MOTIVATING, CONSTRUCTING AND TESTING THE FAMA-FRENCH THREE FACTOR MODEL ON THE JOHANNESBURG STOCK EXCHANGE

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DECLARATION

I, Patryk Basiewicz, hereby declare that this research report is my own, unaided work, the substance of or any part of which has not been submitted in the past nor will be submitted in the future for a degree to any university and that information contained herein has not been obtained during my employment or working under the aegis of any other person or organisation other than this university.

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LIST OF ABBREVIATIONS

“A” CAPM	“Augmented” Capital Asset Pricing Model
APT	Arbitrage Pricing Theory
BE/ME	Book-to-Market Ratio
CAPM	Capital Asset Pricing Model (Static)
CCAPM	Conditional Capital Asset Pricing Model
CCSR	Cochrane’s Cross-Sectional Regression
C/P	Cashflow-to-Price Ratio
EMH	Efficient Market Hypothesis
E/P	Earnings-to-Price Ratio
FF3F	Fama-French Three-Factor Model
F/P	Fundamental-to-Price Ratio
GMM	Generalised Method of Moments
GLS	Generalised Least Squares
HML	“High minus Low”, The Value Factor
ICAPM	Intertemporal CAPM
IPO	Initial Public Offering
JSE	Johannesburg Stock Exchange
OLS	Ordinary Least Squares
RS-APT	APT variant developed by van Rensburg and Slaney (1997)
RS-FF3F	FF3F variant that includes factors developed by van Rensburg and Slaney (1997)
SMB	“Small minus Big”, The Size Factor
SML	“Small minus Large”, the SMB used in this dissertation
SURE	Seemingly Unrelated Regression
VMG	“Value minus Growth”, the HML used in this dissertation

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ABSTRACT

The purpose of this dissertation is to motivate, construct and test the suitability of the Fama and French (1993) three-factor model in pricing equities listed on the Johannesburg Stock Exchange. Before this can be achieved, however, the existence of the size and the value effects needs to be established, and their resistance to risk adjustment with traditional asset pricing models needs to be ascertained. Once, these two empirical facts are documented, the three-factor model is built and tested.

Results of Fama and French (1992) can be replicated on the Johannesburg Stock Exchange in that a firm’s size and its value-growth indicator have reliable power to forecast stock returns. However, the value effect and, in particular, the size effect, attenuate after market microstructure is controlled for. Both effects are found to be independent of one another and the book-to-market ratio is found to be the best value-growth indicator. The static CAPM and an APT variant cannot explain the size and the value effects. This result is robust to time-series and cross-sectional tests.

The three factor model of Fama and French (1993), and its variant, are constructed. The models can capture a substantial amount of time-series variation in most assets. When applied to the size and book-to-market sorted portfolios, they are not rejected in the vast majority of asset pricing tests. In tests on ungrouped data, the three factor model can explain the value effect, but not the size effect. However, in cross-sectional tests that use the size and book-to-market sorted portfolios as well as industry portfolios, the pricing errors of the three factor model are not substantially different from the ones obtained from the static CAPM.

CHAPTER 1: INTRODUCTION

1.1 Background

The derivation of a parsimonious asset pricing model has been a central theme of financial economics for over half a century. While a substantial body of theoretical work has emerged[1], no model has been accepted by the majority of academics and practitioners. It appears that the theory, which is set in the neoclassical tenant that people are rational utility optimizers, has difficulty capturing the actual behaviour of asset prices, as numerous persistent patterns in stock returns that contradict the rational models have been documented. In particular, two such asset pricing "anomalies" have attracted a considerable amount of attention: the *size effect* and the *value effect*.

A faction of theorists began to fiercely question the fundamentals that underpin the neoclassical school (*inter alia* Black, 1986; De Bondt and Thaler, 1985). In their view, investor irrationality, often dubbed "investor sentiment", has an impact on security prices. However, until very recently, this new *behavioural* school of finance has not been popular as it provided little formal theory on asset price formation[2].

Consequently, for a number of years the focus of the discipline of asset pricing was shifted away from theoretical modeling towards empirical analysis. Financial practitioners have become reliant on statistical constructs with which they aimed to describe the behaviour of asset prices (*inter alia* Chen, Roll and Ross, 1986; Connor and Korajczyk, 1988). One empirically derived asset pricing model appears in Fama and French (1993). The authors have formally incorporated the size and the value effects into an asset pricing equation and they have found the model to be particularly good at pricing many types of stocks. Since its inception, the model has become a staple tool in academic and professional practice (Brealey and Myers, 2000).

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[1] The seminal work in the field consist of *inter alia* Markowitz (1952), Sharpe (1964), Lintner (1965), Fama (1970), Black, (1972), Merton (1973), Ross, (1976) and Roll (1977)

[2] Formal behavioural theory of asset pricing began to form with the models of De Long, Shleifer, Summers and Waldman (1990a, 1990b, 1991). However, this series of papers did not specify asset pricing formulas. Models which do specify asset prices appear in *inter alia* Barberis, Shleifer and Vishny (1998); Daniel, Hirshleifer and Subrahmanyam (1998, 2001); Hong and Stein (1999); Barberis and Shleifer (2003); Peng and Xiong (2006).

1.2 Purpose and objectives of the study

The purpose of this thesis is to motivate and assess the feasibility of the three factor model proposed in Fama and French (1993) for the Johannesburg Stock Exchange (henceforth, the JSE). Before the model is tested, however, a number of empirical stylised facts, which motivated Fama and French (1993) to build their model in the first place, need to be confirmed. In particular, the existence of the size and the value effects must be validated and the rejection of the rational models needs to be shown.

Consequently, the empirical analysis of this thesis is broken down into three parts. In Part I, the size and the value effects are analysed. In Part II, poor ability of rational asset pricing models to explain these "anomalies" is confirmed. Once the rational models are rejected, the three factor model is built in Part III. Of course, if the empirical evidence does not support construction of the model, its formulation will not be undertaken.

1.3 Formal Statement of the Hypotheses

The hypotheses tested in Part I of the empirical analysis:

Hypothesis 1.1: *The size and the value effect do not exist on the JSE, as returns of firms listed on the exchange cannot be predicted by their size or their value-growth indicator. If returns are predictable with these characteristics, it is a result of market microstructure effects.*

Hypothesis 1.2: *The size effect is not independent of the value effect.*

Hypothesis 1.3: *None of the value-growth indicators is a consistently better predictor of returns.*

The hypotheses tested in Part II of the empirical analysis:

Hypothesis 2.1: *Any predictability of asset returns with their size or a value-growth indicator is due to risk and it dissipates after adjustment for risk.*

The hypotheses tested in Part III of the empirical analysis:

Hypothesis 3.1: *The three factor model of Fama and French (1993), or its variant, can price assets that encapsulate the size and the value effect.*

Hypothesis 3.2: *The three factor model of Fama and French (1993), or its variant, is not superior in explaining stock returns when compared to the Capital Asset Pricing Model or a model presented in van Rensburg and Slaney (1997).*

Hypothesis 3.3: *The size and the value effects persist after an adjustment for risk with the three factor model of Fama and French (1993).*

1.4 Methodology

Applied econometric theory in finance has ballooned into a comprehensive body of knowledge and specific methods that relate to asset pricing have been developed. They can be broadly classified into three groups: portfolio tests, time-series tests, and cross-sectional tests; each of these methods will be applied in this thesis. Use of simulated portfolios is an informal, but intuitive, way to augment rigorous statistical procedure. All the time-series are performed with Seemingly Unrelated Regressions (henceforth, SURE) systems. The cross-sectional tests are conducted with the procedures developed by Fama and MacBeth (1973) (henceforth, Fama-MacBeth test) and in Chapter 12 of Cochrane (2001). All tests are undertaken in the "*beta-return*"[3] format[4].

Throughout the empirical analysis an emphasis is made on statistical precision. In particular, since the Generalised Method of Moments (henceforth, GMM) methodology requires few statistical assumptions (Cochrane, 2001), many of the time-series or cross-sectional regressions are mapped into a GMM system[5]. Although the coefficient estimates are identical to the ones obtained from the OLS and its variants, the standard errors computed with GMM are robust to virtually any correlation structure of the data.

The emphasis on the statistical precision extends to tests that cannot (easily) be mapped into GMM. For instance, many of the standard errors in the cross-sectional Fama-MacBeth tests are computed with the correction proposed by Newey and West (1987), while some methods of risk-adjustment employ the powerful method in Brennan, Chordia and Subrahmanyam (1998).

It must be noted that the dataset employed in the thesis is considered to be large, as it includes more than twice the data points than other studies that are similar to the one undertaken in this thesis (e.g. van Rensburg and Robertson, 2003a 2003b). A major weakness of the tests in this thesis is that the return data is not professionally computed, but is put together manually by the author[6].

1.5 Report Outline

Apart from the introduction, there are five additional chapters in the thesis. Chapter 2 outlines the basic concepts of asset pricing theory, with an exclusive focus on linear factor models in the "*beta-return*" format. Subsequently, the efficient

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[3] The more advanced *stochastic discount factor* approach is not used in the tests as it is new and rather complex, while, given that the three-factor model is linear, it does not add any efficiency in econometric estimation (Jagannathan and Wang, 2002).

[4] Tests that simultaneously combine time-series and cross-sectional tests have been explored, and their results are available on request. They are removed from the formal discussion as it is deemed that microstructure of the JSE is, in particular case, not conducive to such complex econometric analysis.

[5] The basics of financial econometrics are discussed in Cochrane (2001). It is suggested that readers familiarize themselves with these methods, as the literature review often refers to them.

[6] In particular, it is believed that the set used in van Rensburg and Robertson (2003a; 2003b) and Auret and Sinclaire (2006) is of higher quality, as these authors use high quality return data computed by the BARRA Corporation.

market hypothesis is presented and critiqued. Lastly, behavioural finance is introduced.

The purpose of Chapter 3 is to show the anatomies of the size effect, the value effect and the empirical model of Fama and French (1993). The chapter also examines literature that links these phenomena to several theoretical frameworks that either assume total investor rationality or allow for irrational sentiment. The focus of this discussion will lean toward the value premium, as the size effect is smaller, is less robust, and has been largely explained. The value premium, however, continues to remain a puzzle. Throughout the review it is assumed that the reader has an understanding of concepts presented in Chapter 2. It is also assumed that the reader is familiar with the structure and the output of time-series and cross-sectional asset pricing tests. If this is not so, these methods are comprehensively detailed in Cochrane (2001).

In Chapter 4, the formal motivation for the methodology and tests is put forward. The data collection and the methodology used in the study are also presented. Chapter 5 shows the empirical results. Chapter 6 summarises and discusses the results and outlines ideas for future research.

1.6 Limitations of the Study

The field of asset pricing is truly vast and it has many branches[7]. In addition, the model of Fama and French (1993), and the related “anomalies”, are well researched. Consequently, a complete review and exhaustive analysis of the topic is not feasible and certainly outside the scope of a single thesis. Thus, the study has to be limited in a number of ways.

The literature review will briefly explore different types of “anomalies”. It, however, is primarily concerned with the size and the value effects, as these are germane to the model of Fama and French (1993). And, only these two “anomalies” are explored in the empirical results. Also, the underlining economics of the phenomena are discussed in review and some indicative tests that discern between

[7] Some examples are: consumption-based asset pricing, mean-variance-based asset pricing, empirical asset pricing, behavioural asset pricing, “microeconomic” asset pricing, studies on aggregate risk-return, studies on “anomalies” and studies on market microstructure.

behavioural and rational explanations for the size and the value effect are undertaken. However, thorough tests of behavioural theories are not performed.

In addition, the focus of the asset pricing tests rests exclusively with the three factor model of Fama and French (1993), the Capital Asset Pricing Model and the two-factor model of van Rensburg and Slaney (1997). Specifically, consumption-based models of asset pricing are not reviewed or tested as they have met with poor empirical support[8]. Other empirical models, like the ones in Chan, Roll and Ross, (1986) and Connor and Korajczyk (1988), do not fare better than the rational models they try to replace. Thus, discussion and tests of these models are not undertaken. Also, a number of asset pricing specifications that seem to "work well" are omitted from the tests[9], as assembly of these models is prohibitively difficult given the data constraints. Besides, the focus of this thesis is on the three factor model. It is not an exhaustive discussion of asset pricing on the JSE.

[8] Cochrane (2001) provides a discussion on the topic.
[9] Some examples are: Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Campbell and Vuolteenaho (2004), Brennan, Wang and Xia (2004) and Chordia and Shivakumar (2006), Petkova (2006), Lettau and Ludvigson (2001b).

CHAPTER 2: FUNDAMENTAL CONCEPTS

2.1 A Brief Outline of the Theory of Factor Asset Pricing Models

2.1.1 Mean-Variance Efficiency and the Capital Asset Pricing Model (the CAPM)

Arguably, the development of portfolio mathematics by Harry Markowitz in 1952 is one of the initial breakthroughs that began the era of modern finance. He bases his argument on a premise that “the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing” (Markowitz, 1952, p 77). He formally introduces the concept of the mean-variance efficiency: a combination of risky securities (share portfolio) is said to be efficient if it possesses the desirable property of yielding the maximum expected return while imposing a minimum level of risk (or variance) onto the investor. Consequently, he develops a concept of the *efficient frontier,* which is a locus of investment opportunities that a mean-variance optimising investor would consider optimal.

Sharpe (1964), following Tobin (1958), extends the concept of the efficient frontier by including an asset (henceforth, the risk-free rate) that offers a constant rate of return in all states of the world. This asset allows investors to discard all but one portfolio of risky assets from their investment opportunity set. This portfolio is unique, because when it is combined with the risk-free asset, it creates yet another set of investment opportunities that supersede the efficient frontier of risky assets, as it allows for even higher returns given any level of risk. In effect, all rational investors who minimise risk and maximise return would hold a portfolio that would be a linear combination of the unique portfolio of risky assets (often referred to as the *tangent portfolio*) and the risk-free asset.

A germane property of the tangency portfolio is that, of all the other portfolios of risky assets, it offers the highest expected return and excess of the risk-free rate at the lowest level of risk. Actually, since the ratio of an asset’s excess expected return and its variance is often referred to as the Sharpe ratio, the tangency portfolio is a portfolio of risky assets that has the highest *ex ante* Sharpe ratio. More importantly, this analysis shows that the entire investment opportunity set can be summarised by two parameters: the risk-free rate, and the maximum attainable Sharpe ratio.

Sharpe (1964) and Lintner (1965) extend the result discussed above into an equilibrium model for asset pricing. At first, they identify the nature of the tangency portfolio by noting that, since all investors hold the same portfolio of risky assets, market clearing prices require the tangency portfolio to be a composite of all risky assets in the economy and, that investors mix this portfolio with the risk-free rate to calibrate the risk they wish to bear. Then the authors posit that the risk of any asset in the economy is not its variance, but the amount of risk it adds to a person's total risk; and, that this incremental risk is measured by a given asset's co-variance with the market portfolio. Since the demand for an asset is determined by its risk, and risky assets are in fixed supply, any asset's price, and hence its return, is a function of its co-variance with the market portfolio (its incremental risk). Formally, Sharpe (1964) and Lintner (1965) show that

$$E_t \;\; r_{i,t+1} \;\; = r_f + \beta_i \lambda^M \tag{2.1}$$

Equation (2.1) is the static Capital Asset Pricing Model (henceforth, the static CAPM). It states that the expected return on an asset is *exclusively* a linear function of its market beta, β_i, and the market premium, λ_M. Beta is the measure of the asset's market risk and is defined as the ratio of the asset's co-variance with the market and the market's variance[10]:

$$\beta_i = \frac{Cov \;\; r_i, r_M}{Var \;\; r_M} \tag{2.2}$$

The market premium is the expected market return in excess of the risk-free rate.

The result in Equation 2.1 rests on a number of assumptions. First, investors want to maximise their expected returns and are averse to risk. Second, variance of the asset's return is a sufficient parameter to summarise its risk - meaning that the distribution of returns is jointly normal. Third, investors have homogeneous beliefs, thus they all arrive at the same estimate of each asset's expected return and its variance structure. Fourth, investors can take large short and long positions in every

[10] The terms used in this thesis for asset's covariance with an asset pricing factor are: a "slope", a "beta", a "factor loading", or simply, a "loading".

asset. Fifth, there are no taxes or transaction costs. And lastly, that the investment horizon of all investors consists of a single period.

Many of these assumptions do not hold in practice. However, relaxing some of them often does not materially change the implications of the model. For instance, Cochrane (2001) shows that CAPM still holds even if returns are not jointly normal under certain assumptions of investor preference for risk. Also, Cochrane (2001) shows that, given that the efficient frontier is constant, the static version of the model prices assets in a multi-period setting. The effect of heterogeneous beliefs is studied *inter alia* by Williams (1977), and he notes that CAPM is valid as long as aggregate estimates of first and second moments of returns are not biased by differences in investor beliefs. Most importantly, Black (1972) develops a model that relaxes the most unrealistic assumption of limitless short positions. His version of CAPM,

$$E_t\left(r_{i,t+1}\right) = E\left(r_z\right) + \beta_i \lambda^{*M} \tag{2.3}$$

is not much different from Equation 2.1. The risk-free rate is simply replaced by a portfolio of risky assets that has a market beta of zero, $E(r_z)$, and the market premium is defined as the expected return on the market in excess of the zero-beta rate.

Nonetheless, the static CAPM provides a poor description of *average realised* returns. Fama and French (1992) show that there is only a weak positive relationship between average returns of a large cross-section of securities and their estimated market betas. However, Lo and MacKinlay (1990a), Kothari, Shanken and Sloan (1995) and Kim (1997) show that Fama and French's (1992) results occur thanks to the methodology they employ. Nonetheless, Brennan, Wang and Xia (2004) test the CAPM on a set of industry-sorted portfolios and do find a positive relationship between average returns and industry market betas. However, in their tests, the differences between the returns predicted by the CAPM and the realised returns are too large to validate the model.

CAPM's poor performance can stem from a variety of reasons. For instance, Elton (1999) shows that tests may be misspecified because *average returns* are very poor estimates of *expected returns*. Kim (1997) argues that CAPM fails in empirical tests because of the error-in-variables problem, which arises because market betas are unobservable and cannot be estimated with high levels of precision. Alternatively, Roll (1977) argues that the market portfolio is unobservable and, as a consequence, the CAPM is untestable.

More importantly, some of the assumptions underlying the model are certainly violated in practice. In particular, the investment opportunity set is stochastic in nature and the moments of asset returns vary through time - both of these ideas are simply assumed away in the static CAPM. In addition, investors are not homogeneous: they may fail to hold the optimal tangency portfolio because of their beliefs or investment preferences (Fama and French, 2004).

Consequently, the remainder of the discussion on rational asset pricing theory focuses on pricing models akin to the CAPM, but derived under more realistic assumptions. The distinguishing feature of these models is that there is more than one relevant variable that is included in the specification for expected returns. Thus, these asset pricing models are known as linear *multi-factor* models. Any variable that is thought to be important in determining asset prices is often referred to in literature as a *state variable,* or, more often, as a *factor.* However, the central predation of the CAPM and the mean-variance framework should not be lost on the reader. It states that the expected return of an asset is a function of its *systematic risk;* the additional factors simply pickup types of risk stemming from other sources than the market.

2.1.2 The "Augmented" CAPM (the "A"CAPM)

A portfolio comprised solely of equities may be a poor proxy for the true market portfolio, as it excludes two important asset classes. In particular, most of the income that an average individual receives in a lifetime is in the form of salaries or wages. Consequently, Mayers (1972) shows that omission of human capital from a test of the static CAPM, at least in theory, can falsely reject the model. The other important asset that is surely omitted from the market proxy is debt, which is untraded or is not directly observable (Ferguson and Shockley, 2003).

Omission of assets from the market proxy does not invalidate CAPM. Roll (1977) shows that, given the assumptions of the CAPM, presented in the previous section, the model *must* hold. Put differently, the linear relationship between an asset's expected return and its beta with the tangency portfolio is a mathematical identity. Actually, Ferguson and Shockley (2003) derive a simple specification for the impact of omission of an asset class from the proxy of the market portfolio. They show that estimation of market betas with an imperfect proxy results in biased estimators. The degree of error is positively related to the size of the true market beta of the asset, and its beta with the omitted assets from the market proxy. They also show that the CAPM can be restored if the omitted assets are known and return on them can be measured. Consequently, it can be shown that expected return on assets in the "Augmented" CAPM is a multifactor model:

$$E_t \;\; r_{i,t+1} \;\; = r_f + \beta_i^E \lambda^E + \sum_{o=1}^{K} \beta_i^o \lambda^o \tag{2.4}$$

In short, the static CAPM, represented by the first two terms on the right- hand side of the equation, is augmented with a number of variables. Each variable *O* represents an asset that is omitted from the equity portfolio and the associated betas are:

$$\beta_j^o = \frac{Cov \;\; r_i, r_o}{Var \;\; r_o} \tag{2.5}$$

The λ_o are the premia related to the missing assets, each being proportional to the true market's premium. Some tests of the model in this form can be seen in Jagannathan and Wang (1996), Lettau and Ludvigson (2001b) and Ferguson and Shockley (2003).

2.1.3 The Market Premium

An assumption of the CAPM, which is surely violated in practice, is that the efficient frontier is non-stochastic. However, the inclusion of a time dimension into the mean-variance framework removes much of the simplicity that makes the CAPM so attractive. In order to keep the analysis palatable, theorists focused on three salient aspects of non-stationary asset moments, each with a progressively more profound impact on asset pricing. The first aspect is the time-variability in the market premium; the second considers the impact of variability in assets' market betas. Lastly, Merton (1973) shows that relocating the mean-variance analysis into continuous time introduces a source of risk, in addition to return variance, that a representative investor aims to unload.

Over the last twenty years, American financial economists have unearthed a number of variables that can in fact predict the return of the aggregate equity portfolio. Consider a regression of a set of variables onto a lead of the realised market return (excess of the risk-free rate). The series of values predicted by the regression would be interpreted as the market premium. Of course, any predictability of the market return can be a consequence of data mining and performance of any one variable may not hold outside the sample. Nonetheless, after extensive research, a consensus has been reached on the identity of factors that drive the market; these variables are often known as *instruments for expected market return*. Some well-known examples include[11]:

1. The *short-term interest rate*. It is negatively related to market return (Fama and Schwert, 1973).
2. The *aggregate dividend yield,* defined as the sum of all dividends paid by the stocks in the index in 12 months scaled by value of the index. It is positively related to market return (Campbell and Shiller, 1988).
3. The *default spread,* defined as the difference between a yield on a long-term Treasury bond (or other 'safe' bond) and a yield on low-grade long-term corporate bonds (or other 'risky' bonds). The spread is positively related to market return (Fama and French, 1989).
4. The *term spread*, defined as the difference between a long-term Treasury bond yield and a short-term Treasury bond yield. This spread is negatively related to market return (Fama and French, 1989).

Algebraically, in order to estimate the market premium, the following regression is run:

$$r_{M,t} - r_{f,t} = \sum_{j=1}^{L} \hat{d}_j z_{j,t-1} + e_i \rightarrow \lambda_{M,t} = \sum_{j=1}^{L} d_j z_{j,t-1} \qquad (2.6)$$

The variables z_j (j = 1,2,3…K) are the different instruments for the expected market return. For instance, Petkova and Zhang (2005) apply Equation (2.6) to model the market premium.

In professional finance practice, however, the market premium is rarely estimated with this method, as its forecasting power wanes with horizons longer than one year. In addition, an estimated value of the market premium is a function of a

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[11] This list is incomplete. For instance, Lettau and Ludvigson (2001a) construct a variable, *cay,* that has a strong ability to forecast returns. (Definition of *cay* is complex, but it can be stated as a deviation of consumption from wealth.) The return on portfolio of small firm with high book-to-market ratio (defined in Chapter 3) can forecast returns (Campbell and Vuolteenaho, 2004). While Kothari and Shanken (1997) show that aggregate book-to-market ratio of the market can also serve as an instrument of expected returns.

particular set of instruments used in a given predictive regression, and the exact specification of the model and the precise definition of the instruments appears to be a matter of taste, and not theory. Thus, the estimates for the premium can differ greatly.

2.1.4 The Conditional CAPM (the CCAPM)

The central idea behind the CCAPM is that assets' market betas vary through time. Chan and Chen (1988) were among the first to observe that market betas exhibit a considerable amount of time variation, and Ferson and Harvey (1991) show that market betas of portfolios formed with industries exhibit strong variation. In particular, Ang and Chan (2005), in a sample period spanning 75 years, show that the standard deviation of the time-series of estimated market betas may be as much as 0.38. Lewellen and Nagel (2006) extend their analysis to include a large variety of assets, but in a shorter period, and find similar results[12].

Time variability of betas gives rise to serious concerns about observability of this risk measure and implementation of the CCAPM. However, Chan and Chen (1988) note that, if assumptions about the stochastic process behind betas is made, then the conditional model can be expressed and tested in an unconditional form. Jagannathan and Wang (1996) derive a robust unconditional representation of the CCAPM. They start by defining the Conditional CAPM, in a conditional form, with

$$E_t\left[r_{i,t+1}\right] = r_{f,t} + \beta_{i,t}\lambda_t^M \tag{2.7}$$

where the true conditional beta of the model is

[12] There are theoretical reasons why market betas change with market conditions, and why this variability is not symmetric among firms. The central prediction of Modigliani and Miller's (1958) Proposition II is that changing leverage of a firm, measured at market values, will change the risk of its equity. Since a shift in market prices shifts market leverage, the risk (or the beta) of asset's equity will be correlated with market's movements. For example, Berk, Green and Naik (1999) show that market betas will exhibit variation with the business cycle. In particular, they argue that during periods of low interest rates, and thus low discount rates, firms, on average, would take on many risky projects, and thus exhibit high betas. However, opportunities for growth for these firms eventually run out, and few new projects can be taken. But, the exiting projects can be lost. Thus, this asymmetry between growth and decay would lead to mean-revision of firms' betas. In a similar model, Zhang (2005) derives a model where firms that have little assets in place (fixed assets) see their betas decline during market downturns. He points out that contraction in firm's productive capacity is more expensive than expansion of it. Thus, firms which have few fixed assets have the flexibility of cutting back on investment, a cheaper alternative to reduction of assets in place, which is a situation other firms have to face.

$$\beta_{i,t} = \frac{Cov_t\left(r_{it}, r_{Mt}\right)}{Var_t\left(r_{Mt}\right)} \tag{2.8}$$

Equation (2.1) and Equation (2.2) are similar to Equation (2.7) and Equation (2.8), respectively, but now all the terms have a time subscript that emphasises time-variability of the moments.

This model, however, cannot be easily applied in practice, because an exact specification of the process underlying market betas is not known and it is often specified with an assumption. Lewellen and Nagel (2006) show evidence that the instruments for market premium have forecasting power for market betas. Consequently, Jagannathan and Wang (1996) assume that a conditional beta is a function of the market risk premium. The authors go on to show that the unconditional expected return of an asset is a function of the time-series mean of its market beta, denoted $\beta_{\mu,i}$, and a parameter υ_i which is a beta's sensitivity to market premium. Thus they define the conditional CAPM as:

$$E_t\left(r_{i,t+1}\right) = r_{f,\mu} + \beta_i^{\mu}\lambda^{M,\mu} + \sigma_{\gamma_M}^2\upsilon_i \tag{2.9}$$

One can interpret υ_i as "beta's beta", meaning it is the sensitivity of the market beta to changes in the business cycle. All the terms with μ subscript represent time-series averages. Note that there are no time subscripts in the Equation (2.9); the model is in unconditional form.

However, the parameters in equation (2.9) are not directly observable. Actually, as Petkova and Zhang (2005) show, a rather complicated econometric model and a long time-series of returns is needed to implement the model in this form. As a result, Jagannathan and Wang (1996) use some algebraic shenanigans to derive:

$$E_t\left(r_{i,t+1}\right) = \gamma_0 + \beta_i\gamma^M + \beta_i^{\lambda_M}\gamma^{\lambda_M} \tag{2.10}$$

The advantage of this model is that the β_i is the familiar market beta of the static (unconditional) CAPM. The second beta in the equation represents sensitivity of the return of an asset to change in the *market premium*. The γ's are the new representations of the "premia", which are specified in the Appendix of Jagannathan and Wang (1996).

The model is rarely tested in such form. It has been discussed that the market premium is a function of many instrumental variables, thus, the CCAPM is usually specified as:

$$E_t\left(r_{i,t+1}\right) = \gamma_0 + \beta_i \gamma^M + \sum_{z=1}^{L} \beta_i^z \lambda_z \quad (2.11)$$ [13]

Equation (2.11) says that the expected return on an asset is a linear function of an asset's unconditional market beta and its betas with different instruments for the expected market return. The λ_j's are the premia associated with the different instruments for expected returns.

2.1.5 The Intertemporal CAPM (the ICAPM)

The models presented thus far offer a level of pragmatism, but fall short of theoretical purity advocated in Cochrane (2001). The intertemporal CAPM, derived by Merton (1973), has a stronger footing in economic theory, as it can be represented and tested in the linear "beta-return" method that is most readily applied in practice.

In the ICAPM, the mean-variance analysis is extended as the "ICAPM investors" care, not only about the return they receive and the return variance they need to bear, but they also consider their long-term wealth (Merton, 1973; Cochrane, 2001). As a result, a second type of risk, above that of variance, is included in the analysis. It is associated with changes in the instantaneous investment opportunity set, as its variation alters the expected risk-return trade-off in the future. For example, an increase in the volatility of market portfolio would force people, given their level of risk aversion, to lower the amount of equity they hold and thus accept lower returns. Investors dislike this uncertainty and are willing to hedge against it. In particular, they will pay a premium for stocks that move against unfavourable shifts in the mean-variance frontier. Hence, keeping betas constant, the price of stocks that unload risk of unwelcome shifts in the efficient frontier will be higher and their expected returns lower (Fama, 1996; Cochrane, 2001). It follows that *unexpected* changes in any of the economic quantities that describe the investment opportunity set would constitute a source of risk to an average investor.

[13] In practice, a time-series regression of the conditional CAPM is:

$$r_{i,t} - r_{f,t} = \hat{a}_0 + \sum_{j=1}^{K} \hat{a}_{j,i} z_{j,t-1} + \hat{b}_{0,i}\left(r_{M,t} - r_{f,t-1}\right) + \sum_{j=1}^{K} \hat{b}_{j,i} z_{j,t-1}\left(r_{M,t} - r_{f,t-1}\right) + \varepsilon_{i,t}$$

It is a regression of asset's return onto the market return, the instrument for the market premium, and the interactions of the market return with the instruments for the market premium. Lattau and Ludvigson (2001a) and Ferson and Harvey (1999) are good examples for such a model.

More precisely, Cochrane (2001) and Campbell (1996) show that the expected return on an asset is:

$$E_t \;\; r_{i,t+1} \;\; = r_{f,t} + \beta_i \lambda^{rra} + \sum_{h=1}^{M} \beta_i^h \lambda^h \tag{2.12}$$

The first beta on the left-hand side of the equation is the market beta, essentially the same as the one in the static CAPM. The premium, however, is not equivalent to the market premium, but is a function of the coefficient of risk aversion (the willingness of investors to bear risk) and the variance of the market portfolio. The betas in the summation term are:

$$\beta_i^h = \frac{Cov \;\; r_{i,t}, u_{h,t}}{Var \;\; u_{h,t}} \tag{2.13}$$

The *u* terms are the innovations in the variables that trace out the path of the efficient frontier and are often referred to as news or shocks. The λ_hs are the premia associated with these risks.

The ICAPM does not explicitly identify the state variables that are included in the model. Fama (1991) alluded to the ICAPM as a “fishing license”, meaning that researchers often add *ad hoc* variables into some multi-factor asset pricing equation and justify their choice of variables with the ICAPM. However, Cochrane (2001) notes that state variables of the ICAPM must themselves be able to forecast the shape of the mean-variance frontier, and this requirement restricts the universe of plausible factors in the multifactor ICAPM equation. Brennan *et al.* (2004) assume that the opportunity set can be exhaustively described with the risk-free rate, the variance of the market portfolio and the premium of the market portfolio, where the ratio of the latter two variables is the Sharpe ratio. Consequently, in simple terms, Equation (2.12) states that an asset’s co-variation with unexpected shifts in either the risk-free rate or the Sharpe ratio must be included, in addition to the market term, in the pricing equation.

One way of specifying factors that constitute Equation (2.12) is to use economic theory and solve for the factors algebraically. For instance Brennan *et al.* (2004) define the Sharpe ratio in terms of other observable variables and synthetically estimate its time-series. They use a similar procedure to compute the evolution of the risk-free rate. However, such an approach is seldom applied. Most researchers use the instrumental variables for expected returns, defined above, and insert the innovations in those variables as the relevant pricing factors in the ICAPM. This practice is motivated by the fact that these variables can forecast the return on the market, its variance, and the interest rate.

Consequently, the specifications for the ICAPM in Equation (2.12) and the CCAPM in Equation (2.11) seem similar, as they both include the market beta and a host of terms that represent the co-variance of returns with variables that proxy for the market premium. The difference is that, in the CCAPM the additional pricing factors are lags of instruments for the market premium, but in the ICAPM the factors are innovations in them. At times, this difference is negligible, as the factors comprise of financial returns, which are unpredictable in nature and strongly co-vary with their own innovations. As a result, the empirical application of the two models may be very similar.

The strong footing of the ICAPM in economic theory is an attractive feature of the ICAPM. Campbell (1996) shows that the size of premia in the ICAPM is linked by the coefficient of the relative risk aversion; and, the premium on each factor is directly related to the power the variable has to forecast the efficient frontier. Such restrictions are important as they guard against empirical specifications that support an asset pricing model, even if it is false.

2.1.6 A Final Note on Multifactor Models

An astute reader will notice that the exposition of Ross' (1976) Arbitrage Pricing Theory (APT) has been omitted; the APT simply states that

$$E_t \left(r_{i,t+1} \right) = \gamma_0 + \sum_{f=1}^{N} \beta_i^f \lambda^f \tag{2.14}$$

The first term is a zero-beta rate and the remainder of the pricing terms represent arbitrary specified asset pricing factors.

Two types of models have surfaced in the literature. The first is a statistical construct ("statistical" APT), where pricing factors are extracted from the return variance-co-variance matrix. The second includes macroeconomic variables in the pricing equation ("macroeconomic" APT).

Although originally the model had strong footing in statistical theory, it has been losing popularity in the finance literature[14] as it is used as a justification for including any factor (variable) into the asset pricing formula. Actually, Cochrane (2001) defined what ought to be a priced factor; it is a source of risk that an *average* investor does not wish to hold, but cannot unload[15]. However, it has become commonplace to empirically determine the suitability of each factor in an APT pricing

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[14] First, it lacks a footing in the economic theory, which makes it convincingly unimplementable. Second, standard version of APT fails to "explain" the asset pricing anomalies. Any correct model in economics must be able to describe reality. Third, APT is based on an assumption that is almost definitely violated in practice. In particular it requires that the asset "being priced" does not exhibit unsystematic (asset specific) variation. Cochrane (2001) shows that if an asset does possess such risk, APT cannot accurately price assets.

[15] To illustrate, consider a rise in prices of commodities such oil, gold, and other metals. It could be good news to some South Africans who work in, or profit from, the mining industry. Let's call them R-investors. On the other hand, if the rise in prices of commodities fuels inflationary pressures, and the Reserve Bank decides to raise interest rates. Many other South Africans, the F-investors, may see their consumption fall and are made worse-off?. Now, consider asset A that co-varies strongly with a basket of commodities. And, by the intuition of the CAPM, everybody in South Africa holds this asset. Asset A is particularly valuable to the F-investors, because movements in the asset's price hedges to movements in commodities, and thus their consumption. They would continue to buy the asset until any decrease in consumption, brought about by increase in interest rates, would be offset by the increase in wealth caused by increase in price of asset A. The R-investors do not want asset A. If commodity prices fall, they lose out on their investment and their income, which stems from commodity cycles also declines. What can be said about the premium on the commodity factor? If there are more R-investors in South Africa than assets which co-vary with the returns to commodities will have low prices and high returns; the resource factor will have a positive premium. The opposite is true in the case where there are more F-investors in South Africa. If, on average, none of the groups is larger, the factor will not be priced, despite the fact that returns of many assets co-vary with it.

equation. The statistical significance, measured with a Student's *t* test, of a factor's premium, ascertains its importance.

Recent evidence suggests that such methodology is seriously flawed. Kan and Zhang (1999) test a premium of a factor that is uncorrelated with returns. Astonishingly, they show that a factor that, by construction, ought to be omitted from the pricing equation is more likely to be considered "important" in tests that are thought to be more powerful. Jagannathan and Wang (1998) extend this analysis and show that *t*-statistics on premium of a factor that, by construction, yields zero premium, are much too large.

Yet these statistical concerns abstract from the most damning property of asset pricing models derived with empirical methods. There is strong evidence that the second-moments of returns vary through time (De Bondt and Thaler, 1985; Fama and French, 1997; 2006). Therefore, even if a correct model works in a specific sample, it is almost sure not to work outside of it. Here is where the APT fails and the ICAPM can succeed. Only a model that is derived from the mean-variance analysis (or more consumption-investment problems of the investor) can show the finance practitioner a set of factors that have the best *ex ante* power to forecast returns.

2.2 From Market Efficiency to Behavioural Finance

2.2.1 Market Efficiency

All of the asset pricing theory described above rests on an assumption that investors in the real world are rational optimisers; they aim to maximise their returns and minimise their risks. Investors are rational in the sense that they correctly estimate the expected return and the co-variance structure of every financial asset, and, consequently, asset prices perfectly correspond to the prediction of the true asset pricing model. Fama (1970) dubs this situation *the efficient market hypothesis* (EMH).

Most undergraduate finance textbooks follow Fama (1970) and discuss the three forms of the EMH: weak, semi-strong, and strong forms. The weak form of market efficiency states that risk-adjusted returns cannot be predicted with historical data. The semi-strong form states that these returns cannot be predicted with publicly available information. The strong form states that risk-adjusted returns cannot be predicted at all. In its purest form, the strong form is always false as much of the information pertaining to an asset is exclusively known to a group of "insiders" who can predict prices from their privately held knowledge. Nonetheless, the texts often do not emphasise the fact that Fama's (1970) argument applies only to *risk-adjusted returns*. The three forms are certainly violated if applied to *raw returns.* Variables that measure risk, such as market betas, or are correlated with risk measures, can, by definition, predict asset returns (Cochrane, 2001).

The central prediction of the efficient market hypothesis is that financial assets are always quoted at a "fair" price, defined as the stream of an asset's' expected cashflows discounted at the appropriate discount rate. Consequently, one of the implications of the EMH is that the price of an asset must change in response to new information about an asset's future cash flow or its discount rate (Campbell and Vuolteenaho, 2004); and, any adjustment in price occurs quickly, often within minutes of an *informational shock.* However, prices may not change if there is no news reaching the market.

Markets are efficient thanks to *arbitrage*, which, in its purest form, is defined as the simultaneous purchase and sale of a number of financial securities that costs zero to set up and results in a risk-less profit. Market efficiency is based on an argument that when investors spot a security that is, for instance, overpriced relative to its fundamental value, they will sell, or sell short, this security and cover their risk with the purchase of an asset that has a nearly identical cashflow to the mispriced asset. Of course, the idea of two equities that offer the same cash flow may be a difficult one to believe. Thus, a more realistic version of arbitrage, dubbed *risk arbitrage*, occurs when investors sell, or sell short, overpriced assets. In such a way they expect to earn positive *risk-adjusted* returns (Shleifer, 2000).

Arbitrage would occur and, consequently, markets would be efficient only if all, or a sufficiently large number, of investors are rational. Friedman (1953) argues that although people, in general, are influenced by emotion and act on misinformation, investors, in particular, must be rational. He notes that people who irrationally buy overpriced assets and sell underpriced ones always find an investor who takes the opposite side of the trade. But, such trades are a zero-sum game. The rational investors profit at the expense of the irrational traders who cannot lose money forever, and, after a series of such trades, are eventually driven out of the market. In the literature, the rational investors are referred to as *arbitrageurs* and the investors who are irrational or misinformed are dubbed *noise traders* (Black, 1986).

The evidence in favour of market efficiency is vast. Actually, many undergraduate finance textbooks list a plethora of studies that document the incredible speed of adjustment of prices to news, the poor profits earned from trading strategies based on historical price information and tendency of stock returns to follow a random walk (a statistical model that implies unpredictability of stock returns). Nonetheless, the EMH is not a paradigm that exhaustively describes financial markets and some salient examples of violation of market efficiently are presented next.

2.2.2 Four Tales of Market Inefficiency

Impact of Public Non-News

Huberman and Regev (2001) study a situation where the appearance of an article describing the discovery of a cancer-curing drug resulted in a one-day return of 330% to a stock that had the licensing rights to that medicine. This price change, by itself, is not too surprising. However, the news of this discovery had already been made public five months prior to the day of this exuberant return. In fact, Huberman and Regev (2001) note that the initial news had been announced by the company itself and a series of television segments had covered the story. Certainly, company press releases and pieces in the public media constitute the type of information that, according to the EMH, ought to be most readily used by investors. Thus, the semi-strong version of the EMH had been grossly violated because market prices moved by a hefty amount in response to what Shleifer (2000) dubs “stale” information, which, by the intuition of the EMH, may not move prices.

The violation of the EMH would not have been deep if the immense return, plausibly caused by irrational traders, was quickly reversed by the rational ones. However, the rise in the drug company’s shares was permanent. In addition, many other firms, which had no claim on the drug, but were in the same industry, had seen their share prices rise at the same time.

Market’s Appetite for Internet Stocks in the Late 1990s.

The EMH predicts that share prices will only react to news that contains information about risk or expected cashflow of an asset. Consequently, it can be argued that an announcement of a change in name of a company would not be material to either parameter that determines prices. Actually, Bosch and Hirschey (1989) find that a small, but statistically insignificant, positive return is associated with a name change.

Cooper, Dimitrov and Rau (2001) look at a specific type of name change: the addition of “.com” to a firm’s name at the height of the internet bubble. The authors find that an average risk-adjusted return of a stock that is announcing such name change is about 53% in one day! Of course, the name change can signal a change in company strategy to one that is (or is thought to be) more profitable. However, Cooper *et al.* (2001) sort firms in their sample into groups according to the line of business the firm is conducting at the time of the name change. They find that firms that are already involved in the internet exhibit the largest return on the day of the announcement and firms that are not primarily involved in e-commerce yield a risk-adjusted return of 23% on the day of the announcement.

This occurrence strongly rejects the EMH, as it seems that a firm can boost its share price by manipulating a characteristic which influences investor sentiment but is unrelated to fundamental value. Perhaps a reversal of the announcement returns in the months subsequent to the event would imply that the forces of arbitrage restored rational pricing. However, Cooper *et al.* (2001) find the opposite: a positive drift in prices after the name change.

Market's Arithmetic

Maybe the EMH does not hold universally in the market, but it is true for most assets most of the time. However, if arbitrage keeps an asset's price aligned with its fundamental value, then the EMH should never be violated in assets for which arbitrage is particularity easy or inexpensive. The purest form of arbitrage can be undertaken in situations where two assets, or a combination of assets, are known to yield identical cashflow in the future. In such cases, the price of these assets ought to be linked by the relation that governs the equivalence of the cashflow.

Froot and Dabora (1999) study firms that have issued two kinds of shares, each with identical cashflow and ownership rights. For instance, Royal Dutch, which is listed in the Netherlands, and Shell, which is listed in London, are an example of such twin shares[16]. Both these equities are represented in the US markets with American Depository Receipts (ADRs). The efficient market hypothesis states that these shares must sell at the same price. If the parity is violated, such that the share price of Royal Dutch exceeds parity, then an arbitrageur would buy the cheaper Shell and sell short the dearer Royal Dutch. There is virtually no risk involved with such a trade, as these shares are perfect substitutes for one another.

[16] The cashflow and ownership rights are divided in the 60:40 ratio. Thus, in effect, one Royal Dutch share is equal to 1.5 Shell shares.

However, Froot and Dabora (1999) and Lamont and Thaler (2003b) examine price parity between Royal Dutch and Shell for 22 years. It rarely, if ever, holds. In fact, for more than two years Shell was 30% overpriced relative to Royal Dutch, while, during five years in the 1990s, it was 10% underpriced relative to its twin. In sum, two identical cashflow streams could have been brought at two different prices: a clear violation of the EMH. The hypothesis is even more strongly rejected given that a US investor can purchase ADRs of both shares, thereby circumventing currency risk and market microstructure effects (taxes, transaction costs, liquidity, etc.).

A Part that is Greater than the Whole

Probably the most interesting instance of a blatant violation of the EMH, studied by Lamont and Thaler (2003a) and Mitchell, Pulvino and Stafford (2002), occurs when a division in a firm has a larger value than the firm itself. In these situations an asset trades at different prices in the *same* market because an investor can buy the subsidiary directly or he can buy it bundled with the parent. Also, in such cases, the market implicitly assigns a negative value to a profitable firm: a situation coined a “negative stub”.

Lamont and Thaler (2003a) provide a vivid example. In 2000, a company called 3Com wanted to spin-off a subsidiary called Palm. Initially, it sold 5% of the stake in Palm to the public. The remainder of the equity of the subsidiary was going to be distributed directly to shareholders of 3Com, where 1.5 shares of Palm were to be awarded for every one share of the parent. At the end of the day of Palm’s IPO, it had closed at $95; 3Com, on the other hand, had closed at $82. In effect, an investor who wished to purchase (say) 1500 shares of Palm, instead of paying its price, could have purchased 1000 shares of 3Com. It would have cost him less, included the 3Com’s other profitable business, and given the investor claim to a substantive amount of cash on the parent’s books. In fact, Lamont and Thaler (2003a) calculate that Palm’s share price implied that 3Com was valued at a negative $22bn!

Such a case of mispricing was not short-lived nor was it unique. Lamont and Thaler (2003a) show that the 3Com/Palm “negative stub” persisted for 48 days - up to the point where the Palm shares were awarded to the parent’s shareholders. Actually, between 1985 and 2000, Mitchell *et al.* (2002) document 82 cases of “negative stubs” and, they find that some of them persist for up to 7 years. In addition, they find that in 30% of cases, this mispricing is never corrected by the market.

2.2.3 The Case against Efficient Markets

In each of the stories told above, forces of arbitrage failed to bring about market efficiency. If fact, few academics in modern finance would argue that the textbook definition of pure arbitrage occurs in equity markets and it is generally believed that arbitrage is limited.

For instance, arbitrage may be limited because it is costly (Grossman and Stiglitz, 1980). Any form of arbitrage requires that traders know the fundamental value of the stock, which requires an unbiased estimate of future cashflow and the discount rate. However, in order to know the profitability of mispricing, a considerable amount of information needs to be gathered and processed such that the expected cashflows of the arbitrage strategy can be predicted. In effect, an arbitrageur needs to pay significant fixed costs associated with gathering of information but is unable to estimate profits the arbitrage would provide (Merton, 1987).

Even in situations where the market suspects that an asset is mispriced and the expected return of arbitrage is high, the risk of the strategy can be difficult to estimate. For instance, a given trade might produce positive risk-adjusted returns against the CAPM, but this excess profitability may dissipate if ICAPM is used to adjust for risk. Since financial economists have not come up with an asset pricing model that is unequivocally supported by the finance community or, more importantly, the data, it is probably impossible to know what types of risk an arbitrage strategy involves. Fama (1970) dubs this situation the *joint-hypothesis problem*; Barberis and Shleifer (2003) call it *bad model risk*.

In addition, it is not clear if implementation costs of an arbitrage strategy would not eliminate profits, even if the distribution of the arbitrage profits were known. Direct transaction costs, such as the bid-ask spread, are important of course, but the salient feature of arbitrage is that it often requires undertaking short positions. Lamont and Thaler (2003a) note that shorting of shares is not done at a centralized market, but requires borrowing of shares from large institutional investors. If shares of some firms are not held by these funds, finding shares to short can be difficult and expensive.

Actually, Fama (1991), following Grossman and Stiglitz, (1980), notes that the market price of an asset can diverge from its fundamental value, as long as the mispricing does not imply a profit after transaction costs are taken into account.

Arbitrage would still be limited if the above-mentioned concerns are assumed to be of secondary importance as there is another type of risk that arbitrageurs face[17]. Consider a case of pure arbitrage. It can only be applied in situations where two securities exhibit the same cashflow and risk. Such perfect substitutes are very rare, thus arbitrageurs often settle for imperfect substitutes. It may be possible to match factor exposures of two different assets, but it is certainly not possible to match the idiosyncratic risks. In fact, Barberis and Thaler (2003) argue that a maximum 25% of return in a particular stock can be matched with a portfolio of other risky assets. Arbitrageurs are highly specialised, thus they cannot unload the idiosyncratic risks through diversification. They expect to be compensated for bearing this *fundamental risk* and will not eliminate mispricing that does not result in an adequately high profit (Shleifer, 2000).

So far it has been argued that transaction costs, information costs and fundamental risk preclude arbitrage in markets that are virtually free of irrational agents. Shleifer and Vishny (1997) show that, assuming that irrational investors are present in the market and arbitrageurs have short investment horizons, arbitrage can be seriously impaired, even if the markets are close to being perfect. The authors note that arbitrageurs do not know the price at which they are forced to liquidate their positions. Of course, they hope that the mispricing they aim to profit from will correct before the end of their investment horizon. However, they face a serious risk of what Shleifer and Vishny (1997) call a noise trader shock, which widens the mispricing and results in an unrealised loss to the arbitrageur. If traders are forced to liquidate their position before mispricing is corrected they have to realise this loss. This type of uncertainty is the *noise trader risk* and although this situation may seem far-fetched, it perfectly describes the implosion of the Long-Term Capital Management (Brealey and Myers, 2000).

Also, it seems that the two assumptions behind the notion of noise trader risk are fairly realistic. For instance, the assumption that arbitrageurs have short

[17] This is true only if it is impossible for one arbitrageur to eliminate the mispricing (Shleifer and Vishny, 1997).

investment horizons is supported by arguments in Shleifer and Summers (1990), who argue that transaction costs in long-term arbitrage strategies may be large and institutional considerations, such as margin calls, may act as an implicit truncation of the investment horizon (Mitchell *et al.* 2002). However, it is Shleifer and Vishny (1997) who provide a strong theoretical reason why arbitrageurs are sensitive to their short-term returns. The authors note that arbitrageurs are agents of larger investors who wish to give funds to the trader with the highest skill. But the providers of capital are naïve and do not understand strategies that the arbitrageurs implement, and communication between the agents and the principals is difficult. However, the providers of capital think they can judge the skill of a given arbitrageur by observing his return. Consequently, the amount of funds an arbitrageur receives is a function of the short-term return he yields. In effect, according to Barberis and Shleifer (2003), this monitoring of arbitrageurs is tantamount to them having short investment horizons, and Shleifer and Vishny (1997) note that arbitrageurs, who want to maximize the funds they have under management, may not make trades that can result in lower returns in the short-term, but do earn positive risk-adjusted returns in the long-run.

The second assumption behind the noise traders' risk impeding arbitrage is that irrational traders are not eliminated by rational ones, and thus persist in the market. Actually, De Long, Shleifer, Summers and Waldmann (1991) show that noise traders can dominate the market. Irrational investors may systematically underestimate the risk of their trades because they are overconfident or optimistic (Daniel and Titman, 1999). As irrational investors take on more risk they earn higher expected returns. De Long *et al.* (1991) show that the excessive risk noise traders take on does eliminate many of them from the market, but as a group they may end up with more wealth than the rational investors. In addition, De Long, Shleifer, Summers and Waldmann (1990b) show that it may be profitable for certain rational investors to trade in the same direction as the noise traders.

