AN EXAMINATION OF VALUE AND GROWTH BASED INVESTMENT STRATEGIES IN THE AUSTRALIAN EQUITIES MARKET

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Abstract

Numerous studies have found that value-based investment strategies yield higher returns than growth-based investment strategies. However, controversy surrounds the interpretation of why value-based yield the higher returns. There is not consensus among researchers as to whether value stocks are fundamentally riskier than growth stocks, or whether psychological biases of investors result in an irrational pricing of stocks, and higher returns to the value stock portfolios. To add to the evidence of this debate, this thesis examines value, and growth-based investment strategies in the Australian equities market from 1990 to 2000. Value portfolios are formed by selecting stocks that have a strong past financial performance, and are expected to have a relatively poor future financial performance as gauged by financial variables. Growth portfolios are formed by selecting stocks that have a poor past financial performance, and are expected to have a relatively strong future financial performance as measured by financial variables. The financial variables used to classify stocks into the growth and value stock portfolios are the earnings-to-price, cash flow-to-price, book-to-market, and growth in sales variables. Examining one and two-year buy-and-hold returns, value stock portfolios are on average, found to yield higher returns than growth stock portfolios. The superiority of the value portfolio returns are also found to be invariant to the monthly calendar initiation date of the investment strategies. As far as an interpretation of the discrepancy in value and growth stock portfolio returns goes, the Capital Asset pricing Model (CAPM) measure of risk, β, is found to be misspecified. It is however, not clear whether the superior value portfolio returns are a consequence of investor irrationality, or value stock investments being riskier than growth stock investments. It seems as if the industry classification may be responsible for growth and value portfolio returns, and this may have an impact on the interpretation of the relationships between financial variables and stock returns. To interpret the relationships between the financial variables and stock returns, a multivariate linear regression model is applied to stock returns. Multicollinearity between the earnings-to-price and cash flow-to-price ratios is found, and when controlled for, the book-to-market variable is the only variable that is linearly related to stock returns.

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INTRODUCTION

An investor who chooses to invest in common stocks, or equities, selects stocks that are deemed worthy of investment according to certain criteria. The criteria according to which stocks are selected define what is termed an investment strategy. A brief review of equities research literature is sufficient to highlight the differing views researchers have on which investment strategies yield the highest risk-adjusted returns. This contentious issue arises because of the complex nature of the relationship between the risk, and the returns yielded by a common stock investment.

Rational asset pricing, or traditional finance theorists believe that investment returns reflect the underlying risk profiles of securities. Higher returns are believed to be associated with riskier securities, and lower returns are believed to be associated with less risky securities. Once security returns are correctly adjusted for risk, traditional finance theorists argue that different investment strategies yield insignificantly different returns from each other.

A fundamental assumption of any rational asset pricing model is that investors, in the aggregate, are able to correctly appraise the risk, and consequently the price, of any security. Behavioural finance theorists believe that investors make mistakes when assessing the risk of different securities. The discrepancy in returns among different investment strategies is therefore attributed, from a behavioural finance perspective, to the inability of investors to rationally appraise the risk of the underlying securities. Behavioural finance theorists therefore believe that investment strategies can be developed to capitalise on the mistakes of investors in the aggregate, yielding higher returns without taking on higher levels of risk.

The conflicting viewpoints of the rational and behavioural asset pricing theorists become apparent when the discrepancy in returns between two long-term investment strategies termed value and growth-based investment strategies, is examined. Value and growth-based investment strategies are defined in numerous ways. However, as far as this thesis is concerned, financial variables that proxy for past, and expected future financial performance are the criteria according to which stocks are selected for value and growth-based investment strategies. A value-based strategy involves investing either in stocks that have had a strong past financial performance, or in stocks that are expected, by investors, to have a poor future financial performance relative to other stocks. A growth-based strategy involves investing either in stocks that have had a poor past financial performance, or in stocks that are expected, by investors, to have a strong future financial performance relative to other stocks.

A growing body of evidence indicates that value-based investment strategies yield higher returns than growth-based investment strategies. The rational asset pricing theorists see this as a consequence of a growth-based investment strategy incorporating less risk than a value-based investment strategy. The behavioural asset pricing theorists argue that the success of value over growth-based investing lies with biases in investor decision making which result in an incorrect appraisal of a security's risk. The value-based strategy is thus seen as an exploitation of this flawed decision making.

The debate as to whether, and why value stocks yield higher long-term returns than growth stocks is not easily resolved. This is because in the first instance, extensive research in the United States of America (US) equity markets, documents the success of value over growth-based investment strategies. There is however, relatively little research on value and growth-based investment strategies in other stock markets of the world. The superiority of the value-based strategies may therefore be specific to the US equities market. No definitive conclusions can be drawn based on the results of studies conducted in one market alone.

Additionally, conflict over why value stocks yield higher returns than growth stocks rests in the inability of researchers to empirically estimate the risk of a security. This is because there is no economic theory that endogenously links economic variables to the prices of assets in a robust framework. Apart from the metaphysical concept that all securities face uncertainty, and incorporate some component of risk, one is therefore incapable of accurately defining the risk profiles of individual securities.

Studies examining the success of value and growth stocks have however, revealed empirical relationships between the financial variables used to differentiate value, from growth stocks, and stock returns. These relationships indicate that these financial variables may proxy for omitted risk variables in the pricing of assets.

From these preceding arguments, this thesis can be defined as an examination of value and growth-based investment strategies in the Australian equities market from a rational, and behavioural asset pricing perspective. The primary aim of this thesis is to see whether a long-term value-based investment strategy yields higher returns than a growth-based investment strategy in the Australian market. Whether risk, as defined by rational asset pricing models, or investor bias, as defined by behavioural asset pricing models, describes value and growth stock portfolio returns is also examined.

This study is important as it analyses the success of value and growth-based investment strategies in the Australian equities market. These investment strategies have not been extensively analysed in the Australian markets in the past. The results of this study therefore contribute to the body of evidence on whether financial variables can be used as criteria to devise a successful investment strategy, or whether the results of previous studies are a consequence of data mining. By considering the relationships between financial variables and stock returns, this study adds to the understanding of how financial markets, and their participants operate. This might shed light on economic theory which links financial variables to asset prices, thereby indicating whether assets are rationally, or irrationally priced.

Unlike previous studies on value or growth-based investments, this thesis also considers the impact an industry classification has on value and growth stock returns. Lastly, the spectre of seasonality as a determinant of stock returns is examined by seeing whether the calendar initiation date of value and growth-based investment strategies can account for the discrepancy in value and growth stock returns. This too is not widely considered in previous studies of value and growth-based investment strategies.

The examination of Australian equity returns is also important given that the Australian equities market has grown substantially over the last 18 years. Domestic market capitalisation has risen from $Au 42 billion in 1982 to $Au 536 billion at the end of 1998. This represents a 12.77-fold increase in 16 years. Daily market turnover has also increased subsequent to the advent of the Stock Exchange Automated Trading System

(SEATS) in 1987. This turnover has increased from $9.5 million per day in 1982 to just over $1 billion dollars per day in 1998 (Lynch, 1993). Thus, the Australian equities market provides a large enough sample size in terms of market capitalisation to warrant an extensive analysis of applicable value-based strategies. Because this market is liquid, microstructural biases in calculating returns are also minimised adding to the appeal of analysing different investment strategies in this market.

Part One of this thesis reviews the literature discussing that which is pertinent to this study. Chapter One discusses the theoretical development of rational and behavioural asset pricing models. This is essential as it provides the foundation on which empirical studies of applied portfolio investment have been based. Chapter Two discusses the rationale behind the inclusion of financial variables as determinants of stock returns. This is then followed by a comprehensive discussion of studies that empirically relate financial variables to stock returns from rational and behavioural asset pricing perspectives.

Based on the literature discussed in Part One, Part Two develops the methodological procedures employed in this thesis. Chapter Three discusses the methodologies employed in the studies discussed in Chapter Two. The criticisms of these studies are taken into account, and the broad methodologies utilised in this study are decided on.

The specific adaptation of the methodologies to suit the data that is used in this study is discussed in Chapter Four. Specifically, an explanation as to how stocks are classified into value and growth stock portfolios is given. Using buy-and-hold returns, the computation of returns to value and growth stock portfolios is discussed. Utilising the rational asset pricing measure of risk, β, the calculation of the risk profiles of value and growth stock portfolios is then explained. This is followed by a discussion of how earnings, and sales growth rates are used to examine portfolio returns from a behavioural asset pricing perspective. A discussion of how seasonality, and the classification of stocks into different industries is incorporated into portfolio returns completes the portfolio analysis of value and growth-based investment strategies. Chapter Four concludes with a discussion about the application of a multivariate regression model that is used to define a linear relationship between financial variables, and stock returns.

Part Three analyses the results of this study. The empirical results of this study are reported in Chapter Five. A discussion relating the results of this thesis to similar studies is then undertaken in Chapter Six. Lastly, the conclusions that are drawn with respect to the success of value and growth-based investment strategies within the Australian equities market completes this thesis.

PART ONE

LITERATURE REVIEW

Part One reviews the literature surrounding portfolio analysis as it relates to this thesis. Chapter One lays the theoretical foundation upon which, the empirical studies revealing security pricing anomalies, and their application in studies of investor over-reaction, have been based. Chapter One begins with an overview of the Efficient Market Hypothesis, and the implications of this for asset prices. Next, the Rational Asset Pricing Models are discussed. The implications of the single-factor Capital Asset Pricing Model (CAPM), multi-factor Intertemporal Capital Asset Pricing Model (ICAPM), and Arbitrage pricing Theory (APT), for the pricing of assets, is discussed. This is then followed by a description of the Behavioural Asset pricing Models. This section starts with a description of behavioural biases that have been detected in investor, and human behaviour in general. A discussion of the Behavioural Asset Pricing Models based on these biases is then conducted. The chapter is concluded with a summary of the different approaches to asset pricing. Chapter Two begins with an overview of the philosophy behind Fundamental Analysis. An examination of Fundamental Analysis creates the framework for the discussion of studies that empirically reveal the relationships among fundamental variables, and security returns. Chapter Two is completed through a review of later studies incorporating these relationships into investment strategies. The crux of reviewing these later studies lies in examining the methodologies employed in explaining the success of different investment strategies from a rational and behavioural asset pricing point of view.

CHAPTER ONE

ASSET PRICING MODELS

1.1 Introduction

The purpose of this chapter is to discuss the different theories that purport to explain how securities or assets are priced. The success of any equity investment depends on the returns that can be earned through following a specific investment strategy, in relation to those earned by following alternative strategies. The returns on equity investments are in turn, directly dependent on the prices that are paid for securities. Unless one establishes what factors determine security price levels, one can not explain, why it is that prices, and security returns change as much as they do. The theoretical foundation of asset pricing is therefore discussed in this chapter. This lays the foundation for Chapter Two, which discusses the literature on studies of investment strategies. Studies of investment strategies are shaped, and directly related to asset pricing theory. Hence the need for this theoretical foundation at the outset of this study.

There are two schools of thought that attempt to explain how security prices are determined. The first claims that investors price securities at levels that allow the investors to be adequately compensated for the risk, or uncertainty involved in buying a specific security. This notion is the foundation of the Rational Asset Pricing Models, which are discussed in Section 1.3. The second school of thought claims that investors are biased in appraising the relative risk of one security over another. It is argued that investors are influenced by factors other than those that are relevant to the risk of securities. Consequently, it is claimed that asset pricing depends on the personal biases of investors. This idea leads to the development of the Behavioural Asset pricing Models, discussed in Section 1.4.

Section 1.2 lays the foundation of these two schools of thought. The rationale behind security price formation, the concept of market efficiency, and implications for asset pricing is discussed. This provides the philosophical overview behind the rational and behavioural asset pricing models.

1.2 Efficient Markets

Granger and Morgenstern (1970) observe that trade in financial markets is a multidirectional exercise. A buyer can become a seller at any given opportunity and vice versa if the market is sufficiently liquid. Because of this, unlike agricultural markets for instance, stockpiling does not occur. The future prices of securities depend on the perceptions of what the future earnings, dividends, and prices might be. These perceptions determine the willingness of interested parties to buy or sell a security, therefore determining its market price. As new information changes these expectations, so too does the willingness to buy or sell the security, and the price is changed. The degree to which financial markets are efficient depends on the extent to which information, which will have an impact on future earnings, is incorporated into the decision making process, and by implication, into the price.

The idea of market efficiency is first postulated by Fama (1970). Efficiency is defined at three levels, the weak form, semi-strong form, and strong form of market efficiency. All three together constitute the Efficient Market Hypothesis.

The weak form of market efficiency states that present prices reflect all relevant, historical information incorporated in past prices. This implies that if historical information conveyed any signals about future earnings or performance, it will already be incorporated into the price. Because of this, no abnormal returns are achievable. Abnormal returns are defined as returns in excess of the expected returns, given the risk profile of the asset.

The semi-strong form states that present prices reflect all historical price information and all publicly available information. This implies that prices will only respond to new information bearing on future returns. New information would have to arrive randomly (or else it would have been anticipated and will not be new) and will be incorporated immediately into the price. Because such information arrives randomly, the prices respond in a random manner.

The strong form and third level of market efficiency states that prices must satisfy the semi-strong form. In addition to this, prices must also include all privately known information. Abnormal returns obtainable through insider trading are therefore also eliminated.

An efficient market does not necessarily imply that investors are rational. Market rationality can be defined as the ability of prices to "accurately reflect investors' expectations about the present value of cash flows." (Elton, Gruber, 1995, p.437). In some instances variables other than the present value of expected cash flows are included in this process. This may indicate investor irrationality. Market rationality is however linked to market efficiency. If investors consider other variables in their security valuations, and a profitable investing or trading strategy can be formulated to take advantage of this, then by implication, markets are inefficient.

Thus, in an efficient market where investors are rational, any discrepancy between the return on two or more assets should be explained through the different impact economic variables, or risk, have on the expected future cash flows of each security.

On the other hand, if the investors are irrational, non-economic variables such as behavioural biases will be taken into account. The discrepancy in returns between different assets will not be explained through differences in risk. If a trading strategy can be implemented to exploit this irrationality, this will then imply market inefficiency.

1.3 Rational Asset Pricing Models

As Sharpe (1964) observes, one can not easily give any real meaning to the relationship between the price of a single asset and its risk. To do so requires one to discover and explain which risk component or components influence the asset's price. This requires the development of a market equilibrium theory of asset prices under conditions of risk. An equilibrium model will explain how, given risky assets, investors in aggregate will act, and how this in turn sets asset prices and returns such that the markets will clear.

Markowitz (1959) lays the foundation for the development of rational asset pricing models through formally developing the mean-variance criterion as a means to form efficient portfolios. This explains the necessity of diversification in order to minimise risk. Building on this, Sharpe (1964), Mossin (1966), and Lintner (1965) independently extend this theory through developing an equilibrium model of asset prices known as the Capital Asset Pricing Model (CAPM).

The CAPM begins with the assumption that investors hold mean-variance efficient portfolios and base their investment solely upon the first two moments of a return distribution. Importantly, the assumption is made that investors have homogenous expectations regarding the inputs in portfolio decisions. Because of this, each investor will demand the same percentage of risky assets, and hence the investment decision will be independent of individual preferences, Mossin (1966).

When choosing a pair of portfolios, one consisting of a riskless security and the other, a mean-variance efficient portfolio of risky assets, in aggregate the investors will hold the same risky portfolio. It is shown that in equilibrium this is the value-weighted market portfolio. This consists of all risky assets held in the same proportion as their relative values in the market. Thus, the investor will hold a very well diversified portfolio. From this, it can be shown that the investor will only be compensated for taking on systematic (non-diversifiable) risk. As a result, investors only consider the systematic risk which is the sensitivity of a security's return to market movements when evaluating the prices of securities.

The CAPM is rather restrictive for a number of reasons. Because it is a single-period model investors do not consider events beyond the present period. As Long (1974) notes, this rules out the assumption that a consumer maximises the expected utility of a lifetime consumption stream in a dynamic world. This assumption can only be included where the investment opportunity set is static and future prices of all goods are known with certainty. If this holds, then the lifetime consumption stream is reduced into a single–period timeframe, emulating the static world of the CAPM.

However, Merton (1973) and Long (1974) highlight the fact that at least one element of the investment opportunity set, in the form of interest rates, is directly observable. This also changes stochastically over time, which indicates that the CAPM might not describe investor behaviour correctly. Merton (1973) develops an Intertemporal Capital Asset Pricing Model (ICAPM) in order to remedy this. It is assumed that returns and opportunity sets are not constant because they are dependent upon state variables, which vary stochastically through time. In addition to this, intertemporal investors are assumed to be concerned with maximising the expected utility of a lifetime consumption stream. Consequently, investors are assumed to be concerned with both current returns and those of future periods when constructing their portfolios.

Given this, Merton goes on to show that the consumer's demand for risky assets is contingent upon the consumer's consumption preferences and consequently the standard separation theorem used in the CAPM, does not hold. Instead, a generalised separation holds whereby ICAPM investors are shown to select risky assets according to a linear combination of three mutual funds. Like the CAPM, the first two funds satisfy the mean-variance criterion. The third fund however, allows investors to invest in an asset as a means to hedge against unfavourable shifts in the investment opportunity set. Unfavourable shifts occur where a change in the state variables would result in a fall in future consumption for a given level of future wealth. Put differently, if the price of an asset is positively correlated with the future prices of consumption goods, and decreases the uncertainty of the future price of such goods (acts as a hedge), the equilibrium price of the asset will be higher, Long (1974).

The intertemporal maximiser will therefore not necessarily select assets according to the standard mean-variance criterion alone. If it can be shown that the price of an asset also takes into account a hedge against unfavourable changes in the investment opportunity set, then the pricing of the asset can still be rational.

Long (1974) extends this form of continuous-time capital market equilibrium by considering the multi-period discrete time case. It is argued that although increases in price level uncertainty increase the uncertainty in real wealth, it also increases the expected value of real wealth, which might compensate for the added uncertainty. Hence, a risk averse investor might not decide to hedge the unfavourable shifts in the investment opportunity set. Although Merton's conclusion seems ambiguous, it is evident that risk aversion implies that investors will not be indifferent between their future wealth and future consumption goods.

In an attempt to eradicate this ambiguity, Long (1974) then goes on to develop an equilibrium model that specifically characterises consumers individual hedging tendencies. This equilibrium portfolio of consumers is decomposed into investments in the stock market portfolio, quasi futures contracts, and bills of various maturities.

Fama (1996) notes that the problem with the approach of both Long (1974) and Merton (1973) is that they lack the simple, powerful intuition of the CAPM and Markowitz's concept of mean-variance efficiency. This intuition is however evident in the multi-factor model known as the Arbitrage-Pricing-Theory (APT) proposed by Ross (1976).

The APT is based on the law of one price. This states that if two items are the same, they can not sell at different prices or else investors will react to this, driving the prices to equilibrium. This allows prices to be influenced by common risk factors in returns as well as means and variances, and retains the intuition of the CAPM. Fama (1996) discusses this in relation to the ICAPM and emphasises that the APT makes the assumption that the investor can hold a perfectly diversified portfolio, which is one of its greatest disadvantages. The ICAPM on the other hand does not make this assumption. There is therefore, undiversifiable residual variance in a multi-factor efficient portfolio that must be compensated for in expected returns. Consequently, expected returns vary independently of the loadings on the factors, which in this case are the state variables.

Fama (1996) therefore returns to the models proposed by Merton (1973) and Long (1974) to simplify and explain how the ICAPM can be built on intuition similar to that used in the CAPM.

In characterising the multifactor-minimum-variance (mmv) and multifactor-efficient (me) portfolios, Fama (1996) establishes that they are important in yielding economic insights into the ICAPM. It is argued that they fulfil the same role as the characterisation of minimum-variance and mean-variance efficient portfolios does in understanding the CAPM. It is shown that ICAPM investors hold Markowitz' mean-variance-efficient portfolios, which are multifactor-efficient. The reason for this is to gain the optimal trade-off between expected returns and non-state-variable variance. ICAPM investors also hold portfolios that mimic portfolios for state variables (other multifactor-efficient portfolios). This in order to hedge the uncertainty of future consumption-investment opportunities. Market equilibrium in the ICAPM therefore requires the market portfolio to be multifactor, rather than mean-variance-efficient.

It is explained that because the market portfolio is multifactor efficient, the ICAPM prices assets in a manner that takes investors who differentiate among sources of risk, as well as those who do not, into account. Leading off this, the state variables that may be of concern to investors are discussed. This is however, done at the cost of determining whether the state variable premiums are positive or negative.

Despite this, Fama (1998a) extends this discussion and explains that as long as one can identify and name the number of state variables that are priced in assets and are potentially of special hedging concern to investors, then one can identify which in fact are of hedging concern. From this, the relevant special premiums in returns can be produced. The problem though, is that one has to know the names and numbers of state variables in different multifactor-minimum-variance sets. This, is required in order to place the portfolios that describe expected returns into specific multifactor-minimum-variance sets. From this, those state variables that are priced in assets can be identified. If these variables can not be named, then the ICAPM collapses to the CAPM because in the latter case, no state variables are priced and so their identities are irrelevant.

This poses a problem when trying to identify the state variables and the corresponding factors that proxy for such variables. If all the state variables are not identified and named, one can not accurately price assets unless the risk factors that proxy for all omitted state variables are used. But even so, because the choice of factors that proxy for state variables is not explained endogenously in the asset pricing models, the choice of these factors seems to be arbitrary. This makes it difficult to justify the choice of these variables and hence provides fodder for the argument that any relationship between the chosen variables and returns is indeed spurious.

Any factors that are related to asset prices, but are not identified to proxy for state variables, are anomalous to the rational pricing of assets. These factors are called anomalies. As is seen in Chapter Two, variables that are seemingly linked to asset prices have been discovered in empirical studies on security returns. These relationships are not conclusively explained through the realm of rational asset pricing models. There is a second school of thought that attempts to create a behavioural asset-pricing framework that does describe these empirical relationships. This is known as the behavioural approach to pricing assets.

1.4 Behavioural Asset Pricing Theory

All the asset-pricing models considered in Section 1.3 do not entirely describe how assets are priced. This is because they are only abstractions of reality and can not be expected to model the behaviour of asset prices perfectly. As discussed, this problem is compounded through the pricing of assets being exogenous to economic theory.

As Fama (1998b) notes, in order to reject the concept of efficient markets, and the rational asset pricing models, one has to proffer an alternative hypothesis. It is no use rejecting the CAPM or ICAPM and market efficiency in favour of esoteric market inefficiency. Instead, one must propose a testable hypothesis that describes asset pricing better than the rational pricing models. The alternative must make allowance for irrational behaviour, and describe the anomalies prevalent in asset pricing literature.

From the behavioural perspective, allowance is made for potential lapses in investor rationality caused by factors such as limited computational capacity. As a consequence, this theory deviates from the explicit assumption of investor rationality. The criticism levelled at this approach is that irrationality can lead to an infinite number of investor actions, with an equally infinite number of consequences. In order to be acceptable, Hong and Stein (1999) argue that such asset pricing theories should be based upon realistic assumptions about investor rationality that are at least observable. The evidence should be described in a parsimonious model, which can be scrutinised and tested.

Behavioural characteristics that satisfy this first assumption are discussed next. This is followed by the models that attempt to describe how behavioural investor biases can be incorporated into models describing the pricing of assets.

1.4.1 Psychological Regularities

When considering the chance, or probability of an event occurring, the estimate thereof should change with the receipt of new information according to Bayes' theorem (Edwards, 1968).[1] In experimental psychology, studies carried out to test the use and application of Bayes' theorem indicate that people do not update their beliefs about the future probability of an event in the manner proposed by this theorem.

In a study conducted by Edwards (1968) it is found that on receiving new information people revise their probabilistic estimates in a Bayesian fashion yet the size of the revision is too small. Typically, the subjects required two to nine observations in order to revise their beliefs by the same amount predicted by Bayes' theorem after one observation. The main cause of this conservatism is deemed to rest in the misspecification of the data. People, while aware of the diagnostic meaning of the data, are unable to incorporate this meaning properly with their prior opinions when changing their estimates.

Tversky and Kahneman (1971) on the other hand find that in some instances decision-makers turn out to rely on educated intuition to form opinions. This intuition is found to contradict Bayes' theorem despite formal statistical training indicating that different methods should be applied. This is discussed further in Tversky and Kahneman (1974). Here they find that experimental subjects tend to place too great an emphasis on recent

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[1] Specifically, Kahneman, Slovic and Tversky (1982) define Bayes' theorem as it applies to decision making in the following manner. The probability of hypothesis, *A*, after date, *D*, is given by $P(H_A \mid D)$. This can be written as:

$$P(H_A|D) = \frac{P(D|H_A)P(H_A)}{P(D)},$$

where: $P(D \mid H_A)$= *The probability that date, D, is observed if* H_A *is true, and*
$P(D)$= *The unconditional probability of date D.*

patterns in data. In contrast to this, too little emphasis is placed on the statistical properties of the population from which the data was drawn. Importantly, this action leads people to believe that they see patterns in random sequences. This bias is known as the representative heuristic.

While representative heuristic and conservatism seem to be conflicting concepts, Griffin and Tversky (1992) resolve this apparent contradiction by explaining how people update their beliefs according to the strength and weight of new information. The strength refers to the nature of the information, and whether the information content is extreme, or coherent. The weight refers more to the statistical validity of the information such as a relevant sample size.

In this framework, people are found to make decisions that are too focussed upon the strength of the information and not enough upon the weight thereof. So for instance, conservatism would occur where the information has a high weight, but low strength. Hence, people will not attach a great deal of importance to the information despite the statistical implications warranting greater attention. Likewise, the representative heuristic will occur where the information is high on strength, but low on weight and hence too much emphasis will be placed on the value of the information.

Another psychological regularity to be uncovered in numerous studies is that of overconfidence. Griffin and Tversky (1992) explain how people in different spheres, from security analysts to negotiators, overestimate their own abilities. Greater weight is given to their own judgements than those judgements that are perceived by the public. This is not so severe however, for those tasks such as stock valuations whose results can only be observed sometime in the future.

The last psychological regularity of consequence for investors is that of biased self-attribution. As Miller and Ross (1975) and Langer and Roth (1975) term it, this bias refers to the case where a person's self-confidence grows when public information agrees with his own, but does not drop commensurately when this information disagrees with his private information.

It is the work in this line that has laid the foundation for the behavioural finance models attempting to document investor irrationality and the impact on asset pricing. The representative heuristic and biased-self attribution concepts both lead to the modelling of over-reaction. Over-reaction refers to the scenario where investors place too much emphasis on past or new information about companies. Over-reaction drives the stock price too high or too low to be warranted in an efficient market. Consequently, the price ends up decreasing in the first and increasing in the second instance to correct for the mistake.

The regularities of conservatism and overconfidence are used to provide the framework for modelling the concept of under-reaction. Under-reaction refers to the scenario where investors do not place enough emphasis on past, or new information about companies. Thus, the price of a security does not rise (fall) enough as would be warranted in an efficient market. In this instance, the price then falls (rises) eventually to correct this mistake.

Both over- and under-reaction have been found in experiments documenting stock trading behaviour. Andreassen and Kraus (1990) find that experimental subjects, tended to sell once prices rose, and bought once prices fell. This, despite being shown a sequence of prices that followed a random walk. This action is consistent with under-reaction. In addition, when shown prices following an apparent trend, subjects reduced trading and seemingly changed to follow the so-called trend. De Bondt (1993) supports the latter findings. In conducting investor surveys and classroom experiments, he also finds that subjects seemed to follow trends once they had supposedly unearthed them.

The psychological evidence seems to point towards the prevalence of both under- and over-reaction. It is from this base that asset pricing models have been formulated taking these behavioural biases into account.

1.4.2 Behavioural Asset Pricing Models

Building on the evidence of the representative heuristic and conservatism, Barberis, Shleifer and Vishny (1998) (BSV) propose an asset pricing model based upon investor sentiment. In this model, investors do not believe that an asset's earnings follow a random walk. Instead, they believe that earnings move according to two regimes.

The first earnings regime, Model 1, is based upon the evidence of conservatism observed by Edwards (1968). When investors believe that a firm's earnings are in this regime, they believe that the earnings are mean-reverting. When the prices move up or down, investors expect the perceived trend to reverse itself.

The second earnings regime, Model 2, is based on the representative heuristic. If a firm has strong, recent past growth, investors will infer that the growth path of the firm will continue. Past results are then extrapolated into the future despite the fact that the earnings follow a random walk.

BSV then model price movements and subsequent returns to investors using these two models. The only difference between the two models lies in the transition probabilities. An earnings shock is likely to be followed by an earnings shock of the opposite sign in the first model and an earnings shock of the same sign in the second model. The investors are assumed not to switch between the two models in the price simulation. Instead, their only aim is to figure out which of the two regimes or models are currently generating earnings, and then to act accordingly.

In order to capture the over-reaction phenomenon, BSV model the scenario so that after a series of positive earnings shocks, the investors perceive Model 2 to be generating earnings in current and future periods. Hence, the investor believes that positive earnings shocks are likely to persist. However, given the random walk of stock prices, if the next period's earnings go down, the return to the investor will be large and negative, as he would not expect that to happen. Conversely, if a positive earnings shock is recorded the return will be small and positive because the investor will be expecting exactly that result to occur.

Following this intuition, the average realised return after a number of positive earnings shocks should be negative, whereas the average realised return after a number of negative earnings shocks should be positive. This is consistent with the observed over-reaction.

A similar argument is used to explain the under-reaction phenomenon. In this instance, investors believe that Model 1 is the model generating earnings. Therefore, investors believe that a positive (negative) earnings shock will be followed by a negative (positive) earnings shock in the next period. Where this is the case, a small positive return will be realised, as the investor will be expecting the earnings shock to occur. If the reverse occurs and a positive (negative) earnings shock is followed by a positive (negative) earnings shock, then the realised return will be large and positive (negative), as it will be unexpected. This leads to under-reaction.

Daniel, Hirshleifer, and Subrahmanyam (1998) (DHS) propose an alternative behavioural asset pricing model. This models asset pricing in an environment consisting of informed and uninformed investors. It is assumed that only the informed investors determine the prices of assets and the uninformed are superfluous to the model. Similar to BSV, DHS propose two scenarios that describe long-term over-reaction, and short-term momentum in the pricing of assets.

Considering over-reaction, informed investors are modelled to suffer from the psychological bias of overconfidence discussed previously. The investor is modelled to receive private information, or signal in the first time period (in other words other investors are not party to this information). This is followed by the receipt of public information in the second time period. In the generalised case, the investor's actions signal the private information to the public, and price adjustments are made. This results in over-reaction, but is not consistent with short-term momentum.

The first scenario described by DHS derives pricing implications for investors whose confidence levels do not change. The second scenario that is proposed, considers instances where investors suffer from biased self-attribution and hence where events do have an impact on the confidence and actions of investors.

In this case, when public information confirms an individual's action or belief, the confidence that the individual has in his own ability increases. This compounds the effect of over-reaction; though repeated releases of public information gradually draws the prices back to fundamental values. It is shown how if biased self-attribution has an effect on investor confidence, and over-reaction is gradually corrected, short-lag positive autocorrelation, or momentum occurs.

Hong and Stein (1999) formulate a behavioural model describing over- and under-reaction. Instead of focussing on the psychology of the agents, the emphasis is put on the interaction between the heterogeneous agents. The action resulting from the interaction of traders with each other rather than the psychological biases of the traders is therefore analysed.

The model is centred around "newswatchers" and "momentum traders". The former predict prices based on private signals they receive about the future fundamentals of securities, while ignoring information on current or past prices. The latter revise their beliefs based on past prices. Their forecasts are however, based solely upon this criterion. Lastly, it is assumed that private information is disseminated slowly across the newswatcher group.

From this, it is shown that when the only people trading are the newswatchers prices adjust slowly to information thereby leading to under-reaction. When momentum traders are added, attempting to profit from the newswatchers under-reaction, the prices accelerate. This leads to over-reaction in the longer term. Hence, it is argued that the prevalence of under-reaction in the first place ultimately leads to over-reaction in the long-term.

The models proposed by DHS, and BSV are based on different psychological regularities. However, they, along with the Hong and Stein (1999) model, which is based on investor interaction, all draw similar conclusions. Because people are prone to psychological biases, the pricing of assets is not always rational.

1.5 Conclusion

This chapter encompasses a review of the literature surrounding the theoretical motivation for rational and behavioural asset pricing models. As discussed above, securities are priced to reflect investor's aggregate perceptions of what future earnings, dividends, and prices might be.

From the perspective of rational asset pricing models, these prices and expected returns should be wholly contingent on economic state variables that have an impact on the future performance of the security. Dependent on the pricing model, the number of state variables could be one, as in the case of the standard CAPM, or many, as in the case of the APT or ICAPM. One can not however, name and identify all the state variables that are priced in assets which are of special hedging concern to investors. Nor can one name and identify the factors that proxy for these state variables. This makes it difficult to theoretically justify the choice of any variables when explaining the pricing and expected returns of assets.

An alternative approach to explaining the pricing of assets draws on experimental psychology to explain asset returns from a behavioural perspective. From this point of view, investors are not wholly rational. Their perceptions of future earnings, dividends and prices of securities are contingent on both economic and non-economic variables. Models developed along these lines document how such non-rational behaviour leads to an irrational pricing of assets, leading to both under- and over-reaction.

CHAPTER TWO

DETERMINANTS OF STOCK RETURNS

2.1 Introduction

The previous chapter highlights the problems inherent in determining which economic variables are priced in assets. Apart from the single measure of risk, beta, in the CAPM, there is no theory endogenously linking any economic variables to the pricing of assets. Studies have however, empirically revealed relationships between some fundamental economic variables and asset prices. As the number of these studies grows, more evidence is provided in support of the inclusion of these fundamental variables in the pricing of assets.

This chapter documents the literature concerned with this evidence. To begin with, the rationale behind the selection of economic variables as a means to differentiate value, from growth-stock investment, is discussed. This is followed by evidence of empirical studies that find a relationship between financial, or fundamental variables, and returns. This chapter is concluded through a discussion of studies documenting the use of these financial variables as a basis for forming investment strategies, the purpose of which is to capitalise on the empirical anomalies.

2.2 Fundamental Analysis

Fundamental analysis is the practice of determining a security's price through the evaluation of a firm's financial statements in relation to those of other firms. The concept of using fundamental analysis as a tool in investment analysis is formally proposed in the seminal work of Graham and Dodd (1934). In this work, it is argued that the highest long-term returns will be earned by those investors who invest in what are termed "value" stocks. This work on security analysis does not measure the proposals in a robust statistical framework. It draws on the intuition governing sound business practices to lay the foundation of fundamental analysis. This has had a marked impact on the way in which investment operations have been carried out subsequent to this work being published. It is therefore, deserving of further consideration.

