariance matrix of stock returns until the addition of the next factor makes no contribution to explanatory power. Using maximum likelihood analysis and generalised least squares (GLS)²⁹ regression, their results support the

²⁹ Maximum likelihood estimation is a method for estimating the parameters of the population from which sample data was drawn. For all possible parameters the probability of observing the sample statistic is computed. The maximum likelihood estimate is the parameter associated with the highest probability.

extraction of four but no more than five asymptotic factors using a sample of forty-two groups of securities in the US from 1962 and 1972³⁰. Their overall results provide support for the APT although they accept their methodology lacks statistical power.

The firmest criticism of the use of factor analytic procedures in the APT comes from Shanken (1982, 1985). He argues that the identification of factors is sample specific and determining which factors are priced is unreliable. Furthermore, he demonstrates that not only are the number of factors needed to complete the model unknown, but the factors provided through factor analysis are not unique. Dhrymes, Friend and Gultekin (1984), Brown (1989) and Trzcinka (1986) all have similar problems with the number of factors derived from factor analytic procedures. Fama (1991) concurs: *"Since multifactor models offer at best vague predictions about the variables that are important in returns and expected returns, there is the danger that measured relations between returns and economic factors are spurious, the result of special features of a particular sample (factor dredging)"*. The above criticisms read together pose a strong argument against the testability of the APT through factor analysis, similar to the untestability argument that Roll (1977) levies at the CAPM.

3.5.1.1 Factor-analytic methodologies on the JSE

Page (1986) is the first to conduct an extraction of APT factors on the JSE using factor analytic techniques. Preferring the principal component methodology to the maximum likelihood approach of Roll and Ross (1980), he extracts three factors through a reduction of the correlation matrices of weekly stock returns from four simulated portfolios from 1973 to 1982³¹. Then, like Roll and Ross (1980), he applies a cross-sectional GLS regression to identify which of the factors are priced. Although Page (1986) acknowledges the power of the tests are very weak, the results show the first two principal components have significant risk premia associated with them. After using an orthogonal rotation criterion that maximises the variance of the squared elements in the columns of the factor matrix, otherwise known as

³⁰ Brown and Weinstein (1983) concur that it is unlikely the number of pervasive factors is greater than five.

³¹ Principal component analysis is a direct method of factoring a correlation matrix conducted without estimating communalities. Linear combinations of variables are estimated which explain the maximum amount of variance in the variables. The first component accounts for the most variance in the variables. The number of factors is chosen using a graphical method called a scree test whereby the eigenvalues are plotted in the sequence of the principal factors. The number of factors is then chosen at a point where the plot levels off to a linear decreasing pattern.

varimax rotation, the factors are identified as being a mining-related factor and an industrial-related factor. Page (1986:40) summarises: “...in terms of the APT, two factors are needed to explain the risky asset returns in the Johannesburg Stock Exchange”.

In a subsequent factor analytic study to establish the identity of the factors associated with shared variation in stock returns on the JSE, van Rensburg and Slaney (1997) apply a variety of factor analysis techniques to the correlation matrix of stock returns³². Conducting factor rotation techniques on the first three factors reveals, similar to Page (1986), that the first factor appears to be a mining-type factor, the second appears to be a financial and industrial-type factor while the identity of the third factor is ambiguous. By graphically depicting a plot between the rotated factor loadings together with a host of observable marker variables, it is confirmed that the JSE All-Gold index and the JSE Industrial index are observable proxies for the first two factor analytic components of stock returns on the JSE. The advantage of using observable proxies lies in their unambiguous economic interpretation, ease of use and increased power when employed in system equations. van Rensburg and Slaney (1997:20) conclude that: “...different sources of risk are rewarded with risk premia of different magnitudes and that the large majority of JSE shares are influenced by either the Mining or Industrial indices but not both”. After the JSE indices were reconstituted in 1998, an updated study is conducted by van Rensburg (2002). The results still show support for an intuitively similar two factor APT model capturing the apparent dichotomous return generating structure of the JSE³³.

3.5.2 Pre-specified variable methodologies

The original APT theory intended there to be a limited number of macroeconomic factors. By prespecifying the factors in the APT model the central point of the Roll (1977) criticism is avoided. Chen, Roll and Ross (1986) are among the first to adopt the prespecified variable approach to estimating the APT in the US. They propose a set of seven macroeconomic variables including industrial production, inflation expectations, risk premia, the term structure of interest rates, market indices, changes in real consumption and oil prices. Their

³² Only the results from the principle factor technique are reported in this study. Principal factor analysis is a method of factor analysis using communality estimates. Successive factors are extracted that explain the most variation in a set of variables.

³³ This model used the reclassified JSE Resources and JSE Financial and Industrial indices as the two factors.

results show that several variables, industrial production, changes in risk premiums and changes in the term structure have significant explanatory power. Berry, Burmeister and McElroy (1988) show that an APT model that incorporates five prespecified macroeconomic variables is superior to CAPM. While there appears to be a lack of a formal discipline in the selection of the macroeconomic factors for APT models, the factors do appear to adequately explain security returns.

While the factor analytic approach may not provide useful information for economic interpretation, it does indicate at least a similar number of pervasive sources of priced risk exist compared with the prespecified variable approach. Although both approaches have distinct benefits, it is unlikely that there will ever be consensus on which method is the most suitable. In spite of the criticisms from Shanken (1982), it is widely accepted that the empirical testability of the APT is superior to that of the CAPM.

3.5.2.1 Pre-specified variable methodologies on the JSE

The first prespecified variable approach to APT factor identification on the JSE is van Rensburg (1996). Using a sample of seventy-two stocks from 1980 to 1989, he selects candidate factors from ten macroeconomic variables then, following McElroy and Burmeister (1988), applies an iterated non-linear seemingly unrelated regression (ITNLSUR) to cross-sectionally evaluate which factors are priced. The results show that the Dow Jones Industrial average, the term structure of interest rates and inflation expectations are associated with statistically significant risk premia. In a more comprehensive study, van Rensburg (1999) again seeks the identity of pervasive factors for use in an APT model from a rich set of thirty-two macroeconomic indicators. Using a time-series analysis, he distills a short-list of candidate factors that are significantly related to stock returns. The candidate factors identified for further cross-sectional testing are the rand gold price, short-term money market rates, the Dow Jones Industrial average, the current account balance and the shortage in the money market.

In van Rensburg (2000) the candidate factors from van Rensburg (1999) are formally incorporated into an estimation of the APT using an adaptation of the prespecified variable technique presented by Chen, Roll and Ross (1986). Using a more powerful cross-sectional

test than the conventional Fama and MacBeth (1973) two-step procedure, van Rensburg (2000) shows that the Dow Jones Industrial average, the long bond rate, the rand gold price and the level of foreign exchange reserves represent priced sources of risk on the JSE over the period 1985 to 1995³⁴. An important conclusion of van Rensburg (2000:41) is that: “...(*a two factor APT model*), using returns on the All-Gold and Industrial indices as explanatory variables subsumes the influence of other prespecified macroeconomic variables on equity returns”.

Overall, the empirical results seem to lead researchers to a similar conclusion that the APT is a more effective framework for pricing systematic risk on the JSE than the CAPM. The first definitive conclusion in this regard is made by Page (1986:41): “*In comparing the CAPM and the APT, the APT was found to be substantially better with regard to the explanation of the variability of returns*”. And again in Page (1993:5-37): “*Under conditions of thin trading, the low power of empirical procedures commonly employed is likely to lead to the conclusion that security returns are more consistent with the Arbitrage Pricing Theory than the Capital Asset Pricing Model*”. Finally, van Rensburg and Slaney (1997:20) concur: “*The findings suggest the two factor APT model has pricing implications not compatible with the CAPM*”.

3.6 Summary and conclusion

The validity of the CAPM is likely to always be a topic for debate. The international literature surveyed in this chapter reveals that while the relationship between the average return and beta is almost linear, the estimated slope of the SML is flatter and the intercept higher than predicted by the theory. By contrast, the evidence from the JSE suggests the possibility that more than one SML and at least two risk factors are required to describe stock returns.

This chapter also documents several empirical contradictions of the CAPM associated with various attributes, termed anomalies. The evidence from the JSE shows the existence of CAPM anomalies that are at least qualitatively similar to those documented for the international markets. Since tests of asset pricing models are all subject to the joint-hypothesis problem that simultaneously evaluates the EMH, it is not strictly possible to know whether the market is inefficient or the asset pricing model is incorrect. The concept

³⁴ The cross-sectional analysis was conducted using the ITNLSUR methodology.

of style effects is then introduced and shown to have a close association with CAPM anomalies. Style investing can be thought of as a strategy employed by fund managers to achieve superior performance. It follows that style effects are therefore likely to be associated with anomalies. While the volume of research into style effects on the JSE is thin relative to the international evidence, the indications are that similar styles are observable on the JSE. A debate is introduced that attributes themselves and not risk factor loadings are associated with stock returns, an area yet to be investigated on the JSE.

The less restrictive assumptions of the APT have lead to a wide belief that the APT offers a testable alternative to the CAPM. In contrast with the anomalies associated with the CAPM, most APT research focuses on the pricing accuracy of the model and the search for factors. The APT research on the JSE has been either factor analytic in nature or followed a prespecified variable approach. Both approaches appear to further propagate the idea of market segmentation on the JSE. Convincing arguments are presented in the South African literature that systematic risk on the JSE can be well captured by a two factor APT model consisting of a mining or resources type factor and an industrial and financial type factor. While theoretically reconcilable, the pricing specification of the two factor APT is not however consistent with the CAPM on the JSE.

Data and Descriptive Statistics

4.1 Introduction

This chapter introduces the data that is analysed in the empirical chapters of this thesis. The data consists of (i) stock returns data and (ii) firm-specific attribute data. While the methodologies described in the later empirical chapters ultimately align these two data sets using cross-sectional test frameworks and portfolio simulation techniques, each data set is described separately in this chapter. In addition to providing details of the constituents of each data set, this chapter uses an array of descriptive statistics to present new comparative evidence of the distributional properties of the firm-specific attribute data for the full market and for the major industry groupings of the JSE.

The remainder of the chapter is set out as follows. Section 4.2 introduces the two principle data sets and provides comprehensive details of their construction and the procedures used in manipulating the data prior to analysis. Section 4.3 contains discussions regarding the economic interpretation of firm-specific attribute data, suggests how these interpretations may vary among firms in different market sectors and presents the descriptive statistics. Section 4.5 summarises and concludes.

4.2 Data

This section provides an overview of the two data sets that were populated for this thesis. Both the stock returns data set and the firm-specific attribute data set contain monthly data for the 120 months from July 1990 to June 2000. The stock returns data is supplied by the BARRA organisation and the firm-specific attribute data is supplied by McGregor's/Bureau of Financial Analysis (McG/BFA).

4.2.1 Stock returns data

The data set of monthly stock returns includes all listed JSE stocks in each month but excludes cash-shell companies. The BARRA organisation electronically collects the data directly from the JSE Equity Data Dissemination Service at the end of every month. The returns have been adjusted for all capital events and all dividends are reinvested on the ex-div date. Pro-rata return is calculated to the event date for stocks that are delisted or suspended from trade during a month¹.

4.2.1.1 Adjustments to the stock returns data

Since stock returns are calculated using periodic price movements, determining the return of a non-traded stock presents a general problem in that the price used in the calculation is the result of transaction in a previous time period. The information content of the price is therefore not matched with the current period, but instead is a carry-over from a prior event. In asset pricing studies this is appropriately known as the non-synchronous problem. The term *thinly traded* is loosely used in the finance literature to describe a stock that either trades infrequently during a period or has a history of prolonged unmatched bids and offers such that it is non-traded.

The first effects of the non-synchronous trading problem are documented in Fama (1965) and Fisher (1966) in the US market. They find evidence of spurious positive serial correlation in the return of an index calculated from infrequently traded stocks. The serial correlation is invoked when the prices of the thinly traded stocks in the index reflect unchanged in the index calculation of a subsequent period. It is not until Ball (1977), Scholes and Williams (1977) and Dimson (1979) that the research into the effects of thin trading is directed towards the area of risk measurement. The general finding is that thin trading introduces a bias into the estimation of systematic risk. This occurs because systematic risk is estimated from the covariance matrix of stock returns and the market return, but since the price of thinly traded stocks is unchanged they do not appear to move with the market.

¹ I am grateful to Michelle Beckwith, risk consultant at BARRA International, Cape Town, for retrieving the data set from their head office in Berkeley, California.

At least three techniques have emerged for dealing with the problem of thin trading. One technique uses a lagged market return technique like Dimson (1979) and Ibbotson (1975). They correct for non-synchronous trading by using an adaptation of the market model with a lagged market index. The systematic risk of the thinly traded stock is then approximated through the summation of contemporaneous lagged market coefficients.

Another technique is that of Dimson and Marsh (1983) who propose an approach to derive the beta coefficients using a technique called the trade-to-trade approach. The technique is a form of weighted least squares regression where the weights are proportional to the frequency of trade. If a stock trades in the immediate previous period it is assigned a full weight whereas if the last trade occurs four periods prior it is assigned only a half weight. This approach calculates the return of thinly traded stocks by measuring the return from one transaction to another transaction regardless of the interval. A difficulty in implementing the trade-to-trade methodology is that the interval between transactions must be known.

The alternative adjusted-beta technique of Scholes and Williams (1977) requires only the information on whether or not a stock is actually traded during the period. The return is calculated and used only if the transaction occurs in consecutive time periods. Although the adjusted beta technique requires fewer data items, it needs a large sample for calculation. This places limitations on the effective use of this technique in emerging markets like South Africa where the problem of thin trading is likely to be more severe².

Research shows that the effects of thin trading on the JSE cannot be overlooked, as Page (1993:4-28) notes: "*The importance of bias in correlation and covariance estimation in empirical research using South African and other thinly traded market data should not be underestimated*". Correcting for the problem of thin trading by omitting thinly traded counters from the sample altogether appears to be the method favoured by researchers studying the JSE. Page (1986), in an empirical study of the APT, uses a sample of thirty randomly selected non-thinly traded stocks while Biger and Page (1993) reconstruct the market portfolio using 244 non-thinly

² Although Bradfield (1989) reports that one-third of JSE listed stocks did not trade for one out of every four weeks in a 500-week sample, the thin trading problem was reduced with the introduction of the automated order-driven JET trading system in 1996 which increased the average number of daily trades by threefold (Business Times 27/07/1997).

traded stocks. Reese (1993) eliminates stocks from her sample that do not trade for twenty weeks. Slaney (1996) also limits the sample size to shares that are frequently traded as does van Rensburg (1999) who, using the same sample as Reese (1993), excludes stocks that have a zero trading volume for twenty consecutive weeks in a ten year sample period.

Since thin trading is likely to be more prevalent among smaller companies, attempting to ameliorate the problem by filtering the sample based on market capitalisation alone is not appropriate. For example, it would be especially problematic for studies that test the relationship between stock returns and, say, an attribute such as size when all the small capitalisation stocks are removed from the sample on the grounds that they are likely to be thinly traded. Therefore, similar to previous authors, the data sets in this thesis are filtered in each month to include only stocks that traded at least once.

Like Fama and French (1992), the filter is calibrated to remove stocks with a monthly turnover of less than 0.01% of the issued share capital at the end of the previous calendar month³. This removes the non-synchronous problem from the data since all analysis is conducted at monthly intervals. The average number of stocks in each one-year period before and after removing non-traded and thinly traded stocks from the stock returns data set is reported in Table 4.1 for the financial, industrial and resource sectors⁴.

Table 4.1 Average number of stocks in the stock returns data set before and after filtering out thinly traded stocks.

The yearly figures represent the average number of stocks in each twelve-month period from July 1990 to June 2000. All years represent the average number of stocks in each month across the full 120-month period.

Years	Before										
	All	1	2	3	4	5	6	7	8	9	10
All stocks	419	313	337	350	361	378	399	421	461	549	629
Financials	80	53	53	55	55	66	73	80	93	134	140
Industrials	273	203	224	233	241	247	261	274	298	342	413
Resources	66	57	60	62	65	65	65	67	70	73	76

³ In a preliminary investigation it was found that applying a more stringent filter resulted in a prohibitively small number of stocks in the final sample.

⁴ The financial, industrial and resource sectors are the second tier of JSE classification below the All Share index. On the 24th June 2002 however, after this study was completed, many sectors were reclassified in accordance with a new free-float system adopted by the JSE.

Table 4.1 Continued.

Years	After										
	All	1	2	3	4	5	6	7	8	9	10
All stocks	336	211	209	220	262	285	326	366	420	500	563
Financials	69	33	40	32	52	51	65	69	93	127	119
Industrials	214	136	130	146	160	182	206	237	265	309	375
Resources	53	42	39	42	50	52	55	60	62	64	69

4.2.2 Firm-specific attribute data

The term *firm-specific attribute*, often abbreviated to simply *attribute*, is used throughout this thesis as a collective term when referring to a financial ratio or technical indicator. What follows is a detailed account of the construction of the attribute data items. The financial ratios are dealt with separately to the technical indicators.

4.2.2.1 Financial ratios

Twenty financial ratios are extracted for all listed JSE stocks in each month from the McG/BFA Raid Station system. Cash shell companies are excluded on the grounds that their financial statement data are usually meaningless. Selection of the financial ratios is based primarily on the availability and completeness of the data in the McG/BFA database. Importantly, no attributes are included or excluded on the basis of any prior empirical evidence of their association with stock returns. Where a ratio is the inverse of another, such as earnings yield and price-to-earnings, only one is selected to avoid the duplication of subsequent test results.

The calculation of the financial ratios is based mainly on the information in the balance sheet and the income statement and often the consolidated versions thereof. All the financial statement data used is drawn from audited reports with interim results being ignored. Where necessary, additional information is extracted from the source and application of funds statements, the directors' report and the auditors' report⁵. A financial ratio is excluded from

⁵ Section 186 of the Companies Act of 1973 as amended, provides that the annual financial statements must consist of a balance sheet, an income statement, a director's report and an auditor's report together with a source and application of funds statement.

the data set in a month where the line item used in the ratio calculation is missing, but remains in the sample otherwise. In the few instances where a firm has multiple share classes such as non-voting issues or other ownership restrictions, the financial ratios that incorporate line items relating to share capital are not adjusted.

When analysing a data set of financial ratios that is based on information drawn from financial statements, two difficulties are sometimes encountered that are not often discussed in the investment literature. Firstly, the financial ratios may not always be comparable across firms if the fiscal periods on which the financial statements are based do not extend neatly to twelve months. This results from the financial ratios being calculated from statements of account that cover either a longer or a shorter period. Secondly, also related to inconsistent fiscal periods, is a problem arising where the data items used in the ratio calculation are drawn from both the income statement and the balance sheet and the two statements cover different periods. This results in the value of the ratios that are calculated not necessarily being comparable with the firm's own past or with that of the other firms within the same period.

In order to find a partial solution to these problems, McG/BFA has identified affected companies and adjusted the appropriate line items used in the ratio calculations on a pro-rata basis to a twelve month period. While this adjustment may overlook certain seasonal fluctuations relating to the business of the firm as well as certain income and expenditure items that are not time related, a convincing case can be made that the adjustment improves the overall consistency of the sample. It is also a particularly useful technique for incorporating the data of non-surviving firms in a way that makes them comparable to other firms in the sample, thereby mitigating any criticisms of sample selection bias linked to survivorship.

4.2.2.2 Technical indicators

Three technical indicators of lagged momentum and a measure of trading volume are constructed for all stocks in each month from July 1990 to June 2000. The indicators of lagged momentum are the cumulative return over the previous one, six and twelve months. The indicator of trading volume is constructed by extracting the trading volume for all stocks

on every day from July 1990 to June 2000 from the I-Net Bridge historical database. Using a technique similar to Lee and Swaminathan (2000) the daily trading volume is expressed as a proportion of shares in issue at the end of the previous trading day. To adjust this to a monthly turnover figure, the cumulative daily trading volume for the month is divided by the number of trading days in the month and then expressed as a proportion of the number of issued ordinary shares on the last trading day of the previous month. This technique of scaling trading volume by the number of issued shares is motivated by evidence in Campbell, Grossman and Wang (1993) that shows a high correlation exists between unscaled trading volume and firm size, which is already one of the attributes in the data set. A list of all financial ratios and technical indicators examined in this thesis is in Table 4.2.

Table 4.2 List of financial ratios and technical indicators contained in the data set of firm-specific attributes.

Financial ratios	
Cashflow-to-price	Price-to-earnings
Current ratio	Price-to-NAV
Debt-to-asset	Price-to-profit
Debt-to-cashflow	Quick ratio
Debt-to-equity	Retention rate
Dividend yield	Return-on-assets
Financial distress	Return-on-equity
Leverage	Shares in issue
LT Loans-to-assets	Size
Owners interest	Sustainable growth
Technical indicators	
One-month prior	Twelve-months prior
Six-months prior	Trading volume

The attribute data set used in this thesis represents the most comprehensive collection of financial ratios and technical indicators yet assembled for a South African study. The data set of attributes holds more than 1.41 million data points including the trading volume data collected at the stock level that involved the collation of more than 1.46 million days of trading volume⁶. The formulas for calculating the financial ratios and technical indicators

⁶ Since number of stocks in the sample does not increase uniformly over the period, the number of data points in the attribute data set, quoted here at 1.41 million, cannot be calculated simply by multiplying the average number of stocks in the sample by twenty-four attributes and then by 120 months.

together with a comprehensive description of the line items used in the formulas is detailed in Appendix A.

4.2.2.3 Adjustments to the stock attribute data

A preliminary inspection of the attribute data set revealed the existence of several cases of extreme outliers. In a US study, So (1987:491) observes that outliers are responsible for the introducing non-normalities in the distribution of financial ratios: *“The empirical evidence indicates that outliers are one of the factors that cause the distribution of the cross-sectional of financial ratios to be skewed and non-normal”*. This offers a plausible explanation for the findings of several earlier US studies that had already documented the existence of non-normalities in the distribution of financial ratios. Deakin (1976) finds that none of the eleven financial ratios of between 454 and 1114 US firms over the period 1954 to 1972 are normally distributed, even after applying a logarithm to the data. A subsequent study of 700 UK firms in 1975 by Bougen and Drury (1980) also shows no evidence that financial ratios are normally distributed. Similar results are reported by Frecka and Hopwood (1983) using a set of commonly used financial ratios drawn from a US sample of between 344 and 1243 firms. Using stronger tests, Lee (1985) confirms all the above findings⁷.

These apparent non-normalities in the distributional properties of financial ratios have prompted researchers into looking for methods of restoring normality to warrant standard parametric statistical tests. Frecka and Hopwood (1983) advocate removing outliers completely from the population to improve the distributional properties. Foster (1986) lists several other approaches including deleting true outliers, adjusting the underlying financial data, winsorising outliers to less extreme values and trimming the tails of the distribution.

In this thesis, a winsorisation method similar to Fama and French (1992) is adopted to remove extreme outliers from the attribute data set. The largest and smallest half-percent of the data points in each month is set equal to the values of the 99.5th and 0.5th percentiles respectively. Although the test frameworks developed in the empirical chapters of this thesis

⁷ While all these studies examine the aggregate distribution of financial ratios, they do not consider the distributional properties of the constituent elements of the ratios. Research in this area can be found in Watson (1990) but falls far enough outside the scope of this thesis not to warrant further attention.

do not necessarily require that the attribute data be normally distributed, the winsorisation procedure successfully purges the extreme outliers from the attribute data set.

4.3 Descriptive statistics

This section highlights the possibility that the attributes in Table 4.3 do not have a uniform economic interpretation across the broad sectors of the JSE. This is of particular interest due to the apparent resource and financial-industrial dichotomy on the JSE discussed in Chapter Three. By investigating whether the attributes appear to have a varying economic interpretation across the sectors of the JSE provides a natural precursor to Chapter Six that investigates whether the attributes that are influential in the cross-section of stock returns for the full market also have predictive power in the sectors⁸.

A ratio conveys the relationship between two numbers, a numerator and a denominator. A utility of a ratio lies in its ability to impart greater knowledge than is discernible from each of the constituent numbers standing alone. Importantly, converting the constituent numbers from financial statements into financial ratios has a scaling effect that allows direct comparisons to be made between different size firms. In this role, financial ratios provide an up-to-date encapsulated and useful view of the financial health of a firm.

The caveat is that no reason exists to suppose that the line items of information contained in the statements of account used to calculate the financial ratios are comparable across firms or across sectors. Since firms are broadly classified into sectors according to the nature of their core business, differences in the economic interpretation of financial ratios are more likely to be pronounced when measured at the sector level. For instance, the structure and content of the financial statements of gold mining companies on the JSE are markedly different to firms in other sectors and usually include several line items specific to mining companies such as prospecting and hedging. The economic interpretation of financial ratios that incorporate a measure of a firm's asset base may be especially susceptible to sector-related differences in asset valuation protocols. For instance, industrial and resource firms on

⁸ This section is the originating work for elements of the article: The interaction between sectors, styles and JSE Securities Exchange returns, *Working paper*, 2002, School of Management Studies, University of Cape Town.

the JSE generally value assets on an annual basis while a large proportion of the assets of financial firms are market related and marked-to-market on a daily basis. Industrial and resource firms also tend to have greater fixed assets in terms of plant, machinery and stock, while financial firms have comparatively fewer fixed assets. On these grounds at least, there is reason to suspect that financial ratios are not automatically comparable across the major sectors of the JSE⁹.

Apart from the anecdotal evidence above, the structural differences in financial ratios across the major market sectors of the JSE is largely undocumented. The objective of this section is therefore to compare whether the attributes, particularly the financial ratios, have similar distributional properties across the sectors. This highlights sectoral-related differences in accounting convention, financial statement structure and economic interpretation. The findings are of interest to asset pricing studies on the JSE that analyse attribute data, particularly if the test designs make assumptions regarding the distributional properties of the attributes. The findings may also be relevant to empirical research involving these variables in disciplines other than finance such as accounting science.

The mean, median and skewness of each attribute is reported for the full market and for the financial, industrial and resource sectors in Tables 4.3 to 4.5. Of lesser importance to the discussion in this section are the kurtosis and standard deviation of the attributes across the sectors. These are therefore reported in Appendix B. The values of the descriptive statistics are the average of the monthly cross-sectional averages for all non-thinly traded stocks from July 1990 to June 2000 after conducting the winsorisation procedure discussed previously. In other results it is observed that the thin trading filter performs the auxiliary purpose of purging outlying data points that result from extreme price action on thin volume and, thereby, removes many of the outliers observed in the financial ratio data. Using a set of single descriptive statistics is arguably not the most efficient way to represent such a large and diverse data set, however the exercise provides new and useful information about the overall distribution of the attributes in the sample.

⁹ I am grateful to banking analyst Henry Hall at HSBC, banking analyst Sven Thordsen at Deutsche Securities and mining analyst David Plemming at BJM Securities for useful discussions on asset valuation and accounting conventions. These analysts were ranked either first or second in the annual Financial Mail analyst ratings for 2001.

Inspecting Table 4.3 reveals that the equal-weighted mean values of some financial ratios, such as dividend yield and price-to-earnings, appear exaggerated when compared to their capitalisation-weighted counterparts quoted on the JSE. This is due to the dramatically higher emphasis placed on smaller capitalisation stocks in the calculation of these values. For almost all attributes, the median value is lower than the arithmetic average providing initial evidence of a right skewness in the data.

4.3 Mean of the attributes.

The mean is calculated by taking the sum of all the data values and dividing by the total number of data values:

$$Mean = \left(\frac{\sum x_i}{n} \right)$$

	Mean			
	All	Financials	Industrials	Resources
Cashflow-to-price	0.24	0.20	0.31	0.79
Current ratio	1.83	2.09	1.67	2.54
Debt-to-assets	0.51	0.54	0.48	0.96
Debt-to-cashflow	4.72	26.88	4.59	3.94
Debt-to-equity	1.18	4.36	1.33	0.66
Dividend yield	0.07	0.08	0.08	0.12
Financial distress	13.11	48.48	11.26	23.58
Leverage	1.57	3.31	1.64	2.94
LT Loans-to-assets	0.18	0.30	0.20	0.16
One-month prior	0.01	0.02	0.01	0.01
Owners interest	0.69	1.46	0.43	1.31
Price-to-earnings	13.96	19.56	12.16	17.74
Price-to-NAV	2.19	2.07	2.62	5.32
Price-to-profit	17.85	21.8	18.98	27.23
Quick ratio	1.34	1.98	1.18	2.07
Retention rate	0.64	0.61	0.68	0.61
Return on assets	0.13	0.09	0.13	0.20
Return on equity	0.14	0.16	0.15	0.17
Shares in issue	136.34	182.47	124.91	128.97
Six-months prior	0.10	0.16	0.09	0.07
Size	19.53	20.28	19.25	19.99
Sustainable growth	9.86	12.39	11.92	6.69
Trading volume	0.08	0.11	0.07	0.10
Twelve-months prior	0.23	0.38	0.22	0.15

In other results, average median values of the ten one-year sub-periods in the sample show that the median is generally more stable through time than the mean. In some instances, particularly around the time of the Asian financial crisis in 1998, the fewer number of stocks

in the financial and resource sectors are found to amplify the distribution of several financial ratios that incorporate price in their construction.

When comparing the mean and median values of the attributes across sectors in Table 4.3 and Table 4.4, the most dramatic sectoral differences are that the financial ratios relating to levels of debt such as debt-to-cashflow, debt-to-equity, leverage, financial distress and long term loans-to-assets are markedly higher for financial stocks.

4.4 Median of the attributes.

The median is a measure of central tendency in a sample. The median is a value that has one-half of the observations, when ranked, above the value and one-half below the value. When the number of values in the sample is even, the median is computed as the average of the two middle values.

	Median			
	All	Financials	Industrials	Resources
Cashflow-to-price	0.15	0.11	0.18	0.13
Current ratio	1.50	1.26	1.51	1.70
Debt-to-assets	0.47	0.58	0.48	0.41
Debt-to-cashflow	3.60	7.53	3.63	2.32
Debt-to-equity	0.83	1.24	0.87	0.53
Dividend yield	0.04	0.04	0.05	0.04
Financial distress	9.45	13.24	9.19	9.34
Leverage	1.39	1.75	1.38	1.25
LT Loans-to-assets	0.10	0.13	0.11	0.03
One-month prior	0.00	0.01	0.00	0.00
Owners interest	0.12	0.40	0.11	0.06
Price-to-earnings	10.14	14.52	9.09	12.68
Price-to-NAV	1.42	1.41	1.33	1.93
Price-to-profit	12.03	13.74	11.69	13.18
Quick ratio	1.02	1.10	0.99	1.14
Retention rate	0.73	0.68	0.74	0.68
Return on assets	0.12	0.08	0.13	0.12
Return on equity	0.15	0.14	0.15	0.12
Shares in issue	83.87	98.45	75.08	102.36
Six-months prior	0.05	0.12	0.05	0.03
Size	19.50	20.34	19.24	19.87
Sustainable growth	9.22	7.87	10.29	5.79
Trading volume	0.02	0.04	0.02	0.03
Twelve-months prior	0.11	0.24	0.12	0.05

The reason is that banks, and other deposit-taking institutions, generally reflect deposits as balance sheet debt. A similar situation exists for several smaller financial services companies

that have acquired banking licenses. Unlike non-financial firms, high leverage is not normally associated with distress among financial firms. Ordinary lending activities tend to inflate the balance sheet assets of banks. This contributes to the low mean return on assets ratio for financial stocks. Financial ratios that incorporate debt are arguably not a fair reflection of the economic condition of financial firms and have been replaced in practice by alternate measures such as embedded value, commonly used for insurers, and cost-to-income ratios commonly used for banks.