2.2.4 Asset Pricing "Anomalies"

In a world where arbitrage is limited there is no reason to believe that the four instances of the violation in the EMH discussed above are exhaustive. Actually, there is a plethora of evidence against efficient markets. Much of it constitutes cases of asset return predictability after adjustment for risk with the static CAPM. However, such predictability is not evidence of violation of market efficiency per se, as Fama (1991) notes that improper control for risk can lead to the false conclusion that markets are inefficient. In fact, his joint-hypothesis problem is a tried and powerful weapon against researchers who are too quick to reject the EMH.

Some instances of predictability in returns are to be briefly discussed. They do not, per se, constitute a violation of market efficiently as risk-based theory can, in principle, explain each of these anomalies. Paradoxically, the most salient of them, the size effect and the value effect, are not discussed here, but are left to Chapter 3 where a thorough exposition of these effects is undertaken.

Overreaction

Does the stock market overreact? How would market overreaction manifest itself in stock prices? De Bondt and Thaler (1985, 1987) show that stock returns exhibit a considerable amount of mean-reversion and interpret this evidence as investor overreaction. Specifically, each year they rank firms based on their prior three-year return, the bottom 35 stocks are placed into a “loser” portfolio and the top 35 go into a “winner” portfolio. Next, they calculate returns for these two composites and find that the “losers” win and the “winners” lose. In fact, one outperforms the other by 25% in subsequent three years and risk adjustment with the CAPM has little effect on this profit.

Of course, the idea of investor overreaction is furiously challenged. Lo and MacKinlay (1990b) show that cross-autocorrelation in returns can manifest itself as market overreaction, but it can exist in rational markets. Jegadeesh and Titman (1995) explicitly test their theory and find that most of the mean-reversion in returns stems from overreaction. Chan (1988) explains the profitability of the mean-reversion in prices with the conditional CAPM and, according to Zarowin (1990), overreaction is an instance of another anomaly: the size effect (to be defined in Chapter 3). However, Chopra, Lakonishok and Ritter (1991) dispel both views and show that the overreaction effect persists after thorough adjustment for risk and removal of confounding effects of other anomalies. On other hand, Ball, Kothari and Shanken (1995) and Conrad and Kaul (1993) show that trading strategies that exploit overreaction may not be profitable after adjustment for trading costs. Loughran and Ritter (1996) question this view by showing that in their tests, which they claim are superior, the anomaly is robust to trading expenses.

A slightly different type of overreaction is shown by Ritter (1991), who documents poor long-horizon returns (up to five years) to firms that underwent an IPO. This finding constitutes overreaction because returns to IPOs are very large on the first day of the offering (Brealey and Myers, 2000). In response to this finding, Fama (1998) invokes the joint-hypothesis problem. He follows the findings of Barber and Lyon (1997a), who show that results of "long-term studies", such as Ritter's (1991), can be misspecified and risk adjustment is difficult. In addition, Brav and Gompers (1997) argue that the drift in prices after an IPO cannot be established independently of another well-known effect, the book-to-market effect (also to be defined in Chapter 3). However, these arguments are not sufficiently convincing and the puzzle of the poor performance in IPOs is left unanswered.

Underreaction

Underreaction in financial markets can take many forms. Generally, it constitutes a drift in prices after an event that, on average, moves prices. The drift can be measured over a few months or many years. The list of such "anomalies" has grown considerably. However, the most salient examples are:

- Negative long-horizon returns following equity issues (Loughran and Ritter, 1995).
- Positive long-horizon returns following share repurchases (Ikenberry, Lakonishok and Vermaelen, 1995).
- Positive price drift after surprisingly good earnings and negative price drift after surprisingly poor earnings (Bernard and Thomas, 1989).
- Negative long-horizon returns following equity-financed takeover offers and positive returns following cash-financed offers (Loughran and Vijh, 1997).

In each of these cases, the average price reaction on the announcement day of these events is of the same sign as the post-event price drift. Hence, it appears that the market price moves "too little" on the announcement day, i.e. it underreacts.

Fama (1998) fiercely defends the efficient market hypothesis. He notes that adjustment of returns for risk is extremely difficult over long horizons (more than a few weeks). Barber and Lyon (1997a) and Kothari and Warner (1997) argue that calculating mean returns and the associated test statistics over long runs is extremely difficult. More importantly, Fama (1998) notes that the joint-hypothesis problem is vastly important in these studies since the modern asset pricing models have a particular problem in predicting returns of firms that exhibit underreaction. Lastly, Mitchell and Stafford (2000) show that statistical inference in these studies is erroneous due to a problem of *cross-sectional dependence* [18]. Nonetheless, they continue to find evidence of underreaction after most of the statistical problems are resolved.

Momentum

The momentum effect dates back to De Bondt and Thaler (1985), but it is Jegadeesh and Titman (1993) who are credited with its discovery. In short, the effect is an observation that over medium horizons (six months to one year) stock returns are predictable with their prior medium-term return. Specifically, Jegadeesh and Titman (1993) sort stocks into portfolios based on their (say) one-year return. A decile of stocks with the highest return is coined "winners" and a decile of stocks with the lowest returns are "losers". Unlike to De Bondt and Thaler (1985), the "winners" continue to win and the "losers" continue to lose. The magnitude of the disparity in returns is about 1% per month. Jegadeesh and Titman (1993) go out of their way to reduce those momentum profits by adjusting for risk with the static CAPM, but the effect continues to persist. The evidence on momentum extends to industries (Moskowitz and Grinblatt, 1999) and is confirmed in international data (Rouwenhorst, 1999). Interestingly, the momentum "anomaly" can be a consequence of overreaction or underraction.

The rational school has difficulty in explaining the momentum effect, as it survives most, if not all, adjustment for risk (Fama and French, 1996a; Brennan *et al.*, 1998). Nonetheless, Conrad and Kaul (1998) show that momentum strategies can be

[18] Cross-sectional dependence occurs when observations are correlated across securities in a given time. Thus, if many events occur as a result of single shock to fundamentals and an econometrician treats these events as independent he (or she) overestimates the importance of this particular shock.

explained with risk, as sorting stocks on past returns also sorts stocks on expected returns. Thus, prior winners continue to win because, on average, these firms are riskier and, by construction, must yield high returns. Jegadeesh and Titman (2001) dispel the risk-based explanations for the momentum because the profits to a strategy that aims to profit from the momentum effect stops being profitable after one year. A risk explanation would predict high profits at any horizon. Nonetheless, Chordia and Shivakumar (2006) show that returns to a momentum strategy can be linked to macroeconomic variables, and Korajczyk and Sadka (2004) show that profits for the momentum strategies are greatly reduced after adjustment for trading costs is made.

2.2.5 Behavioural Finance

In a response to the above-mentioned anomalies, a new branch of financial economics has been developed. It is a set of asset pricing theories that do not require investors to be fully informed and rational. This collection of theories has been dubbed *behavioural finance*[19].

Behavioural models offer a unified explanation for systematic investor underreaction and overreaction, by generally assuming that investors do not correctly (or instantaneously) incorporate new information into asset prices. Prices continue to move in the direction dictated by some informational shock (they underreact) and eventually the market value of an asset overshoots its fundamental value (prices overreact). Eventually, the prices correct back to the rational value, either as a result of rational arbitrage, additional news reaching the market, or a change in the behaviour of the irrational group. (Barberis and Shleifer, 2003; Barberis, Shleifer and Vishny, 1998; Hong and Stein, 1999). More importantly, risk aversion precludes rational traders from trading against irrational investors. (Shleifer and Vishny, 1997).

Models do differ by the explicit specification of investors' irrational behaviour. Often the precise identification of the irrational sub-population is difficult[20]. Some

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[19] For a complete survey of behavioural finance look at Barberis and Thaler (2003).

[20] To illustrate, intuitively professional money managers may appear as the rational segment of the market. However, these investors are agents of individual investors, who may be less informed or rational, and thus, institutional investors, driven by the unsophisticated individual investors, are a source of noise in the market. Alternatively, investment professionals, who dominate the market, may exhibit irrational behaviour that is unique to them and cause mispricing. This lack of agreement is a

models offer insights from cognitive psychology to capture investor behaviour. In particular, they rely on investor *heuristics*[21] to generate the pattern of overreaction and underreaction. Other models note that investor *attention* is scarce, such that they cannot process infinitely large amounts of information. This can manifest itself as *categorization*, which, according to Barberis and Shleifer (2003), manifests itself as overreaction and underreaction.

A less formal type of irrational behaviour is *positive feedback trading*, which, in effect, can be seen as momentum trading (buy assets after prices increase and sell after prices fall). There are many reasons for such behaviour. According to De Long *et al.* (1990b) trend chasing is a consequence of investors forming their beliefs based on explorative expectations, and Black (1986) justifies momentum buying from a rational standpoint. If aversion to risk is negatively related to wealth, a rise in stock prices will translate into a willingness to bear more risk and a larger demand for risky assets[22]. Positive feedback trading can occur in individual stocks or groups of stocks - often dubbed *styles* (Barberis and Shleifer, 2003).

2.2.6 The Characteristic Model

The implication of behavioural finance for asset pricing is that the expected returns are a linear (or linearized) function of a firm's characteristics that are

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major task of the behavioural new branch of financial economics, many models exist but few unify all concepts into an integrated story describing financial markets.

[21] Heuristics (as applied to psychological sciences) are cognitive "rules of thumb" that individuals use to form beliefs and solve problems. Commonly, heuristics are referred to as "hunches" or "a gut feeling". In many cases, use of heuristics leads to biased expectations. Barberis and Thaler (2003) and Shleifer (2000) present a comprehensive list of heuristics (and hence possible biases) pertaining to investment professionals. However, the extant behavioural theory focuses only on a subset of documented heuristics: representatives, conservatism, overconfidence and biased-self attribution.

[22] There are other reasons. Stop loses and liquidation of a position due to margin calls is a natural form of positive feedback trading. Also, most forms of technical analysis can lead to positive feedback trading. Another rational expiation of trend chasing is based on informational cascades. It is easier and cheaper for some investors to trade based on actions of "smarter" professionals who have access to a large pool of information and computing power. Simply, if smart money pushes prices up, then individual investors will follow suit. Barberis and Shleifer (2003) point out that professional money managers can partake in momentum trading. Periodically they need to justify their portfolio decisions to their investors and it is easier to substantiate portfolio holdings of professionally managed funds if those funds consist of stocks with high ex post returns. Lastly, Barberis et al. (1998) note that positive feedback trading can be justified by the representativeness heuristic. Few consecutive up-ticks in an asset's price may indicate the beginning of a trend in a subset of the investing public.

informative about mispricing. Daniel and Titman (1997) and Daniel *et al.* (2001) define the characteristic model as:

$$E_t\left[r_{i,t+1}\right] = \gamma_0 + \sum_{f=1}^{N} \beta_i^f \lambda^f + \kappa^P \theta^P \qquad (2.15)$$

The second term states that an expected return can be a function of asset pricing factors that arise from investors trying to optimise their risk-return trade-off, but in the model there is a premium of θ^P for a firm's characteristic κ^P, which is informative about mispricing. In fact, Daniel *et al.* (2001) show that the importance of the κ^P in the pricing equation is a function of mispricing, which, in a limiting case, subsumes the importance of the risk factors.

In sum, a modern view of financial markets includes irrational investors, and it defines market efficiency where prices are not always at their fundamental values, but where eliminating mispricing is risky or costly. Thus, trading strategies that promise easy profits are as equally unlikely as if the markets were efficient. Perhaps the term *behavioural efficiency* would be more appropriate.

CHAPTER 3: THE LITERATURE REVIEW

3.1 The Size and the Value Premia

The literature review starts with a definition, discussion and robustness of the size and the value effects. Evidence that introduces and quantifies the premia is presented. It is also shown how those effects respond to risk adjustment with the static CAPM and some variants of the APT. In addition, joint tests are shown, as there is an overlap and interaction between the different anomalies. The focus of the review is on more recent studies that use US data. These tests are considered more powerful because US financial markets contain a large cross-section of readily marketable securities that can be observed over long periods of time.

The size effect, documented by Banz (1981), and often referred to as the *size premium*, can be defined as a positive relationship between firm's market equity and its *ex ante* return. A popular measure of a company's size is its market capitalisation, which is defined as a firm's share price multiplied by the number of shares it has outstanding. A related anomaly is the price effect, defined as a positive relation between the firm's share price and its *ex ante* return (Kross, 1985). A strong correlation between prices and market values confounds the size and the price effects. An important property of the size effect is that most of the high returns to small firms occur in the month of January (Keim, 1983).

The *value premium* is a positive and monotonic relation between firms' F/P ratios and *ex ante* returns. A firm's F/P (fundamental-to-price) ratio is defined as its accounting measure of worth scaled by its market measure of worth. Companies with high ratios are "cheap" *value* stocks, while firms with low ratios are "expensive" *growth (glamour)* stocks. Some popular value-growth indicators are the earnings yield (earnings-to-price ratio, E/P), the cashflow yield (cashflow-to-price ratio, C/P), and the ratio of book value of equity to market value of equity (book-to-market ratio, BE/ME). This list is by no means exhaustive[23]. The discovery of the value premium

[23] Other examples are the divided yield and debt-to-leverage ratio. In principal, many F/P ratios could forecast returns. Van Rensburg and Robertson (2003) provide evidence that, in univariate regressions, a wide array of ratios can predict returns.

can be accredited to *inter alia* Basu (1977, 1981), Chan, Hamao and Lakonishok (1991) and Rosenberg, Reid and Lanstein (1985), but the most convincing evidence of the effect appears in Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994). A related anomaly to the value premium is investor overreaction of De Bondt and Thaler (1985, 1987). In fact, Fama and French (1996a) show that the value and overreaction effects are imputed to the same economic phenomena.

3.1.1 US Evidence of the Size Premium

Among others, Banz (1981) and Fama and French (1992, 2006) show that, from 1926 until the end of the 20th century, the size effect has been significant in economic and statistical terms. An extract of their results is presented in Panel A in Table 3.1. Asness, Porter and Stevens (2000a) show that a trading strategy consisting of a long position in an equally-weighted portfolio of small firms, financed with a short position of an equally-weighted portfolio of large firms, has yielded a return of nearly 1% per month. This premium is indeed hefty, and is larger than the reward for bearing equity risk.

The size effect seems to persist after a risk adjustment with the static CAPM. For instance, with a cross-sectional test, Fama and French (1996b) show that the firm's market equity continues to predict returns after its market betas are included as an explanatory variable. The effect is robust to inclusion of the "more precise" market betas calculated with annual intervals.

The relationship between the size premium and CAPM warrants a further discussion. Banz (1981), among many, shows that a firm's market capitalisation is negatively related to its beta. Thus, if a firm's size is a better proxy for *market risk* than the imprecisely estimated beta, it ought to predict returns and the size premium is only a result of multicollinearity between the two variables. Actually, Berk (1995) argues that if beta is measured with imprecision then firm size *must* have power to predict returns even if CAPM holds perfectly. Consequently, Kim (1997) shows that, after the error-in-variables problem in cross-sectional tests of asset pricing models is corrected, the size variable becomes a poor predictor of returns.

Table 3.1
Anatomy of the Size Effect in the US

Period	Mean	t	Reference	Table	Correction	Method
Panel A: The size effect and the CAPM						
1936-1975	**-0.52**	2.91	Banz (1981)[1]	I	β	**GLS**
1963-1990	**-0.15**	2.58	Fama & French (1992)	III	nothing	Fama-MacBeth
1963-1990	**-0.17**	3.41	Fama & French (1992)	III	β	**Fama-MacBeth**
1928-1993	**-0.18**	4.16	Fama & French (1996)	III	β	**Fama-MacBeth**
1928-1993	**-2.75**	3.63	Fama & French (1996)[2]	III	β	**Fama-MacBeth**
1963-1993	**-0.06**	**-1.55**	Kim (1997)[3]	IV	β	**Fama-MacBeth**
1963-1998	**0.95%**	3.68	Asness, Proter & Stevens (2000)	III	nothing	One-Way Sort
1963-1998	**0.94%**	4.07	Asness, Proter & Stevens (2000)[4]	III	nothing	One-Way Sort
Panel B: The size effect in conjunction with the value premium						
1963-1990	**-0.11**	1.99	Fama & French (1992)	III	BE/ME	Fama-MacBeth
1963-2004	0.34%	1.47	Fama & French (2006)[5]	III	BE/ME	Two-Way Sort
1966-1995	**-0.14**	2.7	Brennan, Choridia & Subrahmanyam (1998)	III	BE/ME, Momentum	Fama-MacBeth
1963-1990	**-0.16**	3.06	Fama & French (1992)	III	E/P	Fama-MacBeth
Panel C: The size effect during different periods						
1926-2004	**0.24%**	1.68	Fama & French (2006)[6]	I	BE/ME	Two-Way Sort
1926-1963	**0.23%**	2.06	Fama & French (2006)[6]	I	BE/ME	Two-Way Sort
1963-2004	0.20%	1.23	Fama & French (2006)[6]	I	BE/ME	Two-Way Sort
1981-1995	-0.02	-0.31	Dichev (1999)[7]	III	nothing	Fama-MacBeth
1981-1995	-0.07	-1.04	Dichev (1999)	III	nothing	Fama-MacBeth
1982-2002	0.20%	0.67	Schwert (2003)	I	β	**Time-Series**
Panel D: Finer adjustment for risk						
1966-1995	**-1.50**	4.6	Brennan, Choridia & Subrahmanyam (1998)[8]	III	APT, Size, Momentum	Fama-MacBeth
1963-1989	**-0.20**	-4.41	He & Ng (1994)[9]	I	APT, BE/ME	Fama-MacBeth

[1] The coefficient form Banz (1981) is multiplied by 1000; [2] These estimates are computed at annual frequently; [3] Kim (1997) adjusts for the error-in-variables problem [4] These estimates from Asness, Proter & Stevens (2000) adjust for industry effects; [5] The estimates are only indicative; [6] Actually it's the SMB; [7] The top estimate is for NYSE-AMEX firms, the bottom is for NASDAQ firms; [8] APT is a five factor statistical model of Connor and Korajczyk (1988); [9] APT is a macroeconomic model of Chan, Roll & Ross (1986)

However, Fama and French (1992) dismiss the argument that the CAPM can account for the size premium and show that it is independent of any premium associated with the market beta. They sort stocks into portfolios based on each firm's market equity and its CAPM slope. In a group of stocks with approximately equal betas, small firms continue to yield higher returns than large firms; a clear rejection of the static CAPM. According to Daniel and Titman (1997) this type of test is particularly effective in discerning between characteristics and factor loadings as predictors of returns.

Evidence that a firm's size is correlated with its F/P ratio goes back to Reinganum (1981) and Basu (1983)[24]. Therefore, unavoidably, much of the high return to small firms reported in Banz (1981) and Fama and French (1992, 1996b) can be imputed to the value premium. Consequently, Panel B in Table 3.1 presents results of some tests of the size effect after the influence of other anomalies are taken into account. The coefficient on the size variable in the cross-sectional test in Fama and French (1992) is reduced from 0.15 to 0.11 after BE/ME is included as a regressor. More importantly, the *t*-statistic falls from 2.58 to 1.99. However, multicollinearity may bias the cross-sectional coefficients, thus more weight should be placed on the two-way sorting test in Fama and French (2006). The size premium falls from 0.95% per month (reported in Asness *et al.* (2000a) to just 0.34% after adjustment for the book-to-market effect[25]. A similar pattern is found if the E/P is used as the value-growth indicator (Asness *et al.*, 2000a; Fama and French, 2006).

The size premium may be period specific. As the second last panel in Table 3.1 shows, Fama and French (2006) find that it has only been readily positive between 1926 and 1963. In addition, Schwert (2003) and Dichev (1999) do show that the size effect has disappeared after its documentation by Banz (1981). Actually, in the overall 80-year period studied by Fama and French (2006), the size premium is barely significant, statistically speaking. It should be noted, however, that their measure of the size effect in their study is very conservative and it is likely that a different test would yield a reliably positive premium.

[24] Although these authors focus on the relation between market equity and the E/P ratio, in a long sample, Fama and French (1992) show a strong positive relation between firm's book-to-market ratio and its size.

[25] It must be noted that the results of Fama and French (2006) are not directly comparable to the test in Asness *et al.* (2000), as the sample periods are different (1963–2004 vs 1963–1998) and the t-statistics in the table are only an indication. Importantly, data available from Ken French's website shows that markets in the US ware particularly unkind to small stocks between 1998 and 2004.

Table 3.2
Anatomy of The Value Effect in the US

Period	Variable	Mean	t	Reference	Table	Correction	Method
Panel A: Univariate tests of the BE/ME effect							
1963-1990	BE/ME	**0.50**	5.71	Fama & French (1992)	III	nothing	Fama-MacBeth
1969-1989	BE/ME	**3.90**	2.13	Lakonishok, Shleifer & Vishny (1994)[1]	IV	nothing	Fama-MacBeth
1981-1995	BE/ME	**0.32**	3.26	Dichev (1999)[9]	III	nothing	Fama-MacBeth
1981-1995	BE/ME	**0.79**	5.97	Dichev (1999)[9]	III	nothing	Fama-MacBeth
1940-1963	BE/ME	**0.26**	2.38	Davis (1994)	II	nothing	Fama-MacBeth
1964-1994	BE/ME	0.17	0.74	Lewellen (1999)[9]	III	nothing	Time-Series SUR
1964-1994	BE/ME	**0.27**	3.38	Lewellen (1999)[9]	IV	nothing	Time-Series SUR
1964-1994	BE/ME	**1.02**	3.52	Lewellen (1999)[9]	IV	nothing	Time-Series SUR
1964-1994	BE/ME	**0.51%**	3.18	Asness (1997)[2]	II	Industry	One-Way Sort
1963-1998	BE/ME	**1.11%**	6.71	Asness, Proter & Stevens (2000)	III	nothing	One-Way Sort
1963-1998	BE/ME	**1.08%**	8.80	Asness, Proter & Stevens (2000)	III	Industry	One-Way Sort
Panel B: Joints tests of the BE/ME effect							
1963-2004	BE/ME	**0.55%**	2.83	Fama & French (2006)[5,6]	I	Size	Two-Way Sort
1926-2004	BE/ME	**0.40%**	3.43	Fama & French (2006)[7]	I	Size	Two-Way Sort
1926-1963	BE/ME	**0.35%**	1.78	Fama & French (2006)[7]	I	Size	Two-Way Sort
1963-2004	BE/ME	**0.44%**	3.34	Fama & French (2006)[7]	I	Size	Two-Way Sort
1963-1997	BE/ME	**0.68%**	3.39	Asness (1997)[2,3,5,6]	I	Momentum	Two-Way Sort
1966-1995	BE/ME	**0.30**	4.52	Brennan, Chordia & Subrahmanyam (1998)	III	Size, Momentum	Fama-MacBeth
1963-2004	BE/ME	**0.54%**	3.88	Fama & French (2006)[5]	I	Size	Two-Way Sort
1963-2004	BE/ME	**0.25%**	1.88	Fama & French (2006)[5]	I	Size	Two-Way Sort
1963-1997	BE/ME	**0.86%**	3.97	Asness (1997)[2,5,14]	IV	Momentum, Industry	Two-Way Sort
1963-1997	BE/ME	**0.41%**	2.02	Asness (1997)[2,5,15]	IV	Momentum, Industry	Two-Way Sort
1963-1994	BE/ME	**0.83%**	5.02	Daniel & Titman (1999)[5,14]	I	Size, Momentum	Two-Way Sort
1963-1994	BE/ME	**0.32%**	1.69	Daniel & Titman (1999)[5,15]	I	Size, Momentum	Two-Way Sort

Table 3.2 (continued)

Panel C: Value effect after an adjustment for risk							
1926-1963	BE/ME	**0.05%**	0.31	Fama & French (2006)	V	β	**Time-Series**
1963-2004	**BE/ME**	**0.57%**	4.74	Fama & French (2006)	V	β	**Time-Series**
1982-2002	**BE/ME**	**-0.22%**	0.67	Schwert (2003)	I	β	**Time-Series**
1963-1990	**BE/ME**	**0.50**	5.71	Fama & French (1992)	III	β	**Fama-MacBeth**
1963-1993	**BE/ME**	**0.16**	3.51	Kim (1997)[4]	IV	β,Size	**Fama-MacBeth**
1966-1995	**BE/ME**	**0.25**	4.85	Brennan, Chordia & Subrahmanyam (1998)[10]	IV	APT, Size, Momentum	Fama-MacBeth
1963-1989	BE/ME	**0.27**	3.70	He & Ng (1994)[11]	I	APT, BE/ME	Fama-MacBeth
Panel D: Choosing the right value-growth indicators							
1963-1990	E/P	**4.72**	2.28	Fama & French (1992)	III	nothing	Fama-MacBeth
1969-1989	E/P	**0.53**	2.54	Lakonishok, Shleifer & Vishny (1994)[1]	IV	nothing	Fama-MacBeth
1963-1994	E/P	**4.35**	2.31	Davis (1994)	II	nothing	Fama-MacBeth
1969-1989	C/P	**0.36**	4.24	Lakonishok, Shleifer & Vishny (1994)[1]	IV	nothing	Fama-MacBeth
1963-1994	C/P	**1.64**	1.55	Davis (1994)	II	nothing	Fama-MacBeth
1969-1989	C/P	**0.29**	4.22	Lakonishok, Shleifer & Vishny (1994)[1]	IV	BE/ME, Size	Fama-MacBeth
1968-1989	BE/ME	**0.01**	0.57	Lakonishok, Shleifer & Vishny (1994)[1]	IV	Size, CP	Fama-MacBeth
1940-1963	BE/ME	**-0.05**	-0.35	Davis (1994)	II	CP, Sales Growth	Fama-MacBeth
1963-1990	BE/ME	**0.33**	4.46	Fama & French (1992)	III	Size, E/P	Fama-MacBeth
1963-1990	E/P	**-0.14**	-0.90	Fama & French (1992)	III	BE/ME, Size	Fama-MacBeth

[1] At annual frequency ; [2] Value-weighted results; [3] Adjusted for industry effects ; [4] Kim (1997) adjusts for the error-in-variables problem ; [5] The estimates are only indicative; [6] Fine Sort; [7] Coarse Sort; [8] The top estimate is for NYSE-AMEX firms, the bottom is for NASDAQ firms; [9] The First estimate is obtained when Industry portfolios are test assets, the second is obtained when size-sorted portfolios are test assets, the third estimate is obtained BE/ME-sorted portfolios are test assets; [10] APT is a five factor statistical model of Connor and Korajczyk (1988); [11] APT is a macroeconomic model of Chan, Roll & Ross (1983) ; [12] In small firms; [13] In large firms; [14] In low momentum stocks; [15] In high momentum stocks

Lastly, some authors argue that an APT model of Ross (1976) can explain the effect. For instance, Chen (1983) finds some evidence that a multifactor "statistical" APT can explain the size effect. In addition, Chan, Chen and Hsieh (1985) construct a "macroeconomic" APT model and claim that it can account for the return differential between small and large firms. The last panel in Table 3.1 shows how different, perhaps more sophisticated, methods for risk adjustment impact on the size premium. It can be unequivocally stated that the APT cannot explain the size effect, as the coefficients on size are reliably positive after the risk adjustment. Tests in Brennan *et al.* (1998) and He and Ng (1994) have power due to the use of long sample periods. Specifications in Chen (1983) and Chan *et al.* (1985) have less power to test whether the size effect persists after control for risk[26].

3.1.2 US Evidence of the Value Premium

The anatomy of the value premium is presented in Table 3.2. The most popular value-growth indicator is the book-to-market ratio and thus most of the discussion of the premium will centre on that variable. It can be seen from Panel A that, taken on its own, the book-to-market effect is significant in both statistical and economic terms. For example, a cross-sectional regression of the book-to-market ratios onto realised returns yields a positive coefficient that is nearly six standard deviations from zero (Fama and French, 1992). In addition, a trading strategy based on the value effect can be enormously profitable. Asness *et al.* (2000a) show a long position in a portfolio of value stocks financed with a short position in a portfolio of growth stocks can yield a profit in excess of 1% per month. Also, the profitability of this strategy grows with the investment horizon and Lakonishok *et al*. (1994) show that after a five-year period, on average, value stocks outperform growth firms by nearly 100%. It must be noted, however, that use of value-weighted portfolios in univariate sorts decreases the magnitude of the premium (Asness, 1997).

The value effect is robust to different methodologies. More specifically, Lakonishok *et al.* (1994) capture the effect with annual regressions. This result is not vacuous, as the size effect vanishes in tests that use annual intervals. Lewellen (1999)

[26] These authors do not test if their factors can "price-out" size as an explanatory variable - a condition that is necessary for definitive test of a model (Cochrane, 2001; Jagannathan and Wang, 1998).

uses predictive regressions and finds evidence of the premium. In his regressions time-variation in portfolios' book-to-market ratio can significantly, statistically speaking, predict returns in nearly half of his test assets. It can be seen in Table 3.2 that only returns of industry-sorted portfolios cannot be predicted with their book-to-market ratios. Lastly, Loughran (1997) and Dichev (1999) show that the value effect is much stronger among the stocks listed on NASDAQ than the flagship NYSE and Amex[27].

Interestingly, it may be that Fama and French (1992) understate the pervasiveness of the value premium. Asness *et al.* (2000a) test for the value premium, but they measure a firm's book-to-market ratio relative to the firm's industry. An extract of their results appears in Table 3.2. The authors do not find a difference in the magnitude of the premia accruing to the traditional and the relative ratios. However, profits from a trading strategy that uses their industry-adjusted value-growth indicators are much less volatile. Actually, the t-statistic rises to 8.8 from 6.71 after they use a relative book-to-market ratio. Simply put, the industry-adjusted F/P ratios can predict returns with a larger degree of certainty.

Recall that the firm's size and F/P ratios are correlated. Therefore, the magnitude of the value premium that is unrelated to the size effect needs to be established. Panel B in Table 3.2 shows some tests of the book-to-market premium in conjunction with other characteristics that can predict returns. As expected, the value premium is greatly reduced after size effect is taken into account as it drops from approximately 1.1% per month to about 0.55% per month. However, unlike the size effect, the value premium continues to be reliably different from zero.

Comparison of univariate and bivariate results in Assess (1997) indicates that a control for the momentum effect increases the magnitude of the value effect. To explain, this effect states that firms that fell in value over (say) 12 months continue to perform poorly for the following 12 months and vice versa. Note that Fama and French (1995) show that high BE/ME firms tend to perform poorly before being classified as such. Thus, in univariate sorts, a portfolio containing firms with a high book-to-market ratio should include many prior "losers" that yield poor returns *ex ante*. In short, the momentum effect acts against the value effect. Therefore, control

[27] These acronyms stand for, National Association of Security Dealers Automated Quotations system, New York Stock Exchange and American Stock Exchange, respectively

for the momentum with a two-way sort should increase the magnitude of the value premium. Actually, with a time-series test, Fama and French (1996a) do find that adjustment of the momentum effect with variables that capture value and size premia leads to an increase in the momentum premium. In sum, it can be said that the value effect is understated if a control for past returns is not performed.

A deeper look into the interaction between the value effect and other anomalies reveals that the magnitude of the value premium is not the same among all types of stocks. Loughran (1997) criticised the results of Fama and French (1992) by noting that the value premium can only exist among small stocks that are listed on NASDAQ. Actually, he goes on to claim that the bulk of the value effect can be attributed to poor performance of newly listed growth firms. Put differently, he states that the value effect is actually a manifestation of the IPO effect of Ritter (1991). Thankfully, it can be seen in Table 3.2 that, according to the powerful test in Fama and French (2006), Loughran’s (1997) claim is not entirety true. The value premium is twice as big among small stocks as larger stocks, but the effect is positive, albeit with weak statistical significance, among the large stocks. In addition, Fama and French (2006) do show that in their long sample period the value effect is reliably greater than zero. Actually, the value effect in large stocks was particularly strong before the NASDAQ exchange was opened.

Also, the value premium is stronger among stocks with low medium-term past returns (Asness, 1997; Daniel and Titman, 1999). It appears that value firms with high past returns are good investments, but not that much better than “winning” growth firms. However, stocks with the low BE/ME and low past returns yield markedly higher returns than past “losers” with high BE/ME. The summary of results from Asness (1997) and Daniel and Titman (1999) are shown in Table 3.2 and it seems that the value premium is twice as large among “losers” than “winners”.

Another important property of the value effect is that it persists after adjustment for risk with the CAPM or the APT. Panel C in Table 3.2 shows results of a small selection of tests that aim to explain the premium with one of these models. Fama and French (2006) and Schwert (2003) show that there are periods where CAPM appears to explain the value premium. However, between 1963 and 1982 (not shown in the table) the value premium has remained positive in spite of risk adjustment. Actually, Fama and French (2006) note that, after 1950, market betas of value stocks have been lower betas of growth firms. Nonetheless, Schwert (2003) shows that after the value effect had been documented in the early 1980s, it may have vanished. His time-series tests are not sufficient however. Joint tests of the value premium and the CAPM in Fama and French (1992) and Kim (1997) show that the book-to-market ratio continues to predict returns after market beta is included in the cross-sectional regressions. Kim’s (1997) test is particularly powerful as he adjusts for the bias resulting from imprecisely estimated market betas. More importantly, Fama and French (2006) show that even in the period when time-series tests support the CAPM, the book-to-market ratio is a better predictor of returns market betas. The APT fairs no better against the value premium. Both a “statistical” and a “macro economic” version of the model fail to “price-out” the book-to-market ratios. The tests in He and Ng (1994) and Brennan *et al.* (1998) have much power due to the long sample periods used in these studies.

In addition, the value premium is reliably greater than zero if it is measured with F/P ratios other than the BE/ME. In particular, evidence in Panel D of Table 3.2 shows that the E/P and the C/P ratios are also good predictors of returns. Actually, Lakonishok *et al.* (1994) find that in their annual regressions the C/P and the E/P subsume the effect of the BE/ME. They also show that a univariate sort on C/P gives a wider spread in mean returns than a sort on the BE/ME alone. However, results of Lakonishok *et al.* (1994) may be specific to their methodology and sample. For example, Fama and French (1992) show that the earnings’ yield cannot predict returns after the BE/ME ratio is included in the cross-sectional regressions, but the book-to-market effect does persist after a control for the E/P ratio. Moreover, Kim (1997) finds that if more precise beta estimates are used, the earnings’ yield effect can be explained with the CAPM. Evidence against the C/P ratio in favour of the BE/ME is less damning. Although, Asness *et al*. (2000a) use a univariate sort to show that a trading strategy that exploits the value premium is less profitable when measured with the cashflow yield instead of the book-to-market ratio, Hogan, Jarrow, Teo and Warachka (2004) find that profits from the C/P strategy are more certain. Nonetheless, although it may seem that the book-to-market ratio is a poorer predictor of returns than the C/P ratio, it has been vastly popular with researchers. Consequently, most of the literature review will treat the BE/ME as the “best” value-growth indicator.

There is a degree of disagreement of what the BE/ME ratio really measures. Lakonishok *et al.* (1994) list many reasons for variations in book-to-market ratios across firms. First, firms may operate with different amounts of intangible assets, which do not appear on the accounting statements, and the different book-to-market ratios can capture cross-sectional variations in intangibles. Second, most modern finance textbooks teach that a firm is a sum of its assets in place and unexercised growth opportunities. These options do not appear in the financial statements but are undoubtedly reflected in the share price. Therefore, a firm’s book-to-market ratio can be an indicator of its growth prospects (Brealey and Myers, 2000). Third, all else equal, safer firms will have a higher price. As a result, the BE/ME ratio can be an effective proxy for risk (Ball, 1978; Berk, 1995). Fourth, Fama and French (1992) note that BE/ME can be understood as a measure of involuntary leverage, as it is a difference (if logs are used) between total leverage of the firm (debt-to-market equity) and debt levels chosen by the management (debt-to-book equity). Lastly, the BE/ME can be informative about mispricing. If a stock is overpriced, its observed book-to-market ought to be small and vice versa. It is possible, however, that the ratio is of no consequence and the value, as well as size, effects are statistical illusions.

3.1.3 Statistical Illusions

A considerable amount of time and money is channelled into unearthing profitable trading strategies. Also, financial researchers have an incentive to mine for results because the more interesting (and sometimes controversial) results are more likely to get published (Shleifer, 2000). It is inevitable that, by force of luck, a pattern in stock returns will be found that appears to have yielded easy profits (Black, 1993). In addition, Lo and MacKinlay (1990a) note that a spurious anomaly is more likely to be found if research is continuously conducted on a particular dataset, and Cochrane (2001) humorously notes that there have been more regressions run using data from the leading US datasets like COMPUSTAT or CRSP than data points contained within them. It is thus possible that the size and value effects are just an instance of statistical illusion brought about by data mining or *data-snooping.*

Berk (1995) notes that, by very construction, size and BE/ME should be able to forecast returns, as they can act as a proxy for expected returns. It is failure of the CAPM and APT to account for the effects that is puzzling. However, Lo and MacKinlay (1990a) argue that if the size and value premia are a result of data-snooping, risk adjustment of this effect with a correctly specified asset pricing model will reject the model in favour of the anomalies.

At first, Lo and MacKinlay (1990a) note that most adjustments for risk require grouping of securities into portfolios, where each security is sorted based on some discernable characteristic such as market capitalisation or the BE/ME ratio. Potentially, a subsequent correction for risk is done with a time-series test, where the intercepts are the pricing errors of the risk model. If the relationship between the characteristic used in the sort and returns is spurious, then, invariably, the correct asset-pricing model will yield these non-zero alphas.

Unfortunately, Lo and MacKinlay (1990a) give little guidance regarding what role their data-snooping plays in the size and value effects. Conrad, Cooper and Kaul (2002) directly aim to ascertain the magnitude of the data-snooping bias for various asset pricing anomalies. Although they focus on a broader set of puzzles, their results are relevant for the size and value strategies. To test the impact of data-snooping, Conrad *et al.* (2002) simulate a history of returns and a set of random characteristics is assigned to each firm. By construction, these attributes have no relation to returns. Subsequently, with a simple portfolio sorts, they calculate what kind of mean return would be observed *ex post*, if researchers were to sieve through the data in order to identify a number of profitable strategies. Subsequently, they compute the return on the 15 most profitable strategies that were "mined" out of the data. Since Conrad *et al.* (2002) attach their simulated data to actual firms between 1965 and 1995, they can compare profitability of their data-mined strategies with the magnitude of actual anomalies observed during that time. The real anomalies the authors consider are 15 strategies that use a combination of momentum, value and size effects. In sum, their results point out that about 50% of documented anomalous return from the various effects is a result of data-snooping. The magnitude of the bias is related to how finely the stocks are divided into portfolios and the correlation between variables that are used in two-way portfolio sorts.

There is another statistical shenanigan that is likely to increase the magnitude of the size and the value premia. Banz and Breen (1986) are among the first to note that survival bias may be behind the value anomaly. They note that the leading provider of accounting data in the US, COMPUSTAT, does not include firms that delisted before the research was undertaken. The authors argue that the omission of these firms from the sample may bias results. To test if survival plays a role, they obtain a dataset that is free of this bias. Next they compare the returns from portfolios formed from a complete database with the portfolios obtained from COMPUSTAT. In a formal statistical test, the return between these two portfolios is different at a one percent level. In their relatively short sample period, they show that the value effect (as measured by E/P) is completely explained by the survival bias.

Kothari *et al.* (1995) study another instance of survival bias within the COMPUSTAT database. They note that, at a certain point in the past, the data provider underwent a major restructuring when it chose to widen its coverage of firms. As a result, five years of accounting data from (mostly large) companies that were listed at the time were added. Since a high BE/ME ratio may signal financial distress (Fama and French. 1995; Griffin and Lemmon, 2002), firms that had low book-to-market ratios in the five years prior to expansion, and were added to the database, are likely to have been "turned around" and thus yielded high returns. On the other hand, many other firms that had a high BE/ME ratio during that time may have been delisted due to bankruptcy and never made it to the database. In sum, COMPUSTAT unintentionally biased the sample in favour of finding the value premium, as it may have included only high book-to-market firms that yield high returns. Similarly to Banz and Breen (1986), Kothari *et al.* (1995) quantify the magnitude of the survival bias by calculating returns on firms that are excluded from COMPUSTAT and comparing them to the ones in the database. In accordance with the bias, firms that are absent from COMPUSTAT yield much smaller returns than the surviving firms. They fail, however, to establish a concrete link between these low returns and the value effect (Fama and French (1996b)).

How important are these statistical illusions to the size and the value effects? Survival bias per se seems to have only a trivial effect on the observed value premium. Since Banz and Breen (1986) published their results much of the subsequent research used a database that is free of the bias they study. More importantly, Chan, Jegadeesh and Lakonishok (1995) study the effect of the sample selection that arises from the COMPUSTAT expansion. They show that only a tiny portion (3.1%) of accounting data missing from the provider's database can be attributed to survival. Also, they directly measured the impact of the bias on the value effect. In particular, for a subset of the market, they hand-collected much of the accounting data that was missing from COMPUSTAT and found that the magnitude of premium associated with the book-to-market ratio is virtually unchanged after the correction. Also, Barber and Lyon (1997b) provide further evidence against the survival bias story of Kothari *et al.* (1995). Chan *et al.* (1995) show that the alleged bias is more common among financial firms, as more of them seem to be missing from the COMPUSTAT database. However, Barber and Lyon (1997b) find no difference in returns of size-sorted and BE/ME-sorted portfolios constructed from financial and non-financial firms. Finally, Kim (1997) and Fama and French (2006) use data that is free of the survivor bias, as all data points missing from COMPUSTAT were filled with hand-collected information. Both studies find a reliably positive value premium.

In order to refute the data-snooping explanation for the premia, similar tests to that of Fama and French (1992) need to be replicated in fresh data samples. For example, Barber and Lyon (1997b) estimate the magnitude of the size and value effects in a sub-sample of financial companies. Since many of the studies of size and value premia are conducted on non-financial firms, their sample has not been examined before. Contrary to the data-snooping hypothesis, they do not find any difference in magnitudes of the size and the value effects between financial and non-financial firms. In addition, Fama and French (2006) conduct a powerful test, as they examine the anomalies at hand for nearly an 80-year period. In Table 3.2 it can be seen that their estimate of the value premium is virtually the same regardless of the sample period. Also, Table 3.2 summarises the results of Davis (1994), who used a wider range of F/P ratios to define what constitutes a growth or value firm. In his, also previously unexamined, data set he finds reliable evidence of the value premium.

In sum, there is no denying that the data-snooping bias plays a role in the financial research (Black, 1993) and survival bias can manifest itself as a spurious anomaly (Banz and Breen, 1986). However, it has been shown that the size and value premium retain their magnitude across different samples drawn from US financial markets. A natural extension would be to examine the existence of the anomalies at hand in markets outside the United States.

3.1.4 Evidence from the Rest of the World.

It is necessary to examine the magnitude and the persistence of the size and the value premia in international markets, as it is possible that these effects are sample specific to US financial markets. A study of the anomalies at hand in international markets is difficult however. In general, samples are much smaller. Total number of stocks listed in most countries constitutes only a fraction of firms listed in the US. Also, many international equity markets have not been active for as long as the ones in the US and some emerging economies modernised their financial systems only in the recent past. In addition, much of the listed equity does not trade frequently. The non-synchronous trading is a problem in financial research as it biases computed returns and leads to mismeasurement of risk parameters such as variances and market betas. Thus, it can be said that tests for the size and the value effects in international markets may lack power. A notable exception is the equity market in Japan.

There have been many tests of the size effect in markets other that the US. For example, a comprehensive study of the premium in the Japanese stock market appears in Chan *et al.* (1991). Heston, Rouwenhorst, and Wessels (1999) test for the premium in many industrialised European markets, while Chen and Zhang (1998) study markets in South-East Asia. Rouwenhorst (1999) conducts his tests in the emerging markets. This list of studies is by no means exhaustive. An extract of results from some of these studies can be seen in Table 3.3: from 13 developed equity markets, in 11 of them size effect is positive, but in only four countries is it statistically larger than zero. Although it may seem that the evidence for the size effect is weak, the premium is reliably positive in Japan and the UK, the two countries with the largest capitalisation of listed stocks after the US. These three largest markets account for nearly 60% of world equity. In addition, although it is not explicitly shown in the table, in the UK market, the size effect persists after control of the book-to-market ratio (Leledakis and Davidson, 2001). Nonetheless, Fama and French (2006) show that, after adjusting for the value premium, the size effect is relatively weak in the developed world, as it is, statistically speaking, barely different from zero. Rouwenhorst (1999), among others, studies the returns to small firms in emerging economies and he finds much stronger evidence of the size premium.

Table 3.3
The Size Effect around the World

Country	Period	Size effect	t	Reference	Table	Correction
Panel A: The size effect in the developed world						
Australia	1985-1996	0.49%	1.06	Liew and Vassalou (2000)	III	BE/ME
Belgium	1980-1995	-0.10%	-0.63	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Canada	1981-1995	**0.57%**	2.78	Griffin (2002)	I	BE/ME
France	1980-1995	0.26%	1.63	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Germany	1980-1995	0.11%	0.92	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Hong Kong	1981-1993	0.38%	0.58	Chan & Zhang (1998)	III	BE/ME
Italy	1980-1995	-0.02%	-0.11	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Japan	1981-1995	**0.64%**	1.99	Griffin (2002)	I	BE/ME
Netherlands	1980-1995	0.29%	1.47	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Spain	1980-1995	**0.75%**	2.27	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Sweden	1980-1995	0.34%	1.35	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Switzerland	1980-1995	0.14%	0.91	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
UK	1980-1995	**0.39%**	2.56	Heston, Rouwenhorst & Wessels (1999)	VI	nothing
Joint[1]	1975-2004	0.19%	1.49	Fama & French (2006)	IV	BE/ME

Table 3.3 (continued)

Panel B: The size effect in the developing world						
Argentina	1982-1997	**3.84%**	2.54	Rouwenhorst (1999)	II	nothing
Brazil	1982-1997	1.76%	1.33	Rouwenhorst (1999)	II	nothing
Chile	1982-1997	0.31%	0.61	Rouwenhorst (1999)	II	nothing
Colombia	1986-1997	-0.68%	-0.79	Rouwenhorst (1999)	II	nothing
Greece	1982-1997	0.04%	0.07	Rouwenhorst (1999)	II	nothing
Indonesia	1990-1997	-0.46%	-0.80	Rouwenhorst (1999)	II	nothing
India	1982-1997	-0.35%	-0.89	Rouwenhorst (1999)	II	nothing
Jordan	1982-1997	-0.34%	-0.79	Rouwenhorst (1999)	II	nothing
Korea	1982-1997	0.32%	0.51	Rouwenhorst (1999)	II	nothing
Malaysia	1977-1993	**0.58%**	2.11	Chan & Zhang (1998)	IV	BE/ME
Mexico	1982-1997	**2.39%**	2.17	Rouwenhorst (1999)	II	nothing
Nigeria	1986-1997	-0.59%	-0.62	Rouwenhorst (1999)	II	nothing
Pakistan	1987-1997	-4.20%	-0.75	Rouwenhorst (1999)	II	nothing
Philippines	1987-1997	0.23%	0.29	Rouwenhorst (1999)	II	nothing
Portugal	1989-1997	-0.74%	-1.61	Rouwenhorst (1999)	II	nothing
Taiwan	1986-1997	-0.24%	-0.72	Chan & Zhang (1998)	V	BE/ME
Thailand	1982-1997	0.37%	1.14	Chan & Zhang (1998)	VI	BE/ME
Turkey	1989-1997	0.72%	0.59	Rouwenhorst (1999)	II	nothing
Venezuela	1986-1997	1.37%	1.41	Rouwenhorst (1999)	II	nothing
Zimbabwe	1982-1997	**1.85%**	1.95	Rouwenhorst (1999)	II	nothing
Joint	1982-1997	**0.69%**	2.88	Rouwenhorst (1999)	II	nothing

[1] The test in Fama and French (2006) uses a longer sample and includes Singapore

Table 3.4
The Value Effect around the World

Country	Period	Value Effect	t	Art	Table	Correction
Panel A: The value effect in the developing world						
Australia	1975-1995	1.03%	2.41	Fama & French (1998)	III	nothing
Belgium	1975-1995	**0.37%**	1.99	Fama & French (1998)	III	nothing
Canada	1975-1995	**0.42%**	2.18	Griffin (2002)	I	Size
France	1975-1995	**0.62%**	2.08	Fama & French (1998)	III	nothing
Germany	1975-1995	0.23%	0.92	Fama & French (1998)	III	nothing
Hong Kong	1975-1995	0.60%	1.35	Fama & French (1998)	III	nothing
Italy	1975-1995	-0.50%	-0.91	Fama & French (1998)	III	nothing
Japan	1975-1995	**0.82%**	3.49	Fama & French (1998)	III	nothing
Netherlands	1975-1995	0.19%	0.44	Fama & French (1998)	III	nothing
Singapore	1975-1995	**0.81%**	2.36	Fama & French (1998)	III	nothing
Sweden	1975-1995	0.67%	1.16	Fama & French (1998)	III	nothing
Switzerland	1975-1995	0.29%	0.80	Fama & French (1998)	III	nothing
UK	1975-1995	0.39%	1.08	Fama & French (1998)	III	nothing
Joint**	1975-2004	**0.53%**	2.63	Fama & French (2006)	IV	Size

Table 3.4 (continued)

Panel B: The value effects in the developing world						
Argentina	1982-1997	1.68%	1.08	Rouwenhorst (1999)	II	nothing
Brazil	1982-1997	**3.94%**	2.34	Rouwenhorst (1999)	II	nothing
Chile	1982-1997	**1.07%**	1.74	Rouwenhorst (1999)	II	nothing
Colombia	1986-1997	-0.36%	0.40	Rouwenhorst (1999)	II	nothing
Greece	1982-1997	**1.31%**	1.68	Rouwenhorst (1999)	II	nothing
Indonesia	1990-1997	1.11%	1.57	Rouwenhorst (1999)	II	nothing
India	1982-1997	0.50%	0.08	Rouwenhorst (1999)	II	nothing
Jordan	1982-1997	0.06%	0.15	Rouwenhorst (1999)	II	nothing
Korea	1982-1997	**1.58%**	3.99	Rouwenhorst (1999)	II	nothing
Malaysia	1982-1997	**1.02%**	2.37	Rouwenhorst (1999)	II	nothing
Mexico	1982-1997	1.39%	1.17	Rouwenhorst (1999)	II	nothing
Nigeria	1986-1997	0.25%	0.19	Rouwenhorst (1999)	II	nothing
Pakistan	1987-1997	-0.05%	-0.08	Rouwenhorst (1999)	II	nothing
Philippines	1987-1997	0.51%	0.77	Rouwenhorst (1999)	II	nothing
Portugal	1989-1997	-0.60%	-0.93	Rouwenhorst (1999)	II	nothing
Taiwan	1986-1997	1.01%	0.34	Rouwenhorst (1999)	II	nothing
Thailand	1982-1997	-0.31%	-0.85	Chan & Zhang (1998)	VI	Size
Turkey	1989-1997	2.86%	1.60	Rouwenhorst (1999)	II	nothing
Venezuela	1986-1997	1.27%	0.93	Rouwenhorst (1999)	II	nothing
Zimbabwe	1982-1997	**2.31%**	1.86	Rouwenhorst (1999)	II	nothing
Joint	1982-1997	**0.72%**	3.35	Rouwenhorst (1999)	II	nothing

** The test in Fama and French (2006) uses a longer sample and includes Spain

In his joint test of 20 markets he finds the size effect to be 0.69% per month and it is reliably different from zero. He does not, however, adjust for the value effect; thus his test may lack power.