Graham and Dodd (1934) classify the elements that should be factored into the valuation of shares as income statement factors, indicating earning power, and balance statement factors, indicating asset values. These criteria are jointly considered in relation to the market price of a security when deciding whether a security is worthy of investment or not. This is because it is the ratio of the market price in relation to the fundamental variables, discussed below, that determines what Graham and Dodd (1934) refer to as the margin of safety principle.

This margin of safety principle can be determined in part through analysing the fundamental variables contained in the income statement. To begin with, the market price of a company must be seen in relation to the earnings of a company, the price- to-earnings ratio, or P/E. For this, it is necessary to take earnings that stem from the ordinary operations of a company into account. These it is argued are the most reliable measures of earnings consistency and power of a company. Special items such as extraordinary losses or gains are one-off events and can not be expected to contribute to the continued success of the company in the future. It is argued that if a company consistently earns more than another one, ceteris paribus, it is more likely to continue this trend in the future. Hence, it should be valued more highly.

In contrast to this, a company with a strong past earnings history is sometimes not valued as highly, in terms of the price to earnings ratio, as competing companies with no past record, or alternatively a relatively poor past earnings record. This is because the P/E ratio is seen as being indicative of the market's assessment of the *future* earnings power of a company (Graham, 1984). Thus, despite a company having a good earnings record in the past, if the future earnings prospect of this company is deemed by the market to be poor, the premium paid on each dollar earned will be low. The stock will therefore have a relatively high P/E ratio. Additionally, if a company has a poor earnings record in the past, but is deemed to have good future earnings prospects, the premium on each dollar earned will be high. As Graham, (1984) observes:

> The growth-stock buyer relies on an expected earning power that is greater than the average shown in the past. Thus he may be said to substitute these expected earnings for the past record in calculating his margin of safety (1984, p.281).

Graham (1984), goes on to argue that investors do not conservatively project expected earnings into the future, but are liable to be too liberal in their projections. Thus, the high price paid in relation to earnings is deemed to be speculative in nature. The price paid for such a security is seen to have little, or no margin of safety.

Implicit in this is the argument that there is no better guide to a company's future performance than that of the past. If a company has performed well in the past, barring extraordinary circumstances, one can expect it to perform well in the future. In addition to this, if the price of such a company is low relative to the earnings, Graham and Dodd (1934) argue that it offers the investor a margin of safety. The risk of suffering capital erosion by investing in the stock is seen to be low, and the stock is worth investing in.

The second criterion according to which stocks should be valued, and the margin of safety determined, rests in considering the balance sheet of a company. Specifically, Graham and Dodd (1934) stress the importance of looking at the book value of a company.

The book value, if adequately appraised tells the investor how much the business is worth in terms of the tangible value of the shares. This gives an indication as to whether or not the market price of the shares places a high (or low) premium on this book value. The net tangible asset backing in turn refers to the value of the tangible assets (fixed and net current assets), net of long term debt. This is indicative of the value of the business to investors, should the business be terminated as a going concern.

If the market value of the stock is not far above the book value or rather is selling below the liquidating or current asset value of the business in comparison to other comparable companies, the stock is seen to exhibit an adequate margin of safety. Thus, it is worthy of an investment.

To summarise the margin of safety concept, Graham and Dodd (1934) argue that those stocks exhibiting high earnings yields and that sell at low market values relative to both book values have a sufficient margin of safety. The earnings power, and financial status of a company is appraised according to the company's past record. The earnings power, and value should also be viewed in light of the company's ability to sustain or improve upon the past earnings record. This latter point is what differentiates value, from growth-stocks.

Value-stocks are stocks that have a strong past record in terms of book-to-market value, and that have a consistently high past earnings or cash flows, in relation to the market price. Growth stocks on the other hand, are those that do not have got a good past record in terms of the relationship between these financial variables and price. Additionally, growth-stocks can be seen as those fledgling stocks that are expected to have a good future, but have no historical record to substantiate such views. High market values in relation to current earnings, or in relation to the book value of a security's assets instead reflect expectations of a better future performance.

Note that it is the consideration of future capabilities in relation to the past record of a company's performance that separates growth from value-stock investment strategies. Graham and Dodd (1934) advocate the use of a value-based approach on account of the greater margin of safety that is offered through this approach. This rationale is the corner stone of investing in value-stocks. As Graham (1984) notes:

> Yet every corporate security may best be viewed, in the first instance, as an ownership interest in, or a claim against, a specific business enterprise. And if a person sets out to make profits from security purchases and sales, he is embarking on a business venture of his own, which must be run in accordance with accepted business principles if it is to have a chance of success (1984, p. 286).

2.3 Financial Variables as Determinants of Portfolio Returns

In this section, the literature analysing the empirical relationship between financial variables and security returns is reviewed. Incorporated in this is a review of the literature attempting to quantify the intuition that Graham and Dodd (1934) use in explaining why it is that financial, or fundamental, variables are related to security prices. This is accomplished through linking the relationship between financial variables and asset prices to rational and behavioural asset pricing models.

2.3.1 P/E and Size Effects in Security Returns: Early Evidence

Basu (1977) is one of the first researchers to empirically reveal that stocks with low P/E ratios outperform those with high P/E ratios. Portfolios of stocks listed on the New York Stock Exchange (NYSE) are formed according to P/E ratios.[1] Monthly returns are calculated using a twelve-month buy-and-hold technique, with the amount invested in each portfolio re-balanced annually. Overall results for the entire period studied (14 years) are then pooled and the returns of the respective portfolios compared.

The stocks in the lowest P/E portfolio earn on average 16.3% per annum over the 14-year period in comparison to the highest P/E portfolio, which earns 9.3% on average. In contradiction to the CAPM, when the systematic risk of the portfolios is determined, the risk of the lowest P/E portfolio is less, with a beta of 0.99, than that of the highest P/E portfolio, which has a beta of 1.06. When risk is taken into account, the lowest P/E portfolio earns 4.5% per annum more than the return implied by its risk. Likewise, the highest P/E portfolio earned 2.5-3% less per annum, than the return implied by its risk.

Basu (1977) concludes that the traditional CAPM is misspecified and the results suggest that the P/E ratio proxies for some kind of omitted risk variable. However, when adjustments are made for trading risks (taking bid-ask spreads and transaction costs into account) the differences in returns between investing in the lowest P/E portfolio, and a

[1] From the literature reviewed it is apparent that extensive use is made of NYSE and AMEX data. Because there is a relative lack of studies incorporating data from outside of the U.S., doubts about the robustness of the relationships between fundamental variables and returns is raised. This highlights the need to replicate such studies using other stock-market data.

randomly selected portfolio of assets become statistically insignificant from zero. This does not implicitly refute the Efficient Market Hypothesis.

Basu's work is extended, but contradicted by Reinganum (1981). In this study, a P/E effect is found, but a negative relationship between the size (as measured by market value) of a company and its return is found. Thus, the size effect is seen to subsume the P/E effect. Utilising quarterly earnings data of NYSE and American Stock Exchange (AMEX) listed stocks, and controlling for risk (beta), portfolios are formed according to P/E ratios. The cumulative average abnormal returns (CAAR) are then calculated for the high P/E and low P/E portfolios. Despite controlling for risk, the abnormal returns differ from zero. Based on this, Reinganum (1981) concludes that abnormal returns of between six and seven percent per quarter can be obtained through investing in the low P/E stock portfolio.

Because these abnormal returns are found to persist for up to six months beyond the time of portfolio formation, the likelihood of this anomaly being due to informational inefficiencies is rejected. Instead, it is concluded that the P/E ratio proxies for a determinant of equilibrium not specified by the CAPM. These findings persist even when annual return data (reducing the effect of seasonality in quarterly data) is analysed. Here, low P/E stocks on average achieve returns that are 13% higher than high P/E stocks.

In order to determine if the size (measured by market value) of a stock has any impact on abnormal returns, a two-way classification scheme splitting stocks into portfolios according to both P/E and size ratios is used. When size is controlled for, the P/E effect disappears. In contrast, when the P/E ratio is controlled for, the size effect remains, and a significantly negative relationship between the market value of a firm and its return is found. Hence, it is concluded that the P/E effect is in fact, another way of reflecting the size effect and is not an anomaly itself.

In a study by Cook and Rozeff (1984), Reinganum's (1981) results are found to be sensitive to the methodology used. Cook and Rozeff (1984) use different methodologies to estimate the abnormal returns of the portfolios. The conclusion is drawn that Reinganum's (1981) results are the exception, rather than the rule when different methodologies are compared. It is found that the abnormal returns on all stocks are seasonal. The P/E and size effects are much larger in January than in any other month of the year. However, both effects are found to be statistically significant in all twelve months of the year. This phenomenon, termed the January effect, is seen to be a possible partial explanation of the low P/E and market value portfolios (Cook and Rozeff, (1984)).

Banz (1983) examines the relationship between the size as measured by the market value of common stock, of NYSE firms, and their returns. An inverse relationship is found between the two. This relation is non-linear however. So, the linearly estimated CAPM model is seen to be misspecified, when explaining returns. This does not affect the significance of the size premium as the non-linearity underestimates the true size effect for very small firms. The evidence is thus in favour of a size effect, which is unrelated to the effect of beta in explaining security returns.

The size effect and impact of abnormal returns in January on security returns is also examined by Lakonishok and Shapiro (1986). This study also uses stocks trading on the NYSE. Size is found to be a significant variable in predicting returns. When returns in January are omitted from the data analysed, the size effect loses its statistical significance. This raises the possibility that the size or January effects are the same things. Importantly though, this study finds no support for the contention of Basu (1977), Levy (1978) and Mayshar (1983) that the size effect is due to market frictions such as transaction costs, which limit investors ability to diversify properly. This argument rests in the hypothesis that institutional investors underinvest in small firms. This is seen to contribute to the prevalence of a high proportion of insider holdings in small, illiquid stocks with owners unable to diversify their risks.

Chan and Chen (1991) try to determine why it is that smaller firms should require an added risk premium in comparison to larger firms. They argue that small firms are economically riskier than larger firms. Small firms are shown to have higher financial leverage, not be as profitable as larger firms and to have cash flow problems. They conclude that the size effect is in fact a marginal effect, and smaller firms therefore require a larger risk premium than larger firms.

Jaffe, Keim, and Westerfield (1989) round out the earlier studies on P/E and size effects by analysing both effects over a 35 year time period. They argue that the conflicting conclusions drawn from earlier studies exist because most of the previous studies are limited to a sample period of no more than 20 years. NYSE and AMEX firms are again analysed. By investing in stocks in the lowest P/E portfolio it is found that one could obtain a 3.2% greater return than if one invested in stocks in the highest P/E portfolio. Similarly, by investing in the portfolio comprising the smallest stocks, one could obtain a 3.4% greater return (after controlling for the P/E effect) than an equivalent investment in the largest size portfolio.

Jaffe, Keim, and Westerfield (1989) conclude that size and P/E effects are two different and statistically significant effects. The conflicting results found in previous studies are ascribed to bias introduced by studying short time-periods and this is mitigated when a longer time frame is considered.

From the studies discussed above it is evident that there is an empirical relationship between P/E, size and asset returns. In particular, these relationships seem especially prevalent in the January months. This raises the possibility of a seasonal effect also playing a role in explaining returns. The early literature documents these so-called anomalies. What is not clear however, is what the size, P/E and seasonal effects capture in explaining stock returns. In particular, if these anomalies proxy for risk, it is not clear whether they proxy for different omitted risk variables.

2.3.2 B/M Effects: Early Evidence

Rosenberg, Reid, and Lanstein (1985) analyse a trading strategy which exploits differences in returns between stocks with high and low B/M ratios listed on the S&P COMPUSTAT database over the period from 1973 to 1980. Stocks are sorted into the two respective portfolios. The strategy employed is to sell (short) those stocks in the low B/M ratio portfolio and buy those in the high B/M portfolio. The net monthly returns for the portfolios are then computed.

Rosenberg et al. (1985) find that the net return is positive in 38 of the 54 months analysed, with a mean residual return of 32 basis points per month. This results in a t-statistic of 3.7, which is strong enough to reject the null hypothesis that the mean return is 0. This result is significant in most months considered. However, the return is much higher in January, which has a t-statistic of 4.39. The mean values tend to trend downwards in other months. This adds support to the evidence of a January effect as well. Because the portfolio turnover is less than 5% per month, the effects of trading costs are seen to affect the mean net return by less than 5 basis points per month and are hence, negligible.

Rosenberg, et al. (1985), therefore claim that the B/M effect is positively related to returns. This study is seen as an indirect indictment of the Efficient Market Hypothesis. In looking at the results of this study, it seems appropriate to utilise some balance-sheet variable as a means to calculate the risk, and subsequent desirability of a stock when evaluating one's investment options.

The earlier literature documenting empirical relationships between fundamental variables and asset returns has laid the foundation for comprehensive studies looking at trading strategies based upon these results. Equally, literature highlighting the biases and inadequacies of these early studies has influenced the way in which these later studies have been carried out. As such, it is discussed in the next section.

2.3.3 Criticism of the Early Literature

Roll (1983) provides one of the earlier criticisms of the studies documenting the so-called anomalies discussed in Section 2.3.2. In this paper, the computational problems inherent in computing expected return differences between small and large firms are analysed. It is argued that the methodology used in determining the mean return on portfolios has a substantial effect on the results.

To begin with, it is claimed that the length of the period used to estimate mean returns (the review period) can bias the results when buy-and-hold, re-balanced and arithmetic computational returns are calculated.[2] This is because of the effects of serial dependence induced by microstructure issues such as non-synchronous trading (Scholes and Williams,(1977)) and the institutional arrangement of trading (Niederhoffer and Osborne, 1966)). Negative serial dependence, which is found if short-term periods are used to estimate returns, or if individual stock returns are considered, plagues the buy-and-hold estimated returns. Portfolio serial dependence on the other hand introduces bias into the arithmetic and re-balanced mean returns.

Bearing this in mind, the difference in returns between AMEX (mainly smaller firms), and NYSE (consisting of larger firms) firms is considered. It is found that portfolio dependence is negligible, but that negative serial dependence influences results. This results in the length of the review period having a significant impact on return differences between small and large stocks when buy-and-hold returns are computed. These return differences decrease with an increase in the review period. In fact, where review periods are a month or longer, the return differential drops to around 7% per annum with a negligible t-statistic (Roll (1983)). It is further argued that despite the re-balanced mean calculations being free of this bias, this method is not realistic because of the costs incurred in re-balancing. It is also shown that the arithmetic mean gives a biased estimate of both the re-balanced and buy-and-hold investment returns.

Roll (1983) therefore concludes that studies such as Reinganum's (1981) study, documenting monthly or quarterly returns, overstate the returns that could be obtained by investors utilising a buy-and-hold policy. The returns that Reinganum (1981) finds are calculated using the arithmetic mean and are deemed to be upwardly biased. This casts doubt over the ability to form a practical buy-and-hold investment strategy to capitalise on the small firm premium.

Further criticism of the earlier literature emanates from the work of Banz and Breen (1986), where it is claimed that ex-post-selection bias and look-ahead bias exist in the computation of returns on NYSE and AMEX stocks where the accounting information is obtained from the COMPUSTAT database. Ex-post selection bias in COMPUSTAT

[2] The review period refers to the calendar interval over which the returns are calculated. The returns might be monthly, daily, weekly, or bi-weekly, which are then linked to determine the annualised return.

data refers to bias arising through the exclusion of companies that have been de-listed. Thus, the poor results that one would obtain through investing in such stocks is ignored, and the final results are skewed in favour of successful companies. The look-ahead bias on the other hand refers to a reporting problem. Data that is reported at the end of a specific period is not immediately available to investors. By computing earnings and cash flow yields using this reported data one implicitly assumes that investors have access to this data. By devising an investment strategy based upon this data without allowing for a time lag for the information to become available to investors, one assumes that investors can perfectly predict what the earnings announcements will be. Since this is not the case, it introduces a bias in results since using such data without a time lag makes it impossible to devise an ex-ante strategy that can capitalise on this information.

In testing for the size and P/E effects after mitigating these biases, Banz and Breen (1986) find that the P/E effect is non-existent once size is controlled for. Thus, previous studies endorsing the P/E effect are deemed to have drawn those conclusions because of ex-post selection and look-ahead biases in the methodology. It is concluded that attention must be paid to matching the dates of earnings yield formation (and the formation of other fundamental variables) with the date that this data is available to investors. This mitigates the look-ahead bias. The ex-post selection bias can only be mitigated by including de-listed companies where possible.

Lo and MacKinlay (1990), also criticise studies that identify empirical relationships between fundamental variables and security returns. Because these studies are empirically motivated, the following question is posed: "Are standard tests of significance valid when the construction of test statistics is influenced by empirical relations derived from the very same data to be used in the test?" (Lo and MacKinlay, 1990, p.434).

Lo and MacKinaly (1990), show how historic information only marginally correlated with statistics of interest can result in spurious relationships being identified. This throws into doubt all the empirical relationships such as the P/E and size effects that have been identified, yet not explained theoretically. It is argued that incorrect conclusions are easily drawn where the assumptions of statistical inference are ignored in constructing portfolios according to data-instigated characteristics.

This data-mining bias, unlike the biases identified by Banz and Breen (1986), is a great deal more difficult to mitigate. However, as Lakonishok, Shleifer, and Vishny (1994) argue, there are a number of studies using different data sets and considering several different time series, that document the relationships between the fundamental variables and returns. Because of this, despite the criticism of Lo and MacKinlay (1990), this does seem to indicate economic regularities rather than merely being a case of data-mining. Further research using different data sets can only clarify this point further by empirically supporting previous findings or contradicting such results. This highlights the need for further research into this arena.

The literature that analyses the relationships between the fundamental variables and returns by incorporating these anomalies into investment strategies, is now discussed. This literature also provides explanations as to why these different strategies yield different returns. These explanations are based on the principles of rational, and behavioural asset pricing models.

2.4 Tests of Market Over-Reaction

2.4.1 De Bondt and Thaler (1985), and Related Studies

One of the first studies examining pricing anomalies from a behavioural finance perspective is undertaken by De Bondt and Thaler (1985). In this paper, evidence of over-reaction in the pricing of assets is examined.

Unlike the previous literature on anomalies, the residual post-formation returns of portfolios formed according to a fundamental variable is not considered. Instead, portfolios are formed according to past excess returns. Those achieving the highest returns in the past are assigned to the "winner" portfolio. Those achieving the lowest returns are assigned to the "loser" portfolio. The post formation returns of the winner and loser portfolios are then compared by constructing the arbitrage portfolio.

Using NYSE stocks, the portfolios are formed in the following manner. Monthly return residuals are computed for each stock for 36 months prior to portfolio formation. The residuals are calculated using a market-adjusted model. This model makes no adjustment for risk, as each stock is assumed to have a beta of 1. These residuals are then cumulated for each stock in the 36-month formation period, and then ranked from those with the highest to those with the lowest returns. The winner portfolio is comprised of the 35 stocks with the highest returns, and the loser portfolio of those stocks with the lowest cumulative returns. Once formed, the cumulative average return for each stock in the portfolio for each of the next 36 months is calculated.

This process is repeated for 16 non-overlapping periods. The test of over-reaction lies in seeing whether the average cumulative abnormal return ($ACAR_{lt}$) for the loser portfolio is greater than that of the winner portfolio ($ACAR_{wt}$) in corresponding months, *t*.

De Bondt and Thaler's (1985) results indicate that the loser portfolio out-performed the market on average by 19.6% for the 36 months after portfolio formation, whereas the winner portfolio underperformed the market by 5%. The difference in cumulative returns between the two [$ACAR_{l36}$- $ACAR_{w36}$] is 24.6% with a t-statistic of 2.20. This is significant at the 95% level. When the CAPM-betas are compared, the loser portfolio is also seen to be significantly less risky (1.026) than the winner portfolio (1.369). Hence, the results are even seen to underestimate the over-reaction effect.

Zarowin (1990) extends this analysis by considering the effect of size, risk, and seasonality on the winner/loser anomaly. The fact that losers are found to be smaller than winners (generally) is not surprising given that poor returns will inevitably lead to a lower market capitalisation and vice versa with high returns. Using similar methodology to De Bondt and Thaler (1985) in forming loser and winner portfolios, Zarowin (1990) ranks the firms independently according to size and prior period returns. The residual returns of winner and loser stocks that are comparable in size, are then compared.

The results show that losers only outperform winners in January, with no significant difference in other months. To differentiate the size from the seasonality anomaly, the returns of loser and winner stocks are then compared where size is not accounted for when assigning stocks to portfolios. Contrary to the over-reaction hypothesis, the winner stocks are found to outperform the loser stocks which is consistent with the size anomaly. Zarowin (1990) refutes De Bondt and Thaler's (1985) findings of over-reaction as this is seen as merely a manifestation of the size and January effects. Further evidence is found of the CAPM's inability to correctly specify risk, as loser stocks are found to be less risky (despite being smaller) than winner stocks.

Chopra, Lakonishok and Ritter (1992) also consider the effect of size and risk on abnormal returns. Because of the doubt surrounding the relationship between the CAPM beta and returns, this study defines the risk through calculating an empirically based measure of beta. Betas are estimated in the ranking period (before portfolio formation) instead of merely sorting the stocks according to returns, and then determining the post-formation betas. The post-formation betas are then estimated for the portfolios, which are ranked according to the pre-ranking betas. The returns between the extreme portfolios are then compared.

They find an increase of dispersion in betas between the extreme portfolios from 0.79 when the portfolios are ranked according to excess returns alone, to 0.86 when the extreme portfolios are ranked according to pre-ranking betas. The difference in returns is however, markedly less when pre-ranking empirical betas were used. When ranked according to abnormal returns, the loser portfolio earns 14% per annum more than the winner portfolio. Yet, when the empirical risk is taken into account, the difference between the highest pre-ranking beta portfolio, and the lowest pre-ranking beta portfolio decreases to 7.3%. This occurs despite an increase in risk dispersion.

They conclude that the relationship between the empirically based beta and returns is flatter than that predicted by the CAPM beta. The CAPM beta is not found to explain the difference in returns between the winner and loser portfolios. Support is found instead for the over-reaction effect. It is also found that when adjusting for size (before adjusting for risk) the loser portfolio outperforms the winner portfolio by 9.7% per year.

Because of the correlation between risk, size and prior returns, all three variables are accounted for through constructing multiple regressions on the portfolios. The over-reaction effect is seen to hold, with 5% returns attributed to the arbitrage portfolio per year. It is concluded that the winner-loser anomaly is due to over-reaction, and the difference in returns is too great to be explained by risk factors.

In a comprehensive evaluation of the methodology used in studying the over-reaction phenomenon, Conrad and Kaul (1993) criticise the application of cumulative abnormal returns as used by De Bondt and Thaler (1985). It is argued that any statistical noise (introduced by microstructure issues such as the bid-ask spread) that exists in stock prices will result in an upward bias when returns in a single-period are considered. By cumulating these returns across periods one is also cumulating this upward bias.

Conrad and Kaul (1993) propose using buy-and-hold returns to calculate the success of winner and loser portfolios. This is consistent with a realistic trading strategy of holding stocks for longer periods than one month at a time. It also minimises the bias in portfolio returns, and minimises the effects transaction costs have on frequent trading. The residual, or abnormal return of each stock is calculated as the difference between the average holding period returns of each NYSE security for each 36 month period that is considered, and the average holding period return of the market portfolio (comprising all NYSE stocks). [3]

Conrad and Kaul (1993) then examine the success of a winner and loser arbitrage portfolio formed along the same lines as De Bondt and Thaler (1985). It is found that the holding period abnormal returns to the loser (winner) are less (greater) than the corresponding cumulative abnormal returns for all periods considered. This highlights the effect of the cumulative bias on abnormal returns. Furthermore, it is found that the buy-and-hold returns to the arbitrage portfolio are solely due to the January effect, and bear no relation to the past performance of the security. It is concluded that the over-reaction effect found in De Bondt and Thaler's (1985) results, is merely a combination of the bias induced through cumulating the abnormal returns, and a consequence of the January effect.

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[3] The holding period return of a security over the (k) period interval is given by compounding the single period returns: $HPR\ (k) = (1+R_1)(1+R_2)....(1+R_k)-1$. In this instance, 36 periods are used per interval.

There is another criticism levelled at the methodology used by De Bondt and Thaler (1985), and to those of value-based investment strategies in general. Ball, Kothari and Shanken (1995) document problems in calculating raw, as well as abnormal long-term buy-and-hold returns on stocks. They suggest that microstructure-induced biases such as the bid-ask spread are acute. In particular, this affects value stocks more than growth stocks because by nature, value stocks have decreased in price in the run up to portfolio formation and generally have lower absolute prices than growth stocks.

With regards to the raw returns for value-based, or contrarian investment strategies Ball, Kothari and Shanken (1995) find that the superior performance of value stocks is driven by the low-priced stocks in the portfolio. Again, using NYSE and AMEX data, the winner and loser five-year means are found to differ by 91% yet the median difference is only 14%. The loser stock portfolio appears to be rightly skewed with many low-priced stocks. Small adjustments to the estimated stock prices are then made, to make allowance for the bid-ask spread and transaction costs. This results in the average return on the loser portfolio decreasing by 25% over the five-year post-formation period. The average winners on the other hand only fall by 2%. Whether or not a successful trading strategy can in fact be developed to capitalise on the difference in returns between value and growth stock strategies is seen as questionable.

Also, in trying to account for the January effect, Ball, Kothari and Shanken (1995) change the portfolio year-end from December to June. The resultant change all but eliminates the positive abnormal returns to the loser portfolio. Thus, it is argued that the conclusions of the De Bondt and Thaler (1985) study are far from robust. In fact it is claimed that contrarian, or value-based investment studies, must make allowance for microstructure issues if they are to draw any meaningful conclusions.

The study conducted by De Bondt and Thaler (1985) and subsequent follow-up studies document the difference in returns between portfolios constructed according to prior returns. The subsequent abnormal returns achieved by the winner and loser portfolios are compared, and the difference between the two is put down to investor irrationality. It is contended that investors overreact to the negative (positive) performance of stocks in the manner proposed through the over-reaction models discussed in Chapter One. It is also considered whether the over-reaction effect could be explained through the empirical relationship between the fundamental variables, seasonality and returns. This indirectly tests whether these variables proxy for some aspects of risk. As noted, there is a great deal of criticism surrounding the methodology used in these over-reaction studies. This criticism is further examined through considering the literature linking value and growth-stock returns to rational asset pricing models.

2.4.2 Fama and French (1992) and Related Studies

While the exact relationship between fundamental variables and asset returns discussed in the previous sections is contentious, there is a common thread that links the different conclusions about this relationship. That is, the cross-section of expected returns seems to be better explained through the anomalies than through the CAPM. Beta does not seem to be related to asset returns in the manner predicted through the CAPM. It is further argued that all "these variables can be regarded as different ways to scale stock prices, to extract the information in prices about risk and expected returns" (Fama and French, 1992, p. 428). In this paper, the joint roles of market beta, P/E, leverage (debt-to-equity), size and B/M in explaining asset returns are considered in order to try and separate their different roles in explaining returns.

Using NYSE, AMEX and National Association of Security Dealers Automated Quotation (NASDAQ) stocks, and correcting for look-ahead and survivorship bias, the stocks are sorted into 10 portfolios according to size. Each portfolio is then independently sorted into 10 portfolios according to pre-ranking betas to allow for variation of beta that is unrelated to size. The post-ranking returns and betas are then computed for each of the 100 portfolios. This approach is used because of a strong correlation that is found to exist between size and beta.

By calculating the slopes of the monthly regressions of the cross-section of stock returns on size and beta, a negative relationship of –0.15% (t-statistic of –2.58) is found to exist. This is found for portfolios that are sorted according to size that is unrelated to beta. In contrast to this, beta, on its own exhibits a slope of 0.15% yet is statistically insignificant. When the two variables are combined in a joint regression, size is found to have explanatory power, but beta is found to have a *negative* slope that is only 1.21

standard deviations from zero. This is an indictment on the prediction of the CAPM. This leads to the conclusion that the "evidence on the robustness of the size effect and the absence of a relation between β and average return is so contrary to the (CAPM) model that it behooves us to examine whether the results are special to 1963-1990" (Fama and French, 1992, p.440).[4]

Using a similar portfolio sorting procedure as before, but substituting B/M for size and E/P (the reciprocal of the P/E ratio) for beta, the cross-section between these two variables and expected returns is considered. Results similar to Jaffe, Keim and Westerfield (1989) are found with regards to the E/P ratio, with striking evidence of a strong positive relationship between B/M and returns. Average returns rise from 0.3% per month for the lowest B/M portfolio to 1.83% for the highest B/M. This is twice the spread of 0.74% between the average monthly returns on the smallest, and largest size portfolios.

In further analysis, the effects of leverage are determined through looking at the relationship between two measures of leverage. The first measure, is that of market leverage. This is the ratio of book assets to market equity, (A/M). The second measure is that of book leverage. This is the ratio of book assets to book equity, (A/B) and returns. Higher levels of market leverage are found to be associated with higher returns and the reverse relationship is found to hold between returns and book leverage. Because the study considers the relationship between these variables using the natural logs of the B/M and leverage variables, these relationships are interpreted in two ways.

The high B/M ratio in one instance possibly does capture a relative-distress effect, where the market judges that firms with high B/M ratios have poor prospects. However, the difference between market and book leverage is equivalent to the B/M ratio.[5] The high B/M possibly indicates that the firm has a high level of market imposed leverage because of poor anticipated prospects and hence requires a higher discount rate leading to the low B/M ratio.

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[4] The term in parenthesis is the author's addition.

[5] $ln(B/M) = ln(A/M) - ln(A/B)$.

When considered in a multivariate setting, the E/P and leverage effects seem to be captured by the size and B/M variables. While a correlation between size and B/M exists, the relationship is weak and it is found that when controlling for size, B/M captures a great deal of variation in returns and vice versa. Evidence is therefore found in favour of anomalous variables explaining the returns of stocks. In follow-up papers, this relationship is clarified further and the rationale behind these variables being proxies for omitted risk variables is discussed. A multi-factor model defining the relationship between risk and return from a rational asset pricing approach along the lines of the ICAPM is used.

Fama and French (1993) build on this previous study by extending the number of variables used to describe stock returns. Term structure variables are included that might explain bond returns in the hopes that "if markets are integrated, there is probably some overlap between the return processes for bonds and stocks"(Fama and French, 1993, p.4). In addition to this, instead of using a cross-sectional regression approach to explain returns, a time-series regression approach is adopted. In this setting, monthly excess stock returns (above the one-month Treasury bill rate) are used as the dependent variable with excess returns or returns on a zero-investment portfolio being the explanatory variables. The implication is that if the model adequately describes asset returns, the intercepts produced would be indistinguishable from zero (Fama and French, 1993).

Two portfolio formation procedures are followed. Stocks are firstly split up into two portfolios according to size, small (S) and big (B). They are then independently sorted into three portfolios according to B/M, low (L), medium (M), and high, (H). Six portfolios are finally formed according to the intersections of the B/M and size portfolios.[6] The difference in returns between stocks in the small portfolio and those in the big portfolio (SMB) are then used to mimic risk factors in returns that are related to

[6] So for instance, those stocks in the small (S) portfolio that are also in the low B/M (L) portfolio form portfolio one (SL). Likewise those stocks that are in the small and medium B/M portfolio make up the second portfolio (SM), and so on.

size. Similarly, the difference between returns in the high B/M and low B/M portfolios (HML) proxy for risk factors that are related to the B/M variable.[7]

In analysing the two-factor time-series regressions of excess stock returns on SMB and HML portfolios, the results support the conclusions of Fama and French (1992). These results indicate that size and B/M factors explain average returns *across* stocks. However, the intercepts are found to be around 0.5% per month. Thus, these two factors are deemed not to be able to explain the excess returns of stocks above the risk-free rate. In this instance, the one-month Treasury bill is used. By adding a third factor, computing the excess return of the market portfolio over the risk-free rate, the intercepts decrease to zero.

Thus, it is argued that a three-factor model consisting of the excess market return (R_m-R_f), the B/M effect (HML), and the size effect (SMB) seems to explain asset returns.[8] For this multi-factor model to be in accordance with those models proposed by Ross (1976) or alternatively Merton (1973), as discussed in Chapter One, there would have to be some motivation for these factors to be of special hedging concern to investors. This is in addition to an economic explanation as to why they might or should proxy for risk.

Dealing with the latter question first, the market factor is interpreted as being representative of a "premium for being a stock (rather than a one-month bill) and sharing general stock-market risk" (Fama and French, 1993, p.52). Fama and French (1995) claim that the B/M factor is related to relative profitability with portfolios of high B/M firms having lower ratios of earnings to book value in comparison to firms in the low B/M portfolios. This is found to persist for 11 years around the portfolio formation date. Within the B/M groups, the bigger firms seem to consistently outperform the smaller stocks in terms of profitability. This relationship is found to exist mainly after 1980. Small stocks entered into a recession (in terms of a significant

[7] Note that the difference in returns between the small and big stocks (SMB) is the difference between the three small portfolios (S/L, S/M, S/H) and the three big portfolios (B/L, B/M, B/H). As both small and big portfolios contain a reasonable cross-section of low, medium and high B/M stocks, the size effect is mainly independent of B/M effects. The same holds when the (HML) returns are considered.

[8] The model is proposed as: $R(t)-RF(t)= a + b[RM(t)-RF(t)] + sSMB(t) + hHML(t) + e(t)$.

drop in profitability) in 1981 and 1982. They did not recover from this for the remainder of the decade, despite a boom for large companies in the latter half of the 1980's.

From this discussion, there do seem to be common risk factors in earnings that are prevalent in returns. In terms of the ICAPM however, the underlying state variables that produce variation in earnings and returns related to size and B/M are not named. Furthermore, it is not established whether these state variables "produce variation in consumption and wealth that is not captured by an overall market factor and so can explain the risk premiums in returns associated with size and (B/M)?" (Fama and French, 1995, p.154).[9]

While these factors do seem to be proxies for omitted risk variables, the theoretical motivation behind this is uncertain. Despite this, the three-factor model is at least an attempt to include fundamental variables in a rational asset-pricing framework. It offers an alternative to the behaviourally based approach adopted to explain these anomalies. This literature does however, support the contention that the single variable CAPM inadequately explains asset returns. At the very least, this implies that a multi-factor approach must, where possible, be used if the asset returns are to be explained through a rational asset pricing approach.

2.4.3 Lakonishok, Shleifer and Vishny (1994), and Related Studies

Subsequent to De Bondt and Thaler's (1985) study of over-reaction in stock returns, Lakonishok, Shleifer and Vishny (1994) (LSV) provide the most compelling evidence in favour of market irrationality in the pricing of stocks. This study tries to determine whether over-reaction is prevalent in stock returns. It also directly analyses the success of value, over growth-stock investment strategies incorporating many principles of investment analysis that are proposed by Graham and Dodd (1934).