Differences such as these in the interpretation of accounting data have prompted several researchers in finance to modify their data sets. In the international literature, Fama and French (1992:429) decide to limit their sample to only non-financial firms: *"We exclude financial firms because the high leverage that is normal for these firms probably does not have the same meaning as for non-financial firms"*. For similar reasons Moskowitz and Grinblatt (1999) differentiate between depository and non-depository firms in their study of industry and momentum effects in the US. Researchers investigating the JSE have not been unaware of the problem either. In a study on the influence of accounting-based information on systematic risk estimates, Bergensen and Ward (1996:33) explicitly justify focusing their sample only on the industrial sector based on the rationale that: *"...differences in accounting procedures in other major sectors, notably Mining and Financials, present significant problems in the standardisation of accounting variables"*. In later work, Graham and Uliana (2001:22) exclude the financial and mining sectors from their study of value and growth effects on the JSE on the grounds that: *"...these sectors conduct specialised activities, use different methods of accounting and in the case of the mining sector are subject to the effects of fluctuating intervention commodity prices"*. That the economic interpretation of the attributes is similar across the sectors of the JSE is important for asset pricing studies that evaluate the role of attributes in determining stock returns.

Due to the nature of their construction, some financial ratios have limits on their possible values. The current ratio, debt-to-assets, debt-to-equity, size and price-to-NAV ratios for instance have a lower limit of zero. It is observed in Table 4.5 that those ratios that have an analytic lower bound of zero are often skewed right. Closely related appears to be the observation in Appendix B.1 of positive kurtosis, or fat tails, in all ratios except long term

loans-to-assets and size. Since the lower bounds of many of the ratios essentially truncate the distribution at zero, a heavier left tail is formed causing the kurtosis to increase.

4.5 Skewness of the attributes.

Skewness characterises the degree of asymmetry of a distribution around its mean. Positive skewness indicates a distribution with an asymmetric tail extending toward more positive values. Negative skewness indicates a distribution with an asymmetric tail extending toward more negative values. If s is the sample standard deviation, then the skewness is given by:

$$\frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^3$$

	Skewness			
	All	Financials	Industrials	Resources
Cashflow-to-price	1.24	1.83	1.70	2.29
Current ratio	2.43	1.83	1.09	2.08
Debt-to-assets	2.24	-0.26	0.04	2.50
Debt-to-cashflow	-0.05	1.29	0.97	0.90
Debt-to-equity	0.23	1.33	1.71	0.60
Dividend yield	1.34	1.92	1.80	2.06
Financial distress	1.04	1.77	1.63	2.12
Leverage	-0.62	1.76	0.65	0.89
LT Loans-to-assets	0.71	0.92	1.24	1.17
One-month prior	0.54	0.41	0.57	0.36
Owners interest	2.69	2.13	2.48	2.22
Price-to-earnings	1.76	1.29	1.53	2.23
Price-to-NAV	1.27	1.65	2.25	2.24
Price-to-profit	1.45	1.48	2.13	2.07
Quick ratio	2.11	1.92	1.35	2.20
Retention rate	-2.62	-0.84	-1.00	-0.43
Return on assets	-0.03	1.00	-0.02	1.18
Return on equity	-0.81	0.52	-0.18	0.36
Shares in issue	1.37	1.69	1.17	0.82
Six-months prior	0.76	0.91	0.71	0.53
Size	0.07	-0.18	0.05	0.03
Sustainable growth	-0.69	0.77	0.08	-0.34
Trading volume	2.86	2.20	2.42	2.98
Twelve-months prior	1.06	0.90	1.01	0.69

4.4 Summary and conclusion

This chapter introduces the stock returns data set and the firm-specific attribute data set. To ameliorate the problem of non-synchronous trading, stocks that do not trade at least once during a month are removed from the stock returns data set using a thin trading filter. After

the adjustment, the average number of stocks over the full sample period is reduced by almost one-fifth. The firm-specific attribute data set, which is the largest ever assembled for a South African study in asset pricing, is winsorised in each month to remove the influence of extreme outliers in the analysis which follows.

A set of descriptive statistics is used to investigate the distributional properties of the attributes. Pervasive evidence is presented showing that many financial ratios exhibit right skewness linked to a theoretical lower bound on their values. While the right skewness does not directly impact the cross-sectional techniques employed later in thesis, the results may be relevant for a widely variety of future studies on the JSE that employ financial ratios.

The distributional properties of the attributes are then compared across the financial, industrial and resource sectors of the JSE. It is suggested that due to variation in accounting convention and business activities, not all financial ratios are necessarily comparable across the major market sectors. The most notable sector differences are for financial firms that exhibit markedly higher financial ratios where the ratio is constructed from accounting information relating to levels of debt or gearing. This is consistent with the international evidence suggesting that leverage is likely to have a different economic meaning in the context of financial firms. The implication for asset pricing research on the JSE is that the information content of financial ratios commonly used in empirical evaluations of the theory is not necessarily uniform for all stocks in the market.

Attributes and the Cross-Section of Equity Returns

5.1 Introduction

A cross-sectional model is the empirical counterpart of a theory of asset pricing. When used to evaluate the predictions of the theory, the international evidence surveyed in Chapter Three reports numerous empirical inconsistencies associated with cross-sectional attribute data. While earlier studies such as De Villiers, Lowlings, Pettit and Affleck-Graves (1986), Bradfield, Barr and Affleck-Graves (1988) and Page and Palmer (1993) *inter alia* investigate isolated attributes on the JSE, no exhaustive *cross-sectional* analysis of a broad set of attribute data has yet been conducted¹.

In contrast with the portfolio approach adopted by van Rensburg (2001) to determine the identity of pervasive styles among industrial stocks, this chapter employs a cross-sectional methodology using all JSE stocks. This complements the literature by investigating the role of many previously undocumented attributes on the JSE and provides new evidence on the identity of the attributes that are able to predict the cross-section of stock returns. Unlike Daniel and Titman (1993) however, the focus is not on the relative appropriateness of the attribute-based approach versus the more theoretically appealing risk-based approach. The remainder of the chapter is set out as follows. Section 5.2 discusses the data and methodology, Section 5.3 reports the results and Section 5.4 summarises and concludes.

5.2 Data and methodology

After the attribute data set is manipulated as described in Chapter Four, the attribute values are standardised in each month from July 1990 to June 2000 by subtracting the cross-

¹ This chapter is the originating work for the article: Style characteristics and the cross-section of JSE Securities Exchange returns, *Working paper*, 2002, School of Management Studies, University of Cape Town.

sectional mean and dividing by the cross-sectional standard deviation of the attribute. This allows direct comparisons to be made between the magnitudes of the average cross-sectional coefficients in the regressions that follow².

For each of the twenty-four attributes in Table 4.3, the value of the attribute is taken to be the exposure of the stock to the attribute. The relationship between the individual attributes and non-thinly traded stock returns is then tested using a one factor cross-sectional regression similar to Fama and MacBeth (1973), Ferson and Harvey (1991, 1998) and Fama and French (1992) *inter alia*:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1}A_i + \varepsilon_{i,t+1} \quad (5.1)$$

Where the dependent variable is $r_{i,t+1}$ and represents the realised return on stock i for month t . The single independent variable in the regression is denoted as A_i and is the value of the attribute under consideration for stock i that is available at the beginning of month t . $\gamma_{1,t+1}$ is the cross-sectional coefficient to be estimated using OLS and $\varepsilon_{i,t+1}$ is the error term.

Like Fama and French (1992), the attributes constructed from financial statement data are lagged in each month so that the accounting information for all fiscal year ends in calendar year $t-1$ is aligned with the stock returns for May of year t . This lag conservatively ensures that all financial statement data used in the attribute calculations is available to the public at the time of inclusion³. Unlike the return data, the financial statement information will have an annual rather than monthly periodicity. This, together with the conservative reporting lag, will bias the tests *against* finding significant results. Some of the financial ratios investigated include market prices in their construction and, thus, do have values that may vary on a monthly basis even if their financial statement component remains unchanged. Berk (1995) points out that because returns are mechanically related to prices, financial ratios that use stock prices in their construction may be automatically related to returns. This problem is

² The approach of standardising the regressor variables in the cross-section is used in the commercial risk models of the BARRA organisation, whose 1800 institutional clients in thirty-four countries collectively manage \$1.1 trillion.

³ The minimum lag is therefore five months, for firms reporting in December, while the maximum lag for firms reporting in January is seventeen months. The JSE requires all listed companies to make financial reports available within ninety days of their fiscal year end.

mitigated in this chapter since the financial ratios are lagged with respect to stock returns and contemporaneous relationships are therefore not being investigated.

For each attribute the regression is repeated in each month from July 1990 to June 2000. The time series of cross-sectional coefficients measured in this way are recorded and represent the monthly reward or payoff to each attribute⁴. Candidate attributes for further multifactor testing are identified as those attributes where the time-series average cross-sectional coefficient is significantly different from zero using a Student's *t*-test over the period July 1990 to June 2000⁵.

To determine whether the attributes can explain stock returns beyond that already explained by market beta, a CAPM-based risk adjustment is conducted on the data set of stock returns. Conducting the risk adjustment by first allowing the market and only thereafter the attributes to explain returns is conservative in favour of the market. Using a time series OLS regression across the full sample period, the excess return of each stock is regressed on the excess return of the market⁶. The monthly error term for each stock is recorded and added to the time series intercept term:

$$(\alpha_i + \varepsilon_{i,t}) = (r_{i,t} - r_{f,t}) - \beta_i (r_{m,t} - r_{f,t}) \quad (5.2)$$

Where the monthly error term, $\varepsilon_{i,t}$, is scaled by the time series intercept term, α_i , to provide an expression of the total return, $(\alpha_i + \varepsilon_{i,t})$, for stock i in month t that is not explained by beta, β_i . $r_{i,t}$ and $r_{m,t}$ is the respective return on stock i and the return on the market for month t . $r_{f,t}$ is the risk-free rate of return for month t . By substituting $(\alpha_i + \varepsilon_{i,t})$ from equation (5.2) for $r_{i,t+1}$ in equation (5.1), the univariate cross-sectional regressions of CAPM risk adjusted stock returns on individual attribute values can be restated as:

$$(\alpha_i + \varepsilon_{i,t}) = \gamma_{0,t+1} + \gamma_{1,t+1} A_i + \varepsilon_{i,t+1} \quad (5.3)$$

⁴ The cross-sectional regressions in this chapter are conducted using Minitab v13.1 statistical software. The instruction code sets used by Minitab v13.1 are generated using Microsoft Visual Basic v6.0.

⁵ The *t*-statistic for n observations of variable x is calculated as: $t = (\bar{x}\sqrt{n})/\sigma_x$

⁶ The return of the JSE All Share index is used as the return of the market. The risk-free asset is the 3 month T-Bill.

To determine whether the attributes have explanatory power beyond the risk factors in an APT model, all attributes are re-tested using a data set of stock returns that has been modified using the two factor APT model suggested by van Rensburg (2002). As explained in Chapter Three, using the JSE Financial and Industrial index and JSE Resources index as observable proxies for the first two factor-analytic components of stock returns, the following time series expression is estimated across the sample period using OLS:

$$(\alpha_i + \varepsilon_{i,t}) = (r_{i,t} - r_{f,t}) - \beta_{findi,i}(r_{findi,t} - r_{f,t}) - \beta_{resi,i}(r_{resi,t} - r_{f,t}) \quad (5.4)$$

Where, as before, the monthly error term, $\varepsilon_{i,t}$, is scaled by adding the time series intercept term, α_i , to provide an expression of the total return, $(\alpha_i + \varepsilon_{i,t})$, that is not explained by the two factors in the APT model. $\beta_{findi,i}$ and $\beta_{resi,i}$ are the respective time series estimates of the sensitivities of stock i to the return on the JSE Financial and Industrial index, $r_{findi,t}$, and the return on the JSE Resources index, $r_{resi,t}$ in month t . As with the CAPM risk adjustment, $(\alpha_i + \varepsilon_{i,t})$ from equation (5.4) is substituted for $r_{i,t+1}$ in equation (5.1) and the univariate cross-sectional regressions of APT risk adjusted stock return on individual attribute values takes a similar form to equation (5.3).

To determine which candidate attributes can be used together in a multifactor cross-sectional model, all permutations of pairs of candidate attributes are regressed simultaneously in a two factor cross-sectional regression:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1}A_t + \gamma_{2,t+1}B_t + \varepsilon_{i,t+1} \quad (5.5)$$

Where the pair of candidate attributes are labeled A_t and B_t with $\gamma_{1,t+1}$ and $\gamma_{2,t+1}$ being the respective cross-sectional coefficients to be estimate using OLS. Next, all permutations of significant pairs of candidate attributes together with an additional candidate attribute are tested in a three factor cross-sectional model. In turn, the procedure is repeated in a four factor model with all permutations of three significant candidate attributes plus an additional candidate attribute. This procedure continues until a final model is identified whereby no more candidate attributes can be added without some or all of the existing candidate attributes losing their joint significance.

5.3 Empirical results

The empirical results in this chapter are reported in two sections. The first section reports the univariate regression results while the second section derives a multifactor cross-sectional model for the JSE.

5.3.1 Univariate regression results

The results of the univariate cross-sectional regressions of non-thinly traded stock returns on individual attributes are reported in Table 5.1. Panel A contains the results using unadjusted stock returns, Panel B contains the results after conducting a CAPM risk adjustment and Panel C contains the results after conducting an APT risk adjustment. In each of the three panels, the average coefficient values from July 1990 through June 2000 and their associated t-statistics for all attributes are reported in descending order of significance⁷.

The results from unadjusted stock returns in Panel A show evidence of a significant value effect under which the attributes cashflow-to-price, dividend yield, price-to-earnings, price-to-profit and price-to-NAV may be classified. Evidence of a small firm effect is also observed over the sample period. Unlike the findings of Fraser and Page (2000) and van Rensburg (2001) who confine their analysis to the industrial sector of the JSE, none of the measures of price momentum are found to be cross-sectionally significant.

After conducting a risk adjustment of the stock returns data set using the CAPM, the same list of candidate attributes except for price-to-profit are significant above the ninety-five percent level of confidence, shown in Panel B. While there is some variation in the ordering of the attributes when ranked in descending order of the t-statistics, the payoffs are of similar magnitudes. For the price-to-NAV and size attributes the t-statistics are higher after the CAPM risk adjustment, indicating that a risk adjustment improves the relationship between these attributes and stock returns.

⁷ In other results obtained using both thinly traded and non-thinly traded stocks, five candidate factors are identified. These are the same candidate attributes generated by the non-thinly traded sample with the exception of the price-to-profit attribute

Table 5.1 Monthly cross-sectional regressions.

The average monthly cross-sectional coefficients from July 1990 to June 2000 are reported for each attribute. The coefficients are estimated using univariate cross-sectional regressions of non-thinly traded stock returns, CAPM risk-adjusted stock returns and APT risk-adjusted stock returns on individual attributes. Figures in bold indicate where the time series of cross-sectional coefficients is significant above the ninety-five percent level of confidence.

Panel A: Monthly cross-sectional regressions					
	Average coefficient	t-statistic		Average coefficient	t-statistic
Price-to-NAV	-0.007	-3.699	Return-on-equity	-0.022	-0.773
Dividend yield	0.016	3.530	Owners interest	-0.001	-0.645
Price-to-earnings	-0.007	-3.322	Trading volume	-0.001	-0.566
Size	-0.007	-3.208	Debt-to-equity	0.003	0.549
Cashflow-to-price	0.019	2.513	Sustainable growth	-0.005	-0.479
Price-to-profit	-0.003	-2.050	LT Loans-to-assets	-0.001	-0.389
Retention rate	0.382	1.485	Twelve months prior	-0.001	-0.306
Debt-to-asset	-0.028	-1.331	Current ratio	-0.001	-0.266
Leverage	-0.018	-1.218	Quick ratio	-0.001	-0.247
Return-on-assets	-0.190	-0.902	Debt-to-cashflow	-0.001	-0.031
Shares in issue	-0.190	-0.902	Six months prior	0.713	0.012
Financial distress	0.014	0.834	One month prior	-0.305	0.008

Panel B: Monthly cross-sectional regressions using CAPM risk adjusted stock returns.					
	Average coefficient	t-statistic		Average coefficient	t-statistic
Price-to-NAV	-0.007	-3.748	Debt-to-equity	0.004	0.800
Size	-0.006	-3.590	Six months prior	0.002	0.745
Price-to-earnings	-0.007	-3.277	Owners interest	-0.001	-0.660
Dividend yield	0.022	3.208	Trading volume	-0.001	-0.469
Cashflow-to-price	0.019	2.489	Sustainable growth	-0.005	-0.440
Price-to-profit	-0.003	-1.766	Shares in issue	0.001	0.433
Retention rate	0.422	1.589	One month prior	-0.001	-0.335
Debt-to-assets	-0.027	-1.308	LT Loans-to-assets	-0.001	-0.327
Return-on-assets	-0.179	-0.978	Debt-to-cashflow	-0.007	-0.299
Leverage	-0.011	-0.933	Current ratio	-0.001	-0.274
Financial distress	0.015	0.906	Quick ratio	-0.001	-0.252
Return on equity	-0.023	-0.809	Twelve months prior	0.000	-0.214

Panel C: Monthly cross-sectional regressions using APT risk adjusted stock returns					
	Average coefficient	t-statistic		Average coefficient	t-statistic
Price-to-NAV	-0.008	-3.803	Six months prior	0.002	0.713
Price-to-earnings	-0.007	-3.322	Owners interest	-0.001	-0.645
Size	-0.007	-3.208	Debt-to-equity	0.003	0.549
Dividend yield	0.021	3.090	Trading volume	-0.001	-0.415
Cashflow-to-price	0.021	2.729	Twelve months prior	-0.001	-0.306
Price-to-profit	-0.003	-2.050	LT Loans-to-assets	0.000	-0.294
Retention rate	0.382	1.485	Shares in issue	0.000	0.249
Return on assets	-0.262	-1.419	Current ratio	-0.001	-0.247
Debt-to-asset	-0.028	-1.331	Quick ratio	-0.001	-0.247
Leverage	-0.015	-1.191	Sustainable growth	-0.002	-0.164
Financial distress	0.017	1.034	One month prior	0.000	0.057
Return on equity	-0.023	-0.817	Debt-to-cashflow	-0.001	-0.034

After conducting an APT risk adjustment, the results shown in Panel C indicate that the time series average cross-sectional coefficients and t-statistics are similar in magnitude to those obtained after conducting a CAPM risk adjustment. This result is similar to Page (1996:41) who observes that “...any model misspecification within the CAPM framework is clearly not removed by adopting an APT approach”. For the price-to-earnings, size and price-to-profit attributes, the magnitude of the average coefficients and t-statistics in Panel C are identical to the results from the unadjusted stock returns data set reported in Panel A. This suggests that these attributes do not contain information about either of the risk factors in the two factor APT model.

Overall, the results in this section suggest that either the candidate attributes proxy for yet unnamed risk factors on the JSE or are sources of mispricing⁸. Full results from the cross-sectional regressions of stock returns on individual attributes are reported on a year-by-year basis in Appendix C in a descending order of significance. The year-by-year results of the cross-sectional regressions of the CAPM and APT risk adjusted stock returns on individual attributes show mostly similar results and are therefore omitted from Appendix C for brevity.

5.3.2 Construction of a multifactor model

In anticipation of issues of multicollinearity, the time series correlation of the monthly coefficients of the candidate attributes is inspected⁹. As shown in Table 5.2, if the candidate attributes are rearranged so that price is the numerator, most of the coefficients of the value attributes of cashflow-to-price, dividend yield, price-to-earnings, price-to-profit and price-to-NAV are positively correlated to varying degrees.

The rewards to small size and value attributes are positively correlated. The weakest of these relations is between size and price-to-profit and price-to-earnings. The strongest correlations, being between dividend yield and size and dividend yield and cashflow-to-price, can possibly

⁸ This question is directly addressed in Chapter Eight.

⁹ A correlation matrix of the attributes, as opposed to the coefficients of the attributes, is report in Appendix D.

be explained by the likelihood that smaller companies tend to be at a stage in their lifecycle where a larger portion of earnings are retained to finance future growth.

Table 5.2 Correlation matrix of the time series of coefficients of candidate attributes.

The coefficients represent the average monthly Pearson product correlations from July 1990 to June 2000. Figures in bold indicate significant correlation where the coefficients have an associated p-value of <0.05 (p-values are not shown in the table).

	Price to NAV	Dividend yield	Price to earnings	Size	Cashflow to price	Price to profit
Price-to-NAV	1.00	-0.09	0.08	0.21	-0.12	0.06
Dividend yield		1.00	-0.08	-0.35	0.43	-0.09
Price-to-earnings			1.00	0.17	-0.05	0.29
Size				1.00	-0.24	0.06
Cashflow-to-price					1.00	-0.02
Price-to-profit						1.00

When all possible permutations of paired candidate attributes are tested using a two factor cross-sectional regression, only one pair of candidate attributes, size and price-to-earnings is found to be jointly significant. This is despite price-to-NAV being the most significant value factor on a univariate basis. While Page and Palmer (1993) are the first to consider the joint influence of the size and price-to-earnings attributes on the JSE, this chapter provides the first evidence in a cross-sectional framework conducted at the stock level¹⁰. More importantly, the size and price-to-earnings attributes are not chosen based on any prior empirical precedent, but instead are distilled from an original set of twenty-four attributes. After further tests, it is found that no additional candidate attribute can be added to the size and price-to-earnings pair without eroding the explanatory power of one or both of these attributes. The final cross-sectional model that is derived for the JSE therefore consists of a two factor attribute-based model employing size and price-to-earnings as the explanatory variables, as shown in Table 5.3.

The negative sign on both coefficients indicate that small size and low price-to-earnings effects operate concurrently in the cross-section of stock returns on the JSE from July 1990 to June 2000. Note that, since the cross-sectional regressions are conducted at the individual stock level, the R-Squared term indicates the average variation in a single stock's returns that

¹⁰ Page and Palmer (1993) use the inverse earnings-to-price attribute and adopt the portfolio approach.

is explained by the attributes operating together. This will always be considerably lower than when the research design employs groups or portfolios of stocks sorted by the attribute concerned.

Table 5.3 Final cross-sectional model for the full cross-section of stock returns.

Cross-sectional coefficients that are significantly different from zero above the above the 95% for the 120 months from July 1990 to June 2000 level are indicated in bold.

	Average coefficient	t-statistic	R-Squared
Size	-0.005	-2.112	1.11%
Price-to-earnings	-0.005	-2.481	

5.4 Summary and conclusion

This chapter investigates the cross-sectional influence of firm-specific attributes on JSE stock returns. In each month from July 1990 to June 2000 non-thinly traded stock returns are regressed on twenty-four individual attributes, most of which are financial ratios. The attributes are conservatively lagged with stock returns to ensure the financial statement information is publicly available at the time of inclusion. It is found that price-to-NAV, dividend yield, price-to-earnings, cashflow-to-price, price-to-profit and size all have individual predictive power in the cross-section of stock returns. The lag in the attribute data also reduces the possibility that the explanatory power of these attributes is linked to a contemporaneous relationship between stock price, used to calculate the attribute values, and stock returns.

In contrast to the findings from previous studies on the JSE, albeit through a different methodology, no evidence of any momentum effects are identified. Multifactor tests suggest a two factor cross-sectional model with the size and price-to-earnings attributes as independent variables. It appears that the small size and low price-to-earnings effects are at least qualitatively similar to those documented in Page and Palmer (1993) and van Rensburg (2001). The results are also broadly in agreement with the emerging market evidence,

presented by Bekaert, Erb and Viskanta (1997), showing that stock returns can be described by market capitalisation relative to GDP, inflation and the price-to-earnings multiple¹¹.

The theoretical implications of the findings are that stock returns on the JSE do not strictly follow a random walk since they are mildly predictable using certain firm-specific attributes. As explained in Chapter Two, this in itself does not imply the JSE is inefficient nor does it necessarily constitute a rejection of the EMH. As stated by Fama (1970), such a judgment would require a model of asset prices against which the explanatory power of the candidate attributes can be evaluated. Therefore, the CAPM and the two-factor APT suggested by van Rensburg (2002) are given the opportunity to explain JSE returns, followed only then by the attributes. It is found that the explanatory power of the attributes is robust to a risk adjustment by the CAPM and APT. This confirms the earlier time-series results of Page (1993:6-19): “...the evidence is that none of the APT based models was able to explain anomalies any better than the CAPM”. It is concluded that stock returns on the JSE are not fully explained by single or multifactor sources of risk. Rather it is attributes that explain expected returns. What has been achieved therefore in this chapter is an empirically derived model of cross-sectional JSE returns that at present is void of theoretical backing.

¹¹ In contrast with the stock-level attribute data used in this thesis, Bekaert, Erb and Viskanta (1997) compare the cross-sectional relationships between attributes and returns at the *country-level* for twenty-seven emerging markets.

A Sectoral Comparison of Attributes and the Cross-Section of Equity Returns

6.1 Introduction

The previous chapter identifies six attributes from a set of twenty-four that are individually related to the cross-section of monthly stock returns on the JSE from July 1990 to June 2000. However, a comparison of the distributional properties of the attributes, presented in Chapter Four, suggests that the economic interpretation of certain attributes is not uniform across sectors. The focus of this chapter is to determine the degree to which the attributes that explain the cross-section of stock returns in the financial, industrial and resource sectors of the market are similar to those documented for all stocks¹.

While previous studies such as Fraser and Page (2000), Graham and Uliana (2001) and van Rensburg (2001) *inter alia* investigate the relationship between different sets of attribute data and industrial stock returns, no previous research has contrasted the results between the major sectors of the JSE. This chapter therefore augments the literature in this regard and is of particular interest given the evidence reviewed in Chapter Three that shows a resource and financial-industrial dichotomy in the return generating processes of the JSE. The remainder of the chapter is set out as follows. Section 6.2 provides an overview of the data and methodology used to construct the empirical test framework. Section 6.3 presents the empirical results and Section 6.4 summarises and concludes.

6.2 Data and methodology

Using a similar cross-sectional procedure to Chapter Five, the relationship between the individual twenty-four attributes in Table 4.3 and non-thinly traded stock returns in the

¹ This chapter is the originating work for elements of the article: The interaction between sectors, styles and JSE Securities Exchange returns, *Working paper*, 2002, School of Management Studies, University of Cape Town.

financial, industrial and resource sectors of the JSE is examined. As before, to conservatively ensure that all financial statement data used is available to the public at the time of inclusion, the attributes in each sector are lagged so that the accounting data for all fiscal year-ends in calendar year $t - 1$ is aligned with the returns for May of year t . After modifying the attribute data set as described in Chapter Four, all attribute values in each sector are standardised in each month to allow direct comparisons to be made between the magnitudes of the average cross-sectional coefficients in the regressions that follow.

A dummy-coded coefficient and separate dummy-coded intercept term is inserted into the cross-sectional regression in each month from July 1990 to June 2000 to flag sector membership in a single expression:

$$r_{i,t+1} = \gamma_{0,t+1} + D \cdot \gamma_{1,t+1} + \gamma_{2,t+1} A_t + \gamma_{3,t+1} (D \cdot A_t) + \varepsilon_{i,t+1} \quad (6.1)$$

Where the dependant variable is $r_{i,t+1}$ and represents the realised return on stock i for the month t . $\gamma_{0,t+1}$ and $D \cdot \gamma_{1,t+1}$ are the intercept and dummy-coded intercept terms respectively. The independent variables in the regression are denoted as A_t , the attribute of the stock that is available at the beginning of each month, and $(D \cdot A_t)$, the product of the dummy variable and the attribute. $\gamma_{1,t+1}$ and $\gamma_{2,t+1}$ are the cross-sectional coefficients to be estimated using OLS².

Initially, the dummy variable takes on a value of one for resource stocks and zero otherwise. This evaluates the relationship between the attribute under consideration and the return on financial and industrial stocks while simultaneously testing whether additional reward accrues to resource stocks. To test the direct relationship between the attributes and resource stocks, a set of univariate cross-sectional regressions without the dummy variables is conducted over the sample period for resource stocks only.

² The cross-sectional regressions in this chapter are conducted using Minitab v13.1 statistical software. The instruction code sets used by Minitab v13.1 are generated using Microsoft Visual Basic v6.0.

The sample is then reduced to only financial and industrial stocks and the dummy variable is assigned a value of one for financial stocks and zero for industrial stocks. This tests the relationship between the attribute under consideration and the return on industrial stocks while simultaneously testing whether extra reward accrues to financial stocks. Financial stocks are then tested in isolation. In this manner, each of the major JSE sectors is examined individually and the conglomerate sectors, for all shares and financial and industrial shares, are compared across their primary subcomponents³.

6.3 Empirical results

What follows are the empirical results from the cross-sectional regressions conducted to assess the relationship between the attributes and non-thinly traded stock returns within the financial, industrial and resource sectors. Presentation of the results are organised to allow for a contrast to be drawn between the financial-industrial and resource sectors and then between the financial and industrial sectors.

6.3.1 The financial-industrial and resource sectors

As described in the methodology section, a dummy variable technique is used to compare the magnitudes of the regression coefficients associated with the attributes across the financial-industrial and resource sectors of the JSE. The dummy variable takes a value of one for resource stocks and a value of zero for financial and industrial stocks. As a consequence, the coefficient values on the left hand side of Table 6.1 are equivalent to those when the sample is restricted to only financial and industrial shares.

These results indicate six attributes are cross-sectionally related to stock returns. The first four attributes, in descending order of significance, are all measures of value namely cashflow-to-price, price-to-NAV, price-to-earnings and dividend yield. Similar to the results presented for the full cross-section of stocks returns in Chapter Five, the coefficients of these attributes indicate that greater returns are again associated with stocks that have higher measures of value. The fifth attribute, return on assets, shows that financial and industrial

³ To complete all the tests in this chapter required a total of 11,640 regressions.

stocks with a low return on assets have, on average, higher returns. Lastly, the negative average coefficient for the size attribute shows that smaller stocks outperform larger stocks over the sample period.

Table 6.1 Monthly cross-sectional regressions for all stocks using a dummy variable to code for resource stocks.

