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An investigation of mispricing, analyst forecast optimism and market reactions to earnings surprises of large capitalisation Australian value and growth stocks

Steve J. Tulig
University of Wollongong, stevet@uow.edu.au

TITLE SHEET

AN INVESTIGATION OF MISPRICING, ANALYST FORECAST OPTIMISM AND MARKET REACTIONS TO EARNINGS SURPRISES OF LARGE CAPITALISATION AUSTRALIAN VALUE AND GROWTH STOCKS

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by

STEVE J. TULIG B.E., M.com.

SCHOOL OF ACCOUNTING AND FINANCE

CERTIFICATION

I, Steve J. Tulig, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Accounting and Finance, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Steve J. Tulig

29th May 2011

DEDICATION

This thesis is dedicated to the memory of my parents, whose love and devotion made everything possible.

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education would never have been possible without the love and encouragement of my parents Marian and Katina, who sacrificed much to give me the opportunities they never had.

ABSTRACT

This thesis fills a number of gaps in both the Australian and overseas literature on the value premium, particularly with regard to the dearth of Australian studies on behavioural explanations and the role default-risk plays in such explanations. First, whilst a number of studies have investigated the value premium in Australia in the context of *rational* asset pricing, there are no identified studies in the academic literature that specifically investigate the existence of *mispriced* Australian value and growth stocks. This gap is addressed by exploring the overvaluation of financially distressed growth stocks and the undervaluation of low default-risk value stocks. Second, there are no Australian studies that directly test the errors-in-expectations hypothesis using *biases* in analysts' earnings forecasts, as there are for some overseas markets. This analysis is carried out for the Australian market, but unlike previous studies introduces a highly-relevant control variable: financial distress. Finally, previous studies have shown conflicting patterns of returns and analyst forecast errors across value and growth classifications (high book-to-market stocks simultaneously have over-optimistic forecasts *and* high returns). There have been no attempts to reconcile these conflicting patterns, a gap addressed here by studying the relative importance of book-to-market, default-risk and analyst agreement to the market reaction to earnings surprises.

The findings of this thesis are consistent with overvaluation of distressed growth stocks and undervaluation of low default-risk value stocks, and support the validity of mispricing as a potential explanation of the value premium in Australia; a conclusion

to which previous Australian studies have been averse. The findings also demonstrate a marked bias in analysts' earnings forecasts which is consistent with analyst underreaction to distress, which dominates the relationship between analyst optimism and valuation ratios, and which reveals a previously-undocumented problem with the use of such forecasts to test the errors-in-expectations hypothesis. The findings also shed light on the conflicting patterns of returns and forecast errors across value and growth stocks. This anomaly is largely explainable by the previously-documented asymmetric reactions of value and growth stocks to earnings torpedoes; the novel finding here is that it is *not* explainable by differences in analyst agreement (which affects earnings response coefficients) or in default-risk.

In general terms, the thesis makes contributions to the literature on market and analyst efficiency, behavioural finance, the momentum life cycle, the pricing of default-risk, and earnings response coefficients.

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ABBREVIATIONS

Abbreviation	Meaning
AGSM	Australian Graduate School of Management
APT	Arbitrage pricing theory
ASX	Australian Securities Exchange; formerly the Australian Stock Exchange
B/M	Book-to-market
BHAR	Buy and hold abnormal return
C/P	Cash flow-to-price
CAPM	Capital asset pricing model
DD	Distance-to-default
ΔROA	1-year change in return on assets
E/P	Earnings-to-price
EPS	Earnings per share
ERC	Earnings response coefficient
ES	Earnings surprise
HML	Fama-French high-minus-low B/M factor
I/B/E/S	Institutional Brokers Estimate System
ICAPM	Intertemporal capital asset pricing model
P/E	Price-to-earnings
PR1YR	Carhart prior 1 year return (momentum) factor
ROA	Return on assets
SIRCA	Securities Industry Research Centre of Asia-Pacific
SMB	Fama-French small-minus-big size factor
SPPR	Share price and price relative
UE	Unexpected earnings
UR	Unexpected return

CHAPTER 1: INTRODUCTION

1.1 Background

The value premium is the name given in the asset pricing literature to the observation that value stocks (stocks with low share prices relative to accounting information such as book value of equity or earnings) tend to have higher long-term returns than growth stocks (stocks with high share prices relative to the same accounting information). Research into the value premium is important because it has implications for investment analysis and for the choice of cost of capital used in corporate decision-making. The research frequently centres on the explanation(s) for its existence, which at the present time fall into one of two schools of thought[1].

The first school of thought is that the value premium is due to the rational pricing of risk that is not adequately specified in existing asset pricing models, such as the capital asset pricing model (CAPM). In this framework, investors are unwilling to pay high prices for value stocks because they tend to be more financially distressed than growth stocks. Financially distressed firms are those that are unable to meet or are experiencing difficulty in meeting their financial obligations such as debt repayments (Ross, Westerfield and Jaffe, 2002, pp.854-855; Brealey and Myers, 2003, p.497). The value premium is thus seen as a return premium required by investors for investing in financially distressed companies. A similar argument is that investors are willing to pay high prices for growth stocks because they act as a hedge against risks associated with

[1] A third school of thought that was once prominent but which has now lost support is that the Value Premium is not a real or enduring phenomenon, but is rather an artefact either of inadequacies in the data or of collective 'data snooping' by scores of researchers using the same data set to replicate previous findings.

economic state variables in the spirit of the intertemporal capital asset pricing model (ICAPM) of Merton (1973). This latter argument is frequently cited as the theoretical justification for the Fama-French three-factor model developed in Fama and French (1993) and proposed as an alternative to the CAPM. The Fama-French three-factor model is routinely adopted in empirical work, and *controls* for the size and value premiums in stock returns. The factor in the model that controls for the value premium (referred to as HML) has been interpreted by some researchers as a priced risk factor *however this view is by no means universally accepted* (Ferson, Sarkissian and Simin, 1999; Chan and Lakonishok, 2004).

The second school of thought is that the value premium can be explained in terms of investor behaviour that is less than fully rational. This school of thought argues that growth stocks are overvalued relative to value stocks, and hence the value premium is due to mispricing rather than the rational pricing of an as yet unspecified form of risk, possibly related to financial distress. Equivalently, HML is seen as merely another representation of the value premium without the assumption that it represents a rationally-priced risk factor, since by construction it is the return of a portfolio of value stocks less the return of a portfolio of growth stocks. An important hypothesis regarding the cause of the mispricing in this framework is *the errors-in-expectations hypothesis,* which argues that the relative overvaluation of growth stocks stems from investors' unrealistic expectations of future earnings growth. In other words, investors pay too much for some companies because their growth expectations for these companies are overoptimistic. The actual growth in earnings of highly-priced growth stocks turns out to be much lower than what is justified by their high initial share price, and disappointed investors subsequently lose interest in these companies causing falls in

share prices and relatively poor future stock returns (Lakonishok, Shleifer and Vishny, 1994).

1.2 Key Issues

Within the value premium literature, three issues have been identified which have not yet been adequately addressed and which underlie this thesis. These three issues all involve the implications of financial distress for behavioural explanations of the value premium.

Mispricing as a function of value/growth and default risk

In simple terms the first issue deals with the identification of mispriced securities. In particular, the issue concerns the distinction between *overvalued* growth stocks and *rationally priced* growth stocks, and the distinction between *undervalued* value stocks and *rationally priced* value stocks. The fact that distressed firms are more readily identifiable as value stocks than as growth stocks[2] is consistent with at least some degree of rational pricing of distress by investors. However, returns-based tests of this proposition suggest on balance that default risk, a widely-used measure of financial distress, is not priced in equity markets (Dichev, 1998; Gharghori, Chan and Faff, 2007; Campbell, Hilscher and Szilagyi, 2008). Furthermore, there is growing evidence that a substantial proportion of the value premium is attributable to the stocks whose classification as either value or growth is not commensurate with their level of financial distress. For example, Griffin and Lemmon (2002) find that the relatively poor average returns of growth stocks as a group are concentrated in growth stocks with high default

[2] See, for example, Fama and French (1995), Chen and Zhang (1998), Piotroski (2000).

risk. Similarly, Piotroski (2000) differentiates between undervalued value stocks and otherwise similar value stocks on the basis of financial health measures derived from financial statement analysis; Mohanram (2005) conducts a similar study based on growth stocks; Bird and Casavecchia (2007a) do the same for both value and growth stocks.

The common finding of the above studies is that mispricing is evident when valuation ratios, such as book-to-market (B/M), are either too high or too low relative to a firm's state of financial distress or health. Thus, growth stocks appear to be overvalued when they are financially distressed and value stocks appear to be undervalued when they are financially healthy. This particular result has not yet been verified for the Australian stock market, and the goal of the first empirical study of this thesis is to address this deficiency. The investigation of mispricing as a function of both financial distress and value/growth characteristics constitutes a significant departure from previous Australian studies in the value premium literature which have generally fallen within the rational pricing framework; for example tests of the applicability of the Fama-French three-factor model or other asset pricing models to the Australian market including Halliwell, Heaney and Sawicki (1999), Faff (2001), Durack, Durand and Maller (2004); Gaunt (2004), Durand, Limkriankrai and Smith (2006) and Gharghori, Lee and Veeraraghavan (2009). Gharghori, Chan and Faff (2006a) and Gharghori et al. (2007) also fall within this framework because they both implicitly assume that HML represents a rationally-priced risk factor. Until now, there is little mention in the Australian literature of the possibility that behavioural explanations or mispricing might underlie the value premium[3], despite the fact that this possibility has been recognised in the US literature

[3] A notable exception is Chan, Faff, Ho and Ramsay (2006a), who study market reactions to earnings surprises in the framework of the errors-in-expectations hypothesis. Gaunt (2004) also briefly mentions

(see for example Lakonishok et al., 1994; Daniel, Hirshleifer and Subrahmanyam, 1998; Chan and Lakonishok, 2004; Fama and French, 2004[4]).

Analyst Optimism, Financial Distress and the Errors-in-Expectations Hypothesis

Financial distress is also relevant to the next issue addressed in this thesis, namely the evidence from analysts' earnings forecasts regarding the errors-in-expectations hypothesis. This issue is important primarily because of a study by Doukas, Kim and Pantzalis (2002) which finds a relationship between analyst optimism (measured by the errors in analysts' current year earnings forecasts) and B/M that is the *exact opposite* of that predicted by the errors-in-expectations hypothesis. The errors-in-expectations hypothesis predicts that analyst optimism will be greater for low B/M than for high B/M stocks. However, analysts' earnings forecasts were found by Doukas et al. (2002) to be more optimistic for high B/M stocks than they are for low B/M stocks. Until now, there have been no studies critical of the findings of Doukas et al. (2002), or that have attempted to explain why analysts' *short-term* earnings forecasts appear to defy the errors-in-expectations hypothesis whilst analysts' *longer-term* growth forecasts appear to be consistent with this hypothesis (La Porta, 1996; Dechow and Sloan, 1997; Chan, Karceski and Lakonishok, 2003). The second empirical study in this thesis addresses this deficiency by re-examining the evidence of Doukas et al. (2002) using Australian data and introducing financial distress as a control variable.

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behavioural explanation, as does Gharghori et al. (2009); however neither study finds conclusively in favour of behavioural explanation.

[4] Note that Fama and French are arguably the chief proponents of the rational pricing view. However even they concede in Fama and French (2004) that the debate between rational and irrational pricing is not likely to be resolved.

Financial distress is a relevant control variable in the above context for two reasons. First, value stocks tend to be more distressed than growth stocks (Fama and French, 1995; Dichev, 1998; Chen and Zhang, 1998; Piotroski, 2000). Second, evidence in the analyst efficiency literature suggests that analysts are inefficient and prone to underreaction to information related to financial distress, such as prior earnings changes and prior returns (Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999; Abarbanell and Lehavy, 2003; Cohen and Lys, 2003). Consequently, the relationship between forecast errors and B/M reported in Doukas et al. (2002) might arise because of analyst inefficiency in recognising and underreaction to financial distress and because of the relationship between B/M and financial distress. The second study in this thesis sheds light on the issue by investigating how analyst optimism varies with valuation ratios *as well as* distress.

The Market Reaction to Earnings Surprises, Conditional on Value/Growth, Financial Distress and Analyst Disagreement

The final issue addressed by this thesis is also motivated by the direct relationship between B/M and analyst optimism uncovered by Doukas et al. (2002); a relationship that is counterintuitive because it implies earnings surprises are more negative for value stocks than for growth stocks. Companies with negative earnings surprises are generally punished by the stock market, such that their returns are lower on average than otherwise similar companies. However, value stocks have higher returns than growth stocks, the opposite situation implied by the results of Doukas et al. (2002). Put differently, earnings surprises tend to be large and negative for high B/M stocks, despite the fact that this group of stocks have relatively high returns on average. To increase our

understanding of this apparent anomaly, the third and final study in this thesis investigates the market reaction to earnings surprises.

Previous studies have documented an inverse relationship between B/M and the responsiveness of share prices to earnings surprises. For example, the earnings response coefficient (ERC), the slope of the relationship between unexpected returns and unexpected earnings, has been found to be inversely related to B/M (Collins and Kothari, 1989; Biddle and Seow, 1991). Furthermore, Skinner and Sloan (2002) argue that the 'earnings torpedo', or the *abrupt* price response to even a *slightly* negative surprise, is substantially larger for growth stocks than for value stocks. Skinner and Sloan (2002) attribute the *total* return differential between value and growth stocks to this effect; a result they argue is consistent with the errors-in-expectations hypothesis. Chan, Faff, Ho and Ramsay (2006a) also report similar results for Australian companies, based on earnings surprises computed from management earnings forecasts rather than from the final announced earnings.

However, the previous literature does not explain the counterintuitive result in Doukas et al. (2002), which at first glance implies an inverse relationship between unexpected returns and unexpected earnings for value stocks (because they have relatively high returns at the same time as having relatively negative earnings surprises). For instance, it is not known whether this particular result is due to an absence of market reaction to negative surprises alone, or to the absence of value-relevant information in earnings surprises of any sign for value stocks. Similarly, it is not known whether the result might be due to variation in the market reaction with other variables correlated with B/M. Based on the discussions earlier in this chapter, financial distress might be one

such variable (because of the variation in stock returns with both this variable and B/M and the possibility that analyst underreaction to distress might underlie the distribution of earnings surprises with B/M).

Another potentially relevant control variable in the above context is analyst forecast dispersion, for the following reasons. Market reactions to earnings surprises are known to vary inversely with forecast dispersion (Imhoff and Lobo, 1992; Kinney, Burgstahler and Martin, 2002), and forecast dispersion itself is directly related to B/M (Doukas, Kim and Pantzalis, 2004). Forecast dispersion measures analyst disagreement and therefore uncertainty regarding a firm's future earnings. As forecast dispersion is greater for value stocks than for growth stocks, earnings forecasts and (by implication) the earnings surprises computed from those forecasts are relatively less informative for value stocks than for growth stocks. Differences in forecast dispersion might therefore contribute to an understanding of why value stocks can simultaneously have high returns and negative earnings surprises.

1.3 Research Questions

The issues described above are investigated in this thesis by means of a series of research questions. Following similar literature (for example Fama and French, 1992; Doukas et al., 2002), the research questions operationalise the distinction between value and growth stocks through the use of valuation ratios. Thus, value stocks are defined as those with high B/M, earnings-to-price (E/P) or C/P ratios while growth stocks are defined as those with low B/M, E/P or C/P ratios. Financial distress has been measured in previous studies (for example, Dichev, 1998; Griffin and Lemmon, 2002; Vassalou and Xing, 2004; Gharghori et al., 2007) using models that predict the probability of a

distress-related event, such as actual default on debt or the more extreme event of bankruptcy. This thesis follows Vassalou and Xing (2004) and Gharghori et al. (2007) by operationalising distress in terms of the default risk of debt, measured in terms of distance-to-default (DD). Thus, financially distressed firms are defined as those with high default risk (or equivalently, with low DD) while financially healthy firms are defined as those with low default risk (or equivalently, with high DD). The first issue is therefore the relationship between valuation ratios, default risk and mispricing, and specifically asks whether mispricing defined in terms of valuation ratios and default risk is evident in the Australian stock market. Formally, this can be expressed as the following research question:

Research Question 1: Are Australian stocks mispriced when their valuation ratios (book-to-market, earnings-to-price or cashflow-to-price) are either high or low relative to their level of default risk?

Stocks with valuation ratios that are high relative to default risk are referred to hereafter as ‘low default risk value’ stocks, while stocks with valuation ratios that are low relative to default risk are referred to hereafter as ‘high default risk growth’ stocks. Research question 1 is therefore asking in effect whether low default risk value stocks are undervalued while high default risk growth stocks are overvalued. One way of answering this question is to compare the risk-adjusted returns (alphas) of stock portfolios formed by sorting on the valuation ratios and default risk. Positive risk-adjusted returns for low default risk value stocks and negative risk-adjusted returns for high default risk growth stocks support an affirmative answer to this question. If the asset pricing model used to risk-adjust returns is correct, risk-adjusted returns should be

statistically indistinguishable from zero. Thus, an analysis of portfolio alphas can be seen as a test of the asset-pricing model (used to compute the alpha) against a specific mispricing hypothesis consistent with an affirmative answer to research question 1. Chapter 4, the first empirical study in this thesis, explicitly carries out such tests.

However, it is possible that the portfolio alphas support an affirmative answer to research question 1 because the asset-pricing model is incorrect, and that the true portfolio alphas are actually zero in an alternative but as yet unspecified asset pricing model. It is also debatable whether HML, a factor which features prominently in the risk-adjustment process, does indeed represent a rationally-priced risk-factor rather than the correction of mispricing (Chan and Lakonishok, 2004). Thus, additional evidence besides that obtained from portfolio alphas is required to answer research question 1, in other words to demonstrate whether or not the observed differences in returns are more consistent with rational pricing or with mispricing. Chapter 4 provides the additional evidence in the form of alternative risk and return measures that do not depend on asset-pricing models, and in the form of historical company performance characteristics which demonstrate the role of *market inefficiency* in this type of mispricing.

The second issue is the evidence from analysts' earnings forecasts that is contrary to the errors-in-expectations hypothesis, but which was argued above to be potentially sensitive to the omission of distress as a control variable. The evidence in question shows that analyst optimism, measured in terms of analysts' forecast errors, increases with B/M. The second research question addresses this issue directly, using similar variables and methodology to Doukas et al. (2002) with the exception of a new control variable; namely financial distress measured in terms of default risk:

Research Question 2: How do median analysts' forecast errors vary with valuation ratios and default risk?