LSV provide an explanation of the excess returns of value-based strategies, returns above those achieved through growth-based strategies, that is considered from both a

[9] The term in parenthesis is the author's addition.

behavioural and rational asset pricing perspective. In the first instance it is considered whether the higher returns are a result of investors following naive strategies. LSV state:

> These naive strategies might range from extrapolating past earnings growth too far into the future, to assuming a trend in stock prices, to overreaction to good or bad news, or to simply equating a good investment with a well-run company irrespective of price (1994, p. 1542.).

In the second instance, drawing on the results of the Fama and French (1992, 1993) studies, LSV consider whether value stocks are not fundamentally riskier than growth stocks.

In accordance with Graham and Dodd's (1934) emphasis on a positive earnings record as being an imperative consideration before *any* investment is considered, LSV examine returns on stocks that have positive earnings, excluding those with negative earnings.[10] Unlike the De Bondt and Thaler (1985) study, buy-and-hold returns are calculated for the respective portfolios. This approach mitigates the bias introduced through using cumulative returns noted by Conrad and Kaul (1993). Lastly, the returns from 1963 to 1990 on NYSE and AMEX stocks are analysed using overlapping portfolio formation and post-formation periods in contrast to De Bondt and Thaler's (1985) non-overlapping periods.

Considering the relationship between fundamental variables and returns in a univariate setting, results similar to previous studies are found. Stocks are sorted into portfolios in ascending order according to the cash flow-to-price (C/P) and E/P ratios. On a size adjusted basis, a post-formation difference between the highest and lowest C/P (E/P) portfolios of 8.8% (7.6%) per year is found. Similarly, the difference in returns between stocks in the high and low B/M portfolios is 7.8%. In addition to these variables, the past performance of firms is established through classifying stocks according to past

[10] LSV argue that so long as an ex ante strategy can be devised based upon observable characteristics, the estimated return differences are an unbiased measure of actual return differences between the "subsets of firms that are all part of the set of firms with positive earnings" (1994, p.1546).

sales growth (GS). By sorting stocks into portfolios based on this variable, the difference in returns between the low GS portfolio and the high GS portfolio turns out to be 4.6% per year. By following a simple value strategy over an extended period (five post-formation years are considered) it appears that an investor would systematically achieve higher returns than if a growth stock strategy is followed. This supports the previous literature documenting the effects of fundamental variables on asset returns.

Next, strategies incorporating one variable proxying for past performance and one proxying for expected future performance are considered. For instance stocks are independently sorted into three portfolios each (bottom 30%, middle 40% and highest 30%) according to GS (past performance) and C/P (expected future performance) and nine portfolios constructed through taking the intersections of each of the two classifications in a manner similar to the size and B/M classification of Fama and French (1995). This results in a size-adjusted return difference of 8.7% per year between the value stocks (those in the low GS and high C/P portfolios) and growth stocks (high GS and low C/P). The results of a bivariate sort incorporating the other variables also support the success of a value-based strategy. It is concluded that the bi-variate sort produced higher returns than strategies relying exclusively on one variable.

In a multiple regression setting, it is found that the C/P ratio has greater explanatory power than the B/M factor. All variables however, (C/P, GS, E/P, B/M) have statistically significant predictive power for returns.

From this, direct testing of investor naivety and irrationality is considered. This is done by comparing realised future growth rates with realised past, and expected future growth rates. The point is to see whether investors extrapolate past performance into the future when making their investment decisions.

In looking at past growth rates using cash flow, earnings and sales, unsurprisingly the growth stocks are found to grow substantially faster than value stocks in the five years preceding portfolio formation. The post-formation returns tell a different story however. C/P and E/P ratios are used to measure expected future growth rates based on the premise that holding discount rates and payout ratios constant, differences in expected growth rates will be measured by differences in C/P and E/P ratios.[11]

The post-formation growth rates implied by the low C/P and E/P multiples are realised for the growth portfolio. The net difference between these and the value portfolio growth rates do however, seem to be overestimated. This is particularly pertinent given that the bulk of the growth in cash flows, or earnings of the growth stock portfolio occurs in the first two post-formation years. Hence, it is concluded that the market correctly anticipates the short-term growth rates of growth stocks, but incorrectly extrapolates this into the long term. By the same token, the growth in cash flows for the value-stock portfolio is underestimated in the long term.

It would seem from the evidence above that the success of value over growth stock strategies lies in the incorrect extrapolation of past trends into the future. This offers support to De Bondt and Thaler's (1985) over-reaction hypothesis.

As with De Bondt and Thaler (1985), the above results make no allowance for differences in risk (assuming that discount rates for both value and growth stocks are the same). LSV therefore go on to analyse whether value stocks are inherently riskier than growth stocks. To do so, it is argued that

> Value stocks would be fundamentally riskier than glamour [or growth] stocks if first, they underperform glamour [or growth] stocks in some states of the world, and second, those are on average "bad" states, in which the marginal utility of wealth is high, making value stocks unattractive to risk-averse investors (1994, p.1564).[12]

The returns to value and growth stock portfolios are compared in years in which the United States of America had recessions, and in the months in which the stock market had its worst returns as a whole. As a further test, traditional methods of measuring a

[11] The intuition behind this reasoning is discussed in Chapter Three.

[12] Words in parenthesis are the author's addition.

firm's risk, such as the CAPM beta, are used to compare the riskiness of value and growth stocks.

Using the B/M and the (C/P, GS) classification methods the value stocks outperform the growth stocks in the market's worst 25 months, as well as in most of the months in which the market achieves positive returns. Similar results are obtained when returns using the two strategies are compared over the quarters in which the quarterly change in Gross National Product (GNP) is negative, and when the change is positive. This indicates that "value stocks could be described as having higher up-market betas and lower down-market betas than glamour stocks with respect to economic conditions" (Lakonishok, Shleifer and Vishny, 1994, p. 1569). In estimating the traditional measure of the CAPM beta, value stocks are found to have betas that are 0.1 higher than growth stocks. This difference is attributed to the higher up-market betas of these stocks rather than greater systematic risk. Even though this is still higher, this increased risk premium is seen to only account for about 1% of a return difference per year and not the 10% to 11% return differences observed.

In summary, LSV find that a value-based investment strategy yields significantly higher returns than a growth stock strategy. The success of the value-based strategy is attributed to investor irrationality and over-reaction, and not because value stocks are inherently riskier than growth stocks.

This study makes allowance for methodological criticisms of De Bondt and Thaler's (1985) study. Firstly, buy-and-hold returns and not cumulative average abnormal returns are used. Secondly, risk is accounted for in a number of different ways to see if it explains the difference in returns between value and growth-based strategies. Lastly, the look-ahead and survivorship bias is accounted for by requiring all firms considered in the sample to have been registered on the COMPUSTAT files for five years before they are considered for inclusion in the study.

There has nevertheless still been criticism levelled at this study. As mentioned before, value and growth-stock portfolios are dependent on pre-formation *growth* in earnings or cash flow. Fama and French (1995) on the other hand consider the pre-formation and post-formation profitability *levels* of value and growth stocks. They find that the levels of growth stocks significantly outweigh those of value stocks. In addition to this, the formation of growth (value) stock portfolios in the LSV study depends on growth (value) stocks having high (low) earnings growth rates relative to each other in the pre-formation years. As Fama and French (1995) observe, the growth stocks have positive earnings growth, whereas the value stocks have negative earnings growth in the pre-formation period. Given that the value stocks have such a low level of profitability to begin with, this positive post-formation growth rate is deemed to be expected, as it would not take a large growth rate in absolute earnings to increase the growth rate commensurately. In addition to this, the return to profitability in the value stocks does not capture a substantial portion of the earnings lost in the pre-formation years. (Fama and French, 1995).

From this, the results from the LSV study seem to be inconclusive. However, there is one difference in the data used by Fama and French (1995) and LSV that could account for their different conclusions. LSV, only include those stocks with a positive earnings history. Fama and French (1995) include all stocks so long as they had earnings lodged in the COMPUSTAT files. Implicit in LSV's study, is that an allowance has already been made for those stocks susceptible to economic downturns (and hence require a higher risk premium) because of a poor earnings history. The stocks left in their study would not necessarily have the same level of profitability as those in the Fama and French (1995) study.

Another methodological criticism emanates from Fama (1998b) in which the buy-and-hold method of computing stock returns is criticised. It is argued that one should consider returns over the short-term (like a month) rather than long-term horizons. This is because normality is a more realistic assumption for shorter rather than longer intervals. This is also an argument presented by Ball, Kothari and Shanken (1995), where, using a buy-and-hold long-term strategy, skewness is found to significantly affect the distribution of stocks in the value portfolio. It is therefore argued that cumulative abnormal returns should be used instead of the buy-and-hold return method.[13]

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[13] For further discussion on this, refer to Barber and Lyon (1997) and Kothari and Warner (1997).

Thus, even though LSV find that value-based investment strategies outperform growth-based strategies, it remains unclear as to whether this is due to investor over-reaction or whether it is compensation for bearing greater risk. Given the conflicting views on which methodology should be used, and how this problem should be resolved, it seems unlikely that researchers will agree on which interpretation is the correct one.

In most of the studies discussed above, only data from the NYSE, AMEX and latterly the NASDAQ markets have been looked at. The out-of-sample data that has been analysed in support or in conflict of these previous results is now be discussed.

2.4.4 Out-of-Sample Research

Chan, Hamao and Lakonishok (1991) find that B/M, C/P, E/P and size have similar relationships with stock returns on the Tokyo Stock Exchange as those relationships found in studies done in the U.S. A January effect is also found, but the fundamental variables nevertheless still have a significant effect in the non-January months.

Bauman, Conover, and Miller (1998) analyse returns on value versus growth stocks defined according to P/E, B/M, P/C, and dividend yields (D/P). For this study 28,000 return observations in 21 countries (European, Australasian and Canadian companies are looked at) are used. It is found that as a whole, value stocks outperform growth stocks on a return as well as a risk-adjusted basis. In addition to this, a size effect is found in the returns data. However, the differences between large value and large growth stocks are greater than the differences between small value and small growth stocks. These results support the idea that investor over-reaction possibly drives the success of value-based strategies.

Cai (1997) tests the success of value versus glamour stock performance in an attempt to reconcile the conflicting results of Fama and French (1995) and LSV. Using a similar approach to LSV, value stocks are found to outperform growth stocks by 4% to 7% per annum in the five post formation years. In short, this is attributed to over-reaction. The results support the argument that investors extrapolate past results too far out into the future. Similar results are obtained by Brouwer, Van der Put, and Veld (1997) who analyse the success of value over growth stock strategies within the Netherlands, France, Great Britain, and Germany.

The previous discussion shows that there are numerous studies highlighting the success of value over growth stock strategies. Although most of the research has taken place in the U.S., data from other markets has recently been analysed in an attempt to add to the body of literature explaining the success of value based strategies. The goal of this thesis is to analyse the relative success of value based investment strategies in an Australian context. This is in an attempt to add to the evidence produced by other, similar studies conducted in other markets.

2.4.5 Australian Evidence

In accordance with the studies carried out in America, and those undertaken in other markets, the relationship between fundamental variables and stock returns has been analysed in the Australian equities market. While size and other anomalous effects have been examined, no studies (to the author's knowledge) have compared value and growth-based investment strategies as a means of analysing the impact fundamental variables have on returns.

Brown, Keim, Kleidon and Marsh (1983) consider the effect size has on security returns. Consistent with previous studies, they find that there is a strong negative relationship between firm size and returns in all months. Where firms are split into deciles, the firms comprising the smallest decile are seen to earn a monthly premium that is 4% greater than the larger firms. They also find that returns across all size categories exhibit a strong January seasonal, though August and December returns are also seen to be higher than other months. This evidence is supported by Beedles, Dodd and Officer (1988) who consider a different sample set and period.

While the size effect is deemed to hold in Australia, the strength of the other anomalous effects seems to be ambiguous. Anderson, Lynch and Mathiou (1990) look at the relationship between the size, book-to-market variables, and security returns. This study documents these relationships using a sample of Australian shares over the period from

1975 to 1984. They find that multicollinearity exists between the size, B/M, and P/E variables. While significant relationships exist between these variables and returns when portfolios are formed on one variable, this does not hold when two variables are included. Importantly, they find that the B/M effect seems to be a replica of the size effect.

Thus, the impact of fundamental variables on security returns does not seem to be as definitive as the empirical studies conducted in other markets. This ambiguity extends to studies of over-reaction. Brailsford (1992) looks at the winner/loser anomaly as a means of testing for over-reaction. Similar methodology to De Bondt and Thaler (1985) is employed. The market-model is used in formulating the return metric and no adjustment is made for risk. In contrast to De Bondt and Thaler's (1985) results, significant price reversal is seen to occur with the winner portfolio, but no reversal occurs with the loser portfolio. Furthermore, no significant difference between the returns of the loser and winner portfolios in the test period is found.

Importantly, Brailsford (1992) considers the impact industry classification has on the winner-loser anomaly. This stems from Ball and Brown's (1980) findings that the mining sector companies exhibit greater variability in returns than companies in other sectors. This implies that mining companies might exhibit more extreme returns than other companies and hence might skew the results of the study. In support of this hypothesis, Brailsford does find that the resource sector exhibits greater variability in returns. However, when cumulative abnormal returns are used to calculate returns attributable to the portfolios, the difference between the resource sector and industrial sector returns is found to be insignificant. Thus, the results do not seem to be industry specific.

Allen and Prince (1995) conduct a similar study to Brailsford (1992). Their conclusions support Brailsford's (1992) findings. Allen and Prince (1995) obtain similar results despite making an allowance for risk adjusted returns. Gaunt (2000) however argues that Allen and Prince's (1995) requirement that firms be listed for nine years introduces survivorship bias. Gaunt (2000) examines the winner/loser anomaly, extending both Brailsford's (1992) and Allen and Prince's (1995) sample periods. Gaunt (2000) also considers the role that size plays in the performance of the winner and loser portfolios.

Gaunt (2000) uses a re-balanced version of the cumulative abnormal return approach to calculate asset returns. Adopting this policy, it is found that in contrast to the previous studies, there is reversal for both test period loser and winner portfolios. This reversal, like Brailsford's (1992) results, disappears when buy-and-hold returns are calculated.[14] Gaunt (2000) also makes adjustments for risk, and once doing so finds that the reversal for the loser portfolio is considerably reduced. Furthermore, the loser portfolio is found to be dominated by smaller firms. Hence, the size effect may well be driving the study's results, and not over-reaction.

From the above evidence, it seems as if the evidence in favour of anomalous relationships between fundamental variables and security returns in the Australian market is at best, ambiguous. This stresses the importance of carrying out further research in markets outside America to clarify a universal phenomenon.

2.5 Conclusion

Chapter One establishes the theoretical framework upon which, portfolio analysis is based. Chapter Two discusses the literature related to portfolio analysis that attempts to empirically test the implications of the rational, and behavioural asset pricing models.

While empirical relationships between various accounting, financial variables has been revealed, there is no theoretical justification for the inclusion of these variables in assessing a stock's risk. Chapter Two therefore discusses the rationale behind incorporating these variables in one's investment decision from the standpoint of Graham and Dodd's (1934), margin of safety concept.

This is followed by a discussion of early studies, highlighting the relationship between the level of a stock's P/E and B/M ratios, and realised returns. Additional anomalies in the January seasonal, and size effect are also discovered. This discussion reveals how contentious the results of these studies are. Despite using principally the same NYSE and AMEX data, and in many cases, considering the same time-periods, different

[14] The different methods used to calculate returns are discussed in depth in Chapter Three.

researchers find contradictory results, depending on which methodological approach is used. Whether these anomalies are unique, or whether they are merely different measures of the same phenomenon, is inconclusive.

A discussion of similar, yet more recent studies shows that the focus of these studies is not on attempting to explicitly search for stock-market anomalies. Instead, these studies centre around incorporating the anomalies, revealed in the earlier studies, into trading strategies. The purpose is more to explain the success of trading strategies from a behavioural, and rational asset pricing perspective. The focus has thus shifted to relating the empirical evidence of P/E, B/M, size and seasonal effects to portfolio theory.

These studies confirm the existence of all of the previously discovered P/E, B/M, size, and January seasonal anomalies. As LSV find, it does seem possible that investors can develop trading strategies that capitalise on these anomalies. In particular, there are numerous studies advocating the use of value-based investment strategies as long-term successful trading strategies.

This evidence supports the investment philosophy of Graham and Dodd (1934). What is not resolved, is an explanation as to why value-based strategies outperform growth-based strategies. On the one hand, Fama and French (1992) claim it is because these fundamental variables proxy for omitted risk variables in the spirit of the ICAPM. LSV however, argue that successful value strategies reflect investor over-reaction. This over-reaction is in line with the BSV, DHS, and Hong and Stein (1999) behavioural models.

The methodologies employed in these later studies are improvements on the methodologies employed in earlier studies, with biases such as look-ahead, and survivorship bias taken into account. However, as this chapter explains, there remains a great deal of controversy surrounding methodological issues. Should one use cumulative abnormal returns, or buy-and-hold returns in calculating portfolio returns? Should risk be incorporated in models calculating abnormal returns? These and other questions need to be answered before any study involving portfolio analysis is undertaken. These issues are therefore discussed in detail in Chapter Three.

PART TWO

DATA & METHODOLOGY

Part Two explains the methodological approach that is to be used in this study, and describes the data to be analysed. Chapter Three discusses the different methodologies employed in previous studies of investor over-reaction. The first step discusses the portfolio formation, and describes how an exploratory analysis of portfolio returns is conducted. To this end, the variables upon which the portfolio classification is based, are defined. This is followed by a discussion of the relative merits of different return metrics one can use in portfolio analysis. The exploratory analysis is completed by discussing the advantages and disadvantages of analysing value, or equal-weighted portfolios. The impact of the classification variables on portfolio returns is then examined in a formal statistical framework. For this, a linear, multivariate regression methodology is employed. This is defined, and how it is applied in a cross-sectional regression setting, is described. In order to account for the sequential ordering of the data analysed, time-series techniques are applied to the regression methodology. How this is to be accomplished is specified. This rounds out the discussion of the methodologies employed in this thesis. Chapter Four describes how the methodologies are specifically applied to the Australian equities data used in this study. This chapter begins by defining, and describing the data. Next, the application of the exploratory analysis of portfolio returns to the data is discussed. The specific application of the regression methodology to the portfolios is then examined. Lastly, specific tests are devised to see whether Australian security pricing is related to the rational, or behavioural realm of asset pricing.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

The aim of this chapter is to discuss the methodology used in this thesis in relation to methodologies used in previous, similar studies. Once this has been discussed, the data will be described in relation to the methodological approach. The specific data description is considered in Chapter Four.

To evaluate the success of value and growth-based investment strategies, one has to conduct portfolio analysis. The first step in this process is the portfolio formation itself. This requires the criteria, according to which portfolios are formed, to be justified. In this study, portfolio formation is dependent upon financial variables. These are discussed first in this chapter, with a discussion as to the interpretation of what each of these ranking variables, represents.

The second step in the portfolio analysis involves the computation of returns attributed to the respective portfolios in the post-portfolio formation time period. It is important that the method used in calculating returns, the return metric, is both practical, and statistically reliable. If this is not the case, the results will be rendered useless at the outset.

Once the relative performance of the portfolios has been established, the reasons for the differing performances among portfolios, should they exist, need to be considered. A number of different financial variables are used to rank stocks into portfolios. When forming portfolios however, only one, or at most two, variables are used to differentiate the value, from growth portfolios. This leads one to question whether each classification variable affects portfolio returns, or whether some variables proxy for, or are subsumed by others. Following the approach of LSV, regressions will be run on all of the classification variables in a multivariate setting.

This will allow the individual effects of the classification variables on returns to be highlighted. A discussion of potential problems one encounters in conducting a regression analysis, and possible solutions conclude this chapter.

3.2 The Portfolio Ranking Variables

Value stocks are regarded by investors as having being consistent financial performers in the *past*, with a weak, in comparison to growth stocks, anticipated *future* financial growth. Growth stocks are regarded by investors as being those stocks that are anticipated to have a strong, in comparison to value stocks, future financial performance. Growth stocks consequently do not necessarily have a strong past financial record in comparison to value stocks, and in many cases may have a poor past financial performance.

In order to determine which stocks are value and which are growth stocks, one has to first define how the past, and expected future financial performance of a company, is quantitatively measured. The four variables used to measure past and to estimate future performance, are discussed next. These four variables are known as the ranking variables as the magnitude of a particular stock's variable determines into which portfolio, growth, or value, it is put.

A direct measure of past financial performance is the growth in gross revenue, or sales, of a company over the pre-portfolio formation period. Those stocks with the highest growth in sales, or GS, form the growth, or glamour portfolio. Those stocks with the lowest GS, or worst past performance, form the value portfolio.

The next variable to be used in ranking stocks into growth and value portfolios is the ratio of the book value of stocks, or equity, to the market price thereof. This is denoted as the B/M ratio. As described in the literature review, this variable is important in determining whether a security is in a relatively good, or bad, financial position. As mentioned in Chapter Two, Fama and French (1992) argue that the B/M ratio is indicative of expected future financial performance. This is portrayed through a high market imposed leverage. LSV however, argue that it is not clear what this ratio actually measures. Amongst other things, it is argued that the B/M ratio may reflect the following:

> A low B/M may describe a company with a lot of intangible assets, such as research and development (R&D) capital, that are not reflected in the accounting book value because R&D is expensed. A low B/M can also describe a company with attractive growth opportunities that do not enter the computation of book value but do enter market price (1994, p.1547).

In other words, the B/M ratio can not be specifically related to a single interpretable firm characteristic. Fama and French (1995) in analysing the profitability of firms ranked into portfolios according to the B/M ratio, concur with this argument. Firms with high B/M ratios are found to have sustained low earnings, and profitability, in the pre-portfolio formation time period. Firms with low B/M ratios are also found to have high sustained earnings and profitability in the pre- portfolio formation period. Thus, this ratio might proxy for past company performance. However, these relationships are found to hold in the post-formation period as well. Thus the B/M ratio might also proxy for the expected future performance of a stock. Consequently, when portfolios are formed the B/M ratio is used as a measure of both past, and expected future performance. Those stocks with high B/M ratios are classed as value stocks, and those with low B/M ratios are classed as growth stocks.

The last two ratios, or variables that are used to classify stocks into growth or value portfolios, proxy for expected future financial performance of a company. The first, is the ratio of a stock's earnings to the market price, E/P. The second, is the ratio of a stock's cash flow to the market price, or C/P.

The inclusion of the E/P ratio is based on Graham and Dodd's (1934) work, and empirical results from studies discussed in Chapter Two that find a positive (negative) relationship between E/P (P/E) ratios, and stock returns. Ratios such as the P/E ratio must however, be treated with caution. Ball and Brown (1968), Treynor (1972), and Kaplan and Patell (1977), argue that it might be more reliable to utilise cash flow as a measure of a company's earnings power. This is because companies have the ability to alter their financial results using tools such as special items and accelerated depreciation in order to distort the financial results of the company concerned. It is argued that the true size of cash flow income is not as easy to manipulate. This is known as the quality of earnings effect.

Bernard and Stober (1989) find no economic logic underlying the assimilation of information about cash flows and accruals into security returns. This includes tests for the quality of earnings effect, macroeconomic conditions effects or a reaction to unexpected information contained in accruals data. These results do however, support conclusions drawn by Wilson (1987), and Kaplan and Patell (1977). They find that the securities do react to information contained in both accruals and cash flows over and above a reaction to information contained in a firm's total earnings. Unsurprisingly, cash flows are used in conjunction with earnings in studies, including this thesis, considering the relationships between fundamental variables and security returns.

Again, the question as to what the E/P, or C/P ratios indicate, is posed. The expectation is that companies, or securities with higher E/P and C/P ratios will grow earnings and cash flow at a lower rate than those with lower E/P and C/P ratios. As LSV explain, the reasoning behind this expectation can be explained through Gordon's formula. This states that

$$P = \frac{D(+1)}{r-g}, \tag{3.2.1}$$

where $D(+1)$ is the next time period's dividend, r is the expected rate of return on the security, g, is the expected growth rate of the dividends, and P, is the expected current price of the stock (Gordon and Shapiro, 1956). From this, the cash flow growth expectation can be described by re-writing this formula as:

$$P = \frac{pC(+1)}{r-g}, \tag{3.2.2}$$

where p is the constant fraction of cash flow paid out in dividends, C is the next period's expected cash flow, and g is the growth rate of cash flow assuming that dividends are proportional to cash flow. Similarly, equation (3.2.2) can be re-written to incorporate earnings, but with a different fraction of earnings being paid out in dividends. From this it can be deduced that a high E/P or C/P ratio implies an expectation that future earnings and cash flow growth rates will be low, and vice versa for low E/P or C/P ratios.

This can be best exhibited through a practical example. Consider two stocks, A, and B. Assume that both stocks have 100% pay-out ratios of the next period's expected cash flows, and consider the case of a single future time-period. Further assume that r= 10%. Lastly assume that stock A is a value stock, with a C/P of 0.09 and assume stock B is a growth-stock with a C/P of 0.02. By manipulation of equation (3.2.2), and solving for g, one can show that the expected g for stock A is 1%, and the expected g for stock B is 8%, this on a flow-basis and not a present value basis. Thus, the higher C/P is indicative of a lower expected growth rate.

As LSV explain, this does require a strict assumption that discount rates and payout ratios, p, are constant. Thus, it is important to ascertain the differences in risk between securities to make allowance for differing discount rates. Hence, the risk of a security needs to be incorporated in the analysis before judgements can be made on the interpretation of the E/P and C/P ratios.

3.3 The Return Metric

3.3.1 Calculating Security Returns

The success of any investment strategy rests in the returns that that strategy can earn for the investor in relation to the returns generated by any other specified strategy. It is therefore vital to accurately compute the returns that can be earned using an investment strategy. Any study that attempts to give meaning to the realised returns earned by securities has to test calculated returns jointly with a model for expected returns (Fama (1998)). Thus, a model has to be constructed to compute, and predict the returns one can expect a security to earn over a certain time period.

If the realised returns deviate from the anticipated or expected returns, the discrepancy is denoted as the residual, or abnormal return. As Fama (1998) explains, one can always expect a residual return to exist. This is because any method of computing returns whose purpose is to test a model, or strategy, is deficient. Even if a model is perfect, sample-specific results obtained in testing the model will include a component that is due to chance, thereby deviating from the model's predictions. It is important to limit the deficiencies of models when computing returns. This gives credence to the success of one investment strategy over another.

The different approaches to estimating expected security returns form part of what is known as event study methodology. As Martin, Cox, and MacMinn (1988) explain, the objective of an event study is to identify the degree and speed with which security prices respond to the revelation of publicly held information. In the case of this thesis, the events, or publicly held information consist of the fundamental variables used to explain returns.

In over-reaction studies, there are two different methods that are extensively employed to compute multi-period security returns. The first is known as the arithmetic method, and the second, a buy-and-hold method. Both methods are classed under event study methodology as market-adjusted return models. These are also known as the zero-one market models, Gaunt (2000). According to Brown and Warner (1980) this model assumes that the ex ante expected returns are equal across securities, but are not constant for a given security. In this model, the normal, or expected return on security i at time t, $E(\widetilde{R}_{it})$, is given by the following equation:

$$E(\widetilde{R}_{it}) = E(\widetilde{R}_{mt}) = k, \tag{3.3.1}$$

where $E(\widetilde{R}_{mt})$ is the expected return on the market portfolio at time, t. In this instance, the abnormal or residual return is given by:

$$\varepsilon_{it} = R_{it} - R_{mt}, \tag{3.3.2}$$

where:

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}}. \tag{3.3.3}$$

R_{it}, is the return to security i in the single time-period from t-1, to t. P_{it}, is the price of security i at time t, and P_{it-1} is the price of security i at time t-1. Note that in this thesis, t refers to the end of month t.

The market return is calculated as:

$$R_{mt} = \frac{1}{N}\sum_{i=1}^{N} R_{it}\,, \tag{3.3.4}$$

where: N= the number of stocks making up the market portfolio.

In this type of model, no adjustment is made for risk. Instead, it is assumed that all stocks have equivalent risk premiums, which are equal to the risk premium placed on the market portfolio. Thus, where the security's risk differs from that of the market, one can expect the residual returns to be significantly different from zero. If the residual returns are significantly different from zero, and the security's risk is seen as being equal to that of the market portfolio, this implies that assets are irrationally priced. Consequently, once the residual returns to the value and growth-stocks are determined, rational and irrational asset pricing theories can be tested by considering how each security's residual return is related to measures of risk.

Brown and Warner (1980) find that a single-factor model predicting expected stock returns, such as the market-adjusted model, identifies abnormal returns accurately. It is claimed that more complicated models add little to, or even detract from researchers' results when risk adjustments are added to such models. Consequently, extensive use of market-adjusted models has been made in studies analysing stock returns.

As mentioned, there are two versions of the market-adjusted return model that can be used to calculate security returns. The arithmetic method, or the re-balanced version thereof is extensively employed in earlier studies of stock market anomalies.[1] Drawing on Dissanaike's (1994) work, the arithmetic method of computing returns can be defined in the following way.

$$R_{CAR} = \sum_{t=1}^{T}\left(\sum_{i=1}^{n}\frac{R_{it}}{n}\right) - \sum_{t=1}^{T} R_{mt} \,. \tag{3.3.5}$$

In this equation, *CAR* is the cumulative average residual returns of a portfolio, *n* is the number of stocks in the portfolio, and *T* is the number of time-periods, *t*, under consideration. In this thesis, *T* refers to the number of months under consideration. R_{it} is the total return, adjusted for capital changes, on stock *i* in single time-period *t*.[2]

Studies criticising the different types of return metrics are discussed in this chapter. Empirical shortcomings of each method are assessed in Chapter Two. Because of the importance of utilising a sound methodology when conducting portfolio analysis however, it is necessary to re-iterate some of these findings and elaborate on the arguments behind rejecting, or accepting one or other return metric.

Blume and Stambaugh (1983) point out that the problem with the arithmetic method of computing returns is that if there is any statistical noise in stock prices, this will result in an upward bias when computing single-period returns. By adding returns over time-periods, one then cumulates the upward bias. This problem becomes especially acute when long-term returns are looked at. This is because a single variable at time zero, will not be the only determinant of a stock's price two years hence. It would be prudent to assume that other factors such as a change in business conditions, or interest-rate movements, might also affect the stock's price and add 'noise' into returns.

Conrad and Kaul (1993) go on to explain that "the absolute magnitude of the upward bias in *single-period* returns is invariant with respect to the length of the period over

[1] See Basu (1977), Reinganum (1981), and De Bondt and Thaler (1985).

[2] While other authors such as Roll (1983) and Conrad and Kaul (1993) define the abnormal returns in a different way, the principles of each arithmetic method are in accordance with those of the above equation and hence other variations have been omitted from this discussion.

which the return is measured." (Conrad, Kaul, 1993, p.45). Thus, over the long-term, the shorter the periods considered, the larger the total upward bias. So, if each period, *t*, is one day, or one week long, the bias will be more acute than if each period was one year long.

From equation (3.3.5), one can see that returns are added across stocks as well as over time. Dissanaike (1994) points out that the implication of this arithmetic approach is a re-balancing of the amount invested in each security *i* at the start of each period, *t*. It is argued that by adding returns together across periods one ignores the effect compounding will have on overall returns. The returns generated by equation (3.3.5) are hence, unrealistic. In addition to this, by re-balancing the portfolios so frequently, Roll (1983) argues that transaction costs are increased by a significant margin. Consequently, the arithmetic approach of computing returns is seen to incorrectly describe the returns realised by an investor.

While the transaction costs can not easily be adjusted for in the arithmetic model, a re-balanced version is proposed to take account of the effect compounding will have on returns. This is given below as:

$$R_{RB} = \left\{\left[\prod_{t=1}^{T}\left(1+\sum_{i=1}^{n}\frac{R_{it}}{n}\right)\right]-1\right\}-\left\{\left[\prod_{t=1}^{T}(1+R_{mt})\right]-1\right\}. \tag{3.3.6}$$

In this equation, R_{RB} is the re-balanced return on a portfolio. Again, R_{it} is the return on stock, *i*, in the time-period from *t-1*, to *t*. The number of stocks in the portfolio is depicted by *n*, and *T* is the number of time-periods, *t*, making up the length of the holding period.

Roll (1983) argues that a re-balanced form of computing returns results in unrealistic returns being recorded. As with the arithmetic method, it is argued that the transaction costs that are imposed through monthly re-balancing detract from the validity of calculated returns. Nevertheless, Roll (1983) does concede that this re-balanced method is free of the serial correlation prevalent in the alternative, the buy-and-hold return approach. It does not increase statistical bias induced by adding returns from period to period either.

Fama (1998) argues that there are theoretical reasons for favouring the Cumulative Abnormal Return (CAR) approach represented by equation (3.3.5). As mentioned in Chapter Two, a fundamental assumption of any asset pricing model is that returns have a normal distribution. Normality, it is argued, is a better approximation of returns where short-term horizons such as monthly returns are used. Additionally, many asset pricing tests are also conducted using monthly returns, not three or five year buy-and-hold returns. Comparisons are therefore made more easily by adopting this approach. Furthermore, buy-and-hold returns can be misleading when the speed of price adjustment to an event is considered. This is because buy-and-hold returns "can grow with the return horizon even when there is no abnormal return after the first period." (Fama, 1998, p.294). So, despite the problems encountered when using the CAR or re-balanced CAR approach, it is a plausible option to use when calculating security returns.

The alternative buy-and-hold return approach can be defined as:

$$(R_{PT_{BH}})_t = \tfrac{1}{n}\sum_{i=1}^{n}\left\{\left[\prod_{t=1}^{T}(1+R_{it})\right]-1\right\}-\left\{\left[\prod_{t=1}^{T}(1+R_{mt})\right]-1\right\}. \tag{3.3.7}$$

$(R_{PT_{BH}})_t$, is the buy-and-hold return of the portfolio, formed in month, t, calculated over the holding period T. R_{it} is the return on security, i, for month t, and R_{mt} is the return to the market over month t. Again, as with equation (3.3.5), n represents the number of stocks making up the portfolio.

From equation (3.3.7), the return to stock, i, over, T post-portfolio formation months, can be expressed in the following manner:

$$R_{iT} = \left(\prod_{t=1}^{T}(1+R_{it})\right)-1. \tag{3.3.8}$$

This can be simplified to the following equation:

$$R_{iT} = \frac{P_{iT} - P_{i0}}{P_{i0}}, \tag{3.3.9}$$

where: P_{iT} = price of security i at the end of T months, and

P_{i0}= price of security i at time 0.

While equation (3.3.9) is readily used to calculate returns, where companies have merged, or been taken over by other companies, it is necessary to calculate R_{iT} using equation (3.3.8). This is because where mergers have taken place, P_{iT} would not necessarily be comparable to P_{i0}. Hence the returns in month, t, need to be used to calculate the holding period returns if the merger, or take-over occurs during the holding period, T.

