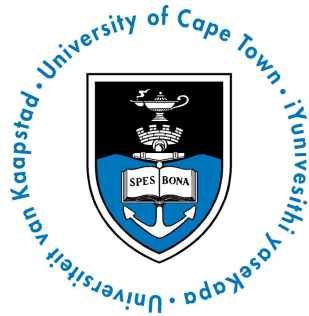


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Beta, size and value effects on the JSE Securities Exchange, 1994-2007

An empirical analysis of the influence of market covariance,
market capitalisation and price-earnings ratio on South African
equity returns

Dissertation submitted in fulfilment of the requirements for the
degree of Master of Philosophy

Author:

Dave Strugnell (student number STRDAV014)

Supervisors:

Associate Professor Evan Gilbert (University of Stellenbosch)

Mr Ryan Kruger (University of Cape Town)

January 2010

Declaration

I, David Mark Strugnell, hereby declare that the work on which this dissertation 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 of Cape Town to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

D M Strugnell
February 2010

Abstract

The Capital Asset Pricing Model (CAPM), which has been at the heart of mainstream finance theory since the mid 1960s, holds that market covariance, measured by a security's beta, is the sole source of rewarded systematic risk in the generation of returns on financial assets. The literature over the past three decades has however revealed key empirical anomalies within this framework, of which two of the most prominent and persistent are the size and value effects, reflecting the additional risk-adjusted returns to small firms and value stocks. These effects imply either market inefficiency or a misspecification of single-index models such as the CAPM.

This dissertation builds on the observations of Van Rensburg and Robertson (2003a), who found persistent size and price-earnings effects in the cross-section of returns on the JSE Securities Exchange, but surprisingly found that beta had, if anything, an inverse relationship with returns. Based on stock returns from January 1994 to October 2007, this portfolio-based study finds support for these earlier findings, confirming that they are not sample-specific results. However, when betas are estimated by the Dimson Aggregated Coefficients method with a lead and lag of at least three months, which is intended to compensate for the weaknesses of Ordinary Least Squares regression in the face of thin trading, the relationship between beta and return loses its statistical significance. We are however left with the conclusion that beta has no predictive power for returns on the JSE, invalidating the CAPM, at least as it is commonly applied, based on a market proxy of the All-Share Index. We find further that the size premium is concentrated in the smallest stocks on the JSE, with no significant difference in returns between the four largest quintiles, and tentative evidence that it has been reducing over time.

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Chapter 1

Introduction

Asset pricing models have a key function in financial economics, attempting to provide parsimonious descriptions of the forces and characteristics driving security returns. For the past 45 years, a central role has been played by the Capital Asset Pricing Model (CAPM), which builds from a foundation of mean-variance optimisation to argue that covariance with the market portfolio constitutes the sole source of rewarded systematic risk for securities. However, the past three decades have seen an abundance of empirical work questioning whether this is a sufficient measure of risk, identifying anomalies which cannot be reconciled with the CAPM. Two of the most persistent anomalies in the international literature describe the additional returns to small firms and those with indicators of value such as low price-earnings ratios or high book-to-market equity ratios; these are commonly referred to as the size and value effects, and may reflect either market inefficiency or a misspecification of single-index models such as the CAPM (or indeed both).

Internationally, market covariance as measured by beta has continued to have a role in multifactor models which incorporate size and value effects, such as the Fama and French three-factor model (Fama and French, 1993). However, an important South African study by Van Rensburg and Robertson (2003a) found that while the data indicate strong size and value effects on the JSE Securities Exchange, beta has, if anything, an inverse relationship

with returns. This is a sufficiently surprising and important result, running quite contrary to theory-led expectations, that it warrants further investigation. This dissertation aims to test whether these conclusions are replicated using a later and longer data sample, as well as testing the effect of different methodology for beta estimation, particularly to compensate for biases in the estimation of betas induced by thin trading on small stocks.

Chapter 2 discusses the pertinent issue of market efficiency and gives an overview of key asset pricing models employed to explain the cross-section of returns. This is followed by a survey of the international literature on the size and value effects in Chapters 3 and 4; exposition of the Fama and French three-factor model, which quantifies these effects in a multifactor model, follows in Chapter 5. South African literature is then surveyed in Chapter 6. Methodological issues are considered in Chapter 7, and Chapter 8 outlines the data and methodology employed in this study. Chapter 9 presents the results of the analysis, while conclusions and suggestions for further research are laid out in Chapter 10.

Chapter 2

Market efficiency

The concept of rational behaviour is fundamental to all branches of economics. *Homo economicus*, the prototypical rational economic man, is assumed to be a utility maximiser free from systematic bias in his decision-making. Indeed, this use of what is arguably a normative ideal as a descriptive characterisation of economic agents is a key point of distinction between economics and the other social sciences. In recent years, a significant body of literature, loosely associated under the banner of behavioural economics, has emerged to challenge the assumption that economic agents do in fact act in their unbiased rational self-interest on a consistent basis. Unsurprisingly, this school of thought has its roots in the pioneering work of academics from other disciplines, notably psychology.

The natural consequence of a model of rational economic agents is that markets will reach equilibrium at their optimal level, i.e. where the aggregate utility gains from trade are maximised. Markets will thus tend to be efficient, in the sense that prices reflect all information available to market participants and abnormal profits from superior skill or insight are not possible. If this is a reasonable characterisation of economic markets in general, it should apply most unambiguously to financial markets, where significant volumes of information relevant to trading are publicly available, where the average financial sophistication of market participants is high and where

the potential rewards from superior trading (and conversely, downside risks from sub-optimal trading) are most pronounced. The notion that financial markets are informationally efficient is encapsulated in the Efficient Markets Hypothesis (EMH), which has three forms, differing in the information set thought to be reflected in market prices:

1. *Strong form*: prices reflect all information, whether available to the public or not. There is thus no return to additional security analysis or even to insider trading.
2. *Semi-strong form*: publicly available information is fully reflected in market prices.
3. *Weak form*: prices reflect only the information embodied in historical price data.

A seminal overview of the evidence on the efficiency of markets was that of Fama (1970), extended in Fama (1976). In the former paper, Fama reviewed the empirical evidence on the three forms of the EMH, concluding that the support for the weak form is incontrovertible and that the consistency of results in testing the semi-strong form is remarkable, even if the quantity of results is not as impressive as for the weak form. As for the strong form, Fama's view was that there are for practical purposes only two groups with any sort of monopolistic access to information with potential relevance for market returns, namely exchange specialists and corporate insiders, and hence for the overwhelming majority of investors, the strong form is a reasonably good approximation to reality as well. Fama concluded that a test suggesting inefficiency must either find trading rules to outperform the market, or take some piece of information available at a prior time and use it to consistently identify deviations of the true expected return from the assumed equilibrium value.

The seed was sown for the EMH with observations in the 1940s and 1950s that professional investment managers do not tend to beat the market, in the

sense of consistent superior returns, over the long run. The formalisation of the rational expectations hypothesis by Muth (1961), the proposition that agents' expectations deviate from realisations only through random variation, and not because of systematic bias, provided the intellectual platform for a formalisation of the EMH.

Although the term 'efficient markets' did not become an everyday part of the economic lexicon until Fama (1970), much of the thinking behind the EMH came into the public domain in the 1960s with the emergence of the CAPM, which has its origins in Sharpe (1964). The CAPM explains the returns on individual securities purely in terms of their covariance with market returns, a measure of systematic risk. The intuitive rationale for this conclusion is that the efficiency of markets allows investors to diversify away any idiosyncratic risk associated with individual securities and hence only systematic risk can expect to be rewarded by the market. This has been the dominant model for the pricing of capital assets from the mid-1960s to the present, although the CAPM has come under increasing criticism over recent years.

The following sections give a brief overview of the CAPM and Arbitrage Pricing Theory, another of the key asset pricing models based on the assumption of efficient markets, as well as a brief discussion of alternative views which suggest that financial markets will not necessarily be efficient. These outlines act as a precursor to an evaluation of the body of literature which highlights two of the major inconsistencies with the CAPM in the time series of security returns, namely the influence of firm size (measured by market capitalisation) and firm value indicators (such as price-earnings ratio) on security returns. As both of these indicators are ex-ante observable, market efficiency suggests that they should not be independently rewarded in the form of superior risk-adjusted returns.

2.1 Models of efficient markets

The single-index market model is the general form of that class of efficient market models which has covariance with the market as its sole source of rewarded investment risk. The market model may be written in the following form:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \epsilon_{i,t} \quad (2.1)$$

where:

$r_{i,t}$ denotes the return on security i in time period t ,
 α_i is the fixed component of the security-specific return,
 β_i is a measure of the co-movement of security i with the market portfolio,
 $r_{m,t}$ is the return on the market portfolio in time period t , and
 $\epsilon_{i,t}$ is the residual (or error) term, assumed normally distributed with zero mean and constant variance.

William Sharpe's seminal paper on the fundamentals of capital asset pricing (Sharpe, 1964) is certainly one of the most influential in the history of financial theory. Extended by the contributions of Lintner (1965), Mossin (1966) and Black (1972), it laid the foundation for what is today widely known as the Capital Asset Pricing Model (CAPM). This has been a significant part of the edifice of finance theory for the past four decades and in spite of numerous empirical and theoretical challenges to its foundations and implications, remains a fundamental element of the armouries of many financial market practitioners today. Building on the earlier work of Markowitz (1952), in particular the notion of mean-variance efficiency which is the cornerstone of Modern Portfolio Theory, Sharpe showed that with the assumptions of homogeneous investor expectations and the introduction of a risk-free asset, rational investors will hold a portfolio split between risky assets and the risk-free asset on a basis determined by their individual preferences and relative

degrees of risk aversion, but that the risky asset component of that portfolio would reflect the composition of the market portfolio (i.e. the basket of all risky assets, in proportion to their market capitalisations) for all investors.

The key component of the CAPM, as far as asset pricing is concerned, is the Security Market Line, which expresses the relationship between the return on an individual security (or that of a portfolio) and the return on the market portfolio as a function of the security's beta only:

$$r_{i,t} = r_f + \beta_i (r_{m,t} - r_f) + \epsilon_{i,t} \quad (2.2)$$

where:

$r_{i,t}$, $r_{m,t}$ and $\epsilon_{i,t}$ are as defined above,
 r_f is the risk-free rate of return, and
 β_i is the beta of security i .

Beta, defined as the covariance of the security's return with that of the market, standardised by dividing by the variance of the market return, can be shown under the (admittedly limiting) CAPM conditions to be the only measure of security risk which is of importance in determining equilibrium pricing. The variance of an individual security's return is irrelevant in this context as the security-specific risk which it represents can be diversified away by investors.

Although the EMH does not necessarily imply the CAPM, the CAPM is often thought of as its model embodiment. In an efficient market, only undiversifiable risk should be expected to be rewarded in the form of additional returns; the CAPM embodies this in the statement that beta is the only measure of risk that is of relevance in asset pricing. It is thus not possible, according to the CAPM, for an investor to outperform the market except by exposing her portfolio to greater systematic risk (i.e. a beta in excess of unity).

However, the literature of the past thirty years abounds with empirical refutations of the CAPM. The size and value effects discussed in the next two chapters are anomalies which are inconsistent with single-index models, including the CAPM, in terms of which market covariance is the only source of rewarded risk, and under which no other ex-ante observable indicators ought to predict superior long-term returns. An alternative equilibrium pricing model which is not reliant on many of the limiting assumptions of CAPM is Arbitrage Pricing Theory (APT), first proposed by Ross (1976). Ross makes use of the principle of no arbitrage (also known as the Law of One Price) in order to define the equilibrium price as a function of a set of universal factors assumed to drive returns and a corresponding set of individual security sensitivities to those factors:

$$r_{i,t} = \lambda_0 + \sum_{j=1}^k \lambda_{j,t} B_{i,j} + \epsilon_{i,t} \quad (2.3)$$

where:

$r_{i,t}$ denotes the return on security i in time period t ,

λ_0 denotes a common factor-insensitive return, analogous to the CAPM's risk-free rate,

$\lambda_{j,t}$ denotes the return to factor j in time period t ,

$B_{i,j}$ denotes the sensitivity of security i to factor j , and

$\epsilon_{i,t}$ is the residual term, i.e. the return on security i in time period t not explained by the APT model.

The APT approach is attractive in that it builds on the principle of no arbitrage which underlies the pricing of one major category of financial assets, namely derivatives, and that it is not reliant on the limiting assumptions of CAPM (e.g. homogeneous expectations of all investors, and the assumption that risk is measured only by variance, without regard to higher moments of the return's distribution). Its great advantage over CAPM is its allowance

for factors other than market covariance to drive the generation of security returns. It is however not prescriptive, or indeed even suggestive, as to the identity of the factors driving returns, and it is up to the researcher to identify these through a combination of economic theory, statistical analysis and good fortune.

APT provides a useful framework for the development of multifactor models which incorporate the anomalies identified in Chapters 3 and 4, such as the Fama and French three-factor model discussed in Chapter 5.

2.2 Challenges to market efficiency

The mainstream hypothesis of market efficiency is not universally supported, however. In the 1980s and early 1990s, Richard Thaler published a series of papers in the *Journal of Economic Perspectives*, which have become known as the anomaly series. These dealt with observations that are at odds with the central tenet of market efficiency, such as seasonal effects (Thaler, 1987a,b), cooperation between economic agents (Dawes and Thaler, 1988), inefficiency in auction outcomes (Thaler, 1988b), deviations from utility maximisation motivated by considerations of fairness (Thaler, 1988a), inefficiencies in choice over time (Loewenstein and Thaler, 1989), wage differentials between industries (Thaler, 1989), inefficiencies on currency markets (Froot and Thaler, 1990), anomalies in the pricing of closed end mutual funds (Lee, Shleifer and Thaler, 1990), irrational changes in investor preference under conditions of complexity (Thaler and Tversky, 1990), mental accounting (Thaler, 1990) and status quo bias (Kahneman, Knetsch and Thaler, 1991).

Much of the groundwork for this questioning, which goes beyond the efficiency of financial markets and straight to the root of *homo economicus*, was laid by the ground-breaking work of Daniel Kahneman and Amos Tversky, who pioneered the development of Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Based on their observations as psychologists in the field of human decision-making under conditions of

uncertainty and risk, Kahneman and Tversky noted numerous violations of commonly-accepted rational economic behaviour and indeed of the axioms of Von Neumann-Morgenstern expected utility theory. These include evidence of preference reversals when subjects are presented with identical information framed in different ways; limits to investor information, intelligence and processing capability mean that it is not possible to be certain that investors will always make decisions perfectly rationally, in a way which would facilitate informational efficiency.

Proponents of market efficiency would however argue that evidence of departures from individual rationality is by no means suggestive of inefficiency at the aggregate market level. Unless departures from rationality are systematic and in a particular direction, they may cancel each other out, leading to the same efficient market outcomes as if all investors acted perfectly rationally. Even faced with examples of precisely such systematic irrational behaviour, the efficiency school would maintain that such irrational investors will be driven out of the market over the long term by the arbitrage opportunities they present to rational market participants; this explains the existence of specialist money managers who act as agents for individual investors, and who may reasonably be expected to act closer to the rational ideal than the broad investor base.

The search for evidence in conflict with the Efficient Markets Hypothesis therefore leads away from the examination of inefficient individual investor behaviour, and toward the investigation of empirical anomalies which may reflect such behaviour in price-setting on investment markets. Two recurring threads in the literature on capital asset pricing anomalies, which has its origins in the early 1980s, relate to firm size and investment value. With regard to the former, a substantial body of literature points to the outperformance of smaller firms (measured by market capitalisation) compared to larger firms, although as will be discussed below this is not a universal outcome and has shown signs of reversing in recent years. Value effects are those linked to measures of stock price being out of line with fundamental indicators of firm

value, such as book value of assets or earnings. The following chapters review the international literature on each of these effects in turn, as well as the most significant attempt in the international literature to incorporate these observations into an asset pricing model, namely the Fama and French three-factor model. The South African literature on size and value effects is reviewed subsequently.

It is important, in considering these empirical anomalies and the explanations advanced for them, to bear in mind what has come to be known as the joint hypothesis problem. In effect, statistical tests in the anomaly literature are always testing the joint hypothesis of efficient markets and the specification of a particular pricing model, usually the CAPM. Failure to support this joint hypothesis could therefore indicate either inefficiency or the misspecification of the model used (or indeed both). Crucially though, the inefficiency of financial markets can never be concluded with certainty.

Chapter 3

The size effect

We now consider the international evidence of a systematic size effect in stock returns, as well as rationalisations of these observations and contrary evidence.

3.1 Evidence of the size effect

Banz (1981) first brought the size effect to prominence. He presented the following model for returns on a security, taking account of both systematic and idiosyncratic (specific) risk:

$$\mathbb{E}(r_i) = \gamma_0 + \gamma_1\beta_i + \gamma_2 \left(\frac{\sigma_i - \sigma_m}{\sigma_m} \right) \quad (3.1)$$

where:

r_i is the return on security i ,

γ_0 is the expected return on a zero-beta portfolio,

γ_1 is the expected market risk premium,

β_i is the beta of security i ,

γ_2 is the specific risk premium,
 σ_i is the standard deviation of returns on security i , and
 σ_m is the standard deviation of market returns.

Under the zero-beta version of the CAPM (Black, 1972), the parameter γ_2 is zero, as specific risk can be diversified away and should not therefore expect to be rewarded. Banz (1981) tested this on a sample of all New York Stock Exchange (NYSE) stocks with a listing period of at least five years between 1926 and 1975, by sorting first into quintiles on firm size and then, within each size quintile, sorting into quintiles on beta, thus creating 25 portfolios in all. His results indicated a significantly negative estimate of γ_2 , suggesting a misspecification of the CAPM. This anomaly owes its existence to the outperformance of small firms: Banz (1981) showed that a zero-cost arbitrage portfolio which is long the smallest firms and short the largest would have delivered an excess return of 1.52% per month over his sample period. He concluded that the anomaly is more likely to be evidence of a misspecified pricing model than of market inefficiency, and that the small firm outperformance may very well have its roots in the lack of publicly available information on such firms in comparison to their larger counterparts, leading to insufficient portfolio diversification and consequently higher returns for neglected small stocks.

Contributing to the debate in the same year, Reinganum (1981b) demonstrated both size and value effects (the latter is dealt with in more detail in Chapter 4). He showed that the twenty highest-ranked firms from a sample of NYSE and American Stock Exchange (AMEX) stocks by earnings-to-price (a positive indicator of value) outperformed the twenty lowest-ranked significantly and consistently over time. The persistence of this effect is evidence that it does not result simply from the informational advantages of immediate action. Furthermore, the two lowest deciles by firm size were shown to significantly outperform the market, even though the beta of these two deciles in aggregate was approximately equal to one. A joint test of the two

effects led Reinganum to the conclusion that earnings-to-price proxies for the factors causing the size effect, and has no material impact once size has been controlled for. Like Banz, he concluded that the persistence of the effect suggests that markets are indeed informationally efficient, but that the CAPM is misspecified.

Brown, Kleidon and Marsh (1983) showed that the size effect has been unstable over time; from January 1967 to December 1975, for example, the correlation between firm size and return was in fact positive (but statistically insignificant), whereas over the period 1973 to 1979 it was significantly negative. This clear nonstationarity of the size premium is a major issue for the statistical testing of the size effect as well as any conclusions to be drawn about its significance and reliability as an asset pricing model factor. The authors noted that the premium should always be positive if there are fundamental factors (such as, for example, poorer diversification opportunities or differential trading costs) underlying the size effect.

They did show however that for the full period of their study (1967 to 1979) there was a significant inverse linear relationship between the natural logarithm of market capitalisation, $\log(MV)$, and excess return, adjusted for beta. While this effect was fairly stable for the middle deciles, the assumption of a non-stochastic firm size premium was clearly inappropriate for the largest and smallest decile portfolios. Their statistical tests allowed rejection of the hypothesis that the excess returns for these portfolios might simply reflect variation around a constant mean. Alternative explanations, in terms of Black's zero-beta portfolio and an imperfect market proxy, were similarly rejected in that they depend on implausible differential returns (for example, a significant excess of the risk-free rate over the return on the zero-beta portfolio). They concluded that the most likely explanation is a misspecification of the CAPM (Brown, Kleidon and Marsh, 1983).

One of the criticisms levelled at studies of the size effect over the years has been that the results are possibly influenced by the effects of thin trading of smaller stocks. Several alternative methods for the calculation of betas

have been proposed to overcome this problem, notably those of Scholes and Williams (1977) and Dimson (1979), which are discussed in section 7.4. Reinganum and Smith (1983) made use of the Dimson approach for estimating betas, and divided the stock universe under consideration into deciles by size. Even allowing for a return of minus 100% on delisting, they found that the three smallest deciles deliver risk-adjusted excess returns more than two standard errors above zero. Their conclusion was that the CAPM is misspecified, omitting a significant risk-related variable, the nature of which they argue cannot be explained by market power or by any factor affecting beta. The most likely underlying sources of risk for which firm size proxies are, in their opinion, imperfect information (including the possibility of a greater degree of insider trading in the stocks of small firms) and constraints on investment, for example regulatory restrictions on small stock investment by pension funds.

Lustig and Leinbach (1983) found that the smallest quintile by firm size outperformed the largest, on a risk-adjusted basis, in six of the nine five-year periods between 1936 and 1979. They likewise concluded that the CAPM is most likely misspecified, with the excess return on small stocks reflecting the opportunity cost of obtaining information about them. Brown and Barry (1984) further showed that the extent of CAPM misspecification is substantially greater for small firms than for their larger counterparts.

Reinganum (1981a) went on to evaluate whether Ross's Arbitrage Pricing Theory was able to do a better job of interpreting the size anomaly. In a two-factor model, the smallest firm decile continued to show returns about 20% per annum in excess of the largest decile; given the APT methodology, this differential is in effect risk-adjusted. Significant differentials persisted for three-, four- and five-factor models. Reinganum (1981a) did however concede that a difficulty of the APT methodology is that statistical tests based on it are in effect jointly testing several hypotheses, and failure of the tests does not definitively reveal which of these hypotheses cannot be supported.

Reinganum's conclusions were however disputed. Chen (1983) found that

the appropriate factor loadings on an APT model were able to explain the size premium. Chan, Chen and Hsieh (1985) further developed a multifactor pricing model with six variables: the return on the equally-weighted NYSE index, seasonally-adjusted growth in industrial production, unanticipated inflation, the change in expected inflation, the differential between the long-term government bond yield and the Treasury bill rate and the risk premium on bonds of less than Baa quality compared to long-term government bonds. They found a differential return between the smallest and largest quintiles by firm size of 0.65% per annum, which they considered insignificant once transaction costs were allowed for. Most of the excess return on smaller firms was accounted for by the factor loading on the corporate bond risk premium. This lent weight to the conclusion that the size effect measures the extra risk of smaller firms. The addition of $\log(MV)$, the natural logarithm of market capitalisation, failed to add to the explanatory power of the six-variable model.