Attributes shown in bold are those attributes where the time-series of their cross-sectional coefficients for the first variable are significantly different from zero above the above the ninety-five percent for the 120 months from July 1990 to June 2000. Results are ranked in descending order of the absolute value of the t-statistics for the non-dummy-coded attribute. The dummy takes a value of zero for financial and industrial stocks and one for resource stocks.

	Average variable coefficient	t-statistic	Average dummy coefficient	t-statistic
Cashflow-to-price	0.052	3.972	-0.036	-1.818
Price-to-NAV	-0.011	-3.681	0.011	1.714
Price-to-earnings	-0.011	-3.594	-0.001	-0.155
Dividend yield	0.017	3.587	0.008	0.370
Return on assets	-1.053	-2.711	1.381	1.968
Size	-0.006	-2.565	0.001	0.301
Leverage	-0.030	-1.821	0.643	1.447
Return on equity	-0.050	-1.685	0.122	0.933
Retention rate	0.431	1.599	0.218	0.682
Current ratio	0.017	1.361	-0.025	-1.616
Price-to-profit	-0.002	-1.297	0.007	0.217
Quick ratio	0.015	0.970	-0.023	-1.269
Financial distress	0.018	0.877	-0.033	-0.551
Owners equity	-0.001	-0.638	0.001	0.443
Shares in issue	0.001	0.596	-0.002	-0.683
Six month prior	0.001	0.464	0.002	0.355
Debt-to-assets	-0.012	-0.318	0.014	0.363
Twelve month prior	-0.001	-0.296	0.002	0.388
Debt-to-equity	-0.002	-0.277	0.054	0.411
Debt-to-cashflow	-0.005	-0.261	0.525	0.542
One month prior	0.000	0.147	-0.003	-0.690
Long term loans-to-assets	0.000	-0.142	-0.004	-1.355
Trading volume	0.000	0.091	-0.003	-0.654
Sustainable growth	0.000	0.031	-0.010	-0.381

Inspecting the dummy coefficients associated with each attribute indicates whether, on average, resource stocks earned a reward beyond that of financial and industrial stocks for being exposed to that attribute. As can be seen in Table 6.1, significant extra reward, almost at the ninety-five percent level, accrues to resource stocks that have higher return on asset ratios. The only other meaningful dummy coefficients are evident among the value indicators

of cashflow-to-price and price-to-NAV. The reverse signs of these coefficients indicate that the value effect may be somewhat milder in the resource sector than in the financial-industrial sector. The size effect is not significantly different from that measured for the financial-industrial sector. While Table 6.1 reports the average for the full period, results for the year-on-year sub-periods can be inspected in Appendix E.

Next, all financial and industrial stocks are deleted from the sample leaving only resource stocks to be tested in a set of univariate cross-sectional regressions. The results for the resource sector are presented in Table 6.2. While no relationship above the ninety-five percent level exists between any of the attributes and stock returns, there is some evidence of a weak small size and even weaker value effect. Like the financial-industrial sector, the prominent indicators of value include cashflow-to-price and price-to-earnings. As with the other sectors, small firms outperform large firms and higher value outperforms lower value.

Table 6.2 Monthly cross-sectional regressions for resource stocks.

Attributes shown in bold, are those attributes where the time-series of their cross-sectional coefficients are significantly different from zero above the above the ninety-five percent for the 120 months from July 1990 to June 2000. Results are ranked in descending order of the absolute value of the t-statistics.

	Average coefficient	t-statistic		Average coefficient	t-statistic
Size	-0.005	-1.915	Current ratio	-0.002	-0.549
Retention rate	0.666	1.795	Return on assets	0.096	0.544
Price-to-earnings	-0.013	-1.750	6 months prior	0.004	0.533
Cashflow-to-price	0.022	1.602	Shares in issue	-0.002	-0.506
LT Loans-to-assets	-0.005	-1.541	Debt-to-equity	0.061	0.504
Leverage	0.941	1.496	Quick ratio	-0.002	-0.424
Dividend yield	0.025	1.106	Sustainable growth	-0.009	-0.404
Price-to-NAV	-0.003	-0.948	Debt-to-asset	0.003	0.401
Trading volume	-0.001	-0.641	12 months prior	0.001	0.306
Return-on-equity	0.034	0.627	Owners interest	0.000	-0.217
Debt-to-cashflow	0.493	0.599	Financial distress	-0.012	-0.199
1 month prior	-0.002	-0.574	Price-to-profit	0.007	0.168

The comparatively small number of firms in this sector, shown in Table 4.2, is perhaps part of the reason for the weaker relationships. The resources sector is also not composed of a homogenous set of macroeconomic drivers. For example, platinum shares will respond to movements in the platinum price while gold shares will react to the gold price. These

movements will be independent of any common fundamental attributes that the companies may exhibit. While the retention rate makes a surprise appearance as one of the more significant attributes, overall there is no evidence that the attributes related to resource stock returns are substantially different in identity or sign from those documented for the rest of the JSE. Year-on-year results are in Appendix F.

6.3.2 The financial-industrial sector

In this portion of the analysis the sample is restricted only to stocks in the financial-industrial sector and the average cross-sectional attribute coefficients are compared across the financial and industrial subcomponents. Table 6.3 shows the results of cross-sectional regressions of stock returns on individual attributes where a dummy variable is assigned a value of one for financial stocks and zero for industrial stocks. Thus, the first column of average attribute coefficients and t-statistics in Table 6.3 is equivalent to the results that would be obtained when directly testing the attributes on industrial stocks only. Sub-period results are in Appendix G.

Table 6.3 Monthly cross-sectional regressions for financial-industrial stocks using a dummy variable to code for financial stocks.

Attributes shown in bold are those attributes where the time-series of their cross-sectional coefficients for the first variable are significantly different from zero above the above the ninety-five percent for the 120 months from July 1990 to June 2000. Results are ranked in descending order of the absolute value of the t-statistics for the non-dummy coded attribute. The dummy takes a value of zero for industrial stocks and one for financial stocks.

	Average attribute coefficient	t-statistic	Average dummy coefficient	t-statistic
Price-to-NAV	-0.007	-4.710	0.002	0.165
Cashflow-to-price	0.021	3.327	-0.004	-0.333
Price-to-earnings	-0.007	-3.034	-0.018	-1.797
Size	-0.007	-2.917	0.000	-0.146
Dividend yield	0.015	2.819	0.014	0.567
LT Loans-to-assets	-0.003	-2.171	0.008	1.529
Return on assets	-1.454	-2.040	-0.647	-0.238
Price-to-profit	-0.003	-2.027	-1.432	-2.541
Retention rate	0.450	1.769	-0.640	-1.119
Debt-to-equity	-0.010	-1.623	0.047	2.294
Debt-to-assets	-0.045	-1.225	-0.062	-0.735
Owners interest	-0.002	-0.834	0.000	0.165
Return on equity	0.011	0.730	-0.119	-0.873
Financial distress	-0.008	-0.663	0.021	0.722

Table 6.3 Continued.

	Average attribute coefficient	t-statistic	Average dummy coefficient	t-statistic
Shares in issue	0.001	0.583	-0.003	-0.854
Sustainable growth	0.007	0.573	0.026	0.877
Debt-to-cashflow	0.013	0.572	-0.321	-0.909
Twelve month prior	-0.001	-0.337	0.002	0.415
Leverage	0.004	0.229	-0.102	-0.452
Six month prior	0.001	0.201	0.010	0.878
Quick ratio	-0.001	-0.173	0.001	0.256
Current	-0.001	-0.166	0.001	0.286
One month prior	0.000	0.039	0.001	0.196
Trading volume	0.000	-0.018	0.008	0.908

The results for the industrial sector show that eight attributes are cross-sectionally related to stock returns. In addition to the six variables listed for the financials-industrial sector, price-to-profit and long term loans-to-assets also significantly influence the cross-section of returns, both being associated with negative coefficients. Unlike van Rensburg (2001), who also conducts his analysis on the industrial sector only, no evidence of any cross-sectional association between industrial stock returns and indicators of lagged momentum is found. The column of dummy coefficients in Table 6.3 measures the extra reward that accrues to financial stocks beyond that of industrial stocks in the case of each attribute. The results show that financial stocks with low price-to-profit ratios earn additional return over their industrial counterparts. Perhaps more importantly, financial stocks with high ratios of debt-to-equity earn a premium over their industrial counterparts.

The association of the debt-to-equity and price-to-profit attributes with financial stock returns is confirmed in the subsequent set of univariate cross-sectional regressions conducted on financial stocks only, as shown in Table 6.4. Full results for all sub-periods are reported in Appendix H. As with the other sectors, the value indicators of price-to-earnings and cashflow-to-price emerge as significant along with a small firm effect. Dividend yield and price-to-NAV are noticeably absent as significant influences. Only in the financial sector is an attribute that incorporates levels of debt significantly positively related to stock returns. Read together with the results of the debt-to-equity ratio in Table 6.3, this points to the Fama and French (1992) observation that higher levels of debt have a different meaning in the context of a financial firm. High debt levels are likely to coincide with growth in deposits,

which is generally indicative of financial prosperity for banks. Also recall that in the descriptive statistics reported in Chapter Four, the mean and median values of the attributes that incorporate levels of debt are markedly higher for financial stocks.

Table 6.4 Monthly cross-sectional regressions for financial stocks.

Attributes shown in bold, are those attributes where the time-series of their cross-sectional coefficients are significantly different from zero above the above the ninety-five percent for the 120 months from July 1990 to June 2000. Results are ranked in descending order of the absolute value of the t-statistics.

	Average coefficient	t-statistic		Average coefficient	t-statistic
Cashflow-to-price	0.052	2.597	Debt-to-asset	-0.070	-0.849
Price-to-profit	-1.335	-2.553	Return on assets	-1.840	-0.764
Size	-0.008	-2.208	Financial distress	0.021	0.704
Price-to-earnings	-0.033	-2.156	Retention rate	-0.259	-0.694
Debt-to-equity	0.044	2.102	Trading volume	0.005	0.551
6 months prior	0.015	1.925	Current ratio	0.007	0.541
Sustainable growth	0.052	1.537	12 months prior	0.001	0.386
Owners interest	-0.002	-1.265	Shares in issue	0.000	-0.294
Dividend yield	0.027	1.098	Quick ratio	0.003	0.256
Return on equity	-0.454	-1.077	1 month prior	0.001	0.169
LT Loans-to-assets	0.005	1.002	Price-to-NAV	-0.005	-0.080
Debt-to-cashflow	-0.309	-0.880	Leverage	0.008	0.063

6.4 Summary and conclusion

The results presented in this chapter provide new evidence on the JSE that small size and a collection of value measures are, to varying degrees of intensity, positively related to the cross-section of stock returns across all of the major sectors. On average, the value effects are stronger in the financial-industrial sector than in the resource sector. On a univariate basis, the small size effect is roughly the same across sectors. Unlike in the financial-industrial sector, attributes associated with growth such as high return on assets and retention rates tend to be positively rewarded in the resource sector. The premium earned by higher debt levels is negative across all sectors except the financial sector where it is positively rewarded on average.

The overall results correspond to the observation in Chapter Four that higher levels of debt among deposit taking institutions does not indicate financial distress in the same sense as for

non-financial firms. The results also support the international evidence that shows small size and value earn a premium in both in developed and emerging markets (Bekaert, Erb and Viskanta (1997), Fama and French, 1998, Patel, 1998 and Rouwenhorst, 1999, inter alia).

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Size, Price-to-Earnings and Beta

7.1 Introduction

As shown in Chapter Five, size and price-to-earnings are the only two attributes from a set of twenty-four that are jointly significant in the full cross-section of stock returns on the JSE from July 1990 to June 2000. Chapter six re-examines all twenty-four attributes individually across the financial, industrial and resource sectors of the JSE and concludes that, to varying degrees, the size and price-to-earnings attributes are broadly applicable in these sectors. For reasons explained in Chapter Two, the empirical results documented so far in this thesis stand contrary to the predictions of the CAPM that postulates market beta alone ought to be able to explain the cross-section of stock returns.

Using a methodology akin to the periodic multi-dimensional portfolio sorting technique of Fama and French (1992), this chapter explicitly investigates the ability of beta to explain the cross-section of stock returns on the JSE in the presence of the small size and low price-to-earnings effects¹. The interaction between the small size and low price-to-earnings effects is also investigated. The remainder of the chapter is set out as follows. Section 7.2 discusses the data and methodology, Section 7.3 presents the empirical results and Section 7.4 summarises and concludes.

7.2 Data and methodology

To ensure that due consideration is given to the financial-industrial and resource dichotomy on the JSE, discussed in Chapter Three, the empirical work in this chapter is conducted first using a sample of all stocks and then repeated using a sample of financial-industrial (Findi)

¹ This chapter is the originating work for the article: Size, price-to-earnings and beta on the JSE, *Working paper*, 2002, School of Management Studies, University of Cape Town.

stocks. This approach is necessary since the small number of stocks in the resource sector, shown in Table 4.2, makes a direct examination of this sector unfeasible using the methodology described below.

In addition to the size and price-to-earnings attributes, a monthly *pre-ranking* beta attribute is calculated for all non-thinly traded stocks in both samples from July 1990 to June 2000². The pre-ranking beta is the single estimated coefficient from an OLS time series regression of the return of each stock on a market proxy using information available up to that time. The market proxy is taken as the JSE All Share index and JSE Financial and Industrial index for the all stocks and Findi samples respectively. As explained in Chapter Two, the JSE All Share index adequately fulfills the role of a market proxy in practical applications of the CAPM. Similar to Fama and French (1992), the pre-ranking beta estimates are calculated on a rolling-window basis using an increasing history of between twelve months, for July 1990, and thirty months from January 1992 onwards. For the all stocks and Findi samples, the size, price-to-earnings and pre-ranking beta attributes are matched with stock returns in each month. Consistent with the previous chapters, the price-to-earnings attribute is lagged to ensure the underlying accounting data is publicly available at the time of inclusion³.

The methodology employed in this chapter moves away from the stock-level cross-sectional techniques of Chapters Five and Six and adopts a procedure that creates simulated portfolios. Sorting stocks into simulated portfolios, as described below, allows several dimensions of stock returns to be examined simultaneously. Analysing the time series of simulated portfolio returns allows the role of the sorting criteria to be examined while considering the role of beta.

While Fama and French (1992) reconstitute their portfolios annually on the anniversary of the first formation date, the simulated portfolios created in this chapter are reconstituted *monthly*. This ensures that only the most up-to-date information is being used in the

² The term pre-ranking beta differentiates this beta from the post-ranking beta introduced later.

³ The monthly data sorting and portfolio simulations in this chapter are conducted using Minitab v13.1 statistical software. The programming script, sub-routines and instruction code sets used by Minitab are assembled using Microsoft Visual Basic v6.0.

construction of the portfolios thereby reducing the chance of any information being lost⁴. Using a periodic one-way and two-way quintile stock ranking methodologies that is procedurally similar to Fama and French (1992), the portfolios in this chapter are created using permutations of the size, price-to-earnings and pre-ranking beta attributes in each month from July 1990 to June 2000. Transaction costs are not accounted for.

For a one-way sort procedure, stocks are ranked each month in descending order of the attribute under consideration. Quintile breakpoints are then inserted in the ranking at twenty, forty, sixty and eighty percent, allowing all stocks to be assigned to one of five quintiles. Using the stocks in each quintile at the end of each month, an equal-weighted portfolio is prepared and rolled forward to the end of the following month. In this way, a time series of monthly returns is generated for each of the five quintile portfolios. A *post-ranking* beta is also estimated for each simulated portfolio by regressing the return of each portfolio in the all stocks and Findi samples on their respective market proxies.

A two-way sort procedure allows two attributes to be examined concurrently. Stocks are first sorted in each month into quintiles by ranking on the first attribute under consideration as described above. Then, within each quintile, stocks are ranked in descending order of the second attribute under consideration. Again, inserting breakpoints in the ranked quintiles at twenty, forty, sixty and eighty percent results in twenty-five groups of stocks. This creates independent variation in each of the attributes thereby allowing the role of one attribute to be examined while holding the other constant. After creating portfolios from each group and calculating the monthly return, twenty-five time series are available for evaluation. As with the one-way sort procedure, a post-ranking beta is then estimated for each simulated portfolio.

Conducting two-way stock sorting procedures discussed above require a sample large enough to create portfolios with cross-sectional variation in the first attribute that is unrelated to the second. Table 7.1 shows the year-on-year average number of non-thinly stocks in the

⁴ In a preliminary investigation, the return of portfolios reconstituted at quarterly and six-monthly intervals were not meaningfully different from those reconstituted at monthly intervals.

monthly one-way and two-way sorted portfolios. The requirement that all price-to-earnings ratios are positive and that all stocks have a price-to-earnings ratio is the reason for fewer number stocks in the universe in Table 7.1 compared with Table 4.2.

Table 7.1 Average number of non-thinly traded stocks in the universe portfolio, first sort portfolio and second sort portfolio for all stocks and for Findi stocks.

The figures represents the average number of stocks in the universe portfolio, the first sort portfolios and the second sort portfolios for all months from July 1990 to June 2000 and for twelve-month sub-periods.

Panel A: All stocks											
Years	All	1	2	3	4	5	6	7	8	9	10
Universe	268	180	176	185	224	246	276	297	328	364	408
First sort	54	36	35	37	45	49	55	59	66	73	82
Second sort	11	7	7	7	9	10	11	12	13	15	16

Panel B: Findi stocks											
Years	All	1	2	3	4	5	6	7	8	9	10
Universe	234	152	150	158	194	214	240	259	287	325	365
First sort	47	30	30	32	39	43	48	52	57	65	73
Second sort	9	6	6	6	8	9	10	10	11	13	15

The average number of stocks in the second sort portfolios varies between seven and sixteen for the all stocks sample in Panel A and between six and fifteen for the Findi stock sample in Panel B. This is roughly comparable to the number of stocks in the Fama and French (1992) two-way sort portfolios where the average number of stocks per month in the largest seven size *deciles* of the size-beta sorted portfolios is between fifteen and forty-one. If the first and second sort portfolios had a prohibitively large number of stocks, it would be difficult to argue the suitability of asset pricing tests on portfolios that do not correspond to reasonably traded positions⁵. Whether or not the number of stocks in the second sort portfolios in the early months is sufficient in numbers to represent a diversified portfolio is a separate empirical question.

⁵ Some arguments supportive of this view are in Huberman, Shmuel and Stambaugh (1987).

7.3 Empirical results

In a preliminary test to assess the interaction between the explanatory variables and pre-ranking beta, the cross-sectional correlation between the size and price-to-earnings attributes and pre-ranking betas is calculated in each month from July 1990 to June 2000. Table 7.2 reports the average of the correlation coefficients over the full period and for each of the ten twelve-month sub-periods.

Table 7.2 Average cross-sectional correlations of the size, price-to-earnings and pre-ranking beta attributes.

Figures represent the average cross-sectional correlation over the all months from July 1990 to June 2000 and for twelve-month sub-periods. Bold indicates where the p-value of the Pearson product correlation coefficient is less than 0.05 (p-values are not shown in the table).

Panel A: Size and pre-ranking beta											
Years	All	1	2	3	4	5	6	7	8	9	10
All stocks	0.19	0.20	0.31	0.26	0.09	0.07	0.11	0.20	0.23	0.15	0.31
Findi stocks	0.29	0.31	0.38	0.40	0.37	0.33	0.28	0.25	0.19	0.16	0.17

Panel B: Price-to-earnings and pre-ranking beta											
Years	All	1	2	3	4	5	6	7	8	9	10
All stocks	-0.01	0.09	0.04	0.02	0.01	0.01	0.00	0.01	-0.04	-0.13	-0.08
Findi stocks	0.02	0.08	0.02	0.06	0.03	0.01	0.11	0.07	-0.06	-0.09	-0.06

Panel C: Size and price-to-earnings											
Years	All	1	2	3	4	5	6	7	8	9	10
All stocks	0.09	0.18	0.12	0.06	0.08	0.11	0.05	0.03	0.05	-0.01	0.04
Findi stocks	0.07	0.15	0.12	0.09	0.08	0.12	0.05	0.04	0.06	-0.01	0.03

Contrary to the findings of Fama and French (1992), the results in Panel A show that the size attribute on the JSE is significantly positively correlated to pre-ranking beta for both samples. For the all stocks sample, the full period monthly average correlation is significantly positive while six of the sub-periods also show significant positive correlations. For the Findi sample, the average correlation is stronger over the full period and significant in eight of the ten sub-periods. The price-to-earnings attribute is not significantly correlated with beta in either sample in Panel B. There is no evidence of a significant cross-sectional correlation between the size and price-to-earnings attributes over the sample or in any of the sub-periods except for the first, as shown in Panel C. Page (1993,6:14) makes a similar observation: "...there does not appear to be any consistent correlation between size and the E/P ratio for

the South African data". The full period average correlation between the two attributes is the same as that reported in Appendix D.

7.3.1 One-way quintile portfolio sorts on size, price-to-earnings and beta

Table 7.3 shows average returns and associated post-ranking betas from July 1990 to June 2000 for one-way quintile sorted portfolios created by ranking JSE stocks in each month by the size, price-to-earnings and pre-ranking beta attributes. The results are reported for both the all stocks sample and the Findi stock sample.

Table 7.3 One-way quintile portfolio sorts on the size attribute, price-to-earnings attribute and pre-ranking beta.

Returns figures, in percent, are the average monthly return of the equally-weighted portfolio for the 120 months from July 1990 to June 2000. Transaction costs are not accounted for. In Quintiles 1 to 5, post-ranking betas for the period are shown in parenthesis. In the last row of each panel, labeled Quintile (5-1), the return figures are the average monthly difference in return between Quintiles 5 and 1 and t is the Students t -statistic indicating whether, on average, the difference is significant. Significance above the ninety-five percent confidence level is indicated in bold. Big/Small relate to the size attribute while High/Low relate to the price-to-earnings attribute and pre-ranking beta. Figures 7.1, 7.2 and 7.3 show a graphical depiction.

Panel A: All stocks	Size	Price-to-earnings	Pre-ranking beta
Quintile 1 Big/High	1.22 (1.01)	1.02 (0.90)	2.07 (0.91)
Quintile 2	1.59 (1.00)	1.16 (0.88)	1.66 (0.79)
Quintile 3	1.61 (0.88)	1.39 (0.77)	1.99 (0.73)
Quintile 4	2.57 (0.86)	2.94 (0.60)	2.16 (0.64)
Quintile 5 Small/Low	3.73 (0.69)	4.36 (0.53)	2.98 (0.61)
Quintile (5-1)	2.50 $t=4.05$	3.33 $t=7.38$	0.90 $t=2.18$

Panel B: Findi stocks	Size	Price-to-earnings	Pre-ranking beta
Quintile 1 Big/High	1.54 (0.96)	1.16 (0.86)	2.23 (0.90)
Quintile 2	2.05 (0.80)	1.54 (0.86)	1.68 (0.80)
Quintile 3	1.65 (0.74)	1.82 (0.72)	1.97 (0.66)
Quintile 4	2.54 (0.66)	2.90 (0.60)	2.97 (0.62)
Quintile 5 Small/Low	4.10 (0.50)	4.66 (0.61)	2.87 (0.59)
Quintile (5-1)	2.56 $t=3.86$	3.49 $t=6.58$	0.64 $t=1.38$

For the size sorted quintile portfolios in the all stocks sample in Panel A, the spread in average return between the smallest quintile sorted portfolio and the largest quintile sorted portfolio is 2.50% per month with a t -statistic of 4.05. Smaller quintile sorted portfolios outperform the next largest by an average of 0.63% per month. For the Findi sample in Panel B, the size effect is stronger with smaller quintile sorted portfolios outperforming

larger quintile sorted portfolios by an average of almost 1% per month with a spread of 2.56% and t-statistic of 3.86. The exception is the second quintile that posts a higher return than the third quintile.

The evidence that smaller firms earn a premium over larger firms is consistent with the international evidence reviewed in Chapter Three. Apart from van Rensburg (2001), other prior research on the JSE is inclusive regarding a small size effect. The results in Table 7.3 also concur with the stock-level cross-sectional tests of the size attribute presented in Chapters Five and Six. In direct contrast with the international evidence the post-ranking betas of the simulated portfolios, shown in parenthesis, increase monotonically as the size quintiles get larger in both samples.

Of particular interest is the evidence showing that when quintile portfolios are created by sorting JSE stocks on the size attribute, the relationship between average portfolio returns and post-ranking beta is exactly opposite to the predictions of the CAPM theory outlined in Chapter Two. This is clearly illustrated by a graphical depiction of post-ranking beta overlaid on the average return of the size sorted quintile portfolios, shown in Figure 7.1.

Figure 7.1 One-way size sorted quintile portfolio returns and post ranking betas.

Returns figures, shown in percent by the vertical bar chart, are the average monthly return of each size sorted quintile portfolio for the 120 months from July 1990 to June 2000. The superimposed line chart shows the post ranking beta of each size sorted quintile portfolio relative to the JSE All Share index.

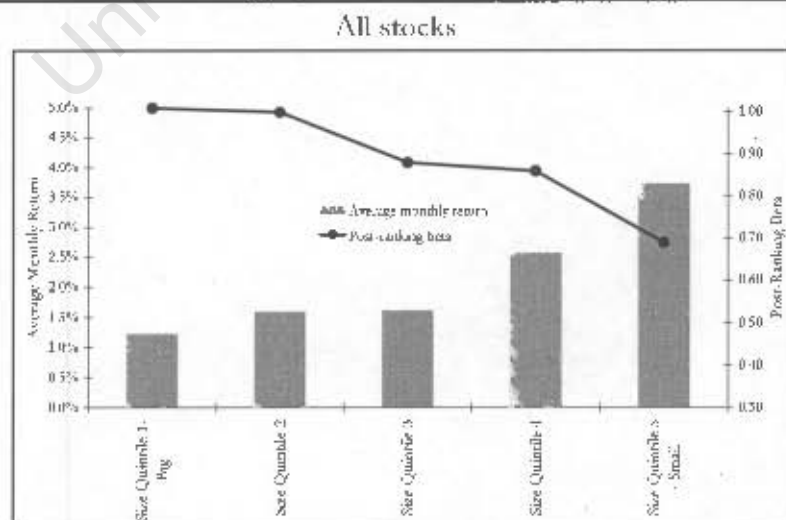
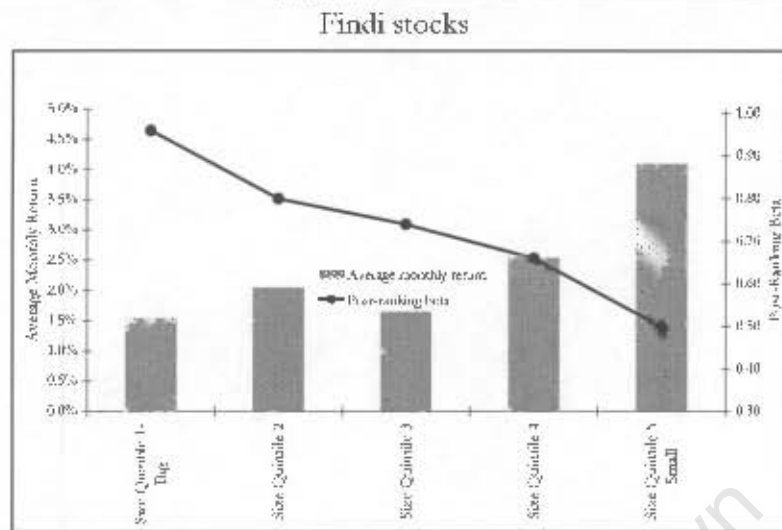


Figure 7.1 Continued.

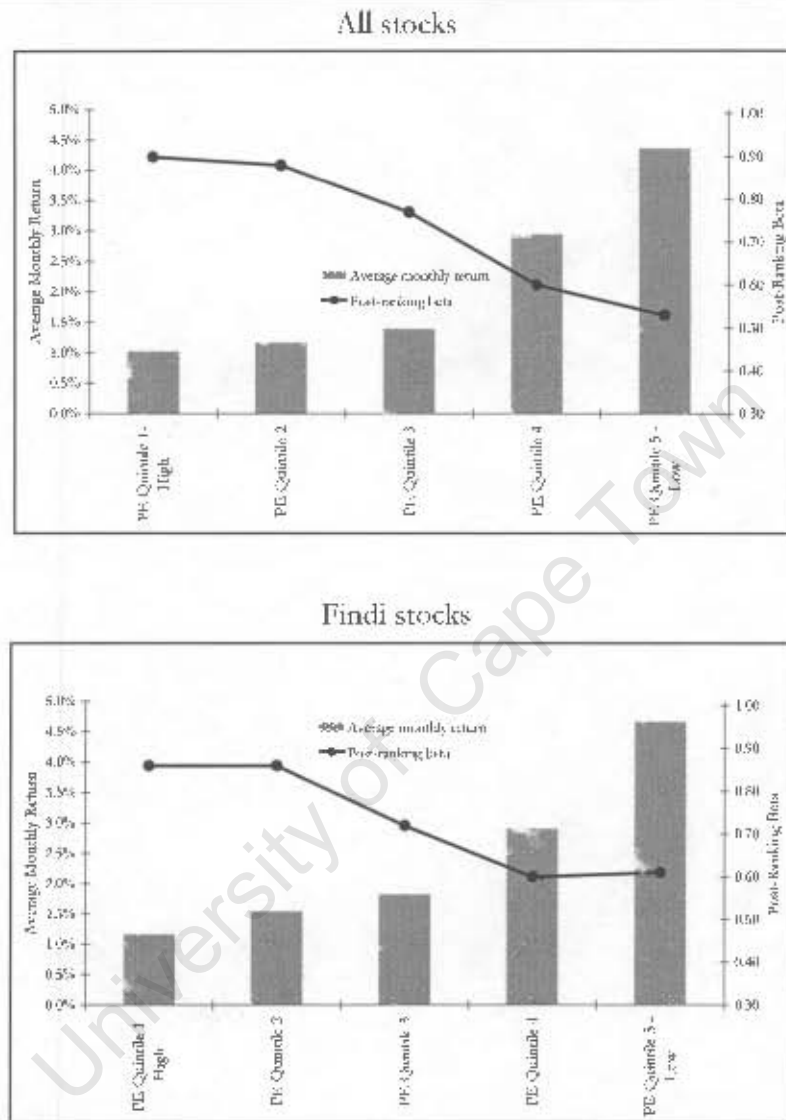


For quintile portfolios created by monthly sorts on the price-to-earnings attribute, the results in Table 7.3 are similar to the independent value strategy documented in Fraser and Page (2000) showing that high value stocks routinely outperform low value stocks. The price-to-earnings effect is more pronounced in the Findi sample with an average inter-quintile return differential of 2.42% compared with the all stocks sample of just 0.85%. The spread of average returns between the lowest and the highest price to earnings quintiles is slightly larger for the Findi sample at 3.50%, with a t-statistic of 6.58, than for the all stocks sample at 3.34%, with a t-statistic of 7.38. Compared with the spread of average returns between the extreme size sorted quintile portfolios, the spread between the extreme price-to-earnings sorted quintile portfolios is markedly wider.