Substituting equations (3.3.9) and (3.3.8) simplifies (3.3.7) to the following:

$$(R_{PT_{BH}})_t = \left(\tfrac{1}{n}\sum_{i=1}^{n} R_{iT} - R_{mT}\right)_t = \left(\tfrac{1}{n}\sum_{i=1}^{n} \frac{P_{iT} - P_{i0}}{P_{i0}} - R_{mT}\right)_t. \tag{3.3.10}$$

The buy-and-hold return for portfolio *P* over the entire sample period can be calculated using:

$$R_{PT} = \frac{1}{t}\sum (R_{PT_{BH}})_t\,, \tag{3.3.11}$$

where *t* is the month in which portfolio *P* is formed.

Equations (3.3.7) and (3.3.10) therefore represent the buy-and-hold market-adjusted returns to portfolio, *P*. From equation (3.3.2) one can see that the residual returns of any portfolio should be zero. Hence the returns difference between *any* two portfolios, should be zero. Thus, when comparing the returns between two portfolios, one need not necessarily include the market return in the calculation. In this thesis, portfolio returns are therefore compared through forming the following arbitrage portfolio:

$$\left(R_{AT}\right)_t = \left(R_{P_1T}\right)_t - \left(R_{P_2T}\right)_t, \tag{3.3.12}$$

where R_{AT} is the return to the arbitrage portfolio estimated over T months from the time of portfolio formation t. R_{P_1T} and R_{P_2T} are the corresponding returns to two different portfolios. Equation 3.3.10 can be substituted into equation (3.3.12) as

$$\left(R_{AT}\right)_t = \left(\tfrac{1}{n}\sum_{i=1}^{n} R_{iT} - R_{mT}\right)_{P_1T_t} - \left(\tfrac{1}{n}\sum_{i=1}^{n} R_{iT} - R_{mT}\right)_{P_2T_t}. \tag{3.3.13}$$

This in turn simplifies to:

$$\left(R_{AT}\right)_t = \left(\tfrac{1}{n}\sum_{i=1}^{n} R_{iT}\right)_{P_1T_t} - \left(\tfrac{1}{n}\sum_{i=1}^{n} R_{iT}\right)_{P_2T_t}. \tag{3.3.14}$$

When comparing returns between portfolios, the market return can therefore be omitted. Residual returns are obtained through forming the arbitrage portfolio, and the market return does not necessarily need to be explicitly included in the analysis, in order to compare portfolio returns.

Roll (1983) observes that buy-and-hold returns are plagued by individual security serial dependence. This is not the case when portfolio returns are considered. Because this thesis attempts to look at practical trading strategies, this is an important consideration. Furthermore, as mentioned before, the effects of transaction costs on realised returns are minimised. Conrad and Kaul (1993) also highlight the fact that the upward bias inherent in the CAR and re-balanced CAR approaches is minimised.

Dissanaike (1994) however, notes that the buy-and-hold return reduces diversification in securities over the long term. This is because "over time, securities whose prices have risen will carry more weight in the portfolio than securities whose prices have fallen." (Dissanaike, 1994, p. 1086). Furthermore, Fama (1998) recognises that the CAR approach adds the spurious component of abnormal returns. However, as the number of time periods considered increases, this error becomes statistically insignificant. [3] The reverse holds with buy-and-hold returns because the standard error is multiplied. Thus, it is argued that the error encountered in the buy-and-hold and by implication, the re-balanced CAR approaches, is greater.

In summary, both the CAR, re-balanced CAR and the buy-and-hold return approaches to calculating returns are deficient to some degree. On balance however, the buy-and-hold approach does seem to proffer a more realistic view of security returns. It is therefore the metric adopted to calculate returns in this thesis.

3.3.2 Assigning Weights to Stocks in Portfolios

In addition to calculating the returns to stock portfolios, one also has to assign weights to each stock. There are two ways of doing this. Firstly, one can assign equal weights to each stock. So for instance, if one had 100 stocks, each stock would constitute 1/100 of the portfolio. This is the method implied by equation (3.3.6), where no adjustments are required to calculating portfolio returns.

An alternative method would be to weight each stock in a portfolio according to the market capitalisation of that stock. In this instance, if a stock comprises 15% of the total market capitalisation of the equity market, it will make up 15% of the portfolio.

Fama (1998) argues in favour of a value-weighted portfolio. He argues that long-term post-event returns disappear when stocks are value as opposed to equal-weighted. He argues that "value-weight returns give the right perspective on an anomaly because they more accurately capture the total wealth effects experienced by investors." (Fama, 1998, p.296). He also goes on to argue that if stocks are weighted equally, then there is bias in the returns because a disproportionate weighting is given to small companies. As Ball et al. (1995) observe, smaller company returns suffer from microstructure-induced biases such as liquidity problems. Thus, the value-weighted method of constructing portfolios

[3] By adding the spurious component each period using the CAR approach, the mean return "increases like N, the number of months summed, but the standard error of the CAR increases like $N^{1/2}$." (Fama, 1998, p. 291).

seems to be favourable. However, there is a problem encountered in smaller markets which favours the use of equal-weighted portfolios.

In equity markets consisting of a small number of stocks relative to the NYSE, a few large stocks tend to make up a large proportion of market capitalisation. Portfolio returns are then skewed towards these large companies when a value-weighted approach is used. As an example, as of 31 December 1999, the largest 5 domestic companies listed on the Australian Stock Exchange made up 31.19% of total domestic market capitalisation.[4] To have 31.19% of a portfolio invested in these companies would skew the returns on value and growth-stocks in their favour. This is evidently not a problem for equal-weighted portfolios.

In this thesis, this latter point is more pertinent than the size effect. This is because the sample is based on the largest 300 companies. Because there are approximately 1200 stocks listed on the Australian Stock Exchange, the smallest companies are omitted from the study and hence the microstructure related issues should be minimised. Therefore, equal-weighted buy-and-hold returns are calculated for stocks making up the value and growth-stock portfolios.

3.4 Multivariate Regression

While different means of classifying value and growth stock portfolios may yield similar results, the different variables used to classify the stocks into portfolios are at most, considered in a bivariate setting. Some of the financial variables may superficially affect returns. However, as the discussion in Chapter Two on early studies highlighting pricing anomalies shows, a bivariate sort does not differentiate among the unique effects different variables have on returns. Consequently, the interaction of the fundamental variables with each other and with stock returns are considered through using a multivariate regression approach.

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[4] These statistics are obtained from the Australian Stock Exchange Fact Book (2000).

Regression analysis can be defined as a method for investigating the functional relationships among different variables (Chatterjee, Hadi, and Price, 2000). The relationships are expressed as an equation. This equation specifies a model connecting the dependent, or response variable, to one or more explanatory, or predictor variables. This model can be of a linear, or non-linear form. This thesis only considers instances where the linear form is considered, and hence the non-linear form is not considered further.

In the simplest context, the response variable *Y,* is linearly related to an explanatory variable, *X,* as follows:

$$Y_t = \gamma_{0t} + \gamma_{1t} X_t + \varepsilon_t , \tag{3.4.1}$$

where Y_t *= response variable, obtained at time, t.*

X_t *= explanatory variable, obtained at time, t.*

γ_{1t} *= coefficient of X, estimated at time, t.*

γ_{0t} *= constant term, estimated at time, t.*

ε_t *= error term, estimated at time, t.*

This model assumes that the unknown parameters, γ_{0t}, and γ_{1t}, which have to be estimated, affect the mean of the response variable's distribution in a linear manner.
The linear equation (3.4.1), can be expanded to include a greater number of predictor variables. This general linear model is defined by equation (3.4.2), as follows:

$$Y_t = \gamma_{0t} + \gamma_{1t} X_{1t} + \gamma_{2t} X_{2t} + \ldots\ldots + \gamma_{zt} X_{zt} + \varepsilon_t . \tag{3.4.2}$$

Based on the work of Chatterjee et al. (2000), the notation for the cross-sectional relationship among the stock returns, the response variable, and the fundamental variables, the predictor variables, can be depicted as in Table (3.4.1).

For a single time period, t:

Table 3.4.1

The Notation Depicting the Relationship among Stock Returns and Fundamental Variables

Stock Number	Returns Y	Predictor X_1	Predictor X_2	Predictor ...	Predictor X_z
1	y_1	x_{11}	x_{12}	...	x_{1z}
2	y_2	x_{21}	x_{22}	...	x_{2z}
3	y_3	x_{31}	x_{32}	...	x_{3z}
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
N	y_N	x_{N1}	x_{N2}	...	x_{Nz}

Leading off this, the parameters, or predictor coefficients, are estimated for each stock, with the γ_{zt} coefficient for predictor X_z estimated by means of regression in each month, t. The time series estimates of the coefficients are portrayed through Table (3.4.2):

Table 3.4.2

Notation used when Estimating Time-Series Coefficients

Time-Period t	Return Y	Coefficient γ_1	Coefficient γ_2	Coefficient ...	Coefficient γ_z
1	y_1	γ_{11}	γ_{21}	...	γ_{z1}
2	y_2	γ_{12}	γ_{22}	...	γ_{z2}
3	y_3	γ_{13}	γ_{23}	...	γ_{z3}
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
t	y_t	γ_{1t}	γ_{2t}	...	γ_{zt}

From Table (3.4.2), the final time series estimate of the coefficient for predictor X_z can be given by the equation (3.4.3). Note that t is the number of time-periods used for the cross-sectional estimations.

$$\gamma_z = \frac{1}{t}\Sigma\gamma_{zt}, \tag{3.4.3}$$

where: γ_z is the final time series estimate of the coefficient for predictor X_z.

There is a problem encountered when estimating the γ_z coefficients using the mean of the cross-sectional γ_{zt} coefficients. The adjacent γ_{zt} coefficients may be correlated given that they are estimated sequentially in time (Chatterjee, et al., 2000). This is known as autocorrelation. Autocorrelation may bias the estimation of the γ_z coefficients and in the process, invalidate the significance of the X_z variables in explaining stock returns. Autocorrelation is therefore tested, and accounted for, before the final γ_z estimates are calculated and interpreted.

The first step in this process involves testing the adjacent γ_{zt} coefficients for correlation over time, using an Autocorrelation Function (ACF). If the ACF highlights any autocorrelation, the Partial Autocorrelation Function (PACF) may be examined. The purpose of this is to help estimate a suitable time series model that is then fitted to the γ_{zt} coefficients to remove the autocorrelation. Lastly, once a suitable time series model has been fitted to the γ_{zt} coefficients, the final γ_z coefficients are calculated. Using statistical tests of significance, these γ_z are tested to see whether they are significantly different from zero. If so, the underlying X_z variable is then significant in explaining stock returns.

This provides an overview of the time-series techniques applied in this study. These concepts are more easily clarified when discussed in conjunction with their application to the data. A more complete discussion on the description, and application of the ACF and PACF functions is therefore given in Chapter Five.

Lastly, Anderson, et al. (1990) discover multicollinearity among the explanatory variables in Australian data. Multicollinearity can be described as linear dependencies that exist between explanatory variables in the data. This breaches one of the fundamental requirements when conducting a regression. That is, the regressors must be orthogonal to accurately estimate the significance of the explanatory variables in explaining the response variable (Myers, (1986)).

If the explanatory variables are orthogonal, there the estimated coefficients for each variable should not be correlated with each other. To test for multicollinearity, the simple correlation coefficients are therefore calculated for the explanatory variable coefficients, and the significance of the correlation computed. This provides an indication of the reliability of the estimated variable coefficients.

3.5 Conclusion

The multivariate regression brings to a close the discussion of the methodologies employed in this study. The methodologies can be segregated into portfolio analysis, and multivariate regression.

To summarise the portfolio analysis, portfolios are constructed by ranking stocks in ascending order according to E/P, C/P, B/M, and GS variables. Those stocks in the highest (lowest) E/P, C/P, B/M (GS) portfolios constitute the value portfolios. Those stocks in the lowest (highest) E/P, C/P, B/M, (GS) portfolios constitute the growth portfolios.

Buy-and-hold returns are then computed for the portfolios, with the arbitrage portfolio used to ascertain the residual return attributable to each portfolio. The success of different investment strategies is then determined by the size of the residual return that investors earn in following certain strategies.

Lastly, the impact of each financial variable on portfolio returns is considered in a multivariate setting. Statistical techniques are incorporated in this analysis to reveal, and correct, potential biases in the results.

An examination as to whether risk, or behaviourally based explanations of portfolio returns differentiate between the differing performances of value, and growth stock portfolios, is the last stage of the analysis in this study. Because the behavioural and risk-based tests are specific to the data used in this study, the methodological approach used in these tests is not discussed in this chapter. Instead, this stage of the analysis is discussed in Chapter Four. Chapter Four explains how the methodological approach of Chapter Three is specifically applied to the data used in this study.

CHAPTER FOUR

DATA

4.1 Introduction

This chapter begins by discussing the data, and sample period that is used in this study. Next, the portfolio ranking variables introduced in Chapter Three are discussed, and it is explained how, using the data, these variables are calculated, and single and double-sort value and growth portfolios, constructed.

There are two aspects that differentiate this study from most previous over-reaction studies. The first factor lies in the incorporation of a stock's industry classification as a possible explanatory variable. The potential impact that the industry classification may have on stock returns is discussed, and it is explained how this factor is accounted for in this study. The second factor differentiating this, from other studies is the construction of portfolios in a manner that specifically accounts for seasonal effects using an approach not employed in many previous overreaction studies. Seasonality, and the resultant impact this has on constructing portfolios is discussed.

The return metric is then briefly discussed, followed by a specification of the regression model that is used in this study. This chapter is then brought to a close with a thorough discussion on how the data is analysed in an attempt to explain portfolio returns from a behavioural, and rational asset pricing perspective.

4.2 Sample Selection and Sample Period

This study utilises share price data, and accounting data from the universe of companies listed on the Australian Stock Exchange. The share price data is obtained from the Securities Industry Research Centre of Asia-Pacific, SIRCA, located in Sydney, Australia. The accounting data is obtained from Jobson's Year Book of Public Companies for the industrial companies, and Jobson's Mining Year Book for the mining and resource listed companies. This information is obtained by examining all the successive publications starting with the 1990 editions, and ending with the 1999 editions. Both books are published by Dun & Bradstreet.

The data is analysed over the time period from 30th June 1990, to 31st May 2000. The reason for selecting this period rests in the stock market crash, which occurred in October, 1987. This crash resulted in an aberration in the sense that market capitalisation and liquidity spiked around that period (Lynch, 1993). Thus, the results may be affected by this aberration, and unusual conclusions drawn.

Using these data, and considering the 1990-2000 time period, value and growth-stock portfolios are formed according to fundamental ratios. The post-formation returns of these portfolios are then compared, and analysed. The fundamental variables and criteria that stocks have to meet in order to qualify for the study, are discussed next. This is followed by a description of how these variables are used to classify common securities into the value, and growth stock portfolios.

4.3 Ranking Variables

Not all of the companies which make up the universe of companies listed on the Australian Stock Exchange are considered for analysis. As Ball, Kothari, and Shanken (1995) observe, microstructure factors can systematically bias measured raw returns. Microstructure factors can be particularly acute for low-priced stocks, and those that are infrequently traded. By including such stocks in an analysis, the validity of the obtained results will at best, be questionable. Of the listed securities in general, the smaller companies in terms of market capitalisation, are more likely to suffer from microstructure related issues.

The largest 300 listed companies in terms of market capitalisation are therefore considered for this study. To be specific, at the portfolio formation date, *t*, a security must be one of the largest 300 listed securities in terms of the market capitalisation. The market capitalisation on the portfolio formation date is calculated by multiplying the total number of common shares outstanding at time, *t*, by the price of those shares at time, t. If the stock meets the other criteria required for this study, it will then be included in the list of securities that qualify for portfolio formation at time, t.

The remaining criteria that stocks have to meet to be considered for selection in portfolios, lie in the valuation, or ranking variables. As discussed in the methodology, the first variable to be considered is growth in sales, or GS. Specifically, GS is computed considering only one year's growth in the pre-formation period. Using equation (4.3.1), stocks are ranked on the portfolio formation date at time, t:

$$GS_i = \frac{Sales_{Q-1} - Sales_{Q-2}}{Sales_{Q-2}}, \tag{4.3.1}$$

where: Q= the year in which the portfolio is formed.
Q= (1990,1991,1992,..., 1998).

GS_i represents the growth in sales for stock *i*. $Sales_{Q-1}$ represents the sales as reported at the financial year-end of year *Q-1*. So for instance, take stocks being considered for portfolios formed at the end of March 1991. The GS is calculated by subtracting the reported gross sales, or revenue figure, at the financial year-end of 1989 from the sales figure reported at the financial year-end of 1990, with the result divided by the sales figure reported in 1989. The Sales, or Revenue figures are defined as the amount of goods and services to third parties relating to normal activities of the company.

The next two valuation ratios that are used to form portfolios are the earnings-to-price ratio, E/P, and the cash flow-to-price ratio, or C/P ratio. The earnings figure is defined as earnings attributable to ordinary shareholders. This is the net profit after tax. Similarly, the cash flow is defined as earnings, but with depreciation added back on.

The E/P ratio is calculated at the time of portfolio formation, t, and is calculated at the date of portfolio construction in year *Q*. The earnings figure reported for year *Q-1* in the Jobson's Year Book published in year *Q*, is divided by the number of ordinary shares outstanding at the time of portfolio formation in year *Q*. This earnings per share figure is then divided by the share price on the day of portfolio formation at time, t.

This share price is defined as the last price before portfolio formation at which a share was traded. The C/P is calculated in a similar manner where the depreciation reported for year *Q-1* is added to the earnings figure before dividing by the share price.

There is an important pre-requisite that companies have to meet with regards to these ratios. That is, stocks must have positive C/P and E/P ratios for the year prior to the portfolio formation date to be considered for portfolios where C/P, or E/P are the classification variables. [1]As LSV mention, this does not introduce bias in the results, because the portfolio returns can be viewed as an unbiased measure of the subset of firms that make up the universe of firms with positive earnings or cash flows.

The last valuation ratio to be used is the Book to market or B/M ratio. The Market value is defined as the total number of shares outstanding multiplied by the share price at the time of portfolio formation. The book value is defined as the net tangible assets of the company. The B/M ratio is calculated at each portfolio formation date, *t*, as the book value for year *Q-1* reported in Jobson's Year Book in year *Q*, and this is divided by the total market capitalisation of the company. The total market capitalisation of the company is calculated as the number of ordinary shares outstanding multiplied by the share price at time, *t*. The share price is defined in a similar manner to that for the E/P and C/P ratios.

Notice that this method of calculating the GS, E/P, C/P, and B/M ratios avoids the look-ahead bias documented by Kothari et al. (1992). By using the Jobson's Year Book published in year *Q*, it is ensured that all accounting data was available for an investor forming portfolios in year *Q*. This approach ensures that the growth and value-based investment strategies remain predictive in nature.

The ex-post selection bias documented by Kothari et al. (1992) is also avoided. This is done by obtaining the accounting information for year *Q-1* from the Jobson's Year Book published in year *Q*. Thus for an investor forming portfolios in 1994, Jobson's Year Book for Public Companies and Jobson's Mining Year Book, both published in

[1] Note that where C/P and E/P are not classification variables, for instance, where B/M is used to rank stocks, then stocks with negative C/P or E/P ratios are considered for portfolio selection.

1994 are used to obtain the relevant accounting information for 1993 and 1992. This information is not obtained using a later edition, which excludes stocks that would have been de-listed in the interim. This allows all companies that might have been de-listed in the post-portfolio formation period to be included for selection. The pricing data obtained from SIRCA also includes prices for all de-listed companies as well, thereby also avoiding this bias.

4.4 Portfolio Construction

4.4.1 Single-Sort Portfolio Classification

To begin with, in a similar manner to LSV, nine portfolios are formed by ranking stocks in ascending order based on each of the B/M, C/P, E/P and GS ratios. This results in four different means of classifying stocks into growth, and value portfolios. Those stocks in the lowest B/M, C/P, and E/P, and the highest GS portfolios, form the growth portfolio. Those stocks in the highest B/M, C/P, and E/P and lowest GS portfolios, form the value portfolio.

On forming these portfolios, the one-year, and two-year post-formation buy-and-hold returns are calculated for all the portfolios. The return to each portfolio is then averaged for the sample time-period using equation (3.3.11). The returns difference between the average value and growth-stock portfolios is examined by forming the arbitrage portfolio using equation (3.3.14). The interim portfolio returns are also considered to see how the returns change from portfolio to portfolio.

4.4.2 Double-Sort Portfolio Classification

Once the differences between value and growth stock returns for the single-sort strategies are considered, more complex growth and value-based investment strategies are analysed. Stocks are sorted into portfolios according to 2 classification variables. The first variable used in the classification is a measure of past financial performance. That is, the GS and B/M variables are used to rank stocks according to past performance. The second variable represents a measure of expected future performance. The variables used here are the E/P, C/P, and B/M variables. As mentioned in Chapter Three, the B/M variable may be interpreted as a measure of both past and expected future performance and is therefore included as such. There are therefore five different means of classification that are used to form portfolios. That is, there are GS and B/M, GS and E/P, GS and C/P, B/M and E/P, and lastly B/M and C/P portfolios that are formed.

Again, following the double-sort approach of LSV, portfolios are constructed as follows. Stocks are ranked on the portfolio formation date in ascending order according to the past performance measure. The stocks are then split into 3 equal portfolios with the top 33.3% of stocks forming the first, the middle 33.3% the second, and the bottom 33.3% the third portfolio.

All these stocks are then independently ranked in ascending order according to the variable representing a measure of expected future financial performance. These stocks are also split into 3 equal portfolios with the top 33.3% of stocks forming the first, the middle 33.3% the second, and the bottom 33.3% of stocks the third portfolio. The final portfolios are then calculated by taking the intersection of both sorts to form six portfolios, and the post-portfolio formation returns for these final portfolios are then analysed. Using GS as the past performance ranking variable, and E/P as the expected future performance ranking variable, this method of portfolio formation can be clarified by examining Table 4.1.

Table 4.1

Portfolio Formation using a Two-Variable Classification Sort

Ranking Variable	Portfolios								
GS	1	1	1	2	2	2	3	3	3
E/P	1	2	3	1	2	3	1	2	3
final portfolio	1,1	1,2	1,3	2,1	2,2	2,3	3,1	3,2	3,3

From this table, one can see that those stocks in the highest GS portfolio, portfolio 3, that are also in the lowest E/P portfolio, form the 3,1 portfolio. This is the growth, or glamour, portfolio. Likewise, those stocks that are in the lowest GS portfolio and that are in the highest E/P portfolio, form the 1,3 portfolio. This constitutes the value portfolio. Table 4.2 gives a summary of the five different value and growth portfolio types that are compared in this study.

Table 4.2

The growth and value-based portfolios

Ranking Variable	Growth portfolio	Value Portfolio
GS and E/P	3,1	1,3
GS and C/P	3,1	1,3
GS and B/M	3,1	1,3
B/M and E/P	1,1	3,3
B/M and C/P	1,1	3,3

Because the final portfolios are formed by taking the intersection of the two sorting schemes, these portfolios will not necessarily have an equal number of stocks in them. This raises a potential problem. One has to ensure that each portfolio has a reasonable number of stocks in them. This is because descriptive statistical measures such as the calculation of the portfolio mean, rely on an assumption that the results are derived from a normally distributed population. By including 20 to 30 stocks in each portfolio, one can assume that results will be normally distributed as the requirements of the Central Limit Theorem should be satisfied. As the sample selection is drawn from the largest 300 publicly listed companies, by dividing stocks into too many portfolios, this pre-requisite is jeopardised. Splitting stocks into 9 equal portfolios using the single-sort portfolio classification may compromise this pre-requisite. It almost certainly will be compromised using the double-sort classification given that the portfolios may have different numbers of stocks in them.

While this is a potential weakness of this portfolio analysis this approach to constructing portfolios has been retained for two reasons. The first, is that anywhere from 89 portfolio-formation time-periods in the case of a single-sort GS classification, to 96 time-periods in the case of the B/M classification, are used to average portfolio returns. Consider a 3,1 GS and B/M portfolio with an average of 12 to 17 stocks in it. The returns to this portfolio might not resemble a normal distribution. However, while there are only 12 to 17 stocks in each portfolio, the average return is calculated using

89 different 3,1 GS and B/M returns for each formation time, t.[2] Thus it can still be assumed that the average portfolio returns over the entire sample-period follow a normal distribution. Secondly, by splitting stocks into 9 portfolios using each classification sort, one ensures that if there are systematic differences in returns across portfolios, this will be picked up. If too few portfolios are used, the difference in returns between extreme portfolios may not be apparent.

Lastly, in order to be classified into a portfolio, a stock must have information available on both variables. If a stock is considered for classification into one of the B/M and E/P portfolios formed on 31 March, 1991 for instance, it must have both B/M and positive E/P ratios calculated for that month.

4.4.3 Industry Classification

Ball and Brown (1980) study returns to Australian stocks over the 1964 to 1973 period. The returns are found to be similar across industry sectors, but the standard deviation of mining sector returns is found to be twice the industrial counterpart. This implies that more extreme returns are likely to be found in the mining sector, and it might be the industry, and not the fundamental variable itself that drives portfolio returns. Brailsford (1992) supports these findings. However, it is concluded that the mean returns between the industrial and resources sectors are insignificant, and hence industry sectors are not seen to be a determinant of returns.

To determine the impact stocks might have on returns, stocks are classified into their respective industries. Like Brailsford's (1992) study, the number of stocks from each industry in the value and growth stock portfolios is looked at to see if a specific industry dominates the returns. While the ASX classifies equities into 24 industries, this classification is not used. Instead, a broader classification is used whereby stocks are grouped into 4 industries: mining, other resources and energy, finance, and other industrials.

[2] Refer to equation (3.3.11) for greater clarity on this.

Companies that are involved in mining gold or any other metals, are grouped under mining. Any other resource or energy companies are grouped into a diversified resources and energy group. Finance is comprised of banks and finance companies, and includes any companies involved with investment and financial services. Lastly, the rest of the industrials are grouped under the other industrials category.

While this is a broad classification system, the purpose is not to analyse differences in returns between each and every industry. The purpose is two-fold. In the first instance, based on the work of Ball and Brown (1980) it remains to be seen whether mining companies are heavily represented in the two extreme portfolios. Secondly, because portfolios are formed according to fundamental variables, the results and valuation ratios of any stocks in the financial services sector may skew portfolio performance. As Fama and French (1992) observe, "the high leverage that is normal for these firms probably does not have the same meaning as for non financial firms, where high leverage more likely indicates distress" (Fama and French, 1992, p.429). Thus, the fundamental variables in the financial sector may be interpreted differently by investors. If clustered into one portfolio, these companies may then have an impact on the portfolio returns. Hence the need for a finance industry classification.

Once stocks have been classified into the four different industries, the number of stocks from each industry in each portfolio is counted. The industry representation in each portfolio is then determined by calculating the number of stocks from each industry as a percentage of the stocks in each portfolio. The industry representation as a proportion of each portfolio is then averaged over the sample period to obtain final estimates of the composition of each portfolio. This is to see whether one industry makes up a large proportion of a portfolio.

To ascertain the impact of industry on stock returns more formally, the industry variables are included in the multivariate regression as dummy variables to test their impact in a multivariate setting. This is further discussed in section (4.5).

4.4.4 Seasonality

The effect that the month of January supposedly has on returns is well documented. In testing for the prevalence of the January effect, previous studies have generally compared the returns that stocks, or portfolios earn in the month of January, with the returns earned by stocks in other calendar months. The returns to the January arbitrage portfolio are then analysed to see whether returns in January are higher than returns in the other months.

This is however, only one way to test for seasonal effects. Because this thesis is concerned with longer-term holding periods of one and two years, seasonal effects such as the January effect can influence returns to value and growth portfolios alike. This may therefore have no net effect on returns to the arbitrage portfolio.[3] Consequently, seasonal effects to portfolio returns are considered from a different angle in this thesis.

In previous studies such as Cai (1997), and Chan et al. (1991), portfolios are formed at the same date every year. This formation date is selected in an attempt to avoid the look-ahead bias. This is done by choosing a formation date that is after the end of the tax year-end, thereby allowing investors to be privy to information used in the portfolio construction. So for instance, given that most companies listed on the ASX have 30 June as their financial year-end, portfolios can be formed on 30 September each year. The three-month lag ensures that look-ahead bias is avoided.

Despite this reasoning, the problem with this approach is that the portfolio formation date is identical for each year. Thus, as Li (1998) argues, while some investment strategies may outperform others, it remains questionable whether the calendar formation date makes a difference to the returns that an investor can achieve in pursuing certain investment strategies. In fact, as reported in Chapter Two, Ball, Kothari, and Shanken (1995) find that changing the portfolio formation date eliminates returns to value portfolios.

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[3]In some studies of overreaction looking at long-term return horizons, seasonality is not considered at all. See LSV, Cai (1997).

Using an approach similar to Li (1998), the impact the calendar formation date has on portfolio returns is therefore examined. The average one, and two-year returns to value and growth portfolios are calculated for each formation month, *j* using equation 4.4.4.1.

$$R_P = \frac{1}{J}\sum R_{Pj} \quad , \tag{4.4.4.1}$$

where: R_{Pj}= *The return to portfolio, P, in month j,*

R_P= *The average return to portfolio, P, formed in month j,*

j= (January, February, March, ..., December), and

J= The number of times portfolio, P, is constructed in month j.

As an example of the use of this equation, consider the case where the B/M variable is used to classify stocks into portfolios. The one-year return for portfolio 1 is averaged for each month across the sample-selection period. These average returns are then compared across the 12 months to see how the one-year returns differ according to the portfolio formation date. This is repeated for portfolio 9, the growth portfolio. This is then also repeated for each different classification variable. By graphing these results, one can see whether the calendar formation date has an impact on the returns to the value and growth portfolios.

4.4.5 Calculation of Returns

Recall from Chapter Three that the buy-and-hold returns over time period *T* for portfolio *P* can be calculated using equation (3.3.10). Likewise over the entire sample period the buy-and-hold return to portfolio *P* over time period *T* is calculated using equation (3.3.11). In this thesis, 12 month returns, T=1 year, and 24 month returns, $T=2$ years, are compared for value and growth portfolios. Portfolios are formed monthly, and there are 96 (89) different portfolios formed, $t=1,2,...96$ *(89).*[4]Using each classification scheme, the value and growth portfolio returns are calculated and then compared to see which strategy outperforms the other.

[4] The numbers in parentheses refer to the number of times portfolios are formed when the GS variable is included as a classification variable.

The returns are adjusted for any capital changes such as stock splits, and bonus issues. Dividends are also assumed to be re-invested. This therefore signifies the entire return that ordinary shareholders would receive.

As mentioned, the portfolios are drawn from the largest 300 publicly listed stocks on the ASX. The composition of portfolios, formed monthly can be expected to change through time because larger stocks are listed, and take the place of others in the top 300. The composition can also change because some stocks de-list, some companies go bankrupt, and other companies merge, or are taken over. If a stock de-lists in the post-portfolio formation period because of bankruptcy, the 12-month and 24-month return is assumed to be –100%.[5]

This does not hold for a company that de-listed because of a merger, take-over, or alternatively had a name change. In this case, the monthly returns attributable to the merged, or new company after the merger, take-over or name change are calculated and incorporated in the calculation of the 12- and 24-month returns using equation (3.3.8). Initially, where price-relative data is missing for companies included in portfolios, the companies are identified and are assumed to have been de-listed. These companies are then checked against the list of dead stocks in Datastream International Limited data base, and checked against the relevant monthly publication of the Australian Stock Exchange Journal, which has in latter years, been re-named as Shares magazine. The relevant adjustments are made to returns where it is found that companies underwent name changes, merged, or are taken-over. Where stocks are found to have de-listed, or where no information is found on the stock concerned, the company is assumed to have de-listed and a –100% return for that stock is assumed.

[5] While a liquidating dividend may be paid out to shareholders, this information was unobtainable. Hence the conservative assumption that in the event of this occurring, the investor will lose all of his initial investment.

4.5 Multivariate Regression

Regressions are conducted on individual stocks at time, *t*. Thus regressions are repeated monthly, with the first regression conducted on the stocks selected for portfolios in January 1991, and the last one conducted on the stocks selected for portfolios in May 1998. January 1991 is chosen so as to begin the regressions where GS information is available.

The regressions are conducted in the manner discussed in section (3.4) in Chapter Three. Specifically, the regression model that is calculated each month is similar to the general linear model described in equation (3.4.2) and can be defined for each month, *t*, as:

$$Y = \gamma_0 + \gamma_1 B/M + \gamma_2 C/P + \gamma_3 E/P + \gamma_4 GS + \gamma_5 I_1 + \gamma_6 I_2 + \gamma_7 I_3 + \varepsilon, \qquad (4.5.1)$$

where Y= *buy-and-hold return,*
B/M= *book to market variable,*
GS= *1 year pre-portfolio formation growth in sales,*
C/P= *cash flow-to-price variable,*
E/P= *earnings-to-price variable,*
I_1= *mining industry dummy variable,*
I_2= *other resources industry dummy variable, and*
I_3= *other industrials industry dummy variable.*

Note that the response variable is the buy-and-hold return. The relationship between the fundamental variables and buy-and-hold returns might be affected by the length of the holding period. Therefore, two different models, one incorporating 12 month, and the other 24 month, buy-and-hold returns, are constructed.

The degree to which stock returns are industry-specific is ascertained through incorporating industry dummy variables in the regression model. Specifically, if a stock belongs to the mining industry, variable I_1 will be 1, and I_2 and I_3 variables will be 0. Likewise if a stock belongs to the other resources (other industrials) industry, the

variable I_2 (I_3) will be 1, and variables I_1 (I_1), and I_3 (I_2) will be 0. The coefficients, γ_5, γ_6, and γ_7, that are produced for the industry variables I_1, I_2, and I_3 are then added to the constant, γ_0 to determine their significance. If a stock belongs to the finance industry, the variables I_1, I_2, and I_3 will all be 0, and in this instance, the significance of the finance industry variable's coefficient, is equal to the significance of the constant, γ_0.
The coefficients estimated for the B/M, GS, C/P, E/P, and industry dummy variables are the γ_{zt} coefficients discussed in section (3.4). These are then put in a table and autocorrelation is tested for using the ACF function. The results of this test determine whether or not a time series model should be fitted to estimate the γ_z coefficients. This is analysed and discussed in the Results and Analysis Chapter.

4.6 Rational and Behavioural Explanations of Portfolio Returns

The next step attempts to explain why growth and value stocks yield the returns that they do. Returning to the realm of traditional finance, an attempt is made to account for portfolio risk. The purpose of this is to see whether risk adjustments explain any discrepancies in returns across portfolios. Alternatively, returning to the realm of behavioural finance, whether any discrepancy in portfolio returns is due to investor irrationality is considered.