Reinganum (1984) however summarised all of the investigation into the size effect as conclusive proof that empirical evidence is incontrovertibly at odds with accepted theory, as embodied by the CAPM. From this point onwards in the literature, the emphasis shifted from establishing the existence of the size effect to attempting to explain it.

3.2 Rationalisations of the size effect

In a summary of the literature on the size effect up to 1983, Schwert (1983) showed that the statistical evidence supporting the positive relationship between risk, as measured by beta under the CAPM, and return is surprisingly weak. Although significant evidence of the existence of a size effect had been presented, Schwert noted that a growing body of literature questioned its financial significance, explaining it as either a statistical artefact, a purely seasonal effect or a nonstationary process, or providing an economic rationale for its existence. These explanations and criticisms of the firm size effect are

discussed in this section.

3.2.1 Seasonality

One of the first and most important explanations of the size effect was in terms of its observed seasonality. Anomalous seasonal effects of stock returns had been noted for some time, for example in the work of French (1980) on the so-called weekend effect, in terms of which Monday returns are consistently negative. An application of Bayes' Rule to any reasonable prior expectation of stock returns on Mondays gives rise to a posterior distribution with a negative mean, a result which is difficult to reconcile with market efficiency. Prior to that, Rozeff and Kinney (1976) had shown that the month of January had a significant risk premium relative to other months in a two-parameter model.

In the case of small firms' stocks, the excess returns in the United States (US) appear to be concentrated in January. Keim (1983) reported that almost half of the size premium is owed to anomalous abnormal returns in the first month of the year. Indeed, more than a quarter arises in the first trading week, and 11% on the first trading day of the year. This suggests that it cannot be accounted for by an extra risk factor term in the CAPM model, nor by differential trading costs. Keim (1983) also noted the downward bias on the estimation of betas by Ordinary Least Squares (OLS) regression for smaller firms' stocks, which are generally more thinly-traded than their larger counterparts, and repeated his analysis using the Scholes and Williams (1977) and Dimson (1979) beta estimation methods. The conclusion however remained essentially the same. Keim (1983) further reported that the instability of the size premiums remains after accounting for the January effect (which is consistently positive), implying that the nonstationarity of the size premiums is unlikely to explain the observed autocorrelation in excess returns. He postulated three hypotheses to explain the January effect:

1. Tax-loss selling, whereby investors sell poor-performing securities to-

wards the end of the trading (and tax) year in order to crystallise capital losses, and rebuy these early in January, driving prices up. According to Keim (1983), this ignores the arbitrage possibilities that would present themselves to non-taxable investors; furthermore, the level of the January effect has not varied over time with changes in the level of personal income tax rates.

2. Differential information, with the additional return to small stocks representing the reward to investors for the extra effort involved in researching smaller firms. Keim conceded that this was a possibility, but noted that it was untested at the time of writing.
3. Spurious causes, such as the influence of “outliers, a concentration of listings and delistings at year-end, or data base errors” (Keim, 1983:31).

Tinic and West (1984) extended the work of Rozeff and Kinney (1976) confirming the significance of January returns in a CAPM model, which was apparent using both equally-weighted and value-weighted indices as market proxies. They noted however that there is no clear benchmark as to what constitutes a sufficient sample size for such an analysis.

The significance of the January seasonality is clear from the conclusions of Lakonishok and Shapiro (1986), who demonstrated that for their sample, only firm size has predictive power for returns, with neither beta (indicating systematic risk) nor stock return variance (indicating specific risk) having any statistical significance. However, the size effect disappears completely once the January data is removed.

A ninety-year perspective on seasonal effects was carried out by Lakonishok and Smidt (1988) who argued that there are good reasons to be skeptical about accepting the conclusion of demonstrable seasonal effects: a selection bias in that papers challenging the status quo are more likely to be published, the fact that nonstationarity in return generation leads to noise which is difficult to separate from true anomalous effects, and finally the risk of ‘data snooping’ (or data mining, the trawling for anomalies of data sets

which are finite and subject to random error, and hence the self-fulfilling but ultimately spurious detection of such anomalies). Nevertheless, they showed that the Monday, January and pre-holiday effects were very much a reality over ninety years of US data, citing a number of possible reasons for their existence. These included inventory adjustments, timing of trades by informed and uninformed investors respectively, tax-loss selling and ‘window-dressing’ by fund managers (selling poor-performing stocks prior to reporting on portfolio holdings at year-end).

Several authors reported evidence on the seasonal nature of the size effect from other countries and data sets. Gultekin and Gultekin (1983) demonstrated a clear seasonal pattern in most major industrial nations, with a spike typically at the turn of the tax year, lending credence to the tax-loss selling hypothesis. Brown, Keim, Kleidon and Marsh (1983) showed an Australian small firm premium of around 4% per month, which is constant across months unlike the US experience, and provides some reasons to question the tax-loss selling hypothesis. Abnormal January returns in Canada were reported by Berges, McConnell and Schlarbaum (1984); however, since this effect predates the introduction of the tax on capital gains in that country in 1973, it does not suggest that tax-loss selling is a plausible explanation. Likewise, Tinic, Barone-Adesi and West (1987) concluded that the persistence of the January effect renders tax-loss selling an implausible explanation of the observed seasonality, although for small stocks listed solely in Canada, there is evidence of some effect on seasonality of the introduction of capital gains tax. Kato and Schallheim (1985) showed a monotonic inverse relationship between size and excess January returns in the Japanese market, as well as a statistically significant excess June return; they suggested that these observed anomalies may be consistent with the Japanese practice of paying bonuses twice annually. January and April effects in returns on the London Stock Exchange, consistent with the tax-loss selling hypothesis given a personal income tax year-end of 5 April and a corporate tax year-end of 31 December for more than a third of companies sampled, were detected by

Reinganum and Shapiro (1987).

The most prominent explanations of the seasonal nature of the size effect are discussed below.

3.2.1.1 Tax-loss selling

Reinganum (1983) tested the tax-loss selling hypothesis by constructing for each stock a measure of potential tax-loss selling, PTS, defined as follows:

$$\text{PTS} = \frac{P_e}{P_m} \quad (3.2)$$

where:

P_e is the closing price of the stock on the last trading day of the year, and P_m is the maximum price attained by the stock over the longest preceding period permitted by the US Internal Revenue Service for purposes of classifying a stock as a short-term holding (usually six months).

Reinganum (1983) divided the data set into ten deciles by firm size (market capitalisation), each of which was further split into four by PTS measure. Two-thirds of firms in the smallest size decile were also in the lowest PTS quartile, with only 10% in the top PTS quartile. The Spearman rank correlation coefficient between the two measures averaged 0.4. The superior January performance of the stocks which had suffered the greatest fall in prices was in line with the tax-loss selling hypothesis. It was further clear that a meaningful size premium remained after controlling for PTS, suggesting either a true residual size effect or a misspecified tax-loss selling indicator. Although the null hypothesis of equal size effects in all months could be rejected at the 5% significance level, it was also evident that the potential profits from a small-cap trading rule were not exorbitant and may disappear altogether after accounting for transaction costs (Reinganum, 1983).

Ritter (1988) put forward a variant of the tax-loss selling hypothesis which he termed ‘parking-the-proceeds’. Based on an observation of the buying and selling behaviour of cash account customers of Merrill Lynch over the fifteen years from December 1970 to December 1985, he concluded that almost half of the variation in the January effect is explained by the behaviour of individual investors, who tend to sell stocks close to the end of the year in order to realise capital losses, and then reinvest these proceeds the following January. This explains why the January effect is strongest following bear markets and why it is concentrated in small stocks (which tend to form a higher proportion of portfolio holdings for individual, as opposed to institutional, investors).

Jones, Lee and Apenbrink (1991) showed a significant change in turn-of-the-year returns on the Cowles Commission Industrial Index following the introduction of capital gains tax. An intraday study further revealed a clear trend from seller-initiated trading to buyer-initiated trading around the turn of the year (Griffiths and White, 1993), implying a systematic shift from transactions at bid price to those at ask price. Slight differences in the day of change in the US and Canadian markets, consistent with those countries’ respective tax year-ends, further supported the claim that tax-loss selling is the primary cause of the observed January seasonal anomaly.

Criticism of the tax-loss selling hypothesis was levelled by Constantinides (1984) who showed that since smaller firms typically have greater variance of returns, the tax timing option on such stocks should be more valuable, leading to *lower* pre-tax mean returns. The observed January effect is therefore consistent with tax-loss selling only if we make the assumption of irrationality or ignorance of investors.

In similar vein, Chan (1986) argued that if tax-loss selling were the sole cause of year-end trade, rational sellers could repurchase stocks sold by others at the same time. The tax-loss selling hypothesis has three testable implications: that the January effect for stocks having suffered short-term losses is positive, that the January effect of stocks having suffered long-term losses is zero and that that January effect of the interaction between the two is zero.

By demonstrating that the second of these implications is violated, in that stocks having suffered long-term losses produce a January effect of similar magnitude to the short-term loss stocks, Chan (1986) concluded that tax-loss selling cannot be a full explanation of the January seasonal effect.

Thaler (1987a) concluded from a review of the literature that while tax-loss selling may contribute to the January effect, it cannot be the sole reason for the observation. He further noted that the effect is not practically exploitable due to thin trading and large bid-ask spreads on small stocks.

Lakonishok and Smidt (1984) sought to explain the January effect in terms of trading volumes. They argued that the prices of smaller stocks may only adjust to equilibrium levels over several trading days, as a result of the low trading volumes: the average trading volume of companies in the lowest decile was less than 0.1% of that in the highest decile. The closing prices of small firms' stocks showed a bias towards bid prices until the last trading day of the year, and then shifted towards ask prices until the fourth trading day in January. It was however not possible to develop a trading rule to exploit this apparent anomaly as a result of the transaction costs involved. They concluded that most investors do not in fact adopt an aggressive tax-loss selling strategy.

3.2.1.2 Insider trading

One alternative explanation of the seasonal effect is the greater opportunity for insider trading in small firms, and so investors require greater returns in January as compensation for increased risk, in that this is a time of year when corporate insiders are likely to have access to material nonpublic information. Seyhun (1988) showed that since there is no evidence that corporate insiders significantly increase their purchasing activity in the financial markets in the month of January, this risk compensation hypothesis cannot be supported.

3.2.2 Transaction costs

Typically, transactions on small-cap stocks induce proportionally greater transaction costs, in the form of wider bid-ask spreads and higher broker commissions. Stoll and Whaley (1983) reported that the typical bid-ask spread and commission for a small-cap stock in a sample of NYSE common stocks over the period from January 1955 to December 1979 were 2.93% and 3.84% respectively, compared to 0.69% and 2.02% for large-cap stocks. After making allowance for these costs, Stoll and Whaley (1983) found that the size effect is reversed based on monthly returns; in other words, for a one-month holding period, large stocks outperform small stocks once transaction costs have been taken into account. Break-even between large and small firms is achieved when securities are held for four months, but the reduction in the number of observations means that this result is not statistically credible.

Schultz (1983) extended the work of Stoll and Whaley by adding AMEX stocks to the NYSE sample. However, he found that small firms earn a significant risk-adjusted excess return even after allowing for transaction costs, and was able to reject the hypothesis of equal risk-adjusted returns at the 1% level. He noted also that the theory that excess small firm returns are driven by transaction costs is inconsistent with an observed variable small firm premium, as reported by Brown, Kleidon and Marsh (1983), and the seasonal effects discussed above.

Blume and Stambaugh (1983) argued the existence of a bid-ask effect resulting from the fact that closing prices can deviate from equilibrium prices if the last transaction of the day reflects an order only from one side. By Jensen's inequality, this biases calculated returns upward, and is particularly pronounced for smaller firms. This bias can be corrected by computing returns on a buy-and-hold basis rather than daily rebalancing. On this basis, the size effect is shown to be clearly nonstationary.

Lamoureux and Sanger (1989) further extended the scope by analysing the over-the-counter (OTC) and National Association of Securities Dealers Automated Quotes system (NASDAQ) markets, which provided a much

larger sample of small firms than prior research. The small firm sample was consequently also less biased towards those firms which had underperformed recently. They reported a significant size effect based on a perfect negative monotonic relationship between firm size and stock price; furthermore, as expected, the relationship between firm size and bid-ask spread is also monotonically negative. These results suggest that transaction costs may explain why the apparent size anomaly has not been removed by the actions of traders.

Evidence from Australia was presented by Aitken and Ferris (1991), who considered the effect of transaction costs on the small firm premium based on review periods of one, two, three, four, six and twelve months, using betas calculated by the method proposed by Scholes and Williams (1977). Their finding was that the t -statistics for the small firm portfolio were all insignificant at the 5% level, although they conceded that their methodology of ‘round-trip’ costs (i.e. allowing for buying and selling costs at the beginning and end of the holding period respectively) may have produced a bias against finding a small firm premium.

3.2.3 Thin trading

Betas obtained by OLS regression may be subject to bias as a result of thin trading. The fact that small firm stocks are subject to less frequent trading implies that risk measures derived from returns over short intervals will tend to underestimate the true risk of such stocks (Roll, 1981). Roll further showed that the ratio of the variance of returns on an equally-weighted index to that on a value-weighted index increases as the holding period increases (from 1.05 for daily returns to 3.166 for half-yearly). The reason for this is that thin trading results in higher autocorrelation of returns for small firms than for their larger counterparts.

The two primary methods of correcting for this bias are the adjustments proposed by Scholes and Williams (1977) and Dimson (1979), which are discussed in detail in section 7.4 below.

Reinganum (1982) made use of Dimson's adjustment, regressing on lagged, leading and contemporaneous returns, which gave rise to the expected result that small firms are indeed riskier than large firms (the ratio of the average beta of the smallest decile compared to that of the largest is 1.74 under the Dimson method, compared to a less intuitive 0.77 under OLS regression). However, Reinganum (1982) noted that for this beta differential to account for the observed 36% per annum return differential between these two deciles would require that the expected market return exceed the risk-free rate by a quite implausible 50%. Thus, he concluded that the size effect remains a significant anomaly.

Another interpretation of the thin trading argument is that the returns to small firms display a liquidity premium. This is the hypothesis evaluated by James and Edmister (1983), who found however that there is no significant difference between the returns of portfolios consisting of the most and least actively-traded firms. Controlling for trading activity, a significant negative correlation between firm size and risk-adjusted returns appears to remain.

3.2.4 Market proxy

The CAPM in theory relates the return on an individual security to the return on the universe of all tradeable securities (the market portfolio) by way of systematic risk measured by the security's beta. This market portfolio is however not observable, and hence empirical testing of the CAPM requires the use of some form of market proxy, typically an index on the stock market from which the sample is drawn. Korkie (1986) argues that anomalies such as the size premium are almost inevitable given a sample-inefficient index.

Berk (1995) also criticised small firm effect findings on methodological grounds. He demonstrated mathematically that market value will in theory be inversely correlated with realised return, even when true firm size (which he measures by expected cashflow) is assumed to be uncorrelated to risk, measured by expected return. In his view, analytical errors arise from the fact that proxy market portfolios are not mean-variance efficient, and that

betas are estimated with error.

The seminal paper on this topic is Roll (1977), which is discussed more fully in Section 7.2 below.

3.2.5 Differential information

The availability of information on which to base investment decisions differs dramatically between small and large firms, and hence the investor wishing to invest in small-cap stocks must make additional effort in gathering the data required to follow an informed strategy. It could be argued that the size premium simply reflects the reward for this additional effort.

Barry and Brown (1984) used the period for which stocks had been listed as a proxy for the quantity of information available. On the basis of standardised excess returns, they found that the size effect is explained in full by the period-of-listing effect, providing some support for an explanation of the size premium in terms of differential information (assuming that period of listing is a reasonable proxy for available information). Interestingly, they further found that while the size effect is in large part due to January performance, the period-of-listing effect persists after controlling for firm size, beta, interactions between independent variables and the exclusion of January returns. Elsewhere (Barry and Brown, 1985), they argued that securities with more information available in fact have smaller betas under a differential information model than they would have under the basic CAPM; if this is allowed for, then what emerges as excess returns may simply be compensation for risk in a well-specified model. In addition to the period of listing, they suggested the number of observed returns and the divergence of analyst opinions as proxies for the level of information available.

Zeghal (1984) measured the value of information provided by financial statements by measuring the ratio of the variance of adjusted returns (relative to a comparison portfolio of firms with similar overall variance) during the earnings announcement period compared to other times, as well as the ratio of transaction volumes in these two periods. Both are statistically sig-

nificantly greater than unity for the sample as a whole, allowing a conclusion that the information contained in financial statements has measurable value for investors. A comparison by firm size shows that small firms' stocks have significantly greater ratios on both measures than larger firms' stocks, allowing a rejection of the null hypothesis of equality regardless of firm size.

On the basis that prices are more informative the more data available about a firm and the greater the energy expended by traders on research, Collins, Kothari and Rayburn (1987) compared earnings forecasts taking account of market price with simple time-series forecasts. Their results confirmed that models taking account of price produced significantly more accurate forecasts than random walk models (with or without drift) for large firms, but the difference was insignificant for small stocks.

In related but subtly different research, Brown and Kim (1993) put forward a hypothesis that the nonearnings disclosures by small firms have a disproportionately positive bias, and are associated with positive stock price reactions. This was motivated by prior research: Verrecchia (1982) argued that managers have an incentive to disclose non-public information when they expect the effects on firm value to exceed the disclosure costs. Likewise, the incentives for information production and distribution by firm outsiders are positively related to firm size (Atiase, 1985), hence small firms' nonearnings disclosures are more likely to be initiated by managers and to be 'good news'. Brown and Kim (1993) found that the evidence from the period 1982 to 1987 corroborated their hypothesis.

Freeman (1987) noted that previous research had consistently supported two hypotheses: that abnormal returns tend to precede the announcement of very high or low accounting earnings by several months, and that earnings announcements tend to trigger further abnormal market activity. His study supported the conclusion that there is a systematic difference between the information supporting prices for large firms and that for small firms. As corollaries to this hypothesis, it was expected that large firm security prices will reflect future accounting earnings at an earlier stage than for small firms,

and that the size of abnormal returns from earnings announcements will be inversely related to firm size; both were corroborated by the evidence (Freeman, 1987).

3.2.6 Price effect

An alternative explanation is that size is simply a proxy for the explanatory variable of stock price. Kross (1985), looking at both size and value, as measured by price-earnings (PE) ratio, effects, noted that both measures include price as a determinant: size (market capitalisation) is the product of price and shares outstanding, while PE ratio is, obviously, price as a multiple of earnings. By decomposing each of these into their constituent parts, Kross was able to demonstrate that price variation explains a greater proportion of the variation of excess returns than either of the other variables. He found that this continues to apply even after correction for possible biases, namely survivorship bias, log returns and betas from the market model.

Bhardwaj and Brooks (1992) investigated the effects of stock price, transaction costs and the bid-ask spread on the January seasonal anomaly. Their most interesting finding was that within bands of stocks with similar prices, returns have little or no relation to firm size, suggesting that price rather than size is the true explanatory variable. Furthermore, the price effect is not subject to the time variability of the size effect, reported in, for example, Keim (1983) and Brown, Kleidon and Marsh (1983).

3.2.7 Size as proxy for risk

Finally, it may be argued that size does indeed play a role, but merely because it is a proxy for true fundamental risk. Friend and Lang (1988) performed a multiple regression on stock returns using two independent variables: RISK and MV. The latter is the natural logarithm of market capitalisation, while for the former the authors used three alternative measures, namely regressed beta, variance of stock returns and the Standard & Poor's Quality Ranking

for Stocks, which is a proprietary evaluation of the quality of stocks' earnings and dividends. Their finding, for a univariate regression on the RISK factor, was that the quality rankings better explain returns than either beta or variance. When both quality and size are regressed, the former is clearly more important. Moreover, for several of the overlapping 25-year periods in their study, the size premium was either negative or statistically insignificant.

Thus it is possible that in conjunction with betas regressed against market returns, where the market portfolio used for regression purposes is very likely an imperfect proxy for the investment universe and where the regression itself is subject to the usual errors, firm size may simply be standing in for more fundamental measures of risk not measured by beta.

A formal interpretation of the risk proxy argument was put forward by Perez-Quiros and Timmermann (2000) in terms of imperfect capital market theory: the requirement for firms to make use of collateral when borrowing is the result of information asymmetries between firms and lenders, and it is consequently small firms who are most exposed to lower liquidity and higher short-term interest rates. A recession may spark a 'flight to quality', in the face of which small firms would find it significantly more difficult to raise capital. Their empirical analysis of the conditional distribution of returns in recession and expansion states, and in particular the significant effect of a recession state on the risk and expected returns of small firms, tended to confirm the hypothesis that the small firm effect is, at least in part, a reflection of differential risk which is linked to business cycles.

Moving away from financial risk, Chan, Chen and Hsieh (1985) argued that small firms have a greater exposure to production risk, and as a result are sensitive to changes in the risk premium (which they measured as the difference in yield between long-term government bonds and low-grade corporate debt). Huberman and Kandel (1987) found that firms of similar size tend to respond to risk factors in similar ways, with the result that their returns tend to move in harmony.

Chan and Chen (1991) put forward the hypothesis that risk differentials

between large and small firms can be ascribed to the fact that small firms tend to be marginal firms, with lower returns on assets and lower interest coverage, which are more likely to have cut their dividends recently. They found the empirical evidence consistent with this hypothesis for most industries. Consequently, they constructed two return indices:

1. the difference between returns on a portfolio of stocks whose dividends have recently been cut and those on a matching portfolio of smaller firms, and
2. the difference between returns on a portfolio of highly leveraged stocks and those on a matching portfolio of smaller firms.

In each case, the marginal firms are larger on average than the matching portfolio, to prevent mistaking a marginal firm effect for a true size effect. They found that firm size has negligible additional explanatory power once beta and the two marginal firm effects are taken into account. Consequently, they concluded that size is simply a proxy for distress, with the additional return to small firms reflecting the accordant risk premium.

3.3 Evidence against the size effect

Recent studies have suggested signs of a reversal of the size effect. Bhargava and Brooks (1993) reported that the period 1982 to 1986 showed results which called into question the continued existence of a size (or price) effect. Reporting on UK experience using the Hoare-Govett Index constituent companies (1,200 companies with market capitalisations of less than £100 million, making up the lowest 10% of the London Stock Exchange), finding maximum likelihood estimators of time-varying betas using the Kalman filter technique, Fraser (1995) found no evidence of abnormal returns to small firms after 1989. Based on three analyses over the period from 1980 to 1996, looking at, respectively, annual returns, cross-sectional regressions and linear

spline regressions, Horowitz, Loughran and Savin (2000) concluded that the size premium has disappeared after 1980.