Table 7.3 further reveals that post-ranking betas exhibit a positive monotonic relationship with the price to earnings sorted quintiles in both the all stocks and Findi samples. Again, an important discovery evident in Table 7.3 is that when simulated portfolios are created on the JSE by sorting stocks on the price-to-earnings attribute, post ranking beta scales inversely with average portfolio returns. This further contradiction of the CAPM theory is illustrated graphically for the all stocks and Findi samples in Figure 7.2.

Figure 7.2 One-way price-to-earnings sorted quintile portfolio returns and post-ranking betas.

Returns figures, shown in percent by the vertical bar chart, are the average monthly return of each price to earnings sorted quintile portfolio for the 120 months from July 1990 to June 2000. The superimposed line chart shows the post-ranking beta of each size sorted quintile portfolio relative to the JSE All Share index.

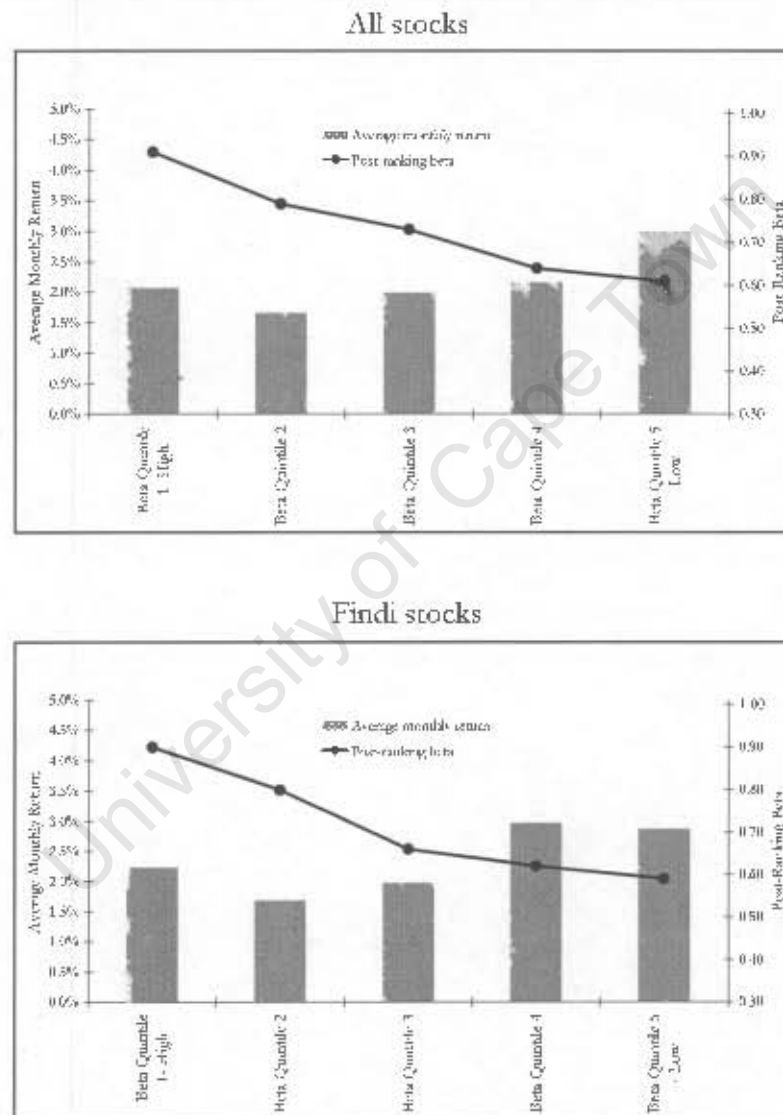


The final results reported in Table 7.3 are for quintile portfolios created from monthly sorts on the pre-ranking beta attributes. The evidence bodes even worse for beta than the results generated by conducting sorts on the size and price-to-earnings attributes. It is shown that the smallest pre-ranking beta sorted quintile portfolio for the all stocks sample earns an average return that is 0.90% larger per month, with a t-statistic of 2.18, than the largest pre-ranking beta sorted quintile portfolio. The same is true for the Findi sample although the difference in average return between the extreme quintile portfolios is less than 1% per month and the t-statistic shows no significance. The results for all stocks and Findi stocks

again directly dispute the role of beta in determining average stock returns on the JSE by showing that portfolios containing high beta stocks do not earn higher returns, and in most instances the reverse is true. Figure 7.3 displays the evidence graphically for both samples.

Figure 7.3 One-way pre-ranking beta sorted quintile portfolio returns and post-ranking betas.

Returns figures, shown in percent by the vertical bar chart, are the average monthly return of each pre-ranking beta sorted quintile portfolio for the 120 months from July 1990 to June 2000. The superimposed line chart shows the post-ranking beta of each size sorted quintile portfolio relative to the JSE All Share index.



There is some evidence that the pre-ranking beta sorted quintile portfolios at least predict the correct ordering of the post-ranking beta portfolios. The findings are not completely unprecedented since they confirm the findings of Reinganum (1983) showing that no reliable relationship exists between average returns and post-ranking beta for pre-ranking beta sorted

portfolios. Overall, the findings presented in Table 7.3 show that beta fails in the simplest of tasks and contributes to growing evidence, reviewed in Chapter Three, which contends that beta is inappropriate as a pricing factor on the JSF.

7.3.2 Two-way quintile portfolio sorts on size and price-to-earnings

In this section, the stocks in both samples are ranked in each month based on their size attributes, assigned to quintiles and ranked again based on their price-to-earnings attributes. The reason for first ranking stocks on the size attribute is because of the evidence in Chan and Chen (1991), Fama and French (1992) and others that shows that size sorts produce a wide range of average returns and post-ranking betas.

The resulting twenty-five portfolios for each sample have cross-sectional variation in the price-to-earnings attribute that is unrelated to the size attribute. For the all stocks sample, the highest recorded average monthly return of the twenty-five simulated portfolios is for the smallest size sorted quintile portfolio comprising the lowest price-to-earnings stocks, in the bottom-right corner of Panel A in Table 7.4.

Table 7.4 Two-way quintile portfolio sorts on size and price-to-earnings and post-ranking beta.

Returns figures, in percent, are the average monthly return of each portfolio for the 120 months from July 1990 to June 2000. In Quintiles 1 to 5 post-ranking betas for the period are in parenthesis. In the last column and last row, labeled Quintile (5-1), the return figures are the average monthly difference in return between Quintiles 5 and 1 and t is the Students t -statistic indicating whether, on average, the difference is significant. Significance above the ninety five percent confidence level is indicated in bold. Figure 7.4 shows a graphical depiction.

Panel A	Size					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Price-to-earnings						
Quintile 1 High	0.24 (1.00)	0.57 (0.88)	1.03 (0.86)	1.67 (0.69)	2.47 (0.41)	2.23 ($t=2.55$)
Quintile 2	1.30 (0.77)	1.32 (0.67)	0.68 (0.47)	1.55 (0.40)	2.35 (0.19)	1.05 ($t=1.26$)
Quintile 3	1.17 (0.84)	1.35 (0.64)	1.10 (0.38)	1.79 (0.33)	2.87 (0.24)	1.70 ($t=1.85$)
Quintile 4	1.15 (0.81)	1.67 (0.65)	1.96 (0.66)	3.19 (0.47)	3.73 (0.20)	2.58 ($t=3.03$)
Quintile 5 Low	2.32 (0.85)	3.02 (0.64)	3.13 (0.62)	4.45 (0.38)	6.46 (0.23)	4.13 ($t=3.81$)
Quintile (5-1)	2.08 ($t=1.78$)	2.46 ($t=2.10$)	2.10 ($t=1.85$)	2.78 ($t=2.39$)	3.99 ($t=3.43$)	

Table 7.4 Continued.

Panel B Findi stocks	Size					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Price-to-earnings						
Quintile 1 High	0.95 (0.95)	0.77 (0.78)	0.98 (0.67)	1.28 (0.65)	2.43 (0.31)	1.25 $t=0.72$
Quintile 2	1.52 (1.00)	1.08 (0.79)	0.65 (0.61)	1.62 (0.50)	2.39 (0.24)	2.38 $t=1.37$
Quintile 3	1.74 (0.87)	2.88 (0.79)	1.20 (0.76)	2.04 (0.42)	3.38 (0.30)	2.45 $t=1.42$
Quintile 4	1.29 (0.73)	2.13 (0.20)	1.90 (0.83)	3.20 (0.60)	3.91 (0.25)	3.00 $t=1.75$
Quintile 5 Low	2.20 (0.81)	3.15 (0.49)	3.43 (0.68)	4.28 (0.48)	7.72 (0.24)	5.28 $t=3.08$
Quintile (5-1)	1.49 $t=1.53$	0.88 $t=0.93$	1.64 $t=1.69$	2.61 $t=2.81$	5.52 $t=3.57$	

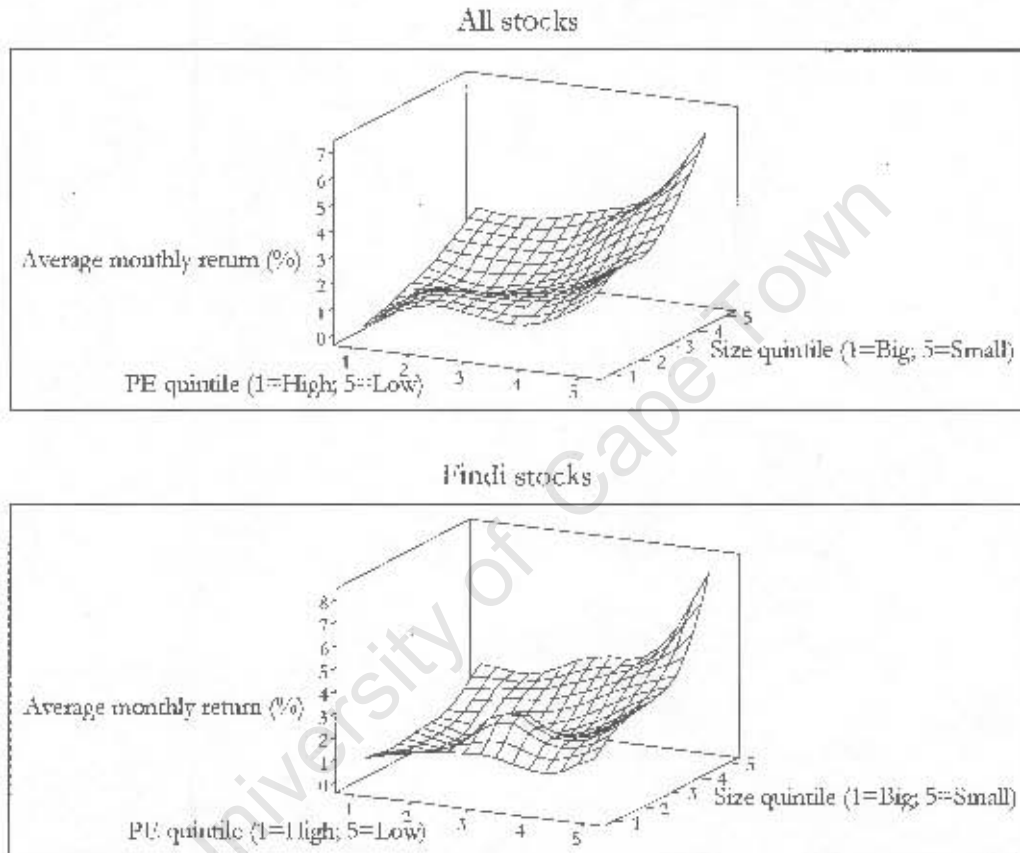
Conversely, the lowest recorded average monthly return of the twenty five test portfolios is for the largest size sorted quintile portfolio comprising the highest price-to-earnings stocks, in the top-left corner of Panel A in Table 7.4. A similar pattern emerges for the Findi stock sample. The highest recorded average monthly return is for smallest size sorted quintile portfolio comprising the lowest price-to-earnings stocks, in the bottom-right corner of Panel B. The lowest recorded average monthly return is however arbitrarily in the middle of Panel B. Results and discussions from additional two-way stock sorting procedures conducted on the size and pre-ranking beta attributes and then on the price-to earnings and pre-ranking beta attribute is presented separately in Appendix I.

The results in Table 7.4 can be graphically depicted for the all stocks and Findi stocks sample using a return surface rendered in three-dimensional space. The vertical axis of each diagram in Figure 7.4 represents the average return for the quintile portfolios over the period July 1990 to June 2000 and is drawn from the intersection of the size and price to-earnings quintiles on the two horizontal axes. The edges of the return surface in each diagram represent the first and last columns and rows of the panels in Tables 7.4. It can be clearly seen by the smoothness of the three-dimensional plane for all stocks and for Findi stocks, sloping in both cases from right to left and top to bottom, that the small size and low price-

to-earnings effects operate simultaneously on the JSF. If the predictions of the CAPM hold and then three-dimensional return surfaces in Figure 7.4 would be flat.

Figure 7.4 Average return and post-ranking betas for all stocks and Findi stocks from two way portfolio sorts on size and price-to-earnings.

Two dimensions of stock returns, size and price-to-earnings, are represented simultaneously in 3D space using a rendered surface. Returns figures along the vertical axis, in percent, are the average monthly return of each size and price-to-earnings sorted quintile portfolio of all stocks for the 120 months from July 1990 to June 2000.



Overall, the results neatly support the findings of the one-way portfolio sorts on size and price-to-earnings in a two-dimensional framework. In the all stocks sample, apart from two exceptions in the third size quintile, all size sorted quintile portfolios have an average return that is higher than the portfolio on their immediate left. Three of the five quintiles horizontally and vertically have t-statistics that indicate significance above the ninety-five percent level when testing for differences in average monthly return between the largest and smallest quintiles. The difference in average monthly return in the extreme quintiles of the Findi sample is less pronounced.

7.4 Summary and conclusion

This chapter explicitly examines the individual and concurrent roles of beta, the small size effect and the low price to earnings effect on the JSE. The stock-level cross-sectional regressions used in previous chapters are replaced with a one-way and two-way portfolio simulation methodology similar to Fama and French (1992). The portfolio sort methodology allows variation in one attribute to be studied independently from another in a single step.

Similar to the findings of Fama and French (1992) and Jegadeesh (1992), a preliminary analysis of the average cross-sectional correlation between the size attribute and pre-ranking beta reveals a significant positive relationship. In spite of the adjustments made to the stock returns data set in Chapter Four, this may be explained by the possibility that the measured betas of small stocks are lower than the betas of large stocks due to thin trading as described by Scholes and Williams (1977), Dimson (1979) and Bradfield (1989). A more obvious explanation is the concentration of large capitalisation stocks in the market portfolio. No significant correlation is observed between the price-to-earnings and size attributes or between the price-to-earnings attribute and pre-ranking beta.

The results of the one-way size sorted quintile portfolios presented in this chapter bode worse for beta on the JSE compared with the international evidence. Whereas Fama and French (1992:453) conclude that the beta of their size sorted portfolios: "...do a fine job on the relation between size and average return, but they do a lousy job on their main task, the relation between β and average return.", the evidence presented here shows that small size earns a higher return on the JSE but has a lower beta. It is further documented that quintile portfolios containing low price-to-earnings stocks earn higher average returns but have lower betas. While confirming the anomaly status of the size and price-to-earnings attributes on the JSE, these findings stand contrary to the central prediction of the CAPM reviewed in Chapter Two that greater average returns should be associated with higher betas.

When two-way simulated portfolios are created by sorting first on the size attribute and then on the price to-earnings attribute, the ordering of the average portfolio returns across the quintiles suggest that small size and low price-to-earnings earn a positive and concurrent

premium on the JSE. This is supportive of the two-factor stock-level cross-sectional results reported in Chapters Five. The post ranking betas still show no reliable relationship with average portfolio return. It is concluded that controlling for the explanatory power of the anomalous attributes does not improve the explanatory power of beta on the JSE. The implication is that the explanatory power of the size and price to earnings attributes does not appear to arise from their role as proxies for beta.

^{The}
This objective of this chapter is not an attack on the theoretical role of beta. Rather, the aim is to empirically assess the role of beta in explaining expected returns on the JSE in the presence of the small size and low price-to-earnings effects. That the results summarised above do not conform to the predictions of the theory does not constitute a rejection of the central intuition behind the CAPM. On the contrary, beta may still have a variety of roles in portfolio construction, risk analysis and performance evaluation.

Attributes or Risk Factors ?

8.1 Introduction

The results from the previous chapter indicate that the size and price-to-earnings attributes do not proxy for the risk factor beta, and that beta does not fulfill its theoretical role as a pricing factor on the JSE. This chapter therefore replaces beta with alternative risk factors constructed to represent the sources of priced risk hypothesised to be associated with the small size and low price-to-earnings premiums. This allows tests to be designed that are explicit about whether average stock returns on the JSE are related to the size and price-to-earnings attributes themselves or to their loadings on corresponding risk factor constructs¹.

The empirical key to discriminating between the attribute and factor view rests on whether diversified portfolios can be formed with similar attributes values but with different risk factor loadings. This chapter therefore constructs a data set of monthly risk factor loadings and then employs a two-way portfolio sorting procedure to determine whether attributes or loadings on risk factors are responsible for determining cross-sectional stock return. The remainder of the chapter is set out as follows. Section 8.2 discusses the data and methodology, Section 8.3 presents the empirical results and Section 8.4 summarises and concludes.

8.2 Data and methodology

In this chapter, a component of the Daniel and Titman (1997) methodology is modified to directly test whether average returns on the JSE are related to the size and price-to-earnings attributes themselves or to the loadings on their respective risk factors constructs. This

¹ This chapter is the originating work for the article: Attributes or risk factors on the JSE?, *Working paper*, 2002, School of Management Studies, University of Cape Town.

requires the construction of risk factors from the attributes followed by several multi-dimensional portfolio sorts similar to those conducted in the Chapter Seven.

Consistent with Chapter Seven, all tests are conducted on a sample consisting of all stocks and a sample consisting of Findi stocks. In this way, a full assessment of the relationship between risk factors and attributes can be conducted while simultaneously considering the financial industrial and resource dichotomy of the JSE discussed throughout the thesis. In addition to the size and lagged price-to-earnings data sets used in Chapter Seven, two additional data sets of risk factor loadings are prepared for all non-thinly traded stocks in each month from July 1990 to June 2000.

8.2.1 Construction of factor mimicking portfolios

Similar to Fama and French (1992, 1993), Daniel and Titman (1997) and others, factor portfolios are constructed to mimic the returns of the priced sources of risk hypothesised to be responsible for the premium earned by small size and low price-to-earnings firms on the JSE². For the all stock and Findi stock samples, factor portfolios are constructed by ranking stocks in each month in descending order of their size and price-to-earnings attributes. Breakpoints are inserted in the ranking in each month at twenty percent and eighty percent. The stocks above and below the breakpoints in each month $t-1$ are assigned to portfolios and the equal-weighted return for each portfolio is calculated for the following month t .

The return of the portfolio consisting of the largest size ranked stocks in each month is assigned the symbol 'L' denoting large, while the return of the smallest portfolio of size ranked stocks in each month is assigned the symbol 'S' denoting small. Similarly, the return of the portfolio containing the stocks with the highest price-to-earnings ratios in each month is indicated as 'H' for high, and the return of the corresponding smallest price-to-earnings portfolio is indicated as 'L' denoting low.

As described in Chapter Three, the return to a factor portfolio for a month is calculated as the difference between the returns of the two extreme portfolios such that the aggregate

² A more detailed review of factor-mimicking portfolios is presented in Chapter Three along with the characteristic versus factor debate of Daniel and Titman (1997).

portfolio is hedged. The notation for the risk factor associated with the small size effect is therefore indicated by 'small-less-large' denoted as 'SLL'. The notation for the risk factor associated with the premium earned by low price-to-earnings stocks is 'low-less-high' denoted as 'LLH'. A time series of monthly returns for the SLL and LLH factor portfolios are recorded for the all stock and Findi stock samples from July 1990 to June 2000.

8.2.2 Estimation of the risk factor loadings

To determine the loadings of the stocks in each month on the SLL and LLH risk factor portfolios, the time series of monthly returns of each stock is regressed in each month on the corresponding return of the SLL and LLH risk factor portfolios:

$$r_{i,t} = \alpha_i + \beta_{SLL} R_{SLL,t} + \varepsilon_i \quad (8.1)$$

$$r_{i,t} = \alpha_i + \beta_{LLH} R_{LLH,t} + \varepsilon_i \quad (8.2)$$

Where, in month t , $r_{i,t}$ is the return on stock i , $R_{SLL,t}$ is the return on the SLL risk factor portfolio and $R_{LLH,t}$ is the return on the LLH risk factor portfolio. α_i is the time series intercept term and $\varepsilon_{i,t}$ is the monthly error term for stock i . The loading on the respective SLL and LLH risk factor portfolios is estimate as the coefficients β_{SLL} and β_{LLH} using OLS.

Similar to the simple time-varying beta estimates in Chapter Seven, loadings on the SLL and LLH risk factor portfolios are calculated on a rolling-window basis for both the all stock and Findi stock samples using an increasing history of between twelve months, in July 1990, and thirty months from January 1992 onwards³. Stock loadings on the SLL and LLH factor portfolios are recorded in each month and used to populate the data sets of factor loadings for the all stock and Findi stock samples.

8.2.3 Construction of test portfolios

To investigate whether average stock returns are related to factor loadings, one-way sorting procedures are performed in each month from July 1990 to June 2000. Non-thinly traded

³ The size of this rolling-window has implications for the test results and is discussed in the next section.

stocks are ranked each month in descending order of the SLL and LLH risk factor loadings. Quintile breakpoints are inserted in the ranking at twenty, forty, sixty and eighty percent, allowing all stocks to be assigned to one of five quintiles. Using the stocks in each quintile at the end of each month $t - 1$, an equal-weighted portfolio is prepared and rolled forward to the end of month t . In this way, a time series of monthly returns is generated for each of the five factor loading sorted quintile portfolios.

To study the interaction between the attributes and the risk factor loadings, a two-way portfolio sorting procedure is conducted similar to that used by Daniel and Titman (1997). Stocks in both samples are ranked in descending order of the size and price-to-earnings attributes in each month. After inserting quintile breakpoints in the ranking at twenty, forty, sixty and eighty percent, stocks are assigned to one of five quintiles. The stocks in each quintile are then re-ranked in each month in descending order of their estimated loadings on the corresponding risk factor. If the first ranking is conducted on the size attribute, then the second ranking is based on the loadings on the SLL risk factor. Similarly, if the first ranking is conducted on the price-to-earnings attribute, then the second ranking is based on the loadings on the LLH risk factor.

Ranking stocks first on their attributes and then on their loadings on the corresponding risk factor construct creates portfolios where the constituents have variation in the attributes that is independent of the risk factor loadings. Consistent with the construction of the risk factor portfolios, the two-way ranked test portfolios are created at the end of each month $t - 1$ on an equal weighted basis and rolled forward to the end of month t . The result is twenty-five price-to-earnings attribute and LLH factor loading sorted test portfolios and twenty-five size attribute and SLL factor loading sorted test portfolios for the all stock and Findi stock samples. Each portfolio has a 120-months of returns. The average number of stocks in each of the one-way and two-way sort portfolios is shown in Table 8.1 for both samples. The elaborate procedures used in this chapter for estimating monthly risk factor loadings for each stock and then conducting monthly bi-directional stock ranking and portfolio simulations required vast amounts instruction be written for the statistical software.

Table 8.1 Average number of non-thinly traded stocks in the universe portfolio, first sort portfolio and second sort portfolio.

The numbers represents the average number of stocks in the universe portfolio, the first sort portfolio and the second sort portfolio for all months from July 1990 to June 2000 and for ten twelve-month sub-periods.

Panel A: All stocks											
Years	All	1	2	3	4	5	6	7	8	9	10
Universe	268	180	176	185	224	246	276	297	328	364	408
First sort	54	36	35	37	45	49	55	59	66	73	82
Second sort	11	7	7	7	9	10	11	12	13	15	16

Panel B: Findi stocks											
Years	All	1	2	3	4	5	6	7	8	9	10
Universe	234	152	150	158	194	214	240	259	287	325	365
First sort	47	30	30	32	39	43	48	52	57	65	73
Second sort	9	6	6	6	8	9	10	10	11	13	15

8.3 Empirical results

A preliminary check of the average cross-sectional correlation between the stock attributes and their loadings on the associated risk factor is conducted. The results, shown in Table 8.2, indicate the size attribute is significantly correlated in all but four sub-periods to the loading on the size risk factor in the all stock and Findi stock samples.

Table 8.2 Average cross-sectional correlations of attributes and associated risk factor loadings.

Figures represent the average cross-sectional correlation over the all months from July 1990 to June 2000 and for twelve-month sub-periods. Bold indicates where the p-value of the Pearson product correlation coefficient < 0.05 (p-values are not shown in the table).

Panel A: Size attribute and SLL factor loading											
	All	1	2	3	4	5	6	7	8	9	10
All stocks	-0.31	-0.24	-0.42	-0.35	-0.41	-0.45	-0.41	-0.09	-0.18	-0.36	-0.20
Findi stocks	-0.30	-0.24	-0.41	-0.33	-0.40	-0.44	-0.40	-0.11	-0.19	-0.35	-0.17

Panel B: Price-to-earnings attribute and LLH factor loading											
	All	1	2	3	4	5	6	7	8	9	10
All stocks	0.06	0.01	0.12	0.11	0.09	0.12	0.04	0.06	0.00	0.01	0.05
Findi stocks	0.03	0.01	0.09	0.07	0.06	0.07	-0.01	0.03	-0.05	-0.02	0.04

This correlation between the size attribute and the loading on the associated size risk factor is similar to the correlations reported in Chapter Seven for the size attribute and pre-ranking

beta. The price-to-earnings attribute is however not significantly correlated with the loadings on the price-to-earnings risk factor in any period.

The average monthly returns from July 1990 to June 2000 of quintile portfolios created from one-way rankings of stocks on the SLL and LLH risk factor loadings are presented for all stocks and Findi stocks in Panels A and B of Table 8.3. This directly tests whether portfolios of stocks with different risk factor loadings have different average returns. If the risk argument holds and it is risk factors that determine average returns, then small firms that earn a premium should have a high loading on the SLL risk factor construct if the risk factor is priced and the size attribute proxies for the loading. This implies that the highest SLL quintile portfolio should consist of smaller stocks and the lowest size SLL quintile portfolio should consist of larger stocks.

If the results from the previous chapters prevail, then the highest SLL quintile portfolio should earn a premium over the lowest quintile SLL. Inspecting Panels A and B of Table 8.3 shows that this is true for both the all stock sample, with an average outperformance of 0.84% per month, and for the Findi sample, with an average outperformance of 1.22% per month. Neither sample has an associated t-statistic of sufficient magnitude for the difference in average performance to be considered with any confidence. Contrary to the average return of size attribute ranked quintile portfolios in Chapter Seven, there is no smooth progression of average return across the quintiles.

Table 8.3 One-way sorted quintile portfolios formed by ranking stocks on their SLL and LLH risk factor loadings.

Returns figures, in percent, are the average monthly return of each portfolio for the 120 months from July 1990 to June 2000. In the last row, labeled Quintile (1-5), the return figures are the average monthly difference in return between Quintiles 1 and 5 and *t* is the t-statistic indicating whether, on average, the difference is significant. Significance above the ninety-five percent confidence level is indicated in bold. Big/Small relate to the SLL factor loading while High/Low relate to the LLH factor loading. Figures 8.1 and 8.2 show a graphical depiction.

Panel A: All stocks	SLL factor loading	LLH factor loading
Quintile 1 Big/High	3.35	2.56
Quintile 2	1.28	1.52
Quintile 3	1.47	1.50
Quintile 4	1.60	1.58
Quintile 5 Small/Low	2.50	3.11
Quintile (1-5)	0.84 <i>t</i> =0.66	-0.55 <i>t</i> =-0.45

Table 8.3 Continued.

Panel B: All stocks	SLL factor loading	LLH factor loading
Quintile 1 High/Big	3.60	2.27
Quintile 2	1.76	1.39
Quintile 3	1.55	1.38
Quintile 4	1.50	1.97
Quintile 5 Low/Small	2.38	3.94
Quintile (1-5)	1.22 $t=0.96$	-1.67 $t=-1.32$

Figure 8.1 compares graphically how the size attribute sorted quintile portfolios from the previous chapter perform relative to the corresponding SLL factor loading sorted quintile portfolios in Table 8.3. If the SLL risk factor loading, as opposed to the attribute itself, determines the average returns of the size sorted quintile portfolios, then the superimposed line in Figure 8.1 should indicate high average returns in Quintile 1-Big that decreases progressively across the quintiles. The concave shape of the superimposed line across the quintiles indicates clearly this is not the case for either the all stock or Findex stock samples.

Figure 8.1 Comparison of average returns of size attribute and SLL risk factor loading sorted quintile portfolios.

Returns figures, shown in percent by the vertical bar chart, are the average monthly return of each size attribute sorted quintile portfolio for the 120 months from July 1990 to June 2000. The superimposed line chart shows the average return of the corresponding SLL risk factor loading sorted quintile portfolio.