4.6.1 A Rational-Based Explanation of Returns

An adapted market-adjusted return model is used to analyse portfolio returns. As already stated, this assumes that the ex ante expected returns are equal across securities. Thus, no adjustment is made for securities with differing levels of risk. In this section, a traditional measure of risk is used to account for these differences between securities, and the resultant impact on returns is considered.

Although the CAPM seems inadequate in explaining stock returns, there is no economically justifiable reason for including different factors in a multi-faceted approach to determining a security's risk. Even when Fama and French's (1992) development of a three-factor model is considered, a number of problems are encountered in using such an approach to measuring risk. The first is that in order to utilise such a model effectively, one has to estimate the SMB, and HML variables for stocks before applying the model.[6] In order to accurately estimate these variables, a large number of stocks is required. Because only 300 stocks are considered for selection in each portfolio, and only 10 years of data are looked at, the accuracy of estimating these variables is compromised. Furthermore, because these stocks are selected on size, the validity of the SMB estimation is further compromised.

Consequently, the measure of risk developed through the CAPM, beta, is used to measure a security's risk profile in this thesis. Beta, as it is used in this study, is defined as the sensitivity of changes in a portfolio's returns, to changes in the market's return. The market return that is used is the return to all 300 stocks that are considered for portfolio selection. The market return is calculated using equation (3.3.4). Beta, (β) is estimated for each portfolio by regressing the portfolio's return on the market return using the following equation:

$$R_{PT} = \alpha + \beta_{PT} R_{mT}, \tag{4.6.1.1}$$

where R_{PT} is the one-year, return to portfolio, P, starting with month, t. R_{mT} is the one-year return on the market portfolio, α is a constant and β_{PT} is the measure of the undiversifiable risk of portfolio P, over one year, starting at time, t.

Each portfolio's beta for the entire time period under consideration is estimated as:

$$\beta_{PT} = \frac{1}{t}\sum(\beta_{PT})_t\,. \tag{4.6.1.2}$$

The betas and returns of the growth and value portfolios are then compared. As already mentioned, beta may not be related to returns in the manner proposed by the CAPM. If not, this analysis is not a waste as it will add to the body of work that has invalidated the use of beta as a risk measure.

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[6] Refer to the literature review for a discussion of this model.

4.6.2 A Behaviourally-Based Explanation of Portfolio Returns

Security returns may not be related to risk. As the behavioural asset pricing models intimate, assets may be irrationally priced. The next goal is to analyse whether security returns are driven by investor irrationality. This is accomplished through comparing past earnings growth rates, expected future growth rates, and realised future growth rates. This is known as a test of naïve extrapolation (Lakonishok, et al., 1994).

Gordon's formula, is adapted to include cash flows in equation (3.2.2). This indicates that by holding the discount rates and payout ratios constant, one can calculate differences in expected growth rates, *g*, between stocks or portfolios by comparing differences in C/P, and hence E/P, ratios (Gordon and Shapiro, 1956).

Naïve extrapolation refers to the situation where investors are too liberal in extrapolating realised past earnings growth trends, into the future. Consequently, their expectations are not met in the future. Realised growth rates, and prices of stocks subsequently adjust to reflect the unanticipated performance. This leads to lower than expected growth stock, and higher than expected value stock returns.

To test for naïve extrapolation, the average earnings growth rates for portfolios are calculated across pre- and post-portfolio formation periods. These are compared to the growth rates implied by the average portfolio E/P. It is then seen whether the expected growth is in fact, realised. If naïve extrapolation takes place, the realised earnings growth rates of growth stock portfolios should be less than that implied by the E/P, and vice versa for value stock portfolios.

A portfolio's one-year earnings growth rate can be calculated using the following equation:

$$AEG_{Pt} = \frac{\left(AE_{Pt} - AE_{P(t-12)}\right)}{AE_{P(t-12)}}, \qquad (4.6.2.1)$$

where:

$$AE_{Pt} = \frac{1}{n}\sum_{i=1}^{n} E_{it} \, . \tag{4.6.2.2}$$

AEG_{Pt} is the average earnings growth rate for portfolio P, from month t-12 to time t. E_{it} is the earnings figure for stock i at time t, and n is the number of stocks making up portfolio P. The 24 month, or two-year growth rates can be computed using the same method, only looking at the time period t-24 to t.

As an additional measure, the pre-portfolio formation and post-portfolio formation realised growth rates in sales are also compared using an identical approach. In this instance, the sales figure replaces the earnings figure in the above equations. Using this approach, it is seen whether investors do naively extrapolate past trends too far into the future, or whether the expected growth rates are in fact realised.

This discussion concludes this chapter. The next few chapters contained in Part Three report the results obtained when the data is analysed using the methods discussed in Part Two.

PART THREE

RESULTS & ANALYSIS

Part Three analyses the results of this thesis. Chapter Five begins by reporting the results of each of the single-sort classification schemes. For each single-sort scheme, the one and two-year average returns to the value and growth stock portfolios are reported. This is followed by the results, and a brief discussion of the rational and behavioural asset pricing explanation of the portfolio returns. The results of the single-sort classification schemes are completed through a discussion of the impact industry classification, and the calendar initiation dates of the value and growth-based investment strategies have on returns to the value and growth stock portfolios. This is followed by a discussion of the returns attributed to the value and growth stock portfolios when stocks are sorted into portfolios according to the double-sort classification scheme. Lastly, Chapter Five reports the results of the multivariate regression and concludes with a brief discussion on the linear relationship, or lack thereof between financial variables and stock returns. Chapter Six summarises the results reported in Chapter Five, and a comparison of the results of this thesis with those of other, similar studies is made. Chapter Six is completed by a discussion of directions for future research, and the conclusions of this thesis are drawn.

CHAPTER FIVE

RESULTS

5.1 Introduction

The empirical results of value and growth-based investment strategies are presented in this chapter. To begin with, returns attributed to the growth and value stock portfolios, classified according to the single-sort classification schemes are presented. As reported, the returns to most of the value portfolios exceed those to the growth portfolios. However, the returns from the interim portfolios, those portfolios that lie between the extreme value and growth portfolios, do not increase in a systematic fashion as one progresses from the growth, to the value portfolio. This indicates that other factors might be driving the portfolio returns.

Chapter Four describes how a fundamental assumption of the market-adjusted model is that the risk profile of each stock, and consequently of each portfolio, is identical. Therefore, the next step reports the results of the estimation of portfolio risk, using the CAPM β. This is to see if risk can explain the portfolio returns.

For an alternative explanation, the average annual earnings and sales growth rates of each portfolio are compared to see whether behavioural bias can explain portfolio returns. This is followed by a presentation of the impact industry classification and seasonality have on value and growth stock portfolio returns. Lastly, the one, and two-year returns to the value, and growth portfolios classified according to the more complex, double-sort portfolio classification schemes, are presented.

The explanatory power of each ranking variable, is then determined through looking at the results of the multivariate regression. The results from tests of multicollinearity in the explanatory variables are reported, along with the measures taken to correct this before conducting the multivariate analysis. Once the regressions on stock returns are conducted, the results for tests of autocorrelation in the coefficients are also presented.

This is followed by a discussion of the modelling that is subsequently applied to the coefficients to correct the autocorrelation before the final coefficient estimates and t-statistics, are obtained.

Chapter Six incorporates these results in a comprehensive discussion about, and interpretation of the success of value-based investment strategies. This is followed by a conclusion, summarising the arguments put forward in this thesis.

5.2 Results of the Single-Sort Classification Schemes

5.2.1 Results of the B/M Portfolios

Section 5.2.1 presents the returns to portfolios formed using the B/M single-sort classification scheme discussed in Chapter Four. Specifically, the average one-year and two-year buy-and-hold returns to portfolios 1 to 9 over the entire sample-period are considered. The one-year and two-year returns signify whether value strategies out-perform growth strategies in the short, and long-term respectively. The average one-year, and two-year returns over the sample-period, to the nine B/M portfolios are presented in Table 5.2.1.1. The value portfolio results are shaded, and those of the growth portfolio are in bold-type.

Table: 5.2.1.1

Average Returns to B/M Portfolios (%)

T	**1**	2	3	4	5	6	7	8	9
1 Yr	**-0.73**	0.76	6.62	5.69	2.96	1.7	6.34	3.39	14.02
2 Yr	**-4.77**	-3.81	8.72	4.97	4.4	7.45	3.95	14.11	30.66

From Table 5.2.1.1, one can see that the value portfolio, portfolio 9, yields on average 14.8% higher returns than the growth portfolio, portfolio 1. This margin increases to 35% over two years. As mentioned in Chapter Four, these differences represent the return to the arbitrage portfolio, termed the value arbitrage portfolio.

Notice that when the interim portfolios are considered, there is not a systematic increase in buy-and-hold returns from the growth, to the value, portfolio. The difference in one-year returns between portfolio 8, and portfolio 1 is for instance only 4.12%, and the difference in two-year returns between portfolio 6, and portfolio 3, is –1.27%. Interestingly, portfolio 6 achieved an approximate return of 5.7% in the second year, whereas portfolio 3 grew by only 2% in the second year. Likewise, portfolio 8 and 9 achieved returns of 10.4% and 14.6% in the second year after portfolio formation. In contrast, portfolios 1 and 2, had negative returns of approximately 4% and 4.5% respectively. This results in portfolio 8 increasing its margin over portfolio 1 from 4.12% over one-year, to 18.88% over two years.

Thus it seems that the value stock portfolios do out-perform the growth stock portfolios, in when portfolios are held for one and two-year periods. The success of the value portfolios does however, seem more prominent, and systematic with the inclusion of the second year of the two-year period, indicating that the value strategy seems to be more of a long-term, rather than short-term strategy. This is however, not conclusive evidence in favour of value stock investing. The non-systematic nature of returns to the interim portfolios leaves one questioning whether the 14.8% one-year, and 35% two-year return to the value portfolio indicates a non-linear relationship between the B/M ratio, and portfolio returns.

To determine how risk is related to portfolio returns, one and two-year betas are calculated for each portfolio. These are presented in Figure 5.2.1.1.

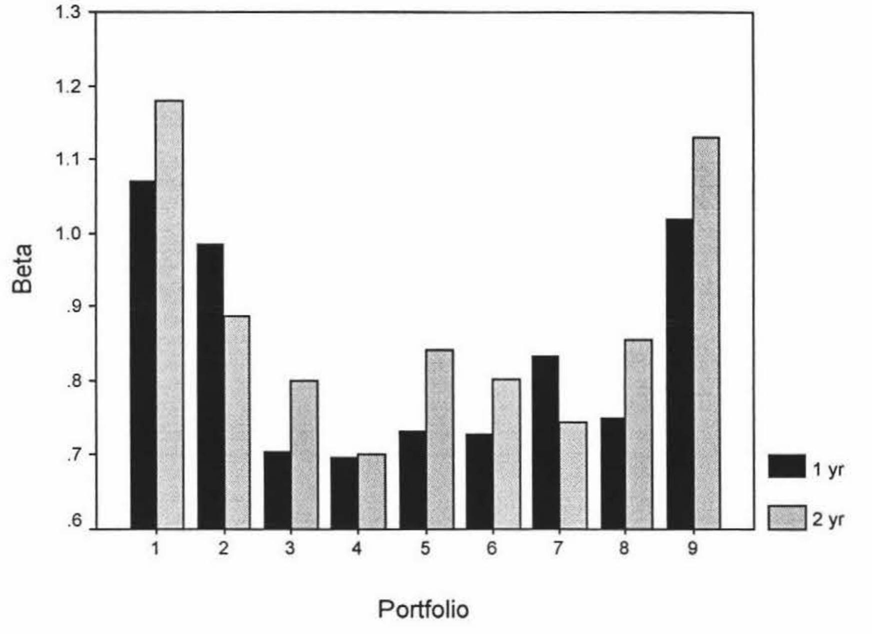

Figure 5.2.1.1. The One-Year and Two-Year Average B/M Portfolio Betas

Except for portfolios 2 and 7, all of the one-year betas are lower than the two-year betas. As the holding period extends, one can expect greater uncertainty with respect to future price movements. One can therefore expect the betas to increase with the length of the holding period. This graph shows that the returns to the arbitrage portfolio are almost certainly not due to risk. In fact the one, and two-year betas of portfolio 1, 1.07, and 1.18, are both on average 0.05 higher than the equivalent betas of portfolio 9 which are 1.02, and 1.13 respectively.

For the interim portfolios, the one and two-year betas are all lower than the betas of the value, and growth portfolios, though some of these portfolios yield higher returns than portfolio 1. For instance, portfolio 3 has a one-year beta of 0.705, and yet yields a return of 6.62% over the one-year holding period. Similarly, portfolio 8 yields on average, an 18.88% higher return over a two-year holding period than portfolio 1, yet has a two-year beta (0.856) that is .324 lower than the beta of portfolio 1.

It therefore seems as if the returns to the value arbitrage portfolio are not explained through differences in risk, as measured by the CAPM β, between portfolios. Alternatively, returns could be related to risk, but are not captured by β because the estimation of β is misspecified.

As explained in Chapter Four, one means of testing to see whether growth and value stock returns are due to investor over-reaction lies in looking at past and future realised earnings growth rates. The purpose of calculating the earnings growth rates is to see whether past earnings growth trends are extrapolated too far into the future. If past trends are extrapolated into the future, then portfolios with high past earnings growth rates should have low E/P and C/P ratios, as these proxy for expected future earnings growth rates. If investors over-react, and extrapolate past trends too far into the future, then future realised earnings growth rates of value stocks should be higher than those of growth stocks. This would then be a possible explanation for the 14.8% one-year, and 35% two-year return to the arbitrage portfolio.

Table 5.2.1.2 represents the average annual earnings and revenue growth rates (AEG, and ARG) for B/M value and growth stock portfolios starting with one year prior to the portfolio formation year, *Q*, and ending in the second year after portfolio formation year, *Q*.[1] The revenue growth rates are calculated as another proxy of past and future financial performance, and are interpreted in the same manner as the earnings growth rates.

Table: 5.2.1.2

The Average Earnings, and Revenue Growth for B/M Portfolios (%)

Year	AEG Value Portfolio	AEG Growth Portfolio	ARG Value Portfolio	ARG Growth Portfolio
Q-1	6.3	-3.5	-8.4	25.6
Q	-4.7	-4.7	-3.7	12.6
Q+1	7.7	1.9	2.3	12.2
Q+2	7.2	-1.6	13.7	41.1

From Table 5.2.1.2, the average earnings growth rates of the value portfolio outperform those of the growth portfolio by 9.8%, 5.8%, and 8.8% in the years, *Q-1*, *Q+1*, and *Q+2*. The growth rates are equal in year *Q*. This indicates that investors do not extrapolate past trends into the future. However, it does indicate that investors might over-react in assessing the expectations of an improved (disappointing) future financial performance of growth (value) stocks, when assigning low (high) B/M ratios to the growth (value) portfolios.

[1] Because the focus of this analysis is to explain the difference in returns between the value and growth stock portfolios, the results of the interim portfolios have been omitted.

In contrast to the earnings data, one can see that in the year prior to portfolio formation, the average revenue growth rate of the growth portfolio is 25.6%, which is 34% higher than that of the value portfolio. Investors do not seem to be over-zealous in extrapolating this trend into the future. The average revenue growth rate for the growth portfolio continues to out-perform that of the value portfolio by 16.3%, 14.5%, and 54.8% in years *Q*, *Q+1*, and *Q+2*. Thus, from this perspective, the lower (higher) B/M ratios for growth (value) stocks do not seem to be unwarranted.

Rational and behavioural explanations of the difference in the returns to value and growth stock portfolios do not yield any significant insights. Therefore, whether the Industry composition of each portfolio might be responsible for generating the returns is considered instead of the B/M anomaly.

The industry classification could have an impact on the returns to different portfolios. Thus, whether Mining (Min), Diversified Resources and Energy (Res), Other Industrials (Ind), and Finance (Fin) stocks are clustered in one particular portfolio is next examined. This is done through calculating the proportion of each portfolio that is made up by each industry. The results are then averaged over the sample-period to produce Figure 5.2.1.2.

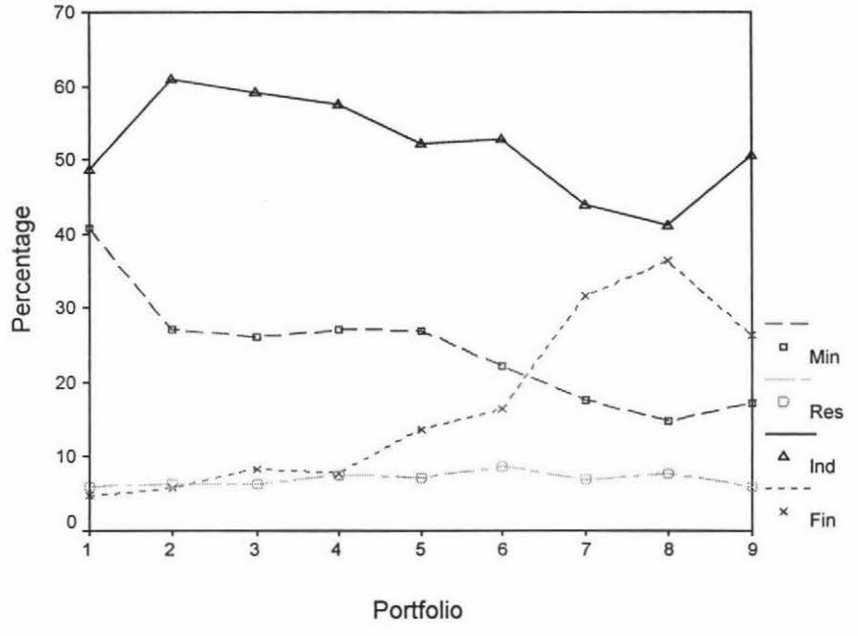

Figure 5.2.1.2. B/M Portfolio Composition by Industry

The Ind group constitutes the greatest proportion of each portfolio ranging from 61% of portfolio 2, to 41% of portfolio 8. This is unsurprising given that this group includes all listed Industrial stocks, barring the Fin stocks, so one can expect high proportions of representation in each portfolio. The Res stocks make up a small proportion of each portfolio, constituting from 6% to 8% of any one portfolio. The representation of the Res stocks is therefore consistent across each portfolio.

The Fin, and Min stocks seem to be clustered in the extreme portfolios. Although portfolio 8 has the greatest proportion of Fin stocks (36%), there is an increase in the representation of the Fin industry from 5% in portfolio 1, to 26% in portfolio 9. The Min stocks in contrast constitute 40% of portfolio 1, and this proportion decreases to 17% of portfolio 9. From this, it would seem that the relatively high (high) proportions of Min (Fin) stocks in a portfolio result on average, in low (high) portfolio returns.

It therefore seems as if the industry classification does have some bearing on portfolio returns. The 35% return to the arbitrage portfolio might be a partial consequence of the industry composition of each portfolio. As the industry classification seems to have an impact on portfolio returns, it is included in the analysis, when the relationships between the fundamental variables and portfolio returns are analysed in a multivariate setting.

The last aspect of B/M value and growth portfolio returns to be considered is the impact the calendar formation period has on the portfolio returns. The one-year and two-year averages for the value and growth portfolios formed in each month are presented in Figure 5.2.1.3, and Figure 5.2.1.4 respectively.

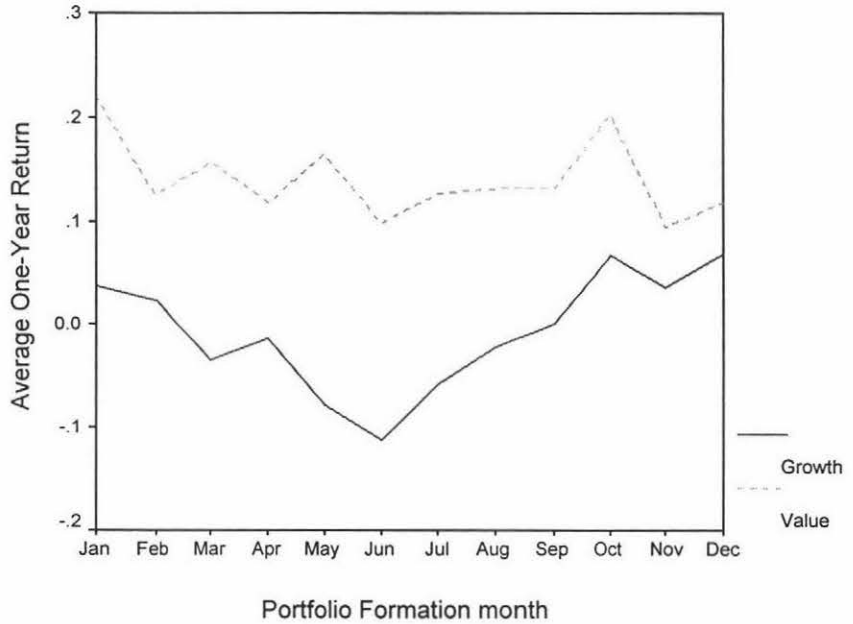

Figure 5.2.1.3. The Calendar Formation Date Effect on One-Year B/M Returns

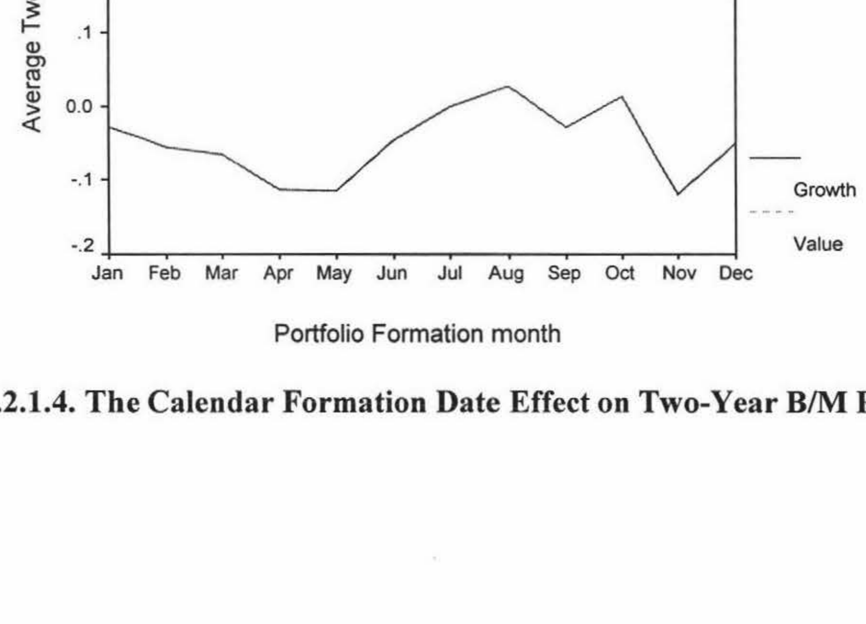

Figure 5.2.1.4. The Calendar Formation Date Effect on Two-Year B/M Returns

The B/M value portfolios yield higher returns irrespective of the portfolio formation date. This holds for both one-year and two-year returns. The average one-year return to the value arbitrage portfolio is greatest when portfolios are formed at the end of May. The one-year return to the May, value arbitrage portfolio is on average 24%.

Given the results of Table 5.2.1.1, it can be expected that the difference between the value and growth portfolio two-year returns is greater than the difference in one-year returns. This proves to be the case for all portfolio formation months. This indicates that the value-based investment strategy is more a long-term, than a short-term strategy. Notice that where the two-year returns are computed, the highest returns to the value arbitrage portfolio are recorder in March (43.4%).

It therefore seems as if the positive returns to the value arbitrage portfolios do not depend on the calendar formation date, otherwise termed the initiation date. While the calendar formation date seems to have some effect on the magnitude of the value arbitrage return, it does not seem likely that one can time an investment strategy to take advantage of this.

To summarise, the B/M classification yields 14.8% one-year, and 35% two-year returns to the value arbitrage portfolio. Thus, the value-based investment strategy outperforms the growth-based investment strategy, and seems to be a better long-term, than short-term investment strategy.

The success of the value-based strategy is not explained through risk, as estimated through the CAPM β, or investor overreaction. Instead, relatively high proportions of finance stocks in the value portfolio, and high proportions of mining stocks in the growth portfolio may have affected portfolio returns. The success of the value-based strategy is also not dependent on the calendar formation date.

From this discussion, it is not clear why the B/M value-based investment strategy is a successful strategy. A discussion as to why the value arbitrage portfolio yields positive returns is discussed further in Chapter Six.

5.2.2 Results of the C/P Portfolios

The next results to be reported, are those comparing value stock portfolio returns with growth stock portfolio returns, using the C/P ratio as a classification measure. These results are presented in Table 5.2.2.1.

Table: 5.2.2.1

Average Returns to C/P Portfolios (%)

T	**1**	2	3	4	5	6	7	8	9
1 Yr	**0.22**	5.7	-2.84	-1.12	0.43	1.03	3.61	10.76	21.25
2 Yr	**-0.6**	4.38	-3.88	-2.71	-0.6	3.36	8.86	18.27	36.57

From Table 5.2.2.1 it is evident that on average, the value portfolio outperforms the growth portfolio by 21% over one year, and 37.1% over a two-year holding period. The returns to these value arbitrage portfolios are even greater than those to the B/M arbitrage portfolios. As with the B/M portfolios, there is not a systematic increase in returns with an increase in the portfolio number from portfolio 1, up to portfolio 9. However, when looking at portfolios 3 to 9, both one and two-year returns increase systematically with an increase in the portfolio number.

In contrast to the B/M classification however, the bulk of the two-year returns to the C/P value portfolio occurs in the first year (21.25%), with the balance of the return, earned in the second year (12.6%). Thus, it seems as if the C/P classification of value and growth stocks yields on average, higher returns for a value-based strategy than the B/M classification.

To see whether the returns are positively correlated with risk, the average CAPM betas are calculated for each portfolio.

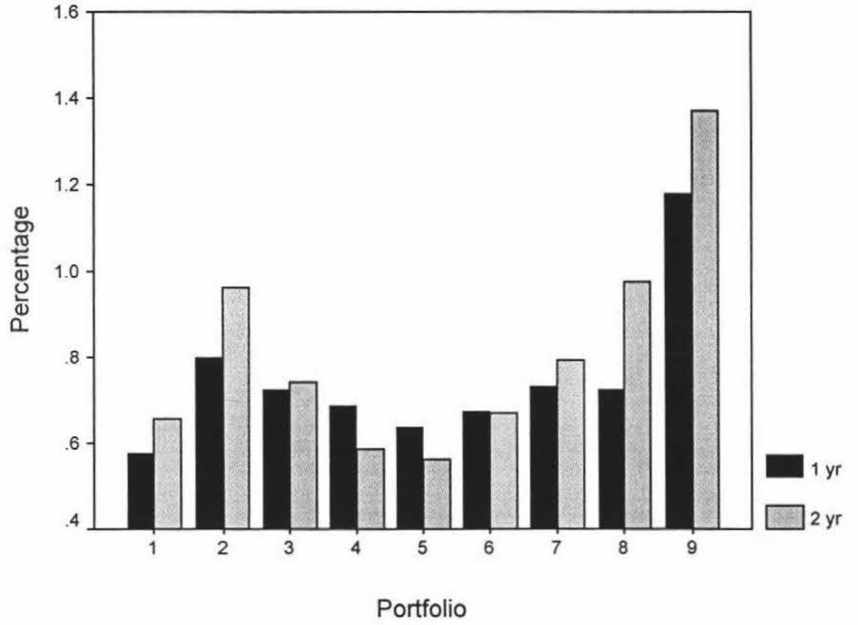

Figure 5.2.2.1. The One-Year and Two-Year Average C/P Portfolio Betas

From Figure 5.2.2.1 one can see that, as with the B/M classification, the risk, β, increases with the length of the holding period for most of the portfolios. The beta of 0.58 for portfolio 1 is 0.6 less than the beta of 1.18 for portfolio 9. Unlike the B/M classification, β does seem to be able to explain some of the differences in portfolio returns.

This evidence is not conclusive however. When one considers that the one-year, and two-year returns increase systematically from portfolio 3 up to portfolio9, one would expect the betas to follow suit if the returns are positively related to risk. Looking at Figure 5.2.2.1, one can see that the one-year (two-year) betas remain flat from portfolio 3, right up until portfolio 9 (8) where the magnitude of the β spikes upwards. Thus, it is not clear whether risk is necessarily responsible for the returns to the glamour, and value portfolios.

When investor over-reaction is considered as a possible alternative explanation of portfolio returns, Table 5.2.2.2, depicting the average earnings and sales growth is produced.

Table: 5.2.2.2

The Average Earnings, and Revenue Growth Rates for C/P Portfolios (%)

Year	AEG Value Portfolio	AEG Growth Portfolio	ARG Value Portfolio	ARG Growth Portfolio
Q-1	3.2	-18.8	-0.6	-20.8
Q	-2.6	7.4	-2.6	21.1
Q+1	31.8	-9.5	51.2	6.2
Q+2	-19.7	34.3	-22.0	26.2

Looking at the AEG for year *Q-1* the growth portfolio had on average, a negative growth rate in comparison to the 3.2% positive growth rate of the value portfolio. Thus past trends do not seem to be extrapolated into the future.

The AEG for the growth portfolio in year *Q+1* is 41.3% less than that of the value stocks. However, in year *Q+2*, this trend is reversed and the AEG of the growth portfolio is 54% higher than that of the value portfolio. The ARG rates are similar, with the growth stock portfolios yielding a -45% growth rate in comparison to the value portfolio in year *Q+1*. This is then overturned with a 48.2% higher return in year *Q+2.*

These results indicate that investors may be too liberal in assessing short-term future growth stock performance. However, this seems to be justified over the long-term. This reversal in AEG and ARG rates seems to have had no impact on growth portfolio returns in the second year after portfolio formation. It may however, be the cause of the better first one-year (21.25%), in comparison to the second one-year (12.6%) performance of the value portfolio.

When the Industry classification of each portfolio is considered, the results depicted in Figure 5.2.2.2 are produced.

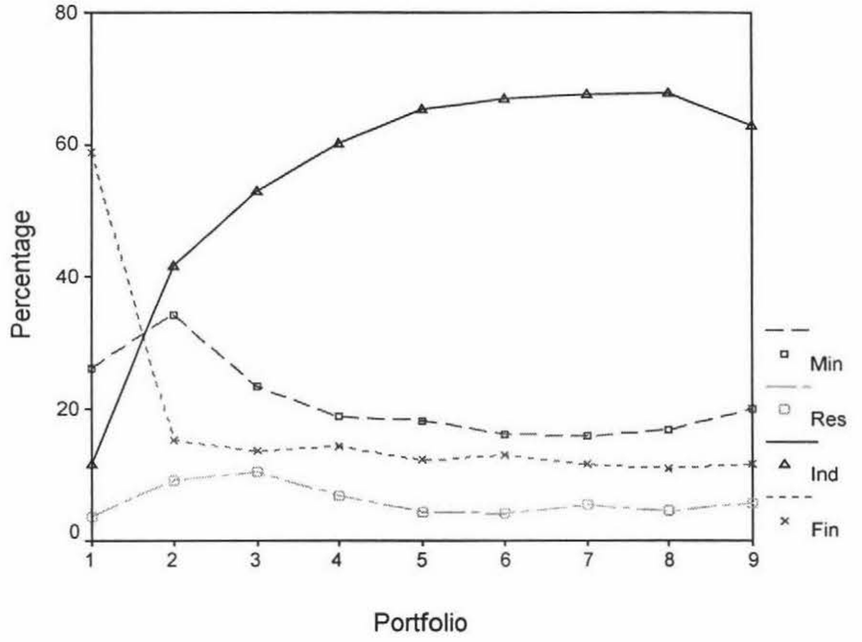

Figure 5.2.2.2. C/P Portfolio Composition by Industry

From Figure 5.2.2.2 one can see that the Fin stocks form a large proportion of portfolio 1 stocks (59%) in comparison to other portfolios which on average have an 11% to 15% Fin representation. As with the B/M classification, growth stock portfolios, portfolio 1 and 2, have a larger proportion of Min stocks (from 26% to 34%) than the other portfolios, which have a 15.8% to 23% Min composition. The relatively high proportion of Fin stocks in portfolio 1 contributes to the relatively low level of Ind stocks (11.5%) in portfolio 1 in comparison to the higher levels in other portfolios (ranging from 41% to 67.8% in portfolios 2 to 9).

Thus, the Fin and Min stocks again seem to influence the portfolio returns. However, unlike with the B/M classification, the relatively high proportion of Fin, and Min stocks in portfolio 1 are both associated with poor returns. In the B/M classification, the value portfolios had higher proportions of Fin stocks, and yielded higher returns.
This indicates that Min stocks, and not Fin stocks, affect the return differential between value and growth portfolios.

Lastly, the impact the calendar formation date has on one-year and two-year portfolio returns is analysed by looking at Figures 5.2.2.3, and 5.2.2.4.

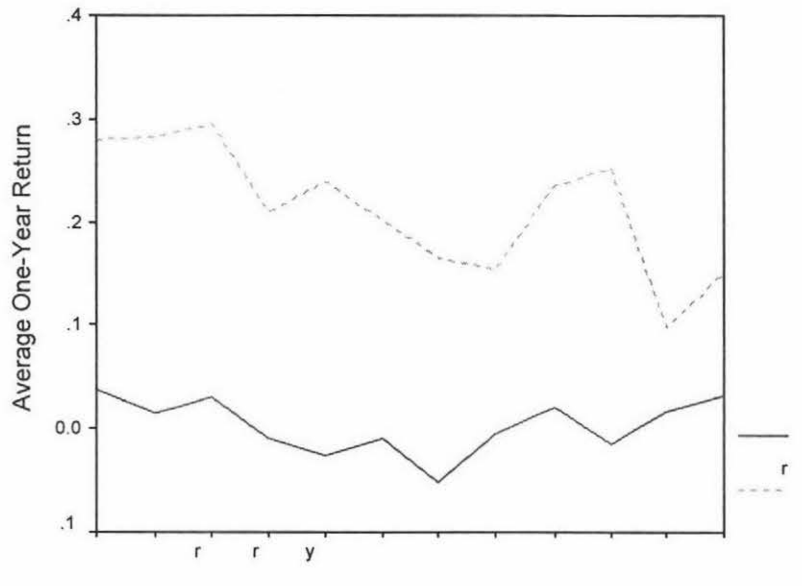

Figure 5.2.2.3. The Calendar Formation Date Effect on One-Year C/P Returns

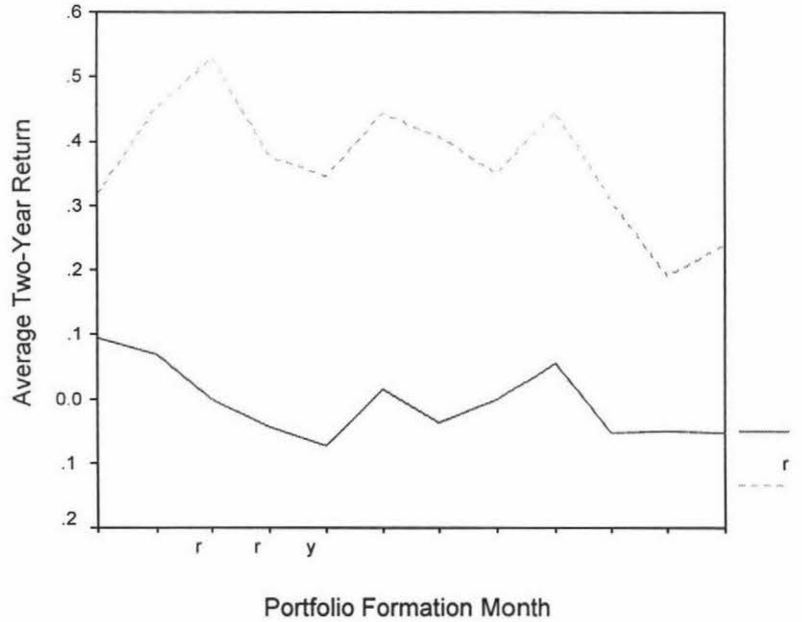

Figure 5.2.2.4. The Calendar Formation Date Effect on Two-Year C/P Returns

The returns to the C/P value portfolio are greater than those to the growth portfolio for any monthly calendar formation period. The largest average one and two-year returns to the value arbitrage portfolio are recorded when portfolios are formed at the end of February (26.8%), and March (53%) respectively. It therefore seems as if the value-based investment strategy can be initiated in any month of the year, and yield higher results than a growth-based strategy.