Evidence for the value effect in international markets is common. Chan *et al.* (1991) were among the first to present convincing evidence of the effect outside of the US. Fama and French (1998) study the value premium in many international markets. Rouwenhorst (1999) focuses on the emerging world, but he omits the economies of Eastern Europe. Lyn and Zychowicz (2004) fill this gap. Table 3.4 shows some of the evidence on the value effect in markets outside of the US. It can be seen that the premium is positive in all but one (Italy) industrialised country and it is statistically significant in six of them. Actually, the value premium in Australia, Japan and Singapore is greater than in the US. Fama and French (2006) jointly test for the value premium across the 14 markets, but they explicitly adjust for the size effect. Predictably, they reject the null hypothesis that the premium is zero. A similar pattern emerges from analysis of the emerging markets. Although Rouwenhorst (1999) reports that the value effect is significant, statistically speaking, only in 6 out of 21 countries does the joint test of the premium spanning these markets reveal that it is significant in both economic and statistical terms. Actually, value investing appears to be more profitable in the emerging markets than in the developed world. In addition, Lyn and Zychowicz (2004) find that the firm's BE/ME ratio can predict its *ex ante* return in the very young equity markets of Eastern Europe. In sum, the value premium is pervasive internationally, thus its existence cannot be imputed to data-mining.

Lastly, research on the size and the value effects conducted with South African data is shown. Although early studies of the subject date back to De Villiers, Lowlings, Pettit and Affleck-Graves (1986) and Plaistowe and Knight (1986), the focus here is on more recent results. Liquidity of the JSE has been poor prior to 1995, and thus the power of early tests is low. Table 3.5 reports some estimates of the size and the value premia on the JSE. In all cases univariate and bivariate sorting procedures are used to quantify theses effects. The documented magnitude of the size and the value effects are exceedingly large. For example, van Rensburg and Robertson (2003) find the size premium to be 2.34% per month after they control for the value effect. It is nearly seven times larger than the size effect in the US reported by Fama and French (2006). Similarly, van Rensburg and Robertson (2003) estimate the E/P effect to be 3.24% per month after controlling for size. It is six times larger than in the US. Curiously estimates in van Rensburg (2001) and Fraser and Page (2000) are smaller, but the bulk of their sample period falls within the “illiquid era” of the JSE. Consequently, it may seem necessary to repeat the study of the size and value effects is South Africa in a period of higher liquidity.

Table 3.5
The Size and the Value Effect in South Africa

Panel A: The size effect in South African market						
Size	1983-1999	**1.12%**	3.88	van Rensburg (2001)	II	nothing
Size	1990-2001	**2.50%**	4.05	van Rensburg and Robertson (2003)	III	nothing
Size	1990-2001	**2.34%**	2.50	van Rensburg and Robertson (2003)	III	BE/ME
Panel B: The value effect in South African market						
BE/ME	1973-1997	**0.63%**	3.49	Fraser & Page (2000)	II	nothing
P/E	1990-2001	**3.33%**	7.38	van Rensburg and Robertson (2003)	III	nothing
BE/ME	1973-1997	**0.59%**	1.72	Fraser & Page (2000)	II	momentum
P/E	1990-2001	**3.24%**	2.31	van Rensburg and Robertson (2003)	IV	size

3.2 Market Frictions

A strong assumption behind the efficient market hypothesis and the CAPM is that financial markets are perfect. In other words, trading in financial securities is costless, untaxed and investors can effortlessly, as well as instantaneously, obtain and process information. These assumptions are undoubtedly violated in practice. Thus, it is plausible that the size and the value effects vanish after costs associated with investing are taken into account, and thus are not anomalous at all.

Markets can be imperfect in a number of ways. Direct costs of trading are often ignored in asset pricing studies, but they may be vastly important (Stoll and Whaley, 1983; Alexander, 2000). According to Amihud and Mendelson (1986), the ease with which a share can be sold is a source of risk that is not captured by the static CAPM, and a proxy that captures assets' liquidity should reliably predict returns. Merton (1987) adds to this point. He notes that gathering and interpreting information is costly and since these search costs are not uniformly distributed in the cross-section of firms, a parameter that measures firms' recognition among investors should predict returns. Interestingly, Hou and Moskowitz (2005) show that the information cost hypothesis of Merton (1987) is separate to Amihud and Mendelson's (1986) illiquidity story, as these two market imperfections affect returns independently of one another. Consequently, in this section it is shown how recognition of transaction costs, information costs and illiquidity risk in asset pricing augments the understanding of the size premium. A brief discussion of the impact of market microstructure effects on the value premium is left to the end.

3.2.1 Direct and Indirect Costs of Trading

In efficient markets, mispricing can persist if its exploitation is not profitable after trading expenses are taken into account (Grossman and Stiglitz, 1980). Stoll and Whaley (1983) are among the first to show that *direct trading costs*, measured by the bid-ask spread and the commission charged by brokers, are negatively related to market capitalisation.

With a wider array of instruments for transaction costs and a longer sample period, Lesmond, Ogden and Trzcinka (1999) show that trading in shares of small firms may be 17 times more expensive than those of large firms. Consequently, Stoll and Whaley (1983) calculate the magnitude of the size effect after trading costs are taken into account. Since calculation of net investment profits requires *ex ante* knowledge of investors' holding period, the authors compute the profitability of the size strategy for a number of investment horizons. The authors find that, if the strategy is implemented for two months or less, the sign of the premium reverses after the adjustment for costs and market risk.

Nonetheless, direct trading costs cannot explain the size effect. Stoll and Whaley (1983) show that the long-term risk-adjusted out-performance of small firms continues to persist, but its significance, in both statistical and economic terms, is attenuated. In fact, using a large sample, Schultz (1983) shows that implementation of the size strategy for long investment horizons is much more profitable than shown in Stoll and Whaley (1983). In addition, Lesmond *et al.* (1999) argue that the actual costs of trading are about half[28] of the quoted spread and commission measure used in Stoll and Whaley (1983).

However, an investor can face a number of *indirect trading costs*. A large order placed on an infrequently traded stock may take time to implement. Also, the act of trading itself may move the price and this buying pressure diminishes the profitability of the trade (Ali, Hwang and Trombley, 2003). These indirect effects, along with direct trading costs, are often referred to as illiquidity[29] and pose a genuine risk to an investor. Consequently, an asset's liquidity should help to predict its expected return (Amihud and Mendelson, 1986).

[28] Petersen and Fialkowski (1994) note that adding the bid-ask–spread and broker's commission overestimates the magnitude trading expenses, as many trades occur inside the spread.

[29] The concept of liquidity is not lucid. It can be broadly defined as "the ability to trade large quantities (of stock) quickly, at low cost and without moving the price" (Pastor and Stambaugh, 2003, p644). In addition, illiquidity is not directly observable. A robust adjustment for some of the market microstructure mechanisms that preclude free trading requires a rich dataset that is unavailable for a wide range of assets for a lengthy period of time. Nonetheless, Brennan and Subrahmanyam (1996) examine the ability of trading costs and illiquidity to forecast future returns. To their credit, they construct highly precise measures of illiquidity over a relatively long (8 year) sample period. They find that it can predict future returns, or, more precisely, they conclude firm idiosyncratic illiquidity is priced. Thus, the risks associated with the stock's ease of trade can, in principal, help to explain size and value effect.

Table 3.6
Market Microstructure and the Size and the Value Effects in the US

Period	Effect	Coefficient	t	Reference	Table	Measure	Control	Method	Freq
Panel A: Size Effect Examined Jointly with Trading Costs									
1960-1979	Size	0.01	7.70	Stoll & Whaley (1983)[1]	VI	Bid-Ask Spread, Broker Commission	β	One-Way Sort	monthly
1961-1980	Size	0.00	-1.12	Amihud & Mendelson (1989)	II	Bid-Ask spread	β & Residual Variance	GLS	annual
1963-1991	Size	-0.07	-7.60	Datar, Naik & Radcliffe (1998)	II	Turnover	Nothing	Fama-MacBeth	monthly
1963-1991	Size	-0.05	-4.50	Datar, Naik & Radcliffe (1998)	II	Turnover	β, BE/ME	Fama-MacBeth	monthly
1966-1995	Size	0.64	1.08	Brennan, Chordia & Subrahmanyam (1998)	V	Price, Turnover	BE/ME, D/P & Momentum	Fama-MacBeth	monthly
1966-1995	Size	0.12	2.58	Brennan, Chordia & Subrahmanyam (1998)	V	Price, Turnover	Risk[2], BE/ME, D/P & Momentum	Fama-MacBeth	monthly
1964-1997	Size	-0.13	-3.50	Amihud (2002)	II	|Return| scaled by |T. Volume|	β, D/P, Residual Variance & Momentum	Fama-MacBeth	annual
1964-1999	Size	-0.091	-1.18	Acharya & Pedersen (2005)	VII	Aggregate liquidity	β, BE/ME	Fama-MacBeth	monthly
1966-2001	Size	0.21	2.87	Hou & Moskowitz (2005)[3]	III	Delay, T.Volume, σ(T.Volume) Zero Return, Price	BE/ME, D/P & Momentum	Fama-MacBeth	monthly
1976-1997	Size	4.43	2.98	Ali, Hwang & Trombley (2003)	IV	Price, Turnover, Zero Return, Analysts' Coverage	β, BE/ME, Residual Variance	Fama-MacBeth	monthly
1981-2001	Size	0.17	1.58	Hou & Moskowitz (2005)[3]	III	Delay, T.Volume, σ(T.Volume), Zero Return, Price, Analysts' Coverage, % Inst. Ownership	BE/ME, D/P & Momentum	Fama-MacBeth	monthly

Table 3.6 (continued)

Panel B: BE/ME Effect Examined Jointly with Trading Costs									
1963-1991	BE/ME	**0.220**	10.42	Datar, Naik & Radcliffe (1998)	II	T. Volume	Nothing	Fama-MacBeth	monthly
1963-1991	BE/ME	**0.140**	5.92	Datar, Naik & Radcliffe (1998)	II	T. Volume	β, Size	**Fama-MacBeth**	**monthly**
1966-1995	**BE/ME**	**0.235**	4.83	Brennan, Chordia & Subrahmanyam (1998)	V	Price, T. Volume	Size, D/P & Momentum	Fama-MacBeth	monthly
1966-1995	BE/ME	**0.181**	3.74	Brennan, Chordia & Subrahmanyam (1998)	V	Price, T. Volume	Risk[2], Size, D/P & Momentum	Fama-MacBeth	monthly
1966-2001	BE/ME	**0.002**	3.93	Hou & Moskowitz (2005)	III	Delay, T.Volume, σ(T.Volume) Zero Return, **Price**	**Size, D/P & Momentum**	**Fama-MacBeth**	**monthly**
1964-1999	**BE/ME**	**0.250**	2.91	Acharya & Pedersen (2005)	VII	Aggregate liquidity	β, Size	**Fama-MacBeth**	**monthly**
1976-1997	**BE/ME**	**0.078**	2.80	Ali, Hwang & Trombley (2003)	IV	Price, T. Volume, Zero Return, Analysts' Coverage	β, Size, Residual **Variance**	**Fama-MacBeth**	**monthly**
1981-2001	**BE/ME**	**0.002**	3.16	Hou & Moskowitz (2005)	III	Delay, T.Volume, σ(T.Volume), Zero Return, **Price, Analysts' Coverage, % Inst. Ownership**	**Size, D/P & Momentum**	**Fama-MacBeth**	**monthly**

1 These estimates are only indicative
[2] APT is a macroeconomic model of Chan, Roll & Ross (1983)
[3] The estimate is calculated by a 1000, for clarity

Studies of the size and the value premia employ long sample periods, thus data is often not available to precisely measure liquidity. As a result, many researchers proxy illiquidity with other easily accessible variables. For example, the bid-ask spread, at annual frequency, is used by Amihud and Mendelson (1989) to substitute for illiquidity. Bhardwaj and Brooks (1992) show that the share price is related to the bid-ask spread and broker's commission, thus it is often used to proxy for these costs. Datar, Naik and Radcliffe (1998) use trading volume scaled by shares in issue (turnover) as a measure of illiquidity, while Lesmond *et al*. (1999) use the instance of zero return as a good proxy for direct and indirect costs of trading. Lastly, Amihud (2002) proposes a measure of illiquidity given by a daily return scaled by daily trading volume. Actually, Acharya and Pedersen (2005) argue that Amihud's (2002) measure is a best proxy for the actual direct and indirect costs of trading.

Table 3.6 summarises a number of studies that jointly study the size effect and liquidity. The results are mixed. For example, Amihud and Mendelson (1989) show that size effect disappears after the bid-ask spread is taken into account. Brennan *et al.* (1998) show that after adjustment for the BE/ME and momentum effects, the additional control for illiquidity actually reverses the size effect. An adjustment for risk with a five-factor statistical APT strengthens their finding. However, share price and the measure of illiquidity is highly correlated with market capitalisation, thus it is possible that the coefficient on size in the cross-sectional regressions is biased, as some of the explanatory power of market capitalisation is captured by the share price. Nonetheless, since Amihud's (2002) measure has been shown to be a very good proxy for illiquidity, his result, that size effect persists after illiquidity is taken into account, is probably most accurate.

3.2.2 Illiquidity as a Priced Factor

Up to now the discussion has focused on an asset-specific measure of liquidity. However, *inter alia* Amihud (2002), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) argue that aggregate market liquidity ought to be a state variable that is included in a multifactor asset pricing model. Amihud (2002) documents significant time-variability in his measure of aggregate liquidity. He argues that it should be related to average share returns[30]; a fact he confirms empirically. Acharya and Pedersen (2005) extend his point and show that there are three distinct risks (factors) that stem from time-variability in liquidity. The first source of risk they explore, referred to as commonality in liquidity, is captured by the co-variance of the asset's idiosyncratic liquidity and market liquidity[31]. The second source of risk is the co-variance of the asset's return and market liquidity[32]. The third source of risk is captured by the co-variance of the asset's idiosyncratic liquidity with market return[33].

The empirical analysis of aggregate illiquidity risk unveils a strong relation between firm size and the three liquidity risks. Pastor and Stambaugh (2003) and Amihud (2002) show that returns on small stocks exhibit a larger correlation with aggregate liquidity than large firms. Their findings imply that when investors expect a fall in the ease of trading they discount small stocks the most. Amihud (2002) also documents a phenomenon, dubbed "flight to liquidity", where small stocks are sold in favour of larger stocks during declines in market liquidity. Formally, Acharya and Pedersen (2005) run a cross-sectional asset pricing test where the relevant factor encapsulates the three types of liquidity risks and the market risk. They find that this "modified beta" can explain 90% of cross-sectional variations in 25 size-sorted portfolios. More importantly, evidence in Table 3.6 shows that market equity loses its explanatory power after their factor is used to adjust for market and liquidity risks.

3.2.3 Some stocks are just more popular than others

Investing requires the ability to obtain and process a large amount of information. The cost of data acquisition and analysis may be large and deviations from market efficiency, such as the size and the value effects, may not be profitable after these search costs are taken into account (Merton, 1987; Grossman and Stiglitz,

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[30] He notes that investors would bid prices down if they expect to increase costs associated with trading because the increase in overall illiquidity must be compensated with higher market-wide returns.

[31] It would seem intuitive that stock that becomes easier to trade when market as a whole becomes more illiquid would be particularly valuable and would yield low returns.

[32] Investors, all else equal, dislike when aggregate illiquidity increases. Thus they would particularly eschew stocks that yield poor returns when stocks on aggregate are more difficult to trade. In effect, relation between expected returns covariance of idiosyncratic return with market liquidity ought to be positive.?

[33] Stocks with high covariance of this type should be associated with high return. Investors would dislike stocks that lose in liquidity when market is falling.

1980). Put differently, investing in firms with (using Merton's (1987) terminology) low *investor recognition* is risky and acquiring the necessary information is costly. Thus, in order to buy these neglected firms, investors need to be compensated with higher expected returns.

As with illiquidity, a stock's investor recognition is difficult to measure and a number of proxies that capture this attribute have been devised. For instance, Ali *et al.* (2003) argue that breadth of ownership is a good proxy for investor recognition. Hong, Lim and Stein (2000) argue that the degree of coverage by investment analysts of a particular stock is a good proxy for the speed with which the market assimilates relevant information. An ingenious measure of a stock's recognition is devised by Hou and Moskowitz (2005). They devise a measure of speed with which information is impounded into a share. They call it *delay*. Subsequently, they show that their measure is highly related to a wide range of proxies for attention a particular share receives[34], in that a regression of the delay measure onto a set of variables that measure a stock's investor recognition yields an R^2 of 0.7.

A priori, the amount of investor recognition a firm attracts should be related to its size. According to Hong *et al.* (2000), investing in a particular share may involve fixed costs associated with the initial information search. Investors would then aim to learn only about stocks that do not preclude large investments. In addition, institutional investors seem to eschew small capitalisation stocks (Falkenstein, 1996). In fact, Hou and Moskowitz (2005) show that a firm's measure of delay contains much of the same information about expected returns as its size. In particular, they show that residuals from a regression of market capitalisation onto the delay measure have no incremental power to predict returns[35]. Thus, the size effect seems to be subsumed by the delay measure - a proxy for risks that stem from poor level of investor recognition.

It can be seen from Panel A of Table 3.6 that Ali *et al*. (2003) and Hou and Moskowitz (2005) perform a joint test of the ability of idiosyncratic measures of liquidity and investor recognition on the size effect. In sum, both of these studies show that an adjustment for these market imperfections unmakes the size premium.

[34] They use a comprehensive set of proxies: institutional ownership, number of analysts that follow the stock, number of shareholders, number of employees, advertising expenditure, difficulty of travel to company headquarters.
[35] ?

Actually, both studies point toward a reversal of the effect. However, both of these studies control for price, which is highly co-linear with market capitalisation, thus there may be a bias on the computed coefficients on the size variable. Nonetheless, evidence presented above supports the view that the size effect is a result of market imperfections.

So far the value effect has been unexplored. A summary of results from various studies that jointly test the anomaly with various measures of market frictions is shown in Panel B of Table 3.6. A significant component, both in the economic and statistical sense, of the value premium, is independent of risks associated with liquidity or investor recognition. The book-to-market effect survives the stringent control in Hou and Moskowitz (2005). They do note, however, that some of the value premium can be explained by their delay measure. Also, when Acharya and Pedersen (2005) use their illiquidity model to price the 25 size and BE/ME sorted portfolios, the R^2 of the cross-sectional test is 0.56, which is higher than the 0.26 obtained from a test with the static CAPM. However, in Table 3.6, the book-to-market ratio continues to reliably predict returns after control with their model.

In sum, it appears that the size effect is a result of market frictions. It attenuates after trading costs are taken into account. Small firms are illiquid and load positively onto the liquidity factor. In addition, they tend to be neglected by investors. As a result, the high return to small stocks is a compensation for risk. On the other hand, after taking various market frictions into account, the value premium remains robust. As a result, much theoretical and empirical work in finance aims to explain this anomaly. Some believe that the F/P ratios are proxies for risk factors that are omitted from the static CAPM (Berk, 1995), while others argue that it is caused by irrational investor behaviour (Lakonishok *et al.*, 1994). The remainder of the literature review joins this debate.

3.3 Irrationality

Few would argue that market efficiency in the sense of Fama (1970) is the correct view of the financial markets. In Chapter 2, compelling evidence has been presented which illustrates that shares can be grossly mis-valued by the market. In addition, the contention of Shleifer and Vishny (1997), that arbitrage is risky, and consequently limited, is widely embraced as it is derived without too lavish assumptions of investor irrationality. However, the unequivocal link of behavioural finance with the size and the value premia is a subject of fierce debate. This section presents empirical evidence that the anomalies, and especially the value effect, are an outcome of investor irrationality.

3.3.1 Limited Arbitrage and the Value Effect

According to the limited arbitrage argument of Shleifer and Vishny (1997), prices are kept away from fundamentals because arbitrage is risky as it exposes the arbitrageur to noise and fundamental risk (Lamont and Thaler, 2003a). Thus, stocks that are difficult to value or those that are popular among noise traders would be most likely to be mispriced (Daniel and Titman, 1999)[36]. Consequently, Ali *et al.* (2003) argue that if the value effect stems from irrational behaviour, it should be the strongest among firms that are most risky to arbitrage. With firm specific noise as a proxy for risks associated with arbitrage, they find that the book-to-market effect is consistent with the mispricing theory. Particularly, in their cross-sectional regressions, the ability of book-to-market to predict returns increases with a firm's level of arbitrage risk.

In addition, the theory of limited arbitrage implies that mispricing is most likely to persist in cases where it is difficult to communicate convincingly (Brav, *et al.* 2004): surely, someone would *know* of the mispricing and would try to exploit it. Firm insiders, for example, would have private information regarding the firm and could estimate mispricing with less noise. Actually, Bem-David and Roulstone (2005)

[36] For example, Bem-David and Roulstone (2005) find that firms use mispricing to their lower cost of capital.? In particular, they show that there is a positive relationship between the firm's level of arbitrage risk and the magnitude of the price drift after a share repurchase.

show that insiders who buy shares when the firm specific noise is at its highest (thus when arbitrage is most limited) earn the highest return. Consequently, for the behavioural story to explain the value effect, insiders would buy more stock of (undervalued) value firms and less stock of (overvalued) growth firms. This is exactly what Rozeff and Zaman (1998) observe. They document a positive, near-monotonic relationship between a firm's book-to-market (or cashflow yield) and net purchases by insiders, whose trading does not eliminate mispricing because their access to capital is limited and the law prohibits them from using their private information to raise more funds.

3.3.2 The error-in-expectations Hypothesis

Arguably, no behavioural theory explicitly talks of the value premium. Instead, behaviourists believe it to be a natural consequence of investor overreaction in the sense of De Bondt and Thaler (1985). For example, a portfolio of value firms may contain many stocks that are erroneously expected to be less profitable than the market and once people learn of their error, they correct mispricing by bidding up prices. In general, the value effect is a consequence of market's systematic error in appraising future profitability of some assets; Lakonishok *et al.* (1994) call it *error-in-expectations hypothesis*. Bias in expectation can be a consequence of either the representativeness heuristic (Barberis *et al.* 1998) or overconfidence on the part of investors (Daniel *et al.* 1998). To its credit, the theory puts forward a number of rejectable hypotheses. Specifically, according to Lakonishok, *et al.* (1994), there ought to be, given a positive relation between past and expected profitability, a negative relationship between an asset's *ex ante* profitability with its subsequent realised return.

In order to test their theory, Lakonishok *et al.* (1994), need to measure expectations. Thus, they look to the Gordon formula:

$$P_0 = \frac{E\ \ D_1}{E(r) - E\ \ g_\infty} \longrightarrow \frac{C_0}{P_0} = \frac{k\ \ E(r) - E\ \ g_\infty}{1 + E\ \ g_1} \qquad (3.1)$$

[37]

Following Equation (3.1), they note that a firm with a high cashflow yield is either discounted at a high discount rate or it is expected to grow at a slow pace. Therefore, by assuming that growth and value firms are, on aggregate, equally risky, Lakonishok *et al.* (1994) rely on the earnings yield and the cashflow yield to act as proxies for expected rate in growth in future earnings. In addition, they use a *sales-growth* measure[38] to quantify firm's past profitability.

In line with the mispricing hypothesis, stocks that the market was too optimistic about turned out to be poor investments. In particular, assets with strong past profitability (a high sales-growth measure) and highest expected future profitability (a low C/P) give low returns in subsequent five years. Actually, these stocks perform the worst of the studied assets. On the other hand, stocks expected to have poor profitability and have low past profitability yield the highest return. The cumulative five-year difference between these two portfolios is about 100%! (Lakonishok *et al.* 1994).

Lakonishok *et al.* (1994) reveal further evidence supporting the hypothesis that the market was too optimistic (or pessimistic) in computing the *ex ante* profitability of growth (or value) firms. At first, they show that the differential in C/P ratios between the two types of firms implies that the market *expects* the earnings of growth firms to expand faster than that of value firms for about 11 years. However, although in the short-term earnings of growth firms do increase markedly faster than that of value firms, after only the second year, the *actual* growth rates in profitability of both types of firms are approximately equal.

Nonetheless, it can be argued that cashflow yield and earnings yield are poor proxies for expected growth in profitability. To address this concern, La Porta (1996) uses the forecasts of investment analysts to measure expectations. His findings are consistent with the error-in-expectations hypothesis. Following Lakonishok *et al.* (1994), he documents that stocks that are expected to grow the fastest underperform firms with low growth expectations by 20% in the first year. He also observes

[37] P is price, D is dividend, g is the growth rate, k in this equation is the payout ratio. Subscripts denote time.

[38] For a detailed description see Lakonishok *et al.* (1994)

subsequent realised growth in earnings of firms that the market is pessimistic about and finds that the earnings of these firms, on average, grow particularly quickly, while the growth in earnings of glamorous firms tends to fall. In short, La Porta (1996) confirms the results in Lakonishok *et al.* (1994) with a cleaner measure for expectations.

Another implication of the error-in-expectations hypothesis is that high returns of value stocks are a consequence of the market correcting its prior mistakes. Of course, the correction will be slow, as it takes more then one informational shock to change investors' perceptions (Barberis, *et al.* 1998; Daniel *et al.* 1998). In light of this, the hypothesis makes three tractable predictions: expected profitability of erroneously analysed firms must change as new information reaches the market, market is surprised with earnings of such firms, and it takes many years before investors completely reverse their prior, and incorrect, assessment of profitability.

In effect, the three predictions of the error-in-expectation hypothesis have been confirmed in the data. La Porta (1996) shows that analysts revise upwards their estimates of growth in earning of the firms they were the most pessimistic about and cut growth forecasts of firms they most favoured. In addition, La Porta, Lakonishok, Shleifer and Vishny (1997) show that investors are systematically surprised by earnings of value and growth firms. More specifically, value firms have a high positive return around their earning announcements, while the returns to growth firms are particularity low when earnings are announced. Also, in line with behavioural theory, the high returns of value firms around earning announcements were higher than that of growth firms for up to five years.

Lastly, it would seem prudent to ascertain how investment professionals understand a firm's market beta or its book-to-market ratio. Accordingly, Bloomfield and Michaely (2004) surveyed a sample of analysts to establish whether market participants think of these attributes as measures of risk or mispricing. The research covered both young and experienced analysts. Their finding supports the static CAPM and the behavioural view. Analysts think that market beta and future return are positively related, but it plays little role as a measure of mispricing. However, professionals exclusively see the book-to-market ratio as a measure of mispricing.

It has been shown that behavioural finance offers plausible explanations for the value effect. However, it is important to remember that few behavioural economists would venture as far as to dismiss the rational view of the markets. Undoubtedly, investors care about risk, estimate expected returns and aim to arbitrage away mispricing (Lamont and Thaler, 2003a). Additionally, some of the empirical facts discussed above have been thrown into question. For example, Doukas, Kim and Pantzalis (2002) cast doubt that the error-in-expectation hypothesis and the book-to-market effect are linked, and Fama and French (1995) reinterpret findings in Lakonishok *et al.* (1994) in the rational paradigm. Consequently, the review goes on to show that risk plays a large role in the size and the value effects.

3.4 Are Small Stocks Riskier? Is Value Riskier than Growth?

Proponents of efficient markets maintain that the asset pricing anomalies are consistent with rational asset pricing theories and are a direct consequence of erroneous adjustment for risk. A connection between size, the book-to-market ratio and risk is established *inter alia* by Berk (1995) and Ball (1978). Using the intuition of the Gordon formula, Ball (1978) noted that, after controlling for dividends and the growth rate, an asset with higher risk must trade at a lower price. Consequently, all else being equal, its market capitalisation is lower, while its F/P ratio is higher. Berk (1995) formally proved that, as long as the true expected return and the expected return predicted by an asset pricing model differ, the relationship between a firm's market size and the residual return must be negative (or the relationship between BE/ME and the residual return must positive).

How to measure risk? Traditional finance theory states that risky assets increase the volatility of peoples' wealth[39] (Brealey and Myers, 2000). A more precise way to look at risk is to follow Cochrane (2001), who states that "risky" assets vary "more" with some state variables that trace out the path of our aggregate long-term wealth. These shares would have lower prices because investors eschew assets that, during times when our long-term wealth is falling, are becoming even less valuable. Consequently, in order to quantify an asset's risk, all that is needed is to measure the co-variance of its return with variables that determine long-term wealth of an average investor. This is not easy! In order to uncover the identity of the state variables, one can turn to theory (such as the static CAPM), or empirically search for some candidate variables. However, a generally accepted theoretical asset pricing model has not yet been derived and, the finance academia warns emphatically against empirically deriving asset pricing factors (Fama, 1991; Kan and Zhang, 1999, Kandel and Stambaugh, 1995).

[39] This is imprecise. Cochrane (2001) noted that people care about their *marginal utility of consumption*. When our marginal utility is high, it is difficult (or expensive) to consume more; it is a "bad" state. Conversely, "good" states occur when our marginal utility is low. Cochrane (2001) notes that marginal utility of consumption is correlated with aggregate consumption. It is assumed that aggregate consumption is a direct consequence of wealth. So agents' concern about wealth is equivalent to peoples' worry about consumption. Thus, for simplicity in this dissertation, aggregate wealth is considered to? marginal utility of consumption.

A more pragmatic definition of a risky stock is given by Chen and Zhang (1998) and Fama and French (1995), who simply classify risky stocks as those with *inter alia* cashflow problems, poor profitability and high financial leverage. The two definitions can, of course, be equivalent, as investment in these *weak* firms may yield relatively low payoffs in poor economic states. However, if a *strong* firm, financially speaking, is a poor hedge for shifts in the efficient frontier (as in Merton's (1973) ICAPM), it can still be considered risky.

In this section, evidence is shown that forges a connection of the size and the value effects with risk. In particular, Fama and French (1992) argue that small or value firms are risky as they are more likely to plunge into bankruptcy, thus, evidence for, and against, their *distress risk hypothesis* is shown. Also, by the strength of the APT intuition, if small or value firms co-vary "more" with some "widely-accepted" macroeconomic sources of risk, such as the level of inflation or interest rates, then it may prove satisfactory to assemble a macroeconomic APT model, and use it to solve the puzzle of the two premia.

3.4.1 Size, BE/ME and the Financial Distress Risk Hypothesis

A weak firm is a firm that has fallen on hard times; it has poor earnings and its market value has fallen. Such decline in value increases its financial leverage, which may indicate difficulty in raising capital. Often, management is forced to cut back on dividends, as the company is low on cash (Chan and Chen, 1991). Consequently, weak firms ought to be risky and weak firms ought to exhibit high *ex ante* returns. Actually, Chan and Chen (1991) show that a portfolio of firms that have cut dividends, or exhibit high leverage, does outperform the market index. Thus, showing that small and value firms are indeed in financial distress could explain their large return[40].

Chan and Chen (1991) are among the first to forge a link between the financial health of the firm and the size effect, and they argue that, at any given time, many small firms may be in financial trouble. In particular, at a given point in time, many

[40] More importantly, for the risk story to hold, a high BE/ME ratio must signal persistently low earnings in the future. Brief periods of high or low profitability should not be the driver of firm's book-to-market ratio or its size (Fama and French; 1995), as investors would not bid down prices if they know that financial trouble is only temporary.

small firms used to be larger. In fact, they note that around two-thirds of small firms, become small as a result of a decline in their market value and only a fifth of small firms are permanently small. Conversely, half of big firms are persistently big. More importantly, Chan and Chen (1991) calculate that more than half of all firms that have significantly cut dividends, or have high financial leverage, are small. In addition, on average, smaller firms in each industry are less profitable and have high interest coverage ratios. Chen and Zhang (1998) document a similar pattern internationally. In addition, Chen and Zhang (1998) find a firm's size and its propensity to cut dividends are highly related. Since managers loath cutting dividends, a decline in a firm's payout is a particularly powerful indication of poor cashflow prospects or anticipation of difficulty in raising capital (Chan and Chen, 1991). It would thus appear that size effect might be closely linked to a risk that stems from a firm's inability to raise new funds.

Fama and French (1995) provide similar evidence for the value effect. With a portfolio sort, they examine profitability, measured by the return-on-equity ratio, of value and growth firms. In accordance with the financial distress hypothesis, they show that, in the five years preceding their classification, profitability of value firms falls sharply, while it increases for growth firms. More importantly, the authors show that profitability of value firms is persistently lower than that of growth firms, as the return-on-equity ratio for high-BE/ME firms is smaller than that of low-BE/ME firms for five years before and after classification. Chen and Zhang (1998) replicate these patterns in Japan, Hong Kong and Malaysia.

Chen and Zhang (1998) go on to provide stronger evidence that links the size and the value effect with measures of financial distress. They examine whether the information that predicts returns contained in market equity and the book-to-market ratio potentially exists in other firm characteristics that are explicitly linked to financial distress. The attributes they use are the decline in dividends paid, volatility of earnings and financial leverage. Chen and Zhang (1998) show that their distress characteristics explain the same amount of cross-sectional variation in returns as market equity and the book-to-market ratio.

Nonetheless, a loose relation between the size and the value premia and financial risk is inadequate. It must be explicitly shown that the risk associated with bankruptcy causes high returns and that it underpins the size and the BE/ME effects. Consequently, for the distress hypothesis to be accepted, its two distinct perditions must be supported in the data. First, it must be shown that distress risk is priced, i.e. there is a monotonic positive relationship between a firm's measure of distress and its realised return. Second, after controlling for financial distress, the market equity and the book-to-market ratio must not have any incremental power to explain returns (Dichev, 1998). In order to test these predictions, a stock characteristic that can predict *actual* bankruptcy needs to be constructed. One way to assess a firm's financial strength is to turn to an accounting measure that forecasts bankruptcy, such as Altman's (1968) Z-score and Olhson's (1980) O-score. Otherwise, probability of default can be obtained from an option pricing model, which has an advantage of being forward-looking. Incidentally, all of these models have found out-of sample success in forecasting bankruptcy.

The contention that distress risk is priced meets with mixed empirical support. For example, using the Z and O scores, Dichev (1998) finds that firms that are likely to go bankrupt yield low returns; she finds a negative premium for distress risk! Dichev (1998) fails, however, to properly adjust for the size and the BE/ME effects. Griffin and Lemmon (2002) repeat her tests with the O-score and a longer sample. They show the connection between a book-to-market ratio and measures of distress that Dichev (1998) missed. More specifically, they find that distressed firms earn higher returns than financially sound companies only if they also happen to have high book-to-market. However, on average, the relationship between the O-score and returns is found to be flat because default has a negative premium in low book-to-market firms. Finally, Vassalou and Xing (2004) estimate default probability for individual firms with an option pricing model. They document a similar interaction between the book-to-market ratio and measure of distress as Griffin and Lemmon (2002). However, their cross-sectional test reveals that firms with high probability do earn higher returns; the default risk is priced[41].

The second prediction of the financial distress story for the size and the value effects is that a cleaner measure of distress should have a stronger predictive power for returns than market capitalisation or the BE/ME ratio. Here the results are in unison. The book-to-market ratio remains a reliable predictor of stock returns after controlling for measures of financial distress. Market equity, however, loses much, if

[41] Aretz *et al.* (2005) show inclusion of the other macroeconomic variables renders it indistinguishable from zero.

not all, of its importance to price assets. The result is robust to many measures of financial distress, such as the Z-score, the O-score (Dichev, 1998) and the *ex ante* measure of survival probability in Vassalou and Xing (2004).

3.4.2 Macroeconomic Risks and the Size and Value Premia

Given that small and value firms possess characteristics that, to the average investor, may be a sign of risk, the natural next step is to determine whether returns on these firms have larger co-variances with plausible variables that trace the path of the business cycle. Weak firms could have higher returns during upturns because they are "saved" from bankruptcy, while low during recessions, as more weak firms are pushed into liquidation (Dichev, 1998).

Chen and Zhang (1998) link the size and the value effects to macroeconomic risks, by showing that the premia do not exist in certain developing countries. Consider an economy that is growing incredibly quickly and firms that are already positioned in the market stand to make high profits. If small or value stocks represent marginal firms, then in a high-growth economy investors may not aggressively discount prices of such firms because financial problems experienced by these weak firms are likely to be temporary. Consequently, size and value effects are moderate in countries with booming stock markets. This is the precise finding of Chen and Zhang (1998). They show that fast-expending economies, such as Taiwan and Thailand, are virtually free of the size and the value effects, while the medium growth economies of Japan, Hong Kong and Malaysia exhibit much smaller size premiums than the mature US market. There appears to be a near-perfect negative correlation (-0.977) between countries' stock market performance and the magnitude of the anomalies.

Perez-Quiros and Timmermann (2000) argue that the stage of a business cycle, which indicates the ease with which firms obtain financing, must determine the returns of small firms. In particular, they note that, often, ample collateral is needed to secure financing. At times of increasing interest rates, asset values shrink due to higher discount rates and the promised cost of debt grows. Consequently, small firms would face difficulty in raising ample funds, as they have little collateral. In addition, at times of falling economy-wide liquidity, commercial banks, faced with reserve requirements, will be the first to stop lending.

Table 3.7
The Spread in Factor Betas

Panel A: Loadings of Small and Large Firms on a Set of Macroeconomic Variables						
	Small	Large	Small less Large	Ave Small less Large %	Period	Reference
Δ E(industrial production)	5.770	5.583	0.187	3%	1971-1998	Aretz, Bartram & Pope (2005)
Unexpected Inflation	-0.733	-0.107	-0.627	336%	1971-1998	Aretz, Bartram & Pope (2005)
Δ Aggregate p(survival)	2.477	1.260	1.217	73%	1971-1998	Aretz, Bartram & Pope (2005)
Δ level of the yield curve	3.420	5.410	-1.990	47%	1971-1998	Aretz, Bartram & Pope (2005)
Δ slope of the yield curve	-1.610	-3.390	1.780	82%	1971-1998	Aretz, Bartram & Pope (2005)
Δ Forex	0.077	-0.063	0.140	202%	1971-1998	Aretz, Bartram & Pope (2005)
Δ price of oil	-0.287	-0.317	0.030	10%	1971-1998	Aretz, Bartram & Pope (2005)
Δ default spread	2.852	-0.886	3.738	276%	1963-2001	Hahn & Lee (2003)
Δ term spread	0.738	0.271	0.467	118%	1963-2001	Hahn & Lee (2003)
Panel B: Loadings of Value and Growth Firms on a Set of Macroeconomic Variables						
	Value	Growth	Value less Growth	Ave Value less Growth %	Period	Reference
Δ E(industrial production)	4.737	6.037	-1.300	24%	1971-1998	Aretz, Bartram & Pope (2005)
Unexpected Inflation	0.420	-0.520	0.940	202%	1971-1998	Aretz, Bartram & Pope (2005)
Δ Aggregate p(survival)	1.570	1.250	0.320	23%	1971-1998	Aretz, Bartram & Pope (2005)
Δ level of the yield curve	1.463	2.323	-0.860	48%	1971-1998	Aretz, Bartram & Pope (2005)
Δ slope of the yield curve	-2.087	-3.927	1.840	68%	1971-1998	Aretz, Bartram & Pope (2005)
Δ Forex	0.013	-0.097	0.110	469%	1971-1998	Aretz, Bartram & Pope (2005)
Δ price of oil	-0.340	-0.407	0.067	18%	1971-1998	Aretz, Bartram & Pope (2005)
Δ default spread	1.622	0.361	1.261	214%	1963-2001	Hahn & Lee (2003)
Δ term spread	-0.036	1.019	-1.055	1517%	1963-2001	Hahn & Lee (2003)

Small firms often do not enjoy access to bond and cash markets because information acquisition costs for these firms are high (Hong *et al.* 2000). Consequently, these firms will be most dependent on private, mostly bank, financing and will experience the largest difficulty in sourcing new funds. In fact, Perez-Quiros and Timmerman (2000) show that the expected return of small stock and their variance grows sharply during recessions[42]. In addition, Liew and Vassalou (2000), in a cross-section of industrial nations, find that, in poor economic states, small firms do underperform but yield especially returns in good states.

Chen *et al.* (1986) were among the first to analyse how macroeconomic variables affect stock returns[43]. The list of such variables is long. For instance, Perez-Quiros and Timmerman (2000) note that default spread is particularly important in pricing of small firms, as it is a good proxy for credit conditions. In addition, Hahn and Lee (2006) argue that changes in borrowing costs, measured by the slope and the level of the yield curve, have a strong effect on firms with high levels of debt. Consequently, given that the book-to-market ratio is related to financial leverage, variables that describe the yield curve can be central in explaining the returns of value firms.

It is clear from panel A in Table 3.7 that small firms exhibit different risk exposures to large firms. For example, low capitalisation stocks tend to co-vary more intensively with unexpected inflation, aggregate survival probability of Vassalou and Xing (2004), the term spread[44] and the default spread. Also, loadings on the yield curve variables and foreign exchange are much different for small firms than for large firms.

A similar pattern emerges if one looks at loadings of value and growth firms in panel B. They differ by their exposure to foreign exchange, unexpected inflation and the default spread. However, it is the term spread (as measured by Hahn and Lee

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[42] Specifically, Perez-Quiros and Timmermann (2000) confirmed that small firms, on average, have larger loadings on default premium than large firms, but also they show that there is a very significant increase in small firm's sensitivity to the default premium during recessions. Also, they find that the sensitivity to movements in the short-rate is much more negative for small firms during recessions. Taken together, these results imply that, during market recessions, small firms become riskier.

[43] The list of such variables is long, but it can generalised into: various inflation measures; variables that capture costs of borrowing; growth in GDP, or in its components; or measures of credit quality.

[44] Of course, the Δ term spread and Δ slope of the yield curve are similar measures. However, Aretz, *et al.* (2005), as do Hahn and Lee (2006), estimated all of their loadings simultaneously. Thus, loadings on the yield curve measure in Aretz *et al.* (2005) captures the shifts in the yield curve that is independent of other state variables, while measure in Hahn and Lee (2006) is orthogonal only to the default spread.

(2006)) that emphasises the difference in the co-variance structure of the two types of firms. Curiously, the difference in exposure to the aggregate survival probability, after other betas are taken into account, is very low between firms with different BE/ME ratios.

It is unlikely that exposure to change in industrial production or oil play a role in capturing the difference in returns to small and value firms. Actually, Aretz, Bertram and Pope (2005) test formally for difference in exposure to the various macroeconomic factors and find that loadings on the aggregate survival probability, the yield curve variables and foreign exchange differ reliably among the size-sorted portfolios. The only significant difference between loadings of different BE/ME-sorted portfolios is in the yield curve factor.

It may appear that the magnitude of the size and, partially, the value effects, are related to macroeconomic sources of risk. However, without analyzing the sign and the magnitude of the different premia, it is hard to establish that small and value firms command a higher return. However, the magnitude of premia to factors that are not expressed as equity returns can only be measured in a cross-sectional test (Cochrane, 2001), and Kandel and Stambaugh (1995) show that the magnitude of an estimated premium is a function of the test assets the regressions employ. Also, Jagannathan and Wang (1998) show that in a standard cross-sectional test, a factor can appear priced, even if its true premium is zero.

Nonetheless, some of the factors, when measured on the size and BE/ME sorted portfolios and shown in Table 3.7, yield statistically significant premia. For instance, on its own, distress risk is priced, but Aretz *et al.* (2005) show that it contains the same information as other macroeconomic variables. Also, Hahn and Lee (2006) show that the asset's co-variance with the default spread seems to be a strong predictor of the cross-sectional dispersion in returns of size and BE/ME sorted portfolios. Curiously, Aretz *et al.* (2005) show that only one of the macroeconomic variables, the exchange rate, is priced. However, co-linearity between the variables may be the culprit for the low statistical significance in their tests.

In sum, the existence of a connection between the book-to-market ratio and financial distress is a subject for debate, and the interpretation of existing results may be a matter of taste. However, it seems that financial risk offers a credible explanation for the size effect. Also, if aggregate distress is a priced factor, then by virtue of the high correlation between BE/ME and measures of bankruptcy, it plays a role for the value effect as well.

More importantly, consistently with a risk-based story, small and value firms co-vary “more” with plausible sources of business cycle risk. Also, some of these risks seem to be priced. In fact, the macroeconomic model of Aretz *et al.* (2005) can explain almost the same amount of cross-sectional variation in returns as a model that actually does explain the disparity between stock returns. In other words, it does nearly as well as the empirically derived three factor specification created in Fama and French (1993); to which the review turns next.

3.5 Enter the Fama-French Three factor Model.

It has been established that the size and value premiums exist, and possible explanations for these effects have been put forward. However, relatively little has been said on how asset allocation, performance appraisal of portfolio managers and the general adjustment for risk need to be modified in order to take into account these "anomalies". In other words, it has not been made clear how to parameterise the size and the value effects into an asset pricing model.

Fortunately, Eugene Fama and Kenneth French developed a linear three factor model (henceforth, the FF3F) that can, statistically speaking, explain the size and the value premia. In effect, their model is an extension of the static CAPM where the market factor is augmented with size and value factors. Algebraically, it is given by:

$$E_t \quad r_{i,t+1} \quad = r_f + b_i \lambda^{Market} + s_i \lambda^{Size} + h_i \lambda^{Value} \tag{3.1}$$

The roman letters in the terms on the right side of Equation 3.1 represent risk exposures, while the λ's are associated with the premiums on the three types of risk. A more common (empirical) specification of the FF3F model is:

$$r_{it} - r_{ft} = \hat{\alpha}_i + \hat{\beta}_i \quad r_{Mt} - r_{ft} \quad + \hat{s}_i SMB_t + \hat{h}_i HML_t + \varepsilon_{it} \tag{3.2}$$

Equation 3.2 represents a regression of realised excess returns of an asset on the market factor and two factor-mimicking portfolios. The SMB (Small minus Big) is the size factor, and is calculated as a return on a zero-cost portfolio that establishes a long position in a portfolio of small firms and finances it with a short position in large firms. Similarly, the value factor, HML (High minus Low), is constructed from a zero-cost portfolio that longs firms with a high book-to-market ratio and shorts firms with a low book-to-market ratio. Because market capitalisation and F/P ratios are correlated, Fama and French (1993) use a sorting procedure that results in portfolios that do not confound the size and the value effects. In sum, the HML factor captures the value premium that is independent of the effect of size and the SMB factor captures the size premium that is independent of the effect of the book-to-market ratio.

The three factor model is not a magic bullet for asset pricing. Actually, it constitutes a mild embarrassment to the field of financial economics because it has not been derived theoretically. At the time of its development, there were few, if any, discernable links between the model and formal asset pricing theory. However, its staggering success and relative ease of application led to growth in the model's popularity among academics and eventually practitioners as well. Perhaps the forceful, but unproved, arguments of Fama and French (1993, 1996a), that their model is consistent with a multi-factor version of Merton's (1973) ICAPM, are sufficiently convincing. Even though Fama and French (2004) begin to take behavioural finance seriously, they continue to maintain that the three factor model is a "good approximation to average returns" (Fama and French, 2004, p12).

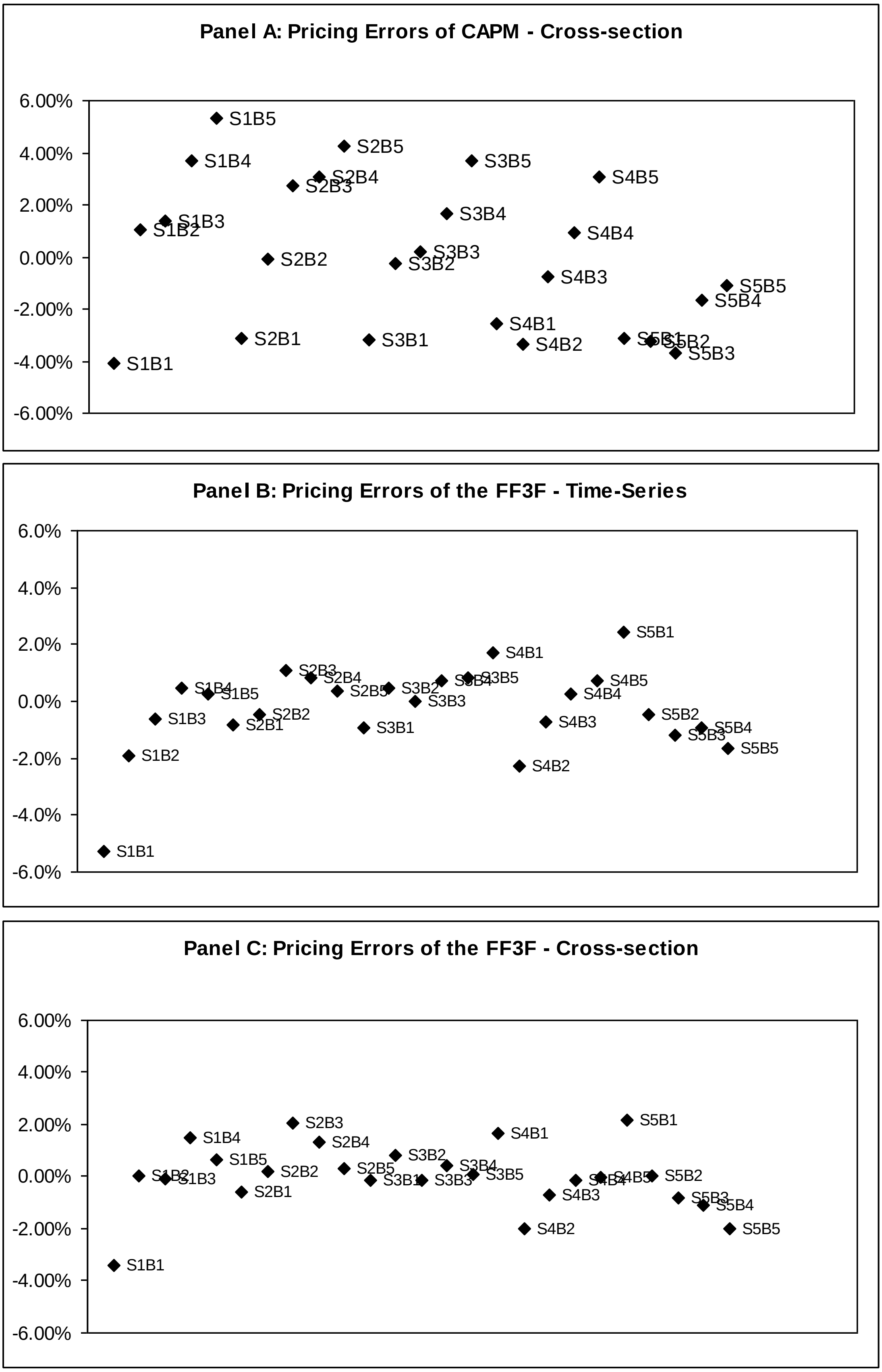
3.5.1 Does it do a good job of explaining Average Returns?

Why is the FF3F is so good? Why is it so much better than the static CAPM? What makes any asset pricing model good? In short, since an asset pricing model's job is to predict returns, it should do just that; the pricing errors of a good model ought to be small. Also, premiums associated with factors of a well-specified model should exhibit the correct sign and be reliably different from zero. A model's pricing power must extend across different sample periods and different assets. Ideally, the R^2 in time-series and cross-sectional tests that use well-diversified portfolios as test assets should be high, meaning that the model can capture systematic components of share returns. Lastly, the model ought to "price-out" firm characteristics that are thought to capture mispricing (Cochrane, 2001).

Figure 3.1 illustrates the ability of the competing models to predict returns on the 25 size and BE/ME sorted portfolios. Panel A shows the performance of the CAPM, while the last two panels present pricing errors of the three factor model. The figure was created from results found in Fama and French (1996a) and Lattau and Ludvigson (2001b), who have used data from 1963 to 1993 and 1998, respectively.