Following similar research, the question is phrased in terms of a measure of central tendency of the distribution of forecast errors, in this case the median. Rather than examining average forecast errors as a measure of analyst optimism, median values are used because they are less sensitive to outliers which are well-known to plague forecast error distributions (Doukas et al., 2002).

For reasons outlined earlier, it is expected that median forecast errors are directly related to default risk, a finding that might potentially explain the *direct* relationship between analyst optimism and B/M documented in Doukas et al. (2002). For example the relationship between analyst optimism and B/M might be apparent only because analysts underreact to financial distress and because financial distress is correlated with B/M. A finding that the relationship between median analysts' forecast errors and default risk subsumes that between median analysts' forecast errors and B/M would be consistent with this explanation. Moreover, it is plausible that analyst optimism might actually vary inversely with B/M after controlling for default risk, a result which if obtained would be consistent with the errors-in-expectations hypothesis despite the contrary evidence in analysts' forecast errors that appears in the absence of controls for default risk.

The final issue still remains as to how value stocks can be subject to greater analyst optimism (and by implication, larger and more prevalent negative earnings surprises)

and yet still deliver higher returns than growth stocks; an issue that leads to the question of how the market reacts to earnings surprises, conditional upon valuation ratios, default risk and forecast dispersion. Valuation ratios are important to this question because they determine a stock's classification as either value or growth. The relevance of default risk is governed by the findings in response to research questions 1 and 2. For example value stocks' high returns might be attributable to *low* default risk value stocks while value stocks' negative surprises might be attributable to *high* default risk value stocks. The question is then whether *high default risk* value stocks respond any differently to earnings surprises than value stocks per se. As discussed earlier, forecast dispersion is known to be an important determinant of the market reaction to earnings surprises, and is relevant here because it might explain any inconsistency between the variation in returns and the variation in earnings surprises across value/growth and default risk categories.

Research Question 3: How does the market reaction to earnings surprises vary with valuation ratios, default risk and forecast dispersion?

The phrase '*market reaction to earnings surprises*' is used in the above question to indicate either the abnormal return that accrues on average after a positive or a negative earnings surprise, or to the abnormal return for a given magnitude of earnings surprise (the abnormal return per unit of earnings surprise or ERC). In other words, research question 3 asks how (i) the abnormal return attributable either to a positive or to a negative earnings surprise, and (ii) the abnormal return per unit of earnings surprise, varies with each of the three variables.

Whilst the previous literature is inconclusive regarding the role played by default risk (Dhaliwal and Reynolds, 1994; Billings, 1999) in the above question, it is expected (based on the previous literature) that the market reaction to earnings surprises is inversely related to valuation ratios (in other words greater for growth stocks than for value stocks) and is inversely related to forecast dispersion. However, the interaction between the three variables is somewhat uncertain prior to undertaking the analysis. One possibility is that a high degree of forecast dispersion might explain the lack of responsiveness to value stocks' earnings surprises; another possibility is that the growth stock earnings torpedo as documented in Skinner and Sloan (2002) can fully account for the fact that negative surprises are punished by the market in the case of growth stocks but not for value stocks, irrespective of the magnitude of the surprise or of differences in default risk and forecast dispersion. Research question 3 thus attempts to determine the incremental effect of each of the three variables on market reactions to earnings surprises, with a view to increasing our understanding of why value stocks simultaneously have earnings forecasts that are more optimistic and returns that are higher than growth stocks.

The answers to this particular research question have implications regarding the applicability of analysts' earnings forecasts to tests of the errors-in-expectations hypothesis. For example, an apparent lack of market reaction for some categories of stocks suggests that the earnings forecast from which the earnings surprise is calculated for these stocks either is not important to or unrepresentative of the views of investors, or carries no valuation-relevant information. Therefore, the answer to this research question potentially raises additional concerns regarding the use of analysts' forecast

errors to test the errors-in-expectations hypothesis across an unrestricted sample of stocks.

1.4 Methodological Issues

The research design throughout this thesis follows conventional practice in the related literature, with a few minor exceptions. The research design for research question 1 is consistent with Fama and French (1992), Fama and French (1993), Gaunt (2004), Halliwell et al. (1999) and others regarding the formation of portfolios and computation of portfolio returns and alphas. The research design for research question 2 is consistent with Doukas et al. (2002). There are some differences with previous studies pertaining to the research design for research question 3 and to the sample selection criteria for the thesis in general, which are discussed as follows.

For all of the studies in this thesis the sample is restricted to the largest 300 companies by market capitalisation, for the following reasons. First, the large-cap emphasis obviates the need to control for size, making the analysis more tractable. Size is not emphasised as a control variable because findings in Halliwell et al. (1999) and Gaunt (2004) show that the size effect in Australia is due to small stocks and largely absent from large stocks; a result which is confirmed in Chapter Four. Second, the market data is substantially less plagued by thin trading than would otherwise be the case and consequently the computations based on share prices are substantially more accurate. Third, analysts' earnings forecasts are only available for large companies, and therefore the second and third studies have a large-cap bias by necessity; the size restriction has the greatest impact on the first study but ensures consistency with regard to the sample amongst all three studies.

The definitions of analyst forecast errors (used in research question 2) and earnings surprises (used in research question 3) are noteworthy. For consistency with Doukas et al. (2002), earnings forecasts used for both variables are selected with an eight month horizon (in other words, the forecasts are those that were current eight months prior to fiscal year end). The forecast error is defined as the price-deflated difference between the consensus forecast and actual earnings-per-share (EPS), and as per Doukas et al. (2002) is *positive* if the forecast is higher than the actual EPS (and thus increasing with ex-ante optimism). The earnings surprise is also the price-deflated difference between the consensus forecast and actual EPS, but in contrast to forecast error and consistent with the related literature, is *negative* if the forecast is higher than the actual EPS. Thus, the forecast error and earnings surprise have the opposite sign but are otherwise identical.

The market reaction to earnings surprise is computed in terms of *both* the slope and intercept from a regression of unexpected returns on earnings surprises. The slope term from a regression of unexpected returns on earnings surprises is the earnings response coefficient, or the unexpected return *per unit* of unexpected earnings. However, the related studies in the value premium literature (for example Skinner and Sloan, 2002; Chan et al., 2006a) are less concerned with the *slope* of the relationship than with differences in the *intercept* term that occur across value and growth stocks and across positive and negative surprises. Asymmetric intercept terms are used to model differences in average returns following positive and negative earnings surprises, regardless of the magnitude of the surprise. Prior to conducting the analysis, it is not known whether the omission of either parameter is appropriate from a modelling

perspective and therefore, for consistency with both the ERC literature and the value premium literature, the analysis allows for variation in both the intercept and slope terms.

Finally, the market reaction to earnings surprise is assessed in research question 3 over a relatively long window (240 trading days) compared with some previous studies. The long window is chosen for consistency with the returns from annually-rebalanced portfolios used to answer research question 1 and the eight-month analysts' forecast errors used to answer research question 2 (the length of time between the issuance of eight-month forecasts and the date of earnings announcement is usually close to one year). Announcement period returns, that is returns within one or two days of the date of earnings announcement, are not considered because recent studies demonstrate the complete market reaction is spread over a substantially longer period, attributable to post-earnings announcement drift and to the fact that earnings news is often released substantially earlier than the announcement date (Skinner and Sloan, 2002; Chan et al., 2006a).

1.5 Contributions

Each of the three empirical studies in this thesis makes contributions to the relevant literature. The first study extends the 'stock-picking' literature, notably the literature concerned with the identification of undervalued value stocks and overvalued growth stocks, to the Australian market. More importantly, it extends the academic value premium literature in Australia by explicitly studying mispricing and by its emphasis on large capitalisation stocks. The second study contributes to our understanding of the determinants of analysts' forecast errors, and therefore contributes to the literature on

analyst efficiency as well as the empirical literature on the errors-in-expectations hypothesis. In particular, the findings represent new evidence of the role of default risk in tests of this hypothesis based on analysts' earnings forecasts. The third study makes contributions to the literature on earnings response coefficients as well to the literature of the value premium. It provides Australian evidence on the determinants of the ERC and on the importance of earnings torpedoes for value-minus-growth return differentials; furthermore it adds to our understanding of the *economic significance* of variation in analysts' forecast errors across value and growth stocks.

In addition, this thesis makes a number of contributions to other areas of interest in the asset-pricing and behavioural finance literatures. It provides further evidence on the question of whether or not default risk is priced in equity markets; this evidence is based both on stock returns and on the market reactions to earnings surprises. Other findings have implications for our understanding of the momentum life cycle proposed by Lee and Swaminathan (2000), and for the validity of various assumptions made in behavioural models such as Barberis, Shleifer and Vishny (1998), Daniel et al. (1998), Hong and Stein (1999), and Barberis and Shleifer (2003). These assumptions include the slow diffusion of information, the relative importance of underreaction and overreaction to describe investor behaviour, and the various cognitive biases (such as representativeness and conservatism) used to generate such behaviour.

1.6 Thesis Structure

The remainder of the thesis is structured as follows. Chapter 2 provides a detailed discussion of the related literature. Chapters 3, 4 and 5 contain the empirical studies, each of which corresponds to one of the three issues/research questions outlined above.

Chapter 3 investigates mispricing in the Australian market as a function of value/growth characteristics and distress; Chapter 4 investigates analyst optimism conditional on value/growth characteristics and distress; and Chapter 5 investigates the market reaction to earnings surprises conditional on value/growth characteristics, distress and analyst disagreement. Chapter 6 then concludes by summarising the salient findings of all three empirical chapters, discussing in detail the contributions of the thesis to the literature, and then commenting on the limitations and potential future extensions of the research.

CHAPTER 2: REVIEW OF LITERATURE PERTAINING TO THE VALUE PREMIUM, ANALYST EFFICIENCY AND MARKET REACTIONS TO EARNINGS SURPRISES

2.1 Introduction

This chapter reviews the literature behind the identification of the value premium, its explanations in terms of both rational pricing and behavioural finance, and the evidence cited in support of the various explanations. As is the case for the thesis in general, the emphasis of the chapter is upon behavioural explanations. The chapter also covers the literature on two subject areas which are of importance to this thesis, which overlap with but are difficult to categorise specifically as belonging to the value premium literature. These two subject areas deal with the issues of analyst efficiency and the market reaction to earnings surprises (including earnings response coefficients).

The chapter begins (Section 2.2) with a review of the evidence for the existence of a value premium, along with similar evidence for the size effect and momentum. All of these empirical phenomena are referred to as asset pricing anomalies because they are inconsistent with standard asset pricing models, such as the capital asset pricing model (CAPM). The value premium and size effect are related and difficult to discuss in isolation because market capitalisation, which is commonly used to measure size, appears as a denominator in valuation ratios which are commonly used to measure value. Unlike the value premium, the size effect has been argued by some authors to have either disappeared or reversed in sign (Black, 1993a; Roll, 1995; Dimson and Marsh, 1999). Therefore, the emphasis of the remainder of the chapter and of the thesis

in general is on the value premium, and not on the size effect. The issue of whether or not the size effect has vanished is largely irrelevant to the rest of this thesis, although it enters the discussion of a number of the risk-based explanations for the value premium. Similarly, momentum is not the main focus of the chapter or of the thesis; however it is mentioned because it enters the discussion of behavioural finance and mispricing-based explanations for the value premium.

The most prominent current explanations for the value premium are discussed in Section 2.3. These explanations generally fall into one of two camps: those based on a rational asset pricing framework where the high returns of value stocks are viewed as compensation for risk, and those based on mispricing and various behavioural assumptions. The explanations based on rational asset pricing include the Fama-French three-factor model and conditional versions of the CAPM and consumption-based models. The empirical basis of the links between size, value and financial distress is discussed in Section 2.3.2; the relationship between value and distress has been used as a basis for the assumption that HML represents a risk factor and therefore to justify its inclusion in rational asset pricing models. However, the same relationship is particularly important for this thesis because financial distress is used as a control variable; the justification for doing so will be made apparent in subsequent sections.

In contrast to the rational asset pricing framework, *behavioural finance* seeks theoretical explanations for a wide variety of financial market phenomena, based on the assumption that not all agents are fully rational. These phenomena include the equity premium puzzle, time-series and cross-sectional predictability of returns, post-earnings announcement drift, abnormal returns following corporate actions, and irrational trading

behaviour by investors (Barberis and Thaler, 2005). In the context of cross-sectional return predictability, behavioural finance is primarily concerned with two seemingly disparate effects, namely the value premium *and* momentum. The behavioural finance explanations that are relevant for the value premium are discussed in Section 2.3.4; the most important being models by Barberis et al. (1998), Daniel et al. (1998), Daniel, Hirshleifer and Subrahmanyam (2001a), and Hong and Stein (1999). The models differ markedly in the overreaction and underreaction mechanisms proposed to explain both the value premium and momentum, and also differ markedly in the psychological biases and other assumptions they employ to generate these mechanisms. The findings of this thesis have implications for behavioural finance theories and the assumptions underlying these theories.

One behavioural explanation for the value premium that is particularly relevant to this thesis is the errors-in-expectations hypothesis, discussed in Section 2.3.5. This hypothesis states that investors are overly optimistic regarding the future prospects of, and pay prices that are too high for, growth stocks. The errors in initial growth expectations are realised upon subsequent earnings announcements, resulting in price corrections which ultimately translate into the value premium. The errors-in-expectations hypothesis is supported by empirical evidence based on historical and forecast *growth* rates (for example, Lakonishok et al., 1994; La Porta, 1996; Dechow and Sloan, 1997, and Chan et al., 2003) and market reactions to earnings surprises (for example Skinner and Sloan, 2002 and Chan et al., 2006a). However, the errors-in-expectations hypothesis is *not* supported by empirical evidence from analysts' *earnings* forecasts, which are found to be more optimistic for high book-to-market (B/M) stocks than for low B/M stocks (Bauman and Miller, 1997; Doukas et al., 2002; Mian and Teo,

2004), the direct opposite of the relationship predicted by this hypothesis. One of the major contributions of this thesis is a critical re-examination of the relationship between analyst optimism and B/M, focusing on an important control variable not considered in previous studies: financial distress. There are two reasons why the failure to adequately control for distress might be a critical oversight in this context: (a) because mispricing is arguably a function of distress *as well as* value and (b) because of analyst inefficiency considerations. Consequently, the chapter moves on to a discussion of the literature that supports these two reasons.

Some relatively recent studies (discussed in Section 2.3.6) identify mispriced stocks as a function of value/growth and of each firm's relative state of financial health or distress, a concept which is central to this thesis. For example, Piotroski (2000), Griffin and Lemmon (2002), and Mohanram (2005) all identify overpriced growth stocks as those with low B/M and poor financial health and underpriced value stocks as those with high B/M and good financial health. A similar scheme is used in Bird and Casavecchia (2007a), with value/growth defined in terms of sales-to-price rather than B/M. Research question 1 and the first empirical study in this thesis follows the overall theme of these studies by testing whether Australian stocks with low valuation ratios and high default risk are overpriced, and those with high valuation ratios and low default risk are underpriced.

Research questions 2 and 3 are based to some extent upon subject areas that are not wholly within the value premium literature. One such subject area is analyst efficiency (or inefficiency), alluded to in the discussion of the errors-in-expectations hypothesis above and to which Section 2.4 is devoted. The literature on analyst efficiency suggests

that analysts' forecasts are inefficient with regard to the incorporation of relevant public information, as forecast errors have been shown to be correlated with variables such as prior changes in earnings-per-share and prior returns (Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999; Abarbanell and Lehavy, 2003; Cohen and Lys, 2003). Analyst inefficiency makes it highly plausible that analysts' forecasts do not adequately reflect a firm's state of financial distress, and that forecast errors are correlated with distress-risk. Consequently, the relationship between forecast errors and B/M reported in Doukas et al. (2002) might arise because of analyst inefficiency in recognising financial distress and because of the relationship between B/M and financial distress. Research question 2 and the second empirical study in this thesis test this hypothesis by examining the variation in analysts' forecast errors with valuation ratios (including B/M) and financial distress.

The final body of literature of relevance to this thesis pertains to the market reactions to earnings surprises, the subject of Section 2.5. This literature includes some of the studies that deal with the errors-in-expectations hypothesis and which are therefore discussed in Section 2.3.5, as well as studies of earnings response coefficients. Research question 3 and the final empirical study in this thesis draw upon both areas of the literature in an attempt to explain another anomalous feature of the results of Doukas et al. (2002). The findings of Doukas et al. (2002) are anomalous in that they imply value stocks have large negative earnings surprises relative to growth stocks despite the existence of the value premium; in effect the value premium itself implies that the large negative surprises of value stocks must escape largely unpunished by the market. Whilst it is acknowledged that a previously documented result pertaining to the asymmetric responses of value and growth stocks to negative earnings surprises (Skinner and Sloan,

2002; Chan et al., 2006a) might fully explain this anomaly, there are a number of other factors suggested by the literature that might also be relevant. These additional factors are elaborated upon in Section 2.5 and include the functional form of the relationship between returns and earnings surprises, and the relative importance of B/M, financial distress and analyst forecast dispersion to this relationship.

2.2 Asset Pricing Anomalies

Asset pricing anomalies are empirical results that historically proved difficult to reconcile with the traditional rational pricing paradigm; a paradigm that includes the efficient market hypothesis and an asset pricing model. The efficient market hypothesis states that security prices reflect all available information; a consequence of which is that abnormal returns are not achievable through the analysis of information related to securities. Abnormal returns are defined in terms of risk-adjusted returns, for which an asset-pricing model is required (Shleifer, 2000, pp.5-6). The most widely used asset-pricing model is the CAPM, which states that investors are only concerned with systematic risk, measured by a security's beta.

Under the CAPM, expected returns are a linear and increasing function of beta, and abnormal returns are measured as the difference between the actual returns of a security and the expected return of the security. Empirical evidence that demonstrates persistent abnormal returns from a specific trading strategy is thus termed an asset-pricing anomaly. For example, the size effect (Banz, 1981) and price-to-earnings (P/E) effect (Basu, 1977) were initially identified by the abnormal returns of portfolios sorted respectively by market capitalisation and P/E ratios. The detection of anomalies such as the size effect and price-to-earnings effect has historically been interpreted either as

evidence that the CAPM is an imperfect model of asset prices or as evidence of market inefficiency[5].