In summary, the C/P value portfolio outperformed the growth portfolio by a greater margin over one, and two-year holding periods, than the equivalent returns earned by the B/M value arbitrage portfolio, irrespective of the investment initiation date. While the C/P value portfolio is on average, riskier than the growth portfolio, the inability of β to explain the returns to the interim portfolios, again casts doubt on the applicability of β as a measure of risk. From a behavioural perspective, investors do not extrapolate past trends, but do seem to be overly optimistic in their expectation of an improved financial performance from growth stocks, in the short term. Lastly, the industry classification may be a cause of poor growth portfolio returns, with the mining stocks in particular, clustering in the growth portfolio relative to other portfolios.

5.2.3 Results of the E/P Portfolios

The next results to be reported, are those of the E/P portfolios. The average returns to the E/P portfolios over the sample period are summarised in Table 5.2.3.1.

Table: 5.2.3.1

Average Returns to E/P Portfolios (%)

T	**1**	2	3	4	5	6	7	8	9
1 Yr	**-1.07**	1.83	0.66	1.92	1.27	3.33	2.35	4.36	11.37
2 Yr	**-7.28**	0.56	-0.19	4.68	0.70	3.24	7.83	10.25	18.76

The value arbitrage portfolio yields a one-year return of 12.44%, and a two-year return of 26.04% in favour of the value-based portfolio. These returns are higher than the equivalent returns earned by the B/M arbitrage portfolio, though lower than the equivalent returns earned by the C/P portfolio.

The value portfolio yields 11.37% in the first year, and 6.64% in the second year following portfolio formation. This is in contrast to the growth portfolio losing 1.07% in the first year and a further 5.68% in the second year. Thus, the annual performance of the value-based investment strategy seems to be better in the short-term, rather than in the long-term.

Again, as with the B/M and C/P portfolio classification sorts, the interim portfolios don not exhibit a systematic increase in returns from portfolio 1 up to portfolio 9. Hence, there remains some doubt as to whether the E/P variable is linearly related to portfolio returns.

Figure 5.2.3.1 displays the differing risk profiles of each E/P portfolio, based on one and two-year returns.

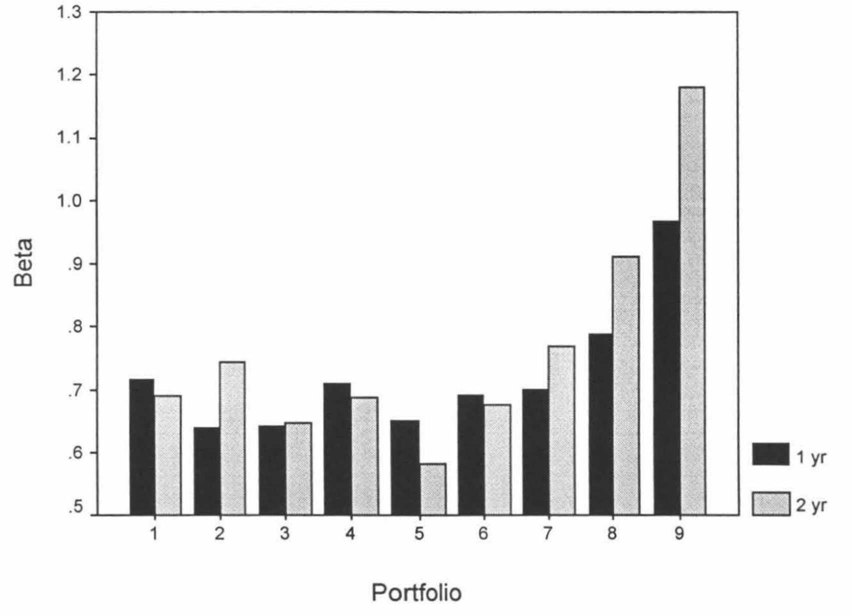

Figure 5.2.3.1. The One-Year and Two-Year Average E/P Portfolio Betas

Figure 5.2.3.1 is similar to Figure 5.2.2.1, which displays the betas calculated for the C/P portfolios. The E/P value portfolio has an average one-year beta of 0.97, and two-year beta of 1.18. It is therefore riskier than the growth portfolio, which has an average one-year beta of 0.72, and a lower two-year beta of 0.69.

While this indicates that portfolio returns may be related to risk in the manner proposed by the CAPM, this is not conclusive, given that the relationship between the estimated betas and portfolio returns is not consistent. Portfolio 7 for instance, yields one-year returns that are 3.4% higher than those of portfolio 1. However, the average one-year beta of portfolio 7 is similar to that of portfolio 1 (in fact it is 0.014 less).

Where C/P and E/P are the portfolio classification variables, the returns to the va arbitrage portfolio may be related to risk in the manner specified by the CA] However, when the interim portfolios are taken into account, the relationship betw risk and portfolio returns is not consistent. The ability of beta to therefore explain returns to the value arbitrage portfolio is questionable.

The explanation of E/P portfolio returns from a behavioural perspective is conside by analysing Table 5.2.3.2 which depicts the AEG and ARG rates for the value a growth stock portfolios.

Table: 5.2.3.2

The Average Earnings, and Revenue Growth Rates for E/P Portfolios (%)

Year	AEG Value Portfolio	AEG Growth Portfolio	ARG Value Portfolio	ARG Growth Portfolio
Q-1	2.8	-8.1	10.0	-10.6
Q	-2.6	7.3	-4.7	9.3
Q+1	2.9	4.5	8.5	1.3
Q+2	-14.3	3.1	-14.5	32.4

Contrary to what one might expect, the AEG and ARG rates of the value portfolios ar 10.9% and 20.6% higher than the equivalent rates for the growth portfolios in year *Q-*. Thus, it does not seem as if investors are extrapolating past trends into the future whe assessing the value of a stock. The lower E/P ratio given to the growth stock portfoli seems warranted when looking at the AEG rates in the years after portfolio formatior The AEG rates of the growth portfolio are on average, 9.9%, 1.6% and 17.4% highe than those AEG rates of the value portfolio in years *Q*, *Q+1*, and *Q+2*. Although AR(rates for year *Q+1* are on average 8.5% higher for the value portfolio, the ARG rates fo the growth portfolio are 14% and 46.9% higher than the value portfolio in years *Q*, an(*Q+2*.

From this, it seems as if investors do not extrapolate past trends into the future. Thei expectations of future financial performance also seem warranted. Thus, the success o the value-based investment strategy using the E/P ratio as a classification ratio does no seem to be because of investor over-reaction.

To complete this analysis of the E/P portfolio results, the effect an industry classification has on results is considered by looking at Figure 5.2.3.2.

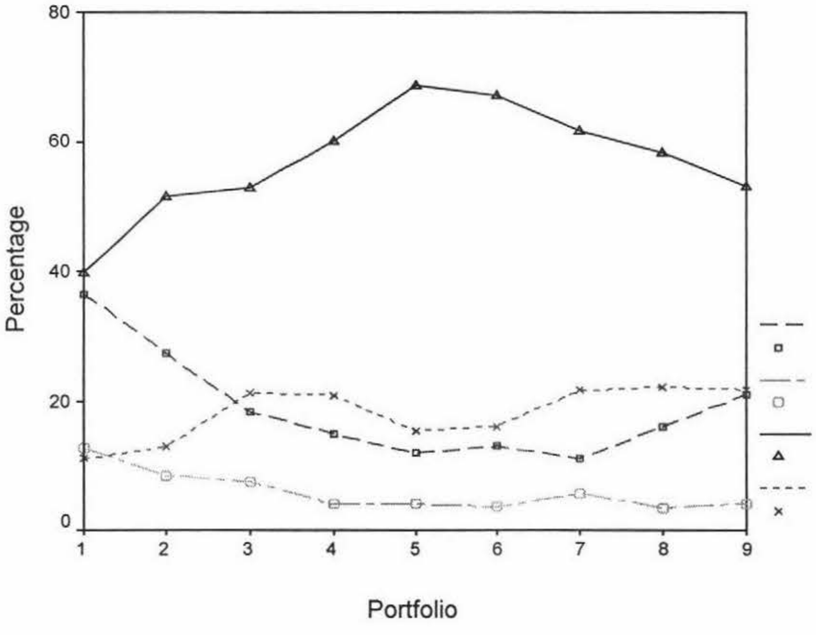

Figure 5.2.3.2. E/P Portfolio Composition by Industry

Figure 5.2.3.2 indicates that an industry classification may well drive portfolio returns. The proportion of Min stocks in portfolio 1 is 36.5%. This is higher than all the other portfolios which range from 27.3% in portfolio 2, to as low as 11.9% in portfolio 5. Min stocks comprise on average, 21.04% of the value portfolio, portfolio 9.

In this instance, the proportion of Fin stocks remains stable across portfolios. Recall that this is not the case where B/M and C/P are used to classify stocks into portfolios. Thus, it seems as if the Min stocks in particular might be responsible for the difference in returns between portfolio 1, and portfolio 9.

To see whether the initiation date affects returns to the value arbitrage portfolio, Figure 5.2.3.3 and Figure 5.2.3.4 are considered.

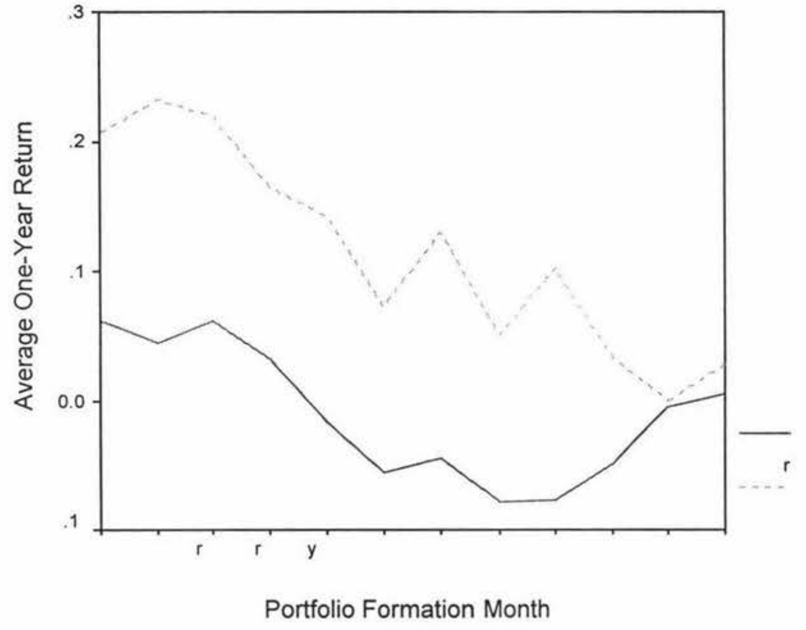

Figure 5.2.3.3. The Calendar Formation Date Effect on One-Year E/P Returns

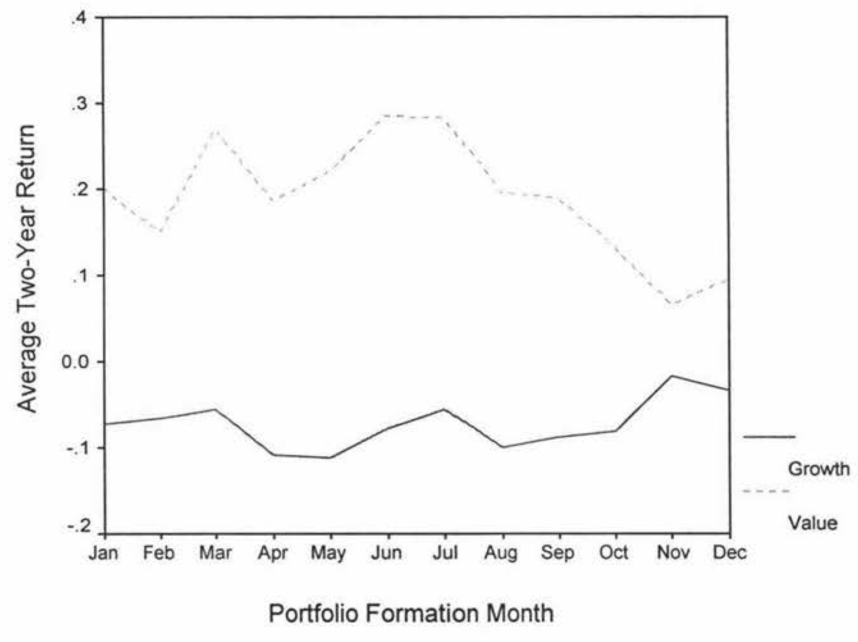

Figure 5.2.3.4. The Calendar Formation Date Effect on Two-Year E/P Returns

The value arbitrage portfolio yields positive returns where the value and growth-based strategies are initiated in any of the 12 months of the year. The highest average one and two-year returns to the value arbitrage portfolio are recorded in February (18.8%) and June (36.4%) respectively.

What this analysis does highlight, is that in November, the value arbitrage portfolio only yields on average, 0.5% one-year, and 0.8% two-year returns. This may potentially highlight a November effect. However, given that the value arbitrage portfolio does not yield such low returns in November where other classification variables are used to classify stocks into portfolios, this is unlikely.

In conclusion, the E/P value-based investment strategy does yield positive returns to the value arbitrage portfolio. Like the C/P classification scheme, annual re-balancing seems to yield higher returns than re-balancing every two years. While the value portfolio appears to be riskier than the growth portfolio, the inability of beta to account for the interim portfolio performances in the manner specified by the CAPM, casts this conclusion in doubt. However, risk seems to explain the returns better than the behavioural biases of investors, given that investors do not seem to over-react in assessing the future financial performance of growth and value stocks. Industry classification may affect portfolio returns with mining stocks clustering in the growth portfolio. Lastly, the initiation date produced some variation in the returns to the value-arbitrage portfolio, potentially highlighting a favourable November effect for growth stock investors.

5.2.4 Results of the GS Portfolios

The returns to the GS portfolios are presented in Table 5.2.4.1.

Table: 5.2.4.1

Average Returns to GS Portfolios (%)

T	1	2	3	4	5	6	7	8	**9**
1 Yr	3.49	2.03	16.95	9.00	0.33	0.79	-3.94	4.57	**6.34**
2 Yr	6.35	9.00	24.99	14.64	0.70	7.88	-7.46	12.21	**8.08**

Notice that in the case of a GS classification, portfolio 1 is the value portfolio, and portfolio 9, is the growth portfolio. From Table 5.2.4.1 it is evident that unlike the other portfolio classification measures, the GS growth portfolio outperforms the value portfolio. The return to the value arbitrage portfolio are on average, -2.9%, and -1.7% over one and two-year holding periods respectively.

The one and two-year returns of 17% and 25% to portfolio 3 are the highest returns achieved by any GS portfolio. This is in contrast to the value portfolios, which yield the highest returns where the B/M, C/P, and E/P are the classification variables. The value portfolio yields higher returns (2.76%) than the growth portfolio (1.64%) in the second year after portfolio formation. This indicates that if a value-based investment strategy is to succeed, it may do so over a longer time-frame than two years.

Figure 5.2.4.1 depicts the average one and two-year betas of each of the GS portfolios.

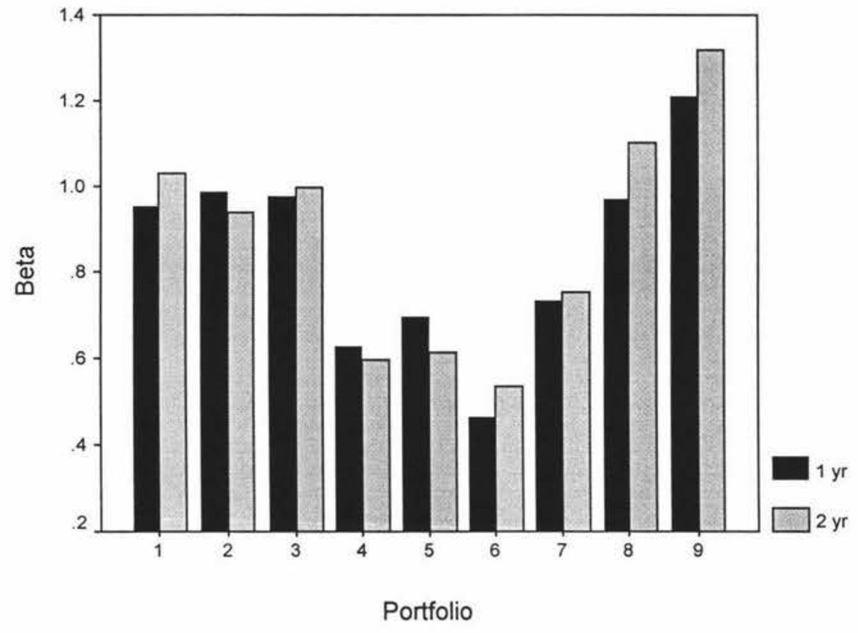

Figure 5.2.4.1. The One-Year and Two-Year Average GS Portfolio Betas

From Figure 5.2.4.1 one can see that the growth portfolio has estimated one-year and two-year betas of 1.21, and 1.32 respectively. These are 0.26, and 0.29 higher than the value portfolio betas of 0.95, and 1.03. This indicates that the returns to the extreme portfolios are positively related to risk. However, the difference in returns between the two portfolios indicates that the risk differential should be smaller for the risk-return relationship to emulate the positive risk-return relationship proposed by the CAPM. The relationship is flatter than that proposed by the CAPM. Notice that the highest returns are achieved by portfolio 3, yet the one and two-year betas are 0.98, and 1.0. Both these betas are lower than the betas of the growth portfolio.

From a behavioural perspective, Table 5.2.4.2 shows the AEG and ARG rates of the GS value and growth portfolios.

Table: 5.2.4.2

The Average Earnings, and Revenue Growth Rates for GS Portfolios (%)

Year	AEG Value Portfolio	AEG Growth Portfolio	ARG Value Portfolio	ARG Growth Portfolio
Q-1	-13.4	14.2	-60.2	14.5
Q	10.8	4.5	36.3	15.2
Q+1	11.4	3.4	13.9	4.1
Q+2	-29.0	19.6	-16.3	26.2

This shows that the average earnings and revenues of the value portfolios decreased by 13.4% and 60.2% in the year prior to portfolio formation. In contrast, the growth portfolio's earnings grew at an average of 14.2% and 14.5% in the same year. While the AEG and ARG rates of the value portfolios outperformed those of the growth portfolios in the year of and the year after portfolio formation, the growth portfolio yielded a 48.6% higher AEG and a 42.5% higher ARG rate in the second year after portfolio formation.

Because the GS ratio is a direct measure of past performance, one would expect the portfolio pre-formation performance of the growth portfolio to exceed that of the value portfolio. The short-term reversal of fortune in the value and growth portfolio growth rates may exhibit investor naivety in extrapolating these poor past records into the future. However, this is unlikely given the superior performance of the growth portfolio in year *Q+2*, and the success of the growth over the value-based investment strategy.

The influence that industry classification might have on the GS portfolio returns is appraised by considering Figure 5.2.4.2.

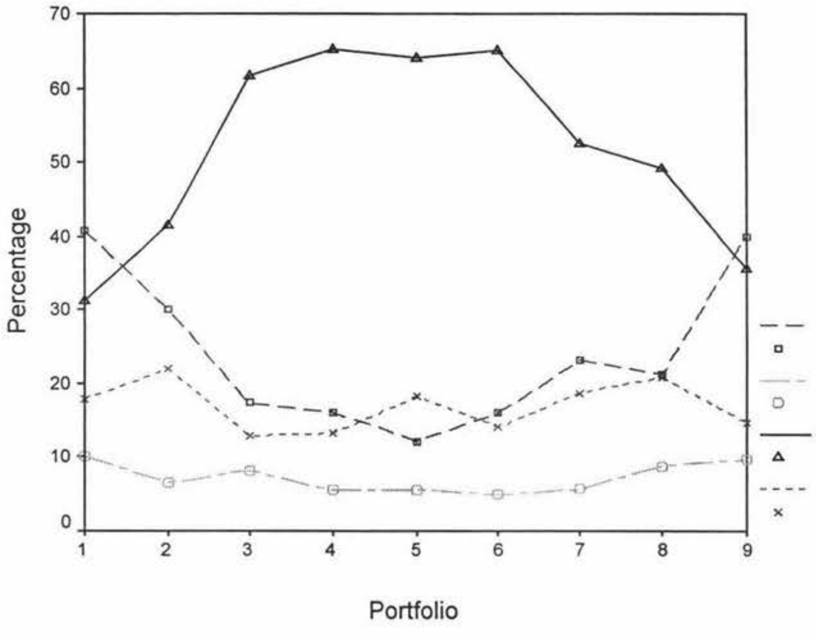

Figure 5.2.4.2. GS Portfolio Composition by Industry

From Figure 5.2.4.2 one can see that the Min stocks constitute a larger proportion of the extreme, value and growth portfolios, than the interim portfolios. Min stocks make up 40.8% and 40% of the value and growth stock portfolio respectively. These high proportions relative to the other portfolios results in the Ind stocks having less representation in the extreme portfolios.

In comparison to the value and growth portfolios where other financial variables are used to differentiate value from growth stocks, the GS value and growth stock portfolios have similar proportions of Min stocks in them. This may be a contributing reason as to why the returns to the growth portfolio outperformed those of the value portfolio, and why the returns to the arbitrage portfolio were of the region of 1.7% and 2.9% for one and two-year returns.

Lastly, the effects of the portfolio formation date on one and two-year returns to the value and growth portfolios are analysed by looking at Figure 5.2.4.3, and Figure 5.2.4.4.

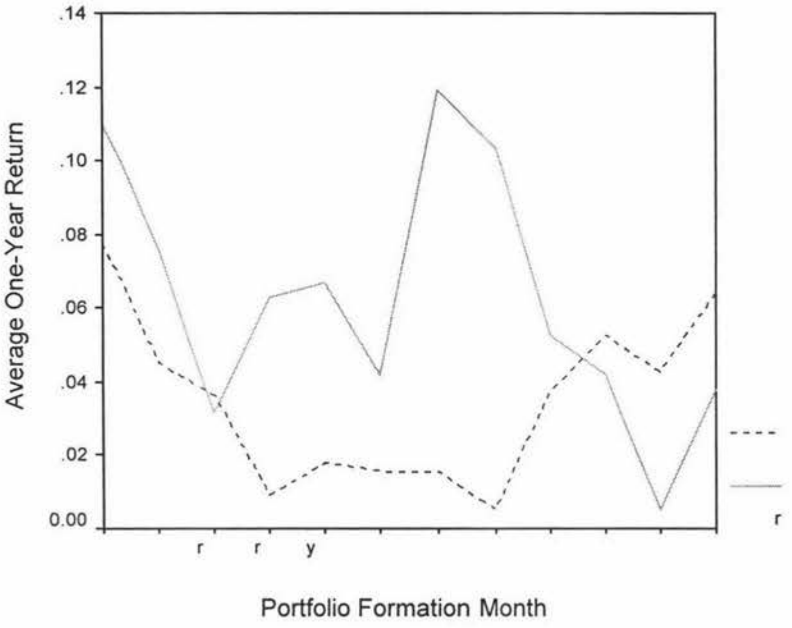

Figure 5.2.4.3. The Calendar Formation Date Effect on One-Year GS Returns

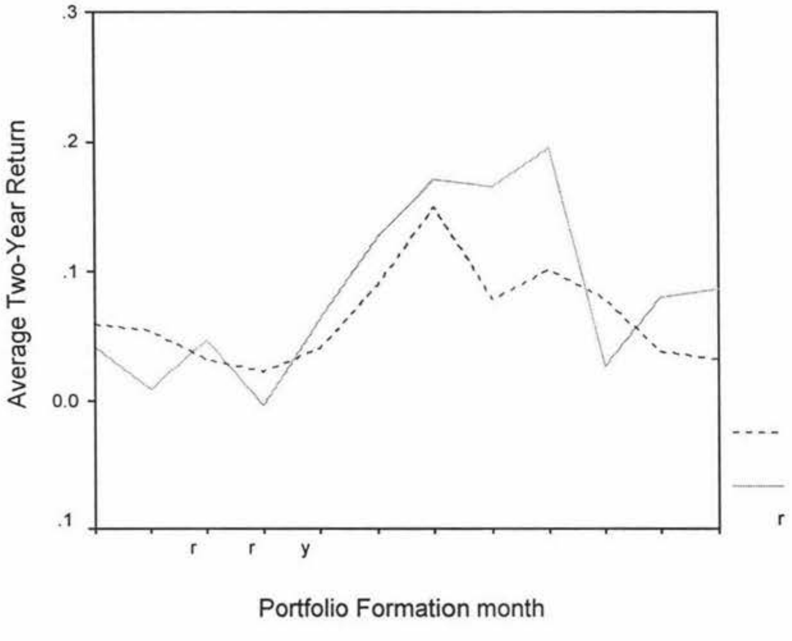

Figure 5.2.4.4. The Calendar Formation Date Effect on Two-Year GS Returns

In contrast to the B/M, C/P, and E/P portfolios, the GS growth portfolio outperforms the value portfolio, as far as one-year and two-year returns are concerned, in eight of the initiation months. Where portfolios are formed in March, October, November, and December, the value portfolio achieves higher one-year returns on average than the growth portfolio. The same can be said for two-year returns where portfolios are formed in January, February, April, and October.

The one and two-year returns to the GS value arbitrage portfolio are marginally negative. However, one can see that this evidence is not compelling given the better performance, of the value portfolios depending on the initiation date of the investment strategies. Because the value arbitrage portfolio yields on average, only -2.9% one-year and -1.7% two-year returns, one can anticipate the value portfolios to outperform the growth portfolios over certain periods of time. It is therefore concluded that the calendar formation date does not have an impact on value, or growth portfolio returns when a one or two-year holding period horizon is considered.

What is highlighted by looking at Figures 5.2.4.3, and 5.2.4.4, is that the one and two-year returns to the GS portfolios are volatile, with one-year returns to the growth portfolios varying from 12% when July is the initiation month, to 0.5% when November is the initiation month. If anything, this highlights the difficulty an investor can have when trying to determine a favourable time to initiate an investment strategy.

To summarise, using the GS variable to classify stocks into portfolios yields marginally negative returns to the value arbitrage portfolio. While β does not seem capable of describing interim portfolio returns, it does seem to explain some of the variation in returns between the growth and value portfolios. The returns do not seem to be related to the behavioural biases of investors. The industry classification does affect returns, with mining stocks possibly contributing to the similar performances of growth and value portfolios. Lastly, there the calendar formation date seems to have an impact on the size of returns to portfolios, indicating that bias may be introduced if portfolios are formed monthly.

5.2.5 Conclusion

The purpose of the single-sort classification schemes is to determine whether different variables that proxy for past, and expected future stock performance can be used to formulate a profitable trading strategy. As reported above, investments in the value stock portfolios do, on average, yield higher returns than growth stock portfolios, where three of the four classification variables are used. This is robust to the monthly calendar formation date of the value and growth portfolios. When the GS classification variable is used, the value arbitrage portfolio yields negative returns, though these are under 3% for one and two-year holding periods. Furthermore, these results are not robust to the monthly calendar formation date, thus detracting from the profitability of following a GS growth investment strategy.

In this univariate analysis, an attempt is made to explain why it is, that value stocks outperform growth stocks. Neither the rational, nor behavioural explanations yield significant insights in this regard. The industry classification does seem to affect returns, with the mining stocks in particular, appearing to cluster in the growth portfolios.

Returns to the value arbitrage portfolios suggest that the B/M, C/P, and E/P ratios are related to portfolio returns. The returns to the interim portfolios do however indicate that this relationship is not linear.

Section 5.3 therefore expands on the univariate analysis by combining two variables, one that proxies for past, and the other for future performance as a means to classify stocks into value and growth portfolios. Whether this classification scheme which implicitly incorporates more information in appraising value and growth stocks yields higher returns to the value arbitrage portfolios than the single-sort classification schemes is examined. In addition, the construction of these portfolios is geared towards revealing how the variation of financial ratios affects portfolio returns within growth, and value portfolios. This is in an attempt to unravel what appears to be a non-linear relationship between these variables and portfolio returns.

5.3 Results of the Double-Sort Classification Schemes

The purpose of the double-sort portfolio classification is two-fold. Firstly, can information contained in the past financial performance of a stock be combined with investors' expectations of future financial performance, to produce a successful value-based strategy? Secondly, this analysis attempts to differentiate between the unique effects of the variables proxying for past performance, and the variables proxying for expected future performance have on portfolio returns.

The first aim is achieved by analysing whether the value arbitrage portfolios using the double-sort portfolio classification schemes yield higher returns than where a single-sort is used to classify stocks into value, or growth portfolios. Thus, the returns to the value arbitrage portfolio are calculated and discussed. Because this is only a refinement of the value-based strategies reported in Section 5.2, an examination of risk, or behavioural-based explanations of portfolio returns is not conducted. The same argument applies for an analysis of the impact seasonality and an industry classification has on portfolio returns.

The second aim, is a more complex matter. The single sort portfolios make for a straightforward comparison of portfolio returns among the different portfolios. Comparing the interim portfolios allows one to see how performances vary from stocks that are in the growth, and "near-growth" portfolios to stocks that are in "near-value" and value portfolios. Thus, the single-sort classification allows one to look at stocks exhibiting more, or less of either the value, or growth stock characteristics. This allows one to determine the nature of the relationships between the fundamental variables and portfolio returns.

When sorting stocks into portfolios using a double-sort classification system, the comparison of returns and portfolio characteristics becomes more complex. This is because stocks are sorted into three portfolios according to the variable that proxies for past performance, and the same stocks are *independently* sorted into three portfolios according to the variable that proxies for expected future performance. As described in Chapter Four, the final portfolios, formed from the intersection of these two sorts splits the sample selection into nine portfolios. Because of the independent sort, the final portfolio may contain elements of both value and growth stock portfolios thereby making it difficult to differentiate between growth, or value effects in returns.

Portfolio returns are therefore analysed by seeing how the variation of each of the two classification variables in relation to one another affects variation in portfolio returns.[2] The variables that proxy for past security performance are the B/M, and GS ranking variables. The variables that proxy for expected future performance, are the B/M, C/P, and E/P variables. Thus, five sets of results are presented. These are the results of the B/M-C/P, B/M-E/P, GS-B/M, GS-C/P, and GS-E/P portfolios.

By holding one variable constant, and allowing the other to vary, one can see within groups of value, or growth stock portfolios classified according to one variable, how the other classification variable affects returns. This process therefore attempts to reveal the nature of the relationship between these fundamental variables, and portfolio returns within the extreme value and growth portfolios. This may shed light on why the value portfolios, using the single-sort classification scheme outperform the growth portfolios.

This is especially relevant given that the returns to the value arbitrage portfolios using the single-sort classification scheme are consistently positive for the BM, C/P, and E/P portfolios, and yet the ratios do not seem to be related to portfolio returns in a linear manner. This is confirmed when the multivariate regression analysis is conducted. The purpose of the double-sort classification is therefore to examine this non-linear relationship, should it exist, further.

[2]This analysis is a precursor to the interaction of all the classification variables as revealed through a multivariate analysis discussed in Section 5.6.

5.3.1 Results of the B/M-C/P Portfolios

The average returns to the B/M-C/P portfolios are presented in Table 5.3.1.1.

Table: 5.3.1.1

Returns to B/M-C/P Portfolios (%)

B/M	**1**	1	1	2	2	2	3	3	3
C/P	**1**	2	3	1	2	3	1	2	3
T									
1 Yr	**-3.49**	-2.46	21.48	-0.34	2.20	6.26	0.05	-0.32	10.54
2 Yr	**-16.14**	-4.08	34.25	5.70	0.84	9.23	2.83	2.72	21.37

The one and two-year returns to the value arbitrage portfolio are on average, 14.03% and 37.51% respectively. The one-year returns are lower than those to the B/M (14.8%) or C/P (21%) value arbitrage portfolios. The two-year return is however, higher than either of the B/M (35%) or C/P (37%) two-year value arbitrage portfolios. Sorting stocks into portfolios based on two-variables therefore seems to yield higher returns long-term, than sorting stocks into portfolios based on one variable.

The interim portfolios are included in the analysis by splitting the portfolios into three subsets. The first subset consists of the (1,1), (1,2), and (1,3) BM-C/P portfolios. The second subset consists of the (2,1), (2,2), (2,3) portfolios and the third subset consists of the (3,1), (3,2), and (3,3) portfolios. The returns within each subset are compared to see how variation in the C/P ratio affects the portfolio returns. This process is repeated for all subsequent double-sort portfolios, to see how the variation in the variable that proxies for expected future performance affects the portfolio returns. The results of the three subsets are presented in Table 5.3.1.2.

Table: 5.3.1.2

Returns to the Value Arbitrage Portfolio in the B/M-C/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
1	25%	50.4%
2	6.6%	3.5%
3	10.5%	18.9%

The first subset of Table 5.3.1.2, shows that as the C/P ratio increases, and investors' aggregate perception of the stocks future performance, or future growth rates wanes, so the one-year and two-year returns increase. The one-year returns increase from –3.49% to the B/M-C/P portfolio (1,1), to 21.48% to portfolio (1,3).