The CAPM does not seem to be a good model. The pricing errors in the first panel are dispersed: some are highly positive and some are very negative. Although, portfolios of big firms (marked "S5") seem to line up around zero, most of the other assets (where prefix "S1" indicates the smallest firms) are not well priced. Also, these pricing errors illustrate how dismally the model fails to adjust for the size and the value effects. In particular, note that as the size of the firm increases so does the dispersion of the pricing errors.

Figure 3.1
The Pricing Errors of the CAPM and the FF3F



In fact, the portfolio containing small value firms (marked “S1B5”) outperforms the market by almost 6% annually! However, it is the value effect that is more evident. Within each size quintile, pricing errors of portfolios with low-BE/ME firms (suffix “B1” indicates growth) always plot below zero; errors of portfolios with high-BE/ME firms (“B5” indicates value) plot above. Mispricing, however, tempers off among the largest firms.

Panels B and C in Figure 3.1 present the pricing errors of the three factor model. The cross-sectional test allows for a mismeasurement of the risk premia (Cochrane, 2001)[45]. That is why the pricing errors in panel C are closer to zero[46]. The pricing ability of the FF3F model is much better than that of the static CAPM. Pricing errors of smaller firms are no bigger than those of large stocks. Some minor relation between the BE/ME and return persist, but its magnitude is nowhere near that of the static CAPM. It can be said that the three factor model accounts for the difference between returns of small and large stocks as well as value and growth firms. Actually, the R^2s of cross-sectional tests are usually around 70% (Ferguson and Shockley, 2002; Hahn and Lee, 2006; Petkova, 2006) and it increases to 77% if quarterly frequency is used in the tests (Lettau and Ludvigson, 2001b). By contrast, the coefficient of variation obtained from cross-sectional tests of the CAPM is usually around zero. In addition, the R^2s from time-series regressions used to estimate the factor loadings are usually larger than 0.9, meaning that the factors in the FF3F absorb much of the variation in returns (Fama and French, 1993; Davis, Fama and French, 2000). On a deeper thought, it should not seem extraordinary that factors that are formed from intersection of the size and BE/ME sorted portfolios can predict returns of portfolios that are constructed with a similar procedure. However, Fama and French (1995) show that the success of the three factor model is not driven by such endogeneity. They divide the entire sample of firms into two sub-samples. The first sub-sample is used to construct the factor portfolios, while the second is used to construct the test assets. A time-series test is run. Subsequently, the role of the samples is reversed, and

[45] On a deeper thought, for a single beta model, a time-series test is essentially a cross-sectional test, where the fitted SML joins the risk-free rate (the intercept) with a point with the x co-ordinate equal to one and the y co-ordinate equal to the time-series average of the realised premium. Every asset’s pricing error is a vertical distance between its mean return and the fitted SML. A proper cross-sectional test allows for variation in the intercept and the slope that minimizes (the squared) pricing errors. (Once again Cochrane, (2001))

[46] The smaller errors can also be a consequence of the quarterly frequency employed in Lattau and Ludvigson (2001b)

a second set of regressions is done. Amazingly, the explanatory power (measured by R^2), as well as the magnitude and statistical significance of the factor loadings are virtually identical for portfolios in both sets of test.

Can the FF3F model measure the value premium as measured by other F/P ratios? How about other anomalies? For example, Lakonishok *et al*. (1994) have made an observation that firms with *ex post* low growth in sales are likely to outperform firms with a healthy growth in sales. There is also the momentum effect of Jegadeesh and Titman (1993) and the overreaction effect of De Bondt and Thaler (1985). Consequently, Fama and French (1996a) explore whether the explanatory power of their model is ubiquitous. To the credit of the FF3F, many of the above-mentioned anomalies are accounted for with the three factor model. In particular, Fama and French (1996a) use E/P, C/P, *ex post* sales growth and *ex post* return as sorting characteristics. The time-series intercepts in regressions of attribute-sorted portfolios' returns onto the FF3F factors are close to zero (Fama and French, 1996a). The notable exception is the momentum effect; actually it strengthens after adjustment with the three factor model.

The ability of a factor model to capture variation in returns is important, but it has little to say about a model's prediction regarding expected returns (Cochrane, 2001). As a result, it should be established whether the value and size factors are associated with positive premia, i.e. if they are priced. Panel A in Table 3.8 shows the results of a cross-sectional test of the FF3F model using the 25 size and BE/ME sorted portfolios as test assets. In sum, regardless of the method employed, the HML is priced but the SMB is not. This can be seen by the statistical significance of the factors. The market factor seems to be priced with the GMM in Aretz *et al.* (2005) and a cross-sectional regression in Brennan *et al.* (2004). Incidentally, the magnitude and the associated *t*-statistic of the estimated value premium are very similar to the time-series estimates of 0.46% and 4.24, respectively (Davis *et al.* 2000). At the same time, the mean realisation of the size premium has been 0.2% (*t*-stat is 1.78), which is larger than the cross-sectional estimate.

Evidence presented in Panel B of Table 3.8 highlights one of the flaws of the three factor model. When a different set of test assets is used, the estimate of the value premium falls in magnitude and becomes indistinguishable from zero. Also, the size factor remains unpriced, even in tests that employ size-sorted portfolios as test assets (Jagannathan and Wang, 1996).

Table 3.8
The Cross-Sectional Tests of the FF3F

Factor	Mean	t	R^2	Table	Method	Frequency	Test Assets	Reference	Period
Panel A: Tests of the FF3F model on the 25 size and BE/ME sorted portfolios									
Market	1.330	0.76	77%	I	Fama-MacBeth	quarterly	25 Size & BE/ME sorted portfolios	Lattau & Ludvigson (2001b)	1963-1998
SMB	0.470	0.86							
VMG	**1.460**	2.98							
Market	-0.650	-1.55	71%	V	Fama-MacBeth	monthly	25 Size & BE/ME sorted portfolios	Petkova (2005)	1963-2001
SMB	0.160	1.00							
VMG	**0.440**	3.09							
Market	**0.580**	3.28	--	II	CS-Regression (no int)	monthly	25 Size & BE/ME sorted portfolios	Brennan, Wang & Xia (2004)	1952-2001
SMB	0.080	0.62							
VMG	**0.400**	3.48							
Market	**0.006**	3.21	53%	V	GMM	monthly	25 Size & BE/ME sorted portfolios	Aretz, Bertram & Pope (2005)	1971-1998
SMB	0.001	0.65							
VMG	**0.004**	3.25							
Panel A: Tests of the FF3F model with various test assets									
Market	0.750	4.18	--	V	CS-Regression (no int)	monthly	30 Industry	Brennan, Wang & Xia (2004)	1952-2001
SMB	**-0.300**	1.82							
VMG	**-0.380**	2.51							
Market	-0.450	-0.94	55%	IV	Fama-MacBeth	monthly	100 Size-sorted portfolios	Jagannathan & Wang (1996)	1964-1990
SMB	0.330	1.51							
VMG	0.250	0.95							
Market	**0.010**	2.56	--	XI	GMM	monthly	27 Size, BE/ME & P(Default) sorted portfolios	Vassalou & Xing (2004)	1971-1999
SMB	0.001	0.53							
VMG	**0.004**	2.06							
Market	**0.650**	3.63	--	VII	CS-Regression (no int)	monthly	25 Size & BE/ME portfolios & 30 Industry	Brennan, Wang & Xia (2004)	1952-2001
SMB	0.020	0.17							
VMG	0.120	1.03							

It is interesting to see how the FF3F model performs with regard to industry portfolios. Returns to industries do not puzzle financial economists in the same way the size and the value effects do. However, practitioners in the field do want to correctly calculate the cost of capital, as estimation errors lead to incorrect capital budgeting decisions. Fama and French (1997) conduct an experiment to see if the FF3F can improve on static CAPM's estimate of industries' cost of capital. Here the improvement over the CAPM is less emphatic. In sum, the FF3F model captures more variation in industry returns than the one-factor alternative (the R^2s are higher), but the estimates of expected returns are only marginally more precise with the three factor model than with the CAPM. Also, a cross-sectional test in Brennan *et al.* (2004) shows that, although the FF3F model yields small pricing errors when industry portfolios are used as test assets, the premiums on the HML and SMB factors are *negative* and it is the market portfolio that has the most pricing power (Panel B in Table 3.8). Brennan *et al.* (2004) also show that, in a time-series test that uses both the size and BE/ME sorted portfolios and industry portfolios, the static CAPM and the FF3F are rejected, but the static CAPM yields slightly smaller pricing errors.

3.5.2 Robustness Concerns

Ferson, Sarkissian and Simin (1999) explore the relationship between an anomaly, such as the BE/ME effect, and a factor that tries to capture it, such as the HML. With a simulation, they show that if a spurious anomaly is created and a factor that captures it is constructed, then the replication of empirical tests of Fama and French (1992, 1993, 1995, 1996a) on this bogus anomaly yields results quantitatively similar to those extant in the literature. Like, MacKinlay and Lo (1990a), they emphasize the importance of out-of-sample testing. In addition, they note that repeating the tests on portfolios sorted on characteristics other than the BE/ME, such as the C/P or the probability of default, does not yield sufficient evidence that the power of the FF3F is pervasive because these alternative attributes are likely to be highly correlated with the book-to-market ratio.

However, the three factor model does survive the attack from Ferson *et al.* (1999). Fama and French (2006) extend the sample period all the way back to 1929and show that time-series estimates of size and value premia exhibit a similar magnitude in different periods. Also, Davis *et al.* (2000) show that the three factor model does a similarly good job of explaining returns in the pre-1963 era. In particular, the model leaves relatively little residual variation, as all time-series regressions yield R^2s above 0.90. The intercepts are mostly indistinguishable from zero and the others are of low economic significance. Curiously, the portfolio of small growth stocks remains overpriced by the FF3F model before and after 1963.

International evidence on the performance of the three factor model can also provide evidence in support of the model. It has become customary to use the Japanese stock market as an appropriate setting where US findings are replicated. Daniel, Titman and Wei (2001) perform a test of the FF3F in Japan. Although they do not explicitly estimate the premia (with a cross-sectional regression), their time-series regressions of the three factors onto the returns of size and BE/ME sorted portfolios yields smaller pricing errors than those in US data. In fact, unlike in Davis *et al.* (2000), a statistical test for joint significance of the intercepts does not reject the FF3F and the small-growth portfolio is priced in the Japanese data. In addition, Griffin (2002), in a slightly simpler set-up, shows that the three factor model performs equally well in Canada and the United Kingdom. Specifically, the pricing errors are small and R^2s in time-series regressions are large, but not as large as in the US. Lastly, although evidence from emerging markets is sparse, with a short sample, Drew, Naughton and Veeraragavan (2005) show that the model can explain the size and book-to-market effects in China.

Perhaps stronger evidence for the existence of a discernable value premium would provide further support for the FF3F model. Although, it has been shown that mean return on the HML factor is positive, Elton (1999) puts forward a trenchant argument that measuring expected returns, thus premia, with realised returns, may be seriously misleading. However, Asness, Friedman, Krail and Liew (2000b) and Cohen, Polk and Vuolteenaho (2003) provide evidence that the HML factor is forecastable. Consequently, the predicted values from their regression can be interpreted as the *expectation* of the value premium. In turn, computing the mean of the predicted HML gives insight as to whether the premium is real. Sadly, Asness *et al*. (2000b) and Cohen *et al.* (2003) do not compute means or any test statistics, but, judging from the time-series of their forecasts, the value premium is reliably greater than zero[47]. Actually, an attempt is being made to formally address the properties of the expected value premium. Chen, Petkova and Zhang (2005) preset a work-in-progress annualized estimate of the expected HML of 5.1% with an associated t-statistic of 40.89!

However, there is a test that the FF3F model does fail. Fama and French (1997) show that factor loadings of industries change over time and, more recently, Ferson and Harvey (1999) provide formal evidence that loadings on the HML and the SMB are stochastic and cast doubt on the model itself. To explain, the success of FF3F is based on the model's ability to produce very small pricing errors (Fama and French 1993, 1995, 1996a). However, the usual tests show unconditional pricing errors and say nothing about the magnitude of the time-variant alphas of the FF3F. Consequently, Ferson and Harvey (1999) test whether these conditional pricing errors of the model are indeed zero. The answer is no. The hypothesis that the time-series intercept for each of the size and BE/ME sorted portfolios is zero is rejected for all but one portfolio. However, in a similar test, CAPM fairs no better (Lewellen and Nagel, 2006).

In sum, the FF3F model does not meet all of the necessary requirements of a correctly-specified asset pricing model. However, its failures are far from dismal, especially given that the size and the BE/ME effects are very difficult to explain and the three factor model's pricing ability is certainly better than that of the static CAPM. Therefore, it can be said that the FF3F provides a good, but not perfect, description for expected returns. The model's adequate performance could be particularly puzzling if behavioural theory is to be taken seriously, as it predicts that *one cannot price something that is mispriced.* Thus, it seems fitting to differentiate between risk and non-risk expiations for the size, but mostly value, premiums - a topic that is presented next.

[47] Exhibit 9 in Asness *et al.* (2000) and figure 3 in Cohen *et al.* (2003).

3.6 Fama and French Three factor Model against the Characteristics

The explanation of success of the thee-factor model in Fama and French (1993) has been a contentious issue in financial economics. Proponents of the rational view argue that the FF3F factors, and particularly the value factor, capture the risks associated with distress, or proxy for relevant ICAPM state variable(s) (Fama and French, 1992; 1993; 1995; 1996a). The behaviourists posit that the three factor model "works" because the loadings on the FF3F factors are instruments for market equity and the book-to-market ratio; and, these characteristics predict returns because they measure mispricing (Lakonishok *et al.* 1994; Barberis and Shleifer, 2003). Naturally, the value, but mostly the size, effect can also be a consequence of illiquidity or the neglect premium. Consequently, included in this section is a survey of literature that aims to discern between risk and non-risk explanations of the three factor model.

The rational theory is well developed and can make Sharpe predictions regarding the risk-return relationship. Daniel and Titman (1997) use it to distinguish between the stringent factor models and their, more general, characteristic model[48]. At first, they assume that the book-to-market ratio measures financial strength. Then they note that some firms become distressed because they co-vary "more" with asset pricing factors; but for some firms, it is the idiosyncratic component of profitability that drove them to the verge of bankruptcy. The rational pricing theory predicts that the book-to-market ratio would predict returns for firms that have high loadings on asset pricing factors[49]. However, in firms that are distressed due to firm-specific factors, the book-to-market ratio will not predict returns. The characteristic model does not distinguish between the reasons for distress. It simply states that there is an inverse relationship between the book-to-market ratio and return. Naturally, behavioural theory implies that the characteristic model, not a factor model, is the correct "story" for predicting returns.

Daniel and Titman (1997) use a simple three-way portfolio sort to distinguish between the factor model and the characteristic model. Initially, they calculate

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[48] A reminder: in the characteristic model, the expected of an asset is exclusively a function of an attribute such as an F/P ratio, and not factor loadings.

[49] This is true under the assumption that the factor realizations are mean-reverting and the premium to the factor is high, which is widely accepted to be true (Cochrane, 2001).

loadings on the HML for all firms. Subsequently, they sort stocks according to their BE/ME ratio, size and betas. This procedure creates an independent variation in the book-to-market ratio that is not related to size or the HML loading. If the characteristic model is correct, and thus the FF3F rejected, returns would not be related to factor loadings after control for the BE/ME. This is exactly what Daniel and Titman (1997) find.

Davis *et al.* (2000) argue that a more rigorous test of the three factor model is to test the significance of the FF3F's pricing error of the *characteristic balanced portfolio*. A characteristic balanced portfolio is an arbitrage portfolio, which is a linear combination of the three-way sorted portfolios, and it longs firms with high, and shorts firms with low, loadings on the value factor. It captures the difference in loadings on the HML factor that is unrelated to characteristics. Davis *et al.* (2000) argue that, if the FF3F model is correct, a time-series regression of this portfolio's return onto the FF3F factors yields a zero intercept. In other words, the return differential between the long and short side of the portfolio is large enough to warrant the difference on the HML loading. If the characteristic model is true, however, then the time-series regression over-predicts return on this portfolio[50]. In accordance with the characteristic model, Daniel and Titman (1997) found that the FF3F model is rejected; the intercept is reliably negative.

The findings of Daniel and Titman (1997), if taken seriously, undermine the foundations of the science of asset pricing. In effect, they show that the most successful linear asset pricing model fails to predict average returns after control for firm characteristics. Fama (1998) puts forward a trenchant argument that any model of behaviour of asset prices can only be discarded in favour of a better model. It is not clear if an *ad hoc* characteristic model is an acceptable alterative to the mathematically pure model of Merton (1973), represented by the intuitive FF3F. It seems imperative that the test employed in Daniel and Titman (1997) is repeated with another test that is more powerful[51].

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[50] The intercept is negative because the return spread between the long and short sides of the portfolio is too small, given the large spread in factor loadings.

[51] Power is defined in statistical terms as the likelihood that the null was correctly rejected in favour of the alternative hypothesis.

Davis *et al*. (2000) are quick to repeat the analysis of Daniel and Titman (1997), but with a much longer sample period[52]. In contrast to Daniel and Titman (1997), they find strong support for the three factor model. More specifically, they show that, after controlling for size and the book-to-market ratio, a portfolio consisting of stocks with a high HML factor outperforms a portfolio with low loadings by 0.12% per month, which is much higher than 0.03% that Davis *et al*. (2000) report for the sample period used in Daniel and Titman (1997). Also, in their sample, the FF3F correctly predicts the returns on the characteristic balanced portfolio and the intercept of the regression is negative only during the sample period in Daniel and Titman (1997). On a closer look, however, it is apparent that Davis *et al*. (2000) fail to discuss that the book-to-market effect still persists after control for the loading on the value factor. It can be calculated from Table III in Davis *et al*. (2000) that there is a BE/ME premium of 0.5% per month that is independent of the betas on the HML. When the premium is calculated after adjustment for the FF3F factors it is still negative at -0.12%. Thus, it appears that a factor structure and characteristics play a role in prediction of stock returns.

Daniel *et al.* (2001) also test the predictive power of characteristics and factor loadings, but in the Japanese market. They show that the value effect in Japan is larger than in the US and the correlation between the BE/ME and loadings on the HML is lower in Japanese data. Consequently, Daniel *et al.* (2001) argue that Japanese data allows for greater power to distinguish between the factor and characteristic models. As in Daniel and Titman (1997), their findings are consistent with the characteristic model and they reject the factor model. In particular, they find a statically significant negative intercept of a regression of the characteristic-balanced portfolio on the FF3F factors and thus emphatically reject the factor model[53].

It seems peculiar that in order to discern between characteristic and factor models, this complex combination of portfolio sorts and regressions needs to be employed - especially, given that Fama and French (1992) provide an intuitive

[52] Daniel and Titman use 20 years, while Davis, Fama and French (2000) use 68 years.

[53] A variant of the test in Daniel and Titman (1997) on South African data has been conducted by van Rensburg and Robertson (2004). Although South African data does not allow for well-specified characteristic balanced portfolios, the authors perform a two-way sort of a P/E and the loading on the value factor. Later, they repeated the sort with size and sensitivity to the size factor. The authors strongly reject the factor model in favour of the characteristic explanation. Their test does lack power, however, as they fail to adjust the portfolios with the FF3F. An examination of Tables III and V in Daniel and Titman (1997) clearly shows that such an adjustment is important.

method for a similar test: estimate the factor loadings, then plug them, along with characteristics, into a cross-sectional regression. The obtained *t*-statistics, or, at the very least, the R^2, point toward the correct model for asset returns. However, in such tests, multicollinearlity between characteristics and loadings biases the coefficients, and the error-in-variables problem is large.

Brennan *et al.* (1998) provide a possible solution to the error-in-variables problem and multicollinearlity in tests that pair up factor models against the characteristic alternative. They adopt a two-stage method. In the first step components of return not attributed to the factor model are computed. The second stage checks whether these pricing errors are predictable with characteristics. Since, the error-in-variables manifests itself on the left-hand side in the second-pass cross-sectional regression, the predictive power of characteristics can be ascertained without a bias. With this procedure, Brennan *et al.* (1998) find that after correction for risk with the FF3F model, characteristics still reliably predict expected returns. Nonetheless, the book-to-market attenuates after control for risk with the FF3F.

In addition, Lewellen (1999) shows that in a time-series test, the results of Daniel and Titman (1997) do not hold. He constructs regressions, where the book-to-market ratio, and the FF3F factors are directly included in a time-series model. After showing that the book-to-market is a good instrument for expected returns, he finds that this predictability vanishes after the FF3F factors are included in the regression. In addition, Lewellen (1999) documents that many industry portfolios load on the HML and SMB *unconditionally*. This is at odds with the behavioural view, as it is highly improbable that assets will be mispriced for a prolonged period of time[54].

In sum, it is apparent that a decisive indication of whether the success of the three factor model stems from behavioural or rational theories does not appear in the literature. Although it seems important to distinguish between the two theories, it must be noted that they are co-integrated, because the unidentified risks associated with the anomalous assets are the very reason that makes behavioural explanations of these effects so plausible (Brav *et al.* 2004). Nonetheless, proponents of the rational

[54] Most behavioural models factor-in the eventual correction to mispricng (Daniel *et al.* 1998; Hong and Stein, 1999), especially at industry level (Barberis and Shleifer, 2003; Peng and Xiong, 2006). On the other hand, Fama and French (1997) found that industry portfolios did exhibit large time-variation in factor sensitivities on the HML and SMB loadings, and industries did behave like small or large firms and value or growth firms at different points in time.

school embrace the results in Davis *et al*. (2000) and they reach to Merton's (1973) ICAPM and the conditional CAPM as solutions to the FF3F puzzle.

3.7 The Size and the Value Effects and Modern Theory of Asset Pricing

Fama and French (1996a) show that the mean return and variance on the SMB and HML factors are of comparable magnitude to the market return. Therefore, they imply that the factors serve as instruments for some state variables missed by the static CAPM. Actually, Aretz *et al.* (2005) find that exposures to macroeconomic risks vary between firms of different market capitalisation and BE/ME ratio. Some of this risk is priced. Therefore, in principal, it could be argued that the size and the value premia are explained with a risk model, an APT.

However, it is always possible to find a factor structure that explains returns *ex post* (Roll, 1977; Fama, 1991; Cochrane, 2001). Also, it is easy to falsely document factors that price a set of portfolios constructed with information contained in previous empirical work (Ferson *et al.* 1999). Most importantly, a factor that does not explain the cross-section of returns may give an illusion of a priced factor (Jagannathan and Wang, 1998). Consequently, it is often argued that a concrete theory needs to identify priced state variables (Fama, 1998), and use of statistical constructs (Connor and Korajczyk, 1988; van Rensburg and Slaney, 1997), or *ad hoc* macroeconomic variables (Chan *et al.* 1986; Aretz *et al.* 2005; van Rensburg, 2000), is inadequate. Therefore, only models that can identify the nature of the priced factors offer a credible description for returns. The Intertemporal CAPM (ICAPM) of Merton (1973) is such a model. Conditional CAPM (CCAPM) in Jagannathan and Wang (1996) and Cochrane (2001) is one as well. Also, the "Augmented" ("A"CAPM), formalised by Ferguson and Shockley (2003), can also play a role.

3.7.1 The "A"CAPM

The static CAPM may provide a correct description of average returns, but its practical implementation may be erroneous. In particular, a value-weighted portfolio of listed stocks may be a poor proxy for the market portfolio (Roll, 1977). It excludes human capital (Mayers, 1972), a substantial source of wealth for most people, and debt (Stambaugh, 1982). This section asks if accounting for these omitted assets is sufficient to price the 25 “troublesome” size and BE/ME sorted portfolios created in Fama and French (1993).

Jagannathan and Wang (1996) and Lettau and Ludvigson (2001b) study the impact of omitting the human capital asset from the market proxy. They measure the realisation on this factor with growth in aggregate labour income. In sum, both studies found it an important factor in asset pricing. In particular, Jagannathan and Wang (1996), who focus exclusively on size-sorted portfolios, find that, in a cross-sectional test, the labour-income factor yields a reliably positive premium. Together with the market factor, it can explain 30% of variation in returns of the size-sorted portfolios. Although this R^2 is much lower than FF3F’s estimate of 55%, it is markedly higher than the 1% obtained from the static CAPM. Lettau and Ludvigson (2001b) extended the test to the size and BE/ME sorted portfolios and found stronger support for labour income growth as a priced factor. In their cross-sectional regressions, the R^2 increased from 1% to 58% after the labour-income factor was added to the market proxy, although coefficient of variation is still smaller then 80% obtained form the FF3F.

Human capital is an unobservable state variable, and needs to be substituted with another variable; measurement error is unavoidable. In addition, human capital may not be the only asset class omitted from the proxy of the true market portfolio and, some of these assets cannot be substituted with instrumental variables. Ferguson and Shockley (2003) show a potential solution to this conundrum. They argue that the divergence between an asset’s true market beta and the one computed with the imperfect proxy can be captured by a firm’s relative leverage, as an asset’s return co-variation with *any* state variable is a linear function of its leverage (Miller and Modigliani, 1958).

Consequently, Ferguson and Shockley (2003) propose a factor model that captures relative leverage. In particular, with methodology of Fama and French (1993), they form a model in which the market factor is augmented with a debt factor and a distress factor. The second factor is necessary, as high level of debt does not signal high financial leverage, and vice versa. In their cross-sectional tests, Ferguson and Shockley (2003) show that the model does a good job in explaining average returns. Both their factors yield economically and statistically significant premia and the R^2 in their tests exceeds even that of the FF3F.

Unfortunately, although the ideas of Ferguson and Shockley (2003) are validated empirically, their results are not convincing. Not only are their model’s theoretical foundations weak, the success of the model can be explained in a variety of ways. For example, Fama and French (1993) have shown that the default spread and level of the yield curve can help to price debt. Thus, these variables are likely to co-vary with the factors in Ferguson and Shockley (2003). However, if the default and the yield curve variables play a role in other models (as it has been shown in Chapter 2 that they do), then the "missing assets" explanation of the empirical success of the debt and distress factors may not only be insufficient, but just plain wrong.

3.7.2 The CCAPM

The static CAPM assumes that loadings on the market factor do not vary through time; they are unconditional. Cochrane (2001) argues that, in principal, all multifactor models ought to be specified in a conditional form and, in most cases, unconditional tests of conditional models are misspecified. Berk (1995) argues that misspecification of the asset pricing model manifests itself as the size and the value premia, which would disappear if a conditional version of the CAPM is used to adjust for risk.

In the CCAPM, loadings are assumed to vary with the market premium, and Lewellen and Nagel (2006) verify empirically that they do. Two types of empirical specifications of the model appear in literature: the *market premium* can be included into a factor linear model (Jagannathan and Wang, 1996); alternatively, the market factor is scaled (interacted) with instruments for expected returns. The scaled terms are included as factors in the pricing equation (Ferson and Harvey, 1999). Cochrane (2001) noted that the two methods are theoretically equivalent.

Arguably, the first test of the CCAPM that aims to explain the size or the value premia appears in Jagannathan and Wang (1996). In their model, the default spread is employed as the instrument for the market premium. On a set of size-sorted portfolios, the authors show that there is a strong negative relation between a firm's market capitalisation and its loading on the market premium. This finding suggests that time-variability of market betas of small firms is different to that of large firms. In addition, in a cross-sectional test of the CCAPM, Jagannathan and Wang (1996) show that the R^2 jumps from 1% to 29% after the market premium factor is added to the static CAPM.

Lettau and Ludvigson (2001b) and Ferson and Harvey (1999) test the CCAPM on the size and BE/ME sorted portfolios. Lettau and Ludvigson (2001b) model the market premium with their *cay* variable, as it has been shown to be a good predictor of market returns in the US (Lettau and Ludvigson, 2001a). Ferson and Harvey (1999) use a number of empirically derived instruments for expected returns[55]. Both studies found, as did Jagannathan and Wang (1996), that the market premium factor is positive and it is priced.

Although Lettau and Ludvigson (2001b) and Ferson and Harvey (1999) do not show how the betas of value and growth stocks vary with the business cycle, Petkova and Zhang (2005), with the aid of a GMM framework and long time-series, directly compute the time-series of market betas of the two types of firms. They show that, during deep recessions, the beta of a portfolio with value firms is 0.25 units higher than that containing growth firms, while at the peak of the business cycle, value stocks' betas are on average 0.31 units lower than growth stocks'.

Jagannathan and Wang (1996) and Lettau and Ludvigson (2001b) combine the "A"CAPM and CCAPM into one pricing equitation. In particular, the model of Jagannathan and Wang (1996) explains the same amount of variation as the FF3F and the risk premia are reliably different from zero. Also, the authors show that their model captures the explanatory power of the macroeconomic variables of Chen *et al.* (1986). In a formal test, however, the model is rejected. However, the model of Lettau and Ludvigson (2001b) is particularly apt at explaining the average returns of the size and the BE/ME sorted portfolios. In particular, they show that their scaled factors, which capture time-variability in lodgings on the market and the human capital factors, are priced, and that the pricing errors of the model are not statistically different form zero, which implies that it may explain the size and the value premia.

Unfortunately, the puzzle conjured by the value effect cannot be solved with the CCAPM. Lewellen and Nagel (2006) argue that the tests discussed above are misspecified, as the cross-sectional tests do not restrict the magnitude of the premia on the instruments for the market premium. However, the CCAPM theory predicts that the premium on each of these variables is dictated by how much information it

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[55] In particular, Ferson and Harvey (1999) use spread between one and three month Treasury Bills, aggregate dividend yield, a variant of the default spread, the spread between one and ten year Treasury bonds and lag of the risk-free rate.

contains about variability of the market betas. They note that the premia in Lettau and Ludvigson (2001b) and Jagannathan and Wang (1996) imply the variance of market betas and the market premium is implausibly large. In Lewellen and Nagel's (2006) view, less than half of the unconditional pricing error of the value strategy can be explained by the CCAPM. In addition, the average conditional alpha of the value strategy seems to be large - as large, in fact, as the unconditional estimate (Petkova and Zhang, 2005; Lewellen and Nagel, 2006). Nonetheless, the importance of the inclusion of the human capital factor into the pricing equation has not been disputed, and it is deemed a salient factor in asset pricing.

3.7.3 Fama and French Three factor Model is an Intertemporal Capital Asset Pricing Model

Fama and French (1993) have always argued that their three factor model is consistent with the ICAPM of Merton (1973) (in which investors price assets to hedge their unfavourable shifts in the efficient frontier.) Liew and Vassalou (2000) provide evidence that Fama and French (1993) may be right, as they show that FF3F factors have power to forecast growth in GDP in ten countries. Testing the equivalence between the three factor model and the ICAPM is difficult, however, as the ICAPM pricing factors are not known *a priori.* But Cochrane (2001) notes that, since the efficient frontier can be summarized with the risk-free rate and the market Sharpe ratio, any variables that proxy for innovations in these two parameters ought to be priced, and hopefully can resolve the size and the value puzzles (Campbell, 1996).

Table 3.9
The Spread in Loadings on ICAPM State Variables

Panel A: Loadings of Small Firms on Plausible ICAPM State Variables

	Small	Large	Small less Large	Ave Small less Large %	Period	Reference
$u^{Default\ Spread}$	2.852	-0.886	3.738	276%	1963-2001	Hahn & Lee (2003)
$u^{Default\ Spread}$	-7.231	3.339	-10.570	231%	1963-2001	Petkova (2006)
$u^{Dividend\ Yield}$	-3.488	-4.853	1.365	34%	1963-2001	Petkova (2006)
u^{Rf}	-1.406	-1.437	0.031	2%	1963-2001	Petkova (2006)
u^{Term}	0.738	0.271	0.467	118%	1963-2001	Hahn & Lee (2003)
u^{Term}	1.113	-0.634	1.747	216%	1963-2001	Petkova (2006)
$u^{Sharp\ Ratio}$	3.673	0.547	3.126	328%	1952-2001	Brennan, Wang & Xia (2004)
u^{Rf}	0.813	-0.182	0.995	335%	1952-2001	Brennan, Wang & Xia (2004)
$u^{CashFlow}$	0.295	0.264	0.031	11%	1924-2001	Campbell & Vuolteenaho (2003)
$u^{Discount\ Rate}$	1.231	0.960	0.271	25%	1924-2001	Campbell & Vuolteenaho (2003)

Panel B: Loadings of Value and Growth Firms on Plausible ICAPM State Variables

	Value	Growth	Value less Growth	Ave Value less Growth %	Period	Reference
$u^{Default\ Spread}$	1.622	0.361	1.261	214%	1963-2001	Hahn & Lee (2003)
$u^{Default\ Spread}$	-5.632	0.901	-6.533	421%	1963-2001	Petkova (2006)
$u^{Dividend\ Yield}$	0.925	-7.217	8.142	497%	1963-2001	Petkova (2006)
u^{Rf}	-2.721	-1.321	-1.400	79%	1963-2001	Petkova (2006)
u^{Term}	-0.036	1.019	-1.055	1517%	1963-2001	Hahn & Lee (2003)
u^{Term}	-2.973	2.864	-5.837	200%	1963-2001	Petkova (2006)
$u^{Sharp\ Ratio}$	3.030	1.417	1.613	84%	1952-2001	Brennan, Wang & Xia (2004)
u^{Rf}	0.144	0.551	-0.407	178%	1952-2001	Brennan, Wang & Xia (2004)
$u^{CashFlow}$	0.307	0.217	0.090	35%	1924-2001	Campbell & Vuolteenaho (2003)
$u^{Discount\ Rate}$	1.146	1.131	0.015	1%	1924-2001	Campbell & Vuolteenaho (2003)

The estimates are performed with a time-series OLS, with on the 25 (or 24) size and book-to-market sorted portfolios in Fama & French (1993). The figures reported in the table are averages across two size or BE/ME quintiles

The ICAPM specification can either be derived empirically or theoretically. The empirical method relies on the evidence that market premium and variance of the market proxy are predictable with a discernable set of instrumental variables. In effect, Campbell (1996) proves that correlation with innovation with these variables should be priced. The alternative method is to directly estimate the pricing equation from representative investors' optimisation problem and, with appropriate proxies for the model's state variables, estimate and test the specification. Both methods are intertwined, as the proxies for most state variables are often identical to the instruments for expected returns[56].

Hahn and Lee (2006) and Petkova (2006) adopt an empirical ICAPM. Hahn and Lee (2006) focus solely on two possible state variables: the default spread and the slope of the yield curve. They do not explicitly model innovation, but simply focus on changes in the absolute level of these variables. On the other hand, Petkova (2006) extends the set of instruments to include the innovations in the aggregate dividend yield and the risk-free rate and uses a multivariate VAR system to model innovations.

Table 3.9 shows the differences in loadings on innovations in the instruments for the risk premium[57]. In general, small firms differ markedly to large firms in their loadings on the innovations term spread and the default spread. In addition, betas with innovations in the aggregate dividend yield, the term spread, and default spread, are vastly different among firms of various book-to-market ratio. Also, the magnitude of the difference in loadings on the innovation in the term spread between value and growth firms, emphasized in Hahn and Lee (2006), attenuates after addition of innovations in the dividend yield and risk-free rate in Petkova (2006). In addition, cross-sectional tests performed by the authors indicate that innovation in the risk-free rate and the term spread play a role in pricing of the 25 size and BE/ME sorted portfolios. Although insignificant, other variables are also relevant in explaining returns, as both models produce R^2s that are very close to that of the FF3F.

The variables used in Petkova (2006) and Hahn and Lee (2006) are validated empirically, but they do not offer an intuitive explanation as to what exact source of

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[56] Invariably, ICAPM is linked to the CCAPM and the "A"CAPM, as instruments for the market premium that played a role in CCAPM (Jagannathan and Wang, 1996) are also central to ICAPM specifications. Also, since many of them price debt (Fama and French, 1993), they may proxy the missing factors in the "A"CAPM (Ferguson and Shockley, 2003). The ICAPM, however, may enforce a more rigorous structure on the asset pricing model then the other two specifications.

[57] The loadings found in Hahn and Lee (2006) in Table 3.9 are identical to those in Table 3.6 as they can be read as "pure" macroeconomic variables or ICAPM state variables.

risk they proxy. Vassalou (2003), following Liew and Vassalou (2000), thought that if HML and SMB can predict GDP growth, they must capture the news regarding future economic activity. She goes on to build a two-factor model that consists of the market portfolio and the "GDP-news" factor. According to the GMM tests of Vassalou (2003), her factor contains similar information to the FF3F. In addition, it has a relatively low correlation with the HML and SMB factors, indicating that there may be a cleaner measure of the underlying sources of risk that lie behind the success of the three factor model. However, the construction of the "GDP-factor" uses a similar set of variables to what researchers use in modelling the market premium. Therefore, it is likely that the specifications in Vassalou (2003), Petkova (2006) and Hahn and Lee (2006) capture the same macroeconomic forces (Petkova, 2006).

Empirically driven factor models are unconvincing tools for asset pricing, at least to the academic community. Consequently, theoretical models need to be constructed and tested. Brennan *et al.* (2004) derive one such theoretical version of the ICAPM. At first, they model the time-series pattern of the efficient frontier by assuming that its two germane characteristics (the risk-free rate and the maximum Sharpe ratio) follow a continuous mean-reverting first-order Markov (an AR(1)) process. Then, with a set of primary assets and the use of a Kalman filter[58], they estimate a time-series of the instantaneous risk-free rate and the instantaneous Sharpe ratio. Subsequently, these factors are combined with the market portfolio to form a three factor ICAPM, which is then tested against the FF3F model by assessing its ability to price the size and BE/ME sorted portfolios.

Table 3.9 indicates that the book-to-market ratio and market equity predict an asset's co-variance with variables that capture the innovation of the efficient frontier. In line with the ICAPM theory, the presumably riskier, small and value firms have high loadings on the innovations on the Sharpe ratio. Also, higher loadings on the innovation in the real interest rate for small stocks are consistent with the story in Brennan *et al.* (2004). However, value firms appear to be less sensitive to news about interest rates than growth firms.

Theoretical ICAPM can make predictions about the sign of the premia. *A priori*, co-variance with the innovation in the Sharpe ratio should command a positive risk

[58] In layman's terms, a Kalman filter is a procedure that species a position of a quantity from a series of incomplete or noisy measurements. In effect, the procedure can specify a time-series of a variable if the underlying stochastic process is known *a priori*.

premium, as stocks that pay poorly when the Sharpe ratio is falling are especially undesirable. Also, innovations in the interest rate should command a negative premium. Investors dislike when the interest rates go up because the return-variance trade-off worsens. Brennan *et al.* (2004), in a cross-sectional test, calculate that the premia on their three factor ICAPM are of the correct sign and their magnitude is similar in tests that use different sets of test assets. Also, Brennan *et al.* (2004) show that, when applied to the "anomalous" 25 portfolios, the composite pricing error of their model is smaller than that of the FF3F and, by merit of a statistical test, it is not different from zero!

Campbell and Vuolteenaho (2004) take a different approach. At first, they note that if the market risk premium is dynamic, then an asset's systematic return may be governed by innovation in two distinct state variables: news of aggregate cashflow and news of the aggregate discount rate. If Merton (1973) is correct, and most investors are in the market for the long haul, then the premia associated with the two sources of risk are not equal. For instance, if there is an increase in the market discount rate, all stock prices fall, but future returns are, on average, higher. Long-term investors suffer contemporaneous decline in wealth, but also enjoy higher returns in the future. For this reason, all else being equal, investors may not discount stocks with strong co-variance with innovation in the discount rate as aggressively as assets that exhibit strong co-movement with innovations in the aggregate cashflow (Campbell and Vuolteenaho, 2004). Since the market beta is equal to the sum of the *cashflow beta* and the *discount rate beta*, stocks with equal market betas may yield vastly different expected returns. For example, an asset with a market beta of 1 that is mostly comprised of the "risky" cashflow beta will yield a higher return to an asset with the same beta that mostly consists of the "passive" discount rate beta.

Subsequently, Campbell and Vuolteenaho (2004) construct a two-factor model. In Table 3.9, it is shown that value stocks do have higher loadings on the more "risky" cashflow factor, while small stocks exhibit only a marginally larger sensitivity to innovation in the aggregate cashflow. Campbell and Vuolteenaho (2004) solve the investor's optimisation problem and, with the ICAPM intuition, formulate a theoretical relationship between the premium on the cashflow innovation and the discount rate innovation. Like Brennan *en al.* (2004), Campbell and Vuolteenaho (2004) show that, in cross-sectional tests and various sets of test assets, their theoretically derived two-factor model yields significant and positive risk premia.

Also, when tested on the size and BE/ME sorted portfolios, the model does yield an R^2 that is nearly as high as that of the FF3F and its composite pricing error is not statistically different from zero at conventional levels.

In sum, it appears that the FF3F is indeed an ICAPM. However, most of these models use a similar set of instrumental variables to model state variables important in the ICAPM[59] specifications. Therefore, it is plausible that their predictive power is sample-specific. In addition, only one of the models is supported by the theoretical rigor stressed by Cochrane (2001); therefore the "fishing for factors" argument of Fama (1991) is still relevant for most ICAPM specifications discussed above. In addition, Brennan *et al.* (2004) show that their model fails to simultaneously price industry portfolios and the size and BE/ME sorted portfolios. Nonetheless, it does appear that the ICAPM framework is a useful tool for thinking about patterns in asset prices and it is more rigorous than the vacuous theory underpinning other multi-factor models.

So far, the review surveyed some of the asset pricing models derived from the static CAPM. It would be prudent to directly test the competing models against the three factor model. Table 3.10 provides some evidence as to how different models discussed so far fare against the FF3F. Since not all articles conducted a joint test, only a sub-set of the studies is considered. In sum, it can be seen in the table that nearly all asset pricing models "price-out" the factors in the FF3F[60]. However, the distress-risk hypothesis is inadequate in explaining the value premium, as the HML factor continues to be priced in Vassalou and Xing (2004). Also, the CCAPM in Ferson and Harvey (1999) leaves a positive premium on the value factor. Nonetheless, the empirical ICAPM specification seems to capture the same information as the three factor model. This result, together with the finding that the theoretical ICAPM in Brennan *et al.* (2004) and Campbell and Vuolteenaho (2004) are not rejected, indicates that the FF3F is an ICAPM and not a CCAPM.

[59] Model of Brennan, Wang and Xia (2004) is an exception.
[60] It must be noted that the SMB never did price the size and BE/ME sorted portfolios, thus the results of most studies pertain to the pricing power of the HML.

Table 3..10
The Cross-Sectional Tests of the FF3F

Factor	Mean	t	R^2	Table	Method	Test Assets	Period
Panel A: Jagannathan and Wang (1996)							
Market	-0.380	-0.800	64%	IV	Fama-MacBeth	100 Size sorted portfolios	1964-1990
Market Premium	**0.220**	3.320					
Labour	0.110	0.160					
SMB	0.160	0.780					
HML	0.220	0.840					
Panel B: Ferson and Harvey (1999)							
Market	0.153	0.491	--	V	Fama-MacBeth	25 Size & BE/ME sorted portfolios	1964-1994
Market Premium	**0.445**	7.537					
SMB	0.092	0.631					
HML	**0.237**	1.715					
Panel C: Ferguson and Shockley (1999)							
Market	-0.670	1.510	81%	III	Fama-MacBeth	25 Size & BE/ME sorted portfolios	1964-2000
Leverage Factor	**1.650**	3.050					
Z-Distress Factor	**1.020**	2.330					
SMB[1]	-0.350	-1.340					
HML[1]	0.170	0.820					
Panel D: Hahn and Lee (2006)							
Market	-0.590	-1.080	76%	IV	Fama-MacBeth	25 Size & BE/ME sorted portfolios	1963-2001
u^{Term}	**0.270**	2.630					
$u^{Default\ Premium}$	-0.020	-0.460					
SMB[1]	-0.040	-0.170					
HML[1]	0.200	0.950					
Panel E: Petkova (2006)							
Market	-0.570	-1.100	77%	V	Fama-MacBeth	25 Size & BE/ME sorted portfolios	1963-2001
$u^{Dividend\ Yield}$	-0.083	-0.940					
u^{Term}	**3.870**	2.560					
$u^{Default\ Premium}$	0.370	0.310					
u^{Rf}	**-2.900**	-2.440					
SMB	0.420	1.400					
HML	0.410	1.560					
Panel F: Vassalou and Xing (2004)							
Market	0.010	2.155	--	XI	GMM	27 Size, BE/ME & Default sorted portfolios	1971-1999
Distress Factor	**0.010**	4.479					
SMB	-0.003	-0.692					
HML	**0.006**	2.662					

[1] The FF3F factors are orthognelized with respect to other factors

3.8. Some Unanswered Questions

The last section has shown some compelling evidence in favour of risk-based explanations for the size and the value effects. In addition, the FF3F model has been linked to discernable sources of economic risk, captured by the ICAPM. However, a slew of empirical facts contradict the rationalists' explanations for the size and the value premia[61].

3.8.1 Holes in Risk Stories can be Patched with Behavioural Finance

Some rationalists believe that the size and the value effects stem from failure to adjust for idiosyncratic or aggregate illiquidity risk (Amihud and Mendelson, 1986, Acharya and Pedersen, 2005). If the size characteristic is tantamount to a measure of liquidity, then a firm's loading on the SMB is a proxy of a stock's liquidity. Actually, Ferson *et al.* (1999) show that if a factor could be crafted from a liquidity attribute it would appear to be priced. However, according to Brennan and Subrahmanyam (1996), the three factor model does not contain a sufficient amount of information on a stock's liquidity. They construct a sophisticated measure of direct and indirect trading costs with which they form 30 portfolios. Subsequently, they use a time-series test and compute the three factor model's pricing errors of the liquidity-sorted portfolios. The model is rejected. In fact, many of the intercepts are bigger than the largest absolute error in tests of FF3F on the size and BE/ME sorted portfolios. Also, the stocks that are most expensive to trade are the most severely mispriced.

There are few, if any, joint tests of the FF3F model and the aggregate liquidity effect of Pastor and Stambaugh (2003). Since Acharya and Pedersen (2005) do show that this factor can explain about half of the cross-sectional variation in returns to size and BE/ME sorted portfolios, it is plausible that the three factor model does contain some information on aggregate liquidity. And, since size is correlated with loadings on the liquidity factor, it ought to be somewhat co-linear with the SMB. The snag is that there is little economic theory that identifies the determinants of the time-series

[61] The aim of this section is only to undermine the risk-based view of financial markets - a complete survey of behavioural finance is left to Barberis and Thaler (2003).

variation in aggregate liquidity. Baker and Stein (2004) propose a model where liquidity is a proxy for overvaluation, both at firm and aggregate level. They note that noise traders, faced with short-sale constraints, can enter the market only when they are optimistic. In effect, liquidity increases and shares become overpriced, and the observed negative relationship between the level of liquidity and the *ex ante* return stems from mispricing being arbitraged away. Therefore, any explanation for the size and the value effects based on illiquidity risk may actually be behavioural, not rational in nature.

Another hypothesis the rationalists propose is that the size and the BE/ME premia are manifestations of systematic risk related to financial distress. They claim that firms that are near bankruptcy ought to have low prices to compensate investors for the added risk. This story is undermined by Dichev (1998), who finds that firms with a high probability of default have very low BE/ME ratios. In addition, her tests were conducted in a period in US history when bankruptcy risk was high but size effect did not exist at all.

In addition, the evidence in support of a separate distress factor is mixed. For example, Daniel and Titman (1997) note that if the factor exists, then as soon as a firm enters financial trouble (its BE/ME ratio rises) its loading on distress factor ought to increase. Because variance of a portfolio of firms that strongly co-vary with each other should be high, relatively speaking, the time-series of the variance of a portfolio with firms that are thought to be distressed is revealing about how within-portfolio co-variance of stocks changes over-time. Put simply, if a distress factor exits, variance of a portfolio of distressed firms ought to increase at some time prior to its formation. Daniel and Titman (1997) use these facts to see if the BE/ME measures distress, by investigating the evolution of the variance of a portfolio containing firms with high book-to-market ratios. They find little evidence of a change. The co-variance of firms with similar BE/ME is equal five years before and after firms became distressed, and the authors interpret this finding as evidence that a separate distress factor does not exist. In a much simpler manner, Lewellen (1999) also provides evidence to suggest that financial distress does not drive the value premium. He shows that many industry assets load unconditionally onto the HML. Thus, this factor measures distress because industries cannot be near default all the time (Lewellen, 1999)[62].

A formal illustration that the factors in the FF3F model have little to do with financial distress appears in Griffin and Lemmon (2002). They measure distress with Ohlson's (1980) measure of probability of bankruptcy (the O-score) and use this characteristic to form a set of test assets. When they run a time-series test, they find that firms that are most distressed are also most mispriced by the FF3F model. Most importantly, the pricing errors of firms with the highest O-score were larger in absolute value than any intercept in the time-series regressions in Fama and French (1993). In addition, the dispersion in loadings on FF3F factors in determined by an asset's BE/ME ratio and not by its probability of bankruptcy.

It is difficult to disentangle the distress story and the behavioural story. Consider a number of firms, possibly across many industries, that experience a string of negative, factor or idiosyncratic, news. These firms are more likely to become distressed, see their BE/ME ratio fall, and load on a distress factor. If this factor is priced with a positive premium then high returns will be observed. At the same time, the extrapolation hypothesis of De Bondt and Thaler, (1985) and Lakonishok *et al.* (1994), or the positive feedback trading story of Hong and Stein (1999) or Barberis and Shleifer (2003), predict that such firms are most likely to become underpriced. Their prices move together as valuations revert back to the "rational" level. This shared variation will appear like a common factor relating to firms that fall in value, i.e. a distress factor.

In addition, evidence in Schwert (2003) of strong attenuation in the realised size and value premia after the 1980s does not sit well with risk-based theory, as the effects seemed to disappear after they have been discovered. Shiller (2003) stresses that the anomalies must wax and wane, as mispricing cannot be constant in time; while the behavioural model of Barberis and Shleifer (2003) predicts that profitability of investment styles must go through cycles. The fact that size effect re-emerged within the value segment[63] in the last few years (2002-2005) strengthens their point.

[62] On other hand, Vassalou and Xing (2004) document stronger evidence for a distress factor. Recall that they construct a cleaner measure of a state variable that measures distress, and it does seem to be priced. However, the authors show that the HML contains information that is orthogonal to the distress factors.
[63] Graciously shown by Chris Muller.

Lastly, Griffin (2002) shows that there is virtually no correlation between the HML factors found in the four most integrated stock markets of the US, Canada, Japan and the UK - even though macroeconomic variables are correlated between these countries. This finding is in line with the models of Peng and Xiong (2004) and Barberis and Shleifer (2003), which assume that investors have limited ability to process relevant information, as they predict that correlation in returns of different asset classes will be much smaller than economic fundamentals.

3.8.2 Multifactor Models cannot explain the Size and Value Premia

Risk does not have to be associated with distress. Merton (1973) shows how intertemporal hedging concerns, which Fama and French (1993, 1996) so emphatically present as the economic explanation for their model, are a source of risk to investors. Although it has been shown that the ICAPM intuition goes far in explaining the successes of the three factor model, Chan (2003) dispels the hope that the book-to-market effect is exclusively driven by the ICAPM. Following Cochrane (2001), he argues that theory, not empirical work, must be used to specify the size of the premia of an ICAPM specification. Unlike most models presented thus far, Chen (2003) develops an ICAPM specification from representative agents' investment-consumption problem. The high level of parameterisation of the model imposes two restrictions: a premia on a factor must depend on the amount of information the given variable contains for predicting market returns, and the premia on all factors must be a function of the aggregate risk aversion. When he tests the ability of his restricted ICAPM to explain the book-to-market effect, the model fails abysmally.