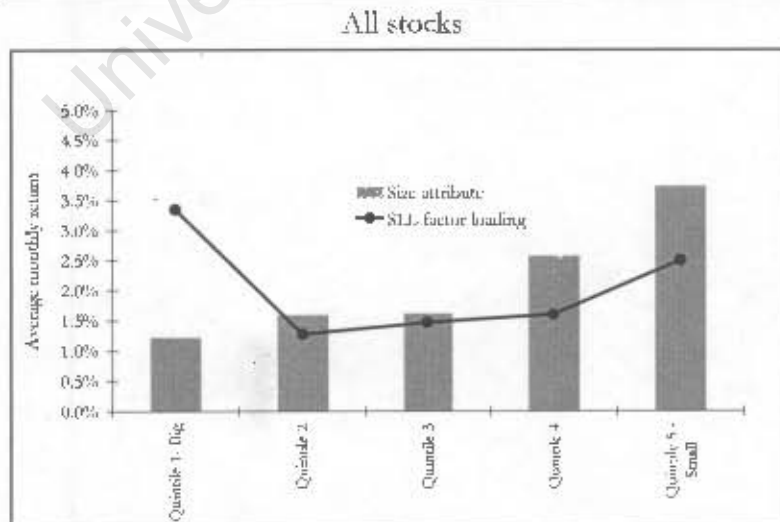
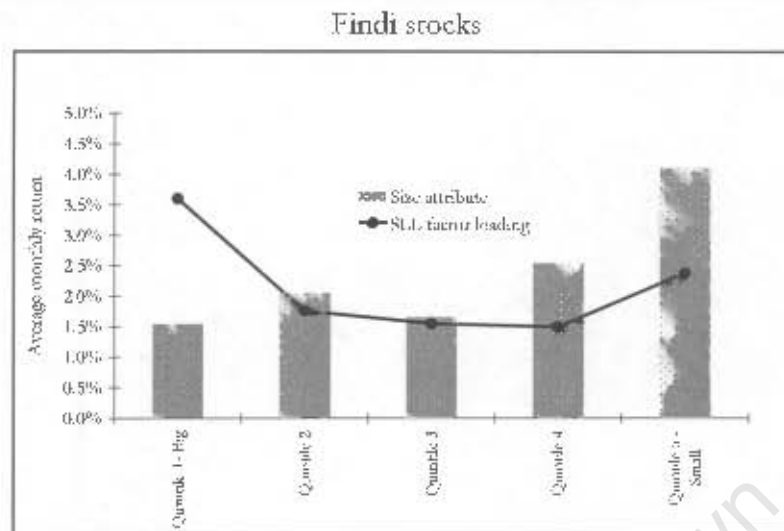


Figure 8.1 Continued



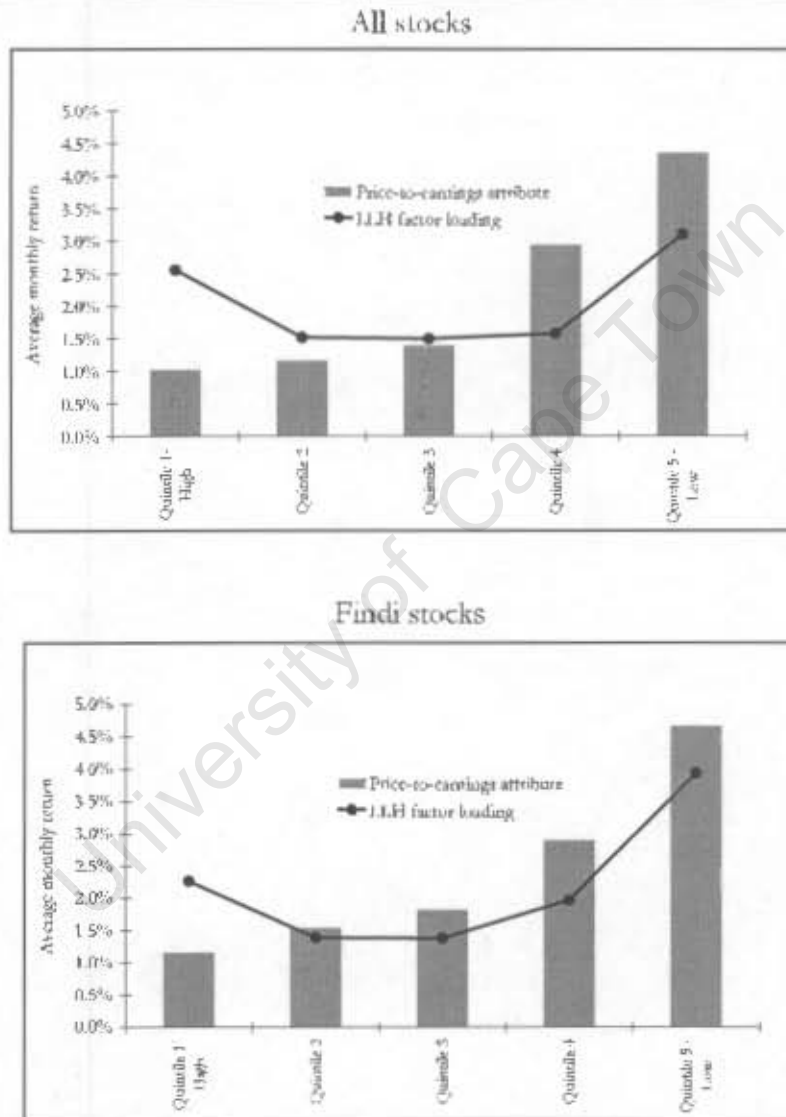
Similarly, if the predictive power of the price to earnings attribute is couched in the associated risk factor construct LLH, then low price-to-earnings stocks should have a high loading on the LLH risk factor portfolio if the factor is priced and the price-to-earnings attribute proxies for the loading. This implies that the highest LLH quintile portfolio should consist of lower price-to-earnings stocks and the lowest size LLH quintile portfolio should consist of higher price-to-earnings stocks. Again, if the evidence from the previous chapters is consistent then the highest LLH quintile portfolio should earn a premium over the lowest quintile LLH. The evidence however in Table 8.3 for the quintile portfolios formed by ranking on the LLH factor loadings is inconclusive and contradictory. For the all stock sample in Panel A, the largest quintile underperforms the smallest quintile by an average of 0.55% per month while, for the Findi stock sample in Panel B, there is an average difference of 1.67% per month. The associated t-statistics are not of any significant magnitude.

In a graphical depiction, Figure 8.2 illustrates how the price-to-earnings attribute sorted quintile portfolios from Chapter Seven perform relative to the corresponding LLH factor loading sorted quintile portfolios in Table 8.3. If the LLH risk factor loading determines the average returns of the price-to-earnings sorted quintile portfolios, then the superimposed line in Figure 8.2 should indicate high average returns in Quintile 1 High that decreases progressively across the quintiles. Similar to Figure 8.1 the concave shape of the

superimposed line across the quintiles indicates this is not the case for either the all stocks sample or for the Findi stocks sample.

Figure 8.2 Comparison of average returns of price-to-earnings attribute and I.I.H risk factor loading sorted quintile portfolios.

Returns figures, shown in percent by the vertical bar chart, are the average monthly return of each price-to-earnings attribute sorted quintile portfolio for the 120 months from July 1990 to June 2000. The superimposed line chart shows the average return of the corresponding LLL risk factor loading sorted quintile portfolio.



While the evidence presented in the previous chapters show that average returns are related to the size and price-to-earnings attributes, the evidence presented in Table 8.3 shows that no reliable relationship exists between average returns and loadings of the corresponding risk factor constructs SLL and I.I.H. To further investigate why the risk factor constructs appear

to lack explanatory power compared to their attribute counterparts, additional portfolio simulations are conducted to jointly determine the interaction of the attributes and risk factors. As discussed, two-way portfolio creation procedures are conducted to investigate whether the cross-sectional explanatory power of the size and lagged price-to-earnings attributes arises from their role as instruments for risk or whether it is the attributes themselves.

Table 8.4 reports the average returns from July 1990 to June 2000 of twenty-five portfolios created by ranking all stocks and Findi stocks on their size attributes and then on their SLL risk factor loadings. Based on the evidence in Chapter Seven, it is expected that quintile portfolios created by sorting on the size attribute will result in the smallest quintile portfolio displaying, on average, a significantly larger return. Reading Panels A and B of Table 8.4 from left to right shows the monotonic scaling of average returns across the size attribute quintiles observed in Chapter Seven is absent. Only in the fourth size attribute quintile is the average return difference between the extreme quintile portfolios significantly different from zero, albeit with the incorrect sign.

Table 8.4 Two-way portfolio sorts on the size attribute and the loading on the SLL risk factor.

Returns figures, in percent, are the average monthly return of each portfolio for the 120 months from July 1990 to June 2000. In the last column/last row labeled Quintile (1-5), the return figures are the average monthly difference in return between Quintiles 1 and 5 and t is the t -statistic indicating whether, on average, the difference is significant. Significance above the ninety-five percent confidence level is indicated in bold. Small/Big relates to the SLL factor loading and the size attribute quintiles. Figure 8.3 shows a graphical depiction.

Panel A	Size attribute					
	Quintile 1 High	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Low	Quintile (1-5)
SLL factor loading						
Quintile 1 High	2.31	3.04	2.97	4.32	3.77	-1.45 $t=-0.94$
Quintile 2	2.20	1.59	1.40	1.16	1.40	0.80 $t=0.94$
Quintile 3	1.54	1.82	1.53	0.74	1.75	-0.20 $t=-0.23$
Quintile 4	1.88	1.75	1.72	1.93	0.16	1.73 $t=2.44$
Quintile 5 Low	2.42	2.72	3.33	1.98	0.98	1.44 $t=1.95$
Quintile (1-5)	-0.11 $t=-0.13$	0.33 $t=0.23$	-0.35 $t=-0.22$	2.34 $t=1.46$	2.79 $t=1.46$	

Table 8.4 Continued.

Panel B Findi stocks	Size attribute					
	Quintile 1 High	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Low	Quintile (1-5)
SLL factor loading						
Quintile 1 High	3.05	2.90	4.42	5.25	4.26	-0.75 $t=-0.61$
Quintile 2	2.28	1.71	1.33	2.20	0.92	0.45 $t=0.29$
Quintile 3	1.89	2.24	1.35	1.95	1.62	-2.09 $t=1.19$
Quintile 4	1.81	1.49	1.79	0.81	0.29	-3.38 $t=-1.98$
Quintile 5 Low	2.54	3.35	2.39	1.87	0.64	-3.63 $t=-1.77$
Quintile (1-5)	-1.21 $t=-0.72$	1.36 $t=1.60$	0.27 $t=0.32$	1.52 $t=1.70$	1.90 $t=2.22$	

Since smaller stocks are expected to have greater loadings on the SLL risk factor, it is expected that the largest quintile portfolio created from stocks sorted on the SLL risk factor will earn a premium. Reading both panels of Table 8.4 vertically reveals this is not the case for either sample. Unlike the results of Chapter Seven reported in Appendix I where the small size effect is robust to a second sort on pre-ranking beta, there is no evidence that portfolios created from small stocks earn greater return in any of the SLL risk factor loading quintiles.

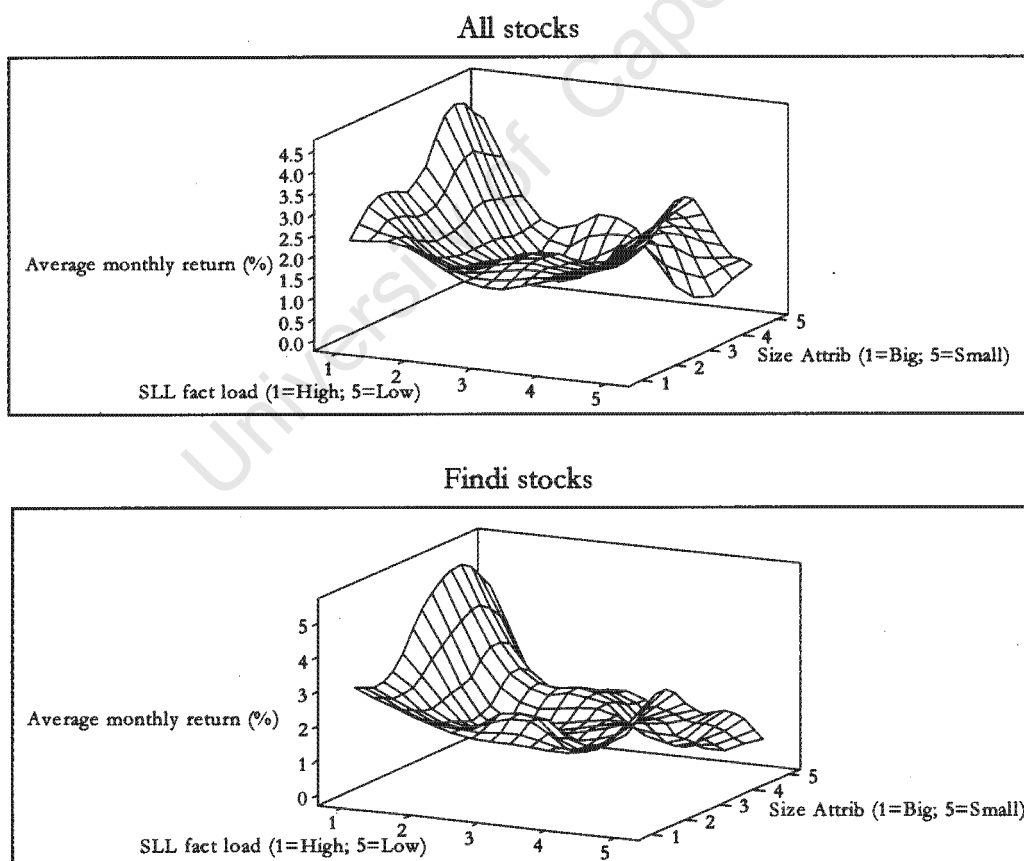
It appears that two-way stock sorting procedures lack the power to create independent variation in two criteria when the attributes are highly correlated, as shown in Table 8.3. The correlation is due to the unlikelihood that there will be extreme variation in firm size, particularly over short time periods. If the rolling-window period for estimation of the loadings on the SLL risk factor was increased, it is likely the correlation between the size attributes and loadings on the risk factor SLL would decrease. This is due to the loadings on the SLL risk factor being estimated on an increasingly longer history of more outdated size attribute information. When the first ranking criteria is a parameter estimate based on the data that is the second ranking criteria such that they are correlated, it is unclear what the length of the rolling-window should be to render the two-way stock sorting procedure effective⁵.

⁵ This is an interesting area for further research.

This point can be usefully illustrated though a graphical representation of the results in Table 8.4 using a return surface drawn in three-dimensional space. The vertical axis of the diagrams in Figure 8.3 represent the average return for the quintile portfolios over the period July 1990 to June 2000 and is drawn from the intersection of the size attribute and SLL factor loading quintiles on the two horizontal axes. The edges of the return surface in each diagram represent the first and last columns and rows of the Panels A and B in Table 8.4. If the attribute view prevails then the three-dimensional surface should slope downwards connecting higher returns in the smallest size attribute quintile with lower returns in the largest size attribute quintile, irrespective of the SLL factor loading quintile.

Figure 8.3 Two-way portfolio sorts on the SLL factor loading and the size attribute.

Two determinants of stock returns, the SLL risk factor loading and the size attribute, are represented simultaneously in 3D space using a rendered surface. Returns figures along the vertical axis, in percent, are the average monthly return of each SLL risk factor and size attribute sorted quintile portfolio of all stocks and Findi stocks for the 120 months from July 1990 to June 2000.



Conversely, if the factor loading view prevails then the three-dimensional surface should slope downwards connecting higher returns in the largest SLL factor loading quintile with lower returns in the smallest SLL factor loading quintile, while remaining flat across the size attribute quintiles. The absence of any such discernable trends in Figure 8.3 confirms graphically new evidence that the attribute view cannot be disentangled from the factor loading view on the JSE in respect of the size effect.

Table 8.5 examines the low price-to-earnings effect and reports the average returns from July 1990 to June 2000 of twenty-five portfolios created by ranking all stocks and Findi stocks on their price-to-earnings attributes and then on their LLH risk factor loadings.

Table 8.5 Two-way portfolio sorts on the price-to-earnings attribute and the loading on the LLH risk factor.

Returns figures, in percent, are the average monthly return of each portfolio for the 120 months from July 1990 to June 2000. In the last column/last row labeled Quintile (1-5), the return figures are the average monthly difference in return between Quintiles 1 and 5 and t is the t -statistic indicating whether, on average, the difference is significant. Significance above the ninety-five percent confidence level is indicated in bold. High/Low relates to the LLH factor loading and the price-to-earnings attribute quintiles. Figure 8.4 shows a graphical depiction.

Panel A		Price-to-earnings attribute				
All stocks	Quintile 1 High	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Low	Quintile (1-5)
LLH factor loading						
Quintile 1 High	2.13	2.49	1.49	3.81	5.51	-3.39 $t=-2.32$
Quintile 2	-0.84	1.08	1.73	1.88	3.05	-3.89 $t=-6.50$
Quintile 3	0.66	0.93	0.87	1.71	3.01	-2.35 $t=-4.01$
Quintile 4	0.99	1.12	1.16	2.12	3.17	-2.18 $t=-3.12$
Quintile 5 Low	0.94	0.46	1.57	3.53	5.87	-4.93 $t=-4.44$
Quintile (1-5)	1.18 $t=0.92$	2.03 $t=1.24$	-0.07 $t=-0.05$	0.28 $t=0.21$	-0.36 $t=-0.17$	

Panel B		Price-to-earnings attribute				
Findi stocks	Quintile 1 High	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Low	Quintile (1-5)
LLH factor loading						
Quintile 1 High	2.16	0.55	1.43	4.48	6.56	-4.40 $t=-2.41$
Quintile 2	0.22	1.07	0.55	2.63	4.06	-3.84 $t=-5.88$
Quintile 3	1.29	0.92	1.08	2.78	2.86	-1.63 $t=-2.49$
Quintile 4	0.64	1.47	1.69	2.09	3.08	-2.45 $t=-4.16$
Quintile 5 Low	0.82	3.00	2.33	1.74	4.07	-3.25 $t=-4.43$
Quintile (1-5)	1.33 $t=0.94$	-2.46 $t=-1.52$	-0.91 $t=-0.74$	2.78 $t=1.98$	2.48 $t=1.08$	

Reading the columns in Panels A and B of Table 8.5 from left to right, the average returns of low price-to-earnings portfolios scale monotonically within each of the LLH risk factor loading quintiles. Testing for differences in average return between the two extreme price-to-earnings attribute quintile portfolios shows a strong significant outperformance of low price-to-earnings stocks over high price-to-earnings stocks above the ninety-five percent level of confidence in all the LLH risk factor loading quintiles.

Similar to the results in Table 8.3 from the one-way portfolio sorts, reading Panels A and B of Table 8.5 downwards through the LLH risk factor loading quintiles shows that portfolios of stocks with higher loadings on the LLH risk factor do not consistently outperform portfolios created from stocks with lower loadings on the LLH risk factor. Inspecting the t-statistics at the bottom of each column in both panels, it is shown that when controlling for the price-to-earnings attribute, there is no evidence of consistency in the average return difference between the extreme LLH risk factor loading sorted portfolios.

As before, a graphical representation of the results in Table 8.5 can be shown using a return surface rendered in three-dimensional space. The vertical axis of the diagrams in Figure 8.4 represent the average return for the quintile portfolios and is drawn from the intersection of the quintiles on the two horizontal axes.

Figure 8.4 Two-way portfolio sorts on the LLH factor loading and the price-to-earnings attribute.

Two determinants of stock returns, the LLH risk factor loading and the price-to-earnings attribute, are represented simultaneously in 3D space using a rendered surface. Returns figures along the vertical axis, in percent, are the average monthly return of each LLH risk factor and price-to-earnings attribute sorted quintile portfolio of all stocks and Findi stocks for the 120 months from July 1990 to June 2000.

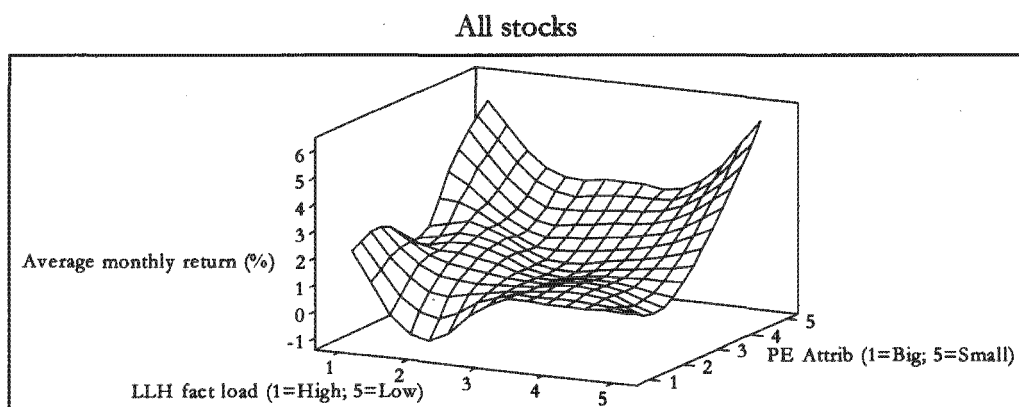
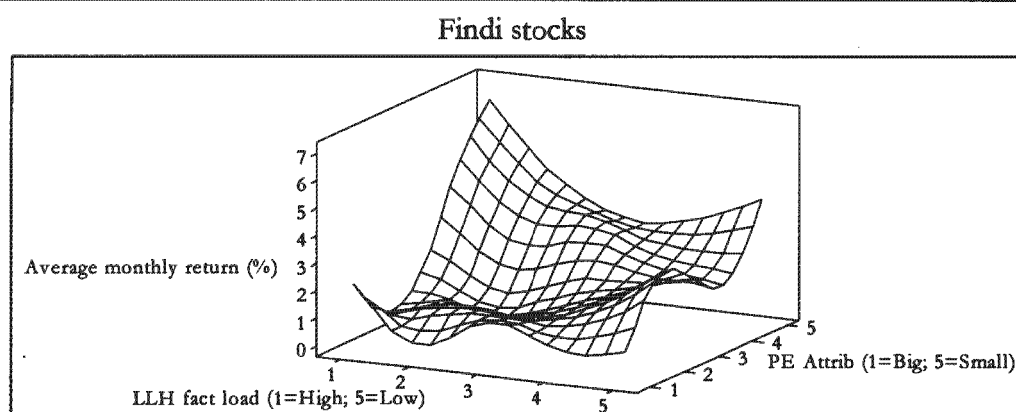


Figure 8.4 Continued.

The edges of the return surface in each diagram represent the first and last columns and rows of the Panels A and B in Table 8.5. If the attribute view prevails then the three-dimensional surface should slope downwards connecting higher returns in the smallest price-to-earnings attribute quintile with lower returns in the largest price-to-earnings attribute quintile, regardless of the LLH factor loading quintile. Conversely, if the factor loading view prevails then the three-dimensional surface should slope downwards connecting higher returns in the largest LLH factor loading quintile with lower returns in the smallest LLH factor loading quintile, while remaining consistent across the size attribute quintiles.

Figure 8.4 displays the same convexity pattern of average portfolio returns as the LLH factor loading quintiles in Figure 8.2 and further shows that this pattern is generally projected across the three-dimensional space of LLH factor loading quintiles. In both the all stock and Findi stock samples, the edges of the plane are always higher in the smallest price-to-earnings quintiles than in the highest price-to-earnings quintiles, irrespective of how the plane lies across the LLH factor loading quintiles. This shows graphically that in respect of the low price-to-earnings effect on the JSE, new evidence that the attribute view prevails.

Two important results emerge from the one-way and two-way portfolio sorting procedures conducted above on the all stock and Findi samples. Firstly, when portfolios are created by sorting stocks on their loadings on the respective size and price-to-earnings risk factor constructs, there is no evidence that high factor loadings earn a premium. Secondly, the explanatory power of the factors is not improved by controlling for the attributes using two-

way portfolio sorting procedures. Although the two-way sorting procedures cannot discriminate between the highly correlated size attribute and SLL factors, the results read together offer support to the Daniel and Titman (1997) argument that it is the attributes themselves and not the factors that determine average returns on the JSE.

8.4 Summary and conclusion

This chapter employs an adaptation of the Daniel and Titman (1997) methodology for the first time on the JSE. The objective is to determine whether the explanatory power of the size and lagged price-to-earnings attributes documented in previous chapters arises from their role as proxies for priced sources of risk, or whether it is the attributes themselves that determine average returns.

It is documented that higher average returns are associated with low price-to-earnings stocks irrespective of their loading on the associated LLH risk factor construct. It is uncertain whether this is also the case for the small size effect due to the high correlation between the size attribute and the loadings on the SLL risk factor. The lack of power in the two-way portfolio sorting procedure is thus exposed, although it is not unique to the JSE. In similar tests on a Japanese sample, Daniel, Titman and Wei (2001) also encounter such difficulties associated with their small size risk factor termed SMB: *"The above numbers also indicate that our tests provide very little power to distinguish between the characteristic and factor models using portfolios sorted by Mkt and SMB factor loadings"*.

At least in respect of the low price-to-earnings effect, the results indicate support for the attribute view of Daniel and Titman (1997) on the JSE. This is in contradiction to the asset pricing theory reviewed in Chapter Two that says the cross-section of stock returns should be related to the cross-sectional structure of the risk factors. The results may be problematic for asset pricing models on the JSE that rely on the covariance of stock returns to predict expected return. However, the findings are not necessarily definitive as Davis, Fama and French (2000) caution: *"...the three-factor model is just a model and thus an incomplete description of expected returns...the model's shortcomings are just not those predicated by the characteristic model ...[of Daniel and Titman, 1997]"*. Much scope still exists on the JSE for further research in this area

such as bootstrapping the sample, varying the time period used to estimate the risk factor loadings and changing the frequency of the factor portfolio rebalancing.

University of Cape Town

Summary, Practical Application and Conclusion

As stated in Chapter One, this thesis has four objectives. The first objective is to determine the cross-sectional influence of a broad set of firm-specific attributes on stock returns and then empirically derive a multifactor attribute-based model for the JSE. The second objective is to compare the cross-sectional results from testing the attributes in the broad sectors of the JSE and evaluate the extent to which they are similar. The third objective is to determine the role of beta in the presence of the attributes in the cross-sectional model. The fourth objective is to establish whether it is risk factor loadings or the attributes themselves that explain cross-sectional returns on the JSE.

The remainder of the chapter is set out as follows. Section 9.1 provides a summary of the main findings regarding each of the objectives above. Section 9.2 presents a return-based style decomposition of General Equity unit trust returns to demonstrate a practical application of some of the findings. Section 9.3 concludes by placing some of the main findings in the context of the theory reviewed in Chapter Two and suggests several areas for further research on the JSE.

9.1 Summary

A data set of twenty-four firm-specific attributes is extracted from the McG/BFA database for all listed stocks at monthly intervals from July 1990 to June 2000. To reduce the potential bias arising from non-synchronous trading, non-traded and thinly traded stocks are removed from the data set. The influence of extreme outliers in the attribute data set is similarly reduced by applying a winsorisation procedure in each month. A set of descriptive statistics is then estimated to investigate the distributional properties of the attributes. It is documented that many financial ratios, by construction, exhibit right skewness linked to a non-negative lower bound on their values. Sectoral differences in the distribution of the financial ratios are particularly pronounced in the case of financial firms where the ratio is

constructed from line item information that relates to levels of debt or gearing. The conclusion is that leverage appears to have a different economic meaning for financial firms on the JSE.

Regarding the first objective, this thesis provides the first extensive use of an attribute-based cross-sectional methodology on the JSE. Six of the twenty-four attributes, price-to-NAV, dividend yield, price-to-earnings, cashflow-to-price, price-to-profit and size are found to have univariate predictive power in the cross-section of returns. A cursory view of the findings in the absence of a model of asset prices is that they are inconsistent with the notion of market efficiency. The CAPM and a two-factor APT model are then introduced as models for expected return. After conducting a risk-adjustment using these models it is observed that the predictive power of the six attributes persists. In multivariate tests, only the size and price-to-earnings attributes are found to operate concurrently in the cross-section of returns, with small size and low price-to-earnings both earning a positive premium. The result is an empirically derived two factor model for the JSE.

For the second objective, the cross-sectional tests are repeated in the broad sectors of the JSE. New evidence shows that small size and a collection of value measures are, to varying degrees of intensity, positively related to the cross-section of stock returns across all of the major industry sectors. Value effects are observed as being stronger in the financial-industrial sector than in the resource sector, while the small size effect is roughly the same all across sectors. Attributes associated with growth tend to be positively rewarded in the resource sector and the premium earned by higher debt levels is negative across all sectors except the financial sector.

Regarding the third objective, a portfolio sorting methodology similar to Fama and French (1992) is used to explicitly examine the individual and concurrent roles of beta, the small size effect and the low price-to-earnings effect on the JSE. Significantly positive average cross-sectional correlation between the size attribute and pre-ranking beta is documented. No significant correlation is observed between the price-to-earnings and size attributes or between the price-to-earnings attribute and pre-ranking beta. Simulated portfolios containing high beta stocks do not earn average returns that are significantly greater than portfolios of

low beta stocks. New evidence shows that while small stocks earn a higher return on the JSE, contrary to the international evidence they have lower betas. Portfolios containing low price-to-earnings stocks earn higher average returns but, similarly, have lower betas. The results from the one-way portfolio sorting procedures make it difficult to argue a case for beta on the JSE. Using two-way stock sorting procedures, new evidence for the JSE is presented showing that controlling for the explanatory power of the anomalous attributes does not improve the explanatory power of beta.

The fourth objective is achieved by providing the first application of the Daniel and Titman (1997) methodology on the JSE. Factor mimicking portfolios are constructed to represent the sources of risk associated with the small size and low price-to-earnings effects. Monthly size and price-to-earnings risk factor loadings are estimated for all stocks by regressing rolling stock returns on the return of the respective factor portfolios. Simulated portfolios are then constructed using two-way stock sorting procedures. The resulting portfolios have cross-sectional variation in both attributes and risk factor loadings and it is investigated whether the attributes themselves or the risk factor loadings explain average returns. It is observed that the size attribute and the size risk factor loading have a significant positive correlation. The two-way sort sorting methodology cannot however distinguish between the risk factor loading and the attribute when they are significantly correlated. The evidence therefore in respect of the size attribute is inconclusive. New evidence for the JSE shows that the price-to-earnings attribute itself explains returns and not the loading on the corresponding risk factor.

9.2 Practical application

Style is defined in Chapter Three as being the characteristic orientation of an investment portfolio. A portfolio constructed by selecting stocks with similar attributes may be said to have a style that is synonymous with the attribute. When expressed at the portfolio level, the small capitalisation and low price-to-earnings effects documented in previous chapters represent the respective small size and value styles. The objective of this section is to investigate whether the small size and value styles have practical implications for professionally managed equity funds on the JSE. The simulated portfolio data from previous

chapters is replaced with equity unit trust return data and a returns-based style analysis technique is employed to investigate the style orientation of the funds in the sample.

9.2.1 Data and methodology

Like Daniel, Grinblatt, Titman and Wermers (1997:1039) who study the role of attributes in US mutual fund returns, it is decided to limit the sample to only equity funds in the General Equity category: *"We exclude sector funds, bonds and preferred funds, and any fund with an investment objective that is not oriented to general equity"*. Incorporating South African equity unit trust funds from categories such as small capitalisation funds and value funds may produce extreme results due to their anecdotal association with the respective small size and price-to-earnings (value) attributes.

While the sample period used in the preceding chapters covers the decade from July 1990 to June 2000, insufficient General Equity unit trust funds were in existence in July 1990 for the analysis to be meaningful¹. After subjectively balancing the number of funds with the length of the sample, it is decided to analyse all the General Equity funds in existence for the sixty months from July 1995 to June 2000. This covers the second and more recent half of the time period used in the previous chapters and incorporates sixteen funds, listed in Table 9.1.

Table 9.1 General Equity unit trust funds in the sample.

Notwithstanding some funds changing names and some consolidating during the period, the sixteen General Equity unit trust funds represent all those in existence for the full period from July 1995 to June 2000.