While this is not systematically repeated when the second and third subsets are considered, there is a positive return to the 'value' arbitrage portfolio when the extreme portfolios within each subset. From Table 5.3.1.2 one can see that the one and two-year returns to the value arbitrage portfolios are greatest for subset 1, yielding 25% and 50.4% respectively.

One can conclude that the C/P may explain returns of growth and value stocks classified according to B/M ratios. While the same argument holds for subset 2, the 'neutral' B/M stocks, the evidence here is not as compelling. This may be a partial explanation for the confusing results obtained for the interim portfolios when the B/M variable is the sole classification variable.

The B/M-C/P portfolios are next grouped into another three subsets. Subset 4 consists of the (1,1), (2,1), (3,1) B/M-C/P portfolios. Subset 5 consists of the (1,2), (2,2), and (3,2) B/M-C/P portfolios. Subset 6 consists of the (1,3), (2,3), and (3,3) B/M-C/P portfolios. Compiling the value arbitrage portfolios from Table 5.3.1.1 produces the results displayed in Table 5.3.1.3. As with subsets 1,2, and 3, this same strategy is followed for all of the other double-sort classification schemes.

Table: 5.3.1.3

Returns to the Value Arbitrage Portfolio in the B/M-C/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
4	3.54%	18.97%
5	2.14%	6.8%
6	-10.94%	-12.88%

The returns to the value arbitrage portfolios are positive in subsets 4 and 5, but negative in subset 6. Even so, the returns to the value arbitrage portfolios in subsets 4 and 5 are not as high as those in subsets 1,2, and 3. In addition to this, the one and two-year returns to the value arbitrage portfolio in subset 6 are –10.94% and –12.88% respectively. This reflects the relatively high 21.48% one and 34.25% two-year returns to the (1,3) portfolio. In fact when the value C/P portfolios in subset 6 are examined, all three of them yield higher returns than any of the other B/M-C/P portfolios. It therefore seems as if variation in the B/M ratio is not positively related to stock returns once the C/P value effect is controlled for. The results of subset 6 indicate that once other value effects are controlled for, the B/M ratio may not in fact be a unique anomaly. This highlights the need for future research into value-based investing in an effort to separate the unique effects of each fundamental variable.

In summary, the B/M-C/P classification scheme seems to be an effective way of differentiating between value and growth stocks, especially over the long-term. Within all portfolios of B/M stocks, the C/P ratio seems to be positively related to returns. However, the B/M ratio is positively related to growth and neutral C/P portfolios, while negatively related to the value C/P portfolio.

5.3.2 Results of the B/M-E/P Portfolios

The next results to be analysed are those of the B/M-E/P portfolios presented in Table 5.3.2.1.

Table: 5.3.2.1

Returns to B/M-E/P Portfolios (%)

B/M	**1**	1	1	2	2	2	3	3	3
E/P	**1**	2	3	1	2	3	1	2	3
T									
1 Yr	**-2.32**	0.31	12.11	2.64	2.65	4.51	2.64	2.97	3.99
2 Yr	**-12.60**	-0.15	16.39	8.97	0.38	6.30	8.28	8.04	12.65

The value arbitrage portfolio yields on average, 6.31% one-year, and 25.25% two-year returns. These returns are lower than both the one and two-year returns of the B/M and E/P value arbitrage portfolios. This indicates that this double-sort scheme complicates, and possibly detracts from the success of the single-sort strategies.

Next, the returns to the value arbitrage portfolio of subsets 1, 2, and 3 are reported in Table 5.3.2.2.

Table: 5.3.2.2

Returns to the Value Arbitrage Portfolio in the B/M-E/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
1	14.43%	28.99%
2	1.87%	-2.67%
3	1.35%	4.37%

Variation in the E/P ratio seems to affect portfolio performance of the lowest 33.3% of stocks in terms of the B/M ratio, with one and two-year returns of 14.43% and 29% to the value arbitrage portfolio. However, E/P variation in the second, and highest 33.3% does produces returns of less than 5% for one, and two-year returns. Consequently, the E/P ratio may not drive portfolio return in the B/M-E/P portfolios to the extent of the C/P ratio in the B/M-C/P portfolio.

Table 5.3.2.3 displays the variation of the B/M ratio within each E/P portfolio.

Table: 5.3.2.3

Returns to the Value Arbitrage Portfolio in the B/M-E/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
4	4.96%	20.88%
5	2.66%	8.19%
6	-8.12%	-3.74%

From Table 5.3.2.3 the B/M variation within the lowest 33.3% of stocks ranked according to E/P ratios produces returns of 5% and 20.9% for one and two-year holding periods. Although the arbitrage portfolio within subset 5 yields an average return of 8.2%, the one-year return is only 2.7%, and the value arbitrage portfolio yields negative returns for both holding periods in subset 6. This indicates that the B/M variation may explain return differences across the growth stocks (ranked according to the E/P ratio), however this is not the case for the value stocks.

When stocks are ranked according to the B/M-E/P classification sort, the E/P ratio seems to be positively related to portfolio returns within the growth B/M portfolio. Likewise, the B/M ratio also seems positively related to portfolio returns within the growth E/P portfolio. However, this does not hold, for either the E/P or B/M neutral, and value portfolios.

5.3.3 Results of the GS-B/M Portfolios

The GS-B/M classification sort alters the interpretation of the B/M ratio, from proxying for past financial performance, as with the B/M-C/P, and B/M-E/P sorts, to proxying for expected future financial performance. The impact this has on returns to the value arbitrage portfolio is therefore examined. Additionally, the GS variable yields marginally negative returns to the value arbitrage portfolio, when used as a single-sort scheme, and hence it is seen what impact this has on portfolio returns when combined with other variables.

The returns to the GS-B/M portfolios are presented in Table 5.3.3.1. Notice that in this instance, the (1,3) and (3,1) portfolios form the value and growth portfolios respectively. This is because the value portfolio is comprised of those stocks with the lowest growth in sales in the past, and are hence in the lowest 33.3% of stocks ranked according to GS. However, the value portfolio stocks also have the highest B/M ratios indicating that investors do not expect an improved change in sales, and profitability growth rates in the future. Hence the value stocks are in the (1,3) portfolio. The reverse argument holds for growth stocks, and therefore the (3,1) portfolio makes up the growth portfolio.

Table: 5.3.3.1

Returns to GS-B/M Portfolios

GS	1	1	1	2	2	2	**3**	3	3
B/M	1	2	3	1	2	3	**1**	2	3
T									
1 Yr	1.89	1.14	13.61	-2.78	3.17	8.23	**2.41**	4.00	-0.14
2 Yr	-2.87	3.78	28.04	-6.42	6.78	19.50	**3.51**	2.49	1.14

The average one and two-year returns to the value arbitrage portfolio are 11.2% and 24.53% respectively. This is lower than the returns to the B/M value arbitrage portfolio, but markedly higher than the –2.9% one-year and –1.7% two-year returns to the GS value portfolio. The combined sort therefore yields returns that favour a value-based investment strategy.

The value portfolio yields annual returns of 13.61% in the first year, and 12.7% in the second year following portfolio formation indicating that the performance of the value portfolio is consistent over the short and long-term.

Considering the first three subsets, the relationship between the variation of the B/M ratio within each GS portfolio, is considered. The returns to the value-arbitrage portfolio for each subset are presented in Table 5.3.3.2.

Table: 5.3.3.2

Returns to the Value Arbitrage Portfolio in the GS-B/M Subsets (%)

Subset	*1 Yr*	*2 Yr*
1	11.72%	30.91%
2	11.01%	25.92%
3	-2.55%	-2.37%

From Table 5.3.3.2 one can see that variation in B/M ratios in the value, and neutral subsets (note that subset 1 is for the GS portfolios, the value portfolio) is positively related to portfolio returns. It is only in the growth subset, subset 3 that the B/M ratio is negatively related to returns, and this relationship is relatively flat, with –2.55% one-year and –2.37% two-year returns to the value arbitrage portfolio.

Table: 5.3.3.3

Returns to the Value Arbitrage Portfolio in the GS-B/M Subsets (%)

Subset	*1 Yr*	*2 Yr*
4	-0.52%	-6.38%
5	-2.86%	1.29%
6	13.75%	26.9%

Table 5.3.3.3 shows that when the B/M ratio is kept constant, the GS ratio is negatively related to stock returns only for the value B/M stocks, with one and two-year returns to the value arbitrage portfolio of 13.75% and 26.9% respectively.

Thus the B/M ratio seems to be positively related to portfolio returns for the lowest 66.67% of stocks ranked according to GS. Likewise, the magnitude of the GS figure seems to be negatively related to the highest 33.3% of stocks ranked according to the B/M ratio. The returns to the value arbitrage portfolio are less than the returns to the B/M-C/P, and B/M-E/P value arbitrage portfolios, indicating that the B/M is possibly a better proxy of past, rather than future financial performance. Given the relatively poor results of the GS single-sort value portfolios, this could also indicate that the GS variable is an unreliable variable on which to base a value investment strategy.

5.3.4 Results of the GS-C/P Portfolios

The next results to be considered, are those of the GS-C/P portfolios. The returns to these portfolios are presented in Table 5.3.4.1.

Table: 5.3.4.1

Returns to GS-C/P Portfolios

GS	1	1	1	2	2	2	**3**	3	3
C/P	1	2	3	1	2	3	**1**	2	3
T									
1 Yr	-4.81	0.65	22.32	-1.42	-0.46	6.75	**-4.73**	-0.82	8.55
2 Yr	-9.82	3.25	37.57	6.03	-0.53	14.51	**-8.10**	-2.78	11.25

The one and two-year returns to the value arbitrage portfolio are 27.05% and 37.57% respectively. These are higher than the 21% (-2.9%) one and 37% (-1.7%) two-year returns to the C/P and GS value arbitrage portfolios. Thus, it seems as if classifying stocks into value and growth portfolios according to GS-C/P yields higher returns than the equivalent single-sort classification schemes.

The value portfolio yields annual returns of 22.32% in the first year, and 12.47% in the second year following portfolio formation. This indicates that the GS-C/P classification scheme might be a better alternative, when employed with annual, as opposed to bi-annual re-balancing.

Looking at the variation of the C/P ratio within subsets 1,2, and 3, the returns to the value arbitrage portfolios are presented in Table 5.3.4.2.

Table: 5.3.4.2

Returns to the Value Arbitrage Portfolio in the GS-C/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
1	27.13%	47.39%
2	8.17%	8.48%
3	13.28%	19.35%

Within the GS value, neutral, and growth subsets, the C/P ratio is positively related to portfolio returns, with all three one and two-year value arbitrage returns yielding positive returns. This is especially noticeable for the value GS subset where the one-year return averages 27.13% and the two-year return averages 47.39% for the value arbitrage portfolio.

Table 5.3.4.3 shows that the GS ratio is negatively related to returns in the value C/P subset, but positively related in the neutral subset. In contrast to this, variation in GS has little effect on returns to the value arbitrage portfolio in the growth subset.

Table: 5.3.4.3

Returns to the Value Arbitrage Portfolio in the GS-C/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
4	-0.08%	-1.72%
5	1.47%	6.03%
6	13.77%	26.32%

This analysis indicates that the GS ratio might well be used to explain variation within value stocks, but not the neutral, or more growth-type stocks where C/P is the ranking variable. The C/P ratio however, seems more adept at explaining returns to portfolios irrespective of the portfolio's GS ranking.

5.3.5 Results of the GS-E/P Portfolios

The last set of returns to be analysed, are those of the GS-E/P portfolios. The returns to the GS-E/P portfolios are presented in Table 5.3.5.1.

Table: 5.3.5.1

Returns to GS-E/P Portfolios

GS	1	1	1	2	2	2	**3**	3	3
E/P	1	2	3	1	2	3	**1**	2	3
T									
1 Yr	-4.58	3.77	16.24	2.54	0.85	2.60	**0.95**	2.27	1.96
2 Yr	-12.05	9.41	34.12	6.96	3.73	3.85	**3.63**	-5.16	5.47

The returns to the GS-E/P portfolios indicate that the value arbitrage portfolio yields on average, one and two-year returns of 15.29% and 30.49% respectively. These are higher than the one and two-year returns of the GS (-2.9% and –1.7%) and E/P (12.44% and 26.04%) value arbitrage portfolios. As with the GS-C/P classification scheme, this double-sort classification scheme seems to be more proficient in yielding higher returns to a value arbitrage portfolio than would a single-sort classification using GS, or E/P variables.

The annual returns to the value portfolio yield 16.24% in the first year, and 15.38% in the second year following portfolio formation. These returns suggest that the GS-E/P strategy is consistent over the short and long-term.

Table: 5.3.5.2

Returns to the Value Arbitrage Portfolio in the GS-E/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
1	20.82%	46.17%
2	0.06%	-3.11%
3	1.01%	1.84%

From Table 5.3.5.2, the E/P ratio seems to describe variation across the value GS subset, subset 1. The returns of between –4% and 2% over one and two-year holding periods to the value arbitrage portfolios of the neutral, and growth GS stocks suggests that the E/P ratio is not necessarily able to explain returns across all GS subsets.

According to Table 5.3.5.3, the GS ratio seems positively related to stocks in growth E/P portfolios, negatively related to those stocks in neutral E/P and value E/P portfolios.

Table: 5.3.5.3

Returns to the Value Arbitrage Portfolio in the GS-E/P Subsets (%)

Subset	*1 Yr*	*2 Yr*
4	-5.53%	-15.68%
5	1.5%	14.57%
6	14.28%	28.65%

In summary, the GS-E/P classification provides evidence for value investing. The E/P variable is positively related to returns across the value GS portfolios, while the GS variable is negatively related to the E/P neutral, and value portfolios. In addition to this, the GS is positively related to returns across the growth E/P portfolios.

5.4 Results of the Multivariate Regression

As explained in Chapter Four, the unique impact of each financial variable on stock returns can be determined through conducting a cross-sectional multivariate regression. The holding period returns for each stock are used as the response variables, and the fundamental variables are used as the explanatory variables. From the results reported in Section 5.2, and Section 5.3 it seems as if the industry classification also has an impact on portfolio returns. Thus, the industry categorical variables are included as dummy variables in the regression.

Two sets of cross-sectional regressions are conducted on individual stock returns to estimate the coefficients of the explanatory variables for each of the 89 portfolio formation periods. The first set estimates the γ_{zt} coefficients where one-year returns are the response variables. The second set estimates the γ_{zt} coefficients where the two-year returns are the response variables.

The correlation among each series of γ_{zt} coefficients is then calculated to test for multicollinearity. As reported, multicollinearity is found among the coefficients indicating that the different variables are not orthogonal. Adjustments are then made to the regression models, and the γ_{zt} coefficients are re-estimated to avoid the multicollinearity.

The coefficients of the industry dummy variables are not included in tests for multicollinearity or autocorrelation. When conducting a regression on stock returns, even if the fundamental variables have no explanatory power in explaining the returns, the constant, α, will inevitably be greater, or less than zero. Given that the industry classification seems to have an effect on portfolio returns, the industry dummy variables are therefore included in the regression to see how they interact with the constant. Specifically, the magnitude of the α is influenced by the industry variables is examined. Hence, the industry coefficients are calculated in relation to the constant, and interpreted accordingly. Thus, the significance of the industry coefficients are not of interest in the regression setting.

Because autocorrelation is found within each of the re-estimated γ_{zt} series, a time series model is fitted to the coefficients before the final γ_z coefficients and t-statistics are calculated. This brings the statistical analysis of the relationship among the fundamental variables and stock returns to a close. Chapter Six elaborates on the results reported in Chapter Five, and a comprehensive discussion is undertaken comparing the results of this study, to those of other similar studies.

5.4.1 The Multivariate Regression and the Test for Multicollinearity

The cross-sectional regressions used to estimate γ coefficients for each explanatory variable are re-specified for each month, *t*, as:

$$Y = \gamma_0 + \gamma_1 B/M + \gamma_2 C/P + \gamma_3 E/P + \gamma_4 GS + \gamma_5 I_1 + \gamma_6 I_2 + \gamma_7 I_3 + \varepsilon, \qquad (4.5.1)$$

where *Y= buy-and-hold return,*

B/M= book to market variable,

GS= 1 year pre-portfolio formation growth in sales,

C/P= cash flow-to-price variable,

E/P= earnings-to-price variable,

I_1= mining industry dummy variable,

I_2= other resources industry dummy variable, and

I_3= other industrials industry dummy variable.

This analysis is conducted for both one, and two-year returns, for the 89 portfolio-formation months. Thus, 89 regressions are conducted, yielding 89 γ coefficients for each explanatory variable. Correlation among each of the γ_1, γ_2, γ_3, and γ_4 coefficient series is then estimated to test for multicollinearity. Because the regression analysis concentrates on obtaining unbiased estimates of the γ_z coefficients, multicollinearity among the coefficients, and not explanatory variables is tested for.

The results of this test conducted on the coefficients estimated for one-year returns are presented in Table 5.4.1.

Table: 5.4.1

The Correlation between the Explanatory Variable Coefficients (*Y*= *1*)

	$\gamma_{1\ (B/M)}$	$\gamma_{2\ (C/P)}$	$\gamma_{3\ (E/P)}$	$\gamma_{4\ (GS)}$
$\gamma_{1\ (B/M)}$	1			
P-Value				
$\gamma_{2\ (C/P)}$	-0.04	1		
P-Value	0.703			
$\gamma_{3\ (E/P)}$	0.005	-0.985	1	
P-Value	0.965	0.000		
$\gamma_{4\ (GS)}$	0.011	-0.05	0.03	1
P-Value	0.916	0.642	0.780	

Observing the correlation between the coefficients as absolute figures, the correlation between the γ_2 and γ_3 coefficients is greatest, with a correlation of -0.985, and a p-value of 0.000, indicating that the correlation is highly significant.[3] Thus multicollinearity exists between these two variables. This is not surprising given that the cash flow figure is derived from the earnings figure.

This multicollinearity is again evident when the correlation between the coefficients estimated using two-year returns is considered in Table 5.4.2. Here the correlation is slightly greater at –0.986.

Table 5.4.2

The Correlation between the Explanatory Variable Coefficients (*Y*= *2*)

	$\gamma_{1\ (B/M)}$	$\gamma_{2\ (C/P)}$	$\gamma_{3\ (E/P)}$	$\gamma_{4\ (GS)}$
$\gamma_{1\ (B/M)}$	1			
P-Value				
$\gamma_{2\ (C/P)}$	-0.323	1		
P-Value	0.01			
$\gamma_{3\ (E/P)}$	0.32	-0.986	1	
P-Value	0.002	0.000		
$\gamma_{4\ (GS)}$	0.276	-0.202	0.105	1
P-Value	0.009	0.059	0.330	

Table 5.4.2 reveals some correlation between the C/P and B/M coefficients with a correlation coefficient of -0.323, and a p-value of 0.01, indicating that the correlation is

[3] The p-value tests the probability that the coefficient is zero. Thus, where a low p-value is recorded, the probability of the coefficient being zero, is low, indicating that the coefficient is highly significant.

significant, however it is difficult to interpret this significance, as the sample size affects the interpretation of the correlation coefficient p-values. Because of this, and given the insignificance of the correlation between the C/P and B/M coefficients for one-year returns, multicollinearity between the C/P and B/M is not adjusted for.

As discussed in Chapter Three, the C/P variable is included as an explanatory variable of stock returns because of companies inability to manipulate their reported cash flow figures using tools such as accelerated depreciation, and special items. The earnings figure is however, more easily manipulated and distorted. Additionally, Bernard and Stober (1989) find that securities do react to information contained in accruals and cash flows over and above a reaction to information contained in a firm's total earnings. The E/P variable is therefore omitted from the multivariate regression. This resolves the problem of multicollinearity between the C/P and E/P variables. This also resolves the multicollinearity that is evident between the E/P and B/M coefficients, with a correlation of 0.32 that is highly significant given a p-value of 0.002.

A new regression model, represented by equation 5.4.1.1, is utilised to test how the explanatory variables affect one and two-year stock returns.

$$Y = \gamma_0 + \gamma_1 B/M + \gamma_2 C/P + \gamma_3 GS + \gamma_4 I_1 + \gamma_5 I_2 + \gamma_6 I_3 + \varepsilon, \tag{5.4.1.1}$$

where Y= *buy-and-hold return,*

B/M= *book to market variable,*

GS= *1 year pre-portfolio formation growth in sales,*

C/P= *cash flow-to-price variable,*

I_1= *mining industry dummy variable,*

I_2= *other resources industry dummy variable, and*

I_3= *other industrials industry dummy variable.*

5.4.2 Autocorrelation

The cross-sectional multivariate regression model represented by equation 5.4.1 is conducted for one and two-year returns. The Autocorrelation Function (ACF) graphs for each of the B/M, C/P, and GS estimated coefficients are then considered. Where autocorrelation is found to exist, the Partial Autocorrelation Function (PACF) graphs are then analysed to estimate appropriate time series models that are then fitted to the series of coefficients. This approach is used to minimise the bias introduced by the autocorrelation of coefficients.

Autoregressive (AR) models are employed where the ACF spikes decrease in length over numerous lags, and where the PACF spikes end abruptly after one or two lags. The order of the AR model is determined by the number of spikes that are significant at the 95% level. So for instance if the PACF has a significant spike at lag 1, and the spikes cut off thereafter, an AR model of order 1 is proposed as a model to correct for autocorrelation. Alternatively, Moving Average (MA) models are proposed where the ACF spikes end abruptly, and the PACF spikes decrease in length over numerous time-lags. Similar to the AR models, the order of the MA model depends on the number of ACF spikes that indicate significant autocorrelation at the 95% level.

The first ACF graph to be considered, is that of the estimated one-year B/M coefficients.

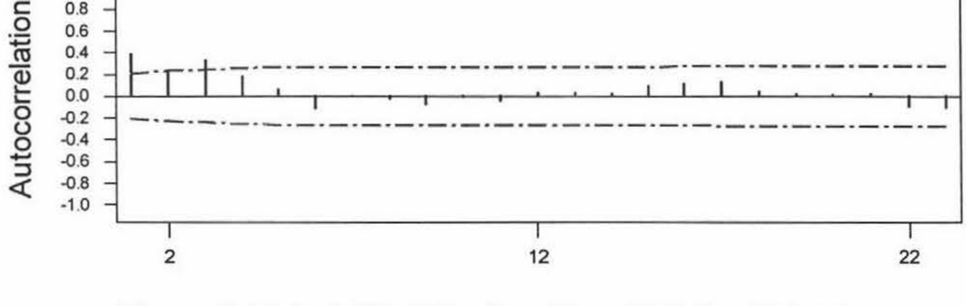

Figure 5.4.2.1: ACF of the One-Year B/M Coefficients

From Figure 5.4.2.1 one can see that there is significant autocorrelation of B/M coefficients at lags 1 and 3. The dashed lines signify the 95% confidence intervals. Any spikes that protrude beyond these confidence intervals are therefore significant at the

95% confidence interval. Thus, there is significant autocorrelation with the one-year coefficient series.

In an attempt to fit a model to the coefficients to reduce, or eliminate the atuocorrelation, Figure 5.4.2.2, the PACF of the B/M coefficients is considered.

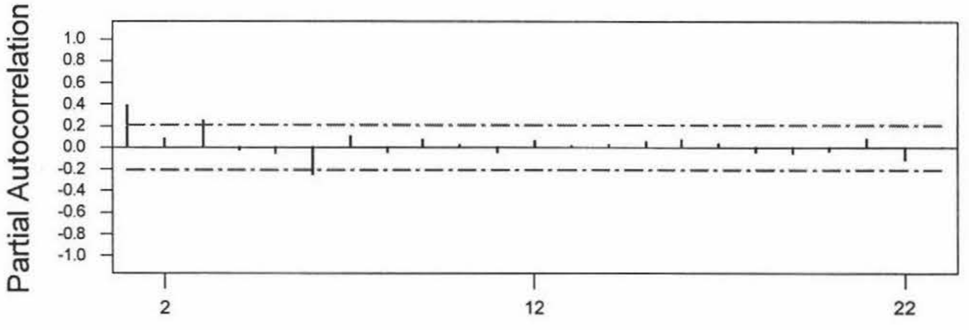

Figure 5.4.2.2: PACF of the One-Year B/M Coefficients

The PACF spikes are significant at lags 1, 3 and at lag 6. Thereafter, the spikes disappear almost completely, whereas the ACF spikes reappear, although insignificantly at lags 15, 16, and 17. This indicates that an AR Model of order 3 (an AR(3)) is a suitable model to fit to the one-year B/M coefficients to correct for the autocorrelation.

Autocorrelation among the one-year estimated C/P coefficients is considered next by referring to Figure 5.4.2.3.

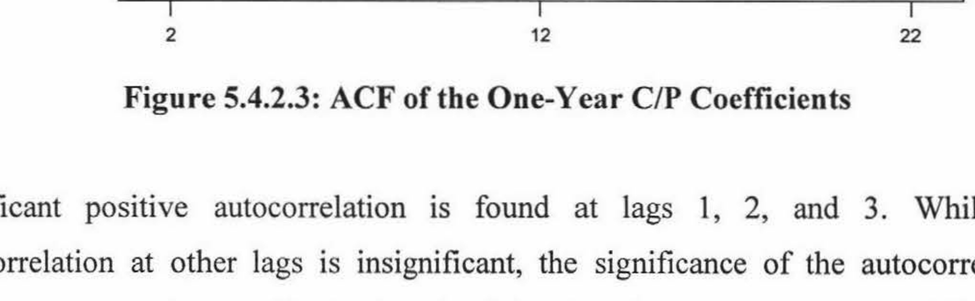

Figure 5.4.2.3: ACF of the One-Year C/P Coefficients

Significant positive autocorrelation is found at lags 1, 2, and 3. While the autocorrelation at other lags is insignificant, the significance of the autocorrelation decreases geometrically with the length of the time-lag. In contrast, as exhibited in

Figure 5.4.2.4, the PACF has two significant spikes at lags 1 and 2, whereafter the spikes disappear abruptly. This indicates that an AR model of order 2 would suffice in controlling for the autocorrelation.

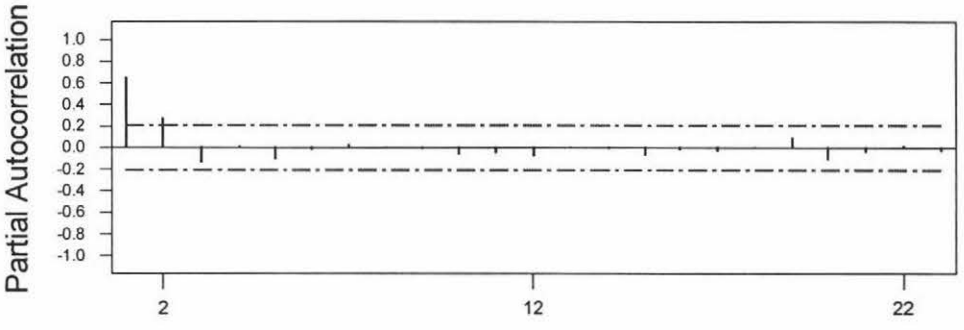

Figure 5.4.2.4: PACF of the One-Year C/P Coefficients

As far as the calculation of autocorrelation among each one-year (γ_{zt}) coefficient series goes, the last series to be considered is that of the estimated GS coefficients.

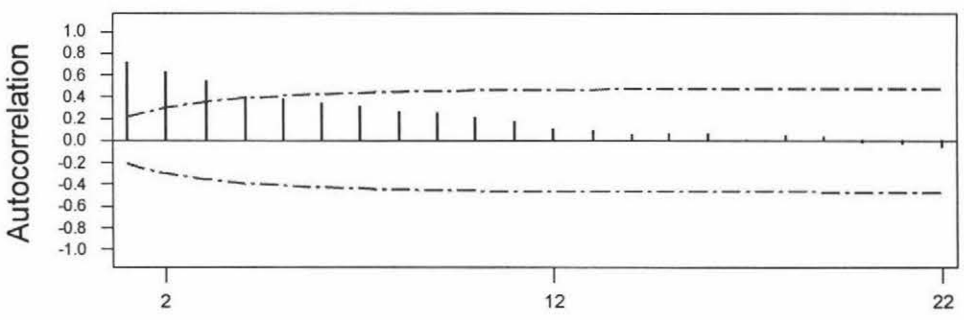

Figure 5.4.2.5: ACF of the One-Year GS Coefficients

Looking at Figures 5.4.2.5, and 5.4.2.6, one can see that significant autocorrelation exists at lags 1,2, and 3. The ACF spikes decay exponentially, whereas the PACF spikes disappear after lag 1. This indicates that an AR model of order 1 might be suitable for eliminating autocorrelation among the coefficients.

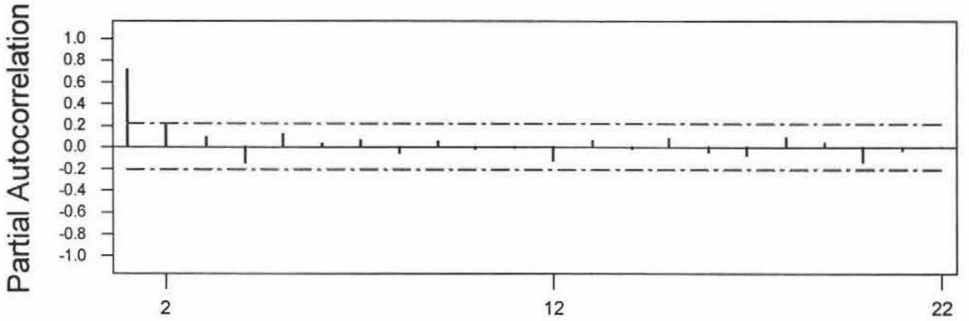

Figure 5.4.2.6: PACF of the One-Year GS Coefficients

From the analysis of the estimated one-year coefficient series for the non-categorical explanatory variables, significant autocorrelation is found among the coefficient series of each variable. Proposed models to remove the autocorrelation range from an AR(1), through to a more complex AR(3) model. Before a final model is settled on, the results of the identical analysis on the equivalent two-year estimated coefficient series are considered.

Figure 5.4.2.7 depicts the ACF of the two-year B/M estimated coefficient series. There is significant correlation at lags 1 and 2, though the autocorrelation is not as prominent as the autocorrelation found among lagged coefficients in the one-year series.

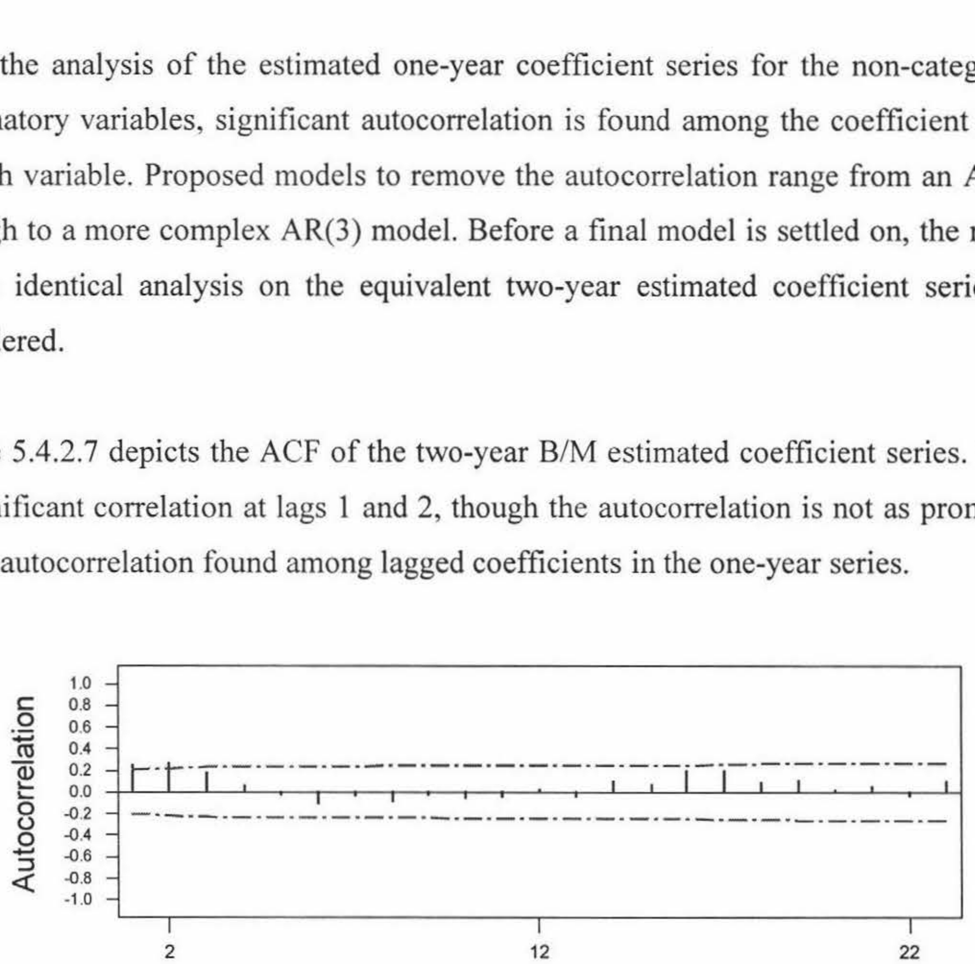

Figure 5.4.2.7: ACF of the Two-Year B/M Coefficients

Figure 5.4.2.8 reveals significant PACF spikes at lags 1 and 2. This series seems to decay in fewer lags than does the ACF. This indicates that an AR model, of order 2 is sufficient to correct for the autocorrelation. However, it might be worth fitting an MA model of order 2 as well, given that the PACF spikes are not remarkably different from the ACF spikes.

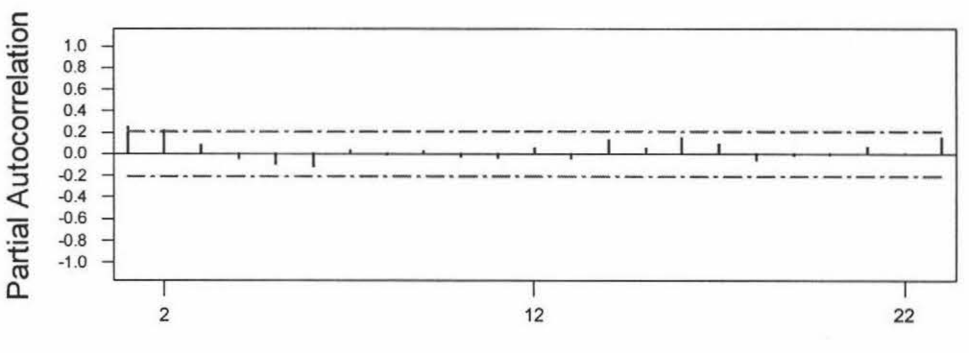

Figure 5.4.2.8: PACF of the Two-Year B/M Coefficients

The ACF in Figure 5.4.2.9 shows that there is significant autocorrelation among the lagged two-year C/P estimated coefficients at lags 1,2,3, and 4. The ACF spikes also have an exponential decay as the number of lags increases. This, coupled with the PACF depicted by Figure 5.4.2.10 shows that an AR of order 1, or order 2 should be sufficient to control the autocorrelation given that the PACF spikes cut off abruptly.