In his view, the successes of other ICAPM methods in pricing the size and the book-to-market portfolios occurs because other methods do not impose the restrictions on their premia. To illustrate, consider innovation in the term spread - a variable that can forecast market's return and is a natural candidate for a state variable in an ICAPM model. Petkova (2006) shows that this state variable is priced, but its cross-sectional estimate of the premium is 11 times higher than that of the HML! In order to explain this large estimate, the term spread must be very volatile (this is not true (Hahn and Lee, 2003)) and it must very precisely forecast the market return (this is also not true (Ferson and Harvey, 1999)).

Table 3.11
Asset Pricing Models against Characteristics

Characteristic	Mean	t	R^2	Table	Method	Test Assets	Reference	
BE/ME	**0.226**	2.282	n/a	VII	Fama-MacBeth	FF25	Ferson & Harvey (1999)	1964-1992
BE/ME	**0.070**	1.760	76%	VIII	Fama-MacBeth	FF25	Petkova (2005)	1963-2001
BE/ME	**1.090**	2.880	81%	IV	Fama-MacBeth	FF25	Lattau & Ludvigson (2001)	1963-1998
Size	**-0.119**	-2.393	n/a	VII	Fama-MacBeth	FF25	Ferson & Harvey (1999)	1964-1992
Size	-0.070	-1.300	65%	II	Fama-MacBeth	FF100	Jagannathan and Wang (1996)	1963-1990
Size	**-0.070**	-1.790	77%	VIII	Fama-MacBeth	FF25	Petkova (2005)	1963-2001
Size	**-0.330**	-1.930	76%	IV	Fama-MacBeth	FF25	Lattau & Ludvigson (2001)	1963-1998

Actually, it seems that the high premiums in Petkova's (2006) cross-sectional regressions are a consequence of the wide spread in mean returns of the size and BE/ME sorted portfolios[64], rather than a reward for holding state variable risk.

Nonetheless, it has been shown that, in principle, some linear asset pricing models can capture the same amount of variation in returns as does the three factor model. However, the critique presented in Daniel and Titman (1997) rings true to any multi-factor model. In particular, for the model to be accepted, it must be shown that the factor loadings, and not the characteristics, describe the cross-section of returns[65]. Table 3.11 shows some, admittedly limited, evidence on how different models fair against predictive power of market equity and the book-to-market ratio. In sum, no model can "price-out" the BE/ME ratio. Only the model in Petkova (2006) reduces the significance of the coefficient to just below 10%. The evidence concerning size is more encouraging, as none of the coefficients are significant at the 5% level. Curiously, the human-capital "Augmented" CCAPM of Jagannathan and Wang (1996) completely removes the importance of size, but an essentially similar model of Lettau and Ludvigson (2001b) does not. Since both studies use a different set of test assets, this puzzle illustrates the argument of Kendal and Stambaugh (1995), who showed that the premium obtained from a cross-sectional test is a function of the test assets employed.

3.3.3 On the Profitability of the Anomalies

The last point in this section centres on the conclusion of many studies which found that the returns on strategy implied by the size and the value effects are too large to be explained by a risk story. A long position in the value portfolio financed with a short on position growth, over a five-year horizon, *always* seems to generate positive profits (Lakonishok *et al.* 1994). Also, it has been shown that the value strategy outperforms the growth strategy during "bad" times, while it is significantly more profitable during "good" times. (Lakonishok *et al.* 1994). The finding is robust

[64] Imagine xy-plane where the variability in y is high and the variability in x is low. In this case the line of best fit must be steep.
[65] For instance, Fama and French (2006) show that in a certain period the CAPM can perfectly explain the value premium. However, they show that portfolios of assets with different market betas but similar size and BE/ME ratio do not yield markedly different returns.

to different measures of economic state, such as growth in GNP or aggregate market return. Liew and Vassalou (2000) obtained similar results. In a broader case of ten industrialized countries, they found that the value firms outperform the growth firms in poor economic states in all countries but the Netherlands.

Daniel and Titman (1999) test the profitability of a strategy that combines value with the momentum effects; they do not use size. Their finding is a trenchant illustration of how lucrative a strategy that uses both of these anomalies can be. Consider a purchase of stocks with high momentum and high book-to-market ratios, and a short position in stocks with low momentum firms and low book-to-market ratios. According to Daniel and Titman (1999), such a strategy yields a negative return only in 3 (out of 34) years. In comparison, Fama and French (1996a) show than the market return is negative about 30% of the time. In addition, this value-momentum "super portfolio" yields an annualised mean return of over 12%, and a CAPM α of 14.04%, with a β of -0.258%!

Even without resorting to momentum strategies, Fama and French (1993) prove that the time-series regressions of excess returns of the size and BE/ME sorted portfolios onto the market factor produce large intercepts. MacKinlay (1995) was among the first to ask whether these intercepts are not perhaps "too large" to be plausible under *any* multifactor model. At first, he notes that the pricing errors (the intercepts) of any model are a function of the Sharpe ratios that the equity market implies. He then imposes a bound on any plausible Sharpe ratio by noting that traditional asset pricing theory states that the tangency portfolio has the highest attainable Sharpe ratio. Consequently, if a linear combination of securities (like the size and BE/ME sorted portfolios in Fama and French (1993)) yield a higher Sharpe ratio than one that is plausible for the tangency portfolio, then a risk-based explanation for these anomalies must be rejected. Next, MacKinlay (1995) calculates what Sharpe ratio can be achieved from the full exploitation of the anomalous returns to the size and BE/ME portfolios. In his view, it is close to one, and thus it implies that a market portfolio with a standard deviation of 18% (the historical estimate) should yield an *ex ante* excess return of 18%! Although, this estimate could be correct for South Africa (an emerging market) it is more than double the equity premium in the US; Brealey and Myers (2000) are "comfortable" with 9%. As a result, MacKinlay (1995) concludes that the returns earned by exploiting the size and the value effect are too large to be plausible under a multifactor model.

Hogan *et al.* (2004) follow MacKinlay (1995) and note that a strategy that offers returns that are too large cannot be consistent with market efficiency. They go on to introduce a concept of statistical arbitrage, which they define as a trading strategy that costs zero to initiate and provides a positive expected profit that eventually becomes risk-less as the length of the investment horizon approaches infinity. Intuitively, a strategy that offers statistical arbitrage, can be seen as “a very good deal” and, just like pure arbitrage in Ross (1976), it contradicts market efficiency. They develop a test, which does not specify a model for risk, to ascertain whether profitability of a strategy is “too good”. Hogan *et al.* (2004) find that value strategies based on *ex post* sales growth and cashflow yield constitute statistical arbitrage. Surprisingly, the evidence of the book-to-market effect contradicting the efficient market hypothesis is weaker and the size effect does not constitute statistical arbitrage.

Brav *et al.* (2004) note that, by very definition, mispricing cannot be easy to prove. Shleifer and Vishny (1997) note that the precise reason why rational arbitrageurs do not fully offset noise-induced mispricing is because they cannot credibly communicate the profitably of doing so to the providers of capital - meaning that markets will never be fully rational, but the efficiency will proceed to the point where mispricing is difficult to unequivocally detect. Therefore, when one is asked which theory offers a better description of the process underlying variation in asset prices, a convenient “both” is the most likely answer.

CHAPTER 4: THE DATA AND THE METHODOLOGY

4.1 Motivation of the Research Objectives

4.1.1 Part I: The Size and the Value Premia on the JSE

Fama and French (1992) show that firm-level returns are forecastable with several easily measurable characteristics and Fama and French (1993) construct a model to capture this predictability. Thus, in order to construct their three factor model for the JSE, the existence of the size and value premia ought to be validated. Although *inter alia* van Rensburg and Robertson (2003a; 2003b) show that the two effects exist on the JSE, it is necessary to repeat the analysis of those studies to ascertain that the results carry over to other samples and remain robust after adjustment for trading costs. Also, the optimal value-growth indicator must be found with which the value factor in the FF3F is to be constructed.

Analysis of the size and the value effect on the JSE is not novel. Although *inter alia* van Rensburg and Robertson (2003a, 2003b), Fraser and Page (2000) and Auret and Sinclaire (2006) provide compelling evidence in favour of these effects, it is believed that some tests must be replicated as there are a number of contradictory facts reported in the studies. First of all, there is some disagreement on the magnitude and independence of the size premium. Van Rensburg and Robertson (2003a, 2003b) find that the effect is strong and independent of the value effect. However in the cross-sectional regressions of Auret and Sinclaire (2006), the size effect disappears after the book-to-market ratio is included as a regressor. This finding is particularly puzzling as one-way portfolio sorts in van Rensburg and Robertson (2003b) show that the premium is very strong at 2.5% per month, and their cross-sectional correlation coefficients between market capitalisations and their measures of value are small.

A second puzzle is the extraordinary strength of the value effect documented by van Rensburg and Robertson (2003b), who show that, on a monthly basis, low P/E shares outperform high P/E shares by 3.3% per month. This return is more than six times larger than the excess (of the risk-free rate) return on the market portfolio during the period. What is more puzzling is that the magnitude of effect attenuates only a fraction after van Rensburg and Robertson (2003b) control for the size effect[66].

Lastly, the studies cannot agree on the optimal value-growth indicator to be used in the South African market. Van Rensburg and Robertson (2003b) favour the price-to-earnings ratio; Auret and Sinclaire (2006) show that the book-to-market ratio is a better predictor of returns (in the cross-section at least), but after they include all of the ratios in a cross-sectional regression the cashflow yield is the only significant variable. Interestingly, both studies find little correlation between the different value-growth indicators. However, in cross-sectional regressions, one often “prices out” the other, indicating a degree of co-linearity between the variables.

The methodology employed in this study may prove to be more conducive in resolving these questions. For instance, the sample size used in this research is larger then the one used in van Rensburg and Robertson (2003a). In all likelihood, it is also larger than the sample in Fraser and Page (2000), who consider a long, but illiquid, period in the history of the JSE - thus adjustment of their data for liquidity would wipe out many usable data points from their sample. Also, the monthly portfolio rebalancing in van Rensburg and Robertson (2003b) (according to Conrad and Kaul (1993)) may bias the computed returns. It may also confound the size and the value effects with the short-term reversal effect of Jegadeesh (1990). More importantly, none of the studies do a thorough robustness test of the size effect. The JSE is an illiquid market and it is likely that much, if not all, of the premium can be explained by market microstructure effects. To their credit, prior studies do apply a liquidity filter, but these restrictions may be too weak. Lastly, few studies perform potentially more powerful portfolio tests that use value-weighting instead of the typical equally-weighted portfolios.

[66] Nonetheless, Fraser and Page (2000) find a much smaller magnitude of the value premium and they use a similar, but longer, sample period to van Rensburg and Robertson (2003a). The test in Fraser and Page (2000) may lack power as their sample period stretches back to the period when the JSE was very illiquid.

4.1.2 Part II: The Static CAPM and the two-factor APT of van Rensburg and Slaney on the JSE

A number of tests show that the Capital Asset Pricing Model, or a multifactor model built on the intuition of Ross' (1976) Arbitrage Pricing Theory, is a reasonable specification of the risk-return relationship in the financial markets in the US (Black, 1993; Brennan *et al.*, 2004; Chen, 1983; Aretz *et al.* 2005). However, at the same time, the size and the value premia cannot be explained by these models (Fama and French, 1992; Fama and French, 2006; Brennan *et al.* 1998; He and Ng, 1994). It is the ability of the size and the value effects to survive risk adjustment with these "traditional" asset pricing models that presents the need for the FF3F. Consequently, the need for the construction of the three factor model may be demonstrated with evidence that the CAPM and the two-factor APT of van Rensburg and Slaney (1997) (henceforth, RS-APT) cannot explain the size and the value premia. In addition, joint tests of the two models against the firm's characteristics are also undertaken. Jagannathan and Wang (1998) and Cochrane (2000) argue that such tests are most powerful testaments to the validity of any asset pricing model.

Actually, van Rensburg (2001) and van Rensburg and Robertson (2003a) have undertaken similar tests. It is believed that no mistakes or misspecification of tests occurred in their analysis. However, the joint tests of the size and the value premia with other "traditional" risk models is repeated in order to, in part, address data-mining concerns of Black (1993), who states that it is prudent to validate results of prior research in new samples.

More importantly, tests in van Rensburg (2001) and van Rensburg and Robertson (2003a) are time-series in nature, which are, according to Cochrane (2001), restrictive, and a cross-sectional alternative seems natural. The importance of the restrictions may not be apparent in van Rensburg and Robertson (2003a), who use cross-sectional Fama-Macbeth regressions. However, since the dependent variable in their tests is a sum of the residual and the intercept of a time-series OLS projection, their cross-sectional tests are subject to two important time-series restrictions (Cochrane, 2001). Implicitly the regressands are generated under the assumption that the risk-free rate is equal to the zero-beta rate and that the mean return on the factor is an unbiased measurement of the true factor premium (Brennan *et al.* 1998). If these two assumptions are not true (actually Elton (1999) does show that the assumptions are false) a systematic bias into the dependant variable is introduced. Consequently, cross-sectional analysis is performed, which allows for free estimation of the risk-free rate and the risk premia.

Nonetheless, the tests in van Rensburg and Robertson (2003a) are repeated as they have power because the error-in-variables problem is solved, and since the data need not be grouped, it resolves the data-snooping concerns of Lo and MacKinlay (1990a). However, the tests in this thesis will differ to the tests in van Rensburg and Robertson (2003a) in two technical aspects. First, the Newey-West (1987) method is employed to correct for possible autocorrelation in the estimated coefficients in the Fama-MacBeth test. Second, Brennan *et al.* (1998) note that coefficients in a method employed in van Rensburg and Robertson (2003a) may be biased and propose a corrective measure which is employed in this thesis.

4.1.3 Part III: the FF3F and the RS-FF3F on the JSE

Fama and French (1993) and Lettau and Ludvigson (2001b) show that the FF3F is a good descriptor of variation in stock prices. Although the model is often rejected with formal tests, it does capture a fair share of time-series and cross-sectional variation in returns. There is much disagreement concerning the economic phenomena that underpin the model's success. On the one hand, *inter alia* Fama and French (1993, 1996a) and Davis *et al.* (2000) argue that the model captures macroeconomic risks, which static CAPM and the APT model fail to pick up. Specifically, the construction of the model is motivated by findings of *inter alia* Aretz, *et al.* (2005), Vassalou and Xing (2004) and Petkova (2006), who show that the FF3F factors contain information regarding the macroeconomic state. More specifically, Petkova (2005) and Aretz *et al.* (2005) show that their macroeconomic factor models do as good a job of pricing assets across size and value spectrum as does the FF3F.

Why not build these macroeconomic models instead? Construction of such linear factor models in South Africa is prohibitively difficult. For example, predictability of the market index has not been adequately documented, thus the pertinent ICAPM state variables have not been identified. Although international studies provide insight into the nature of candidate factors, their construction in the South African market is not easy. Many of the state variables need to be constructed, often with data that is tainted by illiquidity. In particular, an undeveloped corporate bond market inhibits construction of the default spread and the lack of an "on-the-run" Treasury Bill market complicates construction of the yield curve, and other variables associated with it. In addition, researchers in the US often share data and the construction of a full set of certain variables from scratch in the South African market is a Herculean task. Good examples of important sate variables that are difficult to construct are the default factor of Vassalou and Xing (2004), the *cay* variable in Lettau and Ludvigson (2001a), or even the aggregate dividend yield. Lastly, use of some of the data (growth in wages, for example) would force the data frequencies of the tests to change from monthly to quarterly intervals, thus considerably limiting the sample size. In sum, it is the opinion of the author that FF3F might serve as a good proxy for a linear factor model that is more theoretically justified.

The construction of the FF3F can also be motivated by behavioural finance. Specifically, Barberis and Shleifer (2003) and Daniel and Titman (1997) argue that FF3F stems from the violation of perfect rationality on the part of investors and the HML and SMB loadings are correlated with characteristics that indicate mispricing. Ferson *et al.* (1999) provide simulation evidence that misvaluation would manifest itself as a model in the spirit of the FF3F. Therefore, the model can price assets that do not possess characteristics that measure mispricing (such as investment funds). Lastly, Fama and French (2003) stubbornly maintain that their model is still a good model to use, even though they admit that behavioural finance does provide useful insight into asset pricing.

Consequently, in the initial tests contained in Part III of the empirical analysis, the three factor model of Fama and French (1993) is constructed and tested. In addition, a version of the FF3F, which replaces the market portfolios with the two factors of van Rensburg and Slaney (1997) is devised and tested as well. It is referred to as the van Rensburg-Slaney-Fama-French three factor model or RS-FF3F for short[67].

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[67] Although there are four factors in the model, a convention observed in the literature indicated that *the* fourfactor model is presented in Carhart (1997). And, van Rensburg and Slaney (1997) themselves allude to the fact that their two factors are just a better measurement of the one market.

There are few tests of the three factor model on the JSE. Van Rensburg and Robertson (2004) form factors akin to the SMB and HML, and Scher and Muller (2005) use the FF3F to test for investment performance of professionally managed funds. Their analysis is particularly clever, as their use of investment funds as test assets removes any influence of firm specific noise and makes their results relevant to the investment community. However, in spite of the fact that Scher and Muller (2005) do provide time-series intercepts of various assets, they do not test for the overall significance of the model.

Nonetheless, to the best knowledge of the author, no study on South African data employs cross-sectional methods to test the Fama and French (1993) model. Consequently, initially in Part III of the empirical analysis, the model is subjected to various tests, in time-series and cross-sectional form, on several test assets. The emphasis is on the size and F/P sorted portfolios that static CAPM and RS-APT are most likely to misprice.

In the latter section of Part III of the empirical analysis, the FF3F and the RS-FF3F are tested jointly against characteristics. Besides being powerful indicators of the model's suitability (Jagannathan and Wang, 1998), these tests can shed light on the economics underpinning the FF3F, as they have power to discern between the risk and non-risk explanations for the size and the value premia.

Although, van Rensburg and Robertson (2004) do perform a test where the characteristic-based view of asset pricing is paired against the three factor model, it is believed that there are a number of methodological shortcomings in their method. First, van Rensburg and Robertson (2004) use one-factor regressions in loading estimation. Gujarati (2002) shows that omission, from an OLS projection, of a variable that is correlated with one of the repressors, biases the estimated coefficient. For instance, van Rensburg and Robertson (2003a) show a negative correlation between firm size and betas. Thus, the SMB factor is very likely to co-vary negatively with any omitted market factor and the loading on that factor would be biased.

Second, the short estimation period used during computation of the factor loadings is seen as more problematic. van Rensburg and Robertson (2004) use between 12 and 36 months in their regressions, which is too short[68] and may

[68] To explain, casual simulation shows that a typical standard error of an estimated beta that uses a twenty-four month period, with the standard deviation of the error close to that of the market portfolio (very conservative assumption), is about 0.5. Therefore, the length of the 5% confidence interval of a

exacerbate the error-in-variables problem. Berk (2000) provides a formal, and thorough, discussion on the subject.

The third problem is that Van Rensburg and Robertson (2004) use a sequential, and not an independent, sorting procedure during their portfolio formation. It can be argued that sequential sorting on two highly co-linear variables yields very poor, within-group, dispersion of the second characteristic in the final portfolios, and if the dispersion in loadings is low the tests will have less power. In fact, the high correlation between factor loadings and characteristics is the very reason that led Daniel and Titman (1997) to use the independent sorting procedure.

Consequently, portfolio sorts and short-term loading estimation is not used in the joint tests of the FF3F, or the RS-FF3F.Altogether different methodology, which is advocated by Cochrane (2001) and is akin to the one employed in Brennan *et al.* (1998), needs to be used to jointly test the three factor model against the characteristic model. In this procedure, the full listing period is employed during estimation and, since predictive power of characteristics is tested independently of the model, these tests may lead to more power.

In sum, the aim of the empirical section of the thesis is to provide a series of tests that give the reader insight into the size and the value effects and general multifactor asset pricing. It is humbly noted that, apart from the formal test of the three factor model and its variant, the analysis replicates and builds upon the work of van Rensburg (2005), who pioneered this asset pricing research on the JSE.

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typical estimated beta is about 1.96. At the same time, international literature suggests that factor loadings on the FF3F factors are not excessively large (in absolute value). Typically, the coefficients on the HML fall between -0.6 and 0.9, and coefficients on the SMB fall between -0.3 and 1.4 (Fama & French, 1997). Therefore, in short, thus imprecise estimations, it would be very difficult to discern between large and small loadings, as the distribution of most factor loadings covers the bulk of the range the betas can be drawn from. Luckily, van Rensburg and Robertson (2004) form portfolios, which may attenuate the problem, as they hope that estimated factor loading will at least be assigned to the correct portfolio. Nonetheless, it is safe to say that many estimated betas of average value will fall into portfolios that represent high or low loadings, and vice versa.

4.2 Data Collection and Sample Characteristics

One of the key objectives of this research is to perform the tests on a reasonably complete sample of firms. In South Africa, there is a deficiency of publicly available research-quality financial data; thus, a number of data sources are simultaneously used and these are often spliced together. Also, when compared with larger markets, the universe of monthly observations available to an econometrician is limited. Not only does data availability restrict the sample period, but number of listed (and liquid) stocks further constrains the usable sample. Power of test is directly related to sample size; therefore some statistical luxuries open to American researchers are dropped. As a result, all firms are candidates to be included in the sample, regardless of size. Also, rather lax liquidity requirements are imposed when choosing the sample. The liquidity criterion is similar to van Rensburg and Robertson (2003a ,2003b, 2004)

Three types of variables are needed; namely, corporate action data, stock-level type data and accounting data. Corporate action data can be defined as a comprehensive list of companies listed in the sample period, corresponding dates of each firm's listing, de-listing, changing of its name, as well as information on any possible corporate actions such as unbundling transactions and certain capitalisation issues. Stock level data comprises stock prices, shares in issue and trading volume. Lastly, accounting measures of value such as earnings per share, cashflow per share and book value of equity are also needed.

The primary sources of raw data used in the study are I-Net Bridge (henceforth, I-Net), The Buro of Financial Analysis/McGregor's database (henceforth, BFA) Bloomberg Professional Service (henceforth, Bloomberg), McGregor's Who Owns Whom Manual (henceforth, McGregor's Manuals) and finally the JSE monthly bulletin (henceforth, JSE bulletin).

4.2.1 Primary Information

The unrestricted sample comprises all firms listed on the JSE from December 1989 to July 2005. The list of firms was compiled from companies catalogued in the December issue of the JSE bulletin.

Data and date of all-share listing, de-listing, unbundlings, suspensions, name changes and changes were obtained from the back pages of the JSE bulletins. The name change data are used to “string together” companies which changed their name. This procedure is similar to the work in Chan *et al.* (1995), who note that conventions on coding of firms that change names or restructure is often made independently by each data provider. In effect, using historical codes from JSE bulletins allows for un-adjustment for name changes of data from each provider and then a consistent treatment of all such corporate actions.

In total, between December 1989 and July 2005, 799 firms delisted, 428 firms listed and there were 422 name changes. Also, 125 unbundling transactions and special pay-outs were found in the sample period. In order to compile the list of relevant stock splits, consolidations and other capitalisation issues (hereafter, split list), information contained in the Bloomberg and JSE Bulletins is relied on, and 192 such corporate actions are unearthed.

Share prices, shares in issue and monthly trading volume data is obtained from I-Net. The actual (unadjusted) prices (henceforth, real prices) are not only a variable used to explain share returns, but are also required in the calculation of market capitalisation and the dividend yield. To their credit, I-Net factor-in many capitalisation issues, such as stock splits and share consolidations. However, it does not adjust for unbundling transactions and dividends. Hence, the data obtained from I-Net cannot be directly used.

The detailed description of the process behind obtaining real prices can be obtained from the author, however a short description of the method is in order. Each December, real prices are hand-collected from the JSE bulletin and the ratio between the captured price and the price supplied by I-Net calculated: it is the implied split factor. Generally, if a firm has the same split factors in two consecutive calendar year-ends, then it is assumed that the split factor holds between two dates. If two successive split factors are not the same, then the split list (mentioned in the previous section) is used to determine the exact month of the share split or consolidation, and the time series of split factors is adjusted accordingly. In an extreme case, where there is no information suggesting the time of the corporate action, prices are manually captured from the JSE bulletins. Consequently, a spreadsheet that records each firm’s split factor in the sample period is created. Finally, real prices are calculated by dividing the prices supplied by I-Net with a corresponding split factor.

Market capitalisation is calculated, using I-Net data, by calculating number of shares in issue by the price obtained from I-Net. Unfortunately, I-Net does not provide (in its terminal) shares in issue data prior to 1994. In order to calculate market capitalisation prior to 1994, shares in issue data is captured from JSE bulletins. For earlier periods, market capitalisation is obtained by multiplying captured shares in issue by the real price of a share, with an adjustment for certain capitalisation issues. If a firm has two types of shares (say, voting and non-voting) then the market capitalisation equals the sum of the value of the two types of shares.

Trading in a firm's shares may be suspended. The JSE Bulletin often records the precise date of a firm's suspension and, if it exists, its reinstatement. All data time-series are adjusted for a firm's suspended trading. In spite of this, at times the trading volume data reveals that a firm's monthly trading volume falls to zero for a prolonged period of time. Since the JSE manual may not be exhaustive in terms of the firm's suspension dates, and, more importantly, reinstatement dates appear to be sporadically omitted, an additional list of suspensions is compiled. All firms that did not trade for six consecutive months were deemed suspended from the first month of no trading activity until the month where trading volume is not zero. In addition, if a firm does not trade prior to its discontinuation in I-Net price data, the firm is deemed suspended in the month where trading volume falls to zero. Cash shell companies are treated as suspended shares.

4.2.2 Returns

The holding period return of a given firm at time t is calculated with the textbook formula:

$$r_t = \frac{p_{t+1} + d^*_{t+1}}{p_t} - 1 \text{, and } g_t = \frac{p_{t+1} + \delta_{t+1}}{p_t} \text{, alternatively } r_{it} = g_{it} + \frac{d_{t+1}}{p_t} - 1 \qquad (4.1)$$

Trivially, p_t is the share price (in cents) of the asset at time t, r_t is the return and d_{t+1} is the dividend (in cents). Also, g_t is the price appreciation of a stock, adjusted for corporate actions. In this case, d^*_{t+1} is the value of all payouts to shareholders in interval t to $t+1$. It comprises dividend payments and other special payouts, denoted δ_{t+1}. In order to minimise effect of outliers in computation returns, any firm may not yield a return of more than 200% and less than -66.66%. This procedure impacts 283 or 0.27% data points.

In the case of the JSE, the major component of δ_{t+1} is the value of unbundled and distributed shares. The primary use of the g_t variable is to "move forward" ratios of fundamental value to price. To illustrate, if one knows that the book-to-market value of a firm at some point is x, then its book-to-market ratio in the next period will be x/ g_t.[69] Although it is possible to calculate book-to-market value, by dividing the last known book value by market capitalisation in every period, this procedure may not be correct. If a firm issued new shares, (or repurchased them), then the observable book value will not correspond to the market value of the firm. The book value rose at the time of the stock issue.

From (4.1) it is apparent that calculation of returns requires three components: prices, dividends and other payouts δ_{t+1}. It is assumed that all price data provided by I-Net has been adjusted for stock splits, consolidations, capitalisation awards and any other corporate actions that do not directly influence market value of the firm. As a result, stock's price appreciation (or depreciation), calculated using I-Net data, is assumed to be reflective of a capital gain (or loss) of an investor. Dividends and the Last Day to Register (L.D.R.) dates are hand-captured directly from each December issue of the JSE Bulletin. Dividend yields were calculated by dividing the dividend by the real price at the beginning of the L.D.R month. Information on unbundlings, and other payouts are collected from the JSE Bulletin's corporate actions pages, and returns are appropriately adjusted.

4.2.3 Fundamental Ratios

All accounting data used in fundamental ratio calculations is obtained from the BFA and I-Net databases, with the McGregor Manuals being a supplement. Primarily the BFA accounting data is used. Alternatively, I-Net data is relied upon if BFA does not have the information. Surprisingly, I-Net dataset has good coverage of older firms, while BFA covers more recent firm with higher completeness. If data is not available in either database it is captured from the McGregor Manuals. In addition, at times,

[69] Note, given that $\delta_t + p_t = p^*_t$, then e/p_{t+1}, the earning yield in time t+1 is equal to $(e/p_t,)(\, p_t,/\, p^*_{t+1},) = (e/\, p^*_{t+1},)$

data from the McGregor Manuals and the BFA database conflict. In such cases, the BFA database is used. For firms with financial statements denominated in foreign currency, the data from I-Net is used; if data form I-Net is not available the firm is dropped from the sample.

Book-to-market ratio is defined as book value of the equity divided by market value of the equity at the end of the financial year-end. For book value, item 1 in the BFA balance sheet data is used ("Ord Shareholders Interest'), or item LI05 in the I-Net data ("Equity") summed with item BI05 ("Intangibles: "Assets" excluded by analyst"). The definitions are nearly equivalent, as the correlation between book-to-market ratio obtained from BFA and I-Net is 0.993 and is based on 4900 observations.

Headline earnings per share (henceforth, HEPS) are obtained directly from the I-Net and BFA databases. It appears as Item 306 ("EPS-Headline") on the BFA income statement data, and Item IS34 ("Headline Earnings as calculated") in the I-Net data source. Earnings yield is defined as headline earnings per share divided by price at the end of a financial year-end. The price used depends on the source of the financial data. If data is captured from BFA then BFA price is used, and so on. This procedure makes the ratios consistent among different data sources and different conventions regarding stock splits and consolidations. Correlation between earning yield obtained from the I-Net and BFA databases is 0.986 and is based on 4767 observations. Since much of the data is captured, and the McGregor Manuals began to publish HEPS only from 2002, headline earnings are proxied with ordinary earnings per share or net earnings per share. The McGregor Manuals define earnings as profit attributable to shareholders being divided by the number of shares in issue at the financial year-end.

Cashflow per share data is not provided by I-Net, therefore the BFA database and McGregor Manuals are relied on for the information. If the item is not available in the BFA electronic database it is captured from the McGregor Manuals. If it cannot be captured, I-Net data is used to construct the variable from the definition provided by the McGregor Manuals, which, in essence, adjusts headline earnings for non-cash items such as depreciation, deferred tax, minority interest and preferred dividends. This occurred very sporadically and represents less than 100 out of 7714 fiscal year-ends of firms in the sample. Nonetheless, C/P is deemed a relatively poorly measured variable.

A keen reader will notice that use of the financial ratios will result in the look-ahead bias of Banz and Breen (1986): the above-mentioned ratios "come into effect" six months after the financial year-end. To bring the F/P ratio forward it is multiplied by six month buy and hold return beginning at the firm's financial year-end. The buy and hold return does not take into account dividends and can be seen as an adjustment for share movement between the fiscal year-end and the "effective" date. In this way it is assured that the effect of the accounting data being released into the market is reflected in the F/P ratio.

On a technical note, all characteristics are represented as natural logarithms and are standardized. This procedure eliminates effects of inflation on variables in the data set and equalizes cross-sectional distributions - a property that is desirable in asset pricing tests (Chan *et al.* 1991).

4.2.4 Sample Characteristics

The sample period spans June 1992 to July 2005, yielding 156 monthly observations. Since factor estimation requires a minimum of 24 months of prior monthly price data, all stock level and corporate action data was collected from December 1989[70]. Also, it was necessary to capture accounting data prior to June 1992 in order to ensure that accounting data was available to form an F/P ratio on June 1992.

Table 4.1
Sample Composition

Total number of firms listed between December 1989 and July 2005.	1180
less firms without sufficient data	-30
less foreign firms without I-Net accounting data	-9
less firms listed for less than 24 months	-195
less property trusts and property loan stock shares	-53
Firms in the sample	893

[70] This ensures that return for January 1990 is available.

Table 4.1 shows the candidate number of firms and the resultant usable sample of firms. In order to conform to international studies, pure real estate investment trusts are excluded from the sample. The requirement that a firm has been listed for at least 24 months is the largest cost to the sample. However, the effect is rather small, as these firms would not have an F/P ratio for at least six months - thus the impact on the sample is minimal. Cash companies are not explicitly excluded, but are marked as suspended. This procedure removes such firms from any subsequent tests. The total number of firms included in the sample (893) is somewhat misleading, as it does not show how many firms are listed in a given month.

4.3 Methodology

4.3.1 Test of Predictive Power of Characteristics

Tests of the size and the value premia use portfolio sorts and the Fama-MacBeth regressions. Both these methods are standard practice in asset pricing tests (*inter alia* Fama and French (1992, 1993, 2006), van Rensburg (2001) and van Rensburg and Robertson (2003a; 2003b)). They need to be replicated in order to achieve suitable comparisons with international and local studies. Table 4.2 defines the variables.

Portfolio Tests

In tests utilising portfolio sorting, the individual returns in the portfolios can be weighted equally or weighted according to the stock's market capitalisation. Although value-weighting decreases the impact of trading costs (Daniel and Titman, 1999), the equal-weighted results may be preferable as firm specific events are less likely to influence the results. As there is some disagreement among academics regarding the best weighting scheme, both types of results are presented.

In tests utilising one-way sorts, five portfolios are made. The first group consists of stocks with the largest values of the characteristic and the fifth group consists of stocks with the lowest value of the characteristic. The premium associated with the sorting characteristics is computed by subtracting the mean return of portfolios containing stocks with the highest value of the characteristics from the mean return of the portfolio containing stocks with the lowest value of the characteristic. The number of portfolios formed in this way is arbitrary, and is chosen for historical reasons (Fama and French 1993, 1996a; Van Rensburg and Robertson 2003a, 2003b). All two-way sorts use independent sorting, i.e. the breakpoints of the second sort are determined using the entire cross-section of returns at the moment of rebalancing. Thus, the number of portfolios is not known *a priori*. However, sorts are repeated until there are at least two stocks in each portfolio.

Table 4.2
Definition of Variables and Symbols

$\underline{r}_i$ $\underline{r}_i^e$	A vector of return series of asset *i*	$\begin{bmatrix} r_{i1} & r_{i2} & \cdots & r_{iT} \end{bmatrix}'$	Superscript *e* denotes excess returns, e.g. $\underline{r}_i^e$ or $\mathbf{r}_t^e$
$\mathbf{r}_t$ $\mathbf{r}_t^e$	A vector of a cross-section of N asset returns at time *t*	$\begin{bmatrix} r_{1t} & r_{2t} & \cdots & r_{Nt} \end{bmatrix}'$	
$\underline{\varepsilon}_i$	A vector of time-series residuals for asset *i*	$\begin{bmatrix} \varepsilon_{i1} & \varepsilon_{i2} & \cdots & \varepsilon_{iT} \end{bmatrix}'$	
$\mathbf{e}_t$	A vector of a cross-section of N time-series residuals asset returns at time *t*	$\begin{bmatrix} \varepsilon_{1t} & \varepsilon_{2t} & \cdots & \varepsilon_{Nt} \end{bmatrix}'$	
$\underline{f}^j$	A vector of return series of a factor mimicking portfolio of factor *j*	$\begin{bmatrix} f_1^j & f_2^j & \cdots & f_T^j \end{bmatrix}'$	
$\mathbf{f}_t$ $\mathbf{f}_t^k$	A vector of cross-section of K factor mimicking portfolios realisations at time *t*	$\begin{bmatrix} f_t^1 & f_t^2 & \cdots & f_t^K \end{bmatrix}'$	A superscript *k* implies that the first element is one
$\mathbf{f}$	A matrix of T observations on the K factors (K x T)	$\begin{bmatrix} \underline{f}^1 & \underline{f}^2 & \cdots & \underline{f}^K \end{bmatrix}'$	the data matrix is $\mathbf{F} = \iota_N \otimes \mathbf{f}'$
$\underline{\alpha}_i$	A vector of time series of pricing errors	$\begin{bmatrix} \alpha_{i,1} & \alpha_{i,2} & \cdots & \alpha_{i,T} \end{bmatrix}$	Often $\underline{\alpha}_i = \iota_T \otimes \alpha_i$
$\mathbf{a}$	A vector of pricing errors of N assets	$\begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_N \end{bmatrix}'$	
$\mathbf{b}_i$	A vector of loadings of asset *i* on K factors	$\begin{bmatrix} \beta_i^1 & \beta_i^2 & \cdots & \beta_i^K \end{bmatrix}'$	
$\mathbf{b}^j$	A vector of loadings of N on factor *j*	$\begin{bmatrix} \beta_1^j & \beta_2^j & \cdots & \beta_N^j \end{bmatrix}'$	
$\mathbf{b}$	A matrix of loadings of N assets on K factors (K x N)	$\begin{bmatrix} \iota_N & \mathbf{b}^1 & \cdots & \mathbf{b}^K \end{bmatrix}'$	A superscript *0* the first row of ones
$\mathbf{c}_i$	A vector of L characteristics of asset *i*	$\begin{bmatrix} \kappa_i^1 & \kappa_i^2 & \cdots & \kappa_i^L \end{bmatrix}'$	
$\mathbf{c}^k$	A vector of loadings of N on factor *j*	$\begin{bmatrix} \kappa_1^j & \kappa_2^j & \cdots & \kappa_N^j \end{bmatrix}'$	
$\mathbf{c}$	A matrix of L characteristics of N assets (K x N)	$\begin{bmatrix} \mathbf{c}^1 & \mathbf{c}^2 & \cdots & \mathbf{c}^L \end{bmatrix}'$	
$\mathbf{l}$	A vector of the zero-beta rate and K vector premia	$\begin{bmatrix} \gamma_0 & \lambda^1 & \cdots & \lambda^K \end{bmatrix}'$	A superscript *0* the zero-beta rate
$\mathbf{q}$	A vector of the zero-beta rate and L characteristic premia	$\begin{bmatrix} \gamma_0 & \theta^1 & \cdots & \theta^L \end{bmatrix}'$	A superscript *0* the zero-beta rate

During rebalancing, the adjustment for outliers is performed, but only after the first sort. Winzorising is performed by, at first, calculating annual buy and hold return for each stock. It is then standardized by the cross-sectional standard deviation of the buy and hold returns in the portfolio that the stock was assigned to. The stock is excluded from the portfolio if its standardised return is larger than the absolute value of three[71].

In order to account for market microstructure effects, stocks that do not conform to price or liquidity criteria are excluded from the analysis. The use of the share price to account for trading costs is substantiated by Bhardwaj and Brooks (1992), who show a strong relation between prices and dollar cost of trading. Ali *et al.* (2003) also use price as a measure of trading costs. The choice of illiquidity variable follows Hou and Moskowitz (2005), who use a twelve-month average of trading volume scaled by number of shares in issue.

All portfolios are rebalanced annually, at the end of June. The appeal of the simulated portfolio procedure is that it aims to mimic the experience of an average investor. Actually, Barberis and Thaler (2003) note that people evaluate their portfolios once a year, so annual rebalancing may be more aligned with reality. A more frequent rebalancing of portfolios may act against this intuition and it imposes very high trading costs on a representative investor. The potential loss of information caused by an annual portfolio reformation mentioned by van Rensburg and Robertson (2003a) is not present in multivariate cross-sectional regression tests, which also appear alongside the portfolio tests. It is noted that annual rebalancing confounds the value effect with the momentum effect. However, this is not a problem and it actually increases the power of the tests. Value stocks generally perform poorly before the classification date (Fama and French, 1995) and the momentum effect predicts poor return on these stocks. Therefore, for the value premium to manifest itself, it must first "beat" the effect of past price momentum.

All the means and associated *t*-statistics are calculated in Excel. The sorts, restrictions and winzorising are programmed into the worksheet with Visual Basic for Applications.

[71] The unwinzorised results are available upon request.

Regression Tests

The cross-sectional tests are performed with the Fama-Macbeth procedure[72]. The inclusion of shares into the regressions is selective, as firms with low share prices and low liquidity are excluded. Since the Fama-Macbeth procedure assumes that the coefficients are drawn from the same normal distribution in each time period, all characteristics are represented as natural logarithms and are standardized (Chan *et al.* 1991). In short, the observation used in the regression will be the deviation from the mean divided by the cross-sectional standard deviation in month *t*. The mean and standard deviation for the F/P ratios are obtained from a distribution that excludes negative values (van Rensburg and Robertson 2001a, 2001b). This transformation brings the variables closer to the normal distribution.

In order to adjust for outliers, all observations in the top and bottom 2.5% of the cross-sectional distribution will be set to values corresponding to the 97.5^{th} percentile and 2.5^{th} percentiles, respectively.

Formally each cross-sectional regression in the Fama-MacBeth test is:

$$\mathbf{r}_{t+1} = \mathbf{c}_t' \, \hat{\mathbf{q}}_t + \mathbf{a}_t \tag{4.3}$$

The vector of regressors is:

$$\mathbf{c}_t = 1 \quad \mathbf{c}_{Size} \quad \mathbf{c}_{E/P} \quad \mathbf{c}_{C/P} \quad \mathbf{c}_{BE/ME} \quad \mathbf{d}_{E/P} \quad \mathbf{d}_{C/P} \;\; \mathbf{D}$$

and consequently the premia vector is:

$$\hat{\mathbf{q}}_t = \left[\hat{\gamma}_{0,t} \quad \hat{\theta}_{Size,t} \quad \hat{\theta}_{E/P,t} \quad \hat{\theta}_{C/P,t} \quad \hat{\theta}_{BE/ME,t} \quad \hat{\theta}_{D\ E/P\ ,t} \quad \hat{\theta}_{D\ C/P\ ,t} \right] \mathbf{D}$$

The first four elements of the vector are the characteristics that are thought to forecast stock returns. In order to deal with negative F/P ratios, the technique of Fama and

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[72] Econometric textbooks advise a number of panel data specifications to tackle estimation when the sample is a time-series of a cross-section. However, financial data is plagued with a number of statistical problems that invalidate the panel CS-TS approaches. Fama and MacBeth (1973) and, subsequently, Cochrane (2001) argue that standard errors of standard panel techniques are mis-stated due to *cross-sectional dependence* of residuals. This cross-sectional correlation occurs when, for example, a firm's *i* good return today translates into a firm's *j* good return - meaning that the unique risk of an individual asset (the error terms) will be correlated. Another problem with panel approaches is that time-series correlations of most regressors used in the study are very high. To illustrate, a firm's size and its P/E ratio will be, at times, perfectly correlated with the share price. Simply, if price goes up, so does the firm's equity and its P/E ratio. Surprisingly, these three variables may represent different fundamental attributes of a firm, and researchers are often interested in the incremental explanatory power of each of these variables. Too much multicollliniarity, makes the inference difficult. Last, a related problem is encountered where lagged F/P ratios are used in a time series OLS. Time variation of F/P ratios stems from changes in price, but the ratios are also highly auto-correlated, which leads to an endogeneity problem and biases the estimated coefficients (Lewellen, 2004).

French (1992) is used. Specifically, the natural log of the ratio itself is zeroed and a separate dummy variable is assigned a one for negative F/P ratios and zero otherwise. The last two elements in the vector represent these variables. The matrix **D** is a diagonal matrix of indicator variables and specifies the set characteristics applied in each regression.

The vector of coefficients in the Fama -MacBeth regressions is:

$$\hat{\mathbf{q}} = E_T \quad \hat{\mathbf{q}}_t \quad = \frac{1}{T}\sum_{t=1}^{T}\mathbf{q}_t$$

The standard errors of the estimated coefficients are adjusted for serial correlations with the Newey and West (1987) method, with a correction of up to four leads and lags, meaning that:

$$\sigma^2(\hat{\theta}_j) = \frac{1}{T}\sum_{l=-4}^{4}\mathrm{cov}_T \quad \hat{\theta}_{j,t}, \hat{\theta}_{j,t-l} \quad = \frac{1}{T^2}\sum_{l=-4}^{4}\sum_{t=1}^{T} \quad \hat{\theta}_{j,t} - E_T \quad \hat{\theta}_{j,t} \qquad \hat{\theta}_{j,t-l} - E_{T-l} \quad \hat{\theta}_{j,t-l}$$

Trivially:

$$t = \frac{\hat{\theta}_j}{\sigma(\hat{\theta}_j)}$$

All the cross-sectional Fama-Macbeth regressions are performed in Stata. Similarly, calculation of the coefficients and the standard errors is done with a sub-routine programmed into Stata.

4.3.2 Tests of the Asset Pricing Models

Tests of asset pricing models will be conducted in two ways: in a time-series format and a cross-sectional format. The tests are always unconditional. Although there is a much evidence that most loadings in pricing models are time-varying (Fama and French, 1997; Fama and French, 2006), Ghysels (1998) notes that a badly specified process for the time-variation in betas leads to a much larger error than if the variation is ignored. Since little is known about the time-variation in factor loadings on the JSE, the error would be particularly severe if applied. At first, all asset pricing models are tested in a time-series format. Cochrane (2001) notes that in cases, as the one in this thesis, when the asset pricing factors are also returns, the time-series can be used to measure pricing errors. This setup is advantageous because it circumvents a number of statistical problems that plague more complex analysis. However, the time-series test does impose two restrictions on the data. The zero-beta rate is assumed to be equal to the risk-free rate, and the time-series mean of the factor mimicking portfolios is assumed to be equal to the true expectation of the premium it emulates. Both these assumptions imply that the intercept in the time-series tests is an unbiased estimate of the pricing error of the asset the model is asked to price.

In each case, a time-series approach is used and it is followed by a less restrictive cross-sectional approach. Black (1972) argues that the equivalence of the risk-free and the zero-beta rates is violated in imperfect markets, while Elton (1999) gives a trenchant argument that time-series means of portfolios are poor instruments for expected returns. In a cross-sectional analysis, the factor premia are directly estimated and the set-up allows for some measurement error. The zero-beta rate also can be treated as a free parameter (Cochrane, 2001).

To each cross-sectional OLS regression, a corresponding GLS regression is run for two reasons. First, Kandel and Stambaugh (1995) show that the method can check if the estimated premia are specific to the weighing-shame employed during calculation of the test assets. Second, Cochrane (2001) notes that the GLS regressions yield better estimates of the factor premia because the procedure "pays more attention" to information contained in observations (portfolios) which are subject to less statistical noise. In effect, the dependent variables are re-weighed where better-measured regressors receive more weight.

The GLS regressions require an estimate of a particular matrix of second-moments. It is directly used to compute the coefficients; thus any measurement error in matrix elements creeps into the estimates of the factor premia. In order to minimise the imprecision of this estimate, the GLS estimation is only possible when the cross-section of assets is not large relative to the length of the sample period. And, the method requires the use of liquid assets. Considering that moments of infrequently traded assets are measured with an error, the elements of the second-moment matrix can be mis-measured, particularly in an illiquid market such as the JSE. Consequently, the use of GLS estimation is a double-edged sword. It provides a robustness check on a re-weighed set of test assets, and has a stronger footing in statistical theory. But, it may yield biased estimates of the factor premia.

In theory, asset pricing tests ought to be performed on individual securities, but statistical considerations force grouping of shares into portfolios. For one, many formulas used to compute standard errors cannot be applied in situations in which the cross-section of assets is large relative to the length of the sample period. Thus, grouping allows for a decrease in the amount of test assets. In addition, running asset pricing tests on portfolios reduces, if not eliminates, the impact of firm specific risk on estimation of mean returns and factor loadings. However, the method of grouping data into portfolios is an arbitrary one, and since the estimated premia are a function of weights assets receive in the portfolios, the asset pricing tests are conducted on different sets of assets.

Choice of Test Assets

Statistical considerations require the test assets to exhibit wide dispersion in mean returns and factor loadings (Chen, Chen and Hiseh, 1986). For instance, Gujarati (2002) explicitly shows that the standard of errors of OLS estimates are negatively related to the variance of the independent variables. And, MacKinlay and Lo (1990a) prove that if the pricing errors of a model are correlated with some characteristic, using portfolios sorted with that characteristic will increase the power of the asset pricing tests.

Consequently, the choice of test assets used in the empirical analyses follows Brennan *et al.* (2004), who use the 25 portfolios advocated by Fama and French (1993, 1995) and 30 industry portfolios constructed by Fama and French (1997). Inclusion of the industry portfolios ensures variation in CAPM betas and RS-APT loadings, while the size and F/P sorted portfolios ensure dispersion in SML and HML loadings.

The test assets, which capture the size and the value effects, will comprise two sets of assets constructed as an intersection of the four size and three value-growth portfolios. The two-way characteristic sort is performed twice because Leledakis and Davidson (2001) note that more than one value-growth indicator may be relevant. The two value-growth indicators, which are deemed best predictors of returns, are used in the sort.

Stocks are also sorted into 22 industry portfolios. The identification of each firm’s industry is made on the basis of the description of the line of business that appears in the McGregor Manuals. Industries used in the study can be seen in Table 4.3. At times, the categorisation is similar to the one followed by the JSE, but at times new sectors are “created” for the purpose of this thesis, and thus, this categorization is somewhat subjective. In order to remove the influence of firm-specific noise, some industries are merged together, while portfolios with few stocks in them (e.g. Telecommunication) or industries with highly heterogeneous companies (e.g. Healthcare) are dropped altogether [73]. It needs to be stressed that industry classification is necessary to obtain a sufficient variability in factor loadings, and it need not be exact. All in all, the industry assets consist of four portfolios of financial firms, five portfolios of resource firms and 14 portfolios of industrial firms.

Table 4.3
Industry Portfolios

Panel A: Industrial	
Construction & Construction Suppliers	IT Services
Electric Hardware & Electronics	Light Manufacturing – Consumer
Food	Light Manufacturing – Industry
General Services	Packaging & Printing
Hoteling, Tourism & Leisure	Retail – Consumables
Industrial Suppliers	Retail – Durables
Investment Trusts	Transport
Panel B: Financial	
Banks	
L-term Insurance	
Non-Bank Financial Services	
S-term Insurance	
Panel C: Resources	
Gems	
Gold	
Mining Houses	
Other Metals & Minerals	

Construction of CAPM and RS-APT Factors

Because the entire universe of listed shares is captured, it is possible to calculate the Market return from the primary data. Therefore, the market proxy is the value-weighted return of all shares in the database. The correlation between the synthesized market index and the actual "all-share" index published by the FTSE is 0.99. The average outperformance of the synthesized index is 0.312% per month (3.74% annualized). It is closely in line with the average market dividend yield. Also, the synthesized index includes more small stocks than the published index as the all-

[73] For the interested reader, *General Services* includes, among other service and consulting firms, the *Staff Services & Education* sector of the JSE. *Food* and *Beverages* sectors are merged. *Light Manufacturing - Consumer* includes *Textiles*, while *Other Metals & Minerals* includes *Coal & Energy*.

share does not include all shares listed on the JSE.[74] This means that the synthesized index will include "some of the size effect".

The Resource and the Findi factors are calculated in a similar way. The resource factor is the value-weighted return of all mining shares in the dataset, while the Findi factor is the value-weighted return of all Financial and Industrial shares.

Construction of Fama and French (1993) Factors

In their seminal article, Fama and French (1993) constructed their (in)famous factors by initially forming six elementary portfolios and with a linear combination of these composites they formed their factors. To be more precise, these elementary portfolios were obtained from an independent two-way sort of two size portfolios on three value portfolios. They form the SMB factor by subtracting the average return of three portfolios containing small stocks from the average returns of three large stock portfolios. Similarly, they construct the HML factor by subtracting the average return of the two most-value portfolios from the average return of the most-growth portfolios.