It is also clear that the formation and liquidation of small-cap portfolios to take advantage of any size effect is made more difficult by lack of liquidity and transaction costs. Using turn-of-the-year intraday price and volume data from the Toronto Stock Exchange and New York Stock Exchange, Griffiths, Turnbull and White (1999) showed that after adjustment for these costs and constraints, large cap stocks in fact outperform small caps by between 2.4% and 6.5% per annum.

It has also been argued that the size effect is nothing more than a spurious statistical inference based on data truncation (Wang, 2000). This argument holds that small stocks are by definition more likely to face bankruptcy and to fail to meet exchanges' requirements for listing. There is thus an inherent selection and survivorship bias which supports the size effect conclusion. The survivorship bias argument, however, would seem to be easily overcome by a data set which includes all listed firms, no matter how brief the period of listing.

Despite the rationalisations and recent evidence of reversals, there is no doubt that the size effect has been a significant and persistent feature of security returns over time and across the globe, and is suggestive of either inefficiencies in market price-setting, or the misspecification of models which do not account for the effect of firm size (or identify underlying risk factors for which this proxies).

Chapter 4

The value effect

Apart from the size effect, the most significant and persistent anomaly consistently reported in the literature of the past thirty years is what may be termed a value effect, where ‘value’ is typically defined as a ratio of price to a non-market (cashflow- or accounting-based) measure of firm value. The most common indicators are book-to-market equity or price-earnings ratios, although these are far from the only variables which have been analysed. Often the literature considers the size and value effects together, generally finding that they jointly comprise a significant additional explanatory variable beyond what the CAPM describes. A seminal paper by Reinganum (1981b) showed that the 20 highest-ranking firms based on earnings yields significantly outperform the lowest 20, and that this relative performance persists over time, suggesting that it is not due to the informational advantages of immediate action. Reinganum also found that the two lowest size deciles outperform their larger counterparts, even though the beta of these portfolios is roughly unity. A joint test suggested that the earnings yield proxies for the same factors leading to the size effect, and has no material impact after size has been controlled for. He concluded that the persistence of the effect over time suggests that markets are indeed informationally efficient, and the results are consequently suggestive of a misspecification of the CAPM.

Basu (1983) demonstrated a clear negative relationship between return and, respectively, PE ratio and firm size. He found however that the higher returns for small firms are accompanied by greater risk in the form of increased variability of returns; this is not the case for the high earnings yield (low PE ratio) portfolios. These results therefore suggest that the size effect is secondary to the value (earnings yield) effect, contrary to the findings of Reinganum (1981b). Basu's view was that both measures are probably proxies for more fundamental explanatory factors.

The contradiction between the results of the Reinganum and Basu studies was explored further by Cook and Rozeff (1984). Using three different portfolio formation methods, and nine different methods to measure abnormal returns, they were able to show that both the size and value effects are significant, and that neither subsumes the other.

Banz and Breen (1986) argued that the use of COMPUSTAT data for analytical purposes introduces both ex-post selection and look-ahead biases. The former results from the inclusion in the database of only those firms which were viable entities at that point in time, and the exclusion of those which had ceased to exist for whatever reason at a prior date; the latter arises from the backdating of accounting results to their measurement dates (e.g. financial year-end), whereas in reality such results would only have been known several months after their measurement dates. By comparing results for databases corrected for these two biases, the null hypothesis of no differential in results can be rejected, suggesting that each bias is significant. Based on the corrected data, the authors concluded that there is no value effect independent of the size effect.

Based on a study of returns over the period 1970 to 1980, Goodman and Peavy (1986) showed that the size effect often served as a proxy for the price-earnings effect, but that the two factors acted independently on occasion. They concluded that either markets are inefficient or the CAPM is misspecified, or both.

A Seemingly Unrelated Regression (SUR) model was employed by Jaffe,

Keim and Westerfield (1989) to investigate the size and value effects. In their opinion, prior studies suffered from two major shortcomings. First, an analysis of variance (ANOVA), as used by Cook and Rozeff (1984), may reject a null hypothesis of equal mean returns even where there is no obvious relationship between returns and the ranking variables under consideration. Second, considering only extreme portfolios, as in Banz and Breen (1986), is fundamentally flawed, as it ignores the intermediate information available.

Their results, spanning the period from 1951 to 1986, showed statistically significant size and value (earnings-price) effects. However, the size coefficient was significant only in the month of January, suggesting that it is predominantly a seasonal effect, whereas the value effect was significant across all months. The results were clearly also significant in an economic sense: holding size constant, the highest earnings-price quintile outperformed the lowest by 3.2% per annum, and holding earnings-price constant, the smallest size quintile outperformed the largest by 3.4% per annum.

They also noted, however, that an analysis of subperiods suggested that the significance of the earnings-price effect is sensitive to the period in which it is measured; a review of their results over the same subperiods as prior studies reflected that the results of these studies were clearly sample-specific. They further rejected the hypothesis that the size and value effects are simply proxies for a price effect.

Wong and Lye (1990) showed that size and earnings-price effects are significant in the Singapore market, with the Dimson (1979) beta adjustment insufficient to change this conclusion. An interaction study suggested that the size effect is of secondary importance to the earnings-price effect.

A comprehensive review of the earnings-price anomaly was conducted by Ball (1992). He found that there were two broad categories of explanation, either in terms of inefficient markets or in terms of the bias of measured abnormal returns as estimates of economic profits. Potential sources of such bias are information acquisition and processing costs, as well as the misestimation of returns with the estimation error correlated with the earnings

variable being examined.

While Ball (1992) acknowledged that transaction costs are a potential explanation, he argued that their magnitude is uncertain and also varies across the universe of heterogeneous investors, with no clear indication of which investors' costs influence market equilibrium prices. The estimation of investors' returns from Center for Research in Securities Prices (CRSP) data is subject to two sources of error: the recorded prices are not necessarily those at which trading could take place, and they do not account for the differential taxation between dividends and long- and short-term capital gains. Abnormal return measures are also subject to estimation error, since the CAPM is an abstraction with the limitations of all imperfect models.

Ball (1992) cited the following as feasible explanations of the observed earnings-price anomaly:

1. error in the estimation of beta is correlated with earnings: he argued however that this interpretation requires an implausible level of misestimation;
2. the influence of transaction costs: the magnitude of abnormal returns is however too large for this to be a complete explanation;
3. liquidity and trading-mechanism effects, as described in Amihud and Mendelson (1986), but again Ball concludes that the literature suggests that this cannot fully explain the anomaly;
4. systematic understatement of the standard errors of key statistics, leading to overstated t -statistics: this would have to arise from unobserved cross-sectional correlation or over-fitted models, both of which Ball considered unlikely;
5. the earnings variable in fact proxying for expected returns;
6. information acquisition and processing costs; and

7. finally, the possibility that markets are in fact inefficient: Ball considers this a possibility, but laments that the paucity of testable theories of market inefficiency might render efficiency practically irrefutable.

Looking at the value effect as described by book-to-market ratio, Loughran (1997) found that realised returns on value and growth managed funds are not materially different, and in the absence of a size effect, the value effect is not significant. The book-to-market results reported in Fama and French (1993) are driven largely by the smaller firms, and outside the month of January, the effect for larger firms is practically non-existent.

An explanation of the value effect in terms of contrarian investment was put forward by Lakonishok, Shleifer and Vishny (1994). They contrasted their conclusion with the view of Fama and French (1992) that value strategies produce superior returns to growth strategies because value stocks are fundamentally riskier. Using data from April 1963 to April 1990, they defined glamour stocks as those with high recent historic growth in sales and high expected future growth as measured by high cashflow-to-price or earnings-price ratios, and value stocks as those with low past growth and low expected growth into the future. They found that value stocks outperform glamour stocks by an average 10.7% per annum, and that a strategy on both sales growth and PE ratio yields higher returns than one based on only one of these two variables. An analysis on the largest 50% of stocks only gave similar results, suggesting that the results were not confounded by a size effect.

Regressions on individual variables revealed that sales growth, book-to-market, earnings-price and cashflow-to-price all had significant explanatory power, but firm size did not. In addition, in combination with other variables, the explanatory power of book-to-market weakened considerably. Sales growth and cashflow-to-price were the most significant variables (Lakonishok, Shleifer and Vishny, 1994).

One possible explanation of these effects is in terms of what the authors refer to as extrapolation theory: the notion that investors display excessive optimism regarding the prospects of glamour stocks, because they tend to

naïvely extrapolate their expectations of future growth from historic growth. They found that a value strategy outperforms a glamour strategy over any five-year period, in all three-year periods apart from two, often over one year, in three-quarters of the recessionary years and also in the market's worst-performing 25 months. Since the average beta of value stocks is only 0.1 higher than that of glamour stocks, and the difference in standard deviations of returns is also relatively small, conventional measures of additional riskiness are powerless to explain the magnitude of the outperformance. Lakonishok, Shleifer and Vishny (1994) suggested several possible explanations: investors may simply not yet have become aware of the anomaly, it could be a manifestation of data snooping (although they conceded that this is unlikely since there is theory backing up the empirical results), it may reflect the behaviour of institutional investors or it may indicate very short time horizons of investors.

Again, it is evident that indicators of investment value have played a prominent and enduring role in the generation of stock returns, an effect which cannot be reconciled with the CAPM or other market-index models.

Chapter 5

Modelling anomalies: the Fama and French three-factor model

The size and value effects discussed above are only anomalies in the sense that they are incompatible with models, such as the CAPM, which ascribe rewarded systematic risk to market covariance only. More flexible multifactor models, often following Ross' APT, allow for the incorporation of the observed anomalies into an expanded equilibrium pricing model. The most comprehensive attempt so far to incorporate size and value effects into a single theoretical framework is the three-factor model developed by Eugene Fama and Kenneth French in a series of papers in the early 1990s.

5.1 Fama and French 1992: confirming significant factors

Fama and French (1992) attempted to synthesise prior work exposing key anomalies which could not be explained within the CAPM framework. Using a similar approach to that of Chan and Chen (1988), they divided the stocks in their sample (spanning the period from 1962 to 1989 and incorporating NYSE, AMEX and NASDAQ stocks) into ten portfolios, using breakpoints

based on deciles from the NYSE sample. However, they noted that size and beta are highly correlated (with a correlation coefficient of -0.988 in the Chan and Chen study), rendering standard statistical tests unable to distinguish between size and beta effects. The authors consequently subdivided each size portfolio into ten portfolios based on pre-ranking betas (regressed against returns in the 24 to 60 months prior to portfolio formation dates). They then calculated equally-weighted portfolio returns for the year following portfolio formation, and again estimated portfolio betas, using the full sample of post-ranking returns for each portfolio, by regressing against the CRSP value-weighted index of all stocks. Some thin-trading adjustment was made by estimating betas using returns in the current and prior months; the authors noted that the inclusion of an extra lead and lag variable in the regression would have made an immaterial difference.

The formation of portfolios on pre-ranking betas as well as size expanded the range of post-ranking betas and complied with the objective of producing beta variation unrelated to firm size, allowing statistical tests to differentiate between these two effects. Portfolios formed on size only showed a strong negative relationship between size and average return, and a strong positive relationship between beta and average return. Forming portfolios on pre-ranking beta only displayed no obvious correlation between beta and return.

The two-way analysis based on the 100 portfolios formed on both beta and size showed that beta which is uncorrelated with size is, contrary to the central tenet of the CAPM, not compensated in average returns over the sample period. Regressions following the methodology of Fama and MacBeth (1973) confirmed that firm size has explanatory power for portfolio returns, but the beta coefficient is negative and not statistically significant. They argued that these results are not sample-specific, as an extension of the analysis period back to 1941 (on NYSE stocks only) yielded similar results. The reliably positive correlation of beta and market return over the period from 1941 to 1965, reported in Black, Jensen and Scholes (1972) and Fama and MacBeth (1973), among others, disappears entirely when firm size is controlled for.

Fama and French (1992) went on to consider other variables identified in the literature as possibly having explanatory power for returns:

1. Book-to-market: a regression on $\log(\text{BE}/\text{ME})$, where BE is book value of equity and ME its market value, showed a slope coefficient of 0.5% and a t -statistic of 5.71, even more significant than size. However, this did not replace the size effect.
2. Leverage: two measures of leverage were considered, namely the ratio of book assets to book equity, $\log(\text{A}/\text{BE})$, and book assets to market equity, $\log(\text{A}/\text{ME})$, which surprisingly yielded conflicting results: the latter showed positive correlation with returns, and the former negative correlation. The authors' explanation was that it is the difference between market and book leverage which explains average returns, but this is of course simply the book-to-market effect.
3. Earnings-price: a statistically significant positive correlation was displayed, but adding size and book-to-market ratio removed its explanatory power.

The correlation between $\log(\text{ME})$ [size] and $\log(\text{BE}/\text{ME})$ [book-to-market] is -0.26, which is not extreme and led Fama and French (1992) to conclude that both effects are needed to explain average returns, although book-to-market ratio is consistently the more powerful explanatory variable. They conceded that these effects could be explained within the framework of rational, efficient markets or alternatively in terms of irrational behaviour: the book-to-market effect may reflect the correction of earlier overreactions, for example. However, they argued that a three-year lagged return showed no power to explain returns, contrary to the findings of De Bondt and Thaler (1985), which are outlined in section 9.5.2.

5.2 Fama and French 1993: the three-factor model

The three-factor model was fully developed in Fama and French (1993). Building on their earlier paper, the authors expanded their analysis to include bonds, although this summary of their paper will focus on stock returns. They followed the approach of Black, Jensen and Scholes (1972), regressing monthly returns on a market portfolio of stocks and on portfolios constructed to mimic the size and book-to-market equity factors. This was an attempt to compensate for the shortcomings of the CAPM in failing to account for the explanatory power of firm size and the value effect (as measured by the book-to-market equity ratio, or BE/ME), by incorporating these into the model framework. Proponents of irrational markets might question the validity of this approach, arguing that the existence of additional returns to observable factors which are not captured in market covariance (which ought to measure systematic risk) is evidence of market inefficiency. Fama and French (1993), however, countered that these variables proxy for underlying risk factors, both being demonstrably linked to economic fundamentals. Firms with high book-to-market equity ratios tend to have low earnings on assets. They also observed that the recession of the early 1980s turned into a prolonged spell of poor earnings for smaller firms, whereas the earnings of large firms recovered quickly, suggesting that firm size is associated with an underlying risk factor.

Again using breakpoints based on the NYSE sample, they broke the NYSE, AMEX and NASDAQ stocks into two size groups, small (S) and big (B), and three book-to-market equity groups, low (L), medium (M) and high (H), using this division to construct six portfolios. From these, they constructed two mimicking portfolios. The portfolio SMB (small minus big) reflects the monthly difference in returns between the average return on the three small-stock portfolios and that on the three big-stock portfolios, while the portfolio HML (high minus low) reflects the monthly difference in returns between the average return on the two high BE/ME portfolios and that on

the two low BE/ME portfolios; these are, in other words, the returns to a zero-cost arbitrage portfolio which is long the small (high) portfolio and short the big (low) portfolio.

Their excess market return $RM-RF$ reflects the return on the value-weighted portfolio of all stocks in the sample, less the one-month Treasury bill rate (Fama and French, 1993:10).

The formation of 25 portfolios along size and BE/ME quintiles, as in Fama and French (1992), confirmed the conclusion of that study that firm size and return are negatively correlated, while a positive relationship exists between BE/ME and return. The three-factor model presents regressions against $RM-RF$, SMB and HML . The slopes on the latter two variables are significant, confirming that the market return cannot fully explain variations in stock returns. The results showed significantly greater R^2 values than regressions against the market factor alone.

Furthermore, the authors show that the three-factor model accounts for the observed earnings-price anomaly fully (Fama and French, 1993:49); by contrast, the one-factor CAPM fails to account for this apparent contribution to average returns (Basu, 1983).

5.3 Fama and French 1995: factors proxy for risk

Fama and French (1995) presented evidence that firm size and BE/ME are related to profitability, providing theoretical justification for the observation that these factors are systematically related to variations in return. They showed that firms with high BE/ME tend to be those in persistent financial distress, and they reiterated their earlier observation that the recession of the early 1980s turned into a prolonged earnings slump for small firms, an experience not shared by large firms, going on to say: “Though we have no explanation for the small-stock depression of the 1980s, it does suggest that there is a size factor in fundamentals that might lead to a size-related risk

factor in returns” (Fama and French, 1995:154).

5.4 Fama and French 1996: confirmation of the three-factor model

Fama and French (1996) noted that the use of HML as an explanatory variable follows the evidence of Chan and Chen (1991) that part of average returns is attributable to a distress factor, which HML could plausibly measure. Furthermore, the three-factor model explains the mean-reverting returns reported in De Bondt and Thaler (1985), since stocks with low-long term past returns (the ‘losers’ in DeBondt and Thaler’s terminology) tend to have strongly positive slopes on both SMB and HML, which thus predict higher future returns.

The only anomaly left unexplained by the three-factor model is the momentum effect reported by Jegadeesh and Titman (1993), whereby patterns of past returns are perpetuated in the short-term future. However, the three-factor model is a parsimonious explanation of the cross-section of stock returns (Fama and French, 1996:56).

In a more general evaluation of three-factor models, the authors demonstrated that other combinations of three portfolios describe the cross-section of returns as well as their chosen factors (viz. market risk premium, SMB and HML) (Fama and French, 1996:68). They argued also that the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) provides a valuable insight into the limitations of the CAPM as an equilibrium model. Market equilibrium in the ICAPM reflects a market portfolio M which is a multifactor-minimum-variance (MMV) portfolio; such portfolios have minimum variance given the level of expected return and sensitivity to the state variables. Given two state variables, returns may be described by the risk-free rate and any combination of three MMV portfolios (Fama and French, 1996:69). However, M is almost surely not mean-variance efficient, i.e. displaying minimum variance for the level of expected return. It follows that

market betas cannot be sufficient to explain expected returns (Fama and French, 1996:74).

5.5 Explanations of the Fama and French results

There are three possible explanations for the results of Fama and French (1992, 1993, 1996).

The first of these is that, as the authors would argue, the setting of prices on capital asset markets is rational and can be described parsimoniously by a three-factor model conforming to the ICAPM or the APT (Fama and French, 1996:75). This view is supported by the excellent explanatory power of the three-factor model, as well as the fact that other apparent anomalies within the CAPM framework (e.g. earnings-to-price, cashflow-to-price, sales growth and past returns) provide no further explanatory power within the three-factor model framework (Fama and French, 1996:76).

An alternative viewpoint would be that price-setting is irrational, and it is this reality which prevents the CAPM from providing a full explanation of stock returns (Fama and French, 1996:75). For example, Lakonishok, Shleifer and Vishny (1994) were of the view that the HML loading in the three-factor model is far too high to be explained as a relative distress premium; it is in fact so consistently positive that it all but presents an arbitrage opportunity. However, the standard deviation of HML is sufficiently high at 13.11% per annum to remove any arbitrage opportunities (Fama and French, 1996:79). Lakonishok, Shleifer and Vishny (1994) further argued that the fact that high and low book-to-market firms have similar variances of returns supports their contention that the relative distress premium is irrational. However, Fama and French (1996:80) pointed out that “variance is not a sufficient statistic for a portfolio’s risk”.

A third interpretation would be that the CAPM holds, and that the results of anomaly tests, and in particular the existence of a distress premium

in the three-factor model, are spurious. There are three categories into which such arguments fall.

First, Kothari, Shanken and Sloan (1995) argued that selection and survivorship bias in the COMPUSTAT database (resulting from the likely inclusion of distressed firms which survive and the likely exclusion of distressed stocks which fail) lead to an overstatement of the average returns on the H portfolio, and hence an overstatement of the HML loading. However, this is contradicted by the evidence of Chan, Jegadeesh and Lakonishok (1995), who showed that selection bias on COMPUSTAT is immaterial. Furthermore, the concession of Kothari, Shanken and Sloan (1995) that survivorship bias is an insignificant problem for value-weighted portfolios implies that their argument cannot explain the failure of the CAPM to reconcile the value effect, i.e. the return to the HML mimicking portfolio (Fama and French, 1996:80).

Second, several authors (Lo and MacKinlay, 1988; Black, 1993; MacKinlay, 1995) have argued that CAPM anomalies in general are the result of data snooping, i.e. the trawling of data sets (which are by definition finite and therefore subject to random error) in an effort to identify anomalies which may simply be sample-specific data attributes, unlikely to be found in different or longer samples. However, Fama and French (1996) suggested four counter-arguments:

1. It has been shown, for example by Davis (1994) as cited in Fama and French (1996), that the distress premium is not specific to the post-1962 period studied in Fama and French (1992) and Fama and French (1993); Davis found a significant correlation between book-to-market equity and returns over the period from 1941 to 1962.
2. Similar results are observed in international studies.
3. Ball (1978), as cited in Fama and French (1996), put forward the view that scaled versions of stock price, which includes firm size and book-to-market equity, act as proxies for expected return.

4. Given the volumes of data available, there is a limited range of opportunities for data snooping.

Finally, there is the argument that the anomalies are observed, despite the fact that the CAPM holds, because the market proxy used in analysis is imperfect. However, these proxies are precisely those which are used in practical financial applications of the CAPM (Fama and French, 1996:81); in order to have a meaningful role as an applicable theory, the CAPM would need to hold on the basis of an observable market proxy, failing which it ought to make way for multifactor models which provide a better practical explanation of the cross-section of returns.

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Chapter 6

Size and value effects: South African literature

Early work examining the impact of firm size in explaining the cross-section of returns for South African equities was inconclusive, but tended, if anything, towards a rejection of market capitalisation as a significant factor in the return-generating process. No evidence of a small firm effect was found by De Villiers, Lowlings, Pettit and Affleck-Graves (1986); in fact, they provided evidence that larger firms outperformed small firms over the period of their sample (1973 to 1982). The size effect was further examined by Bradfield, Barr and Affleck-Graves (1988), who also looked at the predictive power and role of dividend yield and liquidity, but failed to find any evidence at odds with the CAPM. Page and Palmer (1993) likewise found no indication of a size premium on the JSE. However, Van Rensburg (2001), in his investigation into style-based factor returns, found that there was a significant risk-adjusted return to small firm stocks. Van Rensburg and Robertson (2003a) attributed the lack of significant findings in earlier studies to the small sample sizes employed and the *de facto* exclusion of small stocks due to concerns about how thinly they are traded.