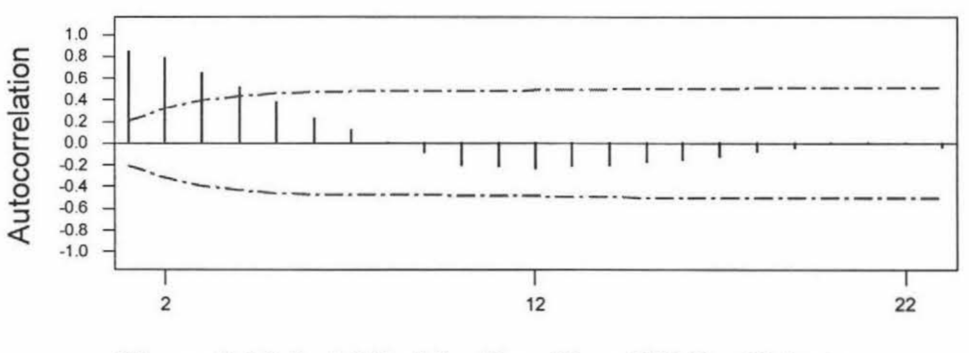

Figure 5.4.2.9: ACF of the Two-Year C/P Coefficients

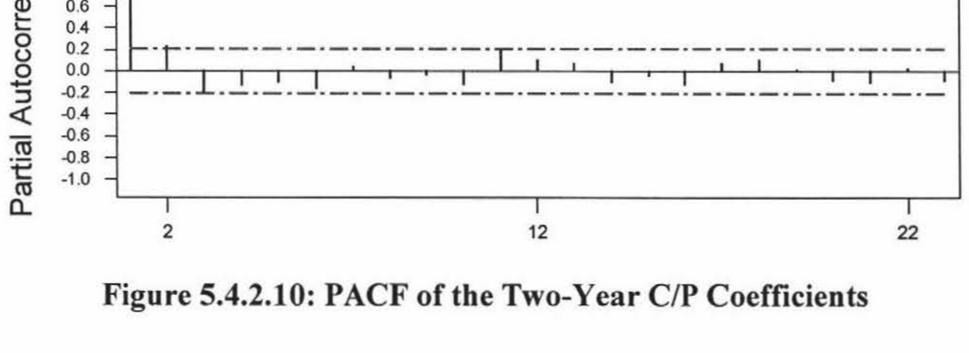

Figure 5.4.2.10: PACF of the Two-Year C/P Coefficients

The last series of coefficients to be checked for autocorrelation is the series of two-year GS coefficients.

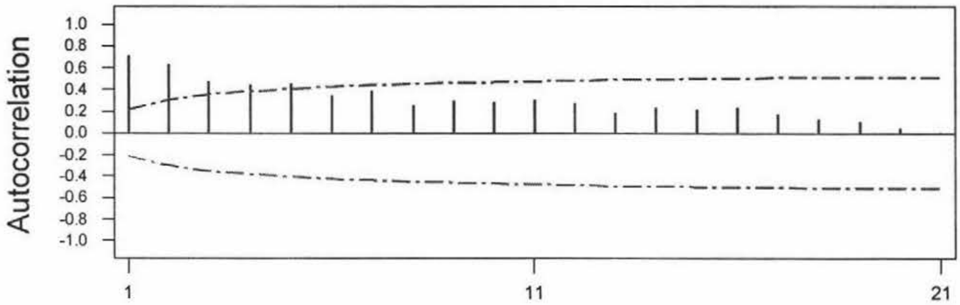

Figure 5.4.2.11: ACF of the Two-Year GS Coefficients

Figure 5.4.2.11, showing the ACF of the GS coefficients, reveals that there is significant autocorrelation at lags 1, 2, 3, 4, and 5. As with Figure 5.4.2.9, the ACF spikes die off exponentially. Figure 5.4.2.12 shows that, like the PACF in Figure 5.4.2.11, the PACF spikes cut off abruptly, and are insignificant beyond lag 2. This indicates that an AR model, of order 2 might be a suitable fit to control for the autocorrelation among the estimated two-year GS coefficients.

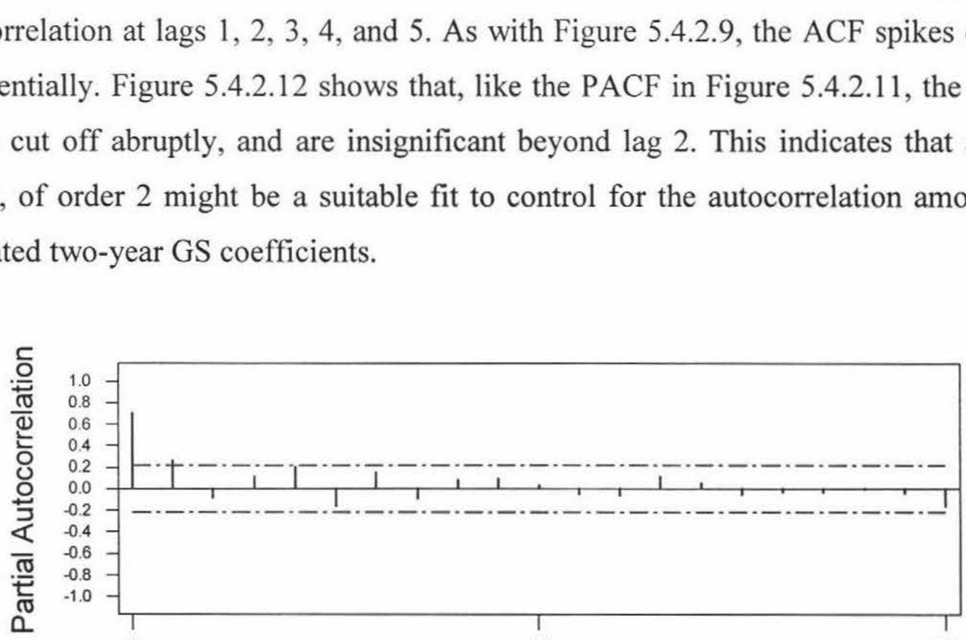

Figure 5.4.2.12: PACF of the Two-Year GS Coefficients

5.4.3 Model Estimation and Final Coefficient Estimates

Section 5.4.2 shows that significant autocorrelation exists within each series of the explanatory variable γ_{zt} coefficients estimated by regressing the explanatory variables on individual stock one-year, and two-year returns. An analysis of each ACF and PACF graph suggests that this autocorrelation can be corrected by fitting AR (1), AR (2), AR (3) or even possibly MA (2) models.

A number of different models, from AR (1) to ARMA (2,2) models are fitted to each series. By analysing the ACF graphs of the resultant residual series, an AR (3) is decided to be the model of best fit that can be applied to each coefficient series. The residual series of each of the coefficients exhibit no autocorrelation, and thus, once the AR (3) is fitted to the coefficients, the final γ_z coefficients are estimated.

The AR(3) model is fitted to each of the γ_{zt} coefficients using equation 5.4.3.1.

$$\gamma_{zt} = \alpha + \Phi_1\gamma_{zt-1} + \Phi_2\gamma_{zt-2} + \Phi_3\gamma_{zt-3} + e_t, \qquad (5.4.3.1)$$

where: $\gamma_{zt-1}, \gamma_{zt-2}, \gamma_{zt-3}$ are the γ_t coefficients lagged by one, two, and three months.

From equation 5.4.3.1, the expected γ_z coefficients can then be estimated as:

$$E[\gamma_z] = \alpha + (\Phi_1 + \Phi_2 + \Phi_3)E[\gamma_z]. \qquad (5.4.3.2)$$

The final γ_z coefficients, and their statistical significance are calculated using equation 5.4.3.3.

$$E[\gamma_z] = \frac{\alpha}{1-(\Phi_1 + \Phi_2 + \Phi_3)}. \qquad (5.4.3.3)$$

The final industry classification coefficients, as well as the constant are estimated using equation 3.4.4. The significance of these coefficients is not considered. The final estimates for the regressions conducted on one-year returns are presented in Table 5.4.3.1.

Table: 5.4.3.1.

Results of the Regression on One-Year Returns

	Constant	B/M	C/P	GS	Ind1	Ind2	Ind3
Mean	-5.6	3.0	37.2	2.2	2.7	6.2	3.3
Std Dev		2.0	2.96	4.7			
T-Statistic		1.51	1.26	0.47			
P-Value		0.135	0.212	0.636			

From Table 5.4.3.1 one can conclude that none of the three financial variables are significant in explaining stock returns in a multivariate setting. All the p-values indicate that the coefficients of 3 for the B/M, 37.2 for the C/P and 2.2 for the GS ratios are all insignificant even at the 10% level. This is unsurprising given that variation in the variables did not result in a systematic increase in returns from growth to value portfolios. This therefore confirms that at the very least, the relationship between fundamental variables and stock returns is not linear.

As explained previously, the significance of the industry variables is not of interest here. Instead, the effect that industry variables have on the level of stock returns is considered. Thus, the coefficients of the three industry variables, and the constant (representing industry 4, the finance industry) can be interpreted as follows.

The finance industry coefficient, is the lowest out of all the industry variables with a – 5.6 coefficient. This indicates that, ceteris paribus, finance companies are associated with the lowest stock returns. Likewise, mining companies (Ind1) are associated with the next lowest stock returns. In this case the magnitude of the coefficient is interpreted by adding it to the constant, resulting in a final estimate of (-2.9).

The industrials group is associated with the second highest return, and the other diversified resources and energy group with the highest stock returns. Consequently, portfolios with high proportions of mining, and finance stocks in them can expect to have on average, lower returns than those with high proportions of diversified resources and energy, and other industrials stocks.

When the two-year returns are used as the response variable, the B/M ratio becomes highly significant. The mean coefficient of 9.9 indicates that if a company's B/M ratio increases by 0.01, then there is likely to be a 9.9% increase in the company's return over the next to years. This is highly significant. Notice that the other coefficients are all insignificant at the 10% level.

Table: 5.4.3.2.

Results of the Regression on Two-Year Returns

	Constant	B/M	C/P	GS	Ind1	Ind2	Ind3
Mean	-6.5	9.9	45.6	13	-2.6	8.7	1.7
Std Dev		2.3	44.3	5.6			
T-Statistic		4.34	1.03	0.24			
P-Value		0.000	0.305	0.814			

When the industry variables are considered, the finance industry is again associated with the lowest returns. This is again followed by the mining industry, with the diversified energy and other resources, and other industrials groups being associated with the highest and second-highest stock returns respectively.

In conclusion, the fundamental variables do not seem to be linearly related to stock returns within a multivariate setting where one-year returns are considered. Only the B/M ratio is significant in explaining returns over a two-year holding period, indicating that the relationship between stock returns and fundamental variables is not linear. This brings Chapter Five to a close. Chapter Six summarises the results presented in Chapter Five, and interprets and discusses the results.

CHAPTER SIX

DISCUSSION & CONCLUSIONS

Section 6.1 summarises the results of the single, and double-sort classification schemes, along with the results of the multivariate regression. These results are discussed in relation to one another, and the results of other similar studies. This leads on to Section 6.2, the conclusion of this thesis.

6.1 Results Summary and Discussion

6.1.1 Summary of the Single-Sort Results

The B/M, C/P, and E/P single-sort classification schemes all yield positive one, and two-year returns, to the value arbitrage portfolio. These returns are all above 10% for one, and above 25% for two-year return, horizons. Given the size of these returns, it is unlikely that these returns will be eliminated when transaction costs are taken into account as found by Ball, Kothari, and Shanken (1994). This conclusion follows from the fact that re-balancing only occurs every two years.

Of the B/M, C/P, and E/P variables, the C/P classification scheme yields the highest returns for both one (21%) and two-year (37.1%) holding periods. This result is similar to the findings of LSV, and Chan, Hamao, and Lakonishok (1991).

Unlike the findings of LSV, Cai (1997), and Chopra, Lakonishok, and Ritter (1992), there is not conclusive evidence that the returns to the value arbitrage portfolios are attributable to the behavioural bias of investors. In the first instance, investors do not seem to extrapolate past trends into the future. This is because in all three cases of the B/M, C/P, and E/P classifications, the AEG and ARG rates of the value portfolios exceed those of the growth portfolios in the year leading up to portfolio formation. If these trends are extrapolated into the future, the magnitude of these financial ratios should be reversed for the value, and growth stocks.

In terms of over-reaction, it is not clear whether investors over-react when appraising the anticipated improved future financial performance of growth stocks. In some cases, such as with the B/M portfolios, the AEG and ARG rates indicate that investors are over-zealous when appraising the future of growth stocks. In other instances, such as with the E/P classification, the AEG rates for the growth portfolio are consistently higher than the equivalent rates of the value portfolio in the years following portfolio formation. This indicates that investors correctly anticipate the improved future financial performance of growth stocks.

A potential problem with this study is that the return horizons considered are too short. LSV find that the AEG rates of the growth portfolios indicate that investors correctly anticipate future financial performance in the first two years following portfolio formation. LSV find that it is only when longer periods of up to five years are considered that the over-reaction becomes apparent. Consequently, given the relatively short-term horizon of this study, it is not clear whether over-reaction is responsible for explaining differences in value and growth portfolio returns.

As far as directions for future research are concerned, the growth rates of the growth and value-based strategies could be compared to the profitability levels of value and growth stocks. This would highlight whether value stocks are less profitable than growth stocks, as Fama and French (1995) find. This may contribute to the difference in earnings, and revenue growth rates.

From a rational asset pricing perspective, risk, as measured by the CAPM β, does not seem to explain differences in returns between the B/M, C/P, and E/P value and growth stock portfolios. The one and two-year betas in the B/M growth portfolio are in fact, 0.05 higher than the betas of the value portfolios. The betas for the growth portfolios of the C/P, and E/P sorts are lower than the betas of the value portfolios. However, when the C/P and E/P interim portfolios are taken into account, the variation in portfolio returns is not related to risk in the manner predicted by the CAPM. The relationship between β and returns appears relatively flat.

This corresponds to the results of the LSV and Fama and French (1992) studies. Fama and French (1992) conclude that the CAPM β is not a reliable measure of risk. They consequently develop the three-factor model as an alternative measure of risk. LSV find that the use of the CAPM β does not explain the returns, and even when other measures of risk are used, risk is seen not to be responsible for the returns to the value arbitrage portfolios. Chopra, Lakonishok, and Ritter (1992), Cai (1997), and Chan, Hamao, and Lakonishok (1991) draw similar conclusions.

As far as this thesis is concerned, there are a few issues that need to be examined before drawing definitive conclusions regarding risk evaluation using β. The first is that in estimating β, the equally-weighted one and two-year returns to the largest 300 stocks listed on the ASX are used as the market return. Thus, if this is an inaccurate proxy for the market return, then the estimation of β will be misspecified. To establish whether β is related to risk, other proxies of the market return could be employed to test the impact that different market returns have on the β estimation.

This is a valid point, given that Faff (1991) finds some support for the zero-beta CAPM when a value-weighted index is used to estimate the market return. However, Anderson, Lynch, and Mathiou (1990), find that β is not related to portfolio returns in the manner predicted by the CAPM. Therefore, this thesis concludes that the success of the value-based investment strategy can not be definitively attributed to the rational pricing of assets. Note however, that this explanation can not be rejected either.

Different specifications of the CAPM β, as well as different measures of risk, such as the Fama and French three-factor model might be used when future research on the determinants of stock returns is carried out. Additionally, when explaining stock returns from a behavioural perspective, longer time-horizons should be considered in an effort to clarify whether investors are over-zealous when anticipating improved future growth rates for growth stocks.

Ball and Brown (1980) find that extreme returns are more likely to occur within the mining sector, than within other industries. Brailsford (1992) finds support for this conclusion given that the variation within mining stock returns is higher than the variation within other industry sectors. However, Brailsford (1992) does not find that the mining stocks are clustered within either the winner or loser portfolios.[1] Brailsford (1992) finds that the mining stocks, form on average, 5.4% less of the winner portfolio, than the loser portfolio. [2]

This study finds that as a proportion, the mining stocks comprise 23.5% more of the growth B/M portfolio than the value B/M portfolio. Likewise, mining stocks comprise 6.2% more of the C/P, and 15.5% more of the E/P growth portfolios than the equivalent value portfolios. Unlike the findings of Brailsford (1992), the industry classification therefore might well drive the returns to the value and growth portfolios. This is especially true given that high proportions of mining stocks in a particular portfolio (relative to other portfolios) is consistently associated with low, relative returns. This is confirmed by the results of the regression on two-year stock returns.

Fama and French (1992) exclude finance companies from their sample selection, on the basis that the financial variables may be interpreted differently for these stocks, than for stocks in other industries. The proportions of finance stocks in each portfolio is therefore of interest in this study. It is found that there is a high proportion of finance stocks in the growth C/P portfolio, relative to other C/P portfolios. The proportion of finance stocks also seems to vary across portfolios where other classification variables are used to construct portfolios. When industry variables are included as dummy variables in a multivariate setting, finance companies are seen to be associated with the lowest stock returns in comparison to stocks from other industries where one-year returns are concerned.

Industry classification seems to have an impact on the returns to portfolios. In future research on value-based strategies, it would be instructive to try to account for mining and finance stocks, when constructing portfolios in an attempt to differentiate between fundamental variable, and industry effects in portfolio returns.

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[1] Note that Brailsford (1992) does not analyse investment strategies based on financial variables. The investment strategies are based on ranking stocks into portfolios according to past returns. Those stocks with the highest past returns form the winner, and those with the lowest past returns, the loser portfolios.

[2] Brailsford (1992) uses a different industry classification system than what is used in this study. His classification system has been adjusted for the results to be comparable with those, in this study.

The calendar formation date does not seem to have an adverse effect on returns to the B/M, C/P, and E/P value arbitrage portfolios. The success of the value strategies seems robust to the market timing of the strategy. This is in contrast to Li's (1998) study, where it is found that the initiation date does affect winner and loser portfolio returns.

Where the GS variable is used to classify stocks into value and growth portfolios, the results do not correspond with those of the other three fundamental variables. Value and growth portfolios have similar performances over one and two-year holding periods. This is in contrast to the findings of LSV and Cai (1997), which show that the GS value portfolios outperform the growth portfolios by similar margins to the returns to the B/M, C/P, and E/P value arbitrage portfolios.

Rational and behavioural explanations of GS portfolio returns yield no significant insights. However, the proportion of mining stocks constitute 40.76% of the value portfolio, and 40% of the growth portfolio. The proportions of mining stocks within the extreme portfolios are therefore relatively similar in comparison to those proportions in the extreme portfolios of the B/M, C/P, and E/P portfolios. The industry classification may be the contributing factor to the results of the GS portfolios.

Lastly, as far as the single-sort portfolios are concerned, the initiation period of the GS value and growth investment strategies seems to result in volatile one-year returns to the value and growth portfolios. This volatility points to a potential bias introduced by considering returns to portfolios that are formed annually. The effect of this volatility and the effect of the investment strategy initiation date, on portfolio returns is also a potential topic for future research.

6.1.2 Summary of the Double-Sort Results

All double-sort portfolios yield positive returns to the value arbitrage portfolios. This includes portfolios when GS is included with a variable that proxies for future financial performance.

In fact the highest one and two-year returns among all single and double-sort portfolios are found when stocks are classified according to the GS-C/P variables. One and two-year returns of 27.05% and 37.57% are recorded for the GS-C/P value arbitrage portfolio.

This indicates that the GS variable may be able to explain stock returns, even though the relationship between the GS variable and stock returns is the opposite of what is anticipated. When the sub-sets of value arbitrage portfolio returns are considered, after controlling for the C/P variable, variation in the GS variable results in variation in returns to the value arbitrage portfolio. However, portfolio returns increase with an increase in the GS variable. This is contrary to what LSV find, where they find the GS variable negatively related to stock returns.

The B/M variable seems to yield higher returns to value portfolios when utilised as a variable that proxies for past performance, rather than future financial performance. This, given that the returns to the B/M-C/P, and B/M-E/P value arbitrage portfolios are higher than returns to the equivalent GS-B/M portfolios. Unlike LSV though, these results do not yield higher returns than the single-sort classification schemes.

Keeping the B/M, and the GS variables constant, the C/P variables is positively correlated with portfolio returns across all classes of B/M, and GS stocks. In addition, the two-year returns to the B/M-C/P, and GS-C/P value arbitrage portfolios are higher than equivalent returns to the single-sort value arbitrage portfolios.

When classifying stocks according to one of the B/M, or GS variables, it might therefore be a good idea to differentiate stocks within each portfolio according to the C/P ratio to devise a profitable trading strategy.

As far as the B/M, E/P, and GS variables are concerned, variation of one of the variables in each double-sort sub-set, in relation to the other yields different results for different portfolios. So for instance, keeping the B/M variable constant, but allowing the E/P ratio to vary produces no systematic pattern in returns for value, and neutral B/M stocks. However, there is a positive relationship between the E/P ratio and B/M growth stocks.

The inconclusive results of the analysis of these sub-sets highlights the complexity of the relationships among the fundamental variables, and stock returns. In particular, to some extent, this reveals that each fundamental variable may not necessarily affect portfolio returns uniquely. Assume for instance, that the E/P and B/M variables are positively related to portfolio returns independently of each other. Controlling for B/M should yield a positive relationship between the E/P ratio, and portfolio returns within each B/M sub-set. As this is not the case, the returns to the E/P value arbitrage portfolio may be attributable to other characteristics such as the B/M ratio, of the value and growth E/P firms.

The double-sort portfolio classification reveals that the four variables do not necessarily capture independent effects in portfolio returns. This highlights the necessity to be cautious when drawing conclusions as to whether these variables are independent pricing anomalies themselves, or merely manifestations of other pricing anomalies.

The complexities of the relationship among the fundamental variables and returns is reiterated when considered in a multivariate setting. As with the findings of Anderson, Lynch, and Mathiou (1990), multicollinearity is found to exist between the fundamental variables. When the multivariate regressions are conducted, autocorrelation is found. This is not surprising given that portfolios are formed monthly.

The final estimation of the B/M, C/P, and GS coefficients, controlling for the multicollinearity and autocorrelation show that these variables are all insignificant when explaining stock returns in a linear manner as far as one-year returns are concerned. The B/M ratio is significant over the longer two-year-holding period. This is unsurprising given the non-systematic increase in returns from the growth and 'near-growth' portfolios, to the 'near-value, and value portfolios.

If future research is to be carried out on value-based investment strategies in the Australian equities market, a non-linear relationship between the variables and returns could be explored. This is relevant given that the size of the returns to the value arbitrage portfolio seem to be too large to be merely a consequence of luck. However, the linear model does not seem to specify the relationship between fundamental variables and portfolio returns.

6.2 Conclusion

This thesis analyses the relative success of value and growth-based investment strategies from rational and behavioural asset pricing perspectives in the Australian equities market from 1990 to 2000. Utilising B/M, C/P, E/P, and GS variables to classify stocks into value and growth stock portfolios, value portfolios are found to yield one and two-year returns that are generally 10% and 25% respectively in excess of equivalent growth stock portfolio returns. This holds for single-sort and double-sort classification strategies.

What is not evident, is whether these returns differences are due to value stock portfolios containing more risk than growth stocks, or whether investors are biased in their estimation of the riskiness of value and growth stock investments. The CAPM β indicates that risk is not responsible for the superior performance of value stock returns, however the estimation of β may be misspecified. In addition to this, the use of β as a sole measure of a stock's risk has been largely discredited in finance literature. The financial variables used to classify stocks into growth and value stock portfolios may proxy for omitted risk variables. Therefore, if value stocks are riskier than growth stocks as implied in the three-factor model of Fama and French (1993), the inability of β to explain the risk of a security is further enhanced through this study.

Unlike the results of LSV, a comparison of earnings and sales growth rates of value and growth stock portfolios does not indicate that investors are biased when appraising the future, or risk of value and growth stocks. The returns to the value arbitrage portfolios can not therefore be attributed to investor irrationality. As Fama (1998) observes, one can not conclude that markets inefficient at least at the semi-strong form of market efficiency.

The returns to the value arbitrage portfolios seem to be invariant to the calendar formation date of the value and growth-based strategies, except where GS is used as a classification variable. This indicates that the value-based strategies can be implemented in any month of the year, and one can still anticipate that value stocks will out-perform growth stocks over one and two-year holding periods.

The most conclusive evidence of this thesis seems to indicate that an industry classification does have an impact on portfolio returns. The financial variables of mining stocks do seem to be interpreted differently by investors from those of stocks in other industries. This highlights the difficulty of interpreting what the B/M, C/P, E/P, and GS variables actually capture. The variables can not necessarily be viewed in the same light for all stocks. This in turn highlights the difficulty of trying to name all the state variables that these financial variables may be proxying for, in explaining stock returns.

When the results of the linear multivariate regression are examined, apart from the B/M variables, none of the other financial variables included in this thesis explain stock returns in a linear manner. This is further confirmed by an analysis of the returns to the single-sort interim portfolios. This does not rule out the possibility of a non-linear relationship between financial variables and stock returns. What is evident however, is that no value stock strategies, based on the systematic ranking of stocks according to financial variables can be devised to yield consistently higher long-term returns than growth stock strategies in the Australian equities market.

References

Allen, D., & Prince, R. (1995), The winner/loser hypothesis: Some preliminary Australian evidence on the impact of changing risk, *Applied Economics Letters* 2, 280-283.

Anderson, D., Lynch, A., & Mathiou, N. (1990), Behaviour of CAPM anomalies in smaller firms: Australian evidence, *Australian Journal of Management* 15, 1-37.

Andreassen, P., & Kraus, S. (1990). Judgmental extrapolation and the salience of change. *Journal of Forecasting,* 9, 347-372.

Australian Stock Exchange. (2000). *Australian Stock Exchange Fact Book 2000.* Sydney: Author.

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 663-681.

Ball, R., & Brown, P. (1980). Risk and return from equity investments in the Australian mining industry, *Australian Journal of Management* 5, 45-66.

Ball, R., Kothari, S., & Shanken, J. (1995). Problems in measuring portfolio performance. An application to contrarian investment strategies. *Journal of Financial Economics,* 38, 79-107.

Banz, R., & Breen, W. (1986). Sample dependent results using accounting and market data: Some Evidence. *Journal of Finance,* 41, 779-793.

Barber, B., & Lyon, J. (1997). Detecting long-horizon abnormal stock returns: the empirical power and specification of test statistics. *Journal of Financial Economics,* 9, 3-18.

Barberis, N., Shleifer, A. & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics,* 49, 307-343.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *Journal of Finance,* 32, 663-682.

Bauman, W., Conover, C., & Miller, R. (1998). Growth versus value and large-cap versus small-cap stocks in international markets. *Financial Analysts Journal,* 54, 75-89.

Beedles, W., Dodd, P., & Officer, R. (1988). Regularities in Australian share returns, *Australian Journal of Management* 13, 1-29.

Bernard, V.L., & Stober, T.L. (1989). The nature and amount of information in cash flows and accruals. *The Accounting Review,* 64, 624-652.

Blume, M., & Stambaugh, R.F. (1983). Biases in computed returns: An application to the size effect. *Journal of financial Economics,* 12, 387-404.

Brailsford, T. (1992). A test for the winner-loser anomaly in the Australian Equity market: 1958-87. *Journal of Business, Finance and Accounting,* 19(2), 225-241.

Brouwer, I., van der Put, J., & Veld., C. (1997). Contrarian investment strategies in a European context. *Journal of Finance and Accounting,* 24, 1353-1366.

Brown, P., Keim, D., Kleidon, A., & Marsh, T. (1983). Stock return seasonalities and The tax-loss selling hypothesis. *Journal of Financial Economics,* 12, 105-127.

Brown, S., & Warner, B. (1980). Measuring security price performance, *Journal of Financial Economics*, 8, 205-258.

Bryant, P., & Eleswarapu, V. (1997). Cross-sectional determinants of New Zealand share market returns. *Accounting and Finance,* 37, 181-205.

Cai, J. (1997). Glamour and value strategies on the Tokyo stock exchange. *Journal of Business, Finance and Accounting,* 24(9), 1291-1310.

Chan, K.C., & Chen, N. (1988). An unconditional asset-pricing test and the role of firm size as an instrumental variable for risk, *Journal of Finance* 43, 309-325.

Chan, K.C., and N. Chen, 1991, Structural and return characteristics of small and large firms, *Journal of Finance* 46, 1467-1484.

Chan, K.C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *Journal of Finance,* 46, 1739-1764.

Chatterjee, S., Hadi, A., & Price, B. (2000). *Regression Analysis by Example,* John Wiley & Sons, New York.

Chopra, N., Lakonishok, J., & Ritter, J. (1992). Measuring abnormal performance. *Journal of Financial Economics,* 31, 235-268.

Conrad, J., & Kaul, G. (1993). Long-term market overreaction or biases in computed returns? *Journal of Finance,* 48, 39-63.

Cook, T.J. & Rozeff, M.S. (1984). Size and Earnings/Price ratio anomalies: One effect or two? *Journal of financial and quantitative analysis,* 19(4), 449-466.

De Bondt, W. (1993). Betting on trends: intuitive forecasts of financial risk and return. *International Journal of Forecasting,* 9, 355-371.

De Bondt, W., & Thaler, R. (1985). Does the stock market overreact?. *Journal of Finance,* 40, 793-805.

Dissanaike, G. (1994). On the computation of returns in tests of the stock market overreaction hypothesis. *Journal of Banking & Finance,* 18, 1083-1094.

Edwards, W. (1968). Conservatism in human information processing. In: Kleinmutz, B. (Ed.), Formal Representation of Human Judgement. John Wiley and Sons, New York, pp. 17-52.

Elton, E.J., & Gruber, M.J. (1995). Modern Portfolio Theory and Investment Analysis, John Wiley & Sons Inc., New York

Faff, R.W. (1991). A likelihood ratio test of the zero-beta CAPM in Australian equity returns, *Accountin and Finance* 31, 88-95.

Fama, E. (1970). Efficient Capital Markets: A review of Theory and Empirical Work. *Journal of Finance,* 25, 383-417.

Fama, E. (1996). Multifactor Portfolio Efficiency and Multifactor Asset Pricing. *Journal of Financial and Quantitative Analysis,* 31(4), 441-465.

Fama, E. (1998a). Determining the number of priced state variables in the ICAPM. *Journal of Financial and Quantitative Analysis,* 33, 217-221.

Fama, E. (1998b). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics,* 49, 283-306.

Fama, E., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance,* 47, 427-465.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics,* 33, 3-56.

Fama, E., & French, K. (1995). Size and book-to-market factors in earnings and returns. *Journal of Finance,* 50, 131-155.

Fama, E., French, K. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance,* 51, 55-84.

Gordon, M., & Shapiro, E. (1956). Capital equipment analysis: the required rate of profit. *Management Science*, 3, 102-110.

Graham, B. *The Intelligent Investor, A Book of Practical Counsel,* 4th rev. ed. New York: Harper & Row Publishers, 1984.

Graham, B., & Dodd, D. (1934). *Security Analysis*, McGraw-Hill, New York.

Granger, C.W.J., & Morgenstern, O. (1970). *Predictability of Stock Market Prices.* D.C. Heath and Company, Lexington, Mass.

Griffin, D., & Tversky, A. (1992). The weighing of evidence and the determinants of overconfidence. *Cognitive Psychology,* 24, 411-435.

Hong, H., & Stein, J. (1999). A unified theory of underreaction, momentum trading and overreaction in asset markets. *Journal of Finance,* 56 (6), 2143-2184.

Jaffe, J., Keim, D., & Westerfield, R. (1989). Earnings yields, market values, and stock returns. *Journal of Finance,* 44, 135-148.

Kaplan, R., & Patell, J. (1977). The information content of cash flow data relative to annual earnings. Working Paper, Stanford University.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgement Under Uncertainty: Heuristics and Biases.* Cambridge University Press

Kothari, S., & Warner, J. (1997). Measuring long-horizon security price performance. *Journal of financial Economics,* 43, 301-339.

Langer, E.J., & Roth, J. (1975). Heads I win tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task. *Journal of Personality and Social Psychology,* 32, 951-955.

Lakonishok, J., & Shapiro, A.C. (1986). Systematic risk, total risk and size as determinants of stock market returns. *Journal of Banking and Finance,* 10, 115-132.

Lakonishok, J., Shleifer, A., & Vishny, R. (1994). Contrarian Investment, Extrapolation, and Risk. *Journal of Finance,* 49, 1541-1578.

Levy, H. (1978). Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio. *American Economic Review*, 643-658.

Li, J. (1998). The controversial contrarian profits: A study on differential returns across months. *Quarterly Journal of Business and Economics*, 37, 3-26.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47, 13-37.

Lo, A. & Mackinlay, C. (1990). Data-snooping biases in tests of financial asset pricing models. *Review of Financial Studies,* 3, 431-467.

Long, J.B. (1974). Stock prices, inflation and the term structure of interest rates. *Journal of Financial Economics,* 1, 131-170.

Lynch, D. (1993). Australian Financial Markets: Growth and Issues. *Centre for Studies in Money, Banking and Finance,* Macquarie University.

Markowitz, H. Portfolio Selection: Efficient Diversification of Investment. New York: John Wiley, 1959.

Mayshar, J. (1983). On divergence of opinion and imperfections in capital markets, *American Economic Review*, 114-128.

Merton, R. (1973). An intertemporal capital asset pricing model. *Econometrica,* 41, 867-887.

Miller, D.T., & Ross, R. (1975). Self-serving bias in attribution of causality: Fact or fiction?. *Psychological Bulletin,* 82, 213-225.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica,* 34, 768-783.

Myers, R. (1986). *Classical and Modern Regression with Applications*. PWS-Kent Publishing Company.

Reinganum, M.R. (1981). Misspecification of capital asset pricing. Empirical anomalies based on earnings yields and market values. *Journal of Financial Economics,* 9, 19-46.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management,* 11, 9-17.

Sharpe, W.F. (1964). Capital Asset Prices: A theory of market equilibrium under conditions of risk. *Journal of Finance,* 19, 425-442.

Treynor, J. (1972). The trouble with earnings. *Financial Analysts Journal,* 27, 41-43.

Tversky, & Kahneman, D. (1974). Judgement under uncertainty: heuristics and biases. Science, 185, 1124-1131.

Tversky, A., & Kahneman, D. (1971). Belief in the law of small numbers. *Psychological Bulletin,* 76, 105-110.

Wilson, P.G. (1986). The relative information content of accruals and cash flows: Combined evidence at the earnings announcement and annual report release date. Supplement to *Journal of Accounting Research,* 24, 165-200.

Zarowin, P. (1990). Size, seasonality, and stock market overreaction. *Journal of Financial and Quantitative Analysis,* 25, 113-125.