ABSA General	Metropolitan General
BoE Equity	Old Mutual Investors
Community Growth	Old Mutual Top Co.
FT NIB Prime Select	RMB Equity
Investec Equity	Sage Fund
Investec Index	Sanlam General
Liberty Prosperity	Standard Bank Index
Liberty Wealthbuilder	Standard Bank Mutual

¹ Although the classifications of unit trust portfolios has been revised in recent years, the Micropal database shows that only eight General equity unit trust portfolios were in existence in July 1990.

To the extent that funds are not absorbed into other funds through corporate action or underwent name changes, all funds in the sample survived. The monthly General Equity unit trust fund returns are extracted from the Micropal database on a gross bid-to-bid basis with all income reinvested.

The return pattern of each unit trust fund in Table 9.1 is decomposed using the Sharpe (1992) effective mix style analysis technique as modified by DiBartolomeo and Witkowski (1997), described in Chapter Three. The objective of the effective mix is to identify the combination of indices that best replicate the return pattern of a fund. In this section, the effective mix technique is used to match the return of each General Equity unit trust fund with the return of the financial-industrial and resource sectors and the return of the SLL and LLH risk factor portfolios from the previous chapter².

The effective mix procedure is not strictly a regression and is akin to a portfolio optimisation with a short-selling constraint. An added benefit of the technique is that the constraints on the coefficients mitigate potential multicollinearity problems arising from any correlations between explanatory variables. No intercept term is specified in the effective mix because the constraints render the parameter unstable when used in multi-period analysis, as noted by Trzcinka (1995:46): “...*(the effective mix)...as a measure of the alpha of a portfolio, the model is very questionable*”. The exact estimation of the style weights is through a Constrained Least Squares (CLS) regression of portfolio returns on a set of explanatory indices. Conducted using the Goldfarb-Idnani (1983) Dual Method in this chapter, the CLS procedure is mechanically similar to the gradient method quadratic programming of Sharpe (1992). For the period July 1995 to June 2000, the following equation is estimated for each unit trust fund:

$$r_p = \sum_{i=1}^k a_i(r_i) + \varepsilon_p \quad (9.4)$$

Subject to the constraints:

$$\sum_{i=1}^k a_i = 1 \quad \text{and} \quad 0 \leq a_i \leq 1$$

² The choice of the financial-industrial and resource indices is motivated by the dichotomy in the return generating processes of the JSE, discussed throughout the thesis, for which these indices represent observable risk proxies.

Where r_p is the return of fund p and a_i is a coefficient representing the Sharpe style weights of fund p in each of k pre-specified sectors and styles. r_i is the return of index i and ε_p is the usual error term. While the constraints on the coefficients render traditional techniques for estimating the confidence intervals of the coefficients unreliable, it is judged that this shortcoming is compensated for by the intuitive role that the constraints have in transforming the regression coefficients into style weights³. In an assessment of the effective mix technique, Trzcinka (1995:46) agrees: *‘In the simplest use of the effective mix, as a form of communication between the money manager and the sponsor, it’s advantages of simplicity and objectivity seem to outweigh it’s disadvantages’*.

9.2.2 Empirical results

The results from the effective mix style analysis conducted through a CLS estimation of equation set 9.4 are presented in Table 9.2. The interpretation of the regression coefficients are the weightings in the JSE Financial and Industrial index, the JSE Resource index, the SLL style factor and the LLH style factor that best mimic the return patterns of the individual General Equity unit trust funds. As described in the previous section, the sector and style weights reported in Table 9.2 sum to unity for each fund due of the constraints placed on the coefficients in equation 9.4.

Table 9.2 Sharpe effective mix sector and style weightings.

The figures, in percent, are the time-series coefficients from a CLS regression of unit trust returns on sector and style factor returns from July 1995 to June 2000. The coefficients represent the weightings in the sector and style indices that best match the return of each unit trust over the period. The sector returns are the Resi, representing the JSE Resources index and the Findi, representing the JSE Financial and Industrial index. The style factor returns are SLL, representing the small size risk factor, and LLH representing the low price-to-earnings risk factor derived in Chapter Eight.

	Sectors		Styles	
	Resi	Findi	SSL	LLH
ABSA General	0.0335	0.9326	0.0339	0.0000
BoE Equity	0.1414	0.2439	0.3274	0.2873
Community Growth	0.0947	0.3486	0.4374	0.1193
FT NIB Prime Select	0.1687	0.2242	0.4639	0.1432
Investec Equity	0.1163	0.4139	0.3221	0.1477
Investec Index	0.3374	0.1485	0.4366	0.0775

³ The constrained regressions in this section are conducted using Koichi Yoshioka Plot v2.0.

Table 9.2 Continued.

Liberty Prosperity	0.0060	0.4233	0.4394	0.1314
Liberty Wealthbuilder	0.1684	0.2627	0.4437	0.1251
Metropolitan General	0.0000	0.4935	0.5065	0.0000
Old Mutual Investors	0.1705	0.3492	0.3470	0.1332
Old Mutual Top Co.	0.0581	0.3564	0.4813	0.1042
RMB Equity	0.1223	0.2997	0.4523	0.1256
Sage Fund	0.1980	0.1928	0.5056	0.1036
Sanlam General	0.0819	0.4305	0.4307	0.0569
Standard Bank Index	0.2818	0.1904	0.3442	0.1836
Standard Bank Mutual	0.0000	0.4127	0.4797	0.1076
Average	0.1237	0.3577	0.4032	0.1154

As mentioned, due to the constraints it is not possible to estimate confidence intervals for the coefficients using traditional techniques. The results show a wide range of sector and style weights across the sample of funds. On average the SLL style factor has the highest weighting followed by the JSE Financial and Industrial index, the JSE Resources index and then the LLH style factor. An important observation is that the SLL and LLH styles together capture more than 55% of the variation in the return of the average General Equity unit trust fund.

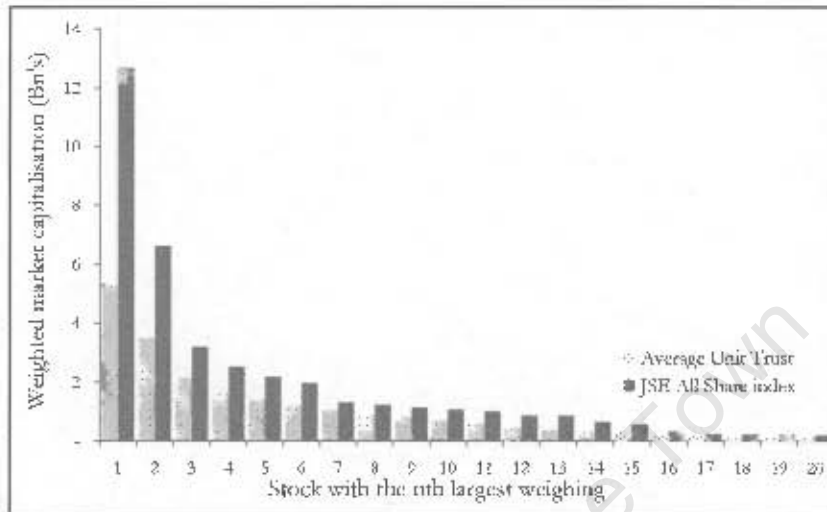
The strong influence of the SLL risk factor in Table 9.2 is likely explained by the structural underweighting that unit trust funds have in large capitalisation stocks relative to the market indices. This structural underweighting of large capitalisation stocks is partly due to industry regulations that limit the maximum holding of equity unit trust funds to no more than ten percent of the value of the fund in any one stock⁴. To illustrate this graphically, the market capitalisation of the largest twenty stock holdings in each unit trust fund is multiplied by its corresponding weighting in the fund⁵. The resulting weighted capitalisation of the largest twenty stock holdings is then averaged across all funds and plotted against the weighted capitalisation of the twenty largest stock holdings in the JSE All Share index, shown in Figure 9.1.

⁴ The regulatory authorities relax the ten percent rule only in the case of passive index tracking unit trust portfolios that endeavour to replicate an index.

⁵ Unit trust constituent stock data at quarter-end is supplied by Moneymate.

Figure 9.1 The weighted market capitalisation of the largest twenty stocks in the average General Equity fund compared to the JSE All Share index.

For each equity unit trust fund, the weighting of each stock is multiplied by the market capitalisation at 30th June 2000 resulting in a measure of weighted capitalisation. The weighted market capitalisation of the largest twenty stocks is averaged across the sixteen unit trusts and contrasted with the weighted capitalisation of the largest twenty stocks in the JSE All Share index.

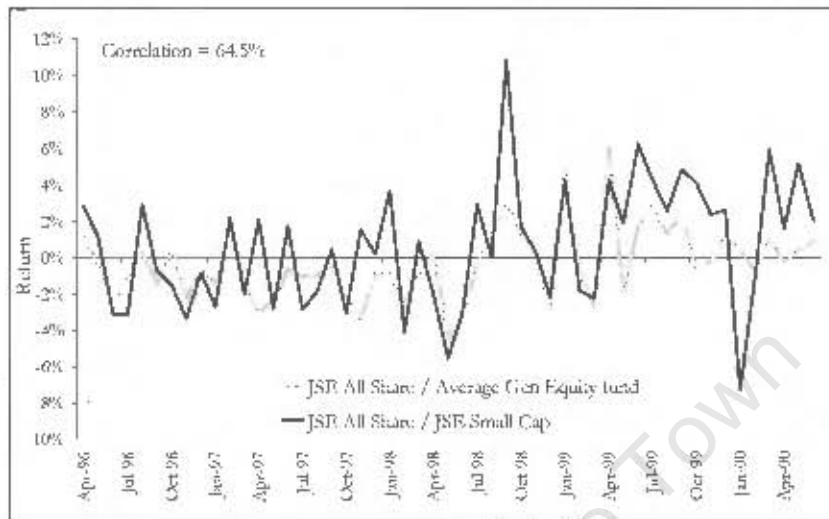


The effect of the above structural underweighting on the performance of the average General Equity fund can be illustrated by comparing the monthly change in the JSE All Share index relative to the JSE Small Capitalisation index with the monthly change in the JSE All Share index relative to the average price of the General Equity funds in the sample. This allows a direct assessment of whether the performance-relative of large capitalisation stocks and small capitalisation stocks is mimicked by the performance-relative of large capitalisation stocks and General Equity unit trusts.

Using monthly data from July 1996 to June 2000, which is the longest history available on I-Net Bridge for these indices, shows a 65% correlation between these two series, as shown in Figure 9.2. This provides a strong argument that the origin of the high explanatory power of the SLL risk factor in the returns-based style analysis in Table 9.2 is directly linked to the structural underweighting of unit trust funds in large capitalisation stocks relative to market indices.

Figure 9.2 Monthly performance-relative figures of the JSE All Share index to the JSE Small Capitalisation and to the average General Equity fund.

The darker line represents the percentage change in the monthly level of the JSE All Share index relative to the JSE Small Capitalisation index. The lighter line represents the percentage change in the monthly level of the JSE All Share index relative to the average General Equity unit trust fund for the period July 1996 to June 2000.



9.2.3 Summary and conclusion

This section provides a practical application of some of the empirical findings of this thesis. Simulated portfolio data is replaced with a data set of monthly General Equity unit trust returns. These funds are assumed to be representative of the investment activities of professional managed equity funds on the JSE. A Sharpe (1992) effective-mix style analysis technique is used to discern the weightings in the financial industrial sector, resource sector, small size style and value style that best mimic the return pattern of each unit trust in the sample.

The results show a broad range of sector and style weights with the small size style and low price to earnings style together explaining almost half the variation in average fund return. The largest average weighting is in the small size style. It is suggested that the structural underweighting of the average General Equity unit trust towards smaller capitalisation stocks, relative to market-related indices, is the likely reason for the high explanatory power of the small size style.

9.3 Conclusion

An argument that often appears in the anomaly-related literature is that observed results are spurious and are unlikely to occur out of sample, consistent with the view of Black (1993:17): *“Most of the so-called anomalies that have plagued the literature on investments seems likely to be the result of data-mining”*. This criticism arises from the possibility, as Lo and MacKinlay (1990) argue, that data-snooping can affect the significance levels of statistical tests. Fama (1991:1580) has similar concerns: *“...there is the danger that measured relations between returns and economic factors are spurious, the result of special features of a particular sample (factor dredging)”*. In defense of the results in this thesis, an important feature of the data set is that none of the attributes selected for inclusion are motivated by prior evidence of their association with stock returns on the JSE. Moreover, the data set examined is ‘fresh’ and has not been previously trawled for factors. This is unlike the CRSP (Center for Research in Securities Prices) and Compustat data sets used in the majority of US studies, and the EMDB (Emerging Markets Database) maintained by the International Finance Corporation. In addition, several previously documented effects on the JSE reappear in the cross-sectional data. Another potential criticism is the Berk (1995) argument that when stock price is used in the numerator or denominator of a financial ratio, the ratio becomes mechanically related to contemporaneous stock returns. This issue is mitigated in this thesis since the attributes are deliberately lagged with stock returns and the results thus reflect non-contemporaneous relationships.

The economic interpretation of the explanatory power of the size and price-to-earnings attribute on the JSE however requires further investigation. For instance Brennan, Chordia and Subrahmanyam (1998) argue that the small size effect is related to trading volume and compensation for liquidity risk. This may be a particularity relevant line of investigation in light of the thin trading that characterises the JSE, reviewed in Chapter Four. Another pressing area for further research is the argument by Chan, Chen and Hsieh (1985) that the relation between size and average return is merely a proxy for otherwise unknown sources of priced economic factors, such as those identified by van Rensburg (2000) for the JSE.

Whether the results are consistent with the CAPM is comparatively easy to assess since the six candidate attributes are clear violations of the theoretical underpinnings of the model. Yet the asset pricing theory - efficient market joint hypothesis asserts however that it is never

possible to know for certain what exactly the results imply about the validity of the CAPM. Nevertheless, it is especially difficult to defend beta on the JSE in light of the inverse relation observed between beta and stock returns documented in Chapter Seven. Beta may however still have a variety of roles in portfolio construction, risk analysis and performance evaluation. It is suggested by Bekaert, Erb and Viskanta (1997:235) that: *"It is likely that these (emerging) markets are not fully integrated into world capital markets. As a result the beta suggested by the CAPM may not be useful in explaining the cross-section of returns"*. More research is required on the JSE to investigate this perspective.

Of particular relevance is the contrast in results with the Fama and French (1993:14) observation that: *"...portfolios constructed to mimic risk factors related to size and BE/ME capture strong common variation in returns, no matter what else is in the time series regressions. This is evidence that size and book-to-market equity indeed proxy for sensitivity to common risk factors in stock returns"*. When similar portfolios are constructed in Chapter Eight to mimic the risk factors associated with the small size and low price-to-earnings effects it is shown this is not the case for the JSE, contrary to asset pricing theory. At least in respect of the price-to-earnings attribute, the source of the explanatory power relates to the attribute itself and not to risk factor loadings, in agreement with Daniel and Titman (1997). However, where the attribute and the factor loading are correlated, as is the case with the size attribute in this thesis, the power of the tests are limited. There remains still some questions over the relative importance of 'covariances' and 'characteristics' in determining expected returns on the JSE and further research is required, especially since Davis, Fama and French (2000:1941) report: *"The Daniel-Titman rejection of the three-factor model in favor of the characteristic model is special to their 20.5-year sample"*.

What exactly the results imply for the practitioner is unclear since transaction costs, liquidity constraints and market impact costs are not accounted for in the test methodologies. When adding these costs to the return premiums associated with the anomalies, it is uncertain whether the documented effects are useful to the practitioner beyond their role in portfolio performance evaluation, as demonstrated in the previous section. Roll (1994:70) arrives at a similar conclusion: *"Over the past decade, I have attempted to exploit many of the seemingly most promising 'inefficiencies' by actually trading significant amounts of money...Many of these effects are*

surprisingly strong in the reported empirical work, but I have never found one that worked in practice". The results of this thesis nevertheless provide new and useful insight into price determination on the JSE and only further research will determine whether the: "... anomalies may be short-lived, almost by definition. The exceptions to the current body of knowledge may be incorporated into that body of knowledge and become tomorrow's conventional wisdom" (New Palgrave Dictionary of Money and Finance, 3, 573).

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Appendix A

A.1 Line item definitions

Based on the information contained in the McG/BFA database, the following are definitions of the line items used in the calculation of the financial ratios.

Current assets

Consists of all stock on hand, raw materials, finished goods, merchandise, consumable stores, work in progress, cash and all outstanding debtors net of any provisions for bad debts or unearned finance charges. Short-term loans that appear in the financial statements under current assets, including those to subsidiaries, are also included provided they are due for redemption within the next financial year.

Current liabilities

Includes provision for dividends and taxation, bank overdraft balances, short-term borrowings and sundry creditors.

Cumulative volume

Is the sum of all ordinary shares bought and sold on all trading days in the month.

Extraordinary items

Includes all profits or losses on transactions of an extraordinary or non-recurring nature, including the realisation of investments and non-trading assets.

Long-term loans

Includes secured long-term borrowings obtained against some form of security over certain assets of the company such as a mortgage bond over land and buildings or a notarial bond over stock on hand. Secured and unsecured debentures, convertible debentures, redeemable debentures as well as issues at different interest rates are also included so long as they are not repayable within the next financial year.

Net asset value

Defined as the difference between the total assets and the total liabilities as defined above.

Non-cashflow items

The items are drawn from the source and application of funds statement. Included is the total of all income and expenditure items included in the income statement which did not represent an actual flow of funds during the year such as losses on sale of assets, losses from scrapped assets, provisions for depreciation and changes in these provisions reflected in the income statement.

Ordinary dividends

Represents those declared or provided in favour of the various classes of ordinary shareholders in respect of the current financial period.

Ordinary share capital

Represents the total amount paid up on the issued ordinary share capital in respect of all classes of ordinary shares. In respect of shares with a par value this figure represents the nominal amount of the shares that are fully paid up, and the amount actually paid upon partly paid shares. Share premiums paid on such shares and non-distributable reserves are not included. No distinction is made between various classes of ordinary shares and all classes of ordinary shares and is grouped together in this item.

Profit after taxation

Is the net profit for the year, including profits and losses of an extraordinary nature, after providing for the taxation for the year.

Profit before interest and taxation

Represents the net profit for the year including profits and losses of an extraordinary nature, but before deducting interest paid on borrowed funds and before providing for taxation for the year.

Profits due to shareholders

Is defined as portion of total profit due to ordinary and preference shareholders but does not include amounts due to minority shareholders.

Retained profit

Is defined as the portion of the profit for the financial year that was retained in the company or the group in order to strengthen the reserves, increase liquidity or provide internal finance for increased activities.

Total assets

Consist of fixed assets, long-term investments and current assets. Fixed assets are represented at book value by taking the total cost or revaluation of all land, buildings and other fixed assets owned by the company, including mining assets, and adjusting for the total accumulated depreciation provided for against these assets during in the current year. Long-term investments are long-term loans advanced, including those to subsidiaries, where the repayment date is not expected to fall within the next financial year. Unlisted and listed investments are included at market value on the last day of the financial year while investments in unconsolidated subsidiaries that are not accounted for in the consolidated financial statements are reflected at book values. Current assets consists of all stock on hand, raw materials, finished goods, merchandise, consumable stores, work in progress, cash and all outstanding debtors net of any provisions for bad debts or unearned finance charges. Short-term loans that appear in the financial statements under current assets, including those to subsidiaries, are also included provided they are due for redemption within the next financial year.

A.2 Calculation of financial ratios

The following are the formulas used for the calculation of the financial ratios, as described in the McG/BFA database. Formulas for the technical indicators are also given.

Cashflow-to-price

$(\text{Ordinary dividends} + \text{Non-cashflow items}) / \text{Ordinary shares in issue} / \text{Price}$

Current ratio

$\text{Current assets} / \text{Current liabilities}$

Debt-to-assets

$(\text{Long-term loans} + \text{Current liabilities}) / \text{Total assets}$

Debt-to-cashflow

$(\text{Long-term loans} + \text{Current liabilities}) / (\text{Ordinary dividends} + \text{Non-cashflow items})$

Debt-to-equity

$(\text{Long-term loans} + \text{Current liabilities}) / \text{Total owners interest}$

Dividend yield

$(\text{Ordinary dividends} / \text{Ordinary shares}) / \text{Price}$

Financial distress

The financial distress indicator is based on a South African adaptation of the widely applied model developed by Altman (1968, 1983). The model was adapted by McG/BFA and is updated monthly. The model generates an index, or z-score, and has been shown to be a reasonable indicator of the likelihood of bankruptcy of an individual firm during the upcoming twelve months. A model for the z-scores is estimated by examining financial statements of a sample of firms one year prior to bankruptcy and financial statements for a sample of firms that survived.

The statistical technique applied is discriminant analysis and is a form of regression that distinguishes the best statistical relationship between the variables hypothesized to indicate financial distress. The weaker a firm's collective measures of financial health, the lower the resulting z-score. The variables include the total profit, outside of financing, before interest and tax expressed as a proportion of total assets and the sum of total current assets and listed investments as a proportion of total liabilities. Also included is profit after taxation relative to average total assets at book value, cashflow profit after tax relative to inflation-adjusted total assets at market value and total stock as a proportion of inflation-adjusted total assets. Once the model has been estimated using samples of bankrupt and surviving firms, its validity is verified using new samples of observations.

Leverage

A proprietary composite indicator of the gearing of a firm compiled and maintained by McG/BFA and included all short-term financing obligations, secured long-term borrowings and debentures.

Long-term loans-to-assets

Long-term loans/Total assets

Price-to-earnings

Price / (Retained profit – Ordinary dividends) / Ordinary shares

Price-to- profit

Price / (Adjusted profit / Ordinary shares)

Price-to-NAV

Price /(Net asset value / Ordinary shares)

Quick ratio

(Current assets – Long-term loans) / Current liabilities

Retention rate

Retained profit / Profits due to shareholders

Return on assets

(Profit before income and taxation - Extraordinary items) / Total assets

Return on equity

Profit after taxation / Total owners interest

Shares in issue

Ordinary shares in issue represents the actual number of ordinary shares issued and is adjusted for partly paid-up shares reduced in the same ratio as that in which the amount paid-up stands to the nominal value of the shares.

Size

Ln (Total market capitalisation of ordinary shares only)

Sustainable growth

Companies faced with growth opportunities are expected to earn a superior return on assets. However, the return on the assets is only one of the factors affecting growth. Given the growth opportunities, the company's financial policies must be of such a nature as to permit

the company to take advantage of those growth opportunities. These financial policies dictate the sustainable growth. Growth is possible primarily if there are growth opportunities and then if the company's financial strategies are structured to allow the company to grow. A company can grow at the rate of return on its assets, provided it does not pay any dividends nor is it financed from outside sources, in other words, it is entirely financed by shareholders' funds.

A composite indicator compiled and maintained by McG/BFA. The indicators in the composite include the percentage return on assets after tax, the proportion of earnings retained, debt, equity and the percentage interest rate on debt after tax. Each of these components are internally consistent meaning that where the return on assets is regarded as return on net assets, the debt figure used is long-term debt and the interest rate applied is the average rate on that debt, whereas if the return on assets is the return on total assets, total debt and the average rate of interest thereon is used.

Total owners interest

Total owners' interest represents the total interest of the ordinary and preference shareholders in the company, plus the outside shareholders' interest in the ordinary and preference shares of the subsidiaries.

A.3 Calculation of technical indicators

The following are the formulas used for the calculation of the financial ratios, as described in the McG/BFA database. Formulas for the technical indicators are also given.

One-month prior return

The one-month prior return for a stock is taken as the reinvested total return for the previous calendar month.

Six-month prior return

The six-month prior return of a stock is taken as the cumulative reinvested total return for the previous six month period ending and the last trading day of the previous month.

Twelve-month prior return

The twelve-month prior return of a stock is taken as the cumulative reinvested total return for the previous calendar year up to the end of the last trading day of the previous month.

Trading volume

Cumulative trading volume (Offers and bids) / Number of trading days in the month.

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Appendix B

B.1 Kurtosis of the attributes.

Kurtosis characterises the relative peakedness or flatness of a distribution compared with the normal distribution. Positive kurtosis indicates a relatively peaked distribution while negative kurtosis indicates a relatively flat distribution. If S is the sample standard deviation, then the kurtosis is given by:

$$\left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

	Kurtosis			
	All	Financials	Industrials	Resources
Cashflow-to-price	0.45	2.61	2.20	5.27
Current ratio	7.14	2.81	0.82	4.67
Debt-to-assets	9.22	-1.38	-0.69	5.67
Debt-to-cashflow	2.22	0.49	1.96	3.04
Debt-to-equity	1.81	0.43	2.71	2.21
Dividend yield	0.62	2.97	2.43	3.23
Financial distress	2.80	2.07	2.33	3.55
Leverage	4.91	2.64	1.70	4.27
LT Loans-to-assets	-0.99	-0.71	0.59	0.08
One-month prior	3.66	1.88	3.38	0.70
Owners interest	6.45	3.54	5.37	3.72
Price-to-earnings	2.78	1.47	2.02	4.33
Price-to-NAV	0.49	2.47	4.52	4.47
Price-to-profit	1.23	1.60	4.23	3.69
Quick ratio	4.54	2.99	1.41	4.89
Retention rate	0.21	0.03	0.45	-0.28
Return on assets	7.99	0.65	-0.35	1.79
Return on equity	4.40	1.37	0.52	1.74
Shares in issue	1.03	2.65	0.17	-0.36
Six-months prior	1.47	3.69	1.36	0.57
Size	-0.56	-0.31	-0.55	-0.96
Sustainable growth	2.27	0.91	0.70	2.48
Trading volume	9.01	5.02	6.26	9.87
Twelve-months prior	1.71	1.92	1.50	0.52

B.2 Standard deviation of the attributes.

The standard deviation is the commonly used measure of variation. If μ is the population mean and n is the population size, then the standard deviation, σ , of a population of values is computed as:

$$\sigma = \left[\frac{\sum (x_i - \mu)^2}{n} \right]^{\frac{1}{2}}$$

	Standard deviation			
	All	Financials	Industrials	Resources
Cashflow-to-price	0.23	0.24	0.34	2.23
Current ratio	1.37	2.44	0.80	2.89
Debt-to-assets	0.36	0.34	0.23	1.69
Debt-to-cashflow	6.54	35.33	5.18	7.29
Debt-to-equity	1.45	5.80	1.49	1.10
Dividend yield	6.47	8.70	8.46	18.71
Financial distress	0.14	0.70	0.08	0.41
Leverage	2.30	4.30	1.69	6.15
LT Loans-to-assets	0.19	0.36	0.23	0.21
One-month prior	0.14	0.11	0.14	0.14
Owners interest	1.40	2.46	0.76	2.76
Price-to-earnings	12.17	15.32	9.74	37.25
Price-to-NAV	2.10	2.01	3.52	9.88
Price-to-profit	16.60	21.45	21.85	38.00
Quick ratio	1.08	2.44	0.70	2.90
Retention rate	0.52	0.36	0.29	0.43
Return on assets	0.14	0.08	0.07	0.30
Return on equity	0.24	0.15	0.19	0.34
Shares in issue	141.49	225.7	122.72	113.01
Six-months prior	0.37	0.37	0.35	0.36
Size	2.16	1.89	2.03	2.60
Sustainable growth	18.55	17.85	18.7	30.08
Trading volume	0.14	0.19	0.11	0.17
Twelve-months prior	0.62	0.68	0.58	0.56

Appendix C

C.1 Monthly cross-sectional regressions of stock returns on individual attributes.

Following Fama and MacBeth (1973), a cross-sectional regression was performed in each month from July 1990 to June 2000 whereby all non-thinly traded stock returns are regressed on individual attributes. For a stock to be included in the cross-sectional regression in a month, it must have both a return for the month and a value for the attribute under consideration. The attribute data for all fiscal year ends in calendar year $t-1$ was matched with the returns for May of year t . The average slopes represent the time-series arithmetic average of the slope coefficients from the cross-sectional regressions in each month. The t-statistics are in respect of the time-series of slope coefficients and indicate whether, on average, returns have responded to the regressor variable in each month in a way that is significantly different from zero. Coefficients significant above the ninety-five percent confidence interval are in bold. Results are ranked in descending order of the absolute value of the t-statistics.