Evidence of the value effect in South Africa has been more uniformly positive. Page and Palmer (1993) were able to support the hypothesis of

excess risk-adjusted returns to firms with high earnings yields (or low PE ratios). Following on this research, Page (1996) found that the value effect, measured by PE ratio, was robust not only to risk-adjustment in line with the CAPM, but also to an APT model with as many as five factors. This was further confirmed by Van Rensburg (2001), who found both earnings yield and dividend yield to be significant value indicators, and proposed earnings yield as a proxy for the value effect in a three-factor model which could describe JSE returns parsimoniously.

In the South African context, perhaps the most important work on the subject of size and price-to-earnings effects on the cross-section of equity returns is that of Van Rensburg and Robertson (2003a,b), based on the PhD thesis of Robertson (2002). Building on the earlier work of Van Rensburg (2001), which identified eleven style-based effects which contributed to the explanation of returns on a sample of JSE industrial stocks from 1983 to 1999, Van Rensburg and Robertson (2003b) applied the multiple regression methodology employed by Daniel and Titman (1997) to identify which style characteristics had a significant effect on returns. They used a sample of stocks covering the ten-year period from July 1990 to June 2000, which was filtered for thin trading by retaining only stocks with an average daily trade in a given month of more than 0.01% of market capitalisation. Furthermore, the influence of outliers was limited by the winsorisation of the extreme 1% of observations (i.e. the highest and lowest 0.5% of returns). Testing was conducted on five measures of value, fourteen measures of future earnings growth and bankruptcy risk, and five measures of momentum and neglect, as follows:

1. Measures of value:
 - (a) Price-to-earnings
 - (b) Dividend yield
 - (c) Price-to-profit
 - (d) Price-to-NAV

(e) Cashflow-to-price

2. Measures of Future Earnings Growth and Bankruptcy Risk

(a) Sustainable growth

(b) Retention rate

(c) Size (Log of market capitalisation)

(d) Return on equity

(e) Return on assets

(f) Debt-to-cashflow

(g) Debt-to-assets

(h) Long term loans-to-assets

(i) Debt-to-equity

(j) Leverage

(k) Financial distress

(l) Current ratio

(m) Quick ratio

(n) Owner's interest

3. Measures of Momentum and Neglect

(a) Previous one month's return

(b) Previous six months' return

(c) Previous one year's return

(d) Trading volume

(e) Shares in issue

Univariate tests identified a significant value effect on all five measures as well as a significant size effect; none of the other variables had a significant influence on return. Neither of these effects are anticipated within the CAPM framework, and must therefore be viewed as anomalies within that paradigm. It was further concluded that the two-factor APT model proposed by Van Rensburg (2002), where the relevant factors are the returns on the JSE Financial and Industrial Index and Resources Index respectively, is similarly unsuccessful in removing these anomalies.

The authors went on to construct a multifactor model to describe the cross-section of returns, testing the joint significance of combinations of individually significant factors. They found that returns were best described by a two-factor model based on the explanatory variables of market capitalisation and price-to-earnings, which “capture the central intuition behind the international evidence of the style effects relating to value and size” (Van Rensburg and Robertson, 2003b:10). Given the high degree of correlation between the various measures of value, it is unsurprising that a parsimonious model can be constructed with a single value factor in addition to the size factor, and such a model avoids the problem of multicollinearity which would inevitably arise with multiple value factors.

Van Rensburg and Robertson (2003a) went on to take a portfolio-based approach to analysis of the size and value effects, subdividing their sample of stocks at each month-end into quintiles by, respectively, firm size and PE ratio (the ‘one-way sort’), and then subdividing each size quintile into further quintiles on PE ratio, thus ending with twenty-five portfolios (the ‘two-way sort’). This latter approach allowed the measurement of the effect of the second attribute within a particular portfolio, controlling for the first. Once again, the problem of thin trading is handled by the application of a thin trading filter of average daily trade in excess of 0.01% of market capitalisation.

The most striking feature of the ‘one-way’ results was the demonstration of a clear inverse relationship between firm size and return and between

PE ratio and return, in line with the international literature, while simultaneously, and unexpectedly, showing an equally clear *inverse* relationship between market model beta and return. It was noted (Van Rensburg and Robertson, 2003a:9) that this may be the result of thinly-traded stocks remaining in the data set, as betas were regressed using OLS techniques without the adjustments suggested in, for example, Scholes and Williams (1977) or Dimson (1979); this may give rise to estimates of beta which are downwardly biased for small, thinly-traded stocks. The lowest beta quintile outperformed the highest beta quintile by an average of a statistically significant 0.90% for a one-month holding period, over the ten-year period of the study.

This surprising and somewhat counter-intuitive result raises a significant challenge to investment theory and practice in South Africa, indicating that beta, if it plays any role at all, is a negative predictor of stock returns. This is a sufficiently unexpected and important observation to merit further analysis.

The ‘two-way’ results suggest that the value and size effects operate independently of each other, and that both are necessary to explain the generation of returns on the JSE Securities Exchange. The size effect does not proxy for the value effect, nor vice versa (Van Rensburg and Robertson, 2003a).

An interesting extension of this work was conducted by Auret and Sinclair (2006), who found book-to-market equity ratio to be a better indicator of the value premium than PE ratio, contrary to the findings of Van Rensburg and Robertson (2003b). In fact, they found that book-to-market completely subsumed not only PE ratio, but also firm size, in multiple regressions on return. However, including book-to-market in a multifactor model did not result in greater explanatory power than a two-factor model using PE ratio and size, which they put down to the high correlation between book-to-market and other candidate variables, while PE ratio and size have the virtue for modelling purposes of low correlation and hence a reduced multicollinearity problem. This suggests that testing the replicability of the Van Rensburg and Robertson (2003a) results, which is the aim of this dissertation, may reasonably use market capitalisation and PE ratio as the size and value indicators

respectively. Consideration of the role of book-to-market would however be a useful extension.

Likewise, Basiewicz and Auret (2009), using both portfolio-based and Fama and MacBeth (1973) regression approaches, found book-to-market to be a better indicator of value than PE ratio. Unlike Auret and Sinclair (2006), however, they found that the size effect was not subsumed by book-to-market, which they ascribed to the prominent size premium on the JSE Securities Exchange over the period from 2003 to 2005, a timespan not included in the earlier work. They also found that the value effect was weakest among the smallest firms.

The significant contribution made by Basiewicz and Auret (2009) was the demonstration of the effects of applying restrictions on liquidity and price to mimic constraints that would be placed on portfolios in practice. These restrictions, which the authors argued acted as a proxy for transaction costs, significantly reduced the estimates of both the size and value premia, suggesting that these are largely influenced by returns on stocks which would not be included in investors' portfolios in practice, at least not in significant volumes. They also formed value-weighted portfolios in addition to the equally-weighted portfolio approach which tends to be favoured in the literature, and found that size and value premium estimates tended to be lower based on value-weighted portfolio formation.

South African evidence on the value effect is clear; while early work on the size effect was inconclusive, recent research demonstrates its existence unequivocally. The literature provides a solid foundation for the analysis reported in this dissertation, the primary aim of which is to examine whether the results presented by Van Rensburg and Robertson (2003a) are replicable using data over a different, and longer, sample period, and whether they are affected by the methodology employed. In particular, we wish to explore whether the unexpected inverse relationship between beta and return which they reported is a function of their choice of methodology for thinly-traded stocks, namely the application of a liquidity filter to exclude the most thinly-

traded stocks, coupled with beta estimation by OLS over periods ranging between 12 and 30 months. This study includes all stocks, but accounts for thin trading by employing beta estimation methods (applied over the 60 months prior to portfolio formation) designed to compensate for the downward bias of thinly-traded stock betas estimated by OLS.

The data and methodology used in this analysis are set out in Chapter 8, after a discussion of some of the key methodological issues in Chapter 7.

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Chapter 7

Methodological issues

The literature reveals numerous methodological difficulties which present themselves with this type of analysis, the most important of which are discussed below.

7.1 Return calculation methodology

There are three major methods of calculating returns: arithmetic average of periodic (e.g. daily) returns, buy-and-hold returns (effectively geometrically compounded returns) and rebalanced returns (buy-and-hold returns for sub-periods with periodic portfolio rebalancing) (Roll, 1983). Roll showed that the buy-and-hold returns tend to increase relative to arithmetic average returns the higher the cross-sectional variation of individual expected returns, but that the reverse is true the wider the dispersion over time of unexpected returns. Furthermore, the rebalanced mean increases with negative serial dependence in individual unexpected returns or positive serial dependence in portfolio returns. Scholes and Williams (1977) demonstrated that as a result of nonsynchronous trading, the returns on individual assets tend to display first-order negative serial dependence while diversified portfolios are more likely to exhibit positive dependence, which leads to buy-and-hold returns tending to fall as the period of assessment increases while arithmetic mean

and rebalanced returns tend to rise. This serial dependence has stronger effects for firms with lower trading volumes and less synchronous trading, which are hallmarks of the shares of small firms. As a result, the small firm premium tends to be less significant when the buy-and-hold method is used, rather than arithmetic mean and rebalanced returns. This has a major impact on the results of Reinganum (1981b), Reinganum (1981c) and Roll (1981), all of which use arithmetic means of daily returns, and on Reinganum (1982), which uses monthly and quarterly returns but based on daily rebalancing. There is however little additional discrepancy in moving from monthly to annual returns, so the results of Banz (1981) are sound.

This study avoids the problems of daily rebalancing by examining effective returns over one-, three-, six- and twelve-month holding periods.

7.2 Market proxy error

Wei and Stansell (1991) considered the impacts of benchmark error, arising from the use of an imperfect market proxy, on the size anomaly. They also argued that betas estimated for smaller firms by OLS regression tend to be understated, giving rise to excessive abnormal returns. The classic approach to compensate for this is the instrumental variables technique, which gives rise to higher betas for portfolios of small firms, suggesting that some size effect conclusions may be partly attributable to benchmark error Wei and Stansell (1991:364). A major advantage of the instrumental variables approach is that it is robust to the choice of market index. Discussion of robust beta estimation follows in section 7.4.

Grauer (1999) argued that the coefficients of OLS and Generalised Least Squares (GLS) regressions making use of near-efficient market proxy portfolios can lead to the conclusion that the CAPM does not hold when it is in fact true; conversely, if the CAPM is not the correct underlying model, it is possible for such regressions to suggest it is true even when the market is grossly inefficient. This echoes the seminal work of Roll (1977), who was

the first coherently to point out that the Sharpe-Lintner market model is essentially a mathematical truism (if we assume that mean-variance optimisation is the goal of all investors). Working with ex-post sample returns, variances and covariances, rather than ex-ante, in order to bring across that the results are a logical implication of the efficient set mathematics rather than a theoretical ideal, Roll (1977) demonstrated that the three hypotheses proposed by Fama and MacBeth (1973) (viz. the linearity of the relationship between expected security returns and their risk in an efficient portfolio, the completeness of beta as a measure of the systematic risk of a security and the positive relationship between risk and return) are in fact not testable, but rather flow from the fundamentals of the mathematics governing efficient sets. In fact, the only refutable hypothesis which Fama and MacBeth can legitimately advance is that the market portfolio (i.e. the basket of all assets in proportion to their market capitalisations) is ex-ante efficient. Proof of this was put forward by Black (1972), who on the basis of the assumptions that investors are rational (and therefore hold efficient portfolios) and have identical expectations with regard to the probability distributions of security returns, shows that the market portfolio must be mean-variance efficient. This follows because the market portfolio is of course a linear combination of all investors' portfolios; any linear combination of efficient portfolios must itself be efficient.

As Roll (1977) pointed out, the fundamental problem with tests of the market model, or indeed any other asset pricing model reliant on a market portfolio, is that we are limited in econometric applications to making use of proxy portfolios, since the universe of all investable assets is not observable. This makes testing very difficult: we are in effect evaluating on every occasion a joint hypothesis of the asset pricing model in question (e.g. the CAPM) and the hypothesis that the particular proxy portfolio used is equivalent to the true market portfolio, consisting of all investable assets (which would include non-observable assets such as human capital, for example) (Roll, 1977:144). The effect of this is that researchers can never be sure which of

the two components is false if statistical tests point to rejection of the joint hypothesis. Indeed, if there is any evidence of non-linearity of the relationship between beta and returns, as is the case in Fama and MacBeth (1973), then it is possible to be certain that the market proxy used is not efficient (Roll, 1977:139).

This compelling analysis leaves researchers in a quandary. If Roll's assertions are accepted, then one must accept that tests of asset pricing models based on market proxy portfolios have no statistical power to reject the model's theories. On the other hand, it is reasonable to ask, from a practitioner's perspective, what use may be attached to a theory which is mathematically elegant but wholly unimplementable by virtue of the non-observability of the true market portfolio. Any practical implementation of an asset pricing model requires that the parameters or portfolios used can be observed or estimated from market data, and it is indeed common practice for market portfolio proxies to be used. Given this requirement, this study follows in the tradition of using a market proxy, but it should be borne in mind that a possible explanation of the irrelevance or reduced statistical power of the market model beta, as found in Van Rensburg and Robertson (2003a), lies in the potential mean-variance inefficiency of the proxy used. In South African research, where the market proxy is typically the JSE All-Share Index (or some other broadly representative equity index), reflecting the value of a stock exchange which is small in global terms, this possibility is particularly relevant.

7.3 Influence of outliers

A further methodological issue relates to the degree to which outliers influence the outcomes. Knez and Ready (1997) noted that OLS and GLS regressions are by definition sensitive to extreme observations. The application of Least Trimmed Squares, removing 5% of observations at the extremes, changes the mean slope coefficient from -12 basis points to +33 basis points,

thus suggesting that the size effect is driven by outliers. The source of this lies in the skewness of small firm returns: the sample skewness coefficient is 1.94 for the smallest quintile. Knez and Ready (1997) argued that this cannot be explained by either a price effect or by takeovers of smaller firms, and that the best explanation is in terms of what they call ‘turtle eggs’, the fact that only a handful of new firms break through as a result of favourable conditions, and the monetary impact of this is greater for young, small firms.

Any methodology which relies heavily on the exclusion of outliers, however, seems an unsatisfactory solution. The reality of the financial markets is that a substantial proportion of total portfolio return owes itself to these extreme observations, and a model which ignores them, no matter how mathematically and econometrically elegant it may be, has the potential to be misleading in practice. The portfolio-based approach adopted in this study limits, but does not eliminate, the impact of individual outliers.

7.4 Beta estimation

Perhaps the most important methodological issue in the study of anomalies within the CAPM framework, particularly in relation to the size effect, concerns the estimation of betas by regression on stocks which are thinly-traded. The CAPM is usually coupled with the assumption that security prices are distributed lognormally (i.e. that their movements may be described by Geometric Brownian Motion), with the result that returns on individual securities and on the market index are distributed normally. If this reflects the true underlying distribution of security returns, then the fact that trades occur in discrete time gives rise to biased estimates of variances and covariances of returns, and to the appearance of serial correlation and leptokurtosis in the reported returns on individual securities. This further leads to betas estimated through OLS regression being asymptotically downward biased for stocks which are either very heavily- or very thinly-traded relative to the average (Scholes and Williams, 1977:310).

Kim (1997) investigated both this errors-in-variables bias which emerges from the estimation of betas with error, and the selection bias imposed by the backfilling procedure employed in the construction of the COMPUSTAT database, as noted in Kothari, Shanken and Sloan (1995). He removed the latter by populating missing data from Moody's, and found that the COMPUSTAT selection bias does not have a material impact on the results. With regard to the former, Kim pointed out that beta estimation by the OLS technique is biased when the cross-sectional sample size is large relative to the time-series sample size.

After correcting for the errors-in-variables bias, Kim (1997) found that beta has significant predictive power, even including firm size, book-to-market ratio and earnings-price ratio in the regression. He noted that the selection of return interval is an important consideration, as a lengthening of the return interval is associated with both a widening of the cross-sectional spread of betas and a narrowing of the spread of buy-and-hold returns. In a multiple regression, neither size nor earnings-price ratio were significant; book-to-market ratio remained significant, in part because the correlation between beta and book-to-market was weaker than between beta and the other variables considered.

The problem of errors in variables in econometric work has the potential to introduce bias into studies of the size effect, as smaller firms tend to have stocks which are traded less frequently, and a downward bias in their beta estimation will lead to the erroneous conclusion of higher risk-adjusted returns. Scholes and Williams (1977) proposed the following unbiased and consistent estimate of beta to overcome the problem of nonsynchronous trading:

$$\hat{\beta}_n = \frac{b_n^- + b_n + b_n^+}{1 + 2\hat{\rho}_m} \quad (7.1)$$

where:

b_n , b_n^- and b_n^+ are the OLS estimators of beta with the security return regressed against the market return from, respectively, the contemporaneous,

preceding and succeeding periods, and

$\hat{\rho}_m$ is the sampling estimator of the first-order autocorrelation coefficient of the market index.

The authors showed that this is a consistent and unbiased estimator of beta provided that the periods of nontrading are independently and identically distributed, which seems a reasonable assumption. They further noted that nonsynchronous trading is a particular problem when estimating betas from daily data (Scholes and Williams, 1977:309). Although it is less of an issue when using monthly data, as is the case in this study, nevertheless it has the potential to cause distortions given the extremely thin trading on certain smaller JSE stocks. Importantly, it is only a consistent estimator of beta if trading takes place in every period. Even with data at monthly intervals, this is not the case for all JSE stocks.

An alternative approach was put forward by Dimson (1979), who proposed the aggregated coefficients (AC) method, based on regressing observed security returns on market returns in the synchronous period, as well as in several leading and lagging periods. He showed that beta can be estimated consistently for thinly-traded stocks by summing the slope coefficients from a multiple regression against all of these market returns, i.e.:

$$\hat{\beta}_i = \sum_{k=-n}^n \hat{\beta}_{i,k} \quad (7.2)$$

where $\hat{\beta}_{i,k}$ is the OLS estimator obtained by regressing the security return against the market return with a lag of $-k$ months, obtained from the following multiple regression:

$$r_{i,t} = \hat{\alpha}_i + \sum_{k=-n}^n \hat{\beta}_{i,k} r_{m,t+k} + \epsilon_{i,t} \quad (7.3)$$

where $r_{i,t}$ represents the return on security i and $r_{m,t}$ the market return in

time period t . The number of lead and lag terms n is variable and should be related to the degree of thin trading in the market.

Dimson showed his measure to be more efficient than the Scholes-Williams estimator based on UK data, and suggested that (again based on UK data) it was appropriate to use one leading and several lagged market returns to fully account for the effects of thin trading.

An excellent summary of the issues relating to beta estimation was provided by Bradfield (2003). He noted that consensus suggests that betas should be estimated over a five-year period when using monthly return data, and highlighted the theoretical need for regressing against returns on a comprehensive market index while noting that many believe that the South African equity market is segmented between financial/industrial and resources stocks, as elaborated in, for example, Van Rensburg (2002). He also discussed an important further methodological issue, namely the observed mean-reverting tendency of betas on individual stocks, for which a Bayesian adjustment has been proposed by Vasicek (1973). An alternative method for correcting for mean reversion is the two-period regression approach proposed by Blume (1975).

Various methods for robust beta estimation were evaluated by Bowie and Bradfield (1998), who noted that “in small samples, ordinary least squares (OLS) estimators are sensitive to departures from normality... and hence are inefficient” (Bowie and Bradfield, 1998:439). They examined robust estimators in three classes:

1. M -estimators, or maximum likelihood estimators, which aim to minimise some function of the regression residuals;
2. L -estimators, which avoid the need for assuming the distribution of the residuals; and
3. R -estimators, which estimate coefficients based only on the ranks of the residuals rather than their values.

They considered several regression methods within each class, and further, for a number of the estimators, considered a ‘bounded influence’ version which downweights extreme observations which would otherwise have undue influence on the fitting of a regression curve. Their ultimate conclusion was that the bounded influence L_p -norm estimator (with p a function of the coefficient of kurtosis of the residuals from a preliminary fit) is the best-performing of the robust estimators, displaying greater efficiency than OLS estimation but also outperforming other estimators in the volatile market conditions of 1987. The L_p -norm estimator belongs to the class of maximum likelihood estimators where the residuals are assumed to conform to the Box-Tiao distribution (Bowie and Bradfield, 1998).

The key issue relating to beta estimation in this study, which builds on the work of Van Rensburg and Robertson (2003a), seems to be the downward bias of betas estimated by OLS for small, thinly-traded stocks; since small stocks in their sample generated higher returns than large stocks, this would tend to bias against finding the expected positive relationship between beta and return. Van Rensburg and Robertson (2003a) partially avoided this thorny issue by applying a thin trading filter, at the cost of the removal of a substantial proportion of points from the data set but without (as the authors admitted) removing the effects of thin trading from the data set entirely.

The following section gives an overview of the data used in this analysis, as well as the methodology employed.

Chapter 8

Data and methodology

8.1 Data

Month-end closing prices, dividend yields, earnings yields, shares in issue and monthly volume traded were obtained from I-Net Bridge (I-Net), for each month-end from 31 December 1988 to 31 October 2007. The choice of data source was a considered one, as the University of Cape Town (UCT) subscribes to the services of four financial data providers. Thomson Reuters was dismissed as an alternative as the interface to which UCT subscribes, Reuters 3000 Xtra, does not provide access to information for stocks which are not currently listed; any results based on a sample of currently listed shares only would be tainted by survivorship bias. Thomson Datastream's database of delisted stocks was found to be incomplete when compared with the relatively fuller offerings of both I-Net and McGregor BFA.

The major factor which told in favour of I-Net rather than McGregor BFA was the former's practice of revising stock history following corporate actions. In the event of a two-for-one share split, for example, I-Net adjust all prior share prices by a factor of 0.5 and all prior shares in issue data by a factor of two. Consequently, accurate capital returns can be calculated by reference to share price data, without the need to factor in the number of shares in issue. Although capital returns can theoretically be calculated from McGregor BFA

data by examining the change in market capitalisation rather than the change in share price, this assumes that all changes in market capitalisation accrue to ordinary shareholders; this is not the case, for instance, where the number of shares in issue changes because of the sale of Treasury stock on the exercise of share options. It has been assumed that I-Net's adjustments have been carried out accurately, consistently and completely, although there are several instances of changes in the number of shares in issue between month-ends which are not accompanied by corresponding price changes, and appear too large to be the result of Treasury stock transactions. In the absence of an authoritative, independent data source, it was necessary to accept these data.

One significant problem with I-Net data for the purposes of econometric research is their practice of retrospectively revising earnings yields once earnings data has been released. The database earnings yield therefore accurately reflects effective earnings per share as a proportion of closing price at a point in time, but this is not the yield which would have been known to the market at that time. This gives rise to look-ahead bias in financial research. The methodological adjustment applied to correct for this is described in the next section.

Appendix A sets out a summary of the number of stocks and total market capitalisation at each month-end over the sample period.