Whilst the CAPM remains the dominant asset pricing model due to its simplicity and theoretical soundness, other asset pricing models have either been confronted by anomalies detected in the context of the CAPM, or indeed proposed as a consequence of these anomalies. The arbitrage pricing theory (APT) was employed with limited success in an attempt to explain the size effect; where the model factors consist either of purely statistical factors (for example Lehmann and Modest, 1988; Connor and Korajczyk, 1988) or of pre-specified economic variables (for example Chan, Chen and Hsieh, 1985; Chen, Roll and Ross, 1986; He and Ng, 1994). Similarly, APT-style pricing models with economic factors (He and Ng, 1994) and statistical factors (Brennan, Chordia and Subrahmanyam, 1998) proved inadequate in explaining B/M effects in stock returns. The Fama-French three-factor model was proposed by Fama and French (1993) as an alternative to the CAPM to explain the existence of the size and B/M effects, with factors determined empirically as the returns of portfolios constructed specifically to capture these effects. This model has been justified as a form of the intertemporal capital asset pricing model (ICAPM), with the factors representing size and B/M effects argued to be the returns of portfolios that investors use to hedge against economic state variables (Fama and French, 1996; Petkova, 2006). Yet another asset pricing model, the Carhart four-factor model, was proposed in Carhart (1997) and augments the Fama-French three-factor model with a fourth factor designed to capture another major CAPM anomaly, namely momentum.

[5] All tests of asset pricing anomalies are thus subject to the critique of Fama (1970), which states that such tests are joint tests of the efficient markets hypothesis and of the asset pricing model used to define abnormal returns. As Shleifer (2000), points out, this critique can be applied to argue that asset pricing anomalies are evidence *only* of the inadequacy of models such as the CAPM, and not of market efficiency.

The anomalies that are of most relevance to this thesis are the size effect, the value premium and momentum, to which Sections 2.2.1 and 2.2.2 are devoted. Other notable anomalies include the weekend effect, January effect, equity premium puzzle, and evidence of abnormal returns following earnings and dividend announcements and share issuance (Barberis and Thaler, 2005). As these anomalies are largely irrelevant to this thesis they will not be discussed further in this chapter.

2.2.1 The Size Effect and Value Premium

The size effect is the observation that small (low market capitalisation) companies have higher risk-adjusted returns than large companies. The value premium is the observation that value stocks (companies with low market value *relative* to an accounting variable such as earnings or book-value of equity) have higher risk-adjusted returns than growth stocks (companies with high market value *relative* to an accounting variable such as earnings or book-value of equity). As size (market capitalisation) enters the calculation of value, the size effect and value premium are related. It is therefore difficult to discuss the value premium literature without a concurrent discussion of the literature on the size effect.

The first important study in this area was that of Basu (1977) which confirms the P/E effect, the inverse relationship between abnormal returns and P/E ratios. This relationship is also confirmed in subsequent studies by Basu (1983), Cook and Rozeff (1984), Jaffe, Keim and Westerfield (1989) and Chan, Hamao and Lakonishok (1991). The ‘size-effect’ is credited to Banz (1981), with later studies arguing that the size effect completely subsumes the P/E effect (Reinganum, 1981). To this end, Banz and

Breen (1986) argue that the evidence of a P/E effect is heavily influenced by ‘ex-post-selection bias’ (also referred to as ‘survivorship bias’) and ‘look-ahead bias’ (the assumption that accounting data are available to investors at the end of the firm’s fiscal year, even though the data are not actually reported until several months later). However, Jaffe et al. (1989) find a P/E effect in a study free of both forms of bias, and a size effect that limited to the month of January only, consistent with previous evidence by Keim (1983) that the size effect is concentrated in January.

Value stocks, and by implication the value premium, have been defined by a number of ratios besides P/E[6]. The most frequently used ratio for this purpose in the academic literature is B/M with innumerable studies documenting a direct relationship between this ratio and stock returns, for example Rosenberg, Reid and Lanstein (1985), Chan et al. (1991), Fama and French (1992) and others. Other value-related ratios documented to have a direct relationship with stock returns include cashflow-to-price or C/P (for example Chan et al., 1991; Lakonishok et al., 1994), sales-to-price (Bird and Whitaker, 2003; Bird and Casavecchia, 2007a) and composite variables based on B/M and C/P and on C/P and past sales growth (Lakonishok et al., 1994; La Porta, Lakonishok, Shleifer and Vishny, 1997). Numerous other studies have since demonstrated that value stocks earn higher returns than growth stocks over the long term including La Porta et al. (1997), Daniel and Titman (1997), Dechow and Sloan (1997), and Chan, Karceski and Lakonishok (1998).

[6] For consistency with other ratios such as B/M which have price or market capitalisation in the denominator, extensive use will be made in this thesis of the inverse of P/E, in other words earnings-to-price or E/P for short. Thus the P/E effect, or inverse relationship between returns and P/E, becomes a direct relationship between returns and E/P.

Evidence of the existence of the value premium in markets outside of the United States is provided by Capaul, Rowley and Sharpe (1993), Arshanapalli, Coggin, Doukas and Shea (1998) and Fama and French (1998). Evidence of a value in premium in Australia is provided in Arshanapalli et al. (1998), Fama and French (1998), Halliwell et al. (1999), Faff (2001), Gaunt (2004) and Gharghori et al. (2009). The studies by Halliwell et al. (1999) and Gaunt (2004) are noteworthy in that neither study unequivocally concludes that a value premium exists in Australia, despite the presentation of results that support this conclusion[7]. The two-way sorts on size and B/M in both studies show returns increasing with B/M in at least the three largest size quintiles, and therefore support the existence of a value premium, at least amongst the largest 60% of stocks by market capitalisation. Furthermore, Halliwell et al. (1999) state that "The mean B/M premium is substantially larger than either the market or the size premium with an average premium of 14.57% per year" (p.129). Therefore, the overall evidence supports the existence of a value premium in Australia.

The value premium is closely related to the return reversal effect of De Bondt and Thaler (1985), whereby stocks with low returns measured over prior five-year periods (losers) tended to have higher future returns than stocks with high five-year returns (winners). De Bondt and Thaler (1987) showed that both value stocks and losers tend to be characterised by high B/M, poor prior performance in earnings and low prior returns, leading to depressed stock prices. Strategies that invest in either value stocks or loser stocks are often referred to as 'contrarian' strategies because they are contrary to the

[7] For example, Halliwell et al. (1999) state "There is little evidence of a statistically significant B/M effect though the magnitude of the B/M parameters are similar to those observed in Fama and French (1993)" (Halliwell et al. (1999), p.136). Similarly, Gaunt (2004) states "There is some *weak* evidence of a BM effect in the raw returns with three of the high BM portfolios possessing a statistically significant higher raw return than the corresponding low BM portfolios" (italics added, p.34).

sentiment expressed by the market, and emphasise out-of-favour stocks (Lakonishok et al., 1994).

A major argument against the findings of a value premium is that the result is due to the ex-post selection (or survivorship) bias first discussed by Banz and Breen (1986). Kothari, Shanken and Sloan (1995) point out this bias is particularly severe in the COMPUSTAT data typically used in value premium studies, because of the under-representation of delisted firms. They also point out that value stocks are generally more financially distressed than growth stocks and therefore more likely to be delisted, inducing an upward bias in estimates of the value premium. However, other studies have demonstrated either that the value premium exists in databases free from survivorship bias (Davis, 1994) or that the effect of the bias in the COMPUSTAT data is insufficient to alter inferences regarding the value premium (Chan, Jegadeesh and Lakonishok, 1995; Kim, 1997).

Another argument against the existence of both the size effect and value premium is that the results are spurious and simply due to a collective data mining effort by many researchers using the same data, following the initial publication of an anomaly. The main advocates of this argument, Lo and MacKinlay (1990), and Black (1993a, 1993b) cite the absence of a theory linking stock returns to the characteristics in question (market capitalisation and scaled-price ratios). This argument has empirical support with regard to the size effect, which is documented to have either diminished, vanished or reversed in sign since it was first announced in 1981 (for example Black, 1993a; Roll, 1995; Dimson and Marsh, 1999). However, the argument has been progressively weakened with regard to the value premium, which has proved robust over long periods

of time and in other markets besides the US (for example, Chan et al., 1991; Capaul et al., 1993; Arshanapalli et al., 1998; Fama and French, 1998). Furthermore, theory has been extended to accommodate the value premium, in terms of both rational asset pricing and behavioural finance. These explanations will be discussed in more detail in Section 2.3.

2.2.2 Momentum

Momentum is a phenomenon that has been observed in stock prices, whereby portfolios of stocks with recent high returns (winners) tend to exhibit higher returns than portfolios of stocks with recent low returns (losers). In other words, momentum describes short term return continuation, as opposed to the long-term return reversals documented by De Bondt and Thaler (1985). The existence of a momentum effect is generally credited to Jegadeesh and Titman (1993), who found that stocks with high (low) six-month returns tend to continue to exhibit high (low) returns around earnings announcement dates in the following six months, although consistent with the effect documented by De Bondt and Thaler (1985) this trend reverses after eight months.

Evidence of a momentum effect in Europe was provided by Rouwenhorst (1998) and internationally by Griffin, Ji and Martin (2003). Momentum has also been documented at the industry level by Moskowitz and Grinblatt (1999), and at the country level by Chan, Hameed and Tong (2000) and Scowcroft and Sefton (2005). In other words, industries within national markets with recent high returns as well as national equity markets with recent high returns are expected, on average, to continue to have high returns. It is significant that momentum is not explainable by the Fama-French three-factor model (Fama and French, 1996); the consequence being the four-factor model

proposed by Carhart (1997) which augments the three-factor model with a momentum factor.

An important link between momentum and value strategies was established by Lee and Swaminathan (2000), and which will subsequently be shown to be consistent with the findings of this thesis. They document that a simple momentum strategy can be improved by buying winners with low trading volume and selling losers with high trading volume. Lee and Swaminathan (2000) observed that stocks with high trading volume possessed many attributes of growth stocks (high analyst coverage, higher long-term growth forecasts and higher profitability), whereas stocks with low trading volume possessed many attributes of value stocks. Given the relationship between trading volume and value/growth, the strategy advocated by Lee and Swaminathan (2000) is similar to a strategy that buys high momentum value stocks and sells low momentum growth stocks, which others have been found to be highly profitable (Bird and Whitaker, 2004; Bird and Casavecchia, 2007b).

2.3 Alternative Explanations for Size and Value Effects

2.3.1 The Fama-French Three-Factor Model

The study by Fama and French (1992) argues that in contradiction to the CAPM, beta appears to play little, if any, role in determining return variation in the cross-section of stock returns. Any relationship between beta and returns, for example the findings of well-known studies such as Black, Jensen and Scholes (1972) and Fama and Macbeth (1973), is due to the correlation between size and beta, and the strong inverse relationship between size and returns. Furthermore, Fama and French (1992) argued that

stock returns are parsimoniously explained by two variables, size (market capitalisation) and B/M, with no role for beta. Both size and B/M appeared to be jointly and independently related to returns, with returns increasing monotonically with both B/M and decreasing size. In cross-sectional regressions, Fama and French (1992) found that the slope coefficients on B/M were much larger (in absolute value) and had more statistically significant t-statistics, and therefore concluded that B/M is more important in explaining returns than size.

As an extension of the results reported in Fama and French (1992), the Fama-French three-factor model was developed in Fama and French (1993) and includes as factors the returns of a market portfolio and two hedge portfolios constructed to capture the effects of size and B/M on stock returns. The Fama-French three-factor model is given by the regression equation (2.1), wherein SMB is the expected return on a portfolio of small stocks minus the return on a portfolio of large ('big') stocks; HML the expected return on a portfolio of high B/M stocks minus the return on a portfolio of low B/M stocks; and $r_m - r_f$ the market return in excess of the risk-free rate. The terms s_j, h_j and b_j are the loadings of security j on the respective risk factors, with b_j analogous to beta in the CAPM, while the a_j term is the pricing error of the model, or simply the intercept term from time-series regressions.

$$r_j - r_f = a_j + b_j E[r_m - r_f] + s_j SMB + h_j HML + e_i \qquad (2.1)$$

Fama and French (1993) test the three-factor model using time series-regressions on a set of 25 portfolios constructed by sorting stocks simultaneously on size and B/M (a five-by-five, two-way sort). Not surprisingly, the portfolios containing high (low) B/M

possessed high (low) regression slopes h on HML, and the portfolios containing small (large) stocks possessed high (low) regression slopes s on SMB.

Without the market factor included, the intercept term a_j in the time-series regressions was found to be large and similar for all 25 portfolios; by including the market factor, the intercept term is effectively pushed to zero, indicating that the market return is needed to explain *total* stock returns. However the loading on the market factor, b_j, was close to unity for all 25 portfolios, indicating that beta does not explain *variation* in the cross-section of stock returns, consistent with the results of Fama and French (1992). Fama and French (1993) also successfully used the three-factor model to explain the anomalous returns of low price-to-earnings stocks and high dividend-yield stocks. Subsequently, Fama and French (1996) claimed the model is able explain the returns of a variety of contrarian strategies, including those based on P/E, C/P, past sales growth (Lakonishok et al., 1994) and long-term return reversals (De Bondt and Thaler, 1985, 1987), but not however the returns of momentum strategies expounded in Jegadeesh and Titman (1993).

Fama and French (1993) interpreted the SMB and HML factors as proxies for underlying sources of economic risk, on the premise that assets are priced rationally and therefore variables (such as size and B/M) associated with returns must proxy for common, undiversifiable sources of risk. They argued that both small firms and high B/M (value) firms tend to be unprofitable, and therefore SMB and HML are related to earnings-risk factors. Fama and French (1995) were able to confirm that size and B/M are indeed related to profitability. A high B/M ratio tends not only to be indicative of recent poor earnings performance, but also to signal continued poor performance. In

two-way sorts on size and B/M, the high B/M portfolios were characterised by firms that had demonstrated consistently low profitability up to five years prior to portfolio formation, and that would continue to be unprofitable for up to five years after portfolio formation. A similar, but weaker result obtained for the small-size portfolios, but this result was conditional upon B/M: given a level of B/M, small firms are consistently less profitable than larger firms, however small, low B/M firms tend to be consistently more profitable than large, high B/M firms.

Fama and French (1996) finalised their exposition of why the three-factor model explains returns in a rational asset pricing framework. They interpreted the ability of the model to explain value-related CAPM anomalies as evidence that SMB and HML capture the effects of economic state variables that investors wish to hedge against, in the spirit of the ICAPM. In particular, they argued that HML is likely to be a risk factor that relates to relative distress: companies, industries and portfolios have high loadings on HML when they are distressed, and relatively lower loadings on HML at times when they are strong. The high average returns of the HML factor, and of assets that load highly on this factor, are therefore argued to be compensation for bearing distress risk. The concept of relative distress in asset pricing is generally attributable to a study by Chan and Chen (1991) (see Section 2.3.2), who argued that distressed firms are more susceptible to adverse economic conditions. However, Fama and French (1996) do not claim to have identified the precise nature of the economic risk factors proxied by SMB and HML (Fama and French, 1996, p.76):

> *One can argue that all of this still falls within a minimalist interpretation of the three-factor model; we have simply found three portfolios that provide a*

parsimonious description or returns and average returns, and so can absorb most of the anomalies of the CAPM…We have not identified the two state variables of special hedging concern to investors that lead to three-factor asset pricing.

The Fama-French three-factor model is an important but controversial contribution to asset pricing. It has become important because researchers now routinely apply the model in portfolio performance measurement to control for size and B/M effects. However, the model is controversial because the theoretical justification for the SMB and HML factors is not universally accepted. Black (1993a) cited data-mining concerns and pointed to the fact that the premium for SMB had disappeared since the early 1980's. Ferson et al. (1999) also argued that size and B/M effects in returns might be spurious relationships, and hence SMB and HML might take on the appearance of risk factors when in fact there is no theoretical basis for the argument that they are indeed risk factors. Chan and Lakonishok (2004) argue that an equally valid interpretation of HML is as a factor that captures returns due to mispricing, rather than risk-based expected returns. These criticisms apply equally to the Carhart four-factor model, which augments the three-factor model with a winner-minus-loser factor to explain away the momentum effect; momentum being a major anomaly that Fama and French (1996) were not able to explain using the three-factor model.

Others have debated whether or not SMB and HML, as risk factors, can even explain the cross-section of stock returns which they were designed to capture. In particular, Lakonishok et al. (1994) argue that the value premium is due to errors of judgment and to pressures on institutional investors to avoid value stocks. Daniel and Titman (1997)

argue that returns are more closely associated with size and B/M characteristics than with loadings on the SMB and HML factors; therefore the cross-sectional variation in returns arises because of mispricing associated with the size and B/M characteristics and not because of sensitivity to priced risk factors represented by SMB and HML. A similar conclusion was reached for the Japanese stock market by Daniel, Titman and Wei (2001b).

A number of studies reached different conclusions to Daniel and Titman (1997) and Daniel et al. (2001b). Lewellen (1999) tested a conditional version of the Fama-French three-factor model where factor loadings as well as the intercept term (alpha) of portfolios are allowed to vary over time with each portfolio's B/M ratio. Similarly to Kothari and Shanken (1997) and Pontiff and Schall (1998), Lewellen (1999) found that the B/M ratio of a portfolio predicts its return. However, he argues this predictability occurs because B/M captures time-variation in the loadings on SMB and HML, and therefore concurs with the risk-based, rather than mispricing-based interpretation of HML. Davis, Fama and French (2000) repeated the Daniel and Titman (1997) study using a longer sample, 1929-1997, and also disagree with their results. They found that the results of Daniel and Titman (1997) are special to the period they consider, i.e. 1973-1993, while the longer 1929-1997 period supports the three-factor model. Gharghori et al. (2006a) also find that loadings on the SMB and HML factors explain Australian stock returns better than the size and B/M characteristics.

Ferson and Harvey (1999) disputed the ability of the Fama-French three-factor model to explain the cross-section of stock returns, because it omitted important economic variables known to be able to predict stock returns. These variables include interest rate

variables and aggregate dividend yields previously studied by Campbell (1987), Campbell and Shiller (1988), Fama and French (1989) and others. Ferson and Harvey (1999) showed that the three-factor alphas of the 25 portfolios originally studied by Fama and French (1993) are in fact time-varying and conditional upon the economic variables, and not close to zero as previously claimed.

Some studies have, however, revealed a link between the Fama-French factors and economic variables. Liew and Vassalou (2000) demonstrated that HML and SMB have some ability to predict future economic growth, even in the presence of popular business cycle variables. They showed that in seven out of the ten countries they investigated, high returns on HML preceded high economic growth (Australia was one of the three countries where the opposite effect was observed). Regression analysis revealed a statistically significant relation between future GDP growth and HML in seven out of ten countries, and between GDP growth and SMB in eight out of ten countries. Petkova (2006) compared the three-factor model with an ICAPM specification that includes as factors changes in market dividend yield, term spread, default spread and one-month T-bill yield. She found that HML is related to changes in the aggregate dividend yield, term spread and default spread, while SMB is related to the default spread. An ICAPM that included these variables outperformed the three-factor model in explaining the cross-section of stock returns, and HML and SMB added no incremental explanatory power to the ICAPM.