The construction of HML and SMB factors (FF3F factors) follow Fama and French (1993) very closely, and consequently differ from the factors of Van Rensburg and Robertson (2004). The constructed factors are re-balanced annually, not monthly. It has already been discussed why the monthly balancing method may overstate the observed size and value premiums. Second, only a subset of stocks is used for determination of the breakpoints for the six element portfolios. This point merits further explanation. Fama and French (1993) formed their six portfolios using breakpoints of the NYSE and did not include NASDQ and Amex shares. In other words, they foresaw that the use of the entire cross-section in the determination of the breakpoints would actually result in a portfolio containing "very small", not "small", stocks. Simply put, cutting the cross-section of listed shares in half culminates with one of the portfolios being filled with many tiny capitalisation shares. This problem would be particularly severe for the JSE, as there are many vary small, and few very large, firms listed on the exchange. In order to address this problem, each June, all listed stocks are ranked according to their liquidity. A stock's measure of liquidity is its twelve-month average of its monthly trading volume scaled by the number of shares in issue. Consequently, the breakpoints for the six portfolios of Fama and

[74] A point made by Chris Muller.

French (1993) are derived using the 200 most liquid stocks. Also, stocks included in the elementary portfolios are subject to the usual restrictions on price and liquidity.

A possibly more preferable method of factor construction would take into account the segmentation of the JSE into Resource as well as financial and industrial shares (i.e. constructing separate HML and SML factors for Resource and Findi stocks). However, such sub-division will induce firm specific variance into the factors and will escalate the endogeneity problem already present in the FF3F model. Although Cochrane (2001) provides thorough theoretical reasons why residual risk in factors is a problem, it can be said intuitively that it is difficult to measure exposure to a risk factor, if the factor itself is measured with an error. In addition, if FF3F factors are indeed instruments for true innovation in state variables (*inter alia* Petkova, 2005; Aretz *et al*. 2005), unnecessarily large factor variance strongly opposes Fama's (1996) argument that the variance of ICAPM factor mimicking must be as small as possible.

It is not a foregone conclusion that the separation of FF3F factors into the two asset classes is theoretically correct. Why would the value and size premiums be different for Resource and Findi stocks? A growing amount of literature (Hahn and Lee, 2006; Vassalou and Xing, 2002) documents that FF3F factors capture risk related to distress and access to finance. Therefore, at any point in time, the composition of factors will change as firms in different industries go into, and climb out of, distress (Daniel and Titman, 1997). The weighting of different asset classes in the SML and HML will adjust automatically. Alternatively, the behavioural view suggests that small and value firms are underpriced. However, as different industries become underpriced due to fickle investor sentiment, so will their relative weights in FF3F factors. Nonetheless, the power of industry adjusted FF3F factors to price assets on the JSE is left for future research.

As a matter of notation, the SMB factor is referred to as SML factor ("Small minus Large"), while HML is referred to as VMG ("Value minus Growth"). This notation distinguishes factors derived in this thesis from the original factors of Fama and French (1993). Although Eugene Fama and Kenneth French did not copyright the names of their factors, the alterative naming system is introduced out of courtesy.

Time-Series Tests

All time-series asset pricing tests will be conducted with the time-series SURE system that is mapped into the GMM system[75]. This procedure yields test statistics, which are robust to heteroskedasticity and auto-correlation in residuals, but incorporate the efficiency gain provided by the SURE methodology.

In all the regressions, a lag of the Market, Resource or Findi factors is included in the specification. This ensures that microstructure effects, such as infrequent trading and slow diffusion of information, are, admittedly imperfectly, taken into consideration. According to Ibbotson, Kaplan and Peterson (1997), omission of the lag can capture a portion of the size effect. Dimson (1979) provides theoretical justification for this procedure, but he also advocates inclusion of lead terms as well. In initial tests of the models, the lead terms were rarely significant and, at times, large in value; thus, in order to avoid a possible bias in estimated betas, it was decided to exclude them from the analysis.

Formally, regression of factors on a asset *i* is:

$$\underline{r}_i^e = \underline{\alpha}_i + \mathbf{f}\hat{\mathbf{b}}_i' + \underline{\varepsilon}_i \text{ for i = 1, 2, 3… N} \tag{4.4}$$

The superscript *e* suggests that the dependant variable is the realized return net of the risk-free rate. In all time-series regression tests it will be assumed that the risk-free asset exists and it is represented by the three-month T-Bill rate, which is obtained from the website of the South African Reserve Bank. Cochrane (2001), following Jensen (1968), notes that the intercept α_i is the pricing error of an *i*th asset. The vector of the factors is:

$$\mathbf{f} = \begin{bmatrix} \underline{f}^{M} & \underline{f}^{M\ lag} & \underline{f}^{R} & \underline{f}^{R\ lag} & \underline{f}^{I} & \underline{f}^{I\ lag} & \underline{f}^{SML} & \underline{f}^{VMG} \end{bmatrix}\mathbf{D}$$

The $\underline{f}^M$ represents the Market factor, which is the return series on the value-weighted return of all securities in the dataset in excess of the risk-free rate. The $\underline{f}^R$ is series of the Resource factor, which is the value-weighted excess return of all mining shares in the dataset. The $\underline{f}^I$ is series of the Findi factor, which is the value-weighted excess return of all financial and industrial shares in the dataset. The series with the *(lag)* subscript are the factors lagged by a month. The $\underline{f}^{SML}$ and the $\underline{f}^{VMG}$ are the size and the value factors. The matrix **D** is a diagonal matrix of indicator variables that specifies the factors in each regression equation.

[75] For more detail see Greene (2003).

Financial assets do not exist in isolation and there is much correlation between residuals of individual assets, and often can be presented as a SURE (Seemingly Unrelated Regressions) system - which Greene (2003) recommends for application in financial markets. The SURE method simultaneously estimates factor loadings for a number of assets and it takes cross-correlation of returns into account and improves the precision of estimates of $\mathbf{b}_i$; estimates are more efficient.

Portfolio returns are stationery, but exhibit a non-negligible auto-correlation (Campbell, Lo and MacKinlay, 1997; Cochrane, 2001). Furthermore, heteroskedasticity (or conditional heteroskedasticity) may be present in monthly data. Meaning standard OLS (and SURE) time-series regressions will not yield efficient estimates, and thus some adjustment to standard errors is often necessary.

Consequently, the standard errors are calculated by mapping N time-series regressions into a GMM system:

$$g_T\left(\hat{\mathbf{a}},\hat{\mathbf{b}}\right) = E_T\left(\mathbf{f}_t^k \otimes \left(\mathbf{r}_t^e - \hat{\mathbf{a}} - \hat{\mathbf{b}}'\mathbf{f}_t\right)\right) = 0 \qquad (4.6)$$

This procedure ensures that the standard errors are heteroskedasticity and auto-correlation consistent. MacKinlay and Richardson (1991) formally advocate use of this method.

According to Cochrane (2001), a non-zero asset pricing error of a single asset does not lead to a rejection of the asset pricing model. However, a good model will yield asset pricing errors that are *on average* small. In fact, the time-series test validates a candidate asset pricing model if the estimated intercepts are jointly zero. Gibbons, Ross and Shanken (1989) develop a statistical test (henceforth, the GRS test) for simultaneous significance of a group of intercepts. It assumes that errors are uncorrelated over time, and homoskedastic. Their GRS-statistic follows an F-distribution, and is given by:

$$\frac{T-N-K}{N}\left[1+E_T(\mathbf{f}_t)'\hat{\Omega}^{-1}E_T(\mathbf{f}_t)\right]^{-1}\hat{\mathbf{a}}'\hat{\Sigma}^{-1}\hat{\mathbf{a}} \sim F_{N,T-N-1} \qquad (4.7)$$

the Σ matrix in the formula often needs to estimated with:

$$\hat{\Sigma} = E\left(\mathbf{e}_t\mathbf{e}_t'\right) = \sum_{i=1}^{T}\mathbf{e}_t\mathbf{e}_t'$$

The parameter $\hat{\Omega}$ in the equation is the variance-co-variance matrix of factor deviations:

$$\hat{\Omega} = \frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{f}_t - E_T \;\; \mathbf{f}_t \;\; \right]\left[\mathbf{f}_t - E_T \;\; \mathbf{f}_t \;\; \right]'$$

Trivially:

$$E_T \;\; \mathbf{f}_t \;\; = \sum_{i=1}^{T}\mathbf{f}_t$$

The GMM estimation of the SURE system is performed with the EViews statistical package. The calculation of the components of the GRS statistic is done in an Excel worksheet, except the matrix, Σ, which is calculated from a GMM system by EViews.

Cross-Sectional Tests

The two-pass cross-sectional tests can be conducted with the cross-sectional regression shown in Chapter 12 of Cochrane (2001) (henceforth, the CCSR regression) or the Fama-MacBeth regressions. Cochrane (2001) proves that the Fama-Macbeth and the CCSR regressions produce identical estimates of the factor premia, if, as is done in this thesis, the betas are estimated with all the available time-series data points. However, the two procedures do differ in two important aspects. First, unlike the Fama-MacBeth tests, the CCSR method is easily modified for GLS estimation, which is ideal, statistically speaking. Second, the standard errors computed with the Fama-MacBeth procedure are not misstated if a large cross-section of test assets is used.

The long estimation period makes sense in light of the findings of Fama and French (1997) that most loadings are mean-reverting and full-period estimates and when compared to ones obtained with rolling regressions, yield very similar estimates of expected returns. In other words, the gain in precision from the longer estimation period is offset by the loss in precision due to ignoring of time-variability of betas - especially, given that betas change less frequently in portfolios (Cochrane, 2001). All the dependant variables are summations of the loadings computed with the contemporaneous factor return and its lag[76].

Formally, the cross-sectional regressions in the CCSR method are:

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[76] An alternative would involve the use of rolling betas with a Fama-MacBeth test and, possibly, individual securities as test assets. However, the rolling procedure would decrease the amount of sample periods usable in the study. Since, as Bradifield? (2003) points out, it is usually suggested to estimate betas over a five-year period, the data series of betas would start only five years after December 1989. In addition, test statistics that test asset pricing models become much more complicated when applied to the Fama-MacBeth procedure.

$$E\ \mathbf{r}_t\ = \mathbf{b}'\hat{\mathbf{l}} + \mathbf{a} \tag{4.8}$$

The dependant variable is the time-series average excess return of asset *i*, and independent variables are the factor betas. The loading vector is:

$$\mathbf{b} = \begin{bmatrix} \iota_N & \mathbf{b}^{Market} & \mathbf{b}^{Resource} & \mathbf{b}^{Findi} & \mathbf{b}^{SML} & \mathbf{b}^{VMG} \end{bmatrix}' \mathbf{D}$$

The estimated coefficients are the premia:

$$\hat{\mathbf{l}} = \begin{bmatrix} \hat{\gamma}_0 & \hat{\lambda}^{Market} & \hat{\lambda}^{Resource} & \hat{\lambda}^{Findi} & \hat{\lambda}^{SML} & \hat{\lambda}^{VMG} \end{bmatrix}' \mathbf{D}$$

can be estimated with the OLS, or GLS, method. The OLS premia are calculated by:

$$\hat{\mathbf{l}} = \ \mathbf{b}\mathbf{b}'\ ^{-1} \mathbf{b}E\ \mathbf{r}_t$$

The vector, **a,** contains N pricing errors of the asset pricing model that is mapped into **D**, a diagonal matrix of indicator variables.

The *t*-statistics associated with the premia in the OLS CCSR tests are obtained with the cross-sectional regression being mapped into a GMM system. Cochrane (2001) shows that a GMM regression of:

$$g_T\ \hat{\mathbf{b}}, \hat{\mathbf{k}}, \hat{\mathbf{l}}\ = \begin{bmatrix} I_N & 0 \\ 0 & \hat{\mathbf{b}} \end{bmatrix} \begin{bmatrix} E_T\ \mathbf{f}_t \otimes\ \mathbf{r}_t^e - \hat{\mathbf{k}} - \hat{\mathbf{b}}'\mathbf{f}_t \\ E_T\ \mathbf{r}_t - \hat{\mathbf{b}}'\hat{\mathbf{l}} \end{bmatrix} = 0 \tag{4.9}$$

yields identical estimates of the factor premia, as does the CCSR method[77]. The standard errors estimated in GMM are corrected for heteroskedasticity, cross-sectional dependence, auto-correlation, cross-correlation of cross-sectional residuals with time-series residuals and cross-correlation of residuals and the factors. In addition, the correction proposed by Shanken (1992) for the bias in the *t*-statistics that arises from the error-in-variables problem is also taken into account. At times, for comparative purposes, the unadjusted OLS standard errors are also shown.

Following Cochrane (2001) and Kandel and Stambaugh (1995), nearly all the asset pricing tests are also conducted with a GLS cross-sectional regression. In those cases, the risk premia vector is:

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[77] To see this, note that the second set of moments in Equation 4.9 is:

$$\mathbf{b}.E_T\ \ \mathbf{r}_t - \mathbf{b}'\mathbf{l}\ \ = 0$$

$$\mathbf{b}.E_T\ \ \mathbf{r}_t\ - \mathbf{b}.E_T\ \ \mathbf{b}'\ \ E_T\ \ \mathbf{l}\ \ = 0$$

$$\mathbf{b}.\mathbf{b}'\ ^{-1}\ \mathbf{b}.E_T\ \ \mathbf{r}_t\ \ = E_T\ \ \mathbf{l}$$

which is the formula for the risk premia in a cross-sectional regression.

$$\hat{\mathbf{l}} = \left(\mathbf{b}\Sigma^{-1}\mathbf{b}'\right)^{-1}\mathbf{b}\Sigma^{-1}E\left(\mathbf{r}_t\right)$$

and the variance-co-variance matrix of residuals:

$$\sigma^2\left(\mathbf{l}\right) = \frac{1}{T}\left(\left(\mathbf{b}\Sigma^{-1}\mathbf{b}'\right)^{-1}\left(1+\mathbf{l}'\Sigma_f^{-1}\mathbf{l}\right) + \Sigma_f\right)$$

The variance-co-variance matrix of the factors, Σ_f, is:

$$\hat{\Sigma}_f = E\left(\mathbf{f}_t\mathbf{f}_t'\right) = \sum_{i=1}^{T}\mathbf{f}_t\mathbf{f}_t'$$

These standard errors are not as efficient as the GMM estimates, but the correction for the cross-sectional dependence and the Shanken (1992) correction for the error-in-variables problem are incorporated into the formula.

In each cross-sectional regression that uses the CCSR method, a formal test of the pricing model is conducted. Cochrane (2001) derives the correct statistical test, which ascertains the cumulative size of the model's pricing errors. The general formula for the test statistic is:

$$\hat{\mathbf{a}}'Cov(\hat{\mathbf{a}})^{-1}\hat{\mathbf{a}} \sim \chi^2_{N-K} \qquad (4.10)$$

In order to make the formulas for the variance-co-variance matrix palatable, it is necessary to make an assumption that the time-series residuals of each asset are homoskedastic, as well as not serially correlated time and independent of the asset pricing factors. If these assumptions hold, Cochrane (2001) shows that the second moment matrix use in Equation (4.10) in OLS tests is:

$$Cov(\hat{\mathbf{a}}) = \frac{1}{T}\left(I_N - \mathbf{b}'(\mathbf{b}\mathbf{b}')^{-1}\mathbf{b}\right)\Sigma\left(I_N - \mathbf{b}'(\mathbf{b}\mathbf{b}')^{-1}\mathbf{b}\right)' \qquad (4.11)$$

the matrix in the GLS setting becomes:

$$Cov(\hat{\mathbf{a}}) = \frac{1}{T}\left(\Sigma - \mathbf{b}'\left(\mathbf{b}\Sigma^{-1}\mathbf{b}\right)^{-1}\mathbf{b}\right)\left(1+\mathbf{l}'\Sigma_f^{-1}\mathbf{l}\right) \qquad (4.12)$$

The last term in the expression above corrects for the fact that the loadings are estimated.

In pricing tests where the cross-section of assets is large relative to the sample period, the Fama-MacBeth regressions are employed. The regressions are:

$$\mathbf{r}_{t+1} = \mathbf{b}_t'\hat{\mathbf{l}}_t + \mathbf{a}_t \qquad (4.13)$$

The loading vector is:

$$\mathbf{b} = \left[\iota_N \quad \mathbf{b}_t^{Market} \quad \mathbf{b}_t^{Resource} \quad \mathbf{b}_t^{Findi} \quad \mathbf{b}_t^{SML} \quad \mathbf{b}_t^{VMG}\right]'\mathbf{D}$$

The estimated coefficients are the premia:

$$\hat{\mathbf{l}}_t = \left[\hat{\gamma}_{0,t} \quad \hat{\lambda}_t^{Market} \quad \hat{\lambda}_t^{Resource} \quad \hat{\lambda}_t^{Findi} \quad \hat{\lambda}_t^{SML} \quad \hat{\lambda}_t^{VMG} \right]' \mathbf{D}$$

The vector of coefficients in the Fama-MacBeth regressions are:

$$\hat{\mathbf{l}} = E_T \left(\hat{\mathbf{l}}_t \right) = \frac{1}{T} \sum_{t=1}^{T} \hat{\mathbf{l}}_t$$

The standard errors of the estimated coefficients are adjusted for serial correlations with the Newey and West (1987) method, with a correction of up to four leads and lags. Meaning that:

$$\sigma^2(\hat{\lambda}_i) = \frac{1}{T} \sum_{l=-4}^{4} \mathrm{cov}_T \left(\hat{\lambda}_{i,t}, \hat{\lambda}_{i,t-l} \right) = \frac{1}{T^2} \sum_{l=-4}^{4} \sum_{t=1}^{T} \left(\hat{\lambda}_{i,t} - E_T \left(\hat{\lambda}_{i,t} \right) \right) \left(\hat{\lambda}_{i,t-l} - E_{T-l} \left(\hat{\lambda}_{i,t-l} \right) \right)$$

The standard errors computed in this form are not as robust as the GMM estimates but do correct for the cross-sectional dependence across assets.

In Fama-MacBeth tests, models are not formally tested because it is deemed that the second-moment matrix cannot be precisely estimated[78].

In all the cross-sectional regressions, calculation and the adjustment of the coefficient of determination follows Jagannathan and Wang (1996) and Gujarati (2002); respectively:

$$R^2 = \frac{Var\left(E_T \left(r_{i,t} \right) \right) - Var\left(E_T \left(\alpha_i \right) \right)}{Var\left(E_T \left(r_{i,t} \right) \right)} \qquad (4.14)$$

and:

$$adj - R^2 = 1 - \left(1 - R^2 \right) \left(\frac{n-1}{n-k} \right) \qquad (4.15)$$

Unlike “textbook” definitions of the coefficient of determination, it can be negative for very poorly fitted models.

The asset pricing tests are performed with an array of statistical software. The cross-sectional regressions, both OLS and GLS, with the CCSR method are computed manually in Excel. However, the second-moment matrix of time-series residuals is taken from GMM estimation with EViews. At times, Stata can be used to check for computational errors. Fama-MacBeth regressions are estimated with a sub-routine programmed into Stata, which is also used to compute the Newey-West (1987) adjusted standard errors. All the test statistics for formal tests of the asset pricing

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[78] In preliminary tests, the computed Student’s *t* and the χ^2 statistics were of implausible magnitudes.

models are calculated with Excel. The coefficients of determination are calculated with either Excel or Stata. Function and sub-routines programmed with Visual Basic for Applications support all Excel calculations.

4.3.3 Tests of the Models against Characteristics

Cochrane (2001), among *many* others, notes that a correctly specified asset pricing model needs to explain all predictable variations in asset returns. Hence, the unexpected part of asset returns (pricing error) should not be predicable with stock characteristics such as size or the BE/ME ratio. Alternatively, in the presence of irrationality in the market, the ability of stock characteristics to explain asset prices should still occur. In order to augment the evaluation of an asset pricing model an additional test is required that will pair the predictive power of the model against the asset's characteristics.

Brennan *et al.* (1998) and van Rensburg and Robertson (2003a) advocate the following approach for testing the importance of characteristics. Cochrane (2001) justifies the methodology within the GMM framework and shows that an OLS cross-sectional regression of pricing errors on characteristics is equivalent to a GMM/SDF estimation that includes characteristics as explanatory variables[79].

Given that:

$$\underline{r}_i^e = \underline{\alpha}_i + \mathbf{f}\hat{\mathbf{b}}_i' + \underline{\varepsilon}_i \quad \text{for i = 1, 2, 3… N} \tag{4.17}$$

each period's pricing error of asset *i* is:

$$\underline{\alpha}_i + \varepsilon_{ti} = r_{ti} - \sum_{j=1}^{K} b_{ij} f_{tj}$$

Time-series regressions include a lag on the market (or Resource and Findi) factors, which, according to Dimson (1979) and Ibbotson, Kaplan and Peterson (1997), corrects for thin trading. However, this correction is not applicable to all firms in the sample, as not all firms suffer from the problem of thin trading. Inclusion of unnecessary factor lags in regressions will affect the time-series of estimates of pricing errors (α_i + $\underline{\varepsilon}_i$); thus the lags of factors are not included in the top 20 percent of largest firms. Also, there is an additional lag (for the total of two) included in the

[79] This is true only if the specification takes the form of a stochastic discount factor model.

estimation of residuals for the smallest 20 percent of firms. The leading term is not added as, in the preliminary tests, it was rarely (if ever) significant and sometimes quite large. Hence, its inclusion would result in significantly biased errors.

Fama-MacBeth regressions are run on the pricing errors of each candidate asset pricing model with asset characteristics as independent variables. Inclusion of individual assets into the Fama-MacBeth tests will be subject to standard restrictions on price and liquidity.

Formally, regressions:

$$\mathbf{a} + \mathbf{e}_{t+1} = \mathbf{c}_t' \, \hat{\mathbf{q}}_t + \mathbf{a}_t \tag{4.18}$$

are run. The vector of repressors is:

$$\mathbf{c}_t = \begin{bmatrix} \iota_N & \mathbf{c}^{Size} & \mathbf{c}^{E/P} & \mathbf{c}^{C/P} & \mathbf{c}^{BE/ME} & \mathbf{d}^{E/P} & \mathbf{d}^{C/P} \end{bmatrix}' \mathbf{D}$$

and consequently the premia vector is:

$$\hat{\mathbf{q}}_t = \begin{bmatrix} \hat{\gamma}_{0,t} & \hat{\theta}_t^{Size} & \hat{\theta}_t^{E/P} & \hat{\theta}_t^{C/P} & \hat{\theta}_t^{BE/ME} & \hat{\theta}_t^{D(E/P)} & \hat{\theta}_t^{D(C/P)} \end{bmatrix} \mathbf{D}$$

Brennan *et al.* (1998) warn that if the error in the factor loadings is correlated with the characteristics, the Fama-MacBeth estimates of characteristic premia may be biased. If such dependence exists, Brennan *et al*. (1998) note that the time-series of estimated premia is correlated with the factors of the asset pricing model that is used to adjust for risk; and, the coefficient estimate is biased by a proposition of the mean of the factor. The bias is particularly important for the JSE, as it is plausible that for small firms, the estimated loading is biased thanks to illiquidity.

Consequently, Brennan *et al.* (1998) propose the estimator that corrects for the mis-measurement. They estimate a premium to characteristic *j*, q_j, as:

$$\underline{\hat{\theta}}_j = \hat{q}_j + \mathbf{f}\hat{\mathbf{k}}_j' + \underline{u}_j \tag{4.19}$$

In effect, the Equation (4.19) is a time-series regression of factors of a given model onto the time-series of the characteristic premia computed in each cross-sectional regression in the Fama-MacBeth procedure. The unbiased premium to the characteristic is the intercept term of regression above. Trivially, $\mathbf{k}_j$ is a vector of estimators and $\underline{u}_j$ is a series of disturbance terms.

The *t*-statistic associated with the intercept is used for inference, but the variance-co-variance matrix of the coefficients computed in regressions of the genus shown above are estimated with the Newey and West (1987) method. Thus, the effects of serial correlation of up to four lags are removed.

On a technical note, all of the tests of pricing models against the characteristic models are done in Stata. The capacity of the program to easily handle panel datasets made it particularly easy to estimate the pricing errors in time-series regressions and compute the characteristics premia in a cross-sectional analysis. Stata's regressions can also easily handle Newey-West (1987) corrections.

CHAPTER 5: THE EMPIRICAL ANALYSIS

5.1 Part I: The Size and the Value Effects on the JSE, Magnitude and Persistence

The purpose of this section is to formally analyse the size and value premia on the JSE. More specifically, it is necessary to establish that these effects survive (admittedly imperfect) adjustment for trading costs. In addition, in order to construct the three factor model of Fama and French (1993), it is necessary to identify the appropriate F/P ratio that has the strongest power to predict future returns. Lastly, a set of test assets, which forms the basis of subsequent asset pricing tests, needs to be ascertained.

A correlation matrix of stock characteristics is shown in Table 5.1. Most strikingly, the correlation between a firm's size and its price is very high at 0.8017. It is re-emphasised that Bhardwaj and Brooks (1992) found a strong negative relation between trading costs and share price. Consequently, it is likely that the apparent high returns earned from investing in small stocks do not survive trading costs. Another important feature of the data is a very high correlation between the E/P and the C/P. Also, the BE/ME is strongly related to these yields. The magnitude of these relationships is to be expected, as all these variables proxies are either proxies for risk or misevaluation. However, it must be noted that the correlation is less than perfect; therefore it is likely that more than one variable is necessary to account for the value effect[80].

Predictably there is a negative relationship between the F/P ratios and the absolute measure of market value. The correlations are not large, however, and only BE/ME seems to exhibit a relatively strong relationship with size and price.

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[80] There is an unexpectedly low correlation between size and trading volume (liquidity). It is likely that the relationship between size and liquidly is non-linear. More specifically, it is believed that all but few large firms are "liquid" and the rest of the listed firms suffer from non-synchronous trading. Since correlation is a measure of a linear relationship, the strength of the relationship can be mismeasured. Actually, Brennan and Subrahmanyam (1996) show that the relationship between illiquidity measures and returns is non-linear, thus it may also be non-linear with variables that predict returns. Nonetheless, it is beyond the scope of this thesis to parameterize the relationship between a firm's market capitalisation and its trading volume; thus this point is left unexplored.

Table 5.1
Characteristic Correlation Matrix

Correlations pool time-series and cross-sectional observations between July 92 and July 05, for the total of 76643 month-firm points. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. E/P is earnings per share scaled by a price. C/P is cash flow per share scaled by a price. BE/ME is the book value of equity scaled by market capitalization. Liquidity measure is a twelve-month average of monthly trading volume scaled by shares in issue. Price variable is the actual price, and thus is unadjusted for share splits and consolidations. All accounting data becomes effective five months after the financial year-end. Negative values of the F/P are replaced with a zero. All variables are standardized and winzorised at 2.5% and 97.5%.

	Size	E/P	C/P	BE/ME	Price	Liquidity
Size	10000	-0.2905	-0.2952	-0.4580	0.8017	0.2202
E/P	-0.2905	1.0000	0.7650	0.5728	-0.2516	-0.0100
C/P	-0.2952	0.7650	1.0000	0.5980	-0.2433	-0.0337
BE/ME	-0.4580	0.5728	0.5980	1.0000	-0.3962	-0.0998
Price	0.8017	-0.2516	-0.2433	-0.3962	1.0000	0.1397
Liquidity	0.2202	-0.0100	-0.0337	-0.0998	0.1397	1.0000

Thus, any tests that use the BE/ME as sorting or explanatory variables need to account for its possible co-linearity with size. In addition, the correlations in Table 5.1 are similar to findings in the international literature. For example, Brennan *et al.* (1998) show that the correlation of size with the BE/ME is -0.24, and with price is -0.79 [81].

Figures in Table 5.1 differ from similar tables in van Rensburg and Robertson (2003a) and Auret and Sinclaire (2006). These researchers find the magnitude of correlations to be significantly lower. For example, in the table in their appendix B, van Rensburg and Robertson (2003a) show that the correlation between C/P and P/E is -.12. However, in unreported results, it appears that the correlation between the cashflow yield and the P/E ratios (an inverse of the earnings yield) collected for this dissertation is about -0.03. In other words, correlations of F/P ratios with other inverted F/P ratios are meaningless. Consequently, it is stressed that when measuring correlations between F/P ratios, the accounting measures of value must be consistently kept in the denominator or the numerator of the ratio, otherwise, this linear measure of relation leads to erroneous inference[82].

[81] Brennan *et al.* (1998) define their price variable as a logarithm of the inverse of the actual price.

[82] Also, unreported analysis shows that if Table 5.1 was to be constructed with inverted F/P ratios then magnitudes of correlations would be lower. This is to be expected because the inverted F/P ratios exhibit larger variation. These ratios are larger in magnitude (say, 10 vs. 0.1) and changes in price result in larger absolute changes (10 to 20 vs. 0.1 to 0.05).

5.1.1 Univariate Results

Shares are sorted into five portfolios. In order to control for market microstructure effects, during re-balancing stocks must conform to certain requirements on price and liquidity in order to be included the portfolio. A size premium is the mean return of an arbitrage portfolio that comprises a long position in a portfolio of smallest stocks and a short position in a portfolio of largest stocks. In order to determine the effect of the two restrictions on price and liquidity, the sort is repeated 15 times with different sets of restrictions being imposed each time. A similar procedure is repeated during calculation of the value effect. In this case, however, the premium is calculated with a mean return of an arbitrage portfolio that comprises a long position in a portfolio of high F/P stocks and a short position in a portfolio of low F/P stocks. Subsequently, the premiums are calculated 16 times for the three value-growth indicators. All means are computed with monthly returns.

The restrictions are chosen to exclude a sufficiently high number of marginal stocks. Imposing the 0.5% restriction on liquidity reduces the average number of stocks in the portfolios from 488 to 310. Similarly, excluding shares priced below 200 cents lowers the average number of stocks in the portfolios to 300. Imposing both of the harshest price and liquidity restrictions lowers the number of usable stocks to an average of 190.

The results of the univariate sorts appear in Table 5.2, and the existence of the size and value premia are confirmed. Generally, the value-weighted estimates are smaller than equally-weighted estimates. In addition, the restrictions on liquidity and price have a profound impact on the magnitude and persistence of the effects, especially the size premium. Also, restrictions on price have a much stronger impact than restriction on liquidity.

As per Panel A of the table, generally, the size premium is positive. The equal-weighted estimate of the effect varies between 0.82% per month to 1.48% per month[83]. The *t*-statistics for the means of the different estimates are always above two, and most of the time the effect is greater than zero at the 1% level.

[83] All cases where the restriction on price is not applied are excluded from the calculation.

Table 5.2

Size and Value Effects on the JSE and Sensitivity of the Effects to Price and Liquidity Restrictions. (Fixed, Cheated)

The table displays the magnitudes of the different effects between July 1992 and July 2005. Also, the impact of restricting the population of firms used to measure the effects with liquidity and price is shown. Size effect is the mean difference in the returns of a portfolio containing stocks in the largest quintile and a portfolio of stocks in the smallest quintile. Value effect is the mean difference in the returns of portfolio containing fifth of stocks highest F/P ratios and return on portfolio containing fifth of stocks lowest F/P ratios. All returns are adjusted for dividends and other payouts. Portfolios are rebalanced annually; at the end of June. The portfolio returns are computed after adjustment for outliers. Liquidity measure is a twelve-month average of monthly trading volume scaled by shares in issue. Price variable is the actual price, and thus is unadjusted for share splits and consolidations. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. E/P is earnings per share scaled by a price. C/P is cash flow per share scaled by a price. BE/ME is the book value of equity scaled by market capitalization. All accounting data becomes effective five months after the financial year-end.

Minimum Liquidity	Minimum Price				Minimum Price			
	0	50	100	200	0	50	100	200
Panel A: The Size Effect and its Sensitivity to Price and Liquidity Restrictions								
	Equal-Weighted				Value-Weighted			
0.00%	3.96%***	1.40%***	1.48%***	0.82%**	0.11%	0.70%	0.77%*	0.78%*
	6.923	3.200	3.449	2.039	0.206	1.486	1.708	1.670
0.02%	3.88%***	1.38%***	1.10%**	0.96%**	0.11%	0.79%*	0.78%*	0.94%**
	6.483	3.173	2.618	2.397	0.197	1.669	1.699	2.013
0.10%	3.50%***	1.39%***	1.08%**	1.05%***	0.00%	0.83%*	0.71%	0.91%**
	6.477	3.291	2.575	2.697	0.004	1.768	1.555	1.965
0.50%	2.79%***	1.24%***	1.20%***	1.07%***	0.17%	0.80%	0.99%**	0.87%*
	5.642	2.788	2.759	2.782	0.313	1.585	2.035	1.855
Panel B: The BE/ME Effect and its Sensitivity to Price and Liquidity Restrictions								
	Equal-Weighted				Value-Weighted			
0.00%	2.81%***	1.77%***	1.71%***	1.51%***	1.10%**	1.57%***	1.50%***	1.48%***
	5.666	4.683	4.393	3.808	1.981	2.824	2.613	2.596
0.02%	2.86%***	1.71%***	1.65%***	1.48%***	1.02%*	1.52%***	1.45%***	1.46%***
	5.804	4.536	4.230	3.650	1.855	2.781	2.544	2.555
0.10%	2.54%***	1.65%***	1.69%***	1.36%***	1.09%**	1.58%***	1.62%***	1.45%***
	5.352	4.227	4.213	3.328	1.982	2.842	2.864	2.403
0.50%	2.43%***	1.71%***	1.83%***	1.36%***	1.06%*	1.56%**	1.61%***	1.32%***
	5.105	3.917	4.072	3.028	1.672	2.433	2.577	2.352

Table 5.2 (continued)

Panel C: The C/P Effect and its Sensitivity to Price and Liquidity Restrictions								
	Equal-Weighted				Value-Weighted			
0.00%	1.58%***	1.30%***	1.25%***	1.31%***	1.00%*	0.97%*	0.87%*	0.95%*
	4.132	3.729	3.569	3.535	1.750	1.862	1.712	1.838
0.02%	1.83%***	1.37%***	1.15%***	1.29%***	1.03%*	0.91%*	0.84%	0.91%*
	4.685	3.855	3.244	3.459	1.797	1.728	1.624	1.745
0.10%	1.55%***	1.20%***	1.18%***	1.22%***	1.16%**	0.97%*	0.94%*	0.89%*
	3.959	3.277	3.188	3.085	2.055	1.851	1.819	1.669
0.50%	1.45%***	1.20%***	1.11%***	1.27%***	1.26%**	0.95%*	0.82%	0.88%*
	3.335	2.896	2.838	3.020	2.165	1.772	1.524	1.658

Panel D: The E/P Effect and its Sensitivity to Price and Liquidity Restrictions								
	Equal-Weighted				Value-Weighted			
0.00%	1.41%***	1.00%***	0.83%**	0.80%**	0.93%	0.85%	0.78%	0.80%
	3.442	2.764	2.273	2.166	1.157	1.355	1.252	1.318
0.02%	1.51%***	1.02%***	0.85%**	0.82%**	0.94%	0.86%	0.83%	0.80%
	3.646	2.800	2.338	2.220	1.412	1.374	1.336	1.312
0.10%	1.27%***	0.90%**	0.82%**	0.72%*	0.94%	0.86%	0.87%	0.80%
	3.146	2.431	2.181	1.864	1.408	1.345	1.381	1.292
0.50%	1.17%***	0.92%**	0.77%**	0.93%**	1.37%**	1.19%*	1.12%*	1.00%
	2.685	2.371	1.986	2.229	2.005	1.821	1.728	1.569

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

If it is assumed that shares that trade for more than 100 cents and exhibit liquidity greater than 0.1% per month (henceforth, 100; 0.01%) are within an investment set of a representative agent, the estimate of the equal-weighted size effect is approximately 1.1% per month. The value-weighting estimates are much lower and less significant, in both economic and statistical terms. Only nine of the estimates are reliably greater than zero. The value-weighted premium varies between 0.7% and 0.99% per month[84]. An estimate of the value-weighted size premium that can be captured by a representative investor (100; 0.01%) is about 0.71% per month and it is not reliably greater then zero.

If the price restriction is not enforced, the computed premia exhibit some peculiar properties. On the one hand, the equal-weighted estimates are exceedingly large, while the value-weighted results are barely different from zero. A likely explanation is that, when no price restriction is made, the sort takes into account a number of very tiny shares. By virtue of liquidly risk premium, these firms ought to yield very high returns and the equal-weighted sort captures them. However, when a value-weighted sort is performed, the returns on these tiny shares are swamped by the return of a few large firms that made their way into the portfolio of smallest shares. Actually, in unreported results, the value-weighted size effect is much larger if the portfolio containing slightly larger firms (than the smallest) is used to compute the premium. Nonetheless, it is safe to say that not imposing price restrictions in the analysis of the size effect may severely bias the results.

Nonetheless, the profitability of the size premium is robust to an explicit adjustment for trading costs, as its magnitude, computed under the most restrictive constraints, is relatively large. Actually, on the value-weighted basis, the premium is *strongest* if the harshest price restriction is applied. Also, these premia are less risky than the effects computed with more lax constraints. Actually, the standard deviation of the equally-weighted premium computed with the harshest restrictions is lower than others. A similar result is obtained with value-weighted portfolios. Consequently, it seems the profitability of the premium can be captured at a relatively low risk.

The results here are similar to those documented in international estimates. For instance, Asness *et al.* (2000a), who use US data, find the size premium to be 0.95% per month and 0.51% per month on the equally-weighted and value-weighted basis,

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[84] All cases where the restriction on price is not applied are excluded from the calculation.

respectively. The estimate of the size premium from the emerging markets, calculated by Rouwenhorst (1999), is 0.69% per month. Also, the results are not markedly different from results obtained by van Rensburg and Robertson (2003b). A typical equally-weighted premium that enforces relatively stringent restrictions on liquidity is around 3% per month. The author's estimate 2.5% per month[85].

Panels B though to D of Table 5.2 show the value effect. The three types of value-growth indicators are individually investigated. Measuring the value anomaly with different attributes alters their magnitude and statistical persistence. The magnitude of the equally-weighted book-to-market premia varies between 1.83% and 1.36% per month[86]. All of the estimates are different from zero at 1% level of significance. Curiously, the highest estimate corresponds to strict restrictions on price and the highest restriction on liquidity. The equally-weighted cashflow effect is smaller: it varies 1.27% and 1.11% per month, but it reliably differs from zero at the 1% level. The corresponding range for the earnings' yield effect falls between 0.93% and 0.77% per month and is greater than zero at the 5% level.

The value-weighted estimate of the book-to-market effect varies between 1.61% and 1.32% per month, while the corresponding ranges for the C/P and the E/P effects are 0.82% and 0.88% per month and 1.12% and 1.00% per month, respectively. The premia computed without restrictions on price are excluded from the analysis. The statistical persistence of the value-weighted book-to-market effect is large, as only one of the 12 estimates is not different from zero at the 1% level, but at the 5% level. The estimates of the value-weighted C/P effect are significant only at the 10% level, while the value-weighted E/P effect is hardly significant, and only two of the estimates are reliably different from zero at the 10% level.

The price and the liquidity sections have the largest impact on the effect measured with the BE/ME. Inclusion of the 50 cents restriction in the sort has a similar effect on the premia as it did in the size effect: the equal-weighted estimates are slashed, while the value-weighted premia are boosted. Nonetheless, the estimates of the BE/ME effect and the E/P effect attenuate as the sequential restrictions are applied. Curiously, the C/P effect is of a similar magnitude across the price and

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[85] In fact, when an attempt to replicate the analysis in van Rensburg and Robertson (2003b) is made, the results are near-identical to theirs.
[86] The estimates computed after excision of the premia that calculated without imposing restriction on price and liquidity.

liquidity restriction spectrum and it seems to increase marginally in the case where the harshest price restriction is imposed.

The magnitude of the value effect presented in Table 5.2 is slightly larger than what is documented in international studies. For instance, with US data, Asness *et al.* (2000a) find that equally-weighted book-to-market effect is approximately 1.11%, while on the value-weighted basis it is 0.44% - much smaller than the estimate presented here. Lakonishok *et al.* (1994) present similar results. They, however, document that the C/P effect is marginally larger than the BE/ME effect. Asness *et al.* (2000a) and Hogan *et al.* (2004) find the opposite, and they note that the C/P strategy was particularly unprofitable in the 1990s. In addition, Hogan *et al.* (2004) find, with the US data, that the E/P effect is puny. Lastly, the average of the equal-weighted value premia, calculated in the emerging markets and reported in Rouwenhorst (1999), is about 0.72% per month. Surprisingly, the results presented here are at odds with the findings of van Rensburg and Robertson (2003b), who, with a univariate sort, document an earnings yield premium of 3.3% per annum. There are a number of methodological differences that can account for the disparity: they re-balance their portfolios monthly [87], survival bias is present in their study[88], and the sample periods are different [89]. Nonetheless, it is not the purpose of this thesis to explain any disparities in results between the two studies - thus this puzzle is left unresolved.

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[87] This procedure may bias the results because it confounds the value premium with the short-term reversal of Jegadeesh (1990). In an unreported univariate random effects regression of returns on its lead, the coefficient is negative and eight standard deviations from zero, meaning that there is a negative auto-correlation between returns on a monthly interval. Thus, it is likely that van Rensburg and Robertson (2003b) capture this effect with their monthly re-balancing, as they include many stocks that fell sharply in price into a portfolio containing firms with high F/P ratios.

[88] van Rensburg and Robertson (2003b) obtain accounting data from the BFA/McGregor database. After a conversation with Professor Brummer, the academic director of the data-house, the author of this thesis has learned that the accounting data for firms that delisted prior to 1998 are not available in the database. Actually, Banz and Breen (1986) argue that such a sample selection has a profound impact on the value premium that is measured with the price-to-earnings ratio. It should be noted that even if there is no survival bias in the sample, the cross-section of returns used in this study is different to the one employed by van Rensburg and Robertson (2003b) and thus the results may not be the same.

[89] Their sample period starts in July 1990 and ends in July 2000, whereas the one sample period in this study begins in July 1992 and ends in July 2005.

5.1.2 Multivariate Results (Fama-MacBeth)

It has been shown that the book-to-market ratio is a better predictor of returns than earnings yield and cashflow yield. There are two caveats, however. First, the one-way sorts in Table 5.2 exclude negative F/P ratios. There are few negative book-to-market ratios, thus most available stocks are included in the sorts that use the BE/ME ratio. At the same time, there is an abundance of observations of negative E/P and C/P ratios. Consequently, if the omitted firms yield high returns, and in an unreported analysis it is found that they do, then value premium calculated with the BE/ME ratio is higher because, in its computation value, firms with high returns are omitted from the sort. Secondly, the large magnitude of the BE/ME premium may be a consequence of confounding this anomaly with the size effect, as book-to-market has a higher correlation with firm size than other F/P ratios.

In order to alleviate the above-mentioned concerns, a multivariate analysis is performed with the Fama-MacBeth procedure. This test allows for negative F/P ratios and joint analysis of many variables. The results of the regressions are shown in Table 5.3. Stocks that cost less than 100 cents and have an average twelve-month turnover of less than 0.1% are excluded from the analysis.

The first four lines confirm the results from the previous sections. Regressions show that there is a negative relationship between size and return. The coefficient is negative and it is more than three standard deviations away from zero. On their own, the BE/ME and the C/P ratios can predict returns. Although both coefficients are reliably larger than zero, the BE/ME effect is stronger. Curiously, the relation between E/P ratio and returns is weak. The estimated coefficient is small in magnitude and is only marginally more than one standard deviation away from zero. In sum, the results from the portfolio sorts are confirmed with a cross-sectional test.

The next three regressions (from four to seven) show the joint power of the size variable and a value-growth indicator in predicting returns. In general, the significance, in both statistical and economic terms, of all the indicators, abates. The coefficient on the size variable remains significant at least at the 5% level, regardless of the value-growth indicator used in the regressions. There are two points worth noting. First, the E/P effect disappears completely after size is included as an explanatory variable.

Table 5.3
A Fama-MacBeth Regression Test of the Size and Value Effects

Coefficients in the table are time-series averages of month-by-month cross-sectional OLS regressions of returns on firm characteristics between July 1992 and July 2005. Each month, only stocks with liquidity measure of more than 0.1% or cost more than 100c are included in the regression. Liquidity measure is a twelve-month average of monthly trading volume scaled by end-month shares in issue. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. E/P is earnings per share scaled by a price. C/P is cash flow per share scaled by a price. BE/ME is the book value of equity scaled by market capitalization. All accounting data becomes effective five months after the financial year-end. All variables are standardized and winzorised at 2.5% and 97.5%. If earnings are positive then E/P(+) is the earnings yield and E/P Dummy is 0, otherwise E/P(+) is set to zero and E/P Dummy is set to 1. Similar conventions pertain to the C/P ratio. The reported R^2 is the average of individual R^2 of each cross-sectional regressions. Calculation of standard errors follows Cochrane (2001) and are adjusted for serial correlation with Newey-West (1987) method. All coefficients are multiplied by 1000, for clarity.

	Constant	Size	E/P(+)	C/P(+)	BE/ME	E/P Dummy	C/P Dummy	Average R^2
(1)	13.20***	-6.26***						0.02
t-stat	2.54	-3.23						
(2)	10.08**		2.37			7.91**		0.02
t-stat	2.06		1.42			2.04		
(3)	10.89**			3.67***			-3.17	0.01
t-stat	2.30			2.81			-0.77	
(4)	11.76***				5.79***			0.02
t-stat	2.36				3.38			
(5)	12.92***	-5.95***	0.54			4.14		0.03
t-stat	2.47	-3.00	0.33			1.04		
(6)	13.74***	-5.93***		2.30**			-5.77	0.03
t-stat	2.71	-3.14		1.99			-1.46	
(7)	13.39***	-4.80***			3.91**			0.03
t-stat	2.57	-2.41			2.25			
(8)	11.38**		-1.27		6.54***	7.02		0.03
t-stat	2.28		-0.57		2.93	1.83		
(9)	11.93***			0.96	5.08***		-2.49	0.03
t-stat	2.46			0.58	2.37		-0.66	
(10)	10.67**		-1.49	4.71***		10.90***	-7.92	0.03
t-stat	2.23		-0.68	2.82		2.32	-1.63	
(11)	13.73***	-4.87***		0.61	3.53		-4.08	0.04
t-stat	2.70	-2.50		0.39	1.62		-1.10	
(12)	13.61***	-4.87**	-3.90	2.64	4.41*	6.57	-6.72	0.06
t-stat	2.64	-2.48	-1.65	1.41	1.87	1.33	-1.45	

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

This attenuation is strongly at odds with the results presented in van Rensburg and Robertson (2003a), who show that a two-attribute model with size and a P/E is a parsimonious representation of returns on the JSE. Second, the book-to-market ratio remains a strong predictor of returns after inclusion of size. In fact, the coefficients on the market equity and the BE/ME variables are both at least two standard deviations from zero. This is at odds with the results of Auret and Sinclaire (2006), who find that the book-to-market ratio subsumes the size effect on the JSE. This disparity is explained by the fact that the size effect was particularly strong between 2003 and 2005, a time period omitted in their sample. The cashflow yield has a minor role to play after size is included in the regressions; its coefficient is significant only at the 5% level.

Regressions eight to ten seek to uncover the best value-growth indicator for the JSE. The book-to-market ratio seems to subsume the other F/P ratios. Curiously, the coefficient on the E/P ratio becomes negative after inclusion of the BE/ME variable, which coefficient increases marginally. The coefficient on the earnings' yield variable also turns negative when the C/P and the E/P ratio are both jointly tested.

The last two regressions jointly test the variables together. In both cases, in accordance with Auret and Sinclaire (2006), the book-to-market ratio is highly persistent. However, in a joint test of all the value-growth indicators the E/P effect has reversed its sign. This reversal of the E/P effect is not unusual. Actually, it is exactly what Chan *et al.* (1991) find in Japanese data. In addition, Davis (1994) finds similar results in US data in a period prior to 1963. Also, Lyn and Zychowicz (2004), who study the emerging markets in Eastern Europe and use a large sample, also document the reversal of the E/P effect after control for size, market beta, and turnover [90].

The large power of the tests, in comparison with van Rensburg and Robertson (2003a; 2003b) are re-emphasized, as the sample applied here is larger. These authors use about 30,000 firm-month observations, while the tests in Table 5.3 use about 45,000 observations. If the price restrictions are dropped, and the liquidity restrictions are made similar to the van Rensburg and Robertson (2003a) study, then the sample

[90] It is believed that Chan *et al.* (1991) and Lyn and Zychowicz (2004) are similar to the tests in this thesis for two reasons. First, the size of the cross-sectional sample used in those studies is relatively close to the one employed here. Chan et al. (1991) use about four times as many stocks compared to Fama and French (1992), who use about twenty times as many; and samples in Lyn and Zychowicz (2004) and the one employed here are of comparable size. Second, both of those studies are likely to be conducted on less liquid markets, similar to the one used here.

increases to about 61,000 - more than twice as large as their study. The increase in sample size is attributed to a longer sample period and larger amount of firms used in the earlier parts of the 1990s.

Lastly, it is noted that the coefficients of determinations are all very close to zero, reflecting the difficulty in predicting returns. The low R^2s are not unusual, and, for instance, are found in Davis (1994). Also, the intercept is readily greater than zero and, on average, corresponds to about 2% per month. Since the average risk-free rate over the period was approximately 1%, there is much cross-sectional variation that is unexplained by the characteristics.

5.1.3 Multivariate Results (Portfolio Sorts)

In the regressions tests of Fama-MacBeth, the correlation between the variables, especially the size and the BE/ME ratio may bias the estimated coefficients (Gujarati, 2002). In order to combat this problem, a two-way sorting procedure, advocated by Fama and French (1992) and Daniel and Titman (1997), is used to confirm the robustness of the results from the cross-sectional results in Table 5.3.

Because it is believed that a sequential sort of two heavily correlated variables reduces power of the tests, the sorting procedure is independent, as in Fama and French (1993), and not sequential, as in van Rensburg and Robertson (2003b). Only 12 portfolios are formed from an intersection of four size portfolios and three value-growth portfolios, as the excessive correlation between the variables precludes a finer sort. In order to address the concern of Leiedakis and Davidson (2001) that value premium needs to be captured by more than one F/P ratio, an independent two-way sort of the C/P and the BE/ME is performed. Unfortunately, an independent two-way sort based on the C/P and the E/P ratios is impossible as some portfolios turn up empty. The unfortunate side-effect of using independent sorts is that some portfolios contain very few stocks, thus the power of the tests is low when a difference between two portfolios is measured. Luckily, tests that determine independence of each effect are linear combinations of few portfolios and thus, some of the noise may be diversified away, thus increasing the power of the test.

Table 5.4
A Two-Way Portfolio Test of BE/ME and Size Effects

This table aims to disentangle the size and BE/ME effects. The portfolios are constructed with an independent sort of four size portfolios and three F/P portfolios. Portfolios are rebalanced annually; at the end of June. During rebalancing, stocks with liquidity measure of less than 0.01% or cost less than 100c and are not included in the portfolio (the restriction). All returns are adjusted for dividends and other payouts and the portfolio returns are computed after adjustment for outliers. Liquidity measure is a twelve-month average of monthly trading volume scaled by shares in issue. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. BE/ME is the book value of equity scaled by market capitalization. Independent size effect is measured as the average of within-group size effects in each F/P group. Similarly, the independent BE/ME effect is measured as the mean of within-group value effects in each size group. Within-group size effect is measured as a mean difference in returns of portfolios containing smallest stocks and largest stocks, and within-group value effect is measured as a mean difference in returns of portfolios containing low BE/ME stocks and high BE/ME stocks. *T* is the number of months in the measurement period. *N* is the average amount of stocks that satisfy liquidity and price criteria at the end of each June. *Average stocks* is the average amount of stocks in portfolios after a second sort.