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Price-to-NAV											
- Average slope	-0.01	0.00	-0.01	-0.01	-0.02	-0.01	0.00	-0.01	-0.01	-0.01	0.00
- t-stat	-3.70	-0.43	-3.03	-1.93	-3.81	-3.28	-0.59	-1.12	-0.72	-1.20	-0.38
Dividend yield											
- Average slope	0.02	0.03	0.00	0.05	0.04	0.01	0.01	0.01	0.00	0.01	0.01
- t-stat	3.53	1.73	-0.75	1.48	2.43	1.08	2.33	2.53	0.26	0.90	1.18
Price-to-earnings											
- Average slope	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.02	0.00	-0.01	-0.01
- t-stat	-3.32	-4.10	-2.42	-0.29	-2.75	-1.69	-2.41	-3.07	-0.19	-0.67	-0.83
Size											
- Average slope	-0.01	0.00	0.01	-0.02	-0.03	-0.01	-0.01	-0.01	-0.01	0.01	0.00
- t-stat	-3.21	0.00	1.21	-2.53	-2.80	-3.15	-2.00	-2.83	-1.20	1.09	-0.82
Cashflow-to-price											
- Average slope	0.02	0.01	-0.01	0.05	0.02	0.00	0.01	0.05	0.03	0.00	0.03
- t-stat	2.51	2.01	-1.65	1.55	2.29	-0.11	0.78	0.98	0.88	-0.12	1.52
Price-to-profit											
- Average slope	0.00	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	0.00	0.00	0.01
- t-stat	-2.05	-0.75	-1.70	-3.04	-1.71	-0.82	-2.17	-2.02	0.06	0.02	1.67
Retention rate											
- Average slope	0.38	-0.01	-0.02	0.29	2.13	1.53	0.02	0.01	0.01	-0.04	-0.09
- t-stat	1.49	-0.31	-1.98	0.57	0.91	1.61	1.65	0.59	0.48	-1.10	-1.64
Debt-to-asset											
- Average slope	-0.03	-0.02	-0.03	0.04	0.00	0.00	0.00	-0.01	0.00	-0.06	-0.20
- t-stat	-1.33	-2.07	-1.67	2.34	-0.12	-0.24	-0.02	-1.01	-0.19	-0.29	-2.22
Leverage											
- Average slope	-0.02	-0.12	0.01	-0.04	-0.01	0.03	-0.04	0.00	0.00	-0.01	0.00
- t-stat	-1.22	-0.91	1.04	-1.26	-1.59	1.72	-0.62	-0.05	-0.13	-0.79	-0.10
Return-on-assets											
- Average slope	-0.19	0.01	0.14	0.48	-0.01	-0.01	0.01	0.00	-0.34	-0.15	-2.04
- t-stat	-0.90	0.61	1.15	2.14	-2.87	-1.15	0.51	-0.12	-1.29	-0.18	-1.07

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Shares in issue											
- Average slope	-0.19	0.01	0.14	0.48	-0.01	-0.01	0.01	0.00	-0.34	-0.15	-2.04
- t-stat	-0.90	0.61	1.15	2.14	-2.87	-1.15	0.51	-0.12	-1.29	-0.18	-1.07
Financial distress											
- Average slope	0.01	-0.05	0.01	0.01	-0.02	0.01	0.01	-0.01	0.00	0.15	0.02
- t-stat	0.83	-1.61	0.36	0.42	-0.92	0.48	0.72	-0.18	-0.33	1.02	0.64
Return-on-equity											
- Average slope	-0.02	-0.02	0.02	0.01	0.00	-0.02	0.00	0.11	-0.01	-0.13	-0.17
- t-stat	-0.77	-2.15	1.97	0.72	0.28	-0.92	-0.08	2.35	-0.75	-1.01	-0.70
Owner's interest											
- Average slope	0.00	0.00	0.01	-0.01	-0.01	0.00	0.00	0.00	-0.01	0.01	0.01
- t-stat	-0.65	0.11	1.49	-1.81	-1.78	-0.89	-0.98	-1.04	-1.93	2.27	1.81
Trading volume											
- Average slope	0.00	0.00	-0.01	0.02	0.00	0.00	-0.01	-0.01	0.00	0.00	-0.01
- t-stat	-0.57	-0.84	-0.62	1.15	-0.45	-0.03	-1.68	-1.92	-0.38	-0.34	-3.76
Debt-to-equity											
- Average slope	0.00	0.00	0.00	0.01	-0.01	0.01	0.02	0.00	0.01	-0.01	0.00
- t-stat	0.55	-0.47	-0.32	0.49	-1.15	0.78	0.43	-0.09	1.38	-0.91	0.14
Sustainable growth											
- Average slope	-0.01	-0.03	0.03	0.03	-0.01	0.00	0.02	0.07	-0.03	-0.09	-0.05
- t-stat	-0.48	-0.64	1.77	1.44	-0.48	0.19	0.56	1.87	-0.60	-1.59	-2.81
LT Loans-to-assets											
- Average slope	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	0.00
- t-stat	-0.39	0.10	0.73	-1.73	-4.06	0.36	0.48	-0.70	0.00	0.95	-0.75
Twelve months prior											
- Average slope	0.00	0.01	0.01	-0.01	0.00	0.00	0.00	0.00	0.01	-0.01	-0.01
- t-stat	-0.31	1.18	1.60	-1.66	-0.19	-0.35	-0.12	0.90	1.28	-1.44	-0.95
Current ratio											
- Average slope	0.00	-0.06	0.00	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01
- t-stat	-0.27	-1.69	0.32	-0.03	-0.27	0.59	1.37	0.76	0.79	0.09	1.33
Quick ratio											
- Average slope	0.00	-0.06	0.00	0.00	-0.01	0.02	0.01	0.01	0.00	0.00	0.01
- t-stat	-0.25	-1.61	0.44	0.14	-0.44	0.59	1.43	0.89	1.10	0.04	1.02
Debt-to-cashflow											
- Average slope	0.00	0.00	-0.02	-0.03	-0.04	0.00	-0.05	0.00	-0.05	0.18	0.01
- t-stat	-0.03	0.02	-1.40	-2.08	-1.13	0.00	-2.12	-0.03	-0.57	1.00	0.66
Six months prior											
- Average slope	0.00	0.01	0.00	-0.01	0.00	0.00	0.00	0.01	0.00	-0.01	0.01
- t-stat	0.71	1.35	0.75	-2.03	-0.09	1.19	0.30	0.77	0.77	-0.99	0.60

	Years										
	All	1	2	3	4	5	6	7	8	9	10
One month prior											
- Average slope	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.01	-0.01
- t-stat	-0.31	-1.99	1.19	0.28	0.35	-0.91	-0.42	1.50	-0.21	0.84	-1.25

Appendix D

D.1 Attribute correlation matrix for all stocks

[illegible]

D.2 Attribute correlation matrix for financial stocks

[illegible]

D.3 Attribute correlation matrix for industrial stocks

	Debt-to-equity	Cashflow-to-price	Current ratio	Debt-to-assets	Volume	Debt-to-cashflow	Dividend yield	LT Loan-to-asset	Price-to-earnings	Price-to-profit	Price-to-NAV	Quick ratio	Retention rate	Return on assets	Shares in issue	Financial distress	Leverage	Size	Return on equity	Sustain growth	Owners interest	One-month prior	Six month prior	12-month prior
Debt- to-equity	1.0	-0.05	-0.08	0.33	-0.02	0.52	-0.01	0.31	0.11	0.45	0.64	-0.04	-0.02	-0.06	-0.03	-0.07	0.25	-0.07	0.10	0.25	-0.07	0.00	-0.02	-0.03
Cashflow-to-price		1.00	0.03	0.00	0.08	-0.08	0.69	-0.10	-0.15	-0.09	-0.11	0.02	0.02	0.01	-0.04	-0.03	0.03	-0.22	0.03	-0.03	-0.03	-0.01	-0.04	-0.04
Current ratio			1.00	-0.24	-0.02	-0.04	-0.01	-0.06	0.02	-0.04	-0.04	0.92	0.07	-0.08	-0.04	0.45	0.03	-0.07	-0.06	-0.05	-0.02	0.00	0.00	-0.02
Debt -to-assets				1.00	0.01	0.21	-0.08	0.29	0.01	0.21	0.24	-0.24	0.19	-0.07	0.01	-0.26	0.11	-0.14	0.21	0.19	-0.16	0.02	0.03	0.03
Trading volume					1.00	-0.03	0.15	-0.03	0.03	-0.02	0.06	-0.01	-0.04	0.08	0.34	-0.01	0.02	0.22	0.06	0.03	0.16	0.01	0.02	0.04
Debt-to-cashflow						1.00	0.02	0.40	0.06	0.61	0.42	-0.02	-0.07	-0.05	-0.07	-0.04	-0.03	-0.04	-0.03	0.04	-0.06	-0.01	-0.02	-0.03
Dividend yield							1.00	-0.04	-0.12	-0.03	-0.08	0.03	-0.12	0.02	0.01	0.03	-0.03	-0.19	-0.01	-0.06	-0.09	-0.02	-0.04	-0.05
LT Loans-to-asset								1.00	0.10	0.28	0.23	-0.01	0.04	-0.08	-0.05	-0.10	-0.02	0.01	-0.02	0.05	0.00	0.00	0.00	0.00
Price-to-earnings									1.00	0.21	0.47	0.04	0.02	-0.10	-0.02	-0.02	0.06	0.11	-0.02	0.03	-0.04	0.00	0.02	0.02
Price-to-profit										1.00	0.41	0.00	-0.13	-0.13	-0.04	0.13	-0.05	0.03	-0.11	0.03	-0.04	0.00	-0.01	-0.02
Price-to-NAV											1.00	-0.01	-0.02	0.03	-0.02	-0.04	0.26	0.09	0.17	0.30	-0.06	0.01	0.02	0.01
Quick ratio												1.00	0.05	-0.09	-0.02	0.46	0.04	-0.06	-0.06	-0.05	-0.04	0.01	0.00	-0.02
Retention rate													1.00	-0.15	-0.05	-0.07	0.05	-0.14	-0.10	0.06	-0.08	0.00	0.00	0.00
Return on assets														1.00	0.13	-0.07	-0.14	0.25	0.37	0.24	0.05	0.03	0.12	0.18
Shares in issue															1.00	0.00	0.01	0.52	0.08	0.04	0.23	0.01	0.01	0.03
Financial distress																1.00	0.01	0.08	-0.03	-0.06	0.06	0.00	0.00	0.00
Leverage																	1.00	-0.06	0.18	0.09	-0.05	0.00	-0.01	-0.01
Size																		1.00	0.11	0.08	0.50	0.02	0.10	0.14
Return on equity																			1.00	0.66	-0.01	0.03	0.10	0.12
Sustain growth																				1.00	-0.02	0.02	0.07	0.10
Owners interest																					1.00	-0.01	0.00	0.00
One-month prior																						1.00	0.37	0.26
Six-month prior																							1.00	0.69
12 -month prior																								1.00

D.4 Attribute correlation matrix for resource stocks

[illegible]

Appendix E

E.1 Monthly cross-sectional regressions of stock returns on individual attributes, including a dummy coded variable for resource stocks.

Following Fama and MacBeth (1973), a cross-sectional regression was performed in each month from July 1990 to June 2000 whereby all non-thinly traded stock returns are regressed on individual attributes. A dummy variable was added to the regression and was assigned a value of one for resource stocks and zero otherwise. For a stock to be included in the cross-sectional regression in a month, it must have both a return for the month and a value for the variable under consideration. The attribute data for all fiscal year ends in calendar year $t-1$ was matched with the returns for May of year t . The average slopes represent the time-series arithmetic average of the slope coefficients from the cross-sectional regressions in each month. The t-stats are in respect of the time-series of slope coefficients and indicate whether, on average, returns have responded to the regressor variable in each month in a way that is significantly different from zero. The average r-squared represents the time-series average coefficient of the cross-sectional regressions in each month over the period. Coefficients significant above the ninety-five percent confidence interval are in bold. Results are ranked in descending order of the absolute value of the t-statistics of the non-dummy-coded attributes.

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Cashflow-to-price											
- Average slope	0.05	0.01	-0.01	0.05	0.03	0.04	0.12	0.15	0.01	0.00	0.04
- t-stat	3.97	1.23	-0.81	1.48	2.21	1.36	2.48	1.85	0.13	-0.12	1.79
Dummy											
- Average slope	-0.04	0.15	0.00	-0.01	-0.02	-0.06	-0.12	-0.16	0.07	0.00	-0.04
- t-stat	-1.82	5.06	-0.30	-0.23	-0.41	-1.80	-2.29	-1.95	1.32	0.04	-1.17
Price-to-NAV											
- Average slope	-0.01	0.00	-0.01	-0.01	-0.02	-0.01	-0.01	-0.02	-0.02	-0.01	-0.02
- t-stat	-3.68	-0.69	-3.18	-2.02	-2.25	-1.85	-3.12	-1.33	-1.06	-1.79	-2.51
Dummy											
- Average slope	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.03	0.03	0.02	0.05
- t-stat	1.71	0.27	-0.48	-0.80	0.00	0.32	0.17	0.99	0.78	1.25	1.34
Price-to-earnings											
- Average slope	-0.01	0.00	-0.01	-0.03	-0.01	-0.01	-0.01	-0.02	0.00	0.00	-0.01
- t-stat	-3.59	-1.07	-0.67	-1.28	-2.01	-1.64	-4.48	-3.42	-0.25	-0.08	-1.63
Dummy											
- Average slope	-0.00	-0.01	0.00	0.03	0.00	0.00	0.01	0.02	-0.02	-0.10	0.01
- t-stat	-0.16	-1.83	-0.30	1.28	0.34	0.35	1.42	1.40	-0.52	-1.29	1.24
Dividend yield											
- Average slope	0.02	0.03	-0.01	0.05	0.04	0.01	0.01	0.01	0.00	0.01	0.01
- t-stat	3.59	1.48	-1.01	1.50	2.46	0.95	1.98	3.04	-0.27	1.55	1.26
Dummy											
- Average slope	0.01	0.28	0.10	-0.04	0.03	0.01	0.00	-0.02	0.01	-0.01	0.00
- t-stat	0.37	4.19	1.53	-0.79	0.42	0.29	-0.39	-1.81	0.56	-1.29	-0.29
Return on assets											
- Average slope	-1.05	0.11	0.12	0.55	-0.01	-0.02	0.05	0.02	-0.20	-0.98	-3.45
- t-stat	-2.71	1.24	0.55	2.49	-0.71	-1.01	0.99	0.72	-1.06	-1.18	-1.76
Dummy											
- Average slope	1.38	-0.11	0.02	-0.11	-0.01	0.02	-0.06	-0.03	-0.14	0.59	0.86
- t-stat	1.97	-1.35	0.10	-0.55	-0.40	0.76	-1.14	-1.14	-1.93	1.18	2.26

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Size											
- Average slope	-0.01	0.00	0.01	-0.01	-0.03	-0.02	-0.01	-0.01	-0.01	0.01	-0.01
- t-stat	-2.57	0.27	1.10	-1.82	-3.21	-3.33	-1.80	-2.70	-0.77	1.07	-0.81
Dummy											
- Average slope	0.00	-0.01	-0.01	-0.01	0.01	0.01	0.00	0.00	-0.01	-0.01	0.01
- t-stat	-0.30	-0.75	-0.49	-0.82	1.77	1.66	0.07	-0.20	-1.10	-0.67	0.51
Leverage											
- Average slope	-0.03	-0.15	0.01	0.01	-0.02	0.01	0.03	-0.01	-0.01	-0.03	-0.01
- t-stat	-1.82	-1.47	1.00	1.09	-1.33	0.30	1.39	-0.25	-0.23	-1.38	-0.69
Dummy											
- Average slope	0.65	0.56	0.21	-0.02	-0.07	0.04	-0.03	0.02	0.01	0.08	0.03
- t-stat	1.45	3.45	1.57	-1.39	-0.64	0.35	-0.33	0.50	0.16	1.79	0.93
Return on equity											
- Average slope	-0.05	-0.02	0.03	0.02	0.02	0.03	0.01	0.14	-0.02	-0.22	-0.40
- t-stat	-1.69	-1.09	1.82	0.73	0.67	0.94	0.19	1.92	-1.02	-1.34	-2.14
Dummy											
- Average slope	0.12	-0.01	-0.02	-0.02	-0.03	-0.12	-0.05	-0.12	0.00	0.31	0.81
- t-stat	0.93	-0.61	-0.84	-0.63	-1.01	-2.09	-0.48	-1.50	-0.03	2.21	2.13
Retention rate											
- Average slope	0.43	0.02	-0.02	0.17	2.18	1.80	0.02	0.01	0.03	-0.08	-0.11
- t-stat	1.60	0.29	-1.83	0.33	0.96	2.04	1.25	0.45	1.33	-1.38	-1.68
Dummy											
- Average slope	0.22	-0.13	0.00	0.20	-0.06	-0.30	-0.02	0.00	-0.07	0.14	0.12
- t-stat	0.68	-1.66	-0.14	1.35	-0.22	-1.47	-0.29	-0.18	-2.68	1.56	1.16
Current ratio											
- Average slope	0.02	-0.10	0.00	-0.01	-0.02	0.00	0.00	0.01	0.00	0.00	0.02
- t-stat	1.36	-2.35	0.07	-1.26	-0.72	0.02	0.62	0.96	0.92	0.28	1.99
Dummy											
- Average slope	-0.25	0.07	0.00	0.01	0.02	0.02	0.01	-0.02	-0.01	-0.01	-0.07
- t-stat	-1.62	0.81	0.13	1.04	0.86	0.16	0.60	-1.21	-1.03	-0.36	-1.92
Price-to-profit											
- Average slope	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	0.00	0.00	0.02
- t-stat	-1.30	-0.63	-2.86	-2.80	-1.48	-1.07	-2.64	-3.96	0.16	0.65	2.28
Dummy											
- Average slope	0.01	0.00	-0.01	-0.04	0.01	0.10	0.15	0.01	-0.02	-0.08	-0.03
- t-stat	0.22	0.19	-0.51	-1.15	0.14	1.56	0.71	0.52	-1.24	-1.34	-2.70
Quick ratio											
- Average slope	0.02	-0.10	0.00	0.00	-0.06	0.01	0.00	0.01	0.00	0.00	0.02
- t-stat	0.97	-2.35	0.12	-0.92	-1.39	0.07	0.67	1.12	0.98	0.27	1.67
Dummy											
- Average slope	-0.02	0.08	0.00	0.01	0.06	0.01	0.01	-0.02	0.00	-0.01	-0.07
- t-stat	-1.27	0.93	0.17	0.87	1.39	0.08	0.59	-1.26	-0.55	-0.40	-1.81
Financial distress											
- Average slope	0.02	-0.10	0.01	0.04	-0.02	-0.02	0.00	-0.02	-0.01	0.19	0.03
- t-stat	0.88	-2.92	0.27	0.89	-1.55	-2.05	-0.04	-0.79	-0.60	1.01	0.74
Dummy											
- Average slope	-0.03	0.16	0.02	-0.10	0.01	0.06	0.02	0.08	0.09	-0.27	-0.39
- t-stat	-0.55	2.10	0.84	-0.66	0.28	1.84	0.66	2.45	1.06	-1.37	-1.23

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Owners equity											
- Average slope	-0.00	0.00	0.01	0.00	-0.02	-0.01	0.00	0.00	-0.01	0.01	0.01
- t-stat	-0.64	-0.05	1.23	-0.82	-2.35	-1.55	-0.59	-1.34	-1.47	1.72	2.20
Dummy											
- Average slope	0.00	0.00	0.00	-0.01	0.01	0.01	0.00	0.00	0.00	0.00	-0.01
- t-stat	0.44	0.13	-0.43	-1.10	2.72	2.45	-0.20	1.26	-0.45	-0.05	-1.32
Shares in issue											
- Average slope	0.00	0.00	0.01	0.01	-0.02	-0.01	0.00	0.00	0.00	0.01	0.00
- t-stat	0.60	-0.45	3.88	1.82	-2.66	-2.07	2.14	-0.22	0.89	0.57	0.58
Dummy											
- Average slope	-0.00	0.01	0.00	-0.04	0.02	0.02	0.00	-0.01	-0.01	0.00	-0.01
- t-stat	-0.68	0.68	0.42	-3.10	1.16	2.13	-0.54	-1.43	-0.50	-0.17	-1.20
Six months prior											
- Average slope	0.00	0.00	0.00	-0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.00
- t-stat	0.46	0.38	0.03	-1.63	-0.04	1.32	0.87	0.46	0.16	-0.09	0.23
Dummy											
- Average slope	0.00	0.02	0.05	-0.01	0.00	0.00	-0.02	0.02	0.02	-0.04	0.02
- t-stat	0.36	1.17	2.15	-0.57	0.21	-0.38	-0.48	0.45	1.32	-1.04	2.06
Debt-to-assets											
- Average slope	-0.01	-0.01	-0.07	0.12	0.02	0.01	0.00	0.12	0.01	-0.06	-0.26
- t-stat	-0.32	-0.29	-2.18	3.64	0.45	0.27	-0.05	2.91	0.19	-0.22	-2.06
Dummy											
- Average slope	0.10	0.00	0.04	-0.11	-0.02	-0.01	0.00	-0.14	-0.03	0.04	0.19
- t-stat	0.36	-0.02	1.10	-2.40	-0.53	-0.42	-0.02	-3.14	-0.86	0.14	1.31
Twelve months prior											
- Average slope	-0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01
- t-stat	-0.30	0.61	0.36	-0.94	0.17	-0.48	0.17	0.81	1.00	-1.13	-1.17
Dummy											
- Average slope	0.00	0.02	0.04	-0.03	-0.01	0.00	-0.01	0.00	0.01	-0.03	0.03
- t-stat	0.39	1.16	2.20	-1.42	-0.41	0.06	-0.46	0.20	0.52	-0.69	2.30
Debt-to-equity											
- Average slope	-0.00	-0.01	0.00	0.01	-0.01	0.00	0.02	-0.01	0.00	-0.01	0.00
- t-stat	-0.28	-1.07	-0.66	0.87	-3.19	0.43	0.38	-1.01	0.35	-0.65	0.10
Dummy											
- Average slope	0.05	0.16	0.09	-0.07	0.08	-0.21	-0.20	0.07	0.06	-0.09	-0.14
- t-stat	0.41	3.60	1.34	-0.65	2.08	-1.55	-0.63	0.98	1.75	-0.39	-1.48
Debt-to-cashflow											
- Average slope	-0.00	0.00	-0.01	-0.02	-0.04	-0.01	-0.05	0.00	-0.06	0.23	0.01
- t-stat	-0.26	-0.02	-0.42	-2.38	-1.11	-0.39	-2.28	-0.07	-0.71	1.20	1.15
Dummy											
- Average slope	0.53	-0.82	-0.08	-0.27	-0.01	-0.18	0.19	-0.40	0.11	-0.40	-0.08
- t-stat	0.54	-5.30	-0.90	-0.81	-0.05	-0.57	0.53	-1.50	1.21	-0.85	-1.48
One month prior											
- Average slope	0.00	-0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.01	-0.01
- t-stat	0.15	-1.07	0.52	0.72	-0.01	-0.51	0.39	1.75	0.10	0.84	-1.22
Dummy											
- Average slope	-0.00	-0.01	0.01	-0.02	0.02	0.00	-0.02	-0.02	-0.01	-0.01	0.01
- t-stat	-0.69	-1.07	2.00	-1.53	1.42	-0.20	-1.13	-1.60	-0.96	-0.50	0.89

	Years										
	All	1	2	3	4	5	6	7	8	9	10
LT loans-to-assets											
- Average slope	-0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	-0.01
- t-stat	-0.14	0.31	0.65	-1.04	-4.70	-0.35	0.72	-0.57	0.65	0.97	-0.99
Dummy											
- Average slope	-0.00	-0.01	0.00	-0.03	0.01	0.01	0.00	0.00	-0.02	-0.01	0.01
- t-stat	-1.36	-0.54	0.20	-1.62	0.85	1.43	-0.10	-0.13	-2.76	-0.69	1.03
Trading volume											
- Average slope	0.00	0.00	-0.01	0.04	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01
- t-stat	0.91	-0.46	-1.13	1.36	-1.35	-0.44	-1.44	-1.72	0.32	-0.83	-4.39
Dummy											
- Average slope	-0.00	0.00	0.01	-0.06	0.01	0.00	0.00	0.00	-0.01	0.01	0.00
- t-stat	-0.65	-0.58	1.48	-1.58	1.12	0.70	0.07	-0.19	-1.42	1.27	0.23
Sustain. growth											
- Average slope	0.00	0.02	0.03	0.03	0.00	0.04	0.05	0.08	-0.04	-0.07	-0.04
- t-stat	0.03	0.26	1.36	0.65	-0.37	2.67	0.88	1.80	-0.60	-1.24	-2.70
Dummy											
- Average slope	-0.01	-0.14	0.02	0.01	0.00	-0.09	-0.08	-0.05	0.05	-0.30	-0.11
- t-stat	-0.38	-1.81	0.82	0.22	0.06	-3.00	-1.08	-1.19	1.21	-0.84	-0.87

Appendix F

F.1 Monthly cross-sectional regressions of resource stock returns on individual attributes

Following Fama and MacBeth (1973), a cross-sectional regression was performed in each month from July 1990 to June 2000 whereby all non-thinly traded resource stock returns are regressed on individual attributes. For a stock to be included in the cross-sectional regression in a month, it must have both a return for the month and a value for the variable under consideration. The attribute data for all fiscal year ends in calendar year $t-1$ was matched with the returns for May of year t . The average slopes represent the time-series arithmetic average of the slope coefficients from the cross-sectional regressions in each month. The t-statistics are in respect of the time-series of slope coefficients and indicate whether returns have responded to the regressor variable in each month in a way that is significantly different from zero. Coefficients significant above the ninety-five percent confidence interval are in bold. Results are ranked in descending order of the absolute value of the t-statistics.

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Size											
- Average slope	-0.01	0.01	0.01	-0.03	-0.02	0.00	0.00	-0.01	-0.01	0.00	0.00
- t-stat	-1.92	1.18	1.60	-2.71	-1.25	0.09	-0.34	-1.75	-2.06	0.15	-0.35
Retention rate											
- Average slope	0.67	-0.06	-0.01	1.84	5.53	-0.63	0.01	0.00	0.00	0.03	-0.06
- t-stat	1.80	-1.68	-1.39	0.85	2.15	-0.68	0.22	0.36	0.09	1.16	-0.79
Price-to-earnings											
- Average slope	-0.01	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	-0.03	-0.08	-0.01
- t-stat	-1.75	-1.13	-1.08	-0.17	-1.67	0.05	-0.12	-0.27	-1.21	-1.15	-0.53
Cashflow-to-price											
- Average slope	0.02	0.13	0.00	0.08	0.03	0.00	0.00	0.00	0.01	0.00	0.00
- t-stat	1.60	1.03	-1.17	2.00	0.59	-1.91	-0.25	-1.85	1.22	-0.53	-0.45
LT Loans-to-assets											
- Average slope	-0.01	-0.01	0.00	-0.03	0.00	0.00	0.00	-0.01	-0.02	0.01	0.01
- t-stat	-1.54	-1.81	-0.12	-1.94	0.14	0.90	-0.17	-1.08	-2.99	0.40	0.71
Leverage											
- Average slope	0.94	9.20	0.23	0.01	-0.14	0.03	0.02	0.01	0.00	0.05	0.01
- t-stat	1.50	1.54	1.15	0.73	-1.96	0.74	0.26	0.25	0.40	1.75	0.51
Dividend yield											
- Average slope	0.03	0.05	-0.01	0.16	0.06	-0.02	0.01	0.00	0.01	0.00	0.00
- t-stat	1.11	0.33	-0.09	3.06	0.54	-0.46	0.95	-0.53	0.83	-0.79	0.43
Price-to-NAV											
- Average slope	0.00	0.01	-0.01	-0.02	-0.02	0.00	0.00	0.00	0.01	0.01	0.01
- t-stat	-0.95	0.42	-1.18	-1.24	-1.90	-0.99	-0.37	0.08	1.00	1.15	0.64
Trading volume											
- Average slope	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00
- t-stat	-0.64	0.98	-0.15	-1.35	0.59	1.86	-1.08	-0.76	-1.55	0.40	-0.22
Return on equity											
- Average slope	0.03	0.00	0.02	0.00	-0.01	-0.02	-0.01	0.02	-0.01	0.08	0.29
- t-stat	0.63	0.15	1.38	-0.55	-1.00	-1.50	-0.22	1.37	-0.34	1.78	0.52

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Debt-to-cashflow											
- Average slope	0.49	-0.34	-0.17	-0.92	1.48	-4.96	7.82	0.01	-0.46	2.49	-0.04
- t-stat	0.60	-1.05	-2.06	-1.66	1.06	-1.39	1.19	0.03	-1.14	0.98	-1.09
One month prior											
- Average slope	0.00	0.00	0.02	-0.01	0.02	0.00	-0.02	-0.02	-0.01	0.00	0.00
- t-stat	-0.57	-0.31	2.88	-0.64	1.34	-1.07	-1.59	-2.29	-1.04	0.37	0.01
Current ratio											
- Average slope	0.00	-0.01	0.00	0.01	0.00	0.01	0.01	-0.01	0.00	0.00	-0.03
- t-stat	-0.55	-1.27	0.35	0.54	-0.19	1.46	1.03	-0.86	-0.18	-0.18	-1.13
Return on assets											
- Average slope	0.10	0.01	0.30	0.01	-0.01	0.00	0.00	-0.01	-0.15	0.06	0.75
- t-stat	0.54	1.57	1.32	0.05	-1.15	0.18	-0.98	-1.39	-0.51	0.07	0.47
Six months prior											
- Average slope	0.00	0.02	0.06	-0.01	0.00	0.00	0.01	-0.03	0.02	-0.03	0.01
- t-stat	0.53	1.04	2.71	-0.87	0.05	-0.06	0.48	-0.72	1.37	-1.46	0.66
Shares in issue											
- Average slope	0.00	0.01	0.01	-0.03	0.01	0.01	0.00	-0.02	-0.01	0.01	-0.01
- t-stat	-0.51	1.05	2.44	-2.53	0.30	1.17	0.00	-1.96	-0.55	0.70	-0.77
Debt-to-equity											
- Average slope	0.06	0.08	0.04	-0.08	0.11	0.21	0.07	-0.09	0.03	0.33	-0.09
- t-stat	0.50	1.07	0.43	-0.67	1.65	0.92	0.06	-0.87	0.41	1.56	-0.89
Quick ratio											
- Average slope	0.00	-0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	-0.03
- t-stat	-0.42	-1.30	0.43	0.49	-0.18	1.47	1.06	-0.69	0.60	-0.20	-1.08
Sustainable growth											
- Average slope	-0.01	-0.01	0.03	0.01	0.00	-0.02	-0.02	0.02	-0.04	0.01	-0.07
- t-stat	-0.40	-0.14	2.04	0.46	-0.35	-1.67	-0.32	0.84	-0.74	0.07	-0.65
Debt-to-asset											
- Average slope	0.00	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	-0.02	0.04	0.01
- t-stat	0.40	-0.35	-1.83	0.91	0.42	-0.09	-0.15	-1.05	-0.70	0.89	0.21
Twelve months prior											
- Average slope	0.00	0.01	0.04	-0.02	-0.01	0.00	0.00	-0.01	0.02	-0.03	0.01
- t-stat	0.31	1.08	3.44	-1.74	-0.72	0.43	-0.19	-0.93	1.09	-1.07	1.02
Owners interest											
- Average slope	0.00	0.01	0.01	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.00
- t-stat	-0.22	1.50	2.63	-2.94	-0.57	0.93	-0.50	0.59	-2.12	1.28	-0.53
Financial distress											
- Average slope	-0.01	-0.01	0.04	0.02	-0.02	0.04	0.02	0.01	0.03	-0.02	-0.24
- t-stat	-0.20	-1.09	0.40	0.12	-0.55	1.22	0.79	0.25	0.24	-0.09	-0.45

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Price-to-profit											
- Average slope	0.01	0.00	-0.02	-0.02	-0.03	-0.15	0.35	0.00	-0.03	-0.04	0.00
- t-stat	0.17	-0.40	-0.88	-0.64	-0.51	-1.39	0.95	-0.58	-1.22	-0.82	-0.54

Appendix G

G.1 Monthly cross-sectional regressions of financial and industrial stock returns on individual attributes, including a dummy coded variable for financial stocks.

Following Fama and MacBeth (1973), a cross-sectional regression was performed in each month from July 1990 to June 2000 whereby the all non-thinly traded financial and industrial stock returns are regressed on individual attributes. A dummy variable was added to the regression and was assigned a value of one for financial stocks and zero otherwise. For a stock to be included in the cross-sectional regression in a month, it must have both a return for the month and a value for the variable under consideration. The attribute data for all fiscal year ends in calendar year $t-1$ was matched with the returns for May of year t . The average slopes represent the time-series arithmetic average of the slope coefficients from the cross-sectional regressions in each month. The t-statistics are in respect of the time-series of slope coefficients and indicate whether, on average, returns have responded to the regressor variable in each month in a way that is significantly different from zero. The average r-squared represents the time-series average coefficient of the cross-sectional regressions in each month over the period. Coefficients significant above the ninety-five percent confidence interval are in bold. Results are ranked in descending order of the absolute value of the t-statistics of the non-dummy-coded attributes.