There were numerous concerns over the quality of the data. While the data for currently listed stocks generally appear accurate and complete, some delisted share data are concerning. A comprehensive analysis of the data yielded numerous anomalies and apparent inaccuracies, and Appendix B itemises the adjustments made to the raw data.

One of the key remaining problems is the lack of information regarding the cause of delisting. Financial research is often silent on the approach taken to calculate returns in the period in which a stock is delisted, but a common approach in the absence of accurate return data, at least for portfolio-based studies such as this one, is to assume a complete loss on delisting, i.e. that a return of minus 100% is earned in this period. This is unsatisfactory insofar

as delistings may be the result of merger activity (in which case it is even possible that shareholders earn a positive return in the month of delisting), while even where such delistings stem from companies being liquidated, it is possible that shareholders will realise some value from their holdings. If indeed small firms are subject to greater bankruptcy risk than larger firms, there should be greater numbers of delistings in the small firm portfolios and consequently this assumption should (subject to the comments below) provide a bias against detecting a size effect.

It has been suggested that the price immediately prior to delisting represents investors' expectations of the liquidation dividend, and hence it would be appropriate to assume a 0% return on delisting. This ignores, however, the possibility of an improvement in outlook for the firm, accompanied by the resumption of trading in the stock and an increase in its price. Section B.6 of Appendix B lists four such stocks which had to be excluded from this analysis because of the undue influence the returns generated by such recoveries had on the equally-weighted portfolio returns. Assuming unbiased expectations, it must therefore be the case that the recovery by shareholders conditional on delisting is on average less than the share price prior to delisting.

In the absence of detailed delisting reason information, it is impossible to make an accurate allowance for these outcomes. The default minus 100% approach was therefore followed, with the analysis repeated assuming a minus 50% return for comparative purposes. As shown in Appendix C, this change in assumption does not make a material difference to the results, indicating that any differences in delisting probability between firms based on the criteria analysed here (notably size and PE ratio) are not economically significant. However, potential bias remains in the sample of delisted stocks if, given that a firm delists, the probability of bankruptcy being the cause is inversely related to firm size.

It should be noted that the data used by Robertson (2002) and Van Rensburg and Robertson (2003a) were provided by the BARRA organisation and included actual monthly returns, thus removing the need (to the extent

that the return calculations are accurate) to make such assumptions about the return on delisting. This data source was unfortunately not available for this study.

The data confirmed that thin trading is a significant issue on the JSE Securities Exchange; some 10.4% of the data points used in portfolio formation and return calculation indicated no trading over the month.

Month-end values for the FTSE-JSE All-Share Index (ALSI) were also obtained from I-Net. The FTSE-JSE Africa Index series replaced the JSE Actuaries Indices with effect from 24 June 2002, and the Total Return Index (TRI) was retrospectively restated back to 30 June 1995. As a slightly longer period was required for this study, returns in months prior to 30 June 1995 were calculated as the capital gain, measured by the movement of the restated ALSI as reported by I-Net, plus one-twelfth of the ALSI dividend yield for the month.

8.2 Methodology

The intention of this research is to establish whether the conclusions of Van Rensburg and Robertson (2003a) are robust and generally valid. Similar methodology was therefore applied, with several key differences aimed at answering the following questions:

1. Are the results sample-specific?
2. What is the impact of using 60 months' data to estimate beta, as is considered optimal in the literature as summarised for example in Bradfield (2003), rather than a period of 12 to 30 months?
3. What is the impact of keeping a full data set and not excluding thinly-traded stocks, but rather using beta estimation methods which are robust to thin trading?

4. Are results obtained by analysing three-, six and twelve-month holding period returns consistent with those from one-month returns?
5. Is further insight to be gained from the examination of intermediate quintiles, rather than basing conclusions only on differences between the extreme quintiles?
6. Are both the size and value effects jointly significant, and what is the nature of their interaction?
7. Are there any other possible explanations for the observed phenomena?

The portfolio formation, return calculations and statistical testing were coded in the free statistical software environment R (R Development Core Team, 2009).

Security returns were estimated by calculating the capital gain and adding to this one-twelfth of the dividend yield for the month:

$$r_t = \frac{P_t}{P_{t-1}} + \frac{D_t}{12} - 1 \quad (8.1)$$

where r_t is a security's return in month t , P_t is the closing share price at the end of month t and D_t is the dividend yield at that date.

Ideally, actual dividend data would have been used, but dividend payment dates were not available from the I-Net data. The approximation set out in Equation 8.1 above is sufficiently accurate at portfolio level, given a spread of financial year-ends across the calendar year.

As discussed above, delisted stocks were assumed to earn minus 100% in the month of delisting. Comparative figures assuming a minus 50% return are reported in Appendix C, but did not materially affect the high-level conclusions of this study.

Betas were estimated for each stock by regressing security returns over the preceding 60 months against market returns, as measured by movement in the ALSI TRI. These are thus market model betas, rather than CAPM

betas, consistent with the approach taken in Van Rensburg and Robertson (2003a); the two beta measures are in any event very similar provided there are no dramatic fluctuations in the risk-free rate over the estimation period. Thinly-traded stocks were not excluded from the database, but in addition to estimating beta by OLS, beta estimates were obtained by both the Scholes-Williams and Dimson methods (with lead and lag of 2, 3 and 5 months in the case of the latter).

Given that 60 months' return data were required to estimate beta, and that in the case of the Dimson method, security returns were regressed against market returns lagged by up to five months, it was only possible to form portfolios at month-ends from 31 December 1993 onwards. In view of the structural shift in the socio-political landscape of the country, and as a consequence its economy, from 1994, this is thought to be an appropriate period for analysis. In addition, I-Net's pre-1994 shares in issue data are incomplete, and hence the formation of portfolios on firm size would not have been possible prior to 1994 using this data set. As we wished to track portfolio returns over holding periods of up to twelve months, the last portfolio was formed at 31 October 2006.

I-Net's practice of retrospectively changing Earnings Per Share (EPS) data (and related fields such as earnings yield and PE ratio) has the unfortunate consequence of giving rise to look-ahead bias in econometric work, as the PE ratios on which portfolios are formed in this study would not be those known to the market at the respective points in time. To compensate for this, a three-month lag was assumed between accounting and reporting dates, and PE ratio was consequently calculated as the price at a given month-end divided by the implied EPS from three months prior.

At each month-end in this portfolio formation period, quintile portfolios were formed on beta (all five methods), market capitalisation and PE ratio. For purposes of forming portfolios on the latter, stocks with negative PE ratios were excluded from the database. In addition to these one-way sorts, two-way quintile-quintile portfolios were also formed: by splitting each size

quintile into PE ratio quintiles, and by splitting each PE ratio quintile into size quintiles. Two sets of twenty-five portfolios were thus formed at each month-end for each of the two-way sorts.

The returns of each portfolio were then calculated for the ensuing holding periods considered (one, three, six and twelve months), and mean returns calculated for each quintile across the sample period. The statistical significance of the difference in mean returns between quintiles was calculated using the form of Student's *t*-test proposed by Welch (1947), which does not require the assumption of equal population variances. This choice involves the sacrifice of some power, but this implies a bias against the detection of spuriously significant relationships. A more significant loss of power is implied by the decision to test significance using a two-tailed test, rather than one-tailed; in other words, to test the null hypothesis against the alternative that a given difference in mean returns is not equal to zero, as opposed to greater than or less than zero. This decision was motivated by the desire for scientific neutrality. It would of course be possible to conduct a one-tailed test in the direction of the expected relationship based on theory and the literature, but this would yield no useful outcome for a relationship between beta and return which is the opposite of what theory suggests. Alternatively, the one-tailed test could be based on the relationships observed in the data, but this seems self-fulfilling and prone to accusations of data mining. The practice employed by some researchers of using a one-tailed test if the direction of the relationship is as expected, and a two-tailed test if not, is equivalent to an increase of 50% in the level of significance (results shown to be significant at the 5% level, for example, can in fact only be said with confidence to be significant at the 7.5% level) (Nosanchuk, 1978; Abelson, 1995). The adoption of two-tailed tests throughout therefore seems appropriate. Once again, this choice provides an inbuilt bias against reporting statistical significance, with the result that greater confidence may be placed in the significance of the results reported in Chapter 9. Where the use of a one-tailed test would have a material impact on the reported significance of key results, this is however

noted.

This study follows the approach taken by Van Rensburg and Robertson (2003a) of quantifying size and value premia based on the gross unadjusted returns of the quintile portfolios, without accounting for risk. This is theoretically flawed in that it does not account for correlations between systematic risk, as measured by beta, and the size and value measures used. For example, if small firms tend to have higher betas, the size effect may simply be a beta effect. The results obtained by portfolio sorts on beta, both in Van Rensburg and Robertson (2003a) and in this study, however, indicate an inverse relationship between beta and return, suggesting that any beta-risk-adjustment would only exacerbate the size and value effects reported. It was consequently deemed unnecessary to adjust the portfolio returns for beta risk.

Chapter 9

Empirical analysis: size, value and beta effects

Results are presented below as follows: for each of the one-way sort criteria (market capitalisation, PE ratio and each of the five measures of beta) the average one-, three-, six- and twelve-month returns achieved over the sample period by each of the quintile portfolios are reported. The difference in mean returns between the first (smallest/lowest) and fifth (largest/highest) quintiles is then examined, as well as that between intermediate quintiles where such analysis yields further insights. A similar analysis is presented for the two-way sorts by market capitalisation and PE ratio.

In all tables, statistical significance of the difference in mean returns between pairs of quintile portfolios is indicated as follows:

- * significant at 10% level
- ** significant at 5% level
- *** significant at 1% level

9.1 Firm size (market capitalisation)

Mean returns, and differences in means between selected quintiles formed on market capitalisation, are set out in Table 9.1. The mean returns are

depicted graphically in Figure 9.1, which also shows the results reported for a one-month holding period by Van Rensburg and Robertson (2003a) for comparative purposes. It should however be borne in mind that these are based on a different sample using different methodology.

As in Van Rensburg and Robertson (2003a), the difference in mean returns between the smallest and largest size quintiles is striking: 1.36% over a one-month holding period, 3.05% over 3 months, 4.67% over 6 months and 10.81% over 12 months. All of these results are statistically significant at the 5% level, with the six- and twelve-month returns being significant at the 1% level (p -values of 0.0088 and 0.0004 respectively). Furthermore, the three-month return differential is significant at 1% (p -value of 0.0059) using a one-tailed rather than two-tailed test. This is very clear evidence of a persistent size effect which is not merely an artefact of the sample used by Van Rensburg and Robertson (2003a).

Figure 9.1 shows a significant drop between quintiles 1 and 2, with a somewhat flatter graph between quintiles 2 and 5. This suggests that it would be instructive to consider differences between the mean returns of these intermediate quintiles, and the statistical significance thereof. Table 9.1 indicates that the difference between the mean returns of quintiles 1 and 2 is positive and significant at the 5% level for all holding periods considered, and indeed at the 1% level for three- and six-month holding periods (use of a one-tailed test further renders the twelve-month differential significant at the 1% level). By contrast, the difference in returns between quintiles 2 and 5 is not significantly different from zero at the 10% level for any of the holding periods. This indicates that the size effect is primarily a function of excess return to the smallest quintile of stocks in the FTSE-JSE All-Share Index universe. Any attempt to build an equilibrium pricing model using market capitalisation as one of the factors is consequently unlikely to yield reasonable results unless the factor has a binary quality: it does not appear to be a factor which is rewarded progressively across the entire stock universe.

This concentration in the smallest quintile is consistent with the obser-

Table 9.1: Results for portfolios formed on market capitalisation

Portfolio	Holding period			
	1	3	6	12
1	2.52%	6.59%	11.76%	24.68%
2	1.13%	3.30%	6.63%	16.34%
3	1.34%	3.97%	8.43%	16.84%
4	0.91%	3.22%	6.37%	14.13%
5	1.16%	3.53%	7.09%	13.87%
Differences between portfolios				
1-5	1.36% **	3.05% **	4.67% ***	10.81% ***
1-2	1.39% **	3.29% ***	5.13% ***	8.34% **
2-5	-0.03%	-0.23%	-0.46%	2.47%

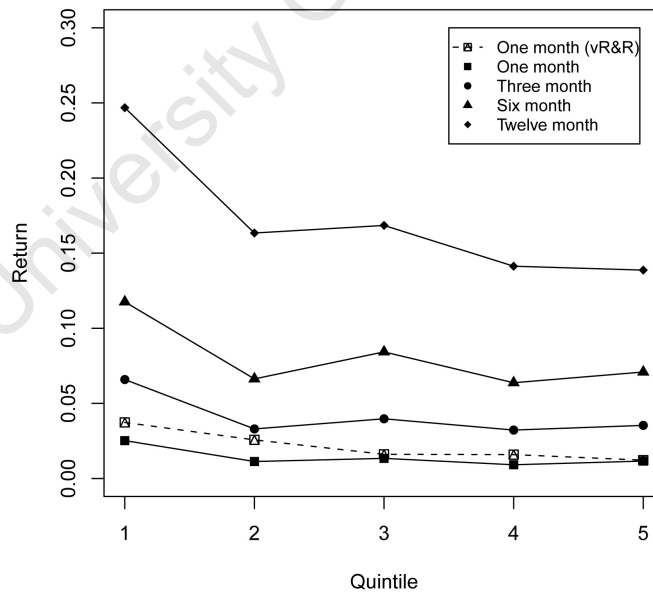


Figure 9.1: Mean returns by quintiles formed on market capitalisation

vation of Basiewicz and Auret (2009) that estimates of the size premium are much reduced once price or liquidity filters are applied. Since it would be expected that many of the smallest stocks would be those with the lowest share prices, as well as lowest trading volumes, the size premium observed in this study may likewise be removed or significantly reduced if the lowest-priced or least-traded stocks were screened out of the universe under consideration. This suggests that the size effect may reflect a premium for illiquidity, or a market inefficiency caused by constraints on institutional investment.

9.1.1 Does the size effect proxy for risk?

One of the possible explanations of the size effect is that it reflects the reward for bankruptcy risk; this is the position adopted by, for example, Chan, Chen and Hsieh (1985), Fama and French (1995) and Perez-Quiros and Timmermann (2000). Such risk ought over time to be reflected in the statistical properties of the returns of small firm portfolios. Given that the CAPM is rooted in a mean-variance framework, and that the size effect does not appear to be captured by the CAPM beta, we may perhaps expect this risk to be reflected in higher moments of the return distribution, notably skewness and kurtosis.

In the figures below, the standard deviation, skewness and excess kurtosis of the size quintile portfolio returns have been calculated as the unbiased estimates of the population moments.

Figure 9.2 shows the standard deviation of the quintile portfolio returns.

With the exception of the returns over twelve-month holding periods, there is little apparent difference between the standard deviations of returns in quintile portfolios 1 and 2, or indeed between any pair of quintile portfolios. The p -values of the F -test for differences in variance between portfolios 1 and 2 are in excess of 0.84 for the one-, three- and six-month holding periods. This is consistent with the expectation that if the size effect is not encapsulated within beta, it is likely to show up in moments higher than the second, if indeed it is reflected in statistical measures of variability.

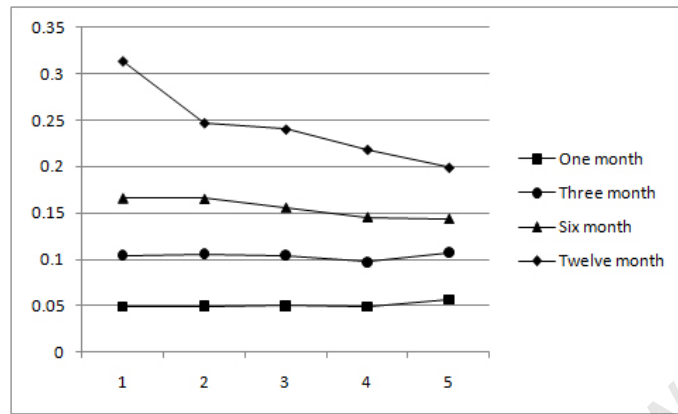


Figure 9.2: Standard deviation of size quintile portfolio returns

The skewness of returns in the quintile portfolios is depicted in Figure 9.3.

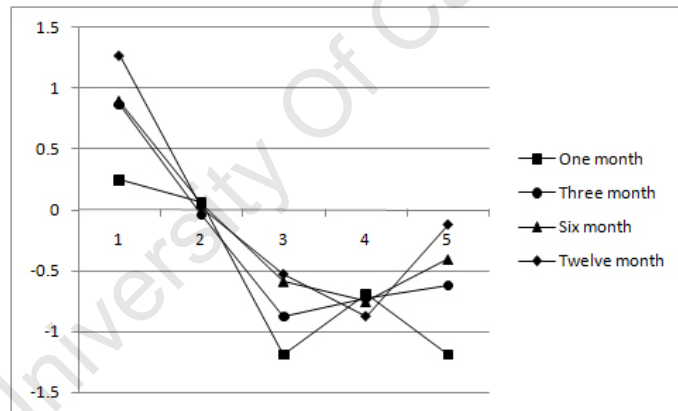


Figure 9.3: Skewness of size quintile portfolio returns

Once again, we cannot draw any meaningful conclusions from this figure. The returns for quintile 1 are uniformly positively skewed, and the degree of skewness appears to increase with the length of the holding period. Returns for quintile 2 exhibit close to zero skewness for all holding periods, while those of quintiles 3 to 5 are negatively skewed. A priori, we may expect that investors would prefer as little skewness as possible, but that for a given

level, positive skewness (characterised by consistent low returns punctuated by several very high returns) would tend to be preferred to negative skewness, in which the shocks are on the downside. However, much of the positive skewness of small firm returns is likely to be due to the fact that very few small firms break through to become established, successful operations, and there is risk involved in small stock investment because of the need to identify these stocks. It should be noted though that the results of this study indicate that much of this risk can be mitigated by a diversified small stock portfolio holding; this does however ignore transaction costs and liquidity constraints.

Figure 9.4 shows the excess kurtosis of the size portfolio returns.

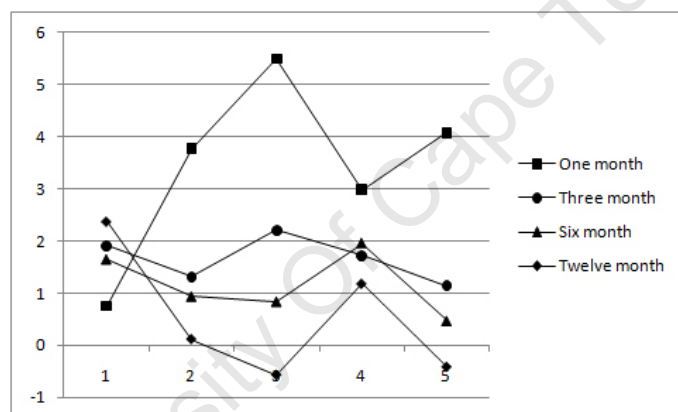


Figure 9.4: Excess kurtosis of size quintile portfolio returns

This evidence is inconclusive. The returns of the smallest quintile do not appear to be systematically more leptokurtic than those of the other quintile portfolios. With the exception of quintiles 3 and 5 for the twelve-month holding period, all portfolio returns display excess kurtosis, as is typical of equity returns. It is worth noting however that these results may stem in part from the assumption of complete loss on delisting for all stocks. If there is a systematic difference in delisting returns between small and large stocks, then it is possible that the kurtosis of the larger quintiles is overstated in this analysis. There is however no way to compensate for this within the constraints of the data set available for this study. It is also worth noting

that prior to the removal of four stocks with single-month returns in excess of 900%, discussed in section B.6 of Appendix B, the kurtosis of the smallest quintile was notably higher than the others. This was clearly however an artefact of the extreme returns from these penny stocks.

It is consequently not clear, at least from the statistical properties of small stock returns, that the size effect is unequivocally compensation for increased risk.

9.1.2 Trends and seasonality of the size premium

Figure 9.5 shows the size premium, measured as the difference in one-month holding period returns between extreme size quintiles for each month of the portfolio formation period of the sample, as well as the six-month moving average of the size premium and a linear trendline fitted through its points.

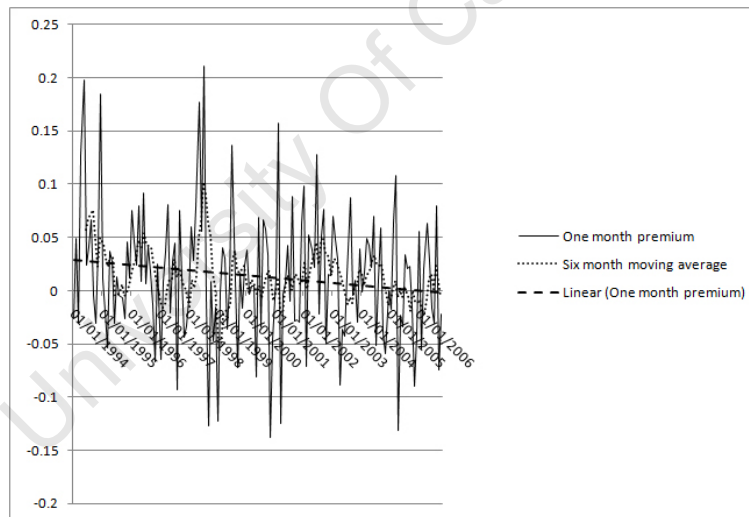


Figure 9.5: Trends in the size premium over time (one-month holding period)

While this figure indicates the volatility of the size premium, it also provides tentative evidence of it shrinking over time, with a clearly downward linear trend line. This is consistent with the hypothesis that the size premium

historically has in part represented market inefficiency, presenting a statistical arbitrage opportunity which has been closed out over time by the participation of greater expertise in South African financial markets, increased asset management competition and access to quicker and more accurate information thanks to the advance of technology. However, the fitting of a simple linear model to such a noisy, volatile time series may not be appropriate, and is influenced by the starting and ending point. If we conclude that the size premium is disappearing, we must do so with caution.

Figure 9.6 shows the average size premium by month over the period of analysis. The only notable feature is the gradual increase in the premium over the year to September, with a subsequent rapid decline in the final quarter of the calendar year. With only twelve or thirteen observations per calendar month, it is difficult to have confidence in the reliability of these results or to read too much into them. Certainly, given South Africa's February tax-year-end, these results are not capable of explanation in terms of tax-loss selling behaviour of investors as discussed in section 3.2.1 above.