	I (Large)	II	III	IV (Small)	IV – I	*t*-stat	
Panel A: Joint BE/ME and Size Sorts: Equal-Weighted							
I (Value)	1.95%	1.83%	2.29%	2.56%	0.61%	0.911	*T*
II	1.76%	1.72%	1.42%	2.32%	0.57%	1.186	156
III (Growth)	1.05%	1.05%	1.45%	1.92%	0.87%*	1.738	*N*
I – III	0.90%*	0.78%*	0.84%**	0.64%			309
t-stat	1.684	1.702	2.041	1.301			*Ave. Stocks*
	Return	*t*-stat			Return	*t*-stat	26
Independent Size effect	0.68%*	1.662	Independent BE/ME effect		0.79%**	2.481	
Panel B: Joint BE/ME and Size Sorts: Value-Weighted							
I (Value)	1.83%	1.58%	2.13%	2.41%	0.59%	0.938	*T*
II	1.67%	1.58%	1.40%	2.33%	0.67%	1.209	156
III (Growth)	1.01%	1.35%	1.35%	2.17%	1.17%**	2.009	*N*
I – III	0.82%	0.23%	0.78%*	0.24%			309
t-stat	1.606	0.546	1.742	0.481			*Ave. Stocks*
	Return	*t*-stat			Return	*t*-stat	26
Independent Size effect	0.81%*	1.800	Independent BE/ME effect		0.52%*	1.696	

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

Table 5.5

A Two-Way Portfolio Test of C/P and Size Effects.

This table aims to disentangle the size and C/P effects. The portfolios are constructed with an independent sort of four size portfolios and three F/P portfolios. Portfolios are rebalanced annually; at the end of June. During rebalancing, stocks with liquidity measure of less than 0.01% or cost less than 100c and are not included in the portfolio (the restriction). All returns are adjusted for dividends and other payouts and the portfolio returns are computed after adjustment for outliers. Liquidity measure is a twelve-month average of monthly trading volume scaled by shares in issue. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. C/P is cash flow per share scaled by a price. Independent size effect is measured as the average of within-group size effects in each F/P group. Similarly, the independent C/P effect is measured as the mean of within-group value effects in each size group. Within-group size effect is measured as a mean difference in returns of portfolios containing smallest stocks and largest stocks, and within-group value effect is measured as a mean difference in returns of portfolios containing low C/P stocks and high C/P stocks. *T* is the number of months in the measurement period. *N* is the average amount of stocks that satisfy liquidity and price criteria at the end of each June. *Average stocks* is the average amount of stocks in portfolios after a second sort.

	I (Large)	II	III	IV (Small)	IV – I	*t*-stat	
Panel A: Joint C/P and Size Sorts: Restricted and Equal-Weighted							
I (Value)	2.02%	2.11%	1.93%	2.64%	0.62%	1.177	*T*
II	1.66%	1.49%	1.97%	2.33%	0.67%	1.376	156
III (Growth)	1.21%	1.34%	1.18%	1.72%	0.52%	1.113	*N*
I – III	0.82%*	0.77%*	0.75%*	0.92%*			309
t-stat	1.930	1.953	1.842	1.894			*Ave. Stocks*
	Return	*t*-stat			Return	*t*-stat	26
Independent Size effect	0.60%*	1.659	Independent C/P effect		0.81%***	2.935	
Panel C: Joint C/P and Size Sorts: Restricted and Value-Weighted							
I (Value)	2.05%	2.05%	1.88%	2.47%	0.42%	0.660	*T*
II	1.60%	1.50%	1.82%	2.36%	0.76%	1.568	156
III (Growth)	1.25%	1.44%	1.23%	1.74%	0.49%	0.823	*N*
I – III	0.81%	0.61%	0.65%	0.73%			309
t-stat	1.618	1.595	1.410	1.271			*Ave. Stocks*
	Return	*t*-stat			Return	*t*-stat	26
Independent Size effect	0.56%	1.290	Independent C/P effect		0.70%**	2.325	

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

According to Table 5.4 and Table 5.5, the size and the value effect are independent of each other. On the equal-weighted basis, the size premia that are independent of the BE/ME and the C/P effects are 0.68% and 0.60% per month, respectively. Both estimates are greater than zero at the 10% level. On a value-weighted basis, the size effect that is independent of the BE/ME effect is larger at 0.81% per month (*t*-statistic of 1.800). The one independent of the C/P effect is lower at 0.56% per month, but it loses its statistical significance.

The independent value premium is persistent. On an equal-value weighted basis, the effect, measured with the BE/ME ratio, is 0.79% per month, and if it is measured with the C/P ratio it is 0.81% per month. Both estimates are significant at the 1% level. If the portfolios are value-weighted, the independent BE/ME effect is substantially lower at 0.52% (*t*-statistic of 1.696). However, the value-weighted independent C/P effect is highly persistent at 0,70% per month and is different from zero at 5% level. It thus appears that some of the univariate size effect, captured by the value-weighting scheme, can be attributed to the C/P effect.

Unlike studies done in the US (*inter alia* Fama and French, 2006; and Loughran, 1997), which documents weaker value premiums among larger stocks, Tables 5.4 and 5.5 show that the value effect is strong among the largest firms. It is, however, meek in the quartile of smallest firms. On an equal-weighted basis, the value effect among the largest firms is reliably different from zero, whether it is measured with the BE/ME ratio or the C/P ratio. Among the smallest firms, the equal-weighted BE/ME effect is not reliably different from zero, but the C/P effect is. The value-weighted BE/ME and C/P effect, measured within separate size groupings, are rarely significant in statistical terms. However, the premia measured among the largest firms are generally stronger than the ones measured among smallest firms. In fact, the BE/ME effect measured among the smallest firms is weak at 0.24% per month. The low rejection of the null is not surprising, as value-weighting induces more firm-specific noise into the *t*-statistics.

The estimates of the size effect among various F/P groups are noisy. However, it does appear that the bulk of the size effect occurs among firms with low BE/ME ratios. In fact, the estimate of the size premium in that trecile is statistically different from zero, regardless of whether equal-weighted or value-weighted portfolios are used.

Table 5.6

A Two-way Portfolio Test of BE/ME and C/P Effects.

This table aims to disentangle the BE/ME and C/P effects. The portfolios are constructed with an independent sort of three BE/ME portfolios and three C/P portfolios. Portfolios are rebalanced annually; at the end of June. During rebalancing, stocks with liquidity measure of less than 0.01% or cost less than 100c and are not included in the portfolio (the restriction). All returns are adjusted for dividends and other payouts and the portfolio returns are computed after adjustment for outliers. Liquidity measure is a twelve-month average of monthly trading volume scaled by shares in issue. BE/ME is the book value of equity scaled by market capitalization. C/P is cash flow per share scaled by a price. Independent effect is measured as the average of within-group value effects in opposing F/P group. Within-group value effect is measured as a mean difference in returns of portfolios containing low F/P stocks and high F/P stocks. *T* is the number of months in the measurement period. *N* is the average amount of stocks that satisfy liquidity and price criteria at the end of each June. *Average stocks* is the average amount of stocks in portfolios after a second sort.

	I (high BE/ME)	II	III (low BE/ME)	I – III	*t* -stat		
Panel A: Joint BE/ME and C/P Sorts: Restricted and Equal-Weighted							
I (high C/P)	2.50%	1.84%	1.25%	1.25%**	2.313		*T*
II	2.49%	1.67%	1.51%	0.98%**	2.328		156
III (low C/P)	1.88%	1.30%	1.24%	0.64%	1.421		*N*
I – III	0.62%	0.54%	0.01%				356
t-stat	1.274	1.393	0.021				*Ave. Stocks*
	Return	*t*-stat			Return	*t*-stat	30
Independent BE/ME effect	0.96%***	2.910	Independent C/P effect		0.39%	1.337	
Panel C: Joint BE/ME and C/P Sorts: Restricted and Value-Weighted							
I (high C/P)	2.58%	2.21%	1.43%	1.15%	1.53		*T*
II	2.32%	1.72%	1.21%	2.23%***	4.05		156
III (low C/P)	1.25%	1.65%	1.30%	-0.05%	-0.10		*N*
I – III	1.33%**	0.56%	0.13%				356
t-stat	2.385	1.151	0.239				*Ave. Stocks*
	Return	*t*-stat			Return	*t*-stat	38
Independent BE/ME effect	0.74%*	1.738	Independent C/P effect		0.68%*	1.877	

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

The size effect is never statistically significant in any of the C/P groups, but the estimates are somewhat larger in the neutral group.

In Table 5.6 results of the two-way sort on the two value-growth indicators are shown. Evidence of an independent C/P effect of the BE/ME effect is mixed. On an equal-weighted basis, the estimate is 0.39% and it is not statistically different from zero. However, on the value-weighted basis, the computed C/P premium orthogonal of the BE/ME effect is 0.68% and it is different from zero at the 10% level. On a deeper look, it appears that the independent C/P effect is absent among low BE/ME firms. Actually, when the premium is calculated after exclusion of these stocks (results are unreported), it is significant in both economic and statistical terms. On an equal-weighted basis, the C/P effect, which is independent of the book-to-market ratio and calculated in the top two BE/ME treciles, is 0.58%, with a *t*-statistic of 1.847. However, on a value-weighted basis, it is strong at 0.95%, and a *t*-statistic of 2.312. Thus, the C/P may carry information about the value effect that is orthogonal to the information contained in the BE/ME ratio.

Consequently, in spite of the BE/ME ratio being the better predictor of returns, the test assets in asset pricing tests will not only include size and BE/ME sorted portfolios, but size and cashflow yield sorted assets as well. The tables show that there may be some information in the C/P ratio that the book-to-market ratio does not capture, or the superiority of BE/ME as a predictor of returns may be a result of data-mining. Also, Auret and Sinclaire (2006) show that in a multivariate regression of several value-growth indicators, it is the C/P ratio that retains its predictive power, even though the BE/ME is also included in the regressions. Thus, Tables 5.4 and 5.5 also provide a summary of the 24 assets that describe the size and the value anomalies. Unlike prior research, the earning’s yield effect is found to be the weakest, and thus is dropped from the analysis.

5.2 Part II: The Size and the Value Effects on the JSE, Risk Adjustment

The size effect and the value effect are now subjected to risk adjustment with the CAPM and the RS-APT. The philosophy behind the methodology employed in the study stems from arguments made in Lo and MacKinlay (1990a). On the one hand, the authors advocate use of characteristic-sorted portfolios as tests assets because they note that if the characteristic is correlated with the model's pricing errors then the power of the test is increased. On the other hand, they note that if the predictive ability of the characteristic for returns results from data-mining, the test will surely reject the asset pricing model in favour of the characteristic model, even if the asset pricing model is correct. Consequently, tests are performed on 24 size and F/P sorted portfolios, which ought to capture CAPM's (or APT's) pricing errors (Berk, 1995), where the restrictive time-series test is augmented with the robust cross-sectional method.

Since the time-series test makes implicit assumptions, which are violated in practice, a more powerful cross-sectional test of Cochrane (2001) is also performed. In order to test the validity of the assumption that the risk-free rate is equivalent to the zero-beta rate (Black, 1972), the cross-sectional regressions are run with and without the intercept. Because returns are calculated net of the risk-free rate, the statistical significance of the intercept is an implicit test of this restriction. Also, the Generalised Least Squares (GLS) regressions are performed as a robustness exercise. In all tests, the validity of the models is tested by examining the size of the pricing errors. In all tests, the computed factor loading is the sum of the contemporaneous beta and the lagged beta.

In addition, in order to address the data-snooping concerns of Lo and MacKinlay (1990a), the tests of Brennan *et al.* (1998) are preformed. Although in those tests the time-series restrictions do apply, the method does not require grouping of data and circumvents the errors-in-variables problem.

The results of the time-series test of the CAPM that uses the size and BE/ME, as well as size and C/P sorted portfolios as test assets are shown in Table 5.7. The results of the corresponding RS-APT test are shown in Table 5.8.

Interestingly, whether the equal-weighted and value-weighted scheme is used to contract the test assets, only seven (out of the 24) intercepts are different from zero in the CAPM tests. In the RS-APT test with the value-weighted assets, only seven pricing errors are different from zero, but the model is particularly worse than the CAPM at pricing the equal-weighted size and F/P sorted portfolios, as ten pricing errors are different from zero. In both models, however, the direction of the mispricing pans out according to the pattern predicted by the size and the value effects. In other words, intercepts of portfolios with small and value firms are generally positive and intercepts of portfolios with large and growth firms are generally negative.

An important feature of the results, which damns the CAPM and the RS-APT, is the large spread in intercepts of the different portfolios. In all the tests, the pricing errors of the small firms are markedly greater than the ones of the large firms. Similarly, intercepts of the value assets are larger than the ones of the growth portfolios.

Actually, a comparison of the intercepts in these tables, with raw returns shown in Tables 5.4 and 5.5, provides a good indication of the power the two models have in pricing the size and the value effect. In the CAPM test, the spread in mean returns between small and large firms grows in magnitude after risk adjustment. In particular, raw returns show that the average outperformance of small stocks versus large stocks is 0.64% per month on an equal-weighted basis and 0.68% per month on a value-weighted basis.

Table 5.7
The Size and Value Effects after Adjustment for Risk: the CAPM Test

The table shows results of time-series regressions

$r_{i,t} = \alpha_i + b_{i,M}\left(r_{M,t} - r_{f,t}\right) + b_{i,M(lag)}\left(r_{M,t-1} - r_{f,t-1}\right) + \varepsilon_{i,t}$ for t = 1,2,3…T and i = 1,2,3,…N

The regressions are run between July 1992 and July 2005 and are estimated with a SURE system that is mapped into GMM. Spectral density matrix estimated with four leads and lags. The r_M is the return on the market factor, which is the value-weighted return of all securities in the dataset. All returns are adjusted for dividends and other payouts. The size and BE/ME portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The size and C/P sorted portfolios are formed with an intersection of four size-sorted portfolios and three C/P sorted portfolios. The intercept terms are multiplied by 100 for clarity

Panel A: Size and BE/ME sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.32	0.26	0.75**	1.07***	47.3%	57.7%	48.1%	41.6%	0.43	0.48	0.91***	1.32***	59.3%	53.1%	43.8%	27.0%
(Value)	0.660	0.730	2.180	2.610					0.820	1.300	2.490	3.560				
II	0.20	0.25	0.03	1.04**	45.2%	86.7%	57.5%	49.7%	0.34	0.38	0.01	0.99**	81.1%	45.7%	50.1%	31.0%
(Middle)	1.080	0.870	0.070	2.180					1.340	1.150	0.030	2.110				
III	-0.41**	0.02	0.04	1.02*	35.8%	88.0%	57.0%	52.2%	-0.37	-0.29	0.11	0.76	81.4%	56.2%	50.5%	20.0%
(Growth)	-2.390	0.050	0.080	1.800					-1.640	-0.610	0.240	1.420				
	b_M				$b_{M(lag)}$				b_M				$b_{M(lag)}$			
I	1.15***	0.71***	0.61***	0.51***	0.00	0.21***	0.27***	0.24***	1.16***	0.72***	0.61***	0.40***	0.03	0.21***	0.26***	0.23***
(Value)	9.650	12.500	8.750	9.230	-0.040	3.230	3.640	2.440	9.190	10.97	9.680	8.320	0.300	3.090	3.750	2.700
II	1.04***	0.62***	0.62***	0.55***	-0.01	0.21***	0.23***	0.17**	0.89***	0.63***	0.62***	0.53***	0.06**	0.23***	0.25***	0.20***
(Middle)	22.180	15.710	5.260	7.660	-0.410	4.540	4.370	1.990	17.840	9.920	9.040	8.900	2.020	4.660	3.720	2.460
III	1.02***	0.69***	0.71***	0.50***	-0.07***	0.13***	0.25**	0.19***	0.97***	0.71***	0.71***	0.55***	-0.01	0.15***	0.27***	0.10
(Growth)	17.590	7.670	7.060	5.380	-2.220	2.610	3.310	2.590	14.620	8.680	7.510	6.310	-0.400	2.810	3.710	1.350

Table 5.7 **(Continued)**

Panel B: Size and C/P sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I (Value)	0.55	0.76***	0.57	1.24***	67.7%	50.7%	41.6%	27.5%	0.60*	0.77**	0.62	1.43***	61.5%	48.0%	43.9%	36.3%
	1.300	2.380	1.400	2.940					1.720	2.240	1.380	3.830				
II (Middle)	0.20	0.16	0.49	1.02**	82.4%	47.0%	52.7%	32.8%	0.25	0.15	0.59	1.00**	84.7%	59.2%	47.8%	26.2%
	1.060	0.530	1.360	2.140					1.080	0.480	1.610	2.030				
III (Growth)	-0.18	0.10	-0.20	0.39	80.6%	59.5%	47.7%	35.9%	-0.20	-0.03	-0.19	0.42	86.4%	59.8%	42.4%	32.7%
	-0.950	0.240	-0.360	0.770					-0.920	-0.080	-0.380	1.130				
	b_M				$b_{M(lag)}$				b_M				$b_{M(lag)}$			
I (Value)	1.08***	0.58***	0.56***	0.39***	0.11*	0.24***	0.26***	0.25***	0.97***	0.63***	0.54***	0.36***	0.07	0.28***	0.28***	0.23***
	15.170	9.740	8.190	7.020	1.680	4.970	3.740	2.870	14.480	10.380	7.700	5.900	1.260	5.270	3.650	2.950
II (Middle)	0.93***	0.63***	0.63***	0.55***	-0.02	0.21***	0.19***	0.28***	0.90***	0.62***	0.67***	0.50***	0.05**	0.19***	0.23***	0.28***
	23.230	10.270	7.020	6.630	-0.510	4.280	2.750	2.990	20.570	8.050	7.920	7.200	1.940	4.200	3.840	3.440
III (Growth)	1.03***	0.71***	0.76***	0.65***	-0.06***	0.13***	0.27***	0.20***	0.95***	0.74***	0.68***	0.61***	-0.01	0.15***	0.25***	0.18***
	15.010	7.860	6.240	6.590	-2.520	2.930	3.130	2.870	14.660	8.470	7.430	7.760	-0.450	3.000	3.330	2.450

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

Table 5.8

The Size and the Value Effect after Adjustment for Risk: the RS-APT Test

The table shows results of time-series regressions

$$r_{i,t} = \alpha_i + b_{i,R} \; r_{R,t} - r_{f,t} \; + b_{i,R(lag)} \; r_{R,t-1} - r_{f,t-1} \; + \quad \text{for } t = 1,2,3\ldots T \text{ and } i = 1,2,3,\ldots N$$
$$b_{i,I} \; r_{I,t} - r_{f,t} \; + b_{i,I(lag)} \; r_{I,t-1} - r_{f,t-1} \; + \varepsilon_{i,t}$$

The regressions are run between July 1992 and July 2005 and are estimated with a SURE system that is mapped into GMM. Spectral density matrix estimated with four leads and lags. The r_R is return the Resi factor, which is the value-weighted return of all mining shares in the dataset. The r_I is the Findi factor, which is the value-weighted return of all Financial and Industrial shares in the dataset. All returns are adjusted for dividends and other payouts. The size and BE/ME portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The size and C/P sorted portfolios are formed with an intersection of four size-sorted portfolios and three C/P sorted portfolios. The intercept terms are multiplied by 100 for clarity.

Panel A: Size and BE/ME sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.40	0.32	0.83***	1.12***	48.9%	56.8%	54.5%	50.3%	0.51	0.54	0.98***	1.37***	62.8%	58.6%	49.4%	31.9%
(Value)	0.850	0.920	2.360	2.870					1.030	1.580	2.620	3.800				
II	0.31	0.29	0.07	1.07**	50.0%	79.4%	65.1%	57.4%	0.39*	0.41	0.05	1.03***	85.4%	57.6%	58.7%	31.1%
(Middle)	1.200	1.060	0.170	2.320					1.800	1.430	0.130	2.230				
III	-0.33	0.03	0.08	1.04*	42.9%	81.4%	70.8%	62.2%	-0.32*	-0.28	0.14	0.76	87.4%	68.0%	60.2%	27.6%
(Growth)	-1.410	0.090	0.200	1.940					-1.720	-0.650	0.380	1.500				
	b_R				$b_{R(lag)}$				b_R				$b_{R(lag)}$			
I	0.39***	0.29***	0.31***	0.25***	-0.01	0.00	-0.04	0.00	0.41***	0.35***	0.25***	0.24***	-0.05	0.01	0.01	0.01
(Value)	5.090	5.040	4.840	3.920	-0.130	0.100	-0.860	0.070	4.600	6.010	3.940	4.550	-0.650	0.400	0.340	0.160
II	0.33***	0.08**	0.07	0.05	-0.03	-0.03	-0.02	-0.02	0.22***	0.08**	0.11**	0.13***	0.04	-0.05**	-0.04	-0.02
(Middle)	10.390	2.260	1.510	0.810	-1.200	-1.250	-0.440	-0.380	5.780	1.940	2.200	2.230	1.290	-1.810	-0.780	-0.330
III	0.17***	0.01	0.08*	0.19*	-0.01	0.00	-0.07*	-0.06	0.09**	0.00	0.06	0.12	-0.03	0.01	-0.04	-0.02
(Growth)	3.100	0.390	1.780	1.750	-0.240	0.040	-1.950	-0.710	2.350	-0.080	1.310	1.260	-1.140	0.180	-0.990	-0.240

Table 5.8 (Continued)

	b_I				$b_{I(lag)}$				b_I				$b_{I(lag)}$			
I	0.85***	0.54***	0.39***	0.39***	0.00	0.16***	0.24***	0.19***	0.86***	0.52***	0.45***	0.28***	0.08	0.14***	0.21***	0.18***
(Value)	6.880	7.940	5.860	5.780	0.040	3.360	3.640	2.860	7.210	7.220	8.040	4.680	0.790	2.910	3.460	3.020
II	0.73***	0.59***	0.62***	0.55***	-0.02	0.24***	0.22***	0.18**	0.78***	0.62***	0.60***	0.46***	0.00	0.28***	0.25***	0.19**
(Middle)	17.020	16.160	5.300	6.080	-0.440	5.460	4.590	2.000	19.060	13.15	9.860	6.520	0.060	6.010	5.040	2.090
III	0.87***	0.76***	0.70***	0.41***	-0.09**	0.14***	0.30***	0.24***	0.95***	0.79***	0.72***	0.54***	-0.01	0.16***	0.31***	0.12
(Growth)	16.170	11.100	7.760	4.870	-1.770	3.450	4.980	2.920	19.270	12.25	8.790	7.160	-0.240	4.200	5.440	1.580
Panel B: Size and BE/ME sorted portfolios																
	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.72	0.81***	0.62	1.28***	51.7%	51.0%	50.0%	31.9%	0.71***	0.84**	0.65	1.46**	61.8%	53.1%	47.5%	31.1%
(Value)	1.510	2.390	1.520	3.090					2.080	2.290	1.460	3.820				
II	0.27	0.20	0.54	1.05**	83.6%	69.6%	55.5%	43.7%	0.31	0.18	0.64*	1.04**	85.1%	61.1%	60.5%	36.2%
(Middle)	1.320	0.690	1.560	2.310					1.360	0.630	1.830	2.150				
III	-0.10	0.12	-0.15	0.43	81.0%	70.2%	49.4%	37.3%	-0.16	-0.01	-0.16	0.46	88.3%	69.6%	56.1%	39.3%
(Growth)	-0.360	0.350	-0.280	0.930					-1.020	-0.030	-0.340	1.380				
	b_R				$b_{R(lag)}$				b_R				$b_{R(lag)}$			
I	0.45***	0.16***	0.13***	0.17***	0.04	-0.02	-0.07	0.01	0.37***	0.22***	0.10**	0.14***	0.01	-0.05	-0.02	0.00
(Value)	4.160	3.230	2.650	3.170	0.660	-0.420	-1.400	0.170	4.910	4.540	1.900	3.060	0.320	-1.130	-0.410	0.090
II	0.21***	0.08**	0.16***	0.07	0.01	-0.02	-0.07	-0.03	0.16**	0.10**	0.15**	0.07	0.03	-0.02	-0.03	-0.02
(Middle)	5.720	2.250	3.130	1.130	0.410	-0.630	-1.630	-0.540	5.460	2.350	3.210	1.160	1.090	-0.670	-0.750	-0.310
III	0.20***	0.06*	0.14*	0.15*	-0.02	-0.03	0.02	-0.06	0.11***	0.06	0.13**	0.18***	-0.03	-0.03	-0.02	-0.04
(Growth)	3.940	1.900	1.720	1.690	-0.920	-0.770	0.370	-0.810	3.180	1.480	2.100	3.240	-1.090	-0.800	-0.390	-0.700
	b_I				$b_{I(lag)}$				b_I				$b_{I(lag)}$			
I	0.61**	0.48***	0.47***	0.32***	0.05	0.23***	0.32***	0.20***	0.63***	0.48***	0.50***	0.31***	0.05	0.28***	0.30***	0.17***
(Value)	5.930	7.290	7.480	5.390	0.570	4.210	4.850	3.010	9.150	7.790	8.030	5.390	0.760	4.720	4.680	2.940
II	0.79***	0.61***	0.56***	0.55***	-0.06*	0.22***	0.21***	0.28***	0.82***	0.62***	0.61***	0.47***	-0.01	0.20***	0.22***	0.30***
(Middle)	17.520	13.12	6.840	7.830	-1.840	5.370	3.880	3.460	23.670	11.26	9.120	7.300	-0.150	5.230	5.320	3.840
III	0.86***	0.72***	0.71***	0.56***	-0.07*	0.16***	0.23***	0.26***	0.93***	0.75***	0.64***	0.49***	-0.01	0.20***	0.27***	0.21***
(Growth)	16.650	9.400	5.660	4.710	-1.650	4.030	2.450	3.100	21.950	9.410	7.060	6.410	-0.300	5.020	4.040	3.150

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

Correspondingly, the average spread in CAPM intercepts between small and large firms has widened to 0.81% per month on the equal-weighted basis and 0.85% per month on the value-weighted basis. If the RS-APT is used to account for risk, the spread in intercepts grows to 0.79% per month on equal-weighted basis and 0.78% on a value-weighted basis.

The increase in mispricing is a result of the fact that, contrary to the findings with US data, the Market, the Findi, and the Resource betas are lower for smaller firms than larger firms. It is believed that market microstructure effects account for the disparity, which is surprising given that firms included in the sample are already screened for liquidity, and market's lag is included as an explanatory variable.

In addition, it seems that the models cannot account for the value effect. In particular, raw estimates of the average value effect across size groups are 0.8% per month on the equal-weighted basis and 0.61% per month on the value-weighted basis. Risk adjustment with the CAPM brings those spreads marginally down to 0.79% per month on the equal-weighted basis and 0.59% on the value-weighted basis. If the RS-APT model is used to adjust for risk, the spreads marginally grow to 0.83% per month on the equal-weighted basis and 0.62% on the value-weighted basis.

Lastly, the importance of including the lagged term in the regressions is once again shown. In the CAPM test, a vast majority of these loadings are greater than zero at conventional statistical levels. The loadings on the lagged Findi factor in the RS-APT tests are also mostly different from zero. Although, the beta on the lag of the resource factor is scarcely different from zero, it is argued that omission of the lagged term is not advised. Since the lagged loadings on the lagged resource factor ought to be small *a priori*, it is unclear whether a low statistical significance of the lagged terms is a consequence of fast reaction of the mining firms to information or just a statistical noise.

An array of statistical tests of the CAPM and the RS-APT are presented in Table 5.9. The analysis, with the GRS test, of the pricing errors from the time-series regressions, rejects some specifications. But, the CAPM and the RS-APT tested on equally-weighted assets are not rejected at the 5% level of significance. Consequently, although it appears that the models do an adequate job of pricing size and F/P sorted assets, the intercepts seem to be close to zero. However, it is argued that this test has little power to accept or reject the CAPM or the RS-APT models. During the sample period the risk-free rate has been high and stock return have been low.

Table 5.9
Cross-Sectional CAPM and RS-APT Tests with Size-Value Portfolios

The table shows a summary of test of the CAPM and the RS-APT models. The test assets comprise of 12 size-value portfolios that are an intersection of four size sorted portfolios and three BE/ME sorted portfolios, and additional 12 test assets that are a intersection of four size sorted portfolios and three C/P sorted portfolios. The F statistic of overall asset pricing model fit of the time-series models follows Gibbons, Shanken and Ross (1989). The tests for the model fit for the cross-sectional regressions follow Cochrane (2001).

The cross-sectional regressions of the CAPM test are run across 24 size-value portfolios with

$$E_T \; r_{i,t} = \lambda_0 + \lambda_M b_{M,i} + \alpha_i \text{ for } i = 1,2,3\ldots \text{N}$$

The cross-sectional regressions of the APT test are run across 24 size-value portfolios with

$$E_T \; r_{i,t} = \lambda_0 + \lambda_R b_{R,i} + \lambda_I b_{I,i} + \alpha_i \text{ for } i = 1,2,3\ldots \text{N}$$

The cross-sectional regressions can be run with or without an intercept. The dependant variable is the time-series average excess return of an asset i. b_M is sum of a slope of a time-series regressions of each asset's excess returns on to market factor and its lag. b^R is the sum of slopes of time-series regressions of each asset's excess returns on to Resi factor and its lag. Similarly, b^I is the sum of slopes of time-series regressions of each asset's excess returns on to Findi factor and its lag. All returns are adjusted for dividends and other payouts.

		CAPM		RS-APT	
Method		Value-Weighted	Equal-Weighted	Value-Weighted	Equal-Weighted
Time-Series OLS	F	1.577*	1.613*	1.849**	1.774*
	p-value	0.097	0.087	0.041	0.052
	Premia	Positive	Positive	Positive	Positive
Cross-Sectional OLS without the intercept	χ^2	54.685***	42.888***	51.456***	48.195***
	p-value	0.000	0.003	0.000	0.001
	Premia	Positive*	Positive*	Positive*	Positive*
Cross-Sectional GLS without the intercept	χ^2	39.475***	36.315**	37.401**	40.262***
	p-value	0.009	0.020	0.015	0.007
	Premia	Positive	Positive	Positive*	Positive*
Cross-Sectional OLS with the intercept	χ^2	39.984***	42.888***	33.477**	27.293
	p-value	0.007	0.003	0.041	0.161
	Premia	Negative	Negative*	Negative**	Negative***
	Intercept	Positive**	Positive**	Positive***	Positive***
Cross-Sectional GLS with the intercept	χ^2	34.560**	29.483	27.975	25.011
	p-value	0.032	0.103	0.141	0.247
	Premia	Negative*	Negative**	Negative**	Negative***
	Intercept	Positive***	Positive***	Positive**	Positive***

* at least one of the premia is significant at 10% level, ** at least one of the premia is significant at 5% level, *** at least one of the premia is significant at 1% level

Most of the test portfolios in Tables 5.7 and 5.8 do not yield statistically positive excess returns prior to risk adjustment. More importantly, the realisations on the Market, the Resource and the Findi factors have not been reliably different from zero during the sample period. As results, by construction, regression of dependant variable that has a mean close to zero onto an independent variable also with a mean close to zero, will yield small intercepts. Thus, it is not surprising that many of the pricing errors in the time-series tests are not statistically different from zero[91].

A series of the robust cross-sectional tests is also performed. For the sake of brevity, an abridged table of results from these tests is shown in Table 5.9[92]. The table summarises sixteen cross-sectional specifications that test the CAPM and the RS-APT with various specifications.

The cross-sectional tests reveal that the models do a poor job in pricing the size and F/P sorted portfolios and there is little, if any, evidence that the RS-APT is a better model than the CAPM. Specifically, when the models are tested in OLS specifications that assume equivalence between the risk-free and zero-beta rates, Cochrane's (2001) test rejects all models at the 1% level, and the premia are only weakly positive. The GLS robustness regression does recover one of the CAPM specifications and one of the RS-APT specifications, such that the formal test of the model does not reject it at the 1% level.

When the zero-beta rate is treated as a free parameter, the models are strongly rejected. Although Cochrane's (2001) test does provide support for the four specifications, most of the estimated premia are *negative*. The anomalous result is an obvious consequence of the potential under-estimation of betas for small stocks, which stems from market microstructure effects. It is safe to say that, in this form, the CAPM and the RS-APT cannot price the size and F/P sorted portfolios.

Lo and MacKinlay (1990a) show formally that grouping of shares into portfolios and then using these portfolios in tests may falsely reject even a correctly specified equilibrium model of risk and return. As a result, another set of tests is performed on ungrouped data. This luxury comes at a cost.

[91] The low estimates of the premia are just an example of the criticism of Elton (1999), who notes that time-series estimates of expected returns are highly imprecise, as realised returns can diverge from theoretical values for prolonged periods of time (10 years?, 50 years?). Actually, the cross-sectional tests in Section (X.X) have already shown that the market premium, drawn from industry assets, is large and reliably positive.

[92] Detailed results are available on request.

Table 5.10
Tests CAPM and RS-APT against Firm Characteristics

Coefficients in the table are calculated with method in Brennan, Chordia and Subrahmanyam (1998), coefficients are the intercepts of time-series regressions the factors on month-by-month coefficients of cross-sectional OLS regressions of model's pricing errors. Model's pricing error of firm *i* in time *t* is a sum of a intercept of a time-series regression of firm's *i* excess return on model's factors and this regression's a residual at time *t*. t-statistics are calculated with the Newey-West (1987) standard errors. Full listing period was used in the time-series regressions. The regressions of top 20% largest firms do not include lagged factors. The regressions of smallest 20% of firms include two lags of the factors. The remainder of regressions include one lag of the factor. Each month, only stocks with liquidity measure of more than 0.1% or cost more than 100c are included in the regression. Liquidity measure is a twelve-month average of monthly trading volume scaled by end-month shares in issue. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. E/P is earnings per share scaled by a price. C/P is cash flow per share scaled by a price. BE/ME is the book value of equity scaled by market capitalization. All accounting data becomes effective five months after the financial year-end. All variables are standardized and winzorised at 2.5% and 97.5%. If earnings are positive then E/P(+) is the earnings yield and E/P Dummy is 0, otherwise E/P(+) is set to zero and E/P Dummy is set to 1. Similar conventions pertain to the C/P ratio. The reported R^2 is the average of individual R^2 of each cross-sectional regressions. All coefficients are multiplied by 1000, for clarity.

	Constant	Size	E/P(+)	C/P(+)	BE/ME	E/P Dummy	C/P Dummy	Average R^2
Panel A: CAPM-adjusted returns								
(1)	8.37***	-5.94***						0.012
t-stat	2.49	-3.56						
(2)	5.27**		1.69			6.31*		0.018
t-stat	2.00		1.04			1.71		
(3)	6.15***			3.25***			-4.54	0.015
t-stat	2.47			2.63			-1.22	
(4)	6.72***				4.82***			0.010
t-stat	2.49				2.98			
(5)	8.59***	-4.86***			3.04*			0.021
t-stat	2.56	-2.76			1.81			
(6)	9.13***	-5.74***		2.09*			-6.85*	0.051
t-stat	2.78	-3.53		1.87			-1.89	
Panel B: APT-adjusted returns								
(1)	7.54***	-5.69***						0.013
t-stat	2.50	-3.45						
(2)	4.75**		2.13			5.68*		0.017
t-stat	2.10		1.33			1.65		
(3)	5.54***			3.01***			-4.81	0.014
t-stat	2.55			2.46			-1.58	
(4)	6.01***				4.51***			0.008
t-stat	2.54				3.06			
(5)	7.83***	-4.84***			2.75*			0.020
t-stat	2.55	-2.77			1.80			
(6)	8.42***	-5.64***		1.88*			-7.11***	0.047
t-stat	2.82	-3.52		1.74			-2.39	

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

The time-series restrictions of equivalence between the risk-free and the zero-beta rates, and correct estimation of each premium with time-series means of factors, need to be enforced. A robust cross-sectional test on ungrouped data is impractical, as it requires estimates of factor loadings for individual firms. One of the conclusions from the tests above is that it is difficult to estimate loadings on diversified portfolios. The imprecision of firm-level estimates of loadings would be prohibitively high. Although Fama and French (1992) use a portfolio technique to estimate firm level betas, the cross-section of assets listed on the JSE is not large enough to directly apply their technique.

Consequently, the method advocated by Cochrane (2001), and applied by Brennan *et al.* (1998) and van Rensburg and Robertson (2003a), is used to test the resilience to risk adjustment of the size and the value effects. This procedure employs Fama-MacBeth regressions of firm characteristics onto time-series estimates of models' pricing errors. The results of these tests are shown in Table 5.10 and differ from the analysis of van Rensburg and Robertson (2003a) in two ways. The *t*-statistics are adjusted for serial correlation with the Newey and West (1987) method, and the coefficients are adjusted for bias, discussed in Brennan *et al.* (1998), which arises when the estimation error of the coefficients, computed in cross-sectional regressions of the Fama-MacBeth procedure, is correlated with the factors of the asset pricing model being tested.

Judging from the results in the table, the CAPM and the RS-APT do not "price out" firm characteristics. The results presented here are similar to the test show in 12, which is conducted on raw returns. Yet both the value and the size effects are marginally reduced after adjustment for risk. The RS-APT does a somewhat better job at pricing the effects, as the coefficients on all of the characteristics are smaller. The biggest impact occurs in the univariate coefficient on the BE/ME, which is slashed by one. More importantly, the coefficients on value-growth indicators, when tested jointly with the size effect, are no longer different from zero at the 5% level, but are reliably positive at the 10% level. On one hand, this attenuation indicates that the CAPM and the RS-APT can account for a portion of the size and the value effect. Yet it may be a consequence of the overly conservative econometric methods[93]. In fact, it

[93] To explain, In order to correct for this bias, discussed in Brennan *et al.* (1998), the authors propose that the time-series of coefficients from the cross-sectional regressions is regressed onto the factors of the asset pricing model. When the corrective procedure is employed on the coefficients on the value-

can be shown that applying only the Newey and West (1987) adjustment restores significance, at the 5% level, of the coefficients on the BE/ME and the C/P.

It is difficult to compare the results presented in Table 5.10 and the results in van Rensburg and Robertson (2003a) because many of the value-growth indicators they employ are inverses of the F/P ratios. However, the coefficients on all variables, which are specified in the same way, can be compared, especially given the fact that the authors and the methodology employed in this thesis standardise the regressors. The coefficients on the size variable in the CAPM tests computed in van Rensburg and Robertson (2003a) and the ones presented here are almost identical. However, they fail to show a marked difference in coefficients on the value-growth indicators after control for risk is made and the strength of the value-effect seems to increase after the adjustment. The disparity in the results can arise from any of the differences in the methodologies. It is believed that inclusion of the lagged terms in estimation of the pricing errors, and the bias adjustment proposed in Brennan *et al.* (1998), are the chief culprits for the difference in the results.

growth indicators none of the factors comes up significant. Gujarati (2002) does note that inclusion of useless regressors into a regression equation does not induce a bias in the coefficients, but it does lead to miscalculation of the residual variance and, consequently, the standard errors. Thus, the low *t*-statistics associates with the coefficients on the size-value indicators may be a result of the over-identified regressions.

5.3 Part III: Tests of the Fama and French Three factor Model on the JSE

The results in the preceding two parts of the empirical results have provided evidence that allow for a formal construction of the three factor model for the JSE. The model is to be specified in two ways. The first format follows Fama and French (1993), where the market factor is augmented with the size and the value factors. The second format replaces the market factor in the three factor model with the Resource and the Findi factors proposed by van Rensburg and Slaney (1997). Subsequently, the two models are subjected to a series of formal tests. At first, their capacity for pricing the troublesome size and F/P sorted portfolios is investigated. Next, the models are jointly tested against firm characteristics, where their ability to subsume the predictive power of market equity and the value-growth indicators is ascertained. This test also serves as an indication as to whether rational or behavioural theory underpins the success of the three factor model. Lastly, a direct comparison of the two "traditional" models with the FF3F models is made. However, due to limitations in statistical methodology, this test abstracts from statistical rigor and serves only an indicative purpose.

5.3.1 Tests of the Fama and French Models

Since the CAPM and the RS-APT have trouble explaining the size and the value effect, at first, the FF3F and the RS-FF3F are applied to the 24 size and F/P sorted portfolios. As usual, a time-series test, which calculates the factor loadings, is followed by the robust cross-sectional regressions.

The results of time-series tests for the FF3F and the RS-FF3F are shown in Table 5.11 and Table 5.12, respectively. Although, the time-series means of the SML and the VMG are 0.19% per month and 0.52% per month, respectively (none are significantly different from zero), the tests are hugely supportive of both models. The size and the value factors capture a considerable amount of return variation, as the R^2 of all regressions is large - much higher than in the test of the CAPM and the RS-APT.

Table 5.11

The Size and the Value Effect after Adjustment for Risk: the FF3F Test

The table shows results of time-series regressions

$$r_{i,t} = \alpha_i + b_{i,M} \; r_{M,t} - r_{f,t} \; + b_{i,M\,(lag)} \; r_{M,t-1} - r_{f,t-1} \; + b_{i,SML} \; r_{SML,t} - r_{f,t} \; + b_{i,VMG} \; r_{VMG,t} - r_{f,t} \; + \varepsilon_{i,t} \text{ for } t = 1,2,3\ldots\text{T and } i = 1,2,3,\ldots\text{N}$$

The regressions are run between July 1992 and July 2005 and are estimated with a SURE system that is mapped into GMM. Spectral density matrix estimated with four leads and lags. The r_{SML} is a return on a zero-cost portfolio of small capitalization stocks financed with a short position of large capitalization stocks (SML, Small minus Large). Similarly, r_{VMG} is a return on a zero-cost portfolio with a long position in value stocks financed with a short position in growth stocks (VMG, Value minus Growth). SML and VMG are analogous to SMB and HML in Fama and French (1993). The r_M is the return on Market factor, which is the value-weighted return of all securities in the dataset. All returns are adjusted for dividends and other payouts. The size and BE/ME portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The size and C/P sorted portfolios are formed with an intersection of four size-sorted portfolios and three C/P sorted portfolios. The intercept terms are multiplied by 100 for clarity.

Panel A: The GRS test

Value-Weighted Assets		Equal-Weighted Assets	
F	p-value	F	p-value
0.610	0.9577	0.552	0.9810

Table 5.11 (Continued)

Panel B: Size and BE/ME sorted portfolios																
	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.15	0.11	0.37	0.65**	59.5%	58.3%	52.4%	54.6%	0.25	0.31	0.54*	0.86***	60.5%	56.5%	60.3%	57.3%
(Value)	0.340	0.320	1.340	2.020					0.500	0.840	1.870	3.290				
II	0.24	0.02	-0.23	0.65*	46.9%	87.6%	71.8%	70.8%	0.28	0.10	-0.34	0.64*	81.4%	60.2%	72.0%	47.0%
(Middle)	1.350	0.090	-0.870	1.890					1.050	0.410	-1.260	1.850				
III	-0.27*	-0.12	-0.16	0.78*	39.5%	89.0%	65.7%	72.9%	-0.37**	-0.43	-0.12	0.48	84.6%	66.6%	71.2%	32.0%
(Growth)	-1.740	-0.330	-0.600	1.720					-1.970	-1.000	-0.450	1.050				
	b_M				$b_{M(lag)}$				b_M				$b_{M(lag)}$			
I	1.22***	0.85**	0.89***	0.85***	0.02	0.06	0.03	-0.07	1.25***	0.87***	0.91***	0.75***	-0.03	0.11	0.07*	0.01
(Value)	10.480	11.590	11.710	14.850	0.920	1.640	0.920	-0.920	9.800	10.21	15.220	13.700	-0.260	1.440	1.790	0.240
II	0.98***	0.85***	0.92***	0.93***	-0.01	0.01	0.08	0.01	0.96***	0.89***	0.97***	0.84***	0.02	0.06	0.03	-0.01
(Middle)	15.290	15.640	9.350	10.080	-0.410	0.230	1.520	0.100	11.680	11.53	12.840	11.770	0.520	1.550	0.550	-0.100
III	0.92***	0.87***	0.97***	0.78***	0.12	0.09*	0.02	0.04	1.03***	0.90***	0.98***	0.84***	-0.05	0.03	0.09*	-0.09
(Growth)	17.160	10.450	10.110	6.940	1.530	1.820	0.410	0.720	15.080	10.76	11.000	7.280	-1.530	0.610	1.910	-1.190
	b_{SML}				b_{VMG}				b_{SML}				b_{VMG}			
I	0.06	0.33***	0.58***	0.75***	0.26**	0.11	0.39***	0.40***	0.13	0.35***	0.63***	0.71***	0.24**	0.14	0.37***	0.48***
(Value)	0.360	3.280	5.910	6.500	1.980	0.920	5.400	3.990	0.650	3.290	9.050	8.980	1.960	1.210	6.670	7.730
II	-0.16***	0.57***	0.79***	0.92***	0.00	0.16***	0.10	0.27***	0.15	0.63***	0.83***	0.74***	0.04	0.20***	0.25***	0.28***
(Middle)	-2.540	8.100	7.310	6.490	-0.010	2.780	1.360	2.470	1.550	7.620	8.940	6.490	0.500	2.570	3.820	3.050
III	-0.16***	0.50***	0.71***	0.74***	-0.18***	0.03	0.03	0.09	0.21***	0.52***	0.74***	0.74***	-0.08	0.01	0.06	0.16
(Growth)	-3.950	5.960	9.010	5.320	-2.650	0.310	0.340	0.840	3.130	5.420	11.170	5.480	-1.220	0.110	0.680	1.510

Table 5.11 (Continued)

Panel C: Size and C/P sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.42	0.49*	0.15	0.81***	75.0%	55.3%	65.0%	60.2%	0.40	0.46	0.13	1.00***	75.0%	58.8%	67.3%	57.8%
(Value)	1.450	1.800	0.580	2.590					1.400	1.560	0.470	4.070				
II	0.14	-0.03	0.10	0.63*	85.1%	72.9%	69.1%	61.5%	0.16	-0.07	0.24	0.60*	83.1%	59.6%	72.8%	54.0%
(Middle)	0.820	-0.150	0.460	1.720					0.710	-0.300	1.020	1.570				
III	0.01	-0.02	-0.29	0.08	88.8%	67.1%	60.1%	46.9%	-0.17	-0.13	-0.37	0.19	84.9%	69.3%	65.0%	47.3%
(Growth)	0.080	-0.060	-0.700	0.180					-1.090	-0.370	-1.090	0.540				
	b_M				$b_{M(lag)}$				b_M				$b_{M(lag)}$			
I	1.02***	0.76***	0.90***	0.74***	0.15**	0.12**	0.04	0.03	1.02***	0.85***	0.93***	0.69***	0.04	0.14***	0.03	0.02
(Value)	12.420	11.040	12.740	14.110	2.020	2.230	0.890	0.550	13.420	11.71	12.800	12.250	0.720	2.610	0.750	0.530
II	0.96***	0.84***	0.98***	0.91***	-0.03	0.07*	-0.04	0.04	0.99***	0.85***	1.01***	0.84***	-0.01	0.04	0.02	0.06
(Middle)	15.430	13.340	12.110	13.600	-1.350	1.740	-0.610	0.870	14.940	10.10	12.560	13.680	-0.250	1.100	0.360	1.050
III	0.92***	0.87***	0.98***	0.98***	0.00	0.02	0.12	-0.01	1.01***	0.90***	0.94***	0.84***	-0.05	0.05	0.08	0.03
(Growth)	15.460	9.890	12.260	6.860	0.150	0.590	1.990	-0.140	14.150	9.800	13.420	6.980	-1.220	1.050	1.700	0.320
	b_{SML}				b_{VMG}				b_{SML}				b_{VMG}			
I	-0.39***	0.35***	0.78***	0.78***	0.40***	0.30***	0.38***	0.39***	-0.06	0.44***	0.85***	0.72***	0.37***	0.34***	0.46***	0.41***
(Value)	-3.940	4.570	15.070	9.070	2.720	3.640	7.170	4.840	-0.480	5.580	15.250	8.920	3.990	4.830	8.180	6.440
II	0.03	0.55***	0.83***	0.85***	0.09	0.09	0.29***	0.29***	0.18**	0.58***	0.81***	0.80***	0.09	0.13*	0.25***	0.33***
(Middle)	0.320	6.070	13.180	9.360	1.200	1.410	5.690	3.550	2.120	6.080	12.990	11.590	1.200	1.670	4.780	4.780
III	-0.15***	0.44***	0.70***	0.84***	-0.26***	0.00	-0.15	0.15	0.22***	0.45***	0.73***	0.57***	-0.14***	-0.03	-0.01	0.14
(Growth)	-3.110	5.030	7.590	4.040	-6.720	0.060	-1.600	1.000	3.120	4.510	10.100	3.660	-2.640	-0.410	-0.140	1.140

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

Table 5.12
Size and BE/ME Effect after Adjustment for Risk: the RS-FF3F Test

The table shows results of time-series regressions

$$r_{i,t} = \alpha_i + b_{i,R}\left(r_{R,t} - r_{f,t}\right) + b_{i,R(lag)}\left(r_{R,t-1} - r_{f,t-1}\right) + b_{i,I}\left(r_{I,t} - r_{f,t}\right) + b_{i,I(lag)}\left(r_{I,t-1} - r_{f,t-1}\right)$$
$$+ b_{i,SML}\left(r_{SML,t} - r_{f,t}\right) + b_{i,VMG}\left(r_{VMG,t} - r_{f,t}\right) + \varepsilon_{i,t} \quad \text{for } t = 1,2,3\ldots T \text{ and } i = 1,2,3,\ldots N$$

The regressions are run between July 1992 and July 2005 and are estimated with a SURE system that is mapped into GMM. Spectral density matrix estimated with four leads and lags. The r_{SML} is a return on a zero-cost portfolio of small capitalization stocks financed with a short position of large capitalization stocks (SML, Small minus Large). Similarly, r_{VMG} is a return on a zero-cost portfolio with a long position in value stocks financed with a short position in growth stocks (VMG, Value minus Growth). SML and VMG are analogous to SMB and HML in Fama and French (1993). The r_R is return the Resi factor, which is the value-weighted return of all mining shares in the dataset. The r_I is the Findi factor, which is the value-weighted return of all Financial and Industrial shares in the dataset. All returns are adjusted for dividends and other payouts. The size and BE/ME portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The size and C/P sorted portfolios are formed with an intersection of four size-sorted portfolios and three C/P sorted portfolios. The intercept terms are multiplied by 100 for clarity.