2.3.2 The Link between Size, Value and Distress Risk

The relationship between the value premium and financial distress is fundamentally important to this thesis. Although there is evidence that small and value stocks are in general relatively distressed, it has proved difficult to isolate a distress factor that is priced in the equity market and which therefore explains size and value effects in a rational pricing context. Furthermore, deviations in the relationship between distress and B/M have been investigated as a potential source of abnormal trading profits (for example, Piotroski, 2000; Mohanram, 2005) and as evidence of mispricing (Griffin and Lemmon, 2002). An attempt will be made in this thesis to replicate these findings using Australian data and subsequently to use them to explain the findings of Doukas et al. (2002), which are contrary to the errors-in-expectations hypothesis.

Early attempts at risk-based explanations for the size effect primarily used an APT framework to show that small firms possess higher sensitivities to pervasive risk factors (for example, Chan et al., 1985; Chen et al., 1986; Connor and Korajczyk, 1988; Lehmann and Modest, 1988). However, Lo and MacKinlay (1990) objected to the use of returns of size-based portfolios to test asset pricing models, arguing that the size-return relationship is possibly spurious and leads to rejection of the null hypothesis (of asset-pricing model inadequacy) far too often, given that the same data that was used to uncover the size effect is also generally used to test asset pricing models. Similarly, Chan and Chen (1991) argued that attempts to model the risk of small stocks should offer an explanation as to why size should be important in asset pricing at all. To this end, Chan and Chen (1991) focused on identifying the characteristics of small firms that make them more sensitive than larger firms to priced sources of risk in the economy.

The study by Chan and Chen (1991) demonstrated a number of important points about small firms that helped to clarify exactly why they are riskier, in general, than larger firms. One tenet argued forcibly is that small stocks, as a group, contain many stocks that were once much larger, but had suffered declines in market value. Chan and Chen (1991) also directly verified that small firms typically faced much greater financial distress and operational difficulties than larger firms. Smaller firms in general were less profitable, had lower interest expense coverage, higher financial leverage and a greater propensity to cut dividends than larger firms. Chan and Chen (1991) argued that the relative distress suffered by small firms on average makes them less likely to survive adverse economic conditions than larger firms, and this fact explains the sensitivity of small firms to economic risk factors. They support this argument by observing that during regressions, firms with high financial leverage and poor recent operating performance may have restricted access to credit markets. This latter point is confirmed in studies by Gertler and Gilchrist (1993), Gertler and Gilchrist (1994), Bernanke, Gertler and Gilchrist (1996), Oliner and Rudebusch (1996), and Perez-Quiros and Timmermann (2000).

Fama and French (1992) suggest that the Chan and Chen (1991) distress factor may be responsible for the value premium, and indeed value stocks *in general* have been shown to possess many characteristics of financial distress. To this end, Fama and French (1995) examined the average profitability of stocks in portfolios based on size and B/M. They measured profitability by return on equity and performed the calculation for each of the five years prior to and five years after portfolio formation. Small firms were observed to have lower profitability than large firms both before and after portfolio

formation; however this observation is conditional on B/M. The *stronger* result was that high B/M firms had lower profitability than low B/M firms before *and* after portfolio formation, and this result is not conditional upon size. Thus, Fama and French (1995) argue that high B/M, and to a lesser extent small size, are signs of distressed firms that have suffered low profitability in the past and will continue to suffer low earnings in the future. Chen and Zhang (1998) also present findings from six countries that suggest value stocks are more distressed than growth stocks. They examined various measures of risk in order to compare value and growth stocks in six countries. These findings demonstrate that value stocks have higher leverage, higher incidence of cutting dividends and higher time-series variability in earnings-to-price (E/P) ratios (interpreted as earnings uncertainty) than growth stocks.

Studies by Dichev (1998) and Griffin and Lemmon (2002) also explore and confirm the relationship between size, B/M and financial distress; unlike previous studies however, they reject the rational pricing of a distress factor. Dichev (1998) measured distress using numerical bankruptcy prediction models (Altman's Z-score and Ohlson's O-score) and then sorted stocks into decile portfolios based upon their level of bankruptcy risk. In accordance with Chan and Chen (1991) and Fama and French (1995), Dichev (1998) found an inverse relationship between size and bankruptcy risk, confirming that the stocks of firms with a high risk of bankruptcy tend to be small stocks. With the exception of the ten percent of stocks with the highest risk of bankruptcy, B/M also increases with bankruptcy risk, confirming the link between value and distress reported in Fama and French (1995). Dichev (1998) also found, however, that there was no positive relationship between distress risk and subsequent stock returns, and concluded that bankruptcy risk is not compensated by higher returns and therefore cannot explain

size and value effects in returns. On the contrary, Dichev (1998) reported substantial return advantages to investment strategies that avoid stocks with a high probability of bankruptcy.

Similarly, Griffin and Lemmon (2002) found an inverse relationship between the O-score measure of default risk and firm size; however their results indicate that the relationship between distress and B/M is far more complicated than suggested by Fama and French (1995) and Chen and Zhang (1998). In particular, stocks with high default risk (high O-score) include both high B/M and low B/M stocks. Griffin and Lemmon (2002) found that the value premium, although present in all O-score quintiles, increases with O-score and is most prominent in the quintile of stocks with the highest risk of bankruptcy (O-score). They confirmed the earlier result of Fama and French (1995) that in general; high B/M stocks have lower profitability than low B/M stocks; however this relationship is reversed for the quintile of stocks with the highest O-score: high O-score, low B/M stocks were found to have the lowest profitability of all stocks in their sample.

Griffin and Lemmon (2002) also compared the announcement period returns of high and low B/M stocks, and further differentiated the results by O-score. In agreement with La Porta et al. (1997), they found a significant return differential between value and growth stocks in the three-day window surrounding announcement dates (with value outperforming growth), however once again the effect was more pronounced for high O-score stocks. Griffin and Lemmon (2002) argued that their results are consistent with a mispricing explanation for the value premium which is greatest in distressed stocks, a group of stocks which tends to consist of small stocks with low analyst following. In

particular, they argued that the low returns of growth stocks are driven primarily by the very low returns of high O-score (distressed) growth stocks, and which are therefore not explainable in terms of a priced distress factor.

Vassalou and Xing (2004) also investigated the relationship between size, B/M and default risk; however they measured default risk in terms of distance-to-default (DD). The distance-to-default methodology was developed by Moody's KMV and is discussed in detail in Crosbie and Bohn (2003); it is based upon the bond-pricing framework of Merton (1974), which models a firm's equity as a call option on the firm's assets with an exercise price equal to the value of the firm's debt. Unlike Dichev (1998) and Griffin and Lemmon (2002), Vassalou and Xing (2004) found that default risk was indeed priced in equity markets and is related to both the size and B/M effects. The size effect was only present in the quintile of stocks with the highest default risk, and the SMB factor lost its significance in cross-sectional asset pricing tests once an aggregate default risk factor was included. Similarly, the value premium was found to be statistically significant only in the two highest default risk quintiles, but did however retain its significance in cross-sectional asset pricing tests that included an aggregate default risk factor. Vassalou and Xing (2004) conclude that default risk is priced in equity returns, that it completely explains the size effect, and that it partially explains the value premium.

Findings in subsequent studies, however, are inconsistent with those of Vassalou and Xing (2004). Gharghori et al. (2007) perform a similar analysis using DD on Australian data; they find that default risk is not priced in equity returns and that neither SMB nor HML contain any default-related information. Furthermore, a major discrepancy was

uncovered by Da and Gao (2010), in that the returns of high default risk stocks in Vassalou and Xing (2004) are attributable to the *first month after portfolio formation*; however the distress premium is *negative and statistically significant* for the remainder of the year following portfolio formation. Moreover, Da and Gao (2010) are able to explain nearly all of the first-month returns in terms of short term return reversals, which they attribute to institutional selling and illiquidity and *not* to a default risk premium. Since Vassalou and Xing (2004) rebalance their portfolios on a monthly basis, their average portfolio returns for distressed stocks miss the negative returns that accrue to these stocks later in the year, and are hence biased upwards. This conclusion is supported by Campbell et al. (2008) who repeat the Vassalou and Xing (2004) analysis with DD and *annual* rather than monthly portfolio rebalancing, and claim to have refuted the Vassalou and Xing (2004) finding of a positive distress premium. Campbell et al. (2008) also use an alternative distress measure estimated from accounting and equity market variables to demonstrate the existence of a *negative* distress premium in *all* size and B/M quintiles.

In summary, financial distress is related to size and B/M characteristics in firms. However, most studies (with the exception of Vassalou and Xing, 2004) argue that financial distress is not a priced risk factor in equity markets and therefore a distress premium by itself does not appear to be a satisfactory rational pricing explanation for the value premium. Furthermore, profitable trading strategies have been identified that appear to exploit mispricing of financially healthy value stocks and financially distressed growth stocks, the subject of Section 2.3.6. However, the distress factor has been interpreted by some authors as a recession risk factor, because distressed firms tend to perform particularly poorly in recessions. This recession (or downside) risk is

modelled in conditional asset pricing models as time variable systematic risk (Cochrane, 2005). The next section reviews the explanations for the size and value effects based on conditional asset pricing models.

2.3.3 Conditional Asset Pricing

Another range of asset pricing models makes allowance for time variability in risk. Variation in beta over the business cycle seems plausible because distressed and leveraged firms might fare relatively worse during recessions than healthier firms, and hence their leverage and beta risk increase during these times (Jagannathan and Wang, 1996). Time variation in asset covariance has been studied by Bollerslev, Engle and Wooldridge (1988), Harvey (1989) and Ferson and Harvey (1991); in general these studies make the assumption that asset covariances are conditional upon variables such as past covariance, market returns, market dividend yields and spreads in the term structure of interest rates. Similarly, the market risk premium is also expected to vary with the business cycle, as investors require lower prices to invest in risky assets during recessions, when marginal utility is high (Fama and French, 1989).

A relatively important contribution in this area is by Jagannathan and Wang (1996), who use a conditional version of the CAPM, where both beta and expected market returns vary through time, to derive an expression for *unconditional* expected returns. They are able to show that when beta covaries with expected market returns, (unconditional) expected asset returns are a linear function of expected (unconditional) beta and the sensitivity of beta to the market risk premium (a term which they refer to as the 'beta-*prem* sensitivity', and others refer to as 'beta-*premium* sensitivity'). In

essence, the model shows that *time variation* in beta is another source of risk that increases expected returns.

Jagannathan and Wang (1996) attempt to explain the anomalous relationship between average stock returns, market capitalisation and beta reported in Fama and French (1992) using their conditional CAPM. Their main motivation was to explain the size effect, as the distressed and leveraged firms mentioned above are most likely to be small firms (Chan and Chen, 1991), and hence it is expected that the betas of small firms will covary with the market risk premium more than those of large firms. By incorporating time variation in beta related to the market risk premium, Jagannathan and Wang (1996) claimed the percentage of variation in the returns of portfolio sorted by size and beta increases from 1% in the static CAPM to 30% in the conditional CAPM. When human capital is included in the market portfolio, the percentage explained rises to 50%, with size and B/M unable to explain what is left. Their study was replicated on Australian data by Durack, Durand and Maller (2004), whose results were generally supportive of the role of beta-prem sensitivity, but not of the human capital component of the market portfolio.

Lettau and Ludvigson (2001) examined conditional versions of both the CAPM and consumption-oriented CAPM, where systematic risk is allowed to vary with a single variable designed to capture investors' expectations of future returns and consumption. The conditioning variable employed, referred to as cay, is defined in terms of a cointegrating relationship between log consumption (c), log nonhuman wealth (a, defined as household net worth), and log human wealth (y, labour income). The intuition behind this choice of variable is that the consumption to wealth ratio contains

information about investors' expectations of future returns. If consumption is high relative to wealth, investors must be expecting either high future returns on wealth or low growth in consumption. Lettau and Ludvigson (2001) tested the ability of conditional versions of the CAPM and consumption CAPM, using cay as a scaling variable, to explain the anomalous returns of size and B/M sorted portfolios used as test assets by Fama and French (1993). They found that conditional versions of the CAPM and consumption CAPM have much higher explanatory power (R^2) than unconditional versions of these models. The conditional consumption CAPM had a similar R^2 to that of the Fama-French three-factor model, which contains factors constructed specifically for the purpose of explaining size and B/M effects.

Lettau and Ludvigson (2001) attributed the improved performance of conditional asset pricing models over unconditional models to the fact that the conditional models capture time-variation in the systematic risk of small and value stocks. Their results indicate that value portfolios have betas that are more highly correlated with consumption growth (as well as market portfolio returns) when the scaling variable, cay, is high. The cay variable is high when risk aversion is high, in other words in bad economic states, when expected returns are high and asset prices are low. The results of Lettau and Ludvigson (2001) are somewhat consistent with those of Jagannathan and Wang (1996), in that time-variation of systematic risk is compensated by higher (unconditional) required returns, particularly so for assets whose systematic risk increases in bad times.

A number of studies, however, question whether the unconditional returns implied by conditional asset pricing models are high enough to explain the observed cross-section

of stock returns. Lewellen and Nagel (2004) supported claims that systematic risk is time-varying, however they argued that the covariance between conditional betas and the market risk premium is far too small to be able to totally explain the magnitude of returns observable for value and momentum strategies (the size effect was absent from their sample). They also argued that the cay variable of Lettau and Ludvigson (2001) loses its ability to explain conditional betas in the presence of other state variables; the betas of value and small stocks were found to be more closely related to market dividend yields and interest rate variables. Petkova and Zhang (2005) estimated a conditional CAPM that utilises an expected (rather than actual) market risk premium, conditioned on lagged values of the market dividend yield and a number of interest rate variables. They concurred with Lewellen and Nagel (2004) that the magnitude of the covariance between conditional betas and the market risk premium is insufficient to explain the value premium.

2.3.4 Explanations for the Value Premium based on Behavioural Finance

In contrast to the rational asset pricing framework, *behavioural finance* deals with theoretical explanations for anomalies, based on the assumption that not all agents are fully rational (Barberis and Thaler, 2005). There are two basic concepts inherent in this paradigm: (i) a rebuttal of the efficient market hypothesis and (ii) the existence of psychological traits that induce investors to act irrationally and that can explain the anomalies being studied.

A rebuttal of the efficient market hypothesis is required in order for irrationality-induced anomalies to survive in the presence of fully rational arbitrageurs. Shleifer and Vishny (1997) argue that anomalies such as the value premium persist in the market

because it is too costly and too risky for arbitrageurs to take advantage of them and drive prices back to fundamental values. In particular, they maintain that arbitrageurs tend to be inadequately diversified and hence are sensitive to, and avoid taking positions in securities with a high degree of, unsystematic risk. Consistent with this view, Ali, Hwang and Trombley (2003) present evidence to the effect that the B/M effect exists only amongst stocks with a high degree of residual volatility. Similarly, Griffin and Lemmon (2002) argue that it is another cost that prevents the value premium from being arbitraged away: the cost of obtaining information. They postulate that high distress firms tend to be smaller companies with low analyst coverage, and consequently when such a firm happens to exist in a growth industry, uninformed investors mistakenly ascribe the industry's valuation multiple to the distressed firm.

Behavioural finance also relies on psychological traits to justify the assumption that not all agents are fully rational, and which can generate behaviour consistent with the anomalies being studied. In the context of cross-sectional return predictability these anomalies include two seemingly disparate effects, namely the value premium *and* momentum. In general, behavioural finance characterises these two effects in terms of investor overreaction as well as underreaction, and draws upon a number of psychological traits (including representativeness, conservatism, overconfidence, self-attribution bias, loss aversion and narrow framing) to explain why prices overreact in some cases and underreact in others. This reliance on both overreaction in some cases and underreaction in others to explain anomalies is argued by Fama (1998) to be a substantial weakness of behavioural finance. This view has not been contested by the leading proponents of behavioural finance: Barberis and Thaler (2005) highlight the latitude afforded by the plethora of psychological biases, such that "anything can be

explained" (p.64), and the absence of a single, unifying behavioural theory of asset pricing.

A number of behavioural theories have been proposed to explain momentum and long-term reversals, where the term 'long-term reversals' is used to also include the value premium. The most important of these are Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999). Barberis et al. (1998) rely on two cognitive biases in order to explain, on the one hand, the value premium and reversals in terms of overreaction and, on the other hand, momentum in terms of underreaction. Appealing to the representativeness bias, investors who observe a series of earnings increases make the mistake of assuming that earnings changes follow a trend, when in fact the earnings changes are random. Appealing to the conservatism bias, investors who observe a single earnings change make the mistake of assuming that earnings are mean reverting, and update their priors insufficiently. Thus, under the Barberis et al. (1998) model, investors tend to overreact to consistently good performance, causing prices to overshoot their fundamental values, and underreact to changes in performance, resulting in momentum. This model is somewhat consistent with the form of the errors-in-expectations hypothesis (discussed in the next sub-section) originally expounded in Lakonishok et al. (1994), where investors extrapolate previous good performance too far into the future.

There is empirical evidence inconsistent with the representativeness bias interpretation of the value premium. Dechow and Sloan (1997) argue that the value premium appears unrelated to investors' extrapolation of past trends in earnings, arguing instead that it bears a very strong relationship to the biased growth forecasts of analysts. Chan, Frankel and Kothari (2004) find that neither the consistency nor the trends in earnings

performance are related to future stock returns. They do, however, find evidence of an underreaction to recent accounting performance, consistent with a conservatism bias. It must be borne in mind that evidence against the representativeness bias does not necessarily invalidate all behavioural finance models (Daniel, 2004) or other mispricing explanations such as the errors-in-hypothesis, to be discussed in more detail in Section 2.3.5. As Dechow and Sloan (1997) point out, investors' relative optimism about growth stocks may originate from analysts' forecasts which are *not* necessarily based upon extrapolation of past trends.

Daniel et al. (1998) rely on two different cognitive biases, overconfidence and biased self attribution, in order to generate value and momentum effects. Appealing to overconfidence, investors place greater weight on private information and less weight on public information. Appealing to biased self attribution, the investor's confidence increases when public information arrives that confirms their private information, but decreases only slightly when public information disconfirms their private information. The net effect is that public information on average increases investor confidence – biased self attribution means that when their private information accords with public information, they attribute the confirmation to skill, but when their private information is inconsistent with public information, they attribute the discrepancy to bad luck. Thus, investors overreact to private information and underreact to public information. Momentum is seen as a result of the overreaction to private information, causing prices to deviate from fundamental values. On the other hand, the arrival of public information causes a gradual correction of prices, and hence long-term reversals (including the value premium) are seen as a result of the underreaction to public information.