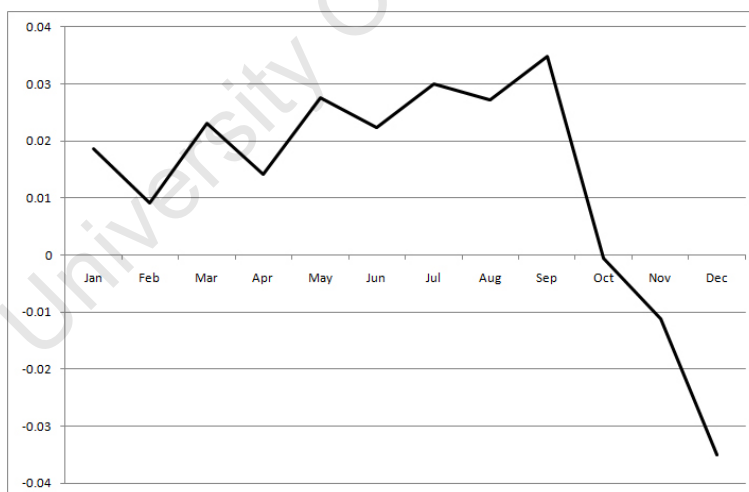


Figure 9.6: Mean size premium by calendar month

9.2 Value (price-earnings ratio)

Mean returns, and differences in means between selected quintiles formed on PE ratio, are set out in Table 9.2. The mean returns are depicted graphically in Figure 9.7. Again the one-month holding period mean returns reported by Van Rensburg and Robertson (2003a) are shown for comparison.

Table 9.2: Results for portfolios formed on PE ratio

Portfolio	Holding period			
	1	3	6	12
1	2.43%	5.55%	8.91%	16.82%
2	1.40%	4.76%	10.09%	20.83%
3	1.48%	4.23%	8.15%	19.33%
4	1.04%	3.50%	7.08%	15.75%
5	0.72%	2.59%	6.08%	13.26%
Differences between portfolios				
1-5	1.71% ***	2.96% ***	2.82% *	3.55%
1-3	0.94%	1.32%	0.76%	-2.51%
3-5	0.77%	1.64%	2.07%	6.06% **

Looking at the difference in returns between extreme quintiles, it is clear that PE ratio is a statistically significant predictor of excess return at the 1% level for one- and three-month holding periods. The evidence over longer holding periods is however less conclusive: the difference in mean returns is significant only at the 10% level for a six-month holding period (significant at 5% based on a one-tailed test) and is not significant for a twelve-month holding period (p -value of 0.1700 based on the two-tailed test).

Figure 9.7 indicates a much smoother downward progression of returns as PE ratio increases than was the case for portfolios formed on market capitalisation, suggesting that PE ratio is a factor which could be incorporated into a multifactor model in the usual way. None of the differences in mean

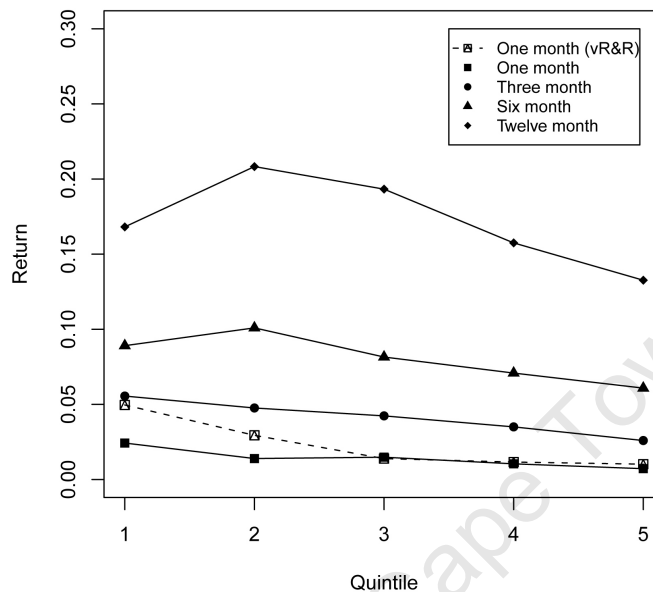


Figure 9.7: Mean returns by quintiles formed on PE ratio

returns between quintiles 1 and 3 are statistically significant, although the one-month holding period differential is significant at the 10% level using a one-tailed test. Of the differences between quintiles 3 and 5, only the twelve-month holding period displays significance (at the 5% level); one-tailed tests however indicate significance at the 10% level for both one- and three-month holding periods.

An interesting feature is that as the holding period increases, the excess return on the lowest PE ratio quintile seems to disappear, to the extent that quintile 1 in fact earns a lower return than quintile 2 over six- and twelve-month holding periods. These differences are however not statistically significant.

9.3 Beta

9.3.1 Ordinary Least Squares (OLS)

Mean returns, and differences in means between selected quintiles formed on OLS beta, are set out in Table 9.3. The mean returns are depicted graphically in Figure 9.8, again showing the comparative Van Rensburg and Robertson (2003a) one-month holding period returns.

Table 9.3: Results for portfolios formed on OLS beta

Portfolio	Holding period			
	1	3	6	12
1	1.82%	5.07%	9.36%	19.40%
2	1.60%	4.88%	10.14%	22.37%
3	1.45%	4.42%	8.76%	18.87%
4	1.52%	4.32%	8.37%	17.40%
5	0.68%	1.95%	3.71%	7.94%
Differences between portfolios				
1-5	1.13% *	3.11% ***	5.64% ***	11.46% ***
1-4	0.30%	0.74%	0.99%	2.00%
4-5	0.83%	2.37% *	4.66% **	9.46% ***

Figure 9.8 indicates a general inverse relationship between beta estimated by OLS and portfolio return. This is consistent with the observations of Van Rensburg and Robertson (2003a), despite differences in the sample period and methodology. The difference in returns between extreme quintiles is significant only at the 10% level for a one-month holding period (5% using a one-tailed test), but is significant at the 1% level for all other holding periods. A noteworthy feature is that this excess return appears to be generated largely by a low return in quintile 5, the portfolio of stocks with the highest beta. The differences in returns between quintiles 1 and 4 are not statisti-

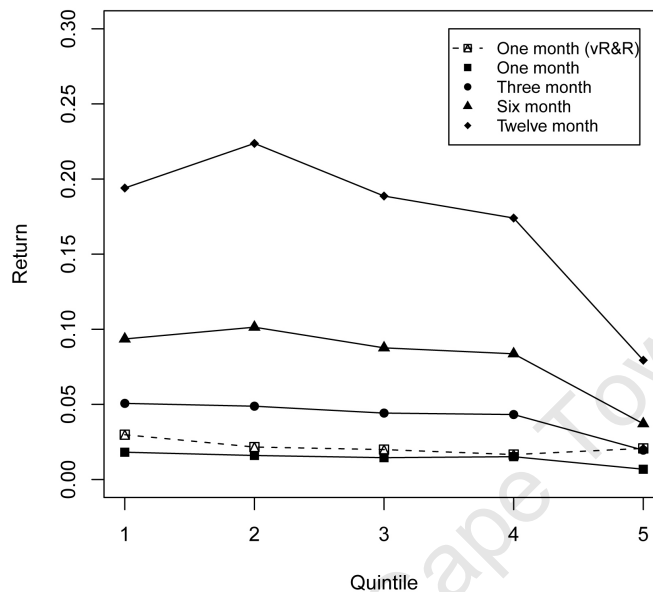


Figure 9.8: Mean returns by quintiles formed on OLS beta

cally significant for any holding period, but are between quintiles 4 and 5. However, the shortcomings of OLS regression in the face of thin trading suggest that alternative beta estimation techniques should be considered before attempting to draw conclusions from these results.

9.3.2 Scholes-Williams

Mean returns, and differences in means between selected quintiles formed on Scholes-Williams beta, are set out in Table 9.4. The mean returns are depicted graphically in Figure 9.9.

It might be expected that, if indeed thin trading and the consequent problems of robust beta estimation are contributors to the somewhat surprising results reported by Van Rensburg and Robertson (2003a), the inverse relationship between return and beta estimated by the Scholes-Williams method would be, at the very least, more muted than was the case with beta esti-

Table 9.4: Results for portfolios formed on Scholes-Williams beta

Portfolio	Holding period			
	1	3	6	12
1	2.08%	5.98%	11.56%	25.57%
2	1.49%	4.19%	8.58%	19.10%
3	1.52%	4.28%	8.06%	17.31%
4	1.09%	3.55%	6.89%	12.16%
5	0.89%	2.63%	5.21%	11.77%
Differences between portfolios				
1-5	1.19% **	3.35% ***	6.35% ***	13.79% ***
1-2	0.59%	1.79% *	2.98% *	6.47% **
2-5	0.60%	1.56%	3.36% *	7.32% ***

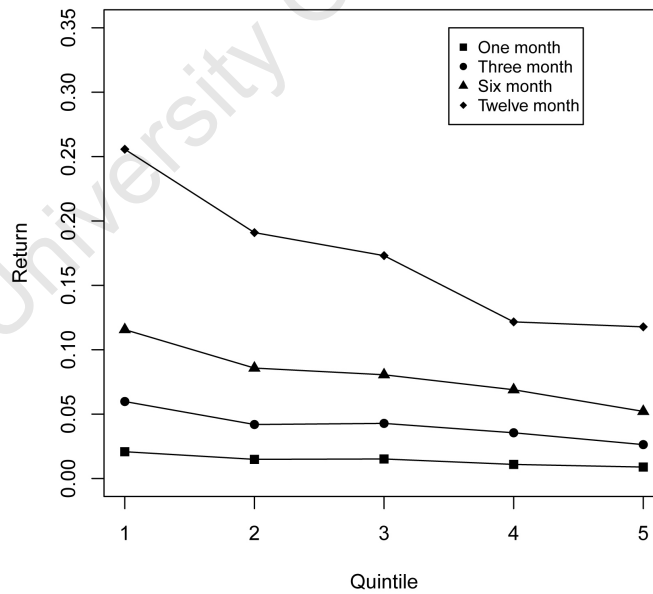


Figure 9.9: Mean returns by quintiles formed on Scholes-Williams beta

mated by OLS. The results however indicate that it is even more pronounced. The difference in return between extreme quintiles is significant at the 5% level for a one-month holding period, and at the 1% level for longer holding periods.

One possible explanation is that the earlier observations are not a function of thinly-traded stocks at all. However, it must be noted, as pointed out in section 7.4 above, that the Scholes-Williams method requires trading in every period for consistency. This is not the case on the JSE Securities Exchange; some 10.4% of data points used in portfolio formation and return calculation in this study indicate no evidence of trading in the preceding month. The Scholes-Williams method is therefore unlikely to be appropriate for beta estimation on the JSE, and we must look to the Dimson Aggregated Coefficients method for further guidance on whether the use of methodology designed specifically to compensate for thin trading could explain, in part or in full, the observed inverse relationship between beta and return.

9.3.3 Dimson (lead and lag 2 months)

Mean returns, and differences in means between selected quintiles formed on Dimson beta with a lead and lag of 2 months, are set out in Table 9.5. The mean returns are depicted graphically in Figure 9.10.

Differences between the returns of extreme quintiles are significant at the 10% level for a three-month holding period, at the 5% level for a six-month holding period, and at 1% when considering returns over twelve months. None of the differences in mean returns between quintiles 1 and 3 are statistically significant, while the difference between quintiles 3 and 5 is significant only for a twelve-month holding period. While slightly more muted than the Scholes-Williams method (the twelve-month differential, for example, is 9.82%, as opposed to 13.79% above), portfolios formed on a Dimson beta estimated with a lead and lag of 2 months again display evidence of an inverse relationship between beta and return, although only for six- and twelve-month holding periods is the difference between extreme quintiles sta-

tistically significant at the 5% level. Given the extent of thin trading on the JSE Securities Exchange, however, it would be instructive to consider Dimson betas estimated with a longer lead and lag.

Table 9.5: Results for portfolios formed on Dimson beta (lead/lag 2 months)

Portfolio	Holding period			
	1	3	6	12
1	1.72%	5.08%	9.86%	21.69%
2	1.34%	4.30%	8.76%	18.38%
3	1.55%	4.05%	8.05%	18.07%
4	1.41%	4.21%	7.83%	15.95%
5	1.05%	2.99%	5.82%	11.87%
Differences between portfolios				
1-5	0.68%	2.09% *	4.04% **	9.82% ***
1-3	0.17%	1.03%	1.81%	3.62%
3-5	0.50%	1.06%	2.23%	6.20% **

9.3.4 Dimson (lead and lag 3 months)

Mean returns, and differences in means between selected quintiles formed on Dimson beta with a lead and lag of 3 months, are set out in Table 9.6. The mean returns are depicted graphically in Figure 9.11.

When the lead and lag period for Dimson beta estimation is extended to 3 months, the difference in return between extreme quintiles is statistically significant only for the twelve-month holding period (p -value of 0.0311). This suggests that, to some extent, the observed inverse relationship between beta and return in Van Rensburg and Robertson (2003a) could owe its existence, at least in part, to the weaknesses of OLS estimation of beta for thinly-traded stocks (despite the application of the thin trading filter, many stocks

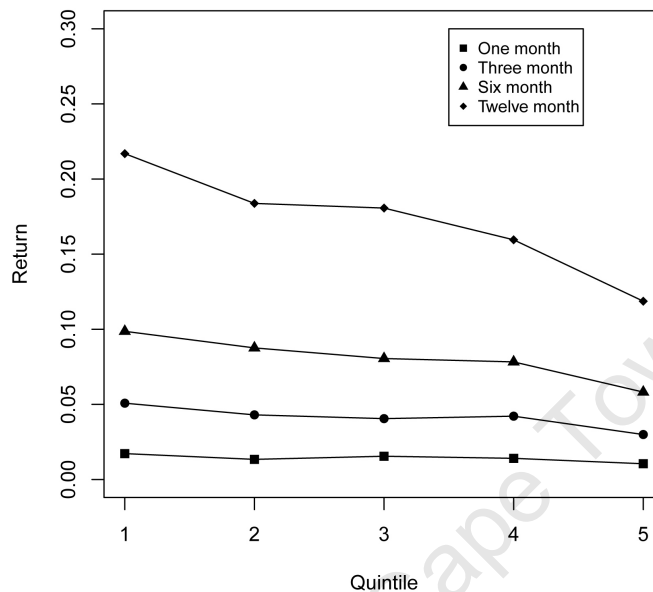


Figure 9.10: Mean returns by quintiles formed on 2 month Dimson beta

would have remained in their universe which are sufficiently thinly-traded for OLS estimation to have been problematic, as conceded by the authors). It is important to note, however, that application of the Dimson Aggregated Coefficients methodology removes only statistical significance from these results; it does not actually reverse the observed inverse relationship between beta and return. It is permissible to conclude from these results that beta has no role to play in the generation of returns on the JSE Securities Exchange, but there is certainly no evidence of the positive relationship which theory would suggest.

9.3.5 Dimson (lead and lag 5 months)

Mean returns, and differences in means between selected quintiles formed on Dimson beta with a lead and lag of 5 months, are set out in Table 9.7. The mean returns are depicted graphically in Figure 9.12.

Table 9.6: Results for portfolios formed on Dimson beta (lead/lag 3 months)

Portfolio	Holding period			
	1	3	6	12
1	1.52%	4.23%	8.28%	19.73%
2	1.51%	4.45%	8.61%	18.45%
3	1.27%	4.11%	8.37%	16.81%
4	1.43%	4.10%	8.12%	17.92%
5	1.34%	3.75%	6.93%	13.05%
Differences between portfolios				
1-5	0.18%	0.48%	1.35%	6.68% **
1-3	0.25%	0.12%	-0.09%	2.91%
3-5	-0.07%	0.36%	1.44%	3.77%

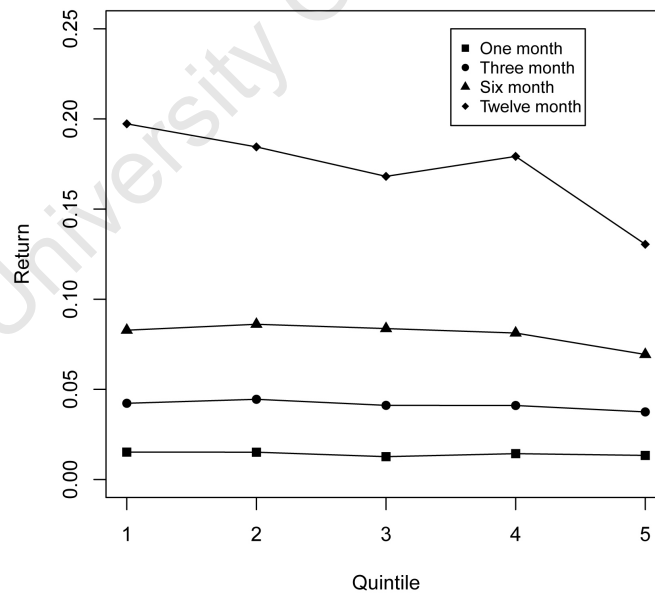


Figure 9.11: Mean returns by quintiles formed on 3 month Dimson beta

Table 9.7: Results for portfolios formed on Dimson beta (lead/lag 5 months)

Portfolio	Holding period				
	1	3	6	12	
1	1.68%	4.66%	8.65%	18.02%	
2	1.42%	4.50%	9.40%	20.81%	
3	1.38%	3.77%	7.81%	17.85%	
4	1.64%	4.49%	8.29%	16.80%	
5	0.95%	3.22%	6.18%	12.51%	
Differences between portfolios					
1-5	0.73%	1.44%	2.46%	5.51%	**
1-3	0.30%	0.89%	0.84%	0.17%	
3-5	0.43%	0.55%	1.63%	5.34%	*

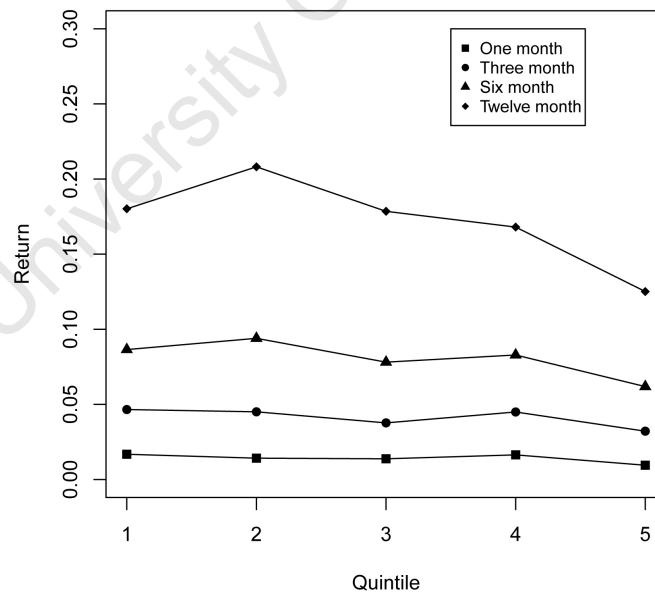


Figure 9.12: Mean returns by quintiles formed on 5 month Dimson beta

Extending the lead and lag to 5 months does not appear to fundamentally alter the conclusions reached with a lead and lag of 3 months. Once again, only the twelve-month holding period return differential is statistically significant at the 5% level (p -value of 0.0493). We may conclude from these results that there is little advantage to be gained from the Dimson methodology with lead and lag longer than 3 months, which appears sufficient to compensate for the degree of thin trading in evidence on the JSE Securities Exchange. We remain with the conclusion that beta appears to have an inverse relationship with return, but that by and large this relationship is not statistically significant. In a nutshell, beta appears to be irrelevant; it has no predictive power for returns on South African equities.

9.4 Two-way analysis: size and value

Two-way analyses were conducted by splitting quintile portfolios formed on, respectively, market capitalisation and PE ratio into further quintiles on PE ratio and market capitalisation respectively, thus resulting in 25 portfolios for each two-way analysis. This allows us to analyse the effect of one factor while keeping the other constant.

Typically, the logarithmic transformation of market capitalisation and PE ratio would be the operational variables used in a multifactor model; the correlation coefficients between these was 0.3368, indicating some positive relationship but not sufficiently high to suggest that one may proxy for the other.

9.4.1 Value within size

Figure 9.13 shows the return in each of the 25 portfolios where quintiles are formed first on market capitalisation and then, within these, on PE ratio. Table 9.8 shows the difference in mean returns between extreme PE ratio quintiles within each size quintile.

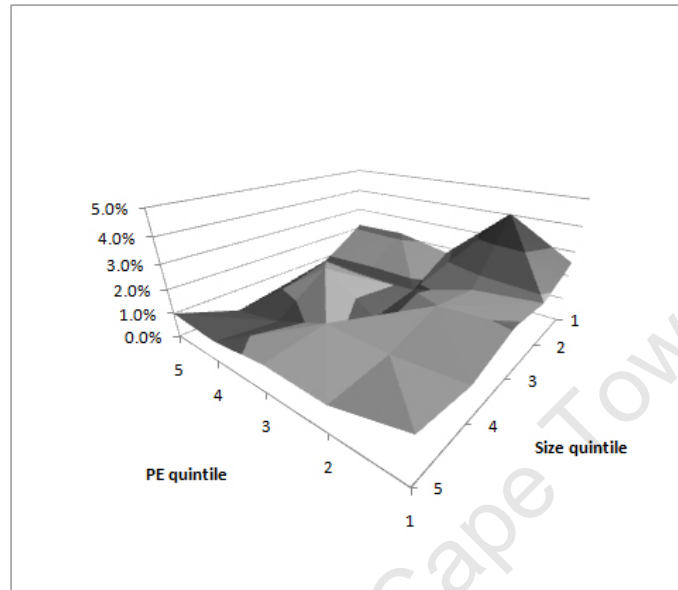


Figure 9.13: Two-way analysis: value within size quintiles

Table 9.8: Difference in returns between extreme PE ratio quintiles within size quintiles

Size quintile	Holding period			
	1	3	6	12
1	0.41%	-2.62%	-7.22% **	-17.39% ***
2	0.98%	1.79%	2.40%	1.00%
3	1.63% *	4.01% **	4.82% **	8.59% **
4	1.38% *	3.99% ***	7.52% ***	11.55% ***
5	0.74%	1.78%	1.80%	2.40%

Within the intermediate size quintiles 3 and 4, PE ratio appears to have strong predictive power for returns. This is not however the case for quintiles 2 and 5, where the returns to low PE ratio are positive but not statistically significant across the holding periods considered. The most interesting result is in the smallest size quintile, which the one-way analysis showed to be the source of almost all of the excess return to firm size. Here the excess return to low PE ratio is in fact negative for holding periods longer than one month, significantly so for six- and twelve-month holding periods.

With the exception of quintile 5, these returns are consistent with those reported by Basiewicz and Auret (2009). They are suggestive of a size effect which dominates for the smallest quintile of firms, and a PE ratio effect which explains more of the variation in returns between larger firms.