		Years									
	All	1	2	3	4	5	6	7	8	9	10
Price-to-NAV											
- Average slope	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	-0.02	-0.02	-0.01	-0.02
- t-stat	-4.71	-0.63	-3.02	-2.13	-0.15	-2.12	-3.13	-1.33	-1.13	-1.80	-2.43
Dummy											
- Average slope	0.00	0.00	-0.01	0.00	-0.02	0.00	-0.02	0.04	0.03	0.01	0.05
- t-stat	0.02	0.16	-0.95	-0.01	-1.05	-0.05	-0.40	0.98	0.82	1.22	1.24
Cashflow-to-price											
- Average slope	0.02	0.01	0.00	0.04	0.03	0.05	0.12	0.14	0.04	0.00	0.05
- t-stat	3.33	2.52	0.34	1.57	2.57	1.78	2.60	2.87	1.31	0.15	2.73
Dummy											
- Average slope	-0.04	0.09	-0.01	0.02	0.04	-0.07	-0.12	-0.16	0.02	0.00	-0.04
- t-stat	-0.33	6.14	-0.92	0.21	0.95	-2.12	-2.47	-2.86	0.58	0.03	-1.39
Price-to-earnings											
- Average slope	-0.01	0.00	-0.01	-0.04	-0.02	-0.01	-0.03	-0.02	0.00	0.00	-0.01
- t-stat	-3.03	-1.37	-1.35	-1.61	-3.07	-1.33	-1.82	-2.03	-0.13	-0.15	-1.49
Dummy											
- Average slope	-0.02	-0.01	0.00	0.04	0.01	0.01	0.03	0.05	-0.02	-0.10	0.01
- t-stat	-1.80	-1.97	0.34	1.62	0.69	0.71	0.97	1.74	-0.63	-1.45	0.93
Size											
- Average slope	-0.01	0.00	0.00	-0.02	-0.03	-0.02	-0.01	-0.01	-0.01	0.01	-0.01
- t-stat	-2.92	0.26	0.51	-1.81	-3.92	-3.16	-2.59	-3.19	-0.90	0.92	-1.18
Dummy											
- Average slope	0.00	-0.01	0.00	0.00	0.01	0.01	0.00	0.00	-0.01	0.00	0.00
- t-stat	-0.15	-0.89	-0.14	-0.08	1.01	1.58	-0.17	-0.61	-0.84	-0.36	0.17
Dividend yield											
- Average slope	0.02	0.03	0.00	0.09	0.04	0.01	0.01	0.02	0.00	0.01	0.01
- t-stat	2.82	1.55	0.13	1.45	2.87	1.03	1.93	3.48	-0.12	1.55	1.10
Dummy											
- Average slope	0.01	0.15	0.10	-0.08	-0.07	0.02	-0.01	-0.02	0.01	-0.01	-0.10
- t-stat	0.57	2.90	2.04	-0.78	-1.31	0.77	-0.53	-2.09	0.53	-1.16	-1.33

	Years										
	All	1	2	3	4	5	6	7	8	9	10
LT Loans-to-assets											
- Average slope	-0.03	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	0.00
- t-stat	-2.17	0.65	0.95	-1.23	-4.15	0.78	-1.07	-0.18	0.35	0.89	-0.59
Dummy											
- Average slope	0.08	-0.01	-0.01	-0.01	0.02	0.00	0.01	-0.01	-0.02	-0.01	0.00
- t-stat	1.53	-2.08	-0.96	-0.86	2.05	-0.44	0.66	-1.25	-3.20	-0.50	0.31
Return on assets											
- Average slope	-1.45	0.22	0.06	-1.88	-1.92	-1.04	-1.38	0.02	-2.02	-2.52	-3.06
- t-stat	-2.04	2.25	0.39	-0.43	-0.86	-0.87	-0.61	0.64	-0.85	-0.62	-1.68
Dummy											
- Average slope	-0.65	-0.23	-0.10	0.26	0.00	0.03	0.06	-0.04	-0.24	0.58	1.01
- t-stat	-0.24	-3.15	-0.73	0.44	0.09	0.67	0.50	-1.24	-2.59	1.12	2.67
Price-to-profit											
- Average slope	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.02	-0.01	0.00	0.01	0.03
- t-stat	-2.03	-1.77	-1.87	-3.24	-1.54	-1.21	-2.80	-2.08	0.05	0.74	1.49
Dummy											
- Average slope	-1.43	-1.55	-1.81	0.02	-1.23	0.11	-0.01	-0.80	-1.02	-1.08	-2.05
- t-stat	-2.54	-0.03	-0.38	1.03	-1.77	1.55	-0.81	-0.57	-1.13	-1.63	-3.11
Retention rate											
- Average slope	0.45	0.01	-0.01	-0.03	0.79	1.94	0.11	0.01	0.06	-0.08	-0.12
- t-stat	1.77	0.10	-0.50	-0.07	0.55	2.11	1.43	0.76	2.55	-1.44	-1.84
Dummy											
- Average slope	-0.64	-0.17	-0.02	0.26	0.10	-0.43	-0.10	0.00	-0.12	0.14	0.16
- t-stat	-1.12	-2.04	-0.54	1.20	0.30	-2.01	-1.19	-0.09	-3.93	1.49	1.60
Debt-to-equity											
- Average slope	-0.01	0.00	0.00	-0.01	0.01	0.00	0.03	-0.01	0.00	0.00	0.00
- t-stat	-1.62	-0.64	0.47	-0.44	0.58	0.38	0.62	-1.15	0.09	-0.66	0.15
Dummy											
- Average slope	0.05	0.26	0.05	0.07	0.09	-0.25	-0.56	0.02	0.07	-0.08	-0.17
- t-stat	2.29	2.89	0.43	0.26	1.43	-1.49	-1.27	0.84	1.76	-0.33	-1.88
Debt-to-assets											
- Average slope	-0.05	0.05	-0.03	0.85	0.11	0.05	0.00	0.12	0.02	-0.06	-0.21
- t-stat	-1.23	0.92	-1.00	1.22	1.74	1.93	-0.01	2.20	0.70	-0.31	-1.66
Dummy											
- Average slope	-0.06	-0.06	0.02	-0.84	-0.11	-0.06	0.00	-0.14	-0.04	0.02	0.07
- t-stat	-0.74	-1.10	0.66	-1.17	-1.82	-2.16	-0.03	-2.47	-1.78	0.10	0.51
Owners equity											
- Average slope	0.00	0.00	0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	0.01	0.01
- t-stat	-0.83	0.50	1.22	-1.03	-2.02	-2.04	-1.65	-1.86	-2.01	1.65	2.07
Dummy											
- Average slope	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	-0.01
- t-stat	0.17	-0.59	-0.56	-0.14	1.96	3.38	0.29	1.41	0.32	0.06	-1.52
Return on equity											
- Average slope	0.01	0.01	0.00	0.31	0.00	0.11	-0.17	0.08	-0.02	-0.21	-0.38
- t-stat	0.73	0.34	0.20	1.09	-0.26	2.28	-0.74	1.63	-1.04	-1.44	-2.46
Dummy											
- Average slope	-0.12	-0.02	-0.01	-0.32	-0.01	-0.18	0.01	-0.08	0.01	0.34	0.83
- t-stat	-0.87	-0.93	-0.44	-1.08	-0.88	-4.17	0.09	-1.22	0.16	2.34	2.10

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Financial distress											
- Average slope	-0.01	-0.08	-0.02	-0.03	-0.02	-0.01	-0.02	0.00	-0.01	0.18	0.04
- t-stat	-0.66	-1.86	-0.87	-0.55	-1.75	-0.46	-0.88	0.07	-0.37	1.03	0.81
Dummy											
- Average slope	0.02	0.07	0.10	0.05	0.00	0.04	0.04	0.08	0.14	-0.24	-0.70
- t-stat	0.72	1.51	1.74	0.41	0.32	1.32	0.93	2.75	1.66	-1.31	-2.13
Shares in issue											
- Average slope	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	0.01	0.01	0.00
- t-stat	0.58	0.03	0.91	0.51	-1.47	-0.51	0.54	2.04	0.96	0.61	0.49
Dummy											
- Average slope	0.00	0.05	0.03	-0.01	0.00	0.03	0.00	-0.01	0.00	0.00	-0.01
- t-stat	-0.85	2.40	2.34	-0.50	0.03	4.07	0.16	-0.83	-0.31	-0.25	-1.51
Sustainable growth											
- Average slope	0.01	0.00	0.01	0.23	-0.01	0.03	0.03	0.05	-0.03	-0.09	-0.05
- t-stat	0.57	-0.13	0.62	1.08	-0.80	2.79	1.37	1.85	-0.49	-1.62	-2.72
Dummy											
- Average slope	0.03	-0.05	0.02	-0.24	0.01	-0.06	-0.07	-0.05	0.04	-0.22	-0.15
- t-stat	0.88	-1.17	1.34	-1.10	0.61	-3.22	-1.24	-1.63	0.97	-0.66	-1.31
Debt-to-cashflow											
- Average slope	0.01	-0.01	0.00	-0.02	-0.03	-0.03	0.29	-0.01	-0.03	0.29	0.01
- t-stat	0.57	-0.65	-0.95	-1.53	-1.21	-0.53	0.67	-0.39	-0.44	1.57	1.05
Dummy											
- Average slope	-0.32	1.07	-0.01	-0.18	-0.04	-0.33	0.19	0.05	-0.13	-0.41	0.00
- t-stat	-0.91	3.39	-0.22	-0.49	-0.19	-0.89	0.53	0.16	-0.59	-0.85	0.13
Twelve month prior											
- Average slope	0.00	0.01	0.00	-0.01	0.00	0.00	-0.01	0.01	0.02	-0.01	-0.01
- t-stat	-0.34	1.16	0.30	-0.60	0.22	-0.55	-0.61	1.04	2.19	-0.90	-1.46
Dummy											
- Average slope	0.00	0.00	0.04	-0.02	-0.02	0.00	0.01	0.00	0.00	-0.03	0.03
- t-stat	0.42	0.23	3.22	-0.89	-0.79	-0.01	0.25	0.21	-0.04	-0.85	2.30
Leverage											
- Average slope	0.00	-0.16	0.01	-0.04	-0.01	0.03	-0.04	-0.01	-0.01	-0.03	-0.01
- t-stat	0.23	-1.24	0.59	-1.11	-1.22	1.61	-0.58	-0.32	-0.28	-1.32	-0.63
Dummy											
- Average slope	-0.10	0.65	0.22	-0.01	-0.04	0.15	-0.01	0.00	0.03	0.08	0.03
- t-stat	-0.45	3.82	1.96	-0.31	-1.18	1.14	-0.14	-0.06	0.27	1.76	0.96
Six month prior											
- Average slope	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00
- t-stat	0.20	0.70	0.10	-0.88	0.10	0.58	0.86	0.82	1.39	0.04	0.09
Dummy											
- Average slope	0.01	0.02	0.05	-0.01	-0.01	0.00	-0.02	0.00	0.01	-0.05	0.02
- t-stat	0.88	0.92	2.89	-0.64	-0.49	-0.40	-0.52	-0.07	0.75	-1.17	2.75
Quick ratio											
- Average slope	-0.01	-0.06	0.00	-0.03	-0.04	0.05	0.00	0.02	0.01	0.00	0.02
- t-stat	-0.17	-1.85	-0.03	-1.10	-1.18	1.40	-0.02	1.45	1.02	0.87	1.36
Dummy											
- Average slope	0.00	0.03	0.01	0.06	0.02	-0.04	0.01	-0.01	0.01	-0.01	-0.07
- t-stat	0.26	0.63	0.39	2.76	0.50	-1.26	0.50	-0.73	0.88	-0.46	-2.36

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Current ratio											
- Average slope	-0.01	-0.06	0.00	-0.04	-0.02	0.05	0.00	0.01	0.01	0.00	0.02
- t-stat	-0.17	-1.86	-0.27	-1.22	-0.61	1.38	-0.18	1.28	1.08	1.14	1.86
Dummy											
- Average slope	0.00	0.03	0.02	0.07	0.00	-0.03	0.01	-0.01	0.00	-0.01	-0.07
- t-stat	0.29	0.63	0.44	2.79	-0.08	-1.13	0.60	-0.75	0.31	-0.48	-2.49
One month prior											
- Average slope	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	-0.01
- t-stat	0.04	-0.65	0.30	0.63	-0.36	-0.66	0.98	1.45	0.94	0.82	-0.99
Dummy											
- Average slope	0.01	-0.02	0.02	-0.01	0.02	0.00	-0.01	0.00	-0.01	0.00	0.01
- t-stat	0.20	-1.83	2.63	-1.00	1.62	0.26	-1.04	-0.21	-1.24	-0.34	0.39
Trading volume											
- Average slope	0.00	0.00	-0.01	0.02	0.00	0.00	-0.01	-0.01	0.00	0.00	-0.01
- t-stat	-0.02	0.05	-1.31	0.65	-0.51	-0.64	-1.58	-2.08	0.21	-0.78	-4.42
Dummy											
- Average slope	0.01	-0.01	0.01	-0.03	0.00	0.01	0.00	0.00	-0.01	0.01	0.00
- t-stat	0.91	-1.54	1.48	-1.10	0.39	0.75	0.25	-0.67	-1.21	1.45	-0.06

Appendix H

H.1 Monthly cross-sectional regressions of financial stock returns on individual attributes

Following Fama and MacBeth (1973), a cross-sectional regression was performed in each month from July 1990 to June 2000 whereby all non-thinly traded financial stock returns are regressed on each attribute individually. For a stock to be included in the cross-sectional regression in a month, it must have both a return for the month and a value for the variable under consideration. The attribute data for all fiscal year ends in calendar year $t-1$ was matched with the returns for May of year t . The average slopes represent the time-series arithmetic average of the slope coefficients from the cross-sectional regressions in each month. The t-statistics are in respect of the time-series of slope coefficients and indicate whether returns have responded to the regressor variable in each month in a way that is significantly different from zero. Coefficients significant above the ninety-five percent confidence interval are in bold. Results are ranked in descending order of the absolute value of the t-statistics.

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Cashflow-to-price											
- Average slope	0.05	0.04	0.08	0.04	0.00	0.04	0.15	0.16	-0.03	-0.02	0.06
- t-stat	2.60	1.21	1.25	0.78	0.04	0.83	1.97	2.16	-0.27	-1.35	0.88
Price-to-profit											
- Average slope	-1.34	0.35	-0.25	-0.54	-0.05	-2.05	-10.7	-0.13	0.03	0.00	0.02
- t-stat	-2.55	1.13	-1.67	-1.48	-0.50	-0.93	-2.75	-1.86	1.46	-0.01	0.21
Size											
- Average slope	-0.01	0.01	0.01	-0.04	-0.03	-0.02	-0.02	-0.01	0.00	0.02	0.00
- t-stat	-2.21	0.95	1.56	-2.59	-2.62	-1.94	-1.96	-1.19	-0.09	0.93	-0.06
Price-to-earnings											
- Average slope	-0.03	0.01	-0.02	-0.02	-0.01	-0.04	-0.07	-0.16	0.00	0.00	-0.01
- t-stat	-2.16	0.25	-1.11	-0.14	-0.26	-1.95	-2.08	-2.06	-0.16	-0.49	-0.88
Debt-to-equity											
- Average slope	0.04	0.01	0.00	-0.02	-0.01	-0.02	0.29	0.09	0.09	0.03	-0.01
- t-stat	2.10	0.84	-0.12	-2.17	-1.54	-0.42	1.81	2.35	0.96	1.22	-0.35
Six months prior											
- Average slope	0.02	0.03	0.01	-0.01	0.01	0.01	0.00	0.08	0.00	0.00	0.02
- t-stat	1.93	3.23	0.67	-0.91	0.72	1.17	-0.22	1.24	-0.41	0.06	1.37
Sustainable growth											
- Average slope	0.05	-0.17	0.01	0.00	-0.02	0.14	0.21	0.36	0.19	-0.01	-0.17
- t-stat	1.54	-2.15	0.27	-0.05	-1.24	1.86	1.00	2.36	1.50	-0.90	-2.54
Owners interest											
- Average slope	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	-0.01	0.00	0.00	0.01
- t-stat	-1.27	0.74	0.94	-0.75	-1.44	-1.04	-3.10	-3.19	-1.01	0.22	1.80
Dividend yield											
- Average slope	0.03	0.05	0.00	0.03	0.15	0.06	0.02	0.02	-0.03	-0.06	0.03
- t-stat	1.10	0.32	-0.01	1.77	1.02	2.50	1.97	2.64	-0.57	-0.56	1.40
Return on equity											
- Average slope	-0.45	-0.04	0.00	-0.03	0.07	0.20	0.26	0.27	0.18	-3.67	-1.79
- t-stat	-1.08	-2.05	0.18	-1.81	1.98	1.95	1.58	2.34	0.70	-0.88	-2.53

	Years										
	All	1	2	3	4	5	6	7	8	9	10
LT Loans-to-assets											
- Average slope	0.01	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.05	0.00
- t-stat	1.00	3.36	0.95	-0.86	-1.86	-0.41	0.93	0.32	0.89	0.93	-0.19
Debt-to-cashflow											
- Average slope	-0.31	0.19	0.03	-0.28	-0.03	-1.76	1.02	-0.03	-0.25	-2.00	0.02
- t-stat	-0.88	2.36	0.31	-1.96	-0.36	-1.33	0.55	-0.74	-0.83	-0.74	0.66
Debt-to-assets											
- Average slope	-0.07	0.16	-0.04	0.06	-0.06	0.02	0.01	0.16	0.03	-0.75	-0.29
- t-stat	-0.85	1.84	-1.01	0.71	-1.28	0.60	0.31	2.55	1.06	-0.96	-1.48
Return on assets											
- Average slope	-1.84	0.02	-0.32	0.58	0.01	-0.02	0.11	0.00	2.95	-14.4	-7.29
- t-stat	-0.76	0.22	-2.44	1.19	0.32	-0.75	0.90	-0.09	0.59	-0.61	-1.48
Financial distress											
- Average slope	0.02	0.05	-0.02	0.07	-0.03	-0.03	-0.03	-0.07	0.00	0.27	0.01
- t-stat	0.70	0.85	-1.24	0.84	-1.30	-1.11	-1.74	-1.88	-0.36	0.97	0.78
Retention rate											
- Average slope	-0.26	-0.10	-0.02	-0.13	-4.36	1.99	0.01	0.00	-0.02	0.05	-0.01
- t-stat	-0.69	-2.02	-1.06	-0.10	-1.40	1.65	0.24	0.33	-0.56	0.53	-0.59
Trading volume											
- Average slope	0.01	-0.01	-0.02	-0.01	-0.02	-0.01	0.00	0.00	0.02	0.09	0.00
- t-stat	0.55	-0.51	-2.29	-0.74	-0.57	-1.32	0.20	0.10	1.63	1.32	-0.93
Current ratio											
- Average slope	0.01	0.08	-0.01	-0.01	-0.01	-0.03	0.03	0.00	0.00	0.00	0.00
- t-stat	0.54	1.06	-0.33	-1.13	-1.27	-0.27	1.14	-1.14	0.94	-0.31	0.79
Twelve month prior											
- Average slope	0.00	0.03	0.01	-0.01	0.01	0.00	-0.02	0.02	0.01	-0.01	-0.01
- t-stat	0.39	2.60	0.98	-0.85	0.52	-0.20	-1.32	1.95	1.30	-0.85	-1.11
Share in issues											
- Average slope	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00
- t-stat	-0.29	-0.22	0.63	-0.81	-1.03	-0.87	1.76	1.15	0.36	-0.30	0.46
Quick ratio											
- Average slope	0.00	0.08	-0.01	-0.01	-0.03	-0.05	0.03	0.00	0.00	0.00	0.00
- t-stat	0.26	1.10	-0.29	-1.00	-1.41	-0.56	1.22	-1.11	0.86	-0.29	0.78
One month prior											
- Average slope	0.00	-0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	-0.01
- t-stat	0.17	-0.85	2.17	-0.22	-0.10	0.65	-0.12	0.97	0.46	-0.01	-1.35
Price-to-NAV											
- Average slope	-0.01	0.02	0.00	-0.01	-0.07	-0.04	0.02	-0.43	0.60	-0.02	-0.11
- t-stat	-0.08	1.50	-0.46	-0.35	-1.70	-1.24	0.16	-1.33	1.15	-1.30	-1.54

	Years										
	All	1	2	3	4	5	6	7	8	9	10
Leverage											
- Average slope	0.01	0.76	0.02	-0.02	0.00	0.01	0.04	-0.01	0.03	-0.75	-0.01
- t-stat	0.06	1.40	1.59	-2.22	-0.08	1.40	2.94	-0.49	0.23	-0.70	-0.09

Appendix I

I.1 Two-way quintile portfolio sorts on size and pre-ranking beta.

The one-way portfolio sorts in Chapter Seven show that while size is related to average returns, quintile portfolios created by ranking stocks on their pre-ranking beta attributes do not produce a return pattern that is consistent with the predictions of the CAPM. To further muddy the situation, Table 7.2 shows a significant positive cross-sectional correlation between size and pre-ranking beta over the period July 1990 to June 2000 (0.19 for all stocks and 0.29 for Findi stocks.)

The empirical key to disentangling these two attributes is to apply a two-way quintile portfolio sort in each month by first ranking stocks according to their size attributes, creating quintiles and then ranking the stocks in each quintile according to their pre-ranking beta attributes. The time series of returns from the resulting portfolios created from the stocks in each quintile and sub-quintiles reflects variation in beta that is unrelated to size. The results for the all stock sample and for the Findi stock sample are presented in the respective top and bottom panels of Table I.1

Table I.1 Average return and post-ranking betas for all stocks and Findi stocks from two-way portfolio sorts on the size attribute and pre-ranking beta.

Returns figures, in percent, are the average monthly return of each portfolio for the 120 months from July 1990 to June 2000. In Quintiles 1 to 5 post-ranking betas for the period are in parenthesis. In the last column and last row, labeled Quintile (5-1), the return figures are the average monthly difference in return between Quintiles 5 and 1 and t is the Students t -statistic indicating whether, on average, the difference was significant. Significance above the ninety-five percent confidence level is indicated in bold.

All stocks	Size					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Pre-ranking beta						
Quintile 1 High	1.03 (1.08)	1.80 (0.91)	1.11 (0.79)	2.09 (0.93)	5.69 (0.49)	4.66 $t=3.97$
Quintile 2	1.21 (0.93)	1.64 (0.75)	1.36 (0.83)	2.58 (0.59)	3.17 (0.34)	1.96 $t=1.87$
Quintile 3	1.26 (0.99)	1.83 (0.86)	2.06 (0.69)	2.21 (0.59)	3.31 (0.30)	2.05 $t=2.25$
Quintile 4	1.09 (1.00)	1.07 (0.64)	1.40 (0.81)	1.95 (0.60)	3.23 (0.38)	2.14 $t=2.72$
Quintile 5 Low	1.65 (1.02)	1.61 (0.82)	1.94 (0.73)	3.95 (0.58)	3.47 (0.25)	1.82 $t=1.92$
Quintile (5-1)	2.89 $t=3.04$	1.50 $t=1.91$	1.57 $t=2.27$	1.10 $t=1.63$	-2.10 $t=-1.96$	

Table I.1 Continued.

	Size					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Pre-ranking beta						
Quintile 1 High	0.98(1.11)	1.32 (0.96)	1.19 (0.84)	2.91 (0.83)	5.89 (1.03)	4.91 $t=3.32$
Quintile 2	1.40 (1.00)	2.22 (0.76)	1.35 (0.76)	2.04 (0.62)	2.42 (0.57)	1.02 $t=2.15$
Quintile 3	1.51 (0.90)	1.68 (0.74)	1.33 (0.62)	2.74 (0.65)	3.73 (0.28)	2.22 $t=2.16$
Quintile 4	1.83 (0.85)	3.34 (0.71)	2.15 (0.68)	2.62 (0.46)	3.47 (0.38)	1.64 $t=1.77$
Quintile 5 Low	1.87 (0.88)	2.80 (0.91)	2.06 (0.77)	2.81 (0.73)	4.34 (0.34)	2.47 $t=2.65$
Quintile (5-1)	0.89 $t=0.53$	1.49 $t=0.89$	0.87 $t=0.52$	-0.10 $t=-0.06$	-1.55 $t=-0.93$	

In the top panel, subtracting the average return of each beta quintile portfolio from the quintile above and taking the average within each size quintile again shows no clear evidence that higher beta portfolios formed within size quintiles earn higher returns. The t-statistics show the average difference between the lowest and highest beta quintiles is significant in size Quintiles 1 and 3 of the all stock sample but not significant in any of the size quintiles for the Findi stock sample. In other words, controlling for size does not improve the explanatory power of beta for the Findi stock sample. Reading the top panel horizontally reveals that, except for the highest beta quintile, the two-way sort creates a narrower dispersion in size-related returns (4.66%, 1.96%, 2.05%, 2.14%, 1.82%) compared with the one-way size sort (2.5%).

The horizontal spread of post-ranking betas within each of the pre-ranking beta quintiles is always tighter for the Findi stock sample (0.08, 0.43, 0.62, 0.47, 0.54) than for all stock sample (0.59, 0.59, 0.69, 0.62, 0.77). Reading Tables I.1 and I.2 from left to right across the size quintiles shows that the average return of the pre-ranking beta sorted quintile portfolios within each size quintile is always higher for the Findi stock sample (1.52%, 2.27%, 1.62%, 2.62%, 3.97%) than for all stock sample (1.25%, 1.59%, 1.57%, 2.56%, 3.77%). Reading top to bottom reveals that, with the exception of the second quintile, the average return across the size quintiles for each pre-ranking beta quintiles is higher for Findi stocks (2.46%, 1.89%, 2.20%, 2.68%, 2.78%) than for all stocks (2.34%, 1.99%, 2.13%, 1.75%, 2.52%). In summary,

most effects are amplified when using the Findi sample inferring that the relationship does not prevail to the same extent for the resource sector.

I.2 Two-way quintile portfolio sorts on price-to-earnings and pre-ranking beta.

Two-way sorts are repeated to investigate the role of beta while controlling for the price-to-earnings attribute. Stocks are first sorted into quintile portfolios in each month based on their price-to-earnings attributes. Each quintile is then further subdivided into another set of quintile portfolios by ranking the stocks in each quintile on their pre-ranking betas. The average monthly returns from July 1990 to June 2000 and post-ranking betas for each of the resulting twenty-five portfolios are shown in Table I.2 for all stocks and for Findi stocks.

Table I.2 Average return and post-ranking betas for all stocks and Findi stocks from two-way portfolio sorts on price-to-earnings and pre-ranking beta.

Returns figures, in percent, are the average monthly return of each portfolio for the 120 months from July 1990 to June 2000. In Quintiles 1 to 5 post-ranking betas for the period are in parenthesis. In the last column and last row, labeled Quintile (5-1), the return figures are the average monthly difference in return between Quintiles 5 and 1 and t is the Students t -statistic indicating whether, on average, the difference was significant. Significance above the ninety-five percent confidence level is indicated in bold.

All stocks	Price-to-earnings					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Pre-ranking beta						
Quintile 1 High	0.87 (1.10)	1.28 (1.09)	1.77 (0.87)	3.09 (0.82)	3.78 (0.70)	2.91 $t=3.79$
Quintile 2	1.11 (0.91)	0.99 (0.92)	1.56 (0.94)	2.85 (0.66)	4.23 (0.59)	3.11 $t=3.41$
Quintile 3	0.52 (0.91)	1.26 (0.81)	1.71 (0.82)	2.96 (0.52)	3.26 (0.44)	2.74 $t=4.02$
Quintile 4	0.96 (0.89)	0.98 (0.84)	1.02 (0.65)	2.60 (0.60)	4.49 (0.51)	3.53 $t=5.35$
Quintile 5 Low	1.77 (0.74)	0.97 (0.72)	1.07 (0.58)	3.14 (0.41)	5.87 (0.47)	4.10 $t=4.61$
Quintile (5-1)	0.90 $t=1.12$	-0.32 $t=-0.39$	-0.70 $t=-0.88$	0.06 $t=0.07$	2.09 $t=2.60$	

Findi stocks	Price-to-earnings					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Pre-ranking beta						
Quintile 1 High	1.32 (1.01)	1.13 (1.00)	1.95 (0.77)	3.22 (0.85)	5.32 (1.10)	4.00 $t=3.20$
Quintile 2	0.65 (0.98)	1.29 (0.99)	2.09 (0.71)	2.60 (0.65)	3.14 (0.60)	2.48 $t=4.02$
Quintile 3	1.06 (0.75)	1.40 (0.78)	0.56 (0.72)	2.30 (0.62)	4.32 (0.40)	3.26 $t=3.58$

Table I.2 Continued.

Findi stocks	Price-to-earnings					
	Quintile 1 Big	Quintile 2	Quintile 3	Quintile 4	Quintile 5 Small	Quintile (5-1)
Pre-ranking beta						
Quintile 4	0.77 (0.75)	2.84 (0.89)	1.82 (0.80)	3.16 (0.46)	5.27 (0.25)	4.50 $t=4.07$
Quintile 5 Low	1.83 (0.84)	1.88 (0.67)	2.57 (0.61)	3.11 (0.40)	5.50 (0.59)	3.67 $t=3.87$
Quintile (5-1)	0.50 $t=0.32$	0.76 $t=0.48$	0.63 $t=0.40$	-0.11 $t=-0.07$	0.18 $t=0.12$	

As with the size attribute, there is no clear evidence that portfolios assembled from high beta stocks within each of the price-to-earnings quintiles earn higher returns. Controlling for price-to-earnings and examining the average returns of the pre-ranking beta sorted quintile portfolios adds yet more support to the evidence that beta does not adequately describe average stock returns on the JSE.

From reading both panels of Table I.2 top to bottom within each size quintile it appears that sorting stocks into quintiles according on pre-ranking betas seems to predict the order of the post-ranking betas in most instances. Within each pre-ranking beta quintile, low price-to-earnings sorted quintile portfolios consistently outperform high price-to-earnings quintile sorted portfolios. This illustrates that the price-to-earnings attribute is robust to the inclusion of a second sort on pre-ranking market beta.

There is no evidence that the spread of post-ranking betas, examined vertically or horizontally, differ to any meaningful degree between the sample of all stocks and Findi stocks. The average return of the pre-ranking beta sorted quintile portfolios across all size quintiles is not noticeably different between the two samples either. The only marked difference between the two samples is that the average return of the pre-ranking beta quintiles within each price-to-earnings quintile, high to low, is always higher for the Findi sample (1.13%, 1.71%, 1.80%, 2.88%, 4.71%) than for the all stock sample (1.05%, 1.10%, 1.43%, 2.93%, 4.33%). The results suggest a value strategy of holding low price-to-earnings stocks is more profitable when resource stocks are excluded from the universe. Similar evidence is reported in Chapter Five in a cross-sectional study over the same period. The results show the average monthly payoff to the (low) price-to-earnings variable is 0.70% when estimate on the full sample but 1.10% for a Findi sample.

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