Finally, Hong and Stein (1999) develop a model based upon two types of investors, ‘newswatchers’ and ‘momentum traders’, and the assumption that information diffuses slowly throughout the market. Newswatchers make forecasts based on private information; momentum traders make forecasts based only upon price changes. As information diffuses only gradually, the activity of newswatchers causes prices to underreact. However, the price changes catch the attention of momentum traders, who then trade and cause prices to move closer to their fundamental value, and then ultimately to overshoot their fundamental value. Thus, momentum traders are seen as causing an overreaction in prices. Hong and Stein (1999) argue that this overreaction explains long-term reversals, including the value premium. Hong, Lim and Stein (2000) provide support for the assumption of slow information diffusion, finding that momentum is most profitable amongst small stocks and stocks with low analyst coverage.

An interesting study which conflicts to some extent with all of the behavioural models discussed above is that of Lee and Swaminathan (2000); who focus on the interaction of trading volume and momentum, but do however draw analogies between trading volume and value-growth measures. They find that momentum appears to be strongest amongst high volume losers, which continue to perform poorly, and amongst low volume winners, which continue to exhibit high returns. Lee and Swaminathan (2000) argue that none of the existing behavioural models allow for the effect of trading volume on momentum, and consequently find inconsistencies between their results and the predictions of these models. For example, the Hong and Stein (1999) model predicts that momentum is greater for stocks with *low* trading volume on the proviso that information diffusion is directly related to trading volume. The findings of Lee and

Swaminathan (2000) are consistent with this prediction for (low volume) winners but not, however, for losers. In contrast, the Daniel et al. (1998) model predicts that momentum is greater for stocks with *high* trading volume, which is consistent with the Lee and Swaminathan (2000) results for losers but not for winners. Therefore, the findings of Lee and Swaminathan (2000) demonstrates that existing behavioural models face similar difficulties to rational asset pricing models in explaining the observed behaviour of stock prices.

Lee and Swaminathan (2000) offer a promising and as yet under-researched explanation of stock price behaviour based upon their results, which they refer to as the momentum life cycle. The findings of this thesis will be shown in subsequent chapters to be consistent with the momentum life cycle, as are those of Bird and Casavecchia (2007a) who study the interaction of value/growth trading strategies with momentum and financial health indicators. According to the momentum life cycle, stocks go through periods of favouritism and neglect. High momentum stocks are argued to be experiencing a period of favouritism in their life cycle, beginning with a phase of low trading volume ('low volume winners'). Low volume winners are the most likely stocks to continue to deliver high returns. As sentiment towards a low volume winner increases, accompanied by high returns, trading volume increases. Eventually, the low volume winners become expensive growth stocks characterised by high trading volume and the tendency to subsequently disappoint investors with return reversals ('high volume winners'). From here, stocks become 'high volume losers', companies with poor recent returns and high trading volume. High volume losers are the most likely companies to continue to deliver poor returns. Stocks in this stage of their momentum life cycle become increasingly unpopular and neglected, resulting in falling trading

volume. Finally, the stocks become 'low volume losers', in other words companies that have had extended periods of poor returns accompanied by diminishing trading volume.

2.3.5 The Errors-in-Expectations Hypothesis

The errors-in-expectations hypothesis states that investors are overly optimistic regarding the future prospects of and consequently pay prices that are too high for growth stocks. Indeed growth stocks are most commonly identified in terms of high market value relative to variables such as earnings, book-value of equity or sales, under the assumption that the high market values reflect expected future growth in these variables. This hypothesis is grounded in a number of principles. First, the expected future growth rates implied by valuation multiples are not only unrealistic, but they bear little resemblance to actual growth rates realised after the measurement of the multiples (Lakonishok et al., 1994). Second, earnings growth itself is extremely difficult, if not impossible, to forecast (La Porta, 1996; Chan et al., 2003). Finally, a substantial proportion of the value premium occurs close to company announcement dates, consistent with the idea that investors are informed by earnings surprises that their initial growth expectations might be too optimistic (La Porta et al., 1997; Skinner and Sloan, 2002). Empirical research has supported most of these principles; although some conflicting evidence has emerged regarding the information content of earnings surprises. Specifically, the errors-in-expectations hypothesis predicts that analysts' *earnings* forecasts should be more optimistic for growth stocks than for value stocks, but the data from analysts' forecasts contradicts this prediction (Doukas et al., 2002; Mian and Teo, 2004). The contradiction regarding analyst forecast optimism forms the basis of much of the investigation in this thesis.

2.3.5.1 Evidence linking valuation multiples to erroneous growth expectations

Lakonishok et al. (1994) argue that the valuation multiples used to distinguish between value and growth firms imply an *unfeasibly high growth rate differential* between value and growth stocks and an *unfeasibly long duration* of this growth rate differential. The evidence they offer in support of this argument essentially shows that the cash flow per dollar invested in a portfolio of growth stocks takes an inordinate length of time to grow to a level comparable with the cash flow per dollar invested in a portfolio of value stocks. Whilst value stocks have a higher cash C/P ratio than growth stocks, growth stocks have a much higher *historical* growth rate of cash flow. Based on *historical* growth rates of cash flow, portfolios of growth and value stocks could be expected to have equivalent cash flow per dollar of initial investment after 11 years. However, *subsequent* growth rates fail to match the historical difference between value and growth stocks; in fact the growth rate differential between growth and value stocks largely disappears only two years after portfolio formation. Hence, the main argument of Lakonishok et al. (1994) is that whilst the higher prices of growth stocks relative to value stocks might be justified by higher expected future growth, the expected growth rates largely fail to materialise or last as long as investors initially anticipate.

Based primarily on the evidence described above, Lakonishok et al. (1994) propose that the value premium is due to “a systematic pattern of expectational errors on the part of investors” (p.1575), in other words, mispricing. They rule out potential risk-based explanations for three main reasons. First, the consistency with which value strategies outperformed growth strategies in their sample, both on a year-by-year and rolling five-year basis, implied very little risk to an investor following such strategies. Second, the

small number of years when growth did outperform value did not appear to correspond to economic recessions; evidence which is inconsistent with the view that the value premium represents a form of priced risk associated with distress and/or recessions. Finally, the magnitude of the value premium, which they estimate to be over 10% annually, is too great to be accounted for by traditional risk measures such as beta or return volatility.

Further evidence that valuation multiples do not reflect reasonable growth expectations can be found in Chan et al. (2003). Their results demonstrate that B/M ratios adjust to reflect *historical* growth; stocks which experience high growth over a five-year period *subsequently* tend to have low B/M, while stocks which experience low growth *subsequently* tend to have high B/M. However, the relationship between B/M and growth is *reversed* when B/M ratios are measured at the *start* of each five-year growth period; stocks which experience the highest growth over a five-year period were actually found to have had the highest B/M ratio at the start of the period. Put differently B/M reflects historical rather than future growth, and future growth expectations impounded in B/M ratios are erroneous.

2.3.5.2 Evidence that future growth is unpredictable

There is evidence that not only is future earnings growth extremely difficult to predict, but that the growth forecasts of professional analysts are often too extreme. First, Bauman and Dowen (1988) and La Porta (1996) demonstrate contrarian strategies that bet *against* analysts' long term growth forecasts to be highly profitable, consistent with an argument that actual earnings performance (and hence stock price) is completely unrelated to these forecasts. These contrarian strategies essentially buy stocks with the

lowest long-term growth forecasts and sell stocks with the highest long-term growth forecasts. More importantly however, La Porta (1996) showed that stocks with relatively high growth forecasts were subject to lower actual (subsequent) earnings growth, larger downward revisions to forecasts and larger forecast errors than stocks with low growth forecasts. Given the extreme biases evident in analysts' growth forecasts and the strong correlation between these forecasts and B/M, La Porta (1996) argues that B/M explains stock returns because investors in growth (low B/M) stocks are systematically disappointed by growth rates that fall short of expectations.

The most compelling evidence of the unpredictability of future growth is Chan et al. (2003). They test the predictability of future growth on the basis of persistence of past growth, industry affiliation, valuation ratios such as B/M, E/P and sales-to-price, and I/B/E/S long term growth forecasts. Although Chan et al. (2003) find evidence of a slight degree of persistence in sales growth they find no evidence of persistence for bottom-line earnings growth beyond what is expected by chance; hence it is doubtful that historical growth can be used to forecast future growth. Chan et al. (2003) also demonstrate that although actual growth rates tend to increase with I/B/E/S long-term forecasts, the actual growth rates for the high forecast growth stocks fall far short of the forecast growth rate. Once differences in survival rate and dividend yield are taken into account, I/B/E/S long-term growth forecasts appear completely unrelated to actual subsequent growth rates. Regression models which include I/B/E/S long term growth forecasts, past sales growth and other variables conjectured to predict growth (sustainable growth rate, dividend yield and research and development intensity)

similarly had low explanatory power over future growth in earnings and sales[8]. In summary, the overall evidence suggests that long-term earnings growth is almost impossible to predict, and price multiples which reflect expected future growth are thus based on expectations which are likely to be erroneous.

2.3.5.3 Extrapolation, Growth Expectations and the Value Premium

Lakonishok et al. (1994) argue that the source of erroneous growth expectations is the tendency of investors to extrapolate past performance into the future. The extrapolation argument is based on studies of long-term return reversals by De Bondt and Thaler (1985, 1987) which show that stocks with poor price and earnings performance in the previous three-to-five years subsequently outperformed stocks that had performed well over the previous three-to-five years. They postulated that investors overreact to earnings news, placing too much emphasis on short-term earnings movements and failing to take into account the mean-reversion of earnings. Therefore, stocks that had performed well in the past are priced too high by the market and consequently become more unattractive investments than stocks that have done poorly in the past. This view is supported by Chopra, Lakonishok and Ritter (1992), who extended the De Bondt and Thaler results by demonstrating that reversals are more pronounced around earnings announcement periods. They interpret this as evidence that the market overreacts to previous earnings results, and subsequently is systematically surprised by earnings announcements that reveal the groundless nature of the overreaction.

[8] Chan et al. (2003) report adjusted R^2 values of 3% or less for regressions in which earnings growth is the dependent variable; however in regressions where sales growth is the dependent variable, they report somewhat higher R^2 values of up to 12%.

Extrapolation of past performance seems a plausible explanation for erroneous growth expectations; however it has not been straightforward to explain the value premium in terms of *errors-in-expectations caused by extrapolation*. La Porta (1996) examined this issue by differentiating between two categories of stocks with high expected future growth, ‘glamour stocks’ and ‘temporary losers’. Glamour stocks have high forecast earnings growth and *high historical sales growth* while temporary losers also have high forecast earnings growth but *low historical sales growth*. Consistent with the extrapolation argument, La Porta’s results demonstrate that glamour stocks have lower future returns than temporary losers. Similarly, La Porta (1996) differentiates between two categories of stocks with low expected future growth, ‘value stocks’ and ‘temporary winners’. Value stocks have low forecast earnings growth and *low historical sales growth*, and temporary winners also have low forecast earnings growth but *high historical sales growth*. In this case however, La Porta’s results are inconsistent with extrapolation: value stocks have lower future returns than temporary winners. Levis and Liodakis (2001) adopt a similar methodology to test for extrapolation in the UK market[9]. Unlike La Porta (1996) who reports mixed results, Levis and Liodakis (2001) find no evidence of extrapolation.

Other studies have also provided mixed evidence regarding extrapolation. When value and growth stocks are defined by E/P and C/P, Dechow and Sloan (1997) find no evidence of reversals of growth rates to suggest extrapolation. They do however find evidence that the B/M ratio itself is related to the extrapolation of past earnings growth. Dechow and Sloan (1997) also report mixed evidence from an analysis of contrarian strategies based upon past growth in sales and earnings. Consistent with extrapolation,

[9] Levis and Liodakis (2001) use past earnings growth valuation ratios such as book-to-market to define temporary winners and temporary losers, unlike La Porta (1996) who uses past sales growth and I/B/E/S forecast growth.

they find that firms with high past growth subsequently revert to average growth rates and earn poor future returns. However, stocks with low past earnings growth subsequently earn only average returns despite abnormally high future earnings growth, inconsistent with extrapolation. Chan et al. (2004) test for evidence of the representativeness bias using measures of past performance such as sales growth and trends in earnings and operating income; the representativeness bias is used in the behavioural model of Barberis et al. (1998) to generate overreaction to trends in past earnings growth. Chan et al. (2004) find that neither past performance nor year-to-year consistency of past performance is related to future stock returns, results that are inconsistent with extrapolation.

Despite the mixed evidence linking the value premium to extrapolation, the evidence from *analysts' growth forecasts* is broadly consistent with the errors-in-expectations hypothesis, in that such forecasts tend to be overly optimistic for growth stocks and that stock returns can be linked to this optimism. Both La Porta (1996) and Dechow and Sloan (1997) find that whilst growth forecasts appear uniformly too optimistic, the error in forecast growth rates increases systematically from low forecast growth firms to high forecast growth firms. Both studies also report a systematic decline in returns as forecast growth increases, however Dechow and Sloan (1997) draw a distinction between this contrarian return pattern and that associated with *past* growth, where return differences are confined solely to the *ten percent* of stocks with the highest past growth. Thus, contrarian strategies based upon forecast growth display a stronger, more uniform pattern than those based upon past growth.

Dechow and Sloan (1997) also present regression evidence demonstrating the importance of analysts' growth forecasts to the value premium. Their results indicate that when compared with actual growth, growth forecasts are too high by a factor of about three; however investors form growth expectations as if there is no bias in the forecasts[10]. In other regressions, they demonstrate that forecast growth has more explanatory power over stock returns than B/M, E/P or C/P. Dechow and Sloan (1997) thus argue that a naïve reliance on analysts' growth forecasts explains a substantial proportion of the returns to contrarian strategies. This conclusion is consistent with the errors-in-expectations hypothesis in that stock returns can be attributable to over-optimistic growth expectations; however the source of optimism does not appear to be extrapolation.

2.3.5.4 Evidence from Announcement Period Returns and Earnings Surprises

Regardless of the source of information, investors with growth expectations that are too optimistic are likely to be disappointed on the dates that companies announce earnings; hence the errors-in-expectations hypothesis predicts that a *substantial amount* of the value premium is earned on company announcement dates. An important study that tests this prediction is La Porta et al. (1997), who examined the stock returns in a three-day window around quarterly earnings announcements. Consistent with the errors-in-expectations hypothesis, they found that a *disproportionate* amount (29%) of the annual value premium is earned over the four three-day periods. Their regression tests confirm that announcement-period returns are significantly large and negative for growth stocks,

[10] Dechow and Sloan (1997) also estimate the same system of equations using past growth instead of forecast growth. Their results indicate that although earnings growth is autocorrelated investors recognise the autocorrelation and price stocks accordingly. They interpret this result, in conjunction with their results for forecast growth, as evidence that analysts' growth forecasts are more important determinants of contrarian returns than (extrapolation of) past growth.

and significantly large and positive for value stocks. La Porta et al. (1997) interpret these findings as evidence of systematically negative earnings surprises for growth stocks and systematically positive earnings surprises for value stocks, whereby errors in growth expectations are resolved. La Porta et al. (1997) reject a risk-based explanation for their results which argues that it is a disproportionate amount of a *risk premium* that is earned over the 12-day period. They point to the fact that the average announcement period return for growth stocks is negative, and thus can be consistent with only a negative ex-ante risk premium.

The manner in which prices respond to earnings surprises has also been studied in an effort to understand how differences in optimism can generate a value premium. To this end, Dreman and Berry (1995) and Levis and Liodakis (2001) document an asymmetric response of value and growth stocks to earnings surprises of different sign: value stocks appear to have much larger positive abnormal returns than growth stocks as a consequence of positive earnings surprises, while growth stocks appear to have much larger negative abnormal returns than value stocks as a consequence of negative earnings surprises. However, these results are argued by Skinner and Sloan (2002) to be unremarkable, as the return differences are to be expected (that is, they are just indicative of the value premium in general) even if the market reaction to earnings surprises does not depend upon value/growth orientation.

Skinner and Sloan (2002) argue that the difference in price response to *bad news* between value and growth stocks is the most important determinant of the value premium. The value premium is thus attributable to an ‘earnings torpedo effect’ that is greater for growth stocks than for value stocks, whereby the act of missing analysts’

forecasts by even a small margin is more important to investors than the size of the earnings surprise. This is interpreted as evidence that, consistent with the errors-in-expectations hypothesis, the value premium is due to the downward revision of "overoptimistic expectations for growth stocks in response to subsequent negative earnings surprises" (p.291). The market reactions of value and growth stocks to positive surprises are shown by Skinner and Sloan (2002) to be statistically indistinguishable, and therefore not instrumental in explaining the value premium. This finding is in direct contrast with the results of Dreman and Berry (1995) and Levis and Liodakis (2001), and inconsistent with La Porta et al. (1997) who report significantly above-average announcement period returns for value stocks. The contrasting findings are attributed by Skinner and Sloan (2002) to the longer announcement period they use. The three-day announcement period window used by La Porta et al. (1997) is argued by Skinner and Sloan (2002) to be inadequate in capturing the asymmetry in price response to bad news, because bad earnings news tends to be announced before this period.

However, Payne and Thomas (2003) argue that the Skinner and Sloan (2002) results are biased due to the rounding errors in stock-split adjusted I/B/E/S data. After repeating the study using unadjusted I/B/E/S data purportedly free of bias, Payne and Thomas (2003) find no evidence that asymmetric market responses to negative earnings surprises (the earnings torpedo effect) explains the value premium. Nevertheless, a related study was carried out by Chan et al. (2006a) who employed the management earnings forecasts of Australian listed companies, in a similar manner to the preannouncements in the Skinner and Sloan (2002) data. Consistent with Skinner and Sloan (2002), Chan et al. (2006a) find that growth stocks have a larger immediate

response than value stocks to bad news, but no difference in response between value and growth stocks when the forecast contains good news.

Another approach in tests of the errors-in-expectations hypothesis has been to compare value and growth stocks with regard to the optimism in analysts' earnings forecasts. The errors-in-expectations hypothesis predicts that these forecasts will be more optimistic for growth stocks than for value stocks, in other words growth stocks will have more negative earnings surprises than value stocks. However, this prediction has generally not been verified in empirical studies. For example, Bauman and Miller (1997) investigated the actual frequency and size of earnings surprises as a function of value/growth classification according to E/P, C/P, B/M and past earnings growth. Although larger negative surprises were observed for growth stocks classified according to E/P, C/P, B/M and past earnings growth, Bauman and Miller (1997) reported the opposite result when growth stocks are defined by B/M: low B/M (growth) stocks were actually found to have less disappointing surprises than high B/M (value) stocks. This latter result is confirmed in a later study by Doukas et al. (2002), which is arguably the most convincing study to challenge the errors-in-expectations hypothesis to date.