9.4.2 Size within value

Figure 9.14 shows the return in each of the 25 portfolios where quintiles are formed first on PE ratio and then, within these, on firm size. Table 9.9 shows the difference in mean returns between extreme size quintiles within each PE ratio quintile.

Table 9.9: Difference in returns between extreme size quintiles within PE ratio quintiles

PE quintile	Holding period			
	1	3	6	12
1	2.95% ***	4.03% **	2.37%	2.00%
2	-0.28%	0.48%	2.42%	9.50% **
3	0.35%	0.08%	0.34%	10.51% *
4	0.49%	1.21%	3.99% *	12.41% ***
5	0.80%	3.06% *	6.03% **	12.69% ***

We may conclude from the above that the size effect is generally more

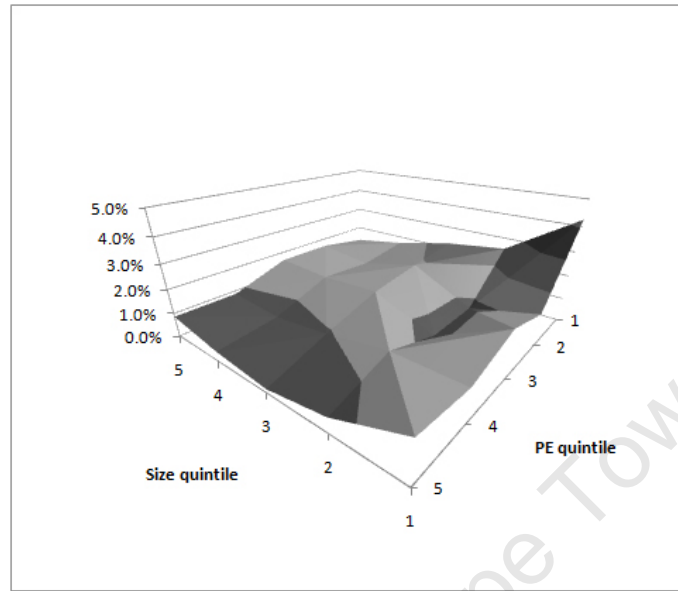


Figure 9.14: Two-way analysis: size within value quintiles

pronounced as the holding period increases. Interestingly, this is not the case for the smallest PE ratio quintile, where the one- and three-month holding period differentials are statistically significant, but the significance disappears for longer holding periods.

It therefore appears that both size and value effects are needed to explain returns on the JSE Securities Exchange, and that one does not proxy for the other.

9.5 Explanation of the results

We consider below two possible explanations for the unexpected relationship between beta and return, namely market proxy error and mean reversion of returns.

9.5.1 Market segmentation and market proxy error

One of the major criticisms of empirical work indicating anomalies within the CAPM framework is that they, of necessity, use market proxies which are narrower than the universe of all risky assets. This is an especially pronounced issue in a relatively small economy such as South Africa. The work of Van Rensburg (2002) suggested that the JSE All-Share Index is very probably mean-variance inefficient in a global context, and found that a two-factor APT model decomposing the JSE Securities Exchange into Financial/Industrial and Resources components was more successful in describing the cross-section of returns than the single-factor CAPM.

Van Rensburg and Robertson (2003a) considered this possibility by repeating their study on a sub-sample of Financial and Industrial stocks, with betas estimated by regression against the Financial and Industrial Index (Findi) returns (the sample of Resources stocks was too small to perform a comparable study). They found little material difference in results when compared to the sample of all stocks. This suggests that there is little to be gained from attempting to extend the analysis presented in this dissertation to betas from the two-factor APT model. This viewpoint was confirmed by Professor Paul van Rensburg in verbal feedback given at a seminar presenting preliminary results of this study at the University of Cape Town on 12 August 2009.

9.5.2 Mean reversion and momentum

One characteristic of an efficient market is that returns should not display systematic under- or overreaction to news, with the result that return patterns ought not to show signs of momentum effects, in which the patterns of past returns continue into the future, or mean reversion, in which past patterns are reversed. There is however ample evidence of both on global markets. Jegadeesh and Titman (1993) showed that stocks which had outperformed the market in the preceding short-term period (between three and

twelve months) tended to continue to outperform over the following three to twelve months, and that these results could not be ascribed to systematic risk in the form of stocks' betas. Quite the opposite effect was detected by De Bondt and Thaler (1985), who looked at returns over longer holding periods of three and five years, and found that the 'loser' portfolio of the 35 stocks with the lowest returns over the preceding three or five years convincingly outperformed the 'winner' portfolio consisting of the 35 stocks with the highest returns over that preceding period. Mean reversion on the South African market has also been reported by Cubbin, Eidne, Firer and Gilbert (2006), although it should be noted that their portfolios were formed on PE ratio rather than past return (the two measures are expected to be positively correlated, however).

This mean reversion effect is a possible explanation for the results observed. In a generally up-trending market, it is plausible that the stocks with the highest returns over the past five years will tend to be those with the highest estimated betas; if mean reversion is present in the market to the extent that these stocks tend to underperform going forward, then this would account to a large degree for the observed inverse relationship between beta and return. This hypothesis was therefore investigated, albeit with little expectation of confirmation, given that the holding periods considered in this study (up to 12 months) are considerably shorter than those considered in De Bondt and Thaler (1985) and other prominent work on mean reversion.

Quintile portfolios were formed on return over the previous 60 months, in the same way as they were formed on size, PE ratio and beta above. Figure 9.15 depicts graphically the mean quintile portfolio returns over each of the four holding periods considered, while Table 9.10 gives the information in tabular format while also considering the difference in returns between extreme quintiles, as well as between intermediate quintiles.

There is little that can be concluded from these results. While there is some indication of an inverse relationship between past and future return comparing quintiles 1 and 3, these differences in return are not statistically

Table 9.10: Results for portfolios formed on preceding 60 months' return

Portfolio	Holding period			
	1	3	6	12
1	2.00%	4.82%	8.63%	18.97%
2	1.63%	4.84%	8.99%	17.41%
3	1.25%	3.53%	6.46%	14.72%
4	0.91%	3.48%	8.01%	17.56%
5	1.27%	3.97%	8.23%	17.24%
Differences between portfolios				
1-5	0.73%	0.86%	0.39%	1.72%
1-3	0.76%	1.30%	2.17%	4.24%
3-5	-0.02%	-0.44%	-1.78%	-2.52%

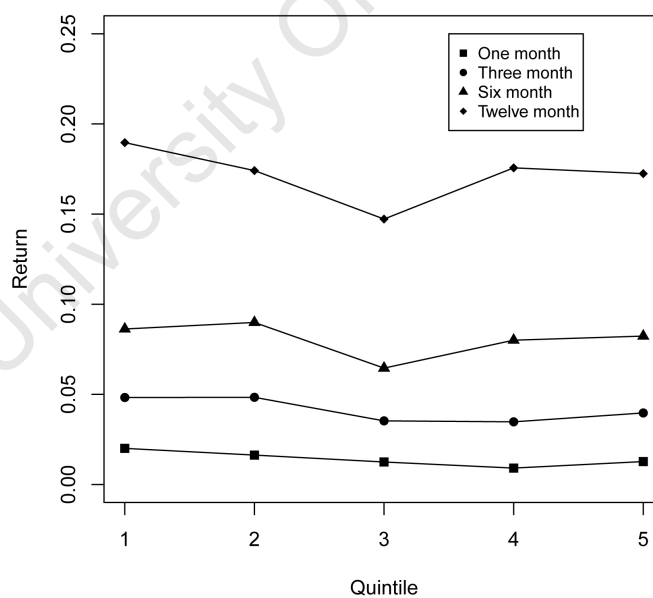


Figure 9.15: Mean returns by quintiles formed on preceding 60 months' return

significant. Furthermore, the relationship appears to be reversed between quintiles 3 and 5, where there typically seems to be a positive relationship between past and future return, although again these differences are not statistically significant. We may thus conclude that mean reversion is not a significant cause of the observed inverse relationship between beta and return.

It was also considered worthwhile to examine momentum effects, and for this reason portfolios were formed based on the past 12 months' return. Table 9.11 and Figure 9.16 present these results.

Table 9.11: Results for portfolios formed on preceding 12 months' return

Portfolio	Holding period			
	1	3	6	12
1	1.28%	2.46%	3.88%	11.27%
2	1.18%	3.95%	7.05%	14.60%
3	1.37%	4.12%	8.48%	17.21%
4	1.35%	4.05%	8.38%	17.65%
5	1.91%	6.12%	12.66%	25.39%
Differences between portfolios				
1-5	-0.63%	-3.66% ***	-8.78% ***	-14.12% ***
1-4	-0.07%	-1.59%	-4.50% **	-6.38% **
4-5	-0.56%	-2.07%	-4.28% **	-7.74% ***

Clear evidence emerges of a momentum effect on the JSE Securities Exchange. While the difference in return between extreme quintiles is not significant for a one-month holding period, it is significant at the 1% level for all longer holding periods. Furthermore, half or more of this difference is concentrated in the fifth quintile, indicating that it is those stocks which have performed best over the preceding year which tend to perform best over the subsequent 3 to 12 months. Momentum is therefore a candidate for inclusion

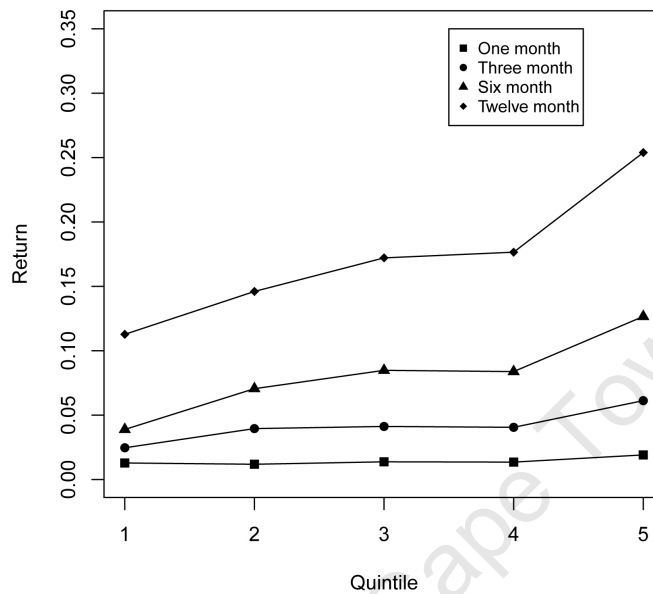


Figure 9.16: Mean returns by quintiles formed on preceding 12 months' return

in a multifactor model describing JSE returns. A multiple regression may however show that it is subsumed by the explanatory variables of size and value (PE ratio).

Chapter 10 summarises the salient features of the findings presented in this chapter, and presents suggestions for further research.

Chapter 10

Conclusions and suggestions for further research

The size effect and value effect (based on the PE ratio) on the JSE Securities Exchange are confirmed by the results of this study. These effects are significant and pervasive, and either indicative of some level of market inefficiency or, perhaps more likely, a misspecification of equilibrium pricing models such as the CAPM which assume that market covariance alone constitutes rewarded systematic risk. There is some tentative evidence of a reduction in the size premium over time, but this is not conclusive.

The most surprising observation of Van Rensburg and Robertson (2003a), namely that beta has, if anything, an inverse relationship with return, also finds support in this study. Their conclusion is clearly not sample-specific, as this analysis covers a later and longer period, and nor is it a result of the short (12 to 30 month) period used for beta estimation, as betas estimated over a 60 month period lead to a similar result. The outcome is however robbed of its statistical significance when betas are estimated using the Dimson Aggregated Coefficients method, designed specifically to compensate for the effects of thin trading and the consequent shortcomings of OLS estimation, using a lead and lag period of at least three months. We may however at best conclude that beta is irrelevant as far as return generation on the JSE

Securities Exchange is concerned, at least based on the (possibly inefficient) market proxy of the FTSE-JSE All-Share Index; there is no support for the positive relationship espoused by finance theory.

Analysis of intermediate quintile portfolios yields further interesting insights. While the value effect appears to apply across the stock universe, with return a monotonically decreasing function of PE ratio, the size effect seems to be concentrated in the smallest quintile of stocks, with little difference in returns between the largest four quintiles. Any attempt to build these observations into a multifactor model would need to recognise this feature of the size premium.

The size and value effects appear furthermore to operate independently, given correlation between the market capitalisation and PE ratio measures which is not excessive, as well as variation within sub-quintiles in the two-way analyses presented in sections 9.4.1 and 9.4.2 above. The value (size) effects are however not uniform over the size (value) quintiles, and again these features would need to be recognised in any sensible multifactor model.

These size and value effects may indicate market inefficiency, and the diminishing size premium over this study's sample period would be consistent with the rational actions of market participants closing out historic inefficiencies. It is however perhaps more likely that they reflect sources of risk which are not measured by market covariance, and hence point to a misspecification of the CAPM and the need for more sophisticated multifactor models to represent the returns on South African equities.

It should be noted that this study takes no account of transaction costs. While many of the results presented in this dissertation are highly statistically significant, their economic significance may be nil if transaction costs prevent trading strategies from taking advantage of them. The incorporation of transaction costs would be a useful extension to this research.

The formation of value-weighted rather than equally-weighted portfolios may also provide some insight. This approach would obviate the need for the removal from the data set of penny-stock shares with an undue influence

on portfolio returns. That being said, the reliability of the data used in this study, particularly for delisted stocks, is subject to question. Appendix B describes the adjustments made to the raw data, the extent of which suggests that there may well be more undetected data inaccuracies. The consistency of data adjustment for corporate actions and capital events is also questionable. Presumably financial researchers across South Africa grapple with the same issues, and consideration ought to be given by finance academics to the (admittedly onerous) collaborative development of a reliable historic equity market data set which can then be maintained with comparatively little effort, along the lines of the database maintained by the University of Chicago's Center for Research in Security Prices (CRSP).

As this study has built primarily on the work of Van Rensburg and Robertson (2003a), PE ratio has been used as the value indicator. In view of the later findings of Auret and Sinclair (2006) and Basiewicz and Auret (2009), it would be useful to consider book-to-market as an alternative value indicator, particularly in a regression-based extension of this research. The application of price and liquidity constraints, following the example of Basiewicz and Auret (2009), would also be a worthwhile avenue for further investigation. Similar filters on price and trading volume would in all likelihood account for much of the size premium reported in this study, which is concentrated in the quintile of smallest stocks, which would tend also to have low prices and trading volumes.

While the Dimson Aggregated Coefficients method of estimating beta seems to compensate best for the effects of thin trading, no attempt has been made to investigate other robust forms of beta estimation, in particular to compensate for the mean-reverting tendency of beta estimates and to reduce the influence of outliers on the estimates. With regard to the former, it should however be noted that the results of a portfolio-based study such as this would not be altered by the estimation of betas on the bases proposed, for example, by Vasicek (1973) and Blume (1975): such methods do not alter the ranking of betas, and hence would not influence the composition of

quantile portfolios. The most robust method for beta estimation for South African equities remains an open question, however, and it is not beyond the realms of possibility that another method may yield the positive relationship between beta and return predicted by theory. However, the evidence so far suggests that it is overwhelmingly unlikely that any single-index model could adequately describe the cross-section of returns on the South African equity market.

Finally, an important extension to this research would be the construction of a multifactor equilibrium pricing model based on its insights, and those which may be provided by the research avenues suggested above. This study provides unambiguous confirmation of the evidence presented by Van Rensburg and Robertson (2003a) that the CAPM is unable to explain or describe the generation of returns on the JSE Securities Exchange, and its contradiction creates a vacuum which begs to be filled.

Bibliography

- Abelson, R. (1995). *Statistics as principled argument*, Lawrence Erlbaum, Hillsdale, NJ.
- Aitken, M. and Ferris, G. (1991). A note on the effect of controlling for transaction costs on the small firm anomaly: Additional Australian evidence, *Journal of Banking and Finance* **15**: 1195–1202.
- Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread, *Journal of Financial Economics* **17**(2): 223–250.
- Atiase, R. (1985). Predisclosure information, firm capitalization and security price behavior around earnings announcements, *Journal of Accounting Research* **23**(1): 21–36.
- Auret, C. and Sinclair, R. (2006). Book-to-market ratio and returns on the JSE, *Investment Analysts Journal* **63**: 31–38.
- Ball, R. (1978). Anomalies in relationships between securities' yields and yield-surrogates, *Journal of Financial Economics* **6**: 103–126.
- Ball, R. (1992). The earnings price anomaly, *Journal of Accounting and Economics* **15**: 319–345.
- Banz, R. (1981). The relationship between return and market value of common stock, *Journal of Financial Economics* **9**(1): 3–18.

- Banz, R. and Breen, W. (1986). Sample-dependent results using accounting and market data: Some evidence, *Journal of Finance* **41**(4): 779–793.
- Barry, C. and Brown, S. (1984). Differential information and the small firm effect, *Journal of Financial Economics* **13**(2): 283–294.
- Barry, C. and Brown, S. (1985). Differential information and security market equilibrium, *Journal of Financial and Quantitative Analysis* **20**: 407–422.
- Basiewicz, P. and Auret, C. (2009). Another look at the cross-section of average returns on the JSE, *Investment Analysts Journal* **69**: 23–38.
- Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* **12**(1): 129–156.
- Berges, A., McConnell, J. and Schlarbaum, G. (1984). The turn-of-the-year in Canada, *Journal of Finance* **39**(1): 185–192.
- Berk, J. (1995). A critique of size related anomalies, *Review of Financial Studies* **8**: 275–286.
- Bhardwaj, R. K. and Brooks, L. D. (1992). The January anomaly: Effects of low share price, transaction costs, and bid-ask bias, *Journal of Finance* **47**(2): 553–575.
- Bhardwaj, R. K. and Brooks, L. D. (1993). Dual betas from bull and bear markets: Reversal of the size effect, *Journal of Financial Research* **16**(2): 269–283.
- Black, F. (1972). Capital market equilibrium with restricted borrowing, *Journal of Business* **45**: 444–455.
- Black, F. (1993). Beta and return, *Journal of Portfolio Management* **20**: 8–18.

- Black, F., Jensen, M. and Scholes, M. (1972). The Capital Asset Pricing Model: Some empirical tests, in M. Jensen (ed.), *Studies in the theory of capital markets*, Praeger, New York.
- Blume, M. (1975). Betas and their regression tendencies, *Journal of Finance* **10**(3): 785–795.
- Blume, M. and Stambaugh, R. (1983). Biases in computed returns: An application to the size effect, *Journal of Financial Economics* **12**(3): 387–404.
- Bowie, D. and Bradfield, D. (1998). Non-normality and robust estimation of beta coefficients, *Journal of Business Finance and Accounting* **25**: 439–454.
- Bradfield, D. (2003). Investment basics XLVI: On estimating the beta coefficient, *Investment Analysts Journal* **57**: 47–53.
- Bradfield, D., Barr, G. and Affleck-Graves, J. (1988). Asset pricing in small markets- the South African case, *South African Journal of Business Management* **19**(1): 11–21.
- Brown, L. and Kim, K. (1993). The association between nonearnings disclosures by small firms and positive abnormal returns, *Accounting Review of Financial Studies* **68**: 668–680.
- Brown, P., Keim, D., Kleidon, A. and Marsh, T. (1983). Stock return seasonalities and the tax-loss selling hypothesis: Analysis of the arguments and Australian evidence, *Journal of Financial Economics* **12**(1): 105–127.
- Brown, P., Kleidon, A. and Marsh, T. (1983). New evidence on the nature of size-related anomalies in stock prices, *Journal of Financial Economics* **12**(1): 33–56.
- Brown, S. J. and Barry, C. B. (1984). Anomalies in security returns and the specification of the market model, *Journal of Finance* **39**(3): 807–815.

- Chan, K. C. (1986). Can tax-loss selling explain the January seasonal in stock returns?, *Journal of Finance* **41**(5): 1115–1128.
- Chan, K. C. and Chen, N.-F. (1988). An unconditional asset-pricing test and the role of firm size as an instrumental variable for risk, *Journal of Finance* **43**(2): 309–325.
- Chan, K. C. and Chen, N.-F. (1991). Structural and return characteristics of small and large firms, *Journal of Finance* **46**(4): 1467–1484.
- Chan, K., Chen, N.-F. and Hsieh, D. (1985). An exploratory investigation of the firm size effect, *Journal of Financial Economics* **14**(3): 451–471.
- Chan, L., Jegadeesh, N. and Lakonishok, J. (1995). Evaluating the performance of value versus glamour stocks: The impact of selection bias, *Journal of Financial Economics* **38**(3): 269–296.
- Chen, N. (1983). Some empirical tests of the theory of arbitrage pricing, *Journal of Finance* **38**: 1393–1414.
- Collins, D., Kothari, S. and Rayburn, J. (1987). Firm size and the information-content of prices with respect to earnings, *Journal of Accounting and Economics* **9**: 111–138.
- Constantinides, G. (1984). Optimal stock trading with personal taxes: Implications for prices and the abnormal January returns, *Journal of Financial Economics* **13**(1): 65–89.
- Cook, T. and Rozeff, M. (1984). Size and earnings/price ratio anomalies: One effect or two?, *Journal of Financial and Quantitative Analysis* **19**(4): 449–466.
- Cubbin, E., Eidne, M., Firer, C. and Gilbert, E. (2006). Mean reversion on the JSE Securities Exchange, *Investment Analysts Journal* **63**: 1–17.

- Daniel, K. and Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* **52**(1): 1–33.
- Davis, J. (1994). The cross-section of realized stock returns: the pre-COMPUSTAT evidence, *Journal of Finance* **49**: 1579–1593.
- Dawes, R. and Thaler, R. (1988). Anomalies: Cooperation, *Journal of Economic Perspectives* **2**: 187–197.
- De Bondt, W. and Thaler, R. (1985). Does the stock market overreact?, *Journal of Finance* **40**(3): 793–805.
- De Villiers, J., Lowlings, P., Pettit, A. and Affleck-Graves, J. (1986). An investigation into the small firm effect on the JSE, *South African Journal of Business Management* **17**(4): 191–195.
- Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* **7**: 197–226.
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work, *Journal of Finance* **25**(2): 383–417.
- Fama, E. F. (1976). Efficient capital markets: Reply, *Journal of Finance* **31**(1): 143–145.
- Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns, *Journal of Finance* **47**(2): 427–465.
- Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* **33**: 3–56.
- Fama, E. F. and French, K. R. (1995). Size and book-to-market factors in earnings and returns, *Journal of Finance* **50**(1): 131–155.
- Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies, *Journal of Finance* **51**(1): 55–84.