Panel A: The GRS test

Value-Weighted Assets		Equal-Weighted Assets	
F	p-value	F	p-value
0.656	0.9286	0.610	0.9576

Table 5.12 (Continued)

Panel B: Size and BE/ME sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.34	0.26	0.58**	0.81***	57.5%	59.7%	56.6%	59.7%	0.45	0.47	0.72**	1.01***	63.6%	59.7%	60.8%	58.5%
(Value)	0.790	0.760	2.010	2.840					0.920	1.380	2.390	4.160				
II	0.44	0.14	-0.07	0.81**	51.6%	84.2%	70.4%	70.3%	0.39	0.21	-0.19	0.80**	85.1%	64.2%	71.3%	41.1%
(Middle)	1.820	0.590	-0.200	2.200					1.610	0.850	-0.590	2.120				
III	-0.13	-0.06	-0.01	0.95**	44.9%	86.4%	71.9%	71.8%	-0.27	-0.37	0.02	0.60	87.3%	69.8%	69.7%	34.1%
(Growth)	-0.690	-0.170	-0.030	2.120					-1.480	-0.880	0.070	1.340				
	b_R				$b_{R(lag)}$				b_R				$b_{R(lag)}$			
I	0.29***	0.34***	0.33***	0.32***	-0.03	0.01	-0.04	0.01	0.33***	0.41***	0.29***	0.28***	-0.07	0.02	0.01	0.00
(Value)	5.070	5.850	6.420	5.650	-0.400	0.220	-0.980	0.140	4.870	6.710	5.380	7.070	-0.820	0.560	0.310	0.080
II	0.26***	0.12***	0.19***	0.15***	-0.04*	-0.03	0.00	-0.01	0.20***	0.11***	0.20***	0.20***	0.04	-0.05*	-0.03	-0.01
(Middle)	8.320	3.270	4.920	2.570	-1.700	-1.250	-0.090	-0.180	3.920	3.280	3.820	3.030	1.120	-1.840	-0.680	-0.240
III	0.12***	0.06	0.18***	0.33***	-0.01	0.01	-0.06	-0.03	0.08***	0.05	0.16***	0.22***	-0.02	0.01	-0.03	0.00
(Growth)	3.240	1.590	4.400	3.460	-0.330	0.190	-1.400	-0.390	3.030	1.040	4.580	2.750	-1.030	0.340	-0.640	-0.010
	b_I				$b_{I(lag)}$				b_I				$b_{I(lag)}$			
I	0.90***	0.57***	0.54***	0.57***	0.07	0.09*	0.13*	0.01	0.90***	0.55***	0.60***	0.49***	0.13	0.07	0.08	0.01
(Value)	8.870	9.680	7.280	9.510	0.760	1.690	1.830	0.270	8.930	8.700	9.760	9.730	1.250	1.130	1.380	0.190
II	0.66***	0.68***	0.69***	0.69***	0.09	0.14***	0.06	0.00	0.78***	0.74***	0.74***	0.60***	0.01	0.17	0.08*	0.04
(Middle)	12.160	18.820	7.640	7.510	1.920	3.480	1.220	-0.040	14.280	13.970	15.460	7.090	0.340	3.740	1.670	0.430
III	0.75***	0.81***	0.74***	0.45***	0.03	0.06	0.18***	0.08	0.92***	0.84***	0.78***	0.63***	0.01	0.08	0.17	-0.04
(Growth)	17.290	12.280	10.540	4.910	0.610	1.500	3.340	0.990	20.460	12.410	11.740	7.110	0.280	1.950	3.380	-0.550
	b_{SML}				b_{VMG}				b_{SML}				b_{VMG}			
I	-0.24	0.23***	0.40***	0.62***	0.17	0.03	0.29***	0.31***	-0.18	0.27***	0.45***	0.59***	0.15	0.04	0.28***	0.39***
(Value)	-1.500	2.360	3.780	4.600	1.560	0.280	3.220	3.000	-0.960	2.710	5.020	6.370	1.480	0.370	3.520	6.150
II	-0.40***	0.32***	0.57***	0.65***	-0.09	0.15***	0.05	0.21**	-0.04	0.38***	0.59***	0.53***	0.02	0.21***	0.22***	0.22***
(Middle)	-7.290	6.690	7.230	5.630	-1.250	3.150	0.730	2.020	-0.680	6.770	8.970	5.340	0.250	3.680	3.780	2.220
III	-0.41***	0.26***	0.45***	0.59***	-0.19**	0.07	0.00	-0.04	-0.08	0.27***	0.48***	0.56***	-0.05	0.05	0.05	0.09
(Growth)	-4.590	5.710	5.930	4.460	-2.370	0.950	0.050	-0.330	-1.280	5.040	7.410	4.670	-0.770	0.700	0.610	0.850

Table 5.12 (Continued)

Panel C: Size and C/P sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I	0.66*	0.60**	0.31	0.95***	71.3%	57.8%	64.7%	58.1%	0.58**	0.61*	0.27	1.12***	69.0%	55.7%	62.2%	61.7%
(Value)	1.860	2.080	1.040	3.190					2.000	1.860	0.890	4.310				
II	0.26	0.08	0.28	0.76**	85.4%	67.0%	71.8%	48.9%	0.26	0.03	0.41	0.75*	86.7%	74.8%	68.2%	60.8%
(Middle)	1.320	0.340	1.080	2.010					1.160	0.120	1.530	1.850				
III	0.16	0.07	-0.09	0.30	88.9%	70.7%	65.1%	44.3%	-0.07	-0.03	-0.20	0.35	86.4%	71.1%	61.4%	42.7%
(Growth)	0.770	0.220	-0.220	0.690					-0.510	-0.090	-0.570	1.080				
	b_R				$b_{R(lag)}$				b_R				$b_{R(lag)}$			
I	0.22***	0.13***	0.17***	0.24***	-0.01	-0.03	-0.08	0.01	0.22***	0.21***	0.13***	0.19***	-0.02	-0.06	-0.03	0.00
(Value)	3.610	2.560	3.580	4.740	-0.120	-0.770	-1.490	0.240	3.520	4.430	2.910	4.660	-0.510	-1.470	-0.590	0.050
II	0.14***	0.14***	0.24***	0.15***	0.00	-0.01	-0.06	-0.02	0.13***	0.15***	0.24***	0.13*	0.02	-0.01	-0.02	-0.02
(Middle)	3.940	5.420	7.080	2.400	0.040	-0.430	-1.600	-0.430	3.480	4.530	7.220	1.880	0.760	-0.510	-0.600	-0.300
III	0.18***	0.11***	0.32***	0.28***	-0.02	-0.02	0.06	-0.04	0.14***	0.11***	0.27***	0.26***	-0.02	-0.02	0.00	-0.03
(Growth)	4.840	2.730	6.180	3.800	-0.750	-0.580	1.230	-0.500	5.030	2.650	6.750	4.650	-0.880	-0.540	0.080	-0.510
	b_I				$b_{I(lag)}$				b_I				$b_{I(lag)}$			
I	0.67***	0.61***	0.65***	0.51***	0.24***	0.18***	0.17***	0.02	0.72***	0.62***	0.73***	0.51***	0.14**	0.21***	0.13***	0.00
(Value)	6.670	8.280	10.310	8.790	3.000	2.840	2.630	0.360	10.900	9.100	12.010	8.480	2.440	3.040	2.560	0.050
II	0.80***	0.68***	0.70***	0.72***	0.00	0.12***	0.04	0.10	0.86***	0.71***	0.74***	0.64***	0.01	0.09***	0.06*	0.14*
(Middle)	19.600	16.210	10.220	9.370	-0.160	3.180	0.760	1.540	21.860	13.42	13.890	7.910	0.240	2.780	1.750	1.870
III	0.71***	0.75***	0.66***	0.62***	0.04	0.10***	0.08	0.10	0.87***	0.76***	0.66***	0.55***	0.00	0.14	0.12**	0.11
(Growth)	14.890	9.330	7.460	5.120	0.910	2.310	1.080	1.000	19.460	9.300	9.840	6.240	-0.050	3.230	2.160	1.270
	b_{SML}				b_{VMG}				b_{SML}				b_{VMG}			
I	-0.69***	0.16**	0.51***	0.64***	0.30**	0.30***	0.33***	0.32***	-0.34***	0.23***	0.58***	0.59***	0.30**	0.31***	0.43***	0.37***
(Value)	-7.020	2.110	7.390	6.400	2.010	3.200	4.470	3.510	-3.460	3.060	9.290	6.160	2.930	3.930	6.440	4.520
II	-0.21***	0.34***	0.59***	0.62***	0.08	0.08	0.22***	0.27***	-0.05	0.37***	0.58***	0.55***	0.10*	0.12**	0.19***	0.30***
(Middle)	-3.990	6.230	8.370	5.190	1.420	1.540	3.610	2.670	-1.080	6.470	9.430	5.930	1.760	2.090	3.200	3.390
III	-0.37***	0.20***	0.52***	0.58***	-0.30***	0.02	-0.25**	0.03	-0.02	0.20***	0.53***	0.37***	-0.13***	-0.03	-0.09	0.05
(Growth)	-4.030	4.060	5.430	3.500	-4.960	0.250	-2.380	0.240	-0.400	3.480	8.820	2.930	-2.720	-0.400	-1.100	0.530

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

More importantly, the GRS tests provide strong support for the FF3F, and its variant, as the p-values are all greater than 0.9.

Generally, the magnitude and sign of the loadings on the FF3F factors corresponds to the size and value-growth indicator captured by each test asset. In other words, loadings on the SML are larger for portfolios containing smaller firms and loadings on the VMG are greater for portfolios containing firms with high value-growth indicators. Curiously, only in the tests of the FF3F, not all of the assets that contain large firms load negatively on the size factor. In fact, in tests that use equal-weighted assets, these loadings are positive and reliably different from zero. This result is an indication of the skewness in the distribution of market values on the JSE; there are few large firms and the rest of the firms are small. In addition, the same loadings on assets that include growth firms are not reliably negative, but are never significant. Could it be a consequence of there being few truly growth firms listed on the JSE[94]? Interestingly, sorting assets with the C/P ratio produces a larger spread in betas on the value factor, perhaps indicating that this variable is a cleaner value-growth indicator.

The SML and the VMG are strongly significant in many of the time-series regressions. In the tests of the FF3F, with value-weighted assets, only two of the 24 estimated loadings on the size factor are not significant; if assets are weighted equally, six of the loadings are not significant. Interestingly, nearly all of the betas that are different from zero are more than three standard deviations from the mean, and some loadings yield *t*-statistics that are as high as those calculated for the market betas. The VMG is not as robust as the SML. In the value-weighted tests, twelve out of 24 loadings on the value factor are not significant, while in the equal-weighted tests 10 are not significant. However, many of the loadings are different from zero at the 1% level, indicating that the factor is important in capturing variations in returns. Also, not all firms must be exclusively value or growth; there are many neutral firms that ought to be uncorrelated with the value factor. In fact, in tests similar to the ones presented here, Fama and French (1996a) do show that about a quarter of the portfolios do not load on their value factor. Lastly, in tests on the RS-FF3F, the size and the significance of the factor loadings on the SML and the VMG are essentially the same as the tests on the FF3F.

[94] In general, technology-intensive stocks are more common in developed countries.

The pattern above can be contrasted with the results in Scher and Muller (2005), who also construct a version of the FF3F. Although they do not form portfolios with the same methods used here, they do show 14 assets that are similar to the 12 size and BE/ME sorted portfolios presented in Panel B of Table 5.11. In their case, 9 out of 14 assets load significantly on the size factor and only six (less then half) are positive at the 1% level. In contrast, in tables presented here, all but one or two of the betas on the size factor are not different from zero at the 1% level. In addition, Scher and Muller (2005) find only 4 out of 14 assets (less than a third) load significantly on the value factor, but none of them at the 1% level. In the tests presented here, five or six (just less than half) of test assets load positively onto the value factor, and five are different from zero at the 1% level.

The pricing errors of the FF3F and the RS-FF3F indicate that the model does not eradicate the size and the value effects. Small, and mostly value, firms continue to produce reliably positive intercepts, and in some specifications the portfolio of large growth firms is also mispriced. Interestingly some of the portfolios with high C/P ratios are also mispriced, suggesting that, given that the FF3F model is rational, some aspect of returns to firms with low cashflow yields is not captured by the model. Nonetheless, it is believed that the low time-series estimates of the premia are the reason behind significant standard errors.

The models' pricing errors can be contrasted to the raw return computes in Tables 5.4 and 5.5. It was shown that across value firms, small stocks, on average, outperformed large stocks by 0.64% per month on an equal-weighted basis and by 0.68% per month on a value-weighted basis. The corresponding average spread in FF3F intercepts has narrowed significantly to 0.54% per month on the equal-weighted basis and to 0.49% per month on the value-weighted basis. If the RS-FF3F is used to account for risk, the average spread in intercepts between small and large portfolios markedly falls to 0.55% per month on the equal-weighted basis and 0.48% on the value-weighted basis. In must be noted that the CAPM and the RS-APT have increased the spread in intercepts, thus the FF3F models must act against that maladjustment. The value effect has also decreased. For instance, raw estimates of the value effect across size groups, documented in Table 5.4 and Table 5.5, is 0.8% per month on the equal-weighted basis and 0.61% per month on the value-weighted basis. Risk adjustment with the FF3F brings those spreads significantly down to 0.61% per month on the equal-weighted basis and 0.39% on the value-weighted basis.

If the RS-APT model is used to adjust for risk, the spreads narrow to 0.65% per month on the equal-weighted basis and 0.42% on the value-weighted basis.

There are two marked differences between the pricing errors of the FF3F presented here and the one constructed with US data by Fama and French (1993). First, the three factor model seen here misprices different types of assets. In the US, it is the return on the portfolios of small and growth firms that is particularly badly predicted by the model; while it is the small and value firms that the South African models fails to price. Second, the difference is the direction of the mispricing. In the US, the model generally overpredicts the return on small firms and underpredicts the return on large firms an opposite pattern to the one observed here. Curiously, the magnitude of the size and the value premia estimated here are very similar to those in the US' thus the disparity in the results is most probably explained by the much larger spread in the loading on the size and the value loadings that is observed in the US. In fact, a typical spread between the loadings on the size factor is about 1.4, while in the South African data, a corresponding spread is about 1. More importantly, the spread between loadings on the value factor is about 1.1 in US data, while the corresponding estimate computed on South African data varies between 0.1 and 0.3[95]. Perhaps it is the non-synchronous trading, so omnipresent on the JSE, that biases down the estimates of value betas.

The results of cross-sectional tests to the FF3F and the RS-FF3F are shown in Table 5.13 and Table 5.14, respectively. In sum, it can be said that the FF3F and the RS-FF3F do a much better job at pricing the size and F/P sorted portfolios than the "traditional" models, such as the CAPM or the RS-APT. Only one specification (out of 16) of the three factor model is rejected with Cochrane's (2001) test. In particular, the FF3F in an OLS, which includes the intercept and is run on equal-weighted assets, performs the worst, while the GLS specifications of the FF3F and the RS-FF3F do a particularly good job at pricing value-weighted portfolios. In contrast, when tested on this set of assets, the CAPM and the RS-APT were rejected in all of their forms. In general, the FF3F models capture the lion's share of the cross-sectional variation in returns, as the R^{2}'s are larger than 0.6 in all but three specifications.

[95] Consequently, given the US spread in value betas and the South African estimate of the value premium, the difference in pricing errors of value and growth firms would fall by 0.45% per month, which is about the average of the observed spread in the FF3F intercepts.

Table 5.13

Cross-Sectional FF3F Test with Size-Value Portfolios

The regressions are run across 24 size-value portfolios with

$$E_T\ r_{i,t} = \lambda_0 + \lambda_M b_{M,i} + \lambda_{SMB} b_{SMB,i} + \lambda_{VMG} b_{VMG,i} + \alpha_i \text{ for } i = 1,2,3\ldots \text{N}$$

The second set of regressions does not include an intercept. The dependant variable is the time-series average excess return of an asset *i*. The independent variables are obtained form time-series regression of asset's *i* return onto the Market factor, its lag, the SML factor and the VMG factor. The SML (Small minus Large) factor is a zero-cost portfolio of small capitalization stocks financed with a short position of large capitalization stocks. VMG (Value minus Growth) factor is a zero-cost portfolio with a long position in value stocks financed with a short position in growth stocks. SML and VMG are analogous to SMB and HML in Fama and French (1993). b_M is the sum of two coefficients on the Market factor. All returns are adjusted for dividends and other payouts. The test assets comprise of 12 size-value portfolios that are an intersection of four size sorted portfolios and three BE/ME sorted portfolios, and additional 12 test assets that are an intersection of four size sorted portfolios and three C/P sorted portfolios. The GMM t-statistics are obtained after the OLS regressions are mapped into a GMM system. Spectral density matrix is estimated with four leads and lags. The GLS coefficients and *t*-statistics follow Cochrane (2001). The adjusted R^2 follows Jagannathan and Wang (1996) and it is adjusted with the method in Gujarati (2003). The tests for the model fit follows Cochrane (2001).

Panel A: Value-Weighted Assets					
	OLS			GLS	
λ_0	1.58%**	n/a	λ_0	1.39%**	n/a
t-stat (OLS)	2.165	n/a	t-stat (GLS)	2.234	n/a
λ_M	-1.06%	0.49%	λ_M	-0.88%	0.52%
t-stat (GMM)	-1.196	1.009	t-stat (GLS)	-1.114	1.076
λ_{SML}	-0.02%	0.19%	λ_{SML}	-0.07%	0.05%
t-stat (GMM)	-0.049	0.437	t-stat (GLS)	-0.174	0.109
λ_{VMG}	1.79%***	1.73%***	λ_{VMG}	1.74%***	1.68%***
t-stat (GMM)	3.280	3.171	t-stat (GLS)	3.485	3.368
Adj. R^2	0.708	0.578	Adj. R^2	0.681	0.561
χ^2	19.837	25.495	χ^2	21.551	26.510
p-value	0.468	0.226	p-value	0.365	0.188

Panel B: Equal-Weighted Assets					
	OLS			GLS	
λ_0	1.68%**	n/a	λ_0	1.65%***	n/a
t-stat (GMM)	2.045	n/a	t-stat (GLS)	2.608	n/a
λ_M	-1.14%	0.40%	λ_M	-1.03%	0.57%
t-stat (GMM)	-1.187	0.770	t-stat (GLS)	-1.302	1.150
λ_{SML}	-0.31%	0.05%	λ_{SML}	-0.20%	-0.01%
t-stat (GMM)	-0.614	0.089	t-stat (GLS)	-0.418	-0.016
λ_{VMG}	2.24%***	2.37%***	λ_{VMG}	1.71%***	1.80%***
t-stat (GMM)	3.635	3.876	t-stat (GLS)	3.116	3.293
Adj. R^2	0.723	0.633	Adj. R^2	0.692	0.568
χ^2	35.129**	23.242	χ^2	20.122	26.879
p-value	0.019	0.331	p-value	0.450	0.175

* significant at 10% level, ** significant at 5% level, *** significant at 1% level (based on the GMM standard errors)

Table 5.14
Cross-Sectional RS-FF3F Test with Size-Value Portfolios

The regressions are run across 24 size-value portfolios with

$$E_T\left(r_{i,t}\right) = \lambda_0 + \lambda_R b_{R,i} + \lambda_I b_{I,i} + \lambda_{SMB} b_{SMB,i} + \lambda_{VMG} b_{VMG,i} + \alpha_i \text{ for i = 1,2,3...N}$$

The second set of regressions does not include an intercept. The dependant variable is the time-series average excess return of an asset *i*. The independent variables are obtained form time-series regression of asset's *i* return onto the Resi factor, its lag, Findi factor, its lag, the SML factor and the VMG factor. The SML (Small minus Large) factor is a zero-cost portfolio of small capitalization stocks financed with a short position of large capitalization stocks. VMG (Value minus Growth) factor is a zero-cost portfolio with a long position in value stocks financed with a short position in growth stocks. SML and VMG are analogous to SMB and HML in Fama and French (1993). b_R and b_I are the sum of two coefficients on the Resi and Findi factors, respectively. All returns are adjusted for dividends and other payouts. The test assets comprise of 12 size-value portfolios that are an intersection of four size sorted portfolios and three BE/ME sorted portfolios, and additional 12 test assets that are an intersection of four size sorted portfolios and three C/P sorted portfolios. The GMM t-statistics are obtained after the OLS regressions are mapped into a GMM system. Spectral density matrix is estimated with four leads and lags. The GLS coefficients and *t*-statistics follow Cochrane (2001). The adjusted R^2 follows Jagannathan and Wang (1996) and it is adjusted with the method in Gujarati (2003). The tests for the model fit follows Cochrane (2001).

Panel A: Value-Weighted Assets

	OLS			GLS	
λ_0	1.64%	n/a	λ_0	1.38%	n/a
t-stat (GMM)	0.203	n/a	t-stat (GLS)	0.171	n/a
λ_R	0.63%	1.99%***	λ_R	0.98%	2.04%***
t-stat (GMM)	0.596	2.323	t-stat (GLS)	1.027	2.539
λ_I	-1.43%	0.30%	λ_I	-1.14%	0.36%
t-stat (GMM)	-1.522	0.578	t-stat (GLS)	-1.184	0.719
λ_{SML}	-0.06%	0.14%	λ_{SML}	-0.04%	0.06%
t-stat (GMM)	-0.134	0.321	t-stat (GLS)	-0.105	0.141
λ_{VMG}	1.75%***	1.75%***	λ_{VMG}	1.69%***	1.62%***
t-stat (GMM)	3.169	3.163	t-stat (GLS)	3.356	3.247
Adj. R^2	0.737	0.609	Adj. R^2	0.730	0.588
χ^2	25.063	22.410	χ^2	19.827	24.887
p-value	0.199	0.319	p-value	0.469	0.206

Panel B: Equal-Weighted Assets

	OLS			GLS	
λ_0	1.47%*	n/a	λ_0	1.62%***	n/a
t-stat (OLS)	1.674	n/a	t-stat (GLS)	2.301	n/a
λ_R	0.86%	2.21%***	λ_R	0.51%	2.08%***
t-stat (OLS)	0.678	2.511	t-stat (GLS)	0.472	2.720
λ_I	-1.26%	0.10%	λ_I	-1.33%	0.30%
t-stat (OLS)	-1.263	0.202	t-stat (GLS)	-1.541	0.593
λ_{SML}	-0.28%	0.05%	λ_{SML}	-0.17%	0.00%
t-stat (OLS)	-0.564	0.096	t-stat (GLS)	-0.371	-0.009
λ_{VMG}	2.09%***	2.31%***	λ_{VMG}	1.65%***	1.85%***
t-stat (OLS)	3.303	3.792	t-stat (GLS)	2.907	3.316
Adj. R^2	0.807	0.709	Adj. R^2	0.785	0.701
χ^2	20.580	24.168	χ^2	20.405	26.521
p-value	0.422	0.235	p-value	0.433	0.149

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

In comparison, the specifications of the "traditional" models that did not yield negative premia, produced negative coefficients of determination. It also appears that the RS-FF3F can capture more of the cross-sectional variation in returns than the FF3F.

The value premium is positive and statistically significant at the 1% level in all the tests. Although the estimates of the value premium vary between specifications, the consensus is approximately 1.7%, especially if it is believed that the GLS coefficients are more efficient. Interestingly, the computed premia are virtually the same in regressions with, and without, the intercept; and, the estimates are nearly identical in all of the GLS specifications, regardless of the assumptions for the zero-beta rate, type of weighting, and/or the assumption for the market factor.

Generally, other factors are not priced. Curiously, the premium on the SML factor is never reliably different from zero. In fact, it is negative, though not significantly, in all the regressions that include the intercept. If the zero-beta rate is restricted, the computed premia do turn positive, but remain undistinguishable from zero. In addition, the premia of factors associated with the CAPM and the RS-APT are rarely, if ever, positive and different from zero. In fact, the Market factor and the Findi factor are never positive in specifications that include the intercept, but are never significantly negative. However, the Resource factor does yield a significant premium in the two models without the intercept. Lastly, the intercept remains reliably different from zero in most of the regressions that specify it, thus there is still a large amount of return that is unexplained by the FF3F models.

The low price of Market and size risk documented in Tables 5.13 and 5.14 is broadly consistent with the results found on US data that use size and BE/ME sorted portfolios as test assets. Examples of cross-sectional analysis of the FF3F appear in *inter alia* Petkova (2006) and Lettau and Ludvigson (2001b). Both studies do not find reliably positive premia on the size and the market factors. However, Brennan *et al.* (2004) do show that, in a cross-sectional regression without an intercept, the market risk is priced. Similarly, in the tests here, restricting the intercept does recover the Resource factor as a significant source of risk.

5.3.2 The Fama and French Models against the Firm Characteristics Model

The three factor models are now tested directly against the characteristics model, for two reasons: the ability of the model to "price out" characteristics is a direct testament to its validity, and, in the case of the FF3F, the test can discern between rational and behavioural underpinnings for the model. The tests use Fama-MacBeth regressions described in Brennan *et al.* (1998), which adjust coefficients for the bias stemming from correlation of individual cross-sectional coefficients and the asset pricing factors. The results are shown in Table 5.15.

The value effect dissipates after adjustment for risk is made. In particular, even in the univariate regressions, none of the value-growth yield coefficients are significant at the 5% level. Although, the coefficient on the BE/ME ratio is reliably positive at the 10% level, any return predictability associated with the ratio disappears after size is included as the explanatory variable. It has been noted that firm market equity and its BE/ME ratio are correlated; thus it is plausible that the coefficient on size captures some of the BE/ME premium. But such bias is likely to be small and, given the small coefficients, certainly not large enough to restore the BE/ME as a valid predictor of returns. The C/P effect is completely extinguished with the FF3F models. In short, the results are consistent with a hypothesis that the three factor model is a risk model and not a manifestation of mispricing.

Although, the size premium remains strong, it is also believed that the persistence of the size effect can be explained within the rational framework of theory. In fact, very little, if any, behavioural models explicitly consider the size effect. In the portfolio time-series tests, it has been shown that the market (or Resource and Findi) betas may be understated for small stocks, even though a lag is included. This bias could be more severe in tests that use individual assets. Thus, the significance of the size coefficient is likely to be a manifestation of badly estimated loadings. In addition, Acharya and Pedersen (2005) and Stoll and Whaley (1983) show that market microstructure effects can explain the size premium and such adjustments (inclusion of a liquidity factor for example) have not been performed here. Thus, the size effect is expected to persist after risk adjustment with methods that do not consider the effects of illiquidity and trading costs. In fact, Brennan *et al.*

(1998) show that the size effect persists after a control for risk with the FF3F is made, but it dissipates after an adjustment for market microstructure effects. In addition, it is possible that these results stem from the overly restrictive methodology of Brennan *et al.* (1998). A set of results, which addresses serial correlation in coefficients, but does not adjust for the bias of Brennan *et al*. (1998), is also performed, but not reported. Although these regressions are marginally more supportive for the BE/ME premium, the results obtained without the bias adjustment are quantitatively the same.

The results presented in Table 5.15 are in stark contrast to the findings of van Rensburg and Robertson (2004). In their results, loadings on the FF3F factors have no power in forecasting returns and characteristics keep their power to forecast returns after control for factor loadings. A possible reason lays in the difference between the methodology empted here and the van Rensburg and Robertson (2004) study. First, the error-in-variables problem does not affect the results of this study because it impacts the dependent variable in the Fama-MacBeth regressions and thus it is captured by the disturbance term. Second, in loading estimation, van Rensburg and Robertson (2004) use a very short estimation period and a univariate regression. In this thesis, the full listing period of each asset is used to estimate the pricing errors in a multivariate regression. And since there is much evidence that the increased precision gained in full-period estimates more than offsets the error induced by failure to incorporate time-variability of loadings, mismeasurement of pricing errors, caused by poorly estimated betas, is kept to a minimum. Third, there are no sorts, thus the multicollinearity between factor loading and characteristics does not present a practical problem.

The findings presented in Table 5.15 contradict one aspect of the results found in Brennan *et al.* (1998). The authors show that the value premium survives control for risk. However, in a longer period, Davis *et al.* (2000) show evidence that if the test employed here was to be used in a longer sample period than the one employed in Brennan *et al.* (1998), the value premium would be “priced out”. In effect, the findings presented here concur strongly with the argument of Davis *et al.* (2000) that the FF3F model is a better speciation for asset returns than the characteristic model.

Table 5.15
Tests FF3F and RS-FF3F against Firm Characteristics

Coefficients in the table are calculated with method in Brennan, Chordia and Subrahmanyam (1998), coefficients are the intercepts of time-series regressions the factors on month-by-month coefficients of cross-sectional OLS regressions of model's pricing errors. Model's pricing error of firm *i* in time *t* is a sum of a intercept of a time-series regression of firm's *i* excess return on model's factors and this regression's a residual at time *t*. t-statistics are calculated with the Newey-West (1987) standard errors. Full listing period was used in the time-series regressions. The regressions of smallest 20% of firms include one lag of the Market, Resi or Findi factors. The remainder of regressions include do not include a lag of the Market, Resi or Findi factors. Each month, only stocks with liquidity measure of more than 0.1% or cost more than 100c are included in the regression. Liquidity measure is a twelve-month average of monthly trading volume scaled by end-month shares in issue. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price. E/P is earnings per share scaled by a price. C/P is cash flow per share scaled by a price. BE/ME is the book value of equity scaled by market capitalization. All accounting data becomes effective five months after the financial year-end. All variables are standardized and winzorised at 2.5% and 97.5%. If earnings are positive then E/P(+) is the earnings yield and E/P Dummy is 0, otherwise E/P(+) is set to zero and E/P Dummy is set to 1. Similar conventions pertain to the C/P ratio. The reported R^2 is the average of individual R^2 of each cross-sectional regressions. All coefficients are multiplied by 1000, for clarity.

	Constant	Size	E/P	C/P	BE/ME	E/P Dummy	C/P Dummy	Average R^2
Panel A: FF3F-adjusted returns								
(1)	7.31***	-4.12***						0.007
t-stat	3.54	-2.89						
(2)	4.25***		-0.40			0.40		0.013
t-stat	3.10		-0.26			0.67		
(3)	4.60***			0.31			0.17	0.011
t-stat	3.83			0.24			0.03	
(4)	5.11***				3.00*			0.006
t-stat	3.49				1.70			
(5)	7.22***	-3.46**			1.52			0.012
t-stat	3.58	-2.30			0.82			
(6)	7.74***	-4.14***		-0.68			-1.28	0.035
t-stat	4.05	-3.07		-0.55			-0.22	
Panel B: RS-FF3F-adjusted returns								
(1)	6.87***	-4.43***						0.007
t-stat	3.10	-3.24						
(2)	3.67***		0.02			0.43		0.014
t-stat	2.70		0.01			0.64		
(3)	3.95***			0.12			0.62	0.013
t-stat	2.93			0.10			0.11	
(4)	4.56***				3.07*			0.007
t-stat	3.05				1.80			
(5)	6.87***	-3.82***			1.57			0.014
t-stat	3.11	-2.54			0.86			
(6)	7.35***	-4.57***		-0.96			-1.06	0.039
t-stat	3.37	-3.54		-0.86			-0.18	

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

5.3.3 Asset Pricing – A synthesis

The evidence presented so far strongly supports the FF3F and its variant, the RS-FF3F. The models are now subjected to yet another test, which not only address the methodological concerns of Kandel and Stambaugh (1995) and the data-snooping concerns of Lo and MacKinlay (1990a), but also provide an illustration of how useful the models are for asset pricing on the JSE.

Table 5.16 represents a series of cross-sectional tests. These are different from the ones set up previously, as the Fama-MacBeth regressions are used instead of the CCSR method, and a full set of 46 test assets forms the basis of the tests. There are the 24 size and F/P sorted portfolios and the 22 industry sorted portfolios. The table shows the different cross-sectional estimates of each factor premia. An average pricing error of each of the models is shown in the last column. Due to a large cross-section of assets and a short data-series, statistical significance testing is not performed.

The results clearly illustrate the argument of Kandel and Stambaugh (1995), i.e. that the estimated premium to a factor is a direct consequence of the test assets employed. The magnitude of the estimated premia of the various models differ from the ones obtained in the cross-sectional test presented above. Unsurprisingly, in comparison to tests conducted on the industry portfolios, the Market, the Resource and the Findi premia are lower in tests presented in the table. Similarly, the premia on the size and the value factors are smaller than the ones estimated with the size and F/P sorted portfolios. In fact, the market premium in the FF3F model and the Findi premium in the RS-FF3F model are the only two estimates that are different from zero at conventional levels. If the zero-beta rate is restricted, however, all of the premia associated with the univariate CAPM and the two-factor RS-APT are different from zero. Consequently, it appears that the FF3F model is not a silver bullet for asset pricing on the JSE, as its factor premia are insignificant and the pricing errors are only marginally lower than the CAPM and the RS-APT. Interestingly, judging from the size of the pricing errors, the FF3F, with the market premium as a factor, seems to outperform the RS-FF3F in all of the specifications. The difference is small, however, and it varies between 0,03% and 0.04% per month.

Table 5.16
A Fama-MacBeth Regression Cross-Sectional Asset Pricing Test of the FF3F and RS-FF3F Models

Coefficients in the table are time-series averages of month-by-month cross-sectional OLS regressions of asset's lead returns on factor loadings between July-92 and July-05. The premiums are the estimated coefficients. Calculation of standard errors follows Newey-West (1987), which adjust for serial correlation up to four lags. The test assets comprise of 12 size-value portfolios that are an intersection of four size sorted portfolios and three BE/ME sorted portfolios, and additional 12 test assets that are a intersection of four size sorted portfolios and three C/P sorted portfolios. Also, the 22 industry portfolios are included. Firm's industry is determined from "Nature of Business" rubric in McGregor's Manuals. Firms cannot change industry if their name does not change. The R^2 follows Jagannathan and Wang (1996) and the adjustment follows Gujarati (2003). The pricing error is a simple average of the absolute values of pricing errors. n/a is assigned to pricing errors that produced from specifications that yield negative premia.

	λ_o	λ_M	λ_R	λ_I	λ_{SML}	λ_{VMG}	Adj. R-sq	Pricing Error
Panel A: Unrestricted Zero-beta Rate; Value-Weighting								
CAPM	0.36%	0.80%					0.0422	0.37%
t-stat	0.57	1.14						
APT	0.15%		0.85%	1.01%			0.0809	0.40%
t-stat	0.27		0.85	1.56				
FF3F	-0.15%	1.17%**			0.21%	0.29%	0.1795	0.36%
t-stat	-0.33	1.97			0.43	0.39		
RS-FF3F	-0.14%		1.13%	1.22%*	0.19%	0.63%	0.2156	0.37%
t-stat	-0.28		1.13	1.89	0.34	0.77		
Panel B: Unrestricted Zero-beta Rate; Equal-Weighting								
CAPM	2.01%**	-0.84%					0.0398	0.51%
t-stat	3.62	-1.37						
APT	1.96%**		-0.51%	-0.77%			0.0457	0.48%
t-stat	3.41		-0.54	-1.27				
FF3F	1.55%**	-0.69%			0.42%	0.80%	0.1506	0.38%
t-stat	3.02	-1.13			0.70	0.93		
RS-FF3F	1.20%**		0.39%	-0.39%	0.90%	0.17%	0.2272	0.42%
t-stat	2.61		0.44	-0.65	1.55	0.17		
Panel C: Restricted Zero-beta Rate; Value-Weighting								
CAPM	n/a	1.19%***					0.0291	0.40%
t-stat	n/a	2.45						
APT	n/a		1.01%	1.17%***			0.0786	0.38%
t-stat	n/a		1.17	2.40				
FF3F	n/a	1.02%**			0.21%	0.29%	0.1772	0.36%
t-stat	n/a	2.17			0.42	0.40		
RS-FF3F	n/a		0.97%	1.08%**	0.16%	0.62%	0.2133	0.38%
t-stat	n/a		1.16	2.32	0.31	0.77		
Panel D: Restricted Zero-beta Rate; Equal-Weighting								
CAPM	n/a	1.46%***					-0.1768	0.52%
t-stat	n/a	2.74						
APT	n/a		1.56%**	1.34%***			-0.1565	0.52%
t-stat	n/a		1.98	2.52				
FF3F	n/a	0.90%*			0.48%	0.87%	0.0031	0.40%
t-stat	n/a	1.81			0.81	1.01		
RS-FF3F	n/a		1.68%**	0.77%*	1.10%*	0.11%	0.1315	0.44%
t-stat	n/a		2.18	1.65	1.85	0.11		

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

However, it is argued that the FF3F and the RS-FF3F should not be scrapped. First, these models capture much more of the cross-sectional variation in returns than the CAPM or the RS-APT, meaning the FF3F loadings can predict returns better than the Market (or the Resource and the Findi) betas. Second, the pricing errors of the model are smaller in the tests that use equal-weighted assets. Actually, in those tests, the pricing errors of the FF3F and the RS-FF3F are about the same magnitude as the mispricing seen in the tests on value-weighted assets. Third, the estimates of the size and the value premia are of about the same magnitude as the ones computed in the US markets, and, more importantly, they are close to the time-series estimates. The low statistical significance for the factors could be a function of the nosiness in the data, as well as its short length. Specifically, the high standard of errors presented here are, in part, a consequence of low diversification of the test assets, which induces an error into the dependant variable. Gujarati (2002) shows that such mismeasurement results in an overstatement of the variance of the residuals and, hence, the standard errors. Fourth, the premiums on the Market (or the Resource and the Findi) are only reliably positive in regressions that include the FF3F factors.

Lastly, the full set of assets is difficult to price in other markets too. The only instance of a test of the FF3F on a set of assets consisting of the size and BE/ME sorted portfolios and industry sorted portfolios in the surveyed literature appears in Brennan *et al.* (2004). Remarkably, their results are near identical to the ones presented in Table 5.16. Particularly, they show that the premia on the size and the value factor dissipate but the VMG premium is slightly larger than the SML premium. Also, the market factor, insignificant in tests on the size and the BE/ME sorted portfolios, becomes reliably different from zero at conventional levels. And the pricing errors in these tests are as large (if not larger) in cases where the industry or the size and BE/ME sorted sets are used in isolation. Perhaps it is the time-variability in factor loadings of industry sorted portfolios, documented by Fama and French (1997), that compounds the error-in-variables problem and biases down the premia on the FF3F factors.

Interestingly, the analysis of the pricing errors does not indicate that the RS-APT is a better model than the static CAPM. Although in one of the specifications, the APT marginally outperforms the CAPM by 0.02% per month, in another it does worse by the approximately the same amount. While in yet another specification, the models perform about the same, and in the test where assets are weighted equally and the intercept is unrestricted, the premia are negative - thus a comparison between the models is not possible. In fact, in the test that is most robust statistically, where the test assets are value-weighted and the zero-beta rate is unrestricted, the CAPM seems to outperform the two-factor APT.

CHAPTER 6: DISCUSSION AND CONCLUSIONS

6.1 Summary of the Empirical Results

In the first empirical part of the thesis, the size and the value effect has been analysed, and the premia exist on the JSE. This finding is robust to various methodologies and, admittedly imperfect, adjustment for trading costs. As in Auret and Sinclaire (2006), the book-to-market has the strongest power to predict returns. Although the equal-weighted estimates of the BE/ME ratio effect are only slightly higher than those obtained with the E/P or the C/P, the value-weighted book-to-market effect is more persistent than the other premia. The E/P effect is the weakest: it is not only small, but it is highly sensitive to trading costs and, on a value-weighted basis, it almost dissipates. This is surprising, as van Rensburg and Robertson (2003a) show the E/P effect to be the strongest predictor of returns. In fact, all of the estimates of the premia are lower than leading prior South African research has shown.

In addition, the value effect and the size effect have been found to be independent of each other. This fact is corroborated with cross-sectional regressions of Fama and MacBeth (1973) and the more powerful independent sorts of Daniel and Titman (1997). The best measure of the value premium is the book-to-market ratio, which, in univariate and bivariate sorts, has produced the widest spread of returns and has been found to subsume all other value-growth indicators in multivariate regressions.

In the second part of the empirical analysis, the static CAPM and the two-factor APT of van Rensburg and Slaney (1997) have been tested. In sum, the models can not be seen as accurate equilibrium models of the risk-return relationship. Although a time-series test on grouped data does not yield strong rejection of the models, this result is seen as a consequence of overall low excess returns during the sample period. In addition, the magnitude of the size premium actually increases after risk adjustment in the time-series format. More importantly, the robust cross-sectional tests reject outright the static CAPM and the RS-APT. In specifications that do not enforce a restriction of equivalence between the risk-free rate and the zero-beta rate, the estimated Market (or Resource and Findi) premia are negative.

Subsequently, a concern that the poor performance of these models is a result of data-mining has been investigated, with an analysis performed on ungrouped data (Lo and MacKinlay, 1990a). It has been found that the CAPM and the RS-APT cannot *completely* “price out” firm characteristics such as size and value-growth indicators. However, in tests on ungrouped data, it has been found that the models do act in the right direction in explaining the value effect. This result has not been fully validated on a cross-sectional test that uses ungrouped data, as such specification, although most powerful in a statistical sense, is unpractical due to the problem associated with imprecision of estimated factor loadings.

Once the size and the value premia have been confirmed and the two “traditional” models rejected in Table 5.9, the three factor model of Fama and French (1993), and its variant, have been constructed and tested. The tests in the third part of the empirical analysis have provided support for these models. The GRS test and Cochrane’s (2001) χ^2 tests have rarely, if ever, rejected the models. Specifically, in the time-series test, the spread in pricing errors between small and large firms, as well as value and growth, is reduced. The models perform well in the cross-sections test too. Although the size risk is not associated with a reliably positive risk premium, the value premium is positive, with the estimate usually falling three standard deviations from the mean. After inclusion of the FF3F factors, the premia to Market (or Resource and Findi) factors are not different from zero.

In a time-series test on ungrouped data, the FF3F and the RS-FF3F models have been able to account for the value effect. In particular, it has been found that none of the F/P ratios have power to predict the pricing errors of these models after size has been included as the explanatory variable. This is a marked success of the three factor model, especially given that the time-series in nature of the test, which is known to be restrictive, increases power. The time-series estimate of the value premium was much lower than the cross-sectional estimate. Thus, the risk-adjusted for value (growth) stocks would have been even lower (higher) if a larger estimate of the premium was used.

In these tests, the size effect has attenuated, but has not been extinguished, as market equity has shown significant power, statistically speaking, to predict the pricing errors left behind by the FF3F and the RS-FF3F. It is believed that market microstructure effects are the main reason for presence of the size effect. In fact, very little, if any, behavioural models explicitly consider the size effect. However, the liquidity story of Amihud and Mendelson (1986) and the information story of Merton (1987) apply directly to the size effect. JSE is an illiquid market, where, in comparison to the US, little time and money is spent on equity research for smaller firms. In addition, the bias in computed betas for illiquid assets may be a substantial reason for the persistence of the size effect.

In a series of cross-sectional tests on industry and size and F/P question the validity of the FF3F models. However, these results are highly consistent with evidence in Brennan *et al.* (2004), who perform similar analysis on US data. Perhaps, as Fama and French (1993) note, the FF3F is just a model and, by construction, it is flawed and its poor performance in the test on a full set of assets is its weakness. Another important result that appears in the Table 21of the thesis is that the static CAPM is not significantly worse, and is, in some instances, better than the other models. Thus, as Black (1993) puts it, announcement of its death is premature.

6.2 Results of the Hypothesis

Formally, Hypothesis 1.1 has been rejected, as market equity and an array of value-growth indicators can predict returns. Hypothesis 1.2 has also been rejected, as the size and the value effect have been found to be independent of one another. Lastly, Hypothesis 1.3 is also rejected, as the BE/ME effect has been found to subsume the other F/P effects.

Broadly, Hypothesis 2.1 has been rejected. However, its rejection is not unequivocal. as the low *t*-statistics associated with the coefficients on value-growth indicators in the Fama-MacBeth tests, shown in Table 5.15, provide support to the hypothesis.

Hypothesis 3.1 is firmly rejected, as all the asset pricing tests on size and the F/P sorted portfolios yield statistically small pricing errors a feat the CAPM and the RS-APT have not achieved. However, Hypothesis 3.2 in not rejected, as the tests on the full set of assets indicates only marginal out-performance of the FF3F models. Lastly, although the value effect dissipates after risk adjustment with the three factor model, or its variant, Hypothesis 3.3 is not rejected outright because the size effect persists.

6.3 Discussion on Endogeneity

A valid criticism of the three factor model is that endogeneity is the sole reason for its successes. In other words, it should not be surprising that returns on a set of assets can be explained by factors computed with a similar method as the test portfolios. It is argued here that it is unlikely that endogeneity plays a major role in the tests shown above

Firstly, the FF3F factors are computed with an intersection of size and BE/ME sorted portfolios. However, the FF3F models capture more variation (loadings on the FF3F factors are more dispersed and more significant) when the set of test assets are formed with the cashflow yield being used as the value-growth indicator. If endogeneity was driving the results, the C/P-sorted assets would load weakly on the value factor. Second, in the construction of the VMG, firms that are neither growth nor value are not included in the factor. However, the loadings on the value factor of portfolios that contain the neutral firms are often reliably different from zero.

Third, it can be said that the "Small" portfolio in the SML ("Small minus Large") is a combination of the two portfolios with the smallest firms (Portfolios III and IV in the tables 5.4 and 5.5). Since it is a value-weighted factor, stocks that constitute the three portfolios with smallest firms (portfolios marked IV in the tables) probably do not receive much weight in the factor, yet they have the highest loadings on the size factor.

Fourth, it was found that some portfolios containing the largest firms load positively on the size factor, especially in tests that use equal-weighted assets. Because of the heavy skewness in the distribution of market equity on the JSE, it is likely that the portfolios of large firms will include some mid-sized firms. If these portfolios are equal-weighted, the mid-sized firms are given a relatively large weight. However, these firms will be in the "Large" part of the SML factor, and, since the portfolios in the factor are value-weighted, these mid-sized firms receive very little weight in the factor. Consequently, a positive SML beta for the portfolios containing large firms in equal-weighted tests implies that the returns of mid-sized firms co-vary with return of small stocks (in the "Small" part of the SML), despite the fact that these firms are themselves included, but with a small weight, in the "Large" part of the SML.

Fifth, it is argued here that the ability of the FF3F models to "price out" firm characteristics is another evidence that endogeneity is not driving the successes of the FF3F models. Because the value effect is predominantly found among the smaller firms, and the VMG factor is value-weighted, many of the individual shares would receive a very small weight in the factors.

The last argument against endogeneity being the driver of FF3F's pricing ability appears in Freidman (2006), who, with the same data set to the one used in this thesis, constructs a variant of the three factor model. Although he excludes firms that constitute his test assets from the FF3F factors, his regressions show that the model can capture a large component of return variation. In fact, his results are quantitatively unchanged from tests that do not exclude constituents of the test assets from the FF3F factors.

However, it is recognised that endogeneity must have an effect on the results of the asset pricing tests. Fama and French (1995) combat this problem by splitting the sample of firms in two; one is used to form the factors, while the other forms the assets. Because the cross-section of returns listed on the JSE is small relative to the markets in the US, such a powerful test not practical.

6.4 Limitations of the Empirical Analysis

The most salient limitation of any financial research on the JSE is the poor quality of the sample. It is short, contains few firms, and consists of assets that do not trade frequently. Admittedly, the sample period is larger than many other studies of this type on the JSE, but it is tiny if compared to the research in the markets in the US. For example, Fama and French (2006) consider nearly 80 years' worth of data (as opposed to the 13 that is used here). The length of the sample impacts many of the tests that have been performed above. For example, the magnitude of the size and the value premia calculated in the thesis are of the same magnitude as the ones found in the markets in the US, but some of the associated *t*-statistics are often smaller. Therefore, it cannot be established whether some of the effects found in this research are real, yet noisy, and that the high standard of errors are a consequence of that noise; or, if the effects are simply not present on the JSE and the low level of significance supports this fact. In addition, the mismeasurement of expected returns with the time-series averages can be reduced with the length of the time-series (Elton, 1999). Consequently, the short sample limits the power of all time-series tests. It also increases standard errors of all coefficients in the cross-sectional tests, as the mean returns and dependant variables are often mismeasured in shorter samples. The length of the sample imparts on the cross-sectional tests too, as the precision of the second-moment matrix of time-series residual increases in longer periods.

The second limitation is the small cross-section of assets on the JSE. The number of sample firms in the US runs into thousands, while it is capped at about 500 here. The problem is particularly conspicuous in the tests that use independent portfolio sorts and it is compounded by the fact that size and the F/P ratios appear to be correlated. As a result, a fine independent sort is impossible and it is still believed that the course sort used in this thesis does not account for the co-linearity of the characteristics. A more serious problem of a limited cross-section of assets is that many of the test-assets are not well diversified. This problem impacts on virtually all tests. The means of portfolios are misstated, as firm-unique incidents are included in the measure. This induces an error in dependent variables in all regressions, which leads to misstated *t*-statistics. Also, variances of all portfolios are overstated and thus inference in the one-way and two-way sort tests is made difficult.

However, the largest problem of any financial research on the JSE is the non-synchronous trading. For instance, it sharply reduces the cross-section of usable assets, exacerbating the problems discussed above. However, it is believed, following Dimson (1979), that the largest problem thin trading instigates is the bias in computed betas. An effort has been made to alleviate the problem by including a lag (sometimes two) in the computations of the factor loadings.

It is believed that some of the results presented above are a direct consequence of incompleteness of the adjustment for this bias. In particular, in cross-sectional regressions the size effect is persistent after risk-control with the FF3F and the RS-FF3F. Or, in some time-series tests, the intercepts in tests that use value-weighted assets are not different from zero at the conventional levels, while the ones that use equal-weighted assets are strongly positive. Since, according to Dimson (1979), non-synchronous trading of shares shrinks the estimates of factor betas, by construction, the estimated intercept is biased upwards. Lastly, cross-sectional tests that use equally-weighted data yielded large intercepts. Certainly, an economy where the zero-beta rate exceeds the risk-free rate by 2% per month is implausible.

Consequently, it can be argued that better measures should have been employed. The trade-to-trade method advocated by Bradfield (2003) could have been employed, or more than one lag of the factors is required to account for thin trading. The unavailability of data precluded the better, according to Bradfield (2003), method of beta estimation. And optimal lag structure for estimation of betas has not been investigated for two reasons.

First, there is no theoretical underpinning as to how many lag (or lead) terms ought to be included in the time-series regressions. Ibbotson, Kaplan and Peterson (1997) use just one and they show that their structure is sufficient. If more lags are to be added, what is the optimal number? Maybe it is two, or ten, or twenty. It is conceivable that one can find an empirically derived lag structure that "works", but such a procedure is akin to data-mining. Second, to the best knowledge of the author, most MBA and undergraduate courses in finance do not teach inclusion of a lagged term in beta estimations. Most likely, many practitioners also do not estimate betas in this extended way. It is the desire of this research report to test the CAPM as it is commonly applied and it is deemed that estimating betas with one additional lag is a sufficient approximation of the methods of most practitioners.

6.5 Directions for Future Research

A shortcoming of the study is that the robustness of the three factor model has not been adequately established. It is believed that the FF3F ought to be tested further. For instance, impact of endogeneity on the FF3F ought to be properly tested, the impact of trading costs assessed, and the effect of winzorising formally addressed. Most importantly, the impact of "segmentation" of the JSE into Resource and Findi "risks" needs to be addressed. Perhaps, construction of industry-neutral factors, as in Lewellen (1999), should be undertaken. However, it is believed a test that uses factors constructed only with Findi shares could serve as a robustness exercise.

The results also indicate that the value effect exists; illiquidity, proxies with size, is important; and that the static CAPM should not be scrapped. Therefore, future research should explore these topics. In particular, the power of market betas, which are robust to the bias stemming from non-synchronous trading, to forecast returns, ought to be re-examined. Perhaps, the inclusion of a richer lead-lag structure in estimations, or the use of the trade-to-trade method, advocated by Bradfield (2003), would recover CAPM pricing for the JSE. Next, the size and the value effects ought to be re-examined in the context of this improved model.

In light of the strength of the size and the value effects and poor performance of the static CAPM, it is unlikely that a “fixed” model would explain the “anomalous” premia. Consequently, a richer specification of the model would be called for. Specifically, it is believed that the liquidity-adjusted CAPM of Acharya and Pedersen (2005) would go far in explaining the effects, particularly the size premium. In addition, conditional versions of the model ought to be constructed, as it has been shown internationally that these specifications can, with varying degrees of success, explain the value premium.

It is also believed that the two-factor APT of van Rensburg and Slaney (1997) ought to be constructed that incorporates illiquidity and time-variability in loadings. However, perhaps it is on the theoretical front that the model needs to be developed. It is unclear how intertemporal hedging concerns of Merton (1973) would apply to a “segmented” market like the JSE. Perhaps, the Resource factor, which is co-linear with the exchange rate, acts as state variable in the ICAPM, and the RS-APT model is the ICAPM.

However, before these improvements are made, the contention of Fama and French (2003) holds. In particular, “A multifactor (model), like that of Fama and French (1993), where the additional factors are portfolios of value and growth stocks, may nevertheless provide a good approximation to average returns.” (Fama and French, 2003, p12).

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