Doukas et al. (2002) disputed the conclusions of both La Porta (1996) and La Porta et al. (1997), that excessive optimism on the part of growth investors explains the value premium, citing methodological concerns with both papers. They argued that La Porta's use of forecast growth rates, rather than B/M, to classify value and growth stocks means he has not explained the value premium, which has been conventionally defined in terms of B/M. Similarly, they argue that the La Porta et al. (1997) evidence that a disproportionate amount of the value premium is realised around earnings

announcement dates might be consistent with explanations other than over-optimistic growth forecasts. For example, Doukas et al. (2002) argued that growth forecasts might be equally optimistic for both value and growth stocks, but as growth stocks react more strongly to negative surprises (as in Skinner and Sloan, 2002) the extreme announcement period returns documented in La Porta et al. (1997) might be due to a small number of negative earnings surprises in growth stocks. However, it should be noted that this argument does not explain the large positive abnormal returns of value stocks in the announcement period reported by La Porta et al. (1997).

Furthermore, Doukas et al. (2002) maintain that the announcement period returns examined by La Porta et al. (1997) are not necessarily indicative of the relative optimism of investors *at the time that stocks are classified as value or growth*. For example, abnormal announcement period returns may be due to earnings surprises measured relative to forecasts issued just prior to actual earnings announcements, rather than as a consequence of *initial* expectations. Doukas et al. (2002) argue that in order to test the errors-in-expectations hypothesis, relative optimism must be measured at the time stocks are classified as value or growth, rather than purely as a function of announcement period returns that may be unrelated to initial expectations. To address this concern, Doukas et al. (2002) measured optimism as a function of analysts' current-year earnings forecasts made immediately after classifying stocks into value and growth portfolios. Therefore, a major difference between Doukas et al. (2002) and earlier comparable studies (Dreman and Berry, 1995; Bauman and Miller, 1997; Levis and Liodakis, 2001) is the importance attached to the timing of the relevant forecasts.

The results obtained by Doukas et al. (2002) are troublesome for proponents of the errors-in-expectations hypothesis. In their study, optimism is measured as the price-deflated error in the consensus analyst earnings forecast. This measure of forecast optimism *increases* almost monotonically with B/M in direct contradiction of the errors-in-the-expectations hypothesis; a result that is highly statistically significant and robust to exchange of listing, alternative forecast error deflators and firm size. Therefore, Doukas et al. (2002) provide fairly strong evidence that analysts are actually more optimistic about value stocks than they are about growth stocks, at least in terms of their short-term earnings forecasts.

A similar study by Mian and Teo (2004) examines analysts' forecast errors in Japan, and also fails to support the errors-in-expectations hypothesis. They compared the average forecast errors of value and growth stocks, and consistent with the results of Doukas et al. (2002), find that analyst optimism increases with both B/M and E/P when forecast errors are deflated by stock price[11]; although this relationship disappears if forecast errors are deflated by the absolute value of actual earnings rather than by stock price. When optimism is determined as either the proportion of forecasts exceeding actual earnings, or the proportion of forecasts subject to downward revisions, Mian and Teo (2004) once again report that analysts' forecasts appear to more optimistic for value stocks than for growth stocks. Thus, there appears to be consistent evidence that analysts' short-term earnings forecasts are systematically more optimistic for value stocks than for growth stocks, evidence that is inconsistent with the errors-in-expectations hypothesis.

[11] Doukas et al. (2002) employ B/M but not E/P to define value and growth stocks.

In summary, evidence from actual growth rates and the errors in analysts' *growth* forecasts appear to be consistent with the errors-in-expectations hypothesis, as is the fact that a disproportionate amount of the value premium is realised in the vicinity of company announcement dates. However, evidence from (the errors in) analysts' *earnings* forecasts is not consistent with the hypothesis. Analysts' earnings forecasts appear to be systematically more optimistic for value stocks than for growth stocks, a direct contradiction of the errors-in-expectations hypothesis. On closer inspection this result is counterintuitive because *both* returns and analyst forecast optimism increase with B/M, and analyst forecast optimism implies negative earnings surprises which are usually punished by the market with negative, not positive, returns. Consequently, two major objectives of this thesis are to attempt an explanation for *why* the optimism of analysts' earnings forecasts increases with B/M, and to investigate why high B/M stocks can simultaneously have high returns and overly-optimistic analyst earnings forecasts (i.e. negative earnings surprises).

2.3.6 Mispricing as a function of Valuation Ratios and Financial Distress

It is common practice in studies of the value premium to classify stocks as value or growth based upon their ranking on a single variable, which is usually B/M. However, behavioural studies of the value premium *do not* necessarily make the assumption that *all* high B/M firms are underpriced and *all* low B/M firms are overpriced. The mispricing explanation favoured by Lakonishok et al. (1994), La Porta (1996), and La Porta et al. (1997) relies on a definition of "out-of-favour" value stocks as those which performed poorly in the past and are expected to continue to perform poorly, and a definition of "overpriced growth" (or "glamour") stocks as those which performed poorly in the past and are expected to continue to perform poorly. These definitions

have been operationalised by the use of a two-way classification system which relies upon a measure of past performance (usually sales growth) as well as a measure of expected future growth (which is measured either by a valuation ratio such as C/P or by analysts' long-term growth forecasts). Other studies have focused on a combination of characteristics related to value and momentum to identify underpriced and overpriced stocks (for example Asness, 1997; Lee and Swaminathan, 2000; Bird and Whitaker, 2003; Bird and Casavecchia, 2007b), while Bartov and Kim (2004) argue that the use of accruals can differentiate high or low B/M firms that are indeed mispriced from those that are rationally priced. Thus, a central idea in the behavioural value premium literature is that simple one-way sorts on B/M or other valuation ratios do not necessarily identify value stocks that are underpriced or growth stocks that are overpriced.

As discussed in Section 2.3.2, the fact that financial distress does not appear to be rationally priced in equity markets suggests the possibility of mispricing and/or profitable trading strategies when value and growth stocks are further differentiated by distress or financial health. Dichev (1998) demonstrates that a strategy that avoids financially distressed firms and buys financially strong firms earns abnormal positive trading profits. Moreover, he demonstrates that the ability of the financial distress/strength measures he uses (Altman's z-score and Ohlson's O-score) to explain returns in cross-sectional regressions actually *increases* when B/M is added as an explanatory variable. A number of subsequent studies confirm results that are consistent with Dichev (1998), in that financially distressed growth stocks earn abnormally low returns while financially strong value stocks earn abnormally high returns (Piotroski, 2000; Mohanram, 2005; Bird and Casavecchia, 2007a). Whilst the distress measures

differ amongst these studies, a common theme is that firms where B/M (or, in the case of Bird and Casavecchia (2007a), sales-to-price) is either too high or low relative to financial distress are likely to be mispriced.

Piotroski (2000) uses financial statement analysis to differentiate financially strong firms from weaker firms amongst high B/M stocks, with the aim of demonstrating that financially strong value stocks are underpriced relative to other value stocks. He identifies nine variables related to a number of specific characteristics he argues are relevant to the valuation of value stocks. These characteristics are profitability, leverage, liquidity, the source of funds (equity issuance) and operating efficiency. His measure of financial health ("F-score") is a simple addition of binary (0, 1) values of the nine variables. Based on this relatively simple measure, Piotroski (2000) finds that an investment strategy that selects only financially healthy value firms greatly outperforms a simple value strategy without other constraints. Put differently, the Piotroski (2000) results are consistent with the underpricing of financially strong value stocks, identified with a relatively simple measure derived from accounting variables.

A similar procedure was adopted by Mohanram (2005) for use on low B/M stocks. He creates a measure of financial health ("G-score") based on eight variables selected to capture characteristics relevant to the valuation of growth firms, with emphasis upon characteristics indicative of profitability, naïve extrapolation and accounting conservatism. Following Piotroski's F-score, G-score is a simple addition of binary (0, 1) values of the eight variables. Mohanram (2005) is able to demonstrate a highly profitable strategy of buying high G-score stocks and selling low G-score stocks from a universe of low B/M stocks, with most of the abnormal returns attributable to the large

negative returns of low G-score stocks. Put differently, Mohanram's results are consistent with the overpricing of financially distressed growth stocks; as was the case with Piotroski (2000) mispriced stocks are identified with a relatively simple measure derived from accounting variables.

The results of Mohanram (2005) are consistent with Griffin and Lemmon (2002) who find evidence of overvaluation amongst financially distressed growth stocks, defined in terms of Ohlson's O-score (as a measure of financial distress) and B/M. In the sample examined by Griffin and Lemmon (2002), stocks with low B/M and high O-score have average annual returns smaller than the risk-free rate and significantly negative three-factor alphas (that is, alphas based on the Fama-French three-factor model), observations which effectively rule out risk-based or rational pricing explanations for their results. Griffin and Lemmon (2002) find evidence consistent with the existence of a value premium in all five financial distress (O-score) quintiles, with the magnitude and statistical significance of the value premium increasing with distress. They do not, however, find that financially strong value firms earn higher returns than other value stocks. This particular observation differs somewhat from the findings in Campbell et al. (2008), who use an alternative distress measure estimated from accounting and equity market variables. They observe a negative distress premium *in all B/M quintiles*; a result which is consistent with outperformance and undervaluation of financially strong value stocks relative to other value stocks.

Finally, in a study of European stocks, Bird and Casavecchia (2007a) find that the best performing value stocks are those with strong financial health whilst the worst

performing growth stocks are those with poor financial health[12]. They define value and growth stocks in terms of their sales-to-price ratio and financial health in terms of a PROBIT model that forecasts the probability of an earnings increase, based on 24 accounting variables. In their sample, Bird and Casavecchia (2007a) show that financially healthy value stocks outperform other value stocks and that financially weak growth stocks underperform other growth stocks.

The studies discussed above provide evidence of overpricing amongst financially distressed growth stocks and of underpricing amongst financially strong value stocks; however this general finding is contradicted to some extent by the findings in Vassalou and Xing (2004). Unlike the majority of related studies they find that financial distress, measured using DD, carries a *positive* return premium; and their results specifically show that value stocks with *high, rather than low, default risk* earn returns higher than any other classification of stocks by B/M and distress. As discussed in Section 2.3.2 however, Da and Gao (2010) show these results to be heavily affected by short-term return reversals and dependent upon the use of monthly portfolio rebalancing, and Campbell et al. (2008) claim to have reversed the Vassalou and Xing (2004) findings of a positive distress premium using DD and annual portfolio rebalancing.

The form of mispricing discussed above, whereby *financially distressed* growth stocks are overpriced while *financially strong* value stocks are underpriced, is the basis for much of the research in this thesis, and in particular for research question 1. Research question 1 directly examines whether mispricing, as specified above, exists amongst

[12] Bird and Casavecchia (2007a) also report a similar but stronger result in the case of value stocks using momentum instead of financial health, and in the case of growth stocks using a combination momentum and financial health instead of financial health alone.

large Australian stocks. Furthermore, the existence of mispricing as a function both of valuation ratios and of financial distress justifies, to some extent, the choice of financial distress as a control variable in research questions 2 and 3, which examine variation in analysts' forecast errors and variation in market reactions to earnings surprises respectively.

2.4 Analyst Efficiency

As discussed in Section 2.3.5.4, analysts' earnings forecasts have been shown to be more optimistic for high B/M stocks than for low B/M stocks, a result which directly contradicts the predictions of the errors-in-expectations hypothesis. In effect, research question 2 examines whether this result is sensitive to the omission of a potentially relevant control variable, namely financial distress. One reason why financial distress might be important in this context is that, as discussed in the previous section, financial distress might differentiate the value and growth firms that are mispriced from those that are rationally priced. Another reason is that the observed relationship between analyst optimism and B/M might be due to analyst underreaction to financial distress. The purpose of this section is to discuss prior evidence that supports analyst underreaction, which exists within the broader literature on analyst efficiency[13].

An early piece of evidence regarding analyst inefficiency is provided in De Bondt and Thaler (1990), who compared the forecast change in earnings (in other words, next year's forecast minus last year's reported earnings) with the actual change in earnings (in other words, next year's reported earnings minus last year's reported earnings). They

[13] A similar line of research studies the recommendations of analysts (for example, 'buy', 'sell', or 'hold'), both for biases and for investment value. Jegadeesh, Kim, Krische and Lee (2004) and Azzi and Bird (2005) find that analysts' recommendations generally favour stocks with high momentum, and growth characteristics.

find that the slope of a regression of actual changes on forecasted changes is less than unity, and consequently argue that forecast earnings changes, and hence earnings forecasts themselves, are too extreme. This result, they argue, is consistent with analyst *overreaction* to prior earnings information. However, the majority of subsequent studies disagree with the De Bondt and Thaler (1990) overreaction conclusion.

A number of studies have found that analysts underreact to prior information, where prior information includes both prior earnings performance and prior stock returns. Klein (1990) finds that analysts tend to be too optimistic in their earnings forecast for stocks that had recently suffered large price declines, consistent with underreaction to the price decline. Both Lys and Sohn (1990) and Abarbanell (1991) find that analysts' forecast errors are correlated with prior stock returns, and therefore analysts' forecasts do not fully reflect the information in prior returns. Abarbanell and Bernard (1992) argue that analysts underreact to prior changes in earnings, and in particular are too optimistic in cases where firms suffered poor earnings performance. They find that analysts' forecast errors are positively autocorrelated for up to three quarters, consistent with analyst underreaction. Similarly to De Bondt and Thaler (1990), they perform regression tests to determine if analysts' forecasts are too extreme. However, they regress *forecast error* (next year's earnings minus the forecast for next year) on last year's *change in earnings* (last year's earnings minus the previous year's earnings). As the slope coefficient from this regression is positive, they find that the prior change in earnings predicts the future forecast error; a result consistent with analyst underreaction to the prior change in earnings.

Further evidence of analyst inefficiency is uncovered by Frankel and Lee (1998), who show that the errors in earnings forecasts up to three years in the future can be predicted using publicly available information. They define forecast error in terms of the difference between actual return on equity and the return on equity implied by the consensus earnings forecast, and show that this difference is predicted by four variables: B/M, historical sales growth, forecast long term growth, and the Edwards-Bell-Ohlson valuation model.

Easterwood and Nutt (1999) report a slightly different result to previous studies. They examine the tendency of analysts to overreact or underreact to prior information, but introduce dummy variables to account for a differential response depending upon whether the prior information was good or bad. Similarly to previous studies, they report that analysts tend to overestimate future earnings when firms had suffered poor prior returns or earnings performance. However, following relatively good prior returns or earnings performance, analysts *also overestimated* future earnings. Easterwood and Nutt (1999) interpret this evidence as being consistent with underreaction to negative informative (that is, relatively poor price and earnings performance) and overreaction to positive information (that is, relatively good price and earnings performance).

Abarbanell and Lehavy (2003) conduct both parametric and non-parametric tests of analyst underreaction and overreaction to prior information, where prior information includes abnormal returns and earnings changes. Using parametric tests, they find that analysts underreact to both types of information regardless of whether the prior information comprises good news or bad news. However, Abarbanell and Lehavy (2003) emphasise the non-normality of the distribution of forecast errors, and hence

argue that non-parametric tests are more appropriate than parametric tests. Using non-parametric tests, they find that analysts underreact to prior bad news only. Cohen and Lys (2003) argue that despite the properties of forecast error distributions, the results of Abarbanell and Lehavy (2003) are consistent with the overall stance of prior literature: analysts underreact to prior information, and hence are inefficient.

In summary, there is evidence in the analyst efficiency literature that suggests analysts' earnings forecasts reflect underreaction to publicly available information, particularly where the information represents bad news. It is pertinent to note that earnings and market prices, the main variables used in this literature as proxies for information, enter financial-distress models including Altman's Z-score, Ohlson's O-score and DD as explanatory variables. Thus, declines in earnings and market prices are consistent with an increase in financial distress, and the observed underreaction to bad news (in both earnings and stock prices) is consistent with an underreaction to financial distress. Analyst underreaction to financial distress is also consistent with the finding in Moses (1990) that forecast optimism is significantly greater for firms that subsequently experience bankruptcy than for non-failing firms; although he attributes this to the withholding of bad news by the failing firm and not to underreaction on the part of the analyst. Analyst underreaction to financial distress is therefore suggested by previous findings; consequently this underreaction might help to explain the Doukas et al. (2002) findings that analyst optimism increases with B/M and is a primary motivating factor behind research question 2.

2.5 The Market Reaction to Earnings Surprises

Stock prices react when companies announce earnings that are either higher or lower than is expected by the market. There is an extensive body of literature that studies this market reaction, in terms of the relationship between unexpected or abnormal returns and the difference between the level of announced returns and the level of expected returns, or earnings surprise. The emphasis of this section is on two particular issues in the literature which are of relevance to this thesis; namely the *functional form* of the relationship between unexpected returns and earnings surprises, and the variables that affect this relationship.

2.5.1 The functional form of the relationship between unexpected returns and earnings surprises

Functional form(s) adopted in the literature on the errors-in-expectations hypothesis

A number of studies in the literature on the errors-in-expectations hypothesis (Section 2.3.5) are concerned with market reactions to earnings surprises. These studies include Dreman and Berry (1995), Levis and Liodakis (2001), Skinner and Sloan (2002), and Chan et al. (2006a) and have as a common feature the reliance upon the *sign* but not the *magnitude* of the earnings surprise. The magnitude of the earnings surprise (referred to hereafter as earnings surprise, or simply ES) plays little if any role in the inferences of these studies; this contrasts with the literature on earnings response coefficients, discussed below, which is concerned with the relationship between ES and abnormal returns. The relevant studies in the value premium literature draw inferences by

classifying firm-year observations into either value or growth stocks, and simultaneously into positive and negative surprises. The main purpose of this classification system is to examine differences between value and growth stocks with regard to their *average* returns from positive and negative surprises *of any magnitude*, rather than with regard to the relationship between returns and ES.