- Fama, E. F. and MacBeth, J. (1973). Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* **81**(3): 607–636.
- Fraser, P. (1995). Returns and firm size: A note on the UK experience 1970-1991, *Applied Economics Letters* **2**: 331–334.
- Freeman, R. (1987). The association between accounting earnings and security returns for large and small firms, *Journal of Accounting and Economics* **9**(2): 195–228.
- French, K. R. (1980). Stock returns and the weekend effect, *Journal of Financial Economics* **8**(1): 55–69.
- Friend, I. and Lang, L. (1988). The size effect on stock returns: Is it simply a risk effect not adequately reflected by the usual measures?, *Journal of Banking and Finance* **12**: 13–30.
- Froot, K. and Thaler, R. (1990). Foreign exchange, *Journal of Economic Perspectives* **4**: 179–192.
- Goodman, D. and Peavy, J. (1986). The interaction of firm size and price-earnings ratio on portfolio performance, *Financial Analysts Journal* **42**(1): 9–12.
- Grauer, R. R. (1999). On the cross-sectional relation between expected returns, betas, and size, *Journal of Finance* **54**(2): 773–789.
- Griffiths, M., Turnbull, D. and White, R. (1999). Re-examining the small-cap myth: problems in portfolio formation and liquidation, *Global Finance Journal* **10**(2): 201–221.
- Griffiths, M. and White, R. (1993). Tax-induced trading and the turn-of-the-year anomaly: An intraday study, *Journal of Finance* **48**(2): 575–598.
- Gultekin, M. and Gultekin, N. (1983). Stock market seasonality: International evidence, *Journal of Financial Economics* **12**(4): 469–481.

- Horowitz, J., Loughran, T. and Savin, N. (2000). Three analyses of the firm size premium, *Journal of Empirical Finance* **7**: 143–153.
- Huberman, G. and Kandel, S. (1987). Value Line rank and firm size, *Journal of Business* **60**(4): 577–589.
- Jaffe, J., Keim, D. B. and Westerfield, R. (1989). Earnings yields, market values, and stock returns, *Journal of Finance* **44**(1): 135–148.
- James, C. and Edmister, R. O. (1983). The relation between common stock returns, trading activity and market value, *Journal of Finance* **38**(4): 1075–1086.
- Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* **48**: 65–91.
- Jones, S. L., Lee, W. and Apenbrink, R. (1991). New evidence on the January effect before personal income taxes, *Journal of Finance* **46**(5): 1909–1924.
- Kahneman, D., Knetsch, J. and Thaler, R. (1991). The endowment effect, loss aversion and status quo bias, *Journal of Economic Perspectives* **5**(1): 193–206.
- Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk, *Econometrica* **47**(2): 263–291.
- Kato, K. and Schallheim, J. (1985). Seasonal and size anomalies in the Japanese stock market, *Journal of Financial and Quantitative Analysis* **20**: 243–260.
- Keim, D. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence, *Journal of Financial Economics* **12**(1): 13–32.
- Kim, D. (1997). A reexamination of firm size, book-to-market, and earnings price in the cross-section of expected stock returns, *Journal of Financial and Quantitative Analysis* **32**: 463–489.

- Knez, P. J. and Ready, M. J. (1997). On the robustness of size and book-to-market in cross-sectional regressions, *Journal of Finance* **52**(4): 1355–1382.
- Korkie, B. (1986). Market line deviations and market anomalies with reference to small and large firms, *Journal of Financial and Quantitative Analysis* **21**: 161–180.
- Kothari, S., Shanken, J. and Sloan, R. (1995). Another look at the cross-section of expected stock returns, *Journal of Finance* **50**: 185–224.
- Kross, W. (1985). The size effect is primarily a price effect, *Journal of Financial Research* **8**: 169–179.
- Lakonishok, J. and Shapiro, A. (1986). Systematic risk, total risk and size as determinants of stock market returns, *Journal of Banking and Finance* **10**: 115–132.
- Lakonishok, J., Shleifer, A. and Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk, *Journal of Finance* **49**(5): 1541–1578.
- Lakonishok, J. and Smidt, S. (1984). Volume and turn-of-the-year behavior, *Journal of Financial Economics* **13**(3): 435–455.
- Lakonishok, J. and Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective, *Review of Financial Studies* **1**: 403–425.
- Lamoureux, C. and Sanger, G. (1989). Firm size and turn-of-the-year effects in the OTC/NASDAQ market, *Journal of Finance* **44**: 1219–1246.
- Lee, C., Shleifer, A. and Thaler, R. (1990). Closed end mutual funds, *Journal of Economic Perspectives* **4**: 153–164.
- Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* **47**: 13–37.

- Lo, A. and MacKinlay, A. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* **1**(1): 41–66.
- Loewenstein, G. and Thaler, R. (1989). Intertemporal choice, *Journal of Economic Perspectives* **3**: 181–193.
- Loughran, T. (1997). Book-to-market across firm size, exchange, and seasonality: Is there an effect?, *Journal of Financial and Quantitative Analysis* **32**: 249–268.
- Lustig, I. and Leinbach, P. (1983). The small firm effect, *Financial Analysts Journal* **39**(3): 46–49.
- MacKinlay, A. (1995). Multifactor models do not explain deviations from the CAPM, *Journal of Financial Economics* **38**: 3–28.
- Markowitz, H. (1952). The utility of wealth, *Journal of Political Economy* **60**: 151–158.
- Merton, R. (1973). An Intertemporal Capital Asset Pricing Model, *Econometrica* **41**: 867–887.
- Mossin, J. (1966). Equilibrium in a capital asset market, *Econometrica* **34**(4): 768–743.
- Muth, J. (1961). Rational expectations and the theory of price movements, *Econometrica* **29**: 315–335.
- Nosanchuk, T. (1978). Serendipity tails: A note on two tailed hypothesis tests with asymmetric regions of rejection, *Acta Sociologica* **21**(3): 249–253.
- Page, M. (1996). Further evidence of firm size and earnings anomalies on the Johannesburg Stock Exchange, *De Ratione* **10**(1): 27–44.

- Page, M. and Palmer, F. (1993). The relationship between excess returns, firm size and earnings on the Johannesburg Stock Exchange, *South African Journal of Business Management* **22**: 63–73.
- Perez-Quiros, G. and Timmermann, A. (2000). Firm size and cyclical variations in stock returns, *Journal of Finance* **55**(3): 1229–1262.
- R Development Core Team (2009). *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0.
URL: <http://www.R-project.org>
- Reinganum, M. (1981a). The Arbitrage Pricing Theory: Some empirical results, *Journal of Finance* **36**(2): 313–321.
- Reinganum, M. (1981b). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yield and market values, *Journal of Financial Economics* **9**(1): 19–46.
- Reinganum, M. (1981c). A new empirical perspective on the CAPM, *Journal of Financial and Quantitative Analysis* **16**: 439–462.
- Reinganum, M. (1982). A direct test of Roll's conjecture on the firm size effect, *Journal of Finance* **37**(1): 27–35.
- Reinganum, M. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects, *Journal of Financial Economics* **12**(1): 89–104.
- Reinganum, M. (1984). Discussion: What the anomalies mean, *Journal of Finance* **39**(3): 837–840.
- Reinganum, M. and Shapiro, A. (1987). Taxes and stock return seasonality: Evidence from the London Stock Exchange, *Journal of Business* **60**(2): 281–295.

- Reinganum, M. and Smith, J. (1983). Investor preference for large firms: New evidence on economies of size, *Journal of Industrial Economics* **32**: 213–227.
- Ritter, J. R. (1988). The buying and selling behavior of individual investors at the turn of the year, *Journal of Finance* **43**(3): 701–717.
- Robertson, M. (2002). *Firm-specific attributes and the cross-section of JSE Securities Exchange returns*, unpublished PhD thesis, University of Cape Town.
- Roll, R. (1977). A critique of the asset pricing theory's tests: Part I: On past and potential testability of the theory, *Journal of Financial Economics* **4**: 129–176.
- Roll, R. (1981). A possible explanation of the small firm effect, *Journal of Finance* **36**(4): 879–888.
- Roll, R. (1983). On computing mean returns and the small firm premium, *Journal of Financial Economics* **12**(3): 371–386.
- Ross, S. (1976). The arbitrage theory of capital asset pricing, *Journal of Economic Theory* **13**: 341–360.
- Rozeff, M. and Kinney, W. (1976). Capital market seasonality: The case of stock returns, *Journal of Financial Economics* **3**: 379–402.
- Scholes, M. and Williams, J. (1977). Estimating betas from non-synchronous data, *Journal of Financial Economics* **5**: 309–327.
- Schultz, P. (1983). Transaction costs and the small firm effect: A comment, *Journal of Financial Economics* **12**(1): 81–88.
- Schwert, G. (1983). Size and stock returns, and other empirical regularities, *Journal of Financial Economics* **12**(1): 3–12.

- Seyhun, H. N. (1988). The January effect and aggregate insider trading, *Journal of Finance* **43**(1): 129–141.
- Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* **19**: 425–442.
- Stoll, H. and Whaley, R. (1983). Transaction costs and the small firm effect, *Journal of Financial Economics* **12**(1): 57–79.
- Thaler, R. (1987a). Seasonal movements in security prices I: The January effect, *Journal of Economic Perspectives* **1**: 197–201.
- Thaler, R. (1987b). Seasonal movements in security prices II: Weekends, holidays, turn of the month and intra-day effects, *Journal of Economic Perspectives* **1**: 169–177.
- Thaler, R. (1988a). Anomalies: The ultimatum game, *Journal of Economic Perspectives* **2**: 195–206.
- Thaler, R. (1988b). The winner’s curse, *Journal of Economic Perspectives* **2**: 191–202.
- Thaler, R. (1989). Interindustry wage differentials, *Journal of Economic Perspectives* **3**: 181–193.
- Thaler, R. (1990). Savings, fungibility and mental accounts, *Journal of Economic Perspectives* **4**: 193–205.
- Thaler, R. and Tversky, A. (1990). Preference reversals, *Journal of Economic Perspectives* **4**: 201–211.
- Tinic, S., Barone-Adesi, G. and West, R. (1987). Seasonality in Canadian stock prices: A test of the tax-loss selling hypothesis, *Journal of Financial and Quantitative Analysis* **22**: 51–63.
- Tinic, S. and West, R. (1984). Risk and return: January vs. the rest of the year, *Journal of Financial Economics* **13**(4): 561–574.

- Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* **5**: 297–323.
- Van Rensburg, P. (2001). A decomposition of style-based risks on the JSE, *Investment Analysts Journal* **54**: 45–60.
- Van Rensburg, P. (2002). Market segmentation on the Johannesburg Stock Exchange II, *Journal for Studies in Economics and Econometrics* **26**(1): 83–99.
- Van Rensburg, P. and Robertson, M. (2003a). Size, price-to-earnings and beta on the JSE Securities Exchange, *Investment Analysts Journal* **58**: 7–16.
- Van Rensburg, P. and Robertson, M. (2003b). Style characteristics and the cross-section of JSE returns, *Investment Analysts Journal* **57**: 7–15.
- Vasicek, O. (1973). A note on using cross-sectional information in Bayesian estimation of betas, *Journal of Finance* **28**: 1233–1239.
- Verrecchia, R. (1982). Information acquisition in a noisy rational expectations economy, *Econometrica* **50**: 1415–1430.
- Wang, X. (2000). Size effect, book-to-market effect, and survival, *Journal of Multinational Financial Management* **10**: 257–273.
- Wei, K. and Stansell, S. (1991). Benchmark error and the small firm effect: A revisit, *Journal of Financial Research* **14**(4): 359–369.
- Welch, B. (1947). The generalization of “Student’s” problem when several different population variances are involved, *Biometrika* **34**(1–2): 28–35.
- Wong, K. and Lye, M. (1990). Market values, earnings’ yield and stock returns: Evidence from Singapore, *Journal of Banking and Finance* **14**: 311–326.

Zeghal, D. (1984). Firm size and the information content of financial statements, *Journal of Financial and Quantitative Analysis* **19**: 299–310.

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Appendices

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Appendix A

Summary of analysis data

Figure A.1 shows the number of stocks, and their total market capitalisation in billions of Rands, at each month-end over the sample period from 31 December 1993 to 31 October 2007.

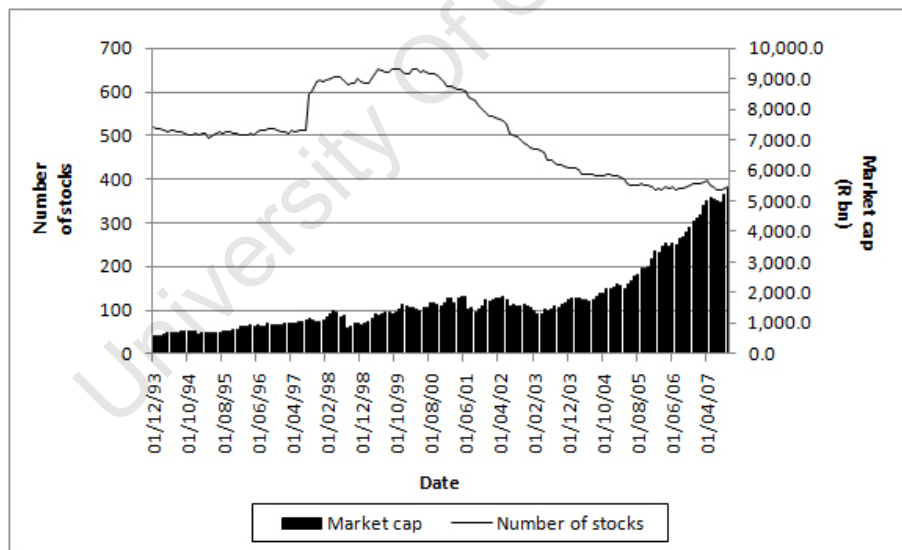


Figure A.1: Summary of number of stocks and market capitalisations at each sample month-end

The respective figures at each year-end in the sample are set out in Table A.1 below.

Table A.1: Summary of data

Date	Number of stocks	Total market capitalisation (R bn)
31/12/93	519	593.4
31/12/94	504	747.0
31/12/95	505	810.2
31/12/96	513	957.0
31/12/97	629	1,045.8
31/12/98	624	954.7
31/12/99	646	1,600.7
31/12/00	623	1,655.6
31/12/01	552	1,744.3
31/12/02	481	1,558.9
31/12/03	427	1,746.9
31/12/04	413	2,144.3
31/12/05	383	3,080.2
31/12/06	388	4,324.3
31/10/07	384	5,400.7

Appendix B

Adjustments to raw data

This Appendix summarises the adjustment made to the data set downloaded from I-Net Bridge prior to performing the analysis described in the dissertation.

B.1 Missing dividend yields

Several records in the downloaded data had blank entries in the dividend yield field. All missing dividend yields were set to zero, except where the correct values were obvious from surrounding data.

B.2 Missing earnings yields

Missing earnings yields were replaced by those calculated from the implied earnings of surrounding records.

B.3 Preference and non-voting shares

All shares other than ordinary shares were denoted by identifying suffixes, and were deleted from the data set.

B.4 High dividend yields

Dividend yields in excess of 150% were set to zero where these persisted for periods of more than twelve months, as these were typically the result of stocks whose prices had collapsed and had suspended trading prior to ultimate delisting. The data was not adjusted where such series persisted for shorter periods.

B.5 Market capitalisation data

Market capitalisation was calculated by multiplying stock price by the number of shares in issue (where the latter item was missing, shares in issue from the last or next available month were used). Where no shares in issue data were available, all data for the stocks in question were discarded: this affected share codes BLRX (30/9/91 to 31/1/96), FSG1X (30/9/91 to 30/9/94), MIMX (30/9/91 to 30/4/94), OMCX (30/11/92 to 30/9/94), OSLX (30/9/91 to 30/4/94), SCOX (30/6/92 to 28/2/94), SFTX (30/9/91 to 31/3/94), VDKX (30/9/91 to 30/9/94) and WELX (30/9/91 to 30/4/94).

Apart from the above, market capitalisation figures were accepted, although there were several instances of significant changes in the number of shares in issue from month to month; according to I-Net's stated policy, rights issues and share splits should have been corrected for in the price and shares in issue history (and in most instances, this appears to have been done correctly).

B.6 High returns

All returns in excess of 100% in a single month were checked; all appeared to be correct in the absence of contradictory evidence from external sources. There were four stocks which exhibited returns in excess of 900% in a single month (share codes BNT, CSY, ISA and LAF), and which had an undue

influence on the results, in particular on the returns (and their skewness and kurtosis) of the smallest quintile. These were mostly stocks whose price had fallen to one cent and then rebounded significantly on the back of positive news. In view of the influence of these stocks' returns on the results, they were excluded from the data set.

B.7 Duplicate share codes

I-Net Bridge's practice is to add an 'X' suffix to a stock's code when it is delisted. In several instances stocks appeared to have two distinct price series with an extra 'X' added onto the second code. Where there was a gap in dates between the two series, all data was retained, with the two being treated as separate series. Where the series overlapped, in some cases it was clear that one series was partially a replication of the other, and the duplication was eliminated from the data set.

B.8 Other

All 30 September 2005 values for share code CENX were zero; these were replaced by the values at 31 August 2005 and 31 October 2005, which were identical to each other. Some obvious errors in price progressions were amended to be in line with surrounding records.

Appendix C

Comparative results assuming minus 50% return on delisting

C.1 Size effect

Table C.1: Results for portfolios formed on market capitalisation (assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	2.95%	7.83%	14.24%	30.34%
2	1.59%	4.70%	9.50%	21.70%
3	1.79%	5.31%	11.04%	22.27%
4	1.30%	4.34%	8.67%	18.52%
5	1.37%	4.19%	8.46%	16.83%
Differences between portfolios				
1-5	1.58%	3.64%	5.78%	13.51%
1-2	1.36%	3.13%	4.74%	8.65%
2-5	0.22%	0.51%	1.05%	4.86%

As was the case with an assumed minus 100% return on delisting, the size premium, defined as the difference between returns of extreme quintiles, is significant across the holding periods considered; in fact, the results for one- and three-month are now significant at the 1% level, as for six- and twelve-month holding periods. Again, this is concentrated in the smallest size quintile, with the difference in mean returns between quintiles 1 and 2 being significant at 5% for a one-month holding periods and at 1% for longer holding periods.

C.2 Value effect

Table C.2: Results for portfolios formed on PE ratio (assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	2.85%	6.78%	11.45%	23.21%
2	1.73%	5.74%	12.26%	25.33%
3	1.88%	5.41%	10.42%	23.55%
4	1.35%	4.44%	8.98%	19.53%
5	1.21%	4.03%	8.84%	18.14%
Differences between portfolios				
1-5	1.64% ***	2.75% **	2.61%	5.07% **
1-3	0.97% *	1.37%	1.03%	-0.35%
3-5	0.67%	1.38%	1.58%	5.42% **

Again, the conclusions are very similar to those based on a minus 100% delisting return, with the main difference being that the difference in mean return between extreme quintiles, of 5.07%, for a twelve-month holding period is significant at the 5% level, whereas the corresponding differential of 3.55%

reported in section 9.2 was not significant.

C.3 Beta effect

C.3.1 OLS beta

Table C.3: Results for portfolios formed on OLS beta (assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	2.26%	6.34%	11.94%	24.36%
2	2.00%	5.98%	12.25%	26.58%
3	1.82%	5.54%	11.01%	23.47%
4	1.78%	5.22%	10.27%	21.68%
5	1.15%	3.33%	6.49%	13.69%
Differences between portfolios				
1-5	1.11% *	3.01% ***	5.45% ***	10.67% ***
1-4	0.48%	1.11%	1.68%	2.68%
4-5	0.63%	1.89%	3.77% **	7.99% ***

The reported significance levels of the above results are the same as those assuming a minus 100% return on delisting.

C.3.2 Scholes-Williams beta

Table C.4: Results for portfolios formed on Scholes-Williams beta (assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	2.50%	7.14%	13.81%	29.96%
2	1.91%	5.53%	11.34%	24.54%
3	1.89%	5.43%	10.35%	21.67%
4	1.43%	4.42%	8.61%	16.41%
5	1.28%	3.88%	7.82%	17.11%
Differences between portfolios				
1-5	1.22% **	3.25% ***	6.00% ***	12.86% ***
1-2	0.58%	1.61%	2.48% *	5.42% **
2-5	0.64%	1.64%	3.52% **	7.44% ***

The reported significance levels of the above results are almost identical to those assuming a minus 100% return on delisting, the only exceptions being that the three-month return differential between quintiles 1 and 2 is no longer significant at 10%, while the reported significance level of the six-month differential between quintiles 2 and 5 improves from 10% to 5%.

C.3.3 Dimson beta (lead and lag 2 months)

Table C.5: Results for portfolios formed on Dimson beta (lead and lag 2 months, assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	2.15%	6.29%	12.21%	26.40%
2	1.70%	5.33%	10.74%	22.31%
3	1.95%	5.21%	10.58%	23.07%
4	1.75%	5.26%	9.94%	20.51%
5	1.46%	4.30%	8.47%	17.45%
Differences between portfolios				
1-5	0.69%	2.00% *	3.74% **	8.95% ***
1-3	0.20%	1.08%	1.63%	3.33%
3-5	0.49%	0.91%	2.11%	5.62% **

The reported significance levels of the above results are the same as those assuming a minus 100% return on delisting.

C.3.4 Dimson beta (lead and lag 3 months)

Table C.6: Results for portfolios formed on Dimson beta (lead and lag 3 months, assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	1.93%	5.33%	10.42%	24.01%
2	1.90%	5.63%	10.99%	23.04%
3	1.69%	5.32%	10.81%	21.87%
4	1.77%	5.15%	10.09%	21.82%
5	1.73%	4.98%	9.63%	19.01%
Differences between portfolios				
1-5	0.19%	0.35%	0.79%	4.99% *
1-3	0.24%	0.02%	-0.39%	2.14%
3-5	-0.04%	0.33%	1.18%	2.86%

The reported significance levels of the above results are almost identical to those assuming a minus 100% return on delisting, with the only exception being the difference between extreme quintiles for a twelve-month holding period now only being significant at the 10% level, against the 5% level reported in section 9.3.4.

C.3.5 Dimson beta (lead and lag 5 months)

Table C.7: Results for portfolios formed on Dimson beta (lead and lag 5 months, assuming -50% return on delisting)

Portfolio	Holding period			
	1	3	6	12
1	1.98%	5.58%	10.50%	21.81%
2	1.81%	5.61%	11.56%	25.15%
3	1.83%	5.00%	10.27%	22.95%
4	2.02%	5.78%	10.92%	22.10%
5	1.37%	4.43%	8.72%	17.78%
Differences between portfolios				
1-5	0.62%	1.16%	1.77%	4.04%
1-3	0.15%	0.58%	0.23%	-1.13%
3-5	0.46%	0.58%	1.55%	5.17% **

The reported significance levels of the above results are almost identical to those assuming a minus 100% return on delisting, with some differences for the twelve-month holding period.