The inferences in Skinner and Sloan (2002) and Chan et al. (2006a) rely primarily on unexpected returns conditioned on the sign of ES, using a return-earnings relationship of similar specification to equation (2.2), which *does not include* ES.

$$\mathrm{UR} = \beta_0 + \beta_1 \mathrm{G} * \mathrm{BAD} + \beta_2 \mathrm{G} * \mathrm{GOOD} + \text{other terms} + \varepsilon \qquad (2.2)$$

In equation (2.2), UR is the unexpected return; G is a dummy variable to indicate value/growth orientation based on B/M (G=0 for high B/M firms and 5 for low B/M firms); BAD is a dummy variable equal to 1 for negative surprises and 0 otherwise; and GOOD is a dummy variable equal to 1 for positive surprises and 0 otherwise. In Chan et al. (2006a), G is replaced by separate dummy variables for Value, Growth and intermediate B/M stocks. The other terms in the specification (which differ between the two studies and are omitted here for brevity) allow for variation in unexpected returns of value stocks with positive and negative surprises. ES plays no part in the above specification, which is intended to capture the effect of an earnings 'torpedo' where the occurrence of a negative earnings surprise is a more important determinant of abnormal returns than ES itself.

However, there is evidence suggesting that a model of the return-earnings surprise relationship that omits ES is misspecified. First, Skinner and Sloan (2002) investigated a number of functional forms of the returns-earnings surprise relation which *do* include ES, and report a higher coefficient of determination (adjusted R^2) for these forms than the forms which *do not* include ES. Therefore, the exclusion of ES results in a poorer goodness of fit of the modelled return-earnings surprise relationship.

Second, Figure 4 (p. 299) in Skinner and Sloan (2002) demonstrates that returns are monotonically increasing with ES for both value and growth stocks. Hand (2002) points out that this figure is actually inconsistent with a torpedo effect, and by itself does not justify the inclusion of intercept dummy variables (that is, GOOD and BAD) at the expense of excluding ES from the return-earnings surprise relationship. Similarly, graphical evidence in Kinney et al. (2002) and Burgstahler and Chuk (2008) is inconsistent with an asymmetric response of value and growth stocks to positive and negative earnings surprises. Kinney et al. (2002) also report that they find no evidence of a torpedo effect in growth stocks.

Finally, Payne and Thomas (2003) argue that the results of Skinner and Sloan (2002) are biased because of the rounding error in adjusted I/B/E/S data (also discussed in Diether, Malloy and Scherbina, 2002) which leads to many zero forecast-error computations when in fact, the forecast error is non-zero[14]. Using unadjusted I/B/E/S

[14] Payne and Thomas (2003) document that most of the misclassified zero forecast errors are actually positive, hence resulting in an upward bias in average return for zero forecast error stocks. This bias tends to exaggerate the earnings torpedo effect: the difference in average returns between zero forecast error stocks and those which miss forecasts is biased upwards, and similarly the difference in average returns between those stocks which beat forecasts and zero forecast error stocks is biased downwards. As the rounding error is more prevalent in growth stocks than in value stocks, owing to their greater frequency of stock splits, the earnings torpedo effect is exaggerated in growth stocks.

data free from the rounding error, Payne and Thomas (2003) are not able to find evidence that the ‘torpedo effect’ is greater for growth stocks than it is for value stocks.

Functional form(s) adopted in the literature on earnings response coefficients

There is an extensive body of literature in the accounting discipline concerned with the relationship between earnings and stock returns, commencing with Ball and Brown (1968). Part of this literature specifically deals with the earnings response coefficient (ERC), defined as the *slope* of the relationship between unexpected earnings (or earnings surprises) and unexpected stock returns. The theory underlying the ERC assumes that earnings changes are related to changes in investors’ expectations of future cash flows, and that stock prices equal the present value of expected future cash flows (Kormendi and Lipe, 1987). The magnitude of the ERC is thus related to the rate at which expected future cash are discounted. For example, if earnings changes correspond exactly to cash flow changes and the appropriate discount rate is r=10%, a permanent change in earnings of $1 has a present value of (1+1/r) =11; the theoretical value of the ERC in this case (Kothari, 2001). In this framework, returns increase monotonically with unexpected earnings and asymmetric intercept terms generally play no part in the return-earnings relationship, unlike the return-earnings relationship either specified or implicitly assumed in the value premium studies discussed above.

The functional form of the return-earnings relationship assumed in most of the ERC literature models unexpected returns as a linear and increasing function of unexpected earnings; the most basic form of which is given by equation (2.3), where the coefficient β_1 represents the ERC. Specific examples include Easton and Zmijewski (1989), Hayn

(1995), Kothari and Zimmerman (1995), and Kinney et al. (2002). The basic functional form given by equation (2.3) has been modified to allow for variation in β_1 (the ERC) with variables such as: growth, persistence, risk and interest rates (Collins and Kothari, 1989; Jones, Morton and Schaefer, 2000); forecast dispersion (Imhoff and Lobo, 1992); business cycle stages (Johnson, 1999); and the presence of dilutive securities (Huson, Scott and Wier, 2001). The modelling of this variation is achieved by the use of dummy variables D such that β_1 is replaced by $\beta_1(1+D)$; the resulting model is still nevertheless consistent with the functional form given by equation (2.3). One variation includes allowance for the S-shaped nonlinearity of the return-earnings relationship; this has been achieved by replacing UE with arctan (UE) (Freeman and Tse, 1992) or by the addition of the term |UE|*UE (Lipe, Bryant and Widener, 1998). To avoid measurement error problems associated with UE, models based upon equation (2.3) have also been estimated in a number of studies using reverse regression as suggested by Collins and Kothari (1989). In these cases UE becomes the dependent variable; however the underlying assumption still remains that the return-earnings relationship is of the form given by equation (2.3).

$$UR = \beta_0 + \beta_1 UE + \varepsilon \qquad (2.3)$$

In summary, the functional form of the return-earnings relationship used in empirical work varies primarily with the purpose of the study and the assumptions underlying the work. Studies in the value premium literature of the effect of errors-in-expectations have modelled returns as a function of the sign of the earnings surprise and value/growth orientation, with little or no consideration of the magnitude of the earnings surprise. In these studies the effect of negative surprises vis-à-vis positive surprises has

been modelled using intercept dummy variables. Studies in the ERC literature have modelled returns as an increasing function of the magnitude of earnings surprise, with the slope of this function conditioned on a number of potentially relevant variables (also by the use of dummy variables). Therefore, there exists some uncertainty about the correct functional form to use in a study of market reactions to earnings surprises which falls within the value premium literature, particularly with regard to the appropriateness of the intercept dummy. For consistency with both sets of literature, the analysis of market reactions to earnings surprises in this thesis will therefore allow for *both* asymmetric intercept terms *and* asymmetric slope terms in the return-earnings relationship.

2.5.2 Key variables identified in the literature

The ERC literature has proposed a large number of variables that affect the market's reaction to earnings surprises (or unexpected earnings); the search for which has been justified as an attempt to explain why empirical estimates of the ERC itself are smaller than values predicted by theory[15]. These variables include (but are not limited to) systematic risk and interest rates (Easton and Zmijewski, 1989; Collins and Kothari, 1989); growth, or the presence of growth opportunities (Kormendi and Lipe, 1987; Collins and Kothari, 1989; Biddle and Seow, 1991; Jones et al., 2000); earnings persistence (Kormendi and Lipe, 1987; Collins and Kothari, 1989; Jones et al., 2000); losses (Hayn, 1995; Lipe et al., 1998); earnings uncertainty or, where analysts' forecast are used to measure expected earnings, forecast dispersion (Freeman and Tse, 1992; Imhoff and Lobo, 1992; Subramanyam, 1996; Kinney et al., 2002); the current stage of business cycle (Johnson, 1999); earnings quality (Ghosh, Gu and Jain, 2005); the

[15] For example, Kothari (2001) states that while the ERC is expected to be between 8 and 20 under reasonable assumptions, actual empirical estimates are generally between 1 and 3.

presence of dilutive securities (Huson et al., 2001); and default risk (Dhaliwal and Reynolds, 1994; Billings, 1999). The main variable in the related value premium literature is B/M, used primarily to differentiate value and growth stocks which are expected to react differently to earnings surprises. Of the above variables, growth (measured by B/M), earnings uncertainty (measured by forecast dispersion) and default risk are of most relevance to this thesis; and therefore the following discussion emphasises these three variables[16].

2.5.2.1 Risk

For changes in earnings that are permanent (that is, not transitory), the ERC is theoretically inversely related to a firm's required rate of return on equity, because the effect of a permanent change in cash flows on equity value is greater for firms with a low discount rate than for firms with a higher discount rate. According to the CAPM, a firm's required rate of return on equity is directly related to the firm's systematic risk, and therefore the ERC is predicted by theory to be inversely related to both systematic risk (as measured by beta) and the risk-free rate of interest. Empirical evidence shows that estimated response coefficients are indeed inversely related to systematic risk (Easton and Zmijewski, 1989; Collins and Kothari, 1989), however the evidence regarding the statistical significance of this relationship is mixed. Easton and Zmijewski (1989) report statistically insignificant correlation coefficients between estimated response coefficients and beta, while Collins and Kothari (1989) report statistically significant coefficients from reverse regressions. Subsequent studies have generally *not* included additional terms in the return-earnings relationship to allow for variation in

[16] Although book-to-market has been used in the ERC literature to measure growth *and* earnings persistence, this thesis remains consistent with the value premium literature in employing book-to-market *solely* as a measure of a firm's value/growth orientation. The fact that low book-to-market stocks exhibit high earnings persistence is irrelevant to the findings herein.

systematic risk (for example Freeman and Tse, 1992; Hayn, 1995; Kinney et al., 2002; Ghosh et al., 2005); some studies do however allow for variation in the ERC across firms due to differences in unmeasured variables including systematic risk (Teets and Wasley, 1996; Lipe et al., 1998).

Whilst there are theoretical reasons why the ERC might be (inversely) related to systematic risk (or beta), Dhaliwal and Reynolds (1994) hypothesise that the ERC might also be inversely related to a firm's default risk of debt. Their argument depends on the concept that equity beta is directly related to the riskiness of a firm's debt; therefore if the CAPM is the correct asset pricing model but beta is measured with error, default risk may contain additional information regarding a firm's systematic risk besides the information in the (erroneously) estimated beta. An alternative argument (which Dhaliwal and Reynolds, 1994, do not cite) for an inverse relationship between the ERC and default risk is that financial distress might be another form of priced risk (as discussed in Chan and Chen, 1991; Fama and French, 1992, and Section 2.3.2) not specified in the CAPM. To test their hypothesis, Dhaliwal and Reynolds (1994) use two measures of default risk, namely bond ratings and leverage (debt-to-equity ratio). In both cases and after controlling for estimated beta, they find a strong and statistically significant inverse relationship between default risk and response coefficients.

On the other hand, Billings (1999) argues that both measures of default risk used by Dhaliwal and Reynolds (1994) are correlated with expected earnings growth, and therefore the observed inverse relation between ERC and default risk is merely capturing the association between ERC and growth (discussed below). Billings tests this idea by re-running the regression analysis in Dhaliwal and Reynolds (1994) and

controlling for two measures of expected growth, namely I/B/E/S long term growth forecasts and return-on-equity. He finds that the relation between bond ratings and ERC disappears and the relation between debt-to-equity ratios and ERC is substantially weakened after controlling for return-on-equity (but not after controlling for I/B/E/S long term growth forecasts). Based on the mixed nature of his results, Billings (1999) raises doubts that default risk explains response coefficients independently of the effect of growth.

2.5.2.2 Persistence, Growth and B/M

B/M is a variable which is related theoretically to the market reaction to earnings surprises. An inverse relationship between B/M and ERC magnitudes is predicted in theory because low B/M firms exhibit both earnings persistence and the presence of growth opportunities (Collins and Kothari, 1989), both of which imply high values of ERC. Earnings persistence is defined simply as the extent to which earnings changes persist in the future, and consequently also to the effect that a change in earnings has on *expectations* of future earnings. Therefore, ERC magnitudes are expected to increase with earnings persistence; a relationship confirmed empirically by Kormendi and Lipe (1987), Easton and Zmijewski (1989) and Collins and Kothari (1989) using time-series measures of persistence. Similarly, Collins and Kothari (1989) argue that the existence of growth opportunities is expected to increase the magnitude of ERC independently of persistence; because the valuation of growth firms is largely dependent upon the growth in future cash flows, and earnings surprises are indicative of changes in growth opportunities. The relationship between ERC magnitudes and growth is confirmed empirically using growth measures such as B/M (Collins and Kothari, 1989; Biddle and

Seow, 1991) Tobin's q (Harikumar and Harter, 1995) and composite growth variables based on factor analysis (Jones et al., 2000).

An inverse relationship between B/M and ERC magnitudes is also implied by equity valuation models that recognise the importance of book value of equity as well as earnings (for example Ohlson, 1995; Burgstahler and Dichev, 1997). When book values decrease relative to earnings, current earnings become increasingly important to firm valuation; consequently response coefficients are larger for low B/M firms than for high B/M firms. Proponents of the errors-in-expectations hypothesis also argue that high B/M stocks are expected to have a larger immediate reaction to negative earnings surprises because such surprises are interpreted by investors as a failure of growth stocks to match over-optimistic growth expectations (La Porta et al., 1997; Skinner and Sloan, 2002).

The predicted inverse relationship between B/M and response coefficients is supported by empirical results in Collins and Kothari (1989) and Biddle and Seow (1991). Skinner and Sloan (2002) estimate a number of models of the relationship between returns and earnings surprises; their results confirm that both the slope of this relationship (which is equivalent to the ERC) and the asymmetric intercept term for negative surprise (the effect of earnings torpedoes) are inversely related to B/M. Payne and Thomas (2003) confirm the Skinner and Sloan (2002) results regarding the slope but not, however, the asymmetric intercept term[17]. Results similar to Skinner and Sloan (2002) were obtained by Levis and Liodakis (2001) and Chan et al. (2006a), who find that low B/M stocks react more severely than high B/M stocks to negative earnings surprises. In summary,

[17] However, Skinner and Sloan (2002) rely most heavily upon the asymmetric intercept term for their inferences.

there is extensive evidence that B/M is an important determinant of the magnitude of market reactions to earnings surprises.

2.5.2.3 Nonlinearity, Uncertainty & Analyst Dispersion

Empirically, the return-earnings relationship has been found to be nonlinear (S-shaped), being steepest for earnings surprises close to zero and flattening out as the magnitude of earnings surprises of either sign increases (Freeman and Tse, 1992; Lipe et al., 1998). Subramanyam (1996) argues that this nonlinearity is caused by uncertainty regarding the precision of earnings signals. Investors are likely to infer a smaller signal-to-noise ratio for more extreme information, where the information is the ex-post magnitude of the earnings surprise. Consequently, the market attaches less weight to extreme earnings surprises resulting in a decline in the response per unit of earnings surprise; an argument which in effect states that extreme earnings surprises have lower persistence.

Kinney et al. (2002) also explain the S-shaped return-surprise relationship in terms of investor uncertainty regarding the precision of earnings signals, where uncertainty is measured from the ex-ante dispersion of analyst forecasts. They demonstrate empirically that extreme earnings surprises are associated with high dispersion forecasts, and more importantly that the return-earnings surprise relationship becomes steeper as dispersion decreases; the latter result having also been obtained by Imhoff and Lobo (1992). Therefore, nonlinearity in the return-earnings relationship can potentially be explained by the observation that extreme earnings surprises coincide with high earnings uncertainty, which is reflected in high analyst forecast dispersion. Both Kinney et al. (2002) and Burgstahler and Chuk (2008) find that the nonlinearity all

but disappears when they control for dispersion before estimating the earnings response coefficient.

Dispersion measures the extent to which *analysts* disagree about the future earnings of a firm but has been employed in the finance literature in a more general sense as a proxy for earnings uncertainty amongst *investors*. For example Diether et al. (2002), Park (2005) and Boehme, Danielsen and Sorescu (2006) employ dispersion as a proxy for divergence of opinion amongst investors, to test the Miller (1977) hypothesis that divergence of opinion and short sales constraints keep pessimists out of the market, and consequently prices reflect only the most optimistic views[18]. Zhang (2006) also uses dispersion in this sense to test whether momentum is greater when uncertainty is greater. Similarly, Doukas, Kim and Pantzalis (2006) argue that investors view low dispersion forecasts as more *reliable* than high dispersion forecasts; an argument consistent with Kinney et al. (2002). They find that a forecast increase in earnings from the previous year, coupled with a low dispersion of forecasts, results in overvaluation and hence low future returns. When analysts forecast a decrease in earnings from the previous year and there is low dispersion in forecasts, stocks tend to be undervalued and have high future returns. They interpret these findings as consistent with the hypothesis that investors regard *low dispersion* stocks for which forecasts are 'optimistic' as sure winners, and *low dispersion* stocks for which forecasts are 'pessimistic' as sure losers[19]. Thus, the importance of dispersion for the market reaction to earnings surprises is supported theoretically as well as empirically.

[18] In other words, securities tend to be overvalued in the presence of uncertainty and short sales constraints.

[19] Note that the terms 'optimism' and 'pessimism' are used here in a different sense to that used elsewhere in this thesis. For the purposes of this thesis an optimistic forecast is one where forecast earnings exceed actual earnings, in other words the forecast is too high. In Doukas et al. (2006) an optimistic forecast is one where earnings-per-share is forecast to increase from the previous year.

Dispersion is of particular relevance to this thesis because it is directly related to B/M (Doukas et al., 2004) and likely to increase with default risk. Dispersion is likely to increase with default risk because analysts are more likely to update and provide accurate forecasts for firms they think will perform well than for firms they think will perform poorly (McNichols and O'Brien, 1997; Hayes, 1998). Given the importance of dispersion to market reactions to earnings surprises it could potentially help explain why high B/M stocks simultaneously have higher returns and larger negative earnings surprises than low B/M stocks (the latter being the main result in Doukas et al., 2002).

2.5.3 Summary of the Literature on the Market Reaction to Earnings Surprises

This section has discussed a number of results from the literature regarding market reactions to earnings surprises, and which are of relevance to the final research question in this thesis. These results pertain to the functional form of the relationship between unexpected returns and earnings surprises and to evidence of the roles played by default risk, B/M and analyst forecast dispersion in this relationship. The value premium literature emphasises the sign of the earnings surprise, while the literature on earnings response coefficients models returns as an increasing function of earnings surprise. The analysis of market reactions to earnings surprises (chapter 5) models the relationship between unexpected returns and earnings surprises in such a way as to maintain consistency with both sets of literature; in other words it allows for variation in both the intercept and slope terms with the key control variables.

2.6 Summary and Conclusions

The value premium is a robust empirical anomaly that is not easily explained by traditional asset pricing models such as the CAPM. It has been observed in most national stock markets including Australia and over a range of time periods. A number of modifications have been proposed to asset pricing models to accommodate the value premium, the most notable of which is the Fama-French three-factor model which includes HML as a risk factor. HML is derived as the size-controlled return differential between a portfolio of value stocks and a portfolio of growth stocks; the justification for its inclusion as a risk factor in asset pricing models is that it proxies for a priced financial distress factor and/or that it captures economic risk factors to which value stocks are more sensitive than growth stocks, and which investors wish to hedge against. In general, the rational pricing explanations for the value premium mainly revolve around the argument that value stocks have low prices because they are more risky than growth stocks, in the sense that they generally possess poorer economic fundamentals and/or are more sensitive to economic downturns than growth stocks.

In contrast to explanations based on rational pricing, behavioural finance advocates argue that the value premium is due to mispricing of value and growth stocks, the subsequent correction of which results in the high (low) returns of value (growth) stocks. Mispricing is argued to be due to cognitive biases on the part of investors which induce them to engage in less-than-optimal behaviour such as extrapolation of past performance, overreaction and/or underreaction to news, and the overweighting of personal information (or information obtained from personal analysis) relative to public information. The most notable behavioural explanation for the value premium is the

errors-in-expectations hypothesis, which argues that investors are overly optimistic about the prospects of growth stocks and overly pessimistic about the prospects of value stocks. The source of the excessive optimism and/or pessimism is argued to be extrapolation of past performance, as the price multiples which distinguish value and growth stocks tend to reflect past, rather than future, growth.

However, problems exist for both the rational pricing and the behavioural explanations of the value premium, and the real explanation most likely includes elements of both. The debate regarding the validity of HML as a risk factor remains unresolved. Whilst value stocks are generally more financially distressed than growth stocks, HML does not appear to be a priced financial distress factor because distress carries a negative, not a positive, return premium. The existence of a negative distress premium opens up the possibility of mispricing of *some* securities where price multiples do not reflect the relative level of distress of the issuing firm. Admittedly, HML is correlated with a number of economic variables, thus lending some support to the concept of a priced recession or economic downside risk variable. Priced downside risk can be modelled as variable systematic risk in conditional asset pricing models, but such models are not completely satisfactory representations of reality because in empirical tests they generally imply a much smaller magnitude of value premium than is actually observed.

Behavioural finance theories that have evolved to explain anomalies such as the value premium also have unresolved problems, including a lack of consensus on the relative importance of certain factors such as overreaction, underreaction and the various cognitive biases argued to drive over/underreaction. The errors-in-expectations hypothesis is supported by arguments that price multiples reflect past and not future

growth, by observed biases in forecast growth rates, and by return patterns observed around earnings announcements and surprises. However evidence exists that is contrary to the extrapolation (of past growth) behaviour underlying this hypothesis, and furthermore, the pattern of analyst optimism across value and growth stocks predicted by the errors-in-expectations hypothesis does not appear to be reflected in analysts' earnings forecasts.

The literature summarised above contains some relatively unexplored issues and which are the focus of this thesis. The first such issue is the existence of mispricing as a function of valuation ratios and financial distress, which has been the subject of a number of overseas studies but is explored in this thesis for the first time in an Australian context. The second issue is the inconsistency between the errors-in-expectations hypothesis and the pattern of analyst optimism (or equivalently, analysts' forecast errors) observed across value and growth stocks; investigated here and for the first time with financial distress as a control variable. The motivation for including financial distress as a control variable is twofold: the potential existence of distress-related mispricing, and evidence of analyst underreaction to distress. The final issue is the inconsistency between stock returns and the same pattern of analyst optimism observed across value and growth stocks; explored in this thesis by examining how B/M, distress and analyst forecast dispersion impact upon market reactions to earnings surprises.

CHAPTER 3: THE VALUE PREMIUM, DEFAULT RISK AND MISPRICING: A STUDY OF LARGE CAPITALISATION AUSTRALIAN STOCKS

3.1 Abstract

This chapter addresses the first research question of this thesis. The chapter is thus an investigation of a mispricing hypothesis whereby stocks with high valuation ratios and low default risk are underpriced while stocks with low valuation ratios and high default risk are overpriced; the valuation ratios in this study being book-to-market (B/M), earnings-to-price (E/P) and cash flow-to-price (C/P). The mispricing hypothesis is tested in a number of ways. First, an investigation is carried out on whether static asset pricing models can explain the returns of portfolios of large capitalisation Australian stocks sorted by value/growth and default risk, by testing against the mispricing hypothesis. Second, portfolio returns and Sharpe ratios are compared against alternative risk measures not included in the asset pricing models. Finally, portfolio returns are compared with various characteristics to facilitate an understanding of the mechanism by which such mispricing (namely, as a function of value/growth and default risk) might arise.

The static asset pricing models tested (the CAPM, Fama-French three-factor model, and Carhart four-factor model) are all rejected in favour of the mispricing hypothesis, regardless of whether value/growth is defined by B/M, E/P or C/P, and regardless of whether returns are equal-weighted or value-weighted. Although asset pricing model misspecification cannot be ruled out, the overall findings are strongly supportive of

mispricing that is consistent with the momentum life cycle postulated by Lee and Swaminathan (2000).

3.2 Introduction

Whilst it is accepted that value stocks are in general more distressed financially than growth stocks (see Fama and French, 1995; Chen and Zhang, 1998), recent studies suggest that financial distress does not command a positive return premium in equity markets (Dichev, 1998; Gharghori et al., 2007; Campbell et al., 2008), and therefore the superior returns of value stocks cannot be due to a rationally-priced distress risk factor. On the contrary, there is growing evidence of systematic overvaluation of financially distressed growth stocks and of systematic undervaluation of value stocks that are otherwise financially strong. Notably, Piotroski (2000) uses financial statement analysis to identify financially strong high B/M firms which are then demonstrated to have much higher returns than other high B/M firms; Mohanram (2005) does the same for low B/M stocks, but uses a different set of variables. Griffin and Lemmon (2002) uses Ohlson's O-score to identify distressed firms, and finds that distressed growth firms have extremely low returns. Bird and Casavecchia (2007a) use a set of 24 variables to derive a measure of financial health which they use (along with momentum) to identify undervalued value firms and overvalued growth firms in Europe.

Although the above studies use different measures of financial health and/or distress, their common identifiable finding is that firms where B/M (or sales-to-price in the case of Bird and Casavecchia, 2007a) is either too high or low relative to financial distress are mispriced. The main objective in this chapter is thus to test whether this broad result also holds in Australia, using the CAPM, Fama-French three-factor model and Carhart

four-factor model as benchmarks. As Fama (1970) argues that tests of market efficiency cannot be differentiated from tests that the asset pricing model is correctly specified, additional use is made of evidence besides the results of asset pricing tests to support the case for mispricing. Specifically, portfolio risk-based measures are used to demonstrate the inconsistency of the results with rational pricing, and the recent earnings and price history of the sample firms are used to demonstrate that the results are consistent with a delayed reaction to information and therefore with market inefficiency.

This study is differentiated in a number of ways from previous studies that test for mispricing as a function of value and financial distress/health. First, the study employs a single default risk indicator to measure financial health amongst both value and growth firms, thus avoiding potential conflicts arising from the use of different indicators across studies, and across value and growth firms. Second, the tests are repeated using each of three valuation ratios: B/M, E/P and C/P, thereby increasing the robustness of the results. Finally, and for reasons which will become apparent, the sample is limited to large stocks, namely those that are ranked in the top 300 by market capitalisation. The study is similar to Gharghori et al. (2007), who test the Fama-French three-factor model and variations of this model on Australian stock portfolios sorted by size, B/M and default risk. However, Gharghori et al. (2007) have as their stated objective the investigation of whether SMB and HML proxy for default risk; not the investigation of mispricing as an explanation for cross-sectional return variation related to value and default risk. Consequently, this study is the first Australian study to deal with the latter objective.

The default risk indicator used in this study is distance-to-default (DD), a measure developed by Moody's KMV (Crosbie and Bohn, 2003), and previously used in value premium studies by Vassalou and Xing (2004) and Gharghori et al. (2007). DD is based upon the bond-pricing framework of Merton (1974) which models a firm's equity as a call option on the firm's assets with an exercise price equal to the value of the firm's debt. Default probabilities based on DD are arguably a more accurate predictor of default risk than models based upon accounting ratios such as Altman's z-score or Ohlson's O-score, and are otherwise preferable because DD implicitly emphasises the information in *current* market values rather than historical data (Vassalou and Xing. 2004; Gharghori, Chan and Faff, 2006b). By using an existing and widely recognised model this study avoids dependency problems caused by estimating a model on the same sample data on which returns-based tests are conducted.

The study concentrates upon large stocks for a number of reasons. Preliminary analysis (presented in Appendix 3A) reveals that size (market capitalisation) plays little, if any, role in stock returns amongst large stocks[20]. In contrast, the value premium is found to be economically and statistically significant amongst large stocks in Australia[21]. On this basis, the tests of mispricing do not include size as a variable and concentrate solely upon the relationships between value, default risk and stock returns. In addition, the emphasis upon large caps allows for a more accurate calculation of returns and of the measure of default risk, namely DD, than would otherwise be possible. The calculation of these variables is more accurate primarily because trading frequency increases with

[20] This result is consistent with Halliwell et al. (1999) and Gaunt (2004) who find the size effect in Australia is mainly due to the smallest quintile of stocks.
[21] The existence of a value premium in Australia is not unanimously accepted. In particular, Halliwell et al. (1999) and Gaunt (2004) argue that the Australian B/M effect is not statistically significant; however their sorts on size and B/M reveal that this inference is mainly due to small stocks. Other studies finding a significant value premium include Faff (2001), Gharghori et al. (2007) and Gharghori et al. (2009).

size. There are thus fewer months where stocks returns are unobservable, leading to more accurate portfolio return calculations. There are also more daily market capitalisation observations, and thus more reliable estimates of the volatility of daily market capitalisation, upon which the DD calculation depends.

However, mispricing is arguably more prevalent amongst small stocks than amongst large stocks, and therefore the results of this study are implicitly biased *against* finding any mispricing. Shleifer and Vishny (1997) argue that mispricing exists firstly because market inefficiency allows prices to deviate from fundament values, and secondly because it is costly for arbitrageurs to profit from mispricing and therefore drive prices back to their fundamental values. Analyst coverage and institutional ownership increase with size, implying greater market efficiency for large stocks; while idiosyncratic volatility, bid-ask spreads and the frequency of zero-volume trading days are all inversely related to size, implying that arbitrage activity is more costly for small stocks (Ali et al., 2003).

In spite of the fact that the sample is biased towards stocks which are not likely to be mispriced, the results reject the asset-pricing models tested and are consistent with the mispricing hypothesis: high default risk growth portfolios have large negative alphas and low default risk value portfolios have large positive alphas. Both the alphas and raw returns of the mispriced portfolios are *inversely* related to risk, where risk is measured not only by default risk, but also by total portfolio volatility and by portfolio idiosyncratic volatility; thus it is extremely difficult for the results to be reconciled with rational pricing. The results are also demonstrated to be inconsistent with market efficiency in that they imply a *gross* underreaction to information. Notably, the high

default risk growth stocks have poor prior returns and declining earnings; however, the poor returns *continue* after the portfolio formation date. Similarly, the high post portfolio-formation returns of low default risk value stocks are also a continuation of their prior earnings and return performance.

The results suggest that the Australian share market is far from efficient, even amongst large capitalisation stocks where mispricing is expected to be minimal or nonexistent. Behavioural explanations for the value premium (which is found to be large and statistically significant amongst large Australian stocks) might therefore prove a fruitful area for future Australian research.

The remainder of the chapter is as follows. Section 3.3 describes the empirical framework for this study. Section 3.4 describes the data and methodology to carry out the empirical tests. The results of the empirical tests are presented in Section 3.5, while Section 3.6 interprets the results and concludes.

3.3 Empirical Framework

The empirical work carried out in this study consists of three parts. First, the relationship between stock returns and each of the main variables in the study is investigated using portfolios formed from one-way sorts. The study then tests whether the variation in returns with each variable is explained by any of the asset-pricing models considered (the CAPM, the Fama-French three-factor model, and the Carhart four-factor model). This part of the analysis is necessary to confirm the earlier assertion that size plays no part in the returns of large stocks, that a large-capitalisation value-premium exists, and that the results from the subsequent two-way sorts are not primarily

driven by any one variable alone. The standard testing methodology from similar studies is employed, namely (i) a t-test of the return differential between the extreme portfolios and (ii) a t-test that the portfolio alphas are zero.

Second, the mispricing hypothesis is tested by double-sorting stocks into three value/growth classifications and independently into three default risk classifications. The returns of each portfolio in excess of the risk-free rate are then regressed in time-series against those of the factors in each asset pricing model. The risk factors and their estimation are discussed in more detail in Section 3.4. The alphas (or pricing errors) under each asset pricing model are the intercept terms from the time-series regressions and form the basis of the tests of mispricing.

The main hypothesis is that mispricing is associated with valuation ratios that are too high or too low relative to default risk[22]. Mispricing associated with valuation ratios that are too high relative to default risk implies undervaluation and a positive alpha (α) for low default risk value portfolios, while mispricing associated with valuation ratios that are too low relative to default risk implies overvaluation and negative α for high default risk growth portfolios. The formal tests for mispricing applied in this study therefore consist of two non-nested hypothesis tests based on portfolio α. The first test is of the hypothesis that the α of high default risk growth portfolios are zero, the rejection which against the one-sided alternative $\alpha<0$ is evidence consistent with overvaluation of high default risk growth portfolios. Similarly, the second test is of the hypothesis that the α of low default risk value portfolios are zero, the rejection of which against the one-sided

[22] As valuation ratios are defined in this study with price or market value in the denominator, value stocks have "high" valuation ratios while growth stocks have "low" valuation ratios.

alternative that $\alpha>0$ is evidence consistent with undervaluation of low default risk value portfolios.

Note, however, that whilst evidence that $\alpha>0$ for low default risk value portfolios and that $\alpha<0$ for high default risk growth portfolios is consistent with mispricing, it may also be consistent with misspecification of the asset pricing models used to compute α. The third part of the empirical analysis therefore provides additional evidence regarding the consistency or inconsistency of the (α-based) mispricing results with rational pricing and with market efficiency.

To demonstrate the inconsistency with rational pricing, it is necessary to show that the overpriced (high default risk growth) portfolios have unambiguously higher risk than the underpriced (low default risk value) portfolios. The analyses based on portfolio returns and alphas by themselves constitute a direct test of the proposition that overpriced stocks have higher risk than underpriced stocks, because one of the variables (default risk) used to construct the portfolios itself measures risk. Consequently, evidence that the returns and alphas of low default risk value stocks exceed those of high default risk growth stocks is consistent with this proposition, with risk measured in terms of default risk. However, this study applies two additional measures of risk to this context, namely total portfolio volatility and residual (that is, idiosyncratic) volatility from a market model. Residual volatility is relevant to behavioural explanations of stock returns in the sense that it is argued by Shleifer and Vishny (1997) to be a significant impediment to arbitrage activity and thus an important reason for the existence of mispricing.

To demonstrate the inconsistency with market efficiency the study then tests for evidence of that the mispricing results are due to underreaction, a line of enquiry that can be justified in terms of the momentum life cycle proposed by Lee and Swaminathan (2000). Whilst overreaction is a frequently-cited behavioural explanation for the value premium[23], the results to this point actually prove to be more consistent with underreaction than with overreaction. As DD incorporates the information in share prices, a low (high) DD score implies that the market has *to some extent* responded to a firm's deteriorating (improving) financial health. In the case of high default risk growth stocks, poor price performance *after* portfolio formation indicates the market response to deteriorating financial health implicit in DD is not yet complete. An incomplete market response to improving financial health is also consistent with the relatively good price performance of low default risk value stocks *after* portfolio formation.

To test the underreaction hypothesis, it is demonstrated that undervalued stocks (which have relatively good price performance after portfolio formation) also have improving financial health and high returns *before* portfolio formation, and that overvalued stocks (which have relatively poor price performance after portfolio formation) also have deteriorating financial health and low returns *before* portfolio formation. The study thus tests for variation in financial health and prior returns across portfolio groupings, using the Kruskal-Wallis test (the non-parametric counterpart of the multivariate ANOVA test). For these tests, financial health is measured by the change in earnings, return-on-assets (ROA) and the change in ROA.

[23] Examples include Barberis et al. (1998), Hong and Stein (1999) and Barberis and Shleifer (2003). However, Daniel et al. (1998) model the value premium as an under-reaction to public information.

3.4 Data and Methodology

The data employed for this study are from four sources. Financial data are sourced from the Aspect Huntley Datalink database, from which are calculated book value of equity, earnings, cash earnings and debt. Monthly market data are sourced from the AGSM SPPR database, from which market capitalisation, used in the computation of the valuation ratios and to measure size, and stock returns are calculated. Daily market capitalisation data are sourced from SIRCA[24], which is used in the calculation of DD. Finally, the Reserve Bank of Australia website is used to obtain short-term interest rate data for the calculation of DD. The financial data span the period from July 1994 till June 2006, the daily market capitalisation data span the period from November 1994 till November 2007, and the monthly market data span the period from January 1996 till December 2008. To be included in the sample, firms must have fully-paid ordinary shares listed on the ASX and be ranked in the top 300 by market capitalisation at December 31st each year. From the resulting list of companies, property trusts, investment trusts and shares of foreign or dual-listed companies are excluded.

The definitions of the valuation ratios B/M, E/P and C/P follow the conventions of similar studies. B/M is calculated as the book value of equity from the company's latest balance sheet in the twelve months prior to June 30, divided by market capitalisation as at June 30 of each year. The book value of equity is defined as the book value of common equity excluding preference capital and outside equity and including balance sheet provisions for deferred taxes. Market capitalisation is the ordinary share price times the number of ordinary shares outstanding. E/P is calculated as earnings from the

[24] Data supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of the Australian Securities Exchange.

company's latest annual report in the twelve months prior to June 30, divided by market capitalisation as at June 30 of each year. The earnings number is earnings after interest, depreciation, taxes and preference dividends but before extraordinary and abnormal items. C/P is defined as cash flow from the company's latest annual report in the twelve months prior to June 30, divided by market capitalisation as at June 30 of each year. Cash flow is earnings with non-cash items depreciation and amortisation added back. Size is defined as market capitalisation, which is defined above.

Following Vassalou and Xing (2004) and Gharghori et al. (2007), the default risk of individual firms is measured using DD. The methodology for calculating DD is defined in Crosbie and Bohn (2003), and following Merton (1974) models a firm's equity as a European call-option on the firm's assets, where the exercise price is the value of the firm's liabilities. The value of the firm's equity is then given by the Black-Scholes equation for a call option, as in equation 3.1:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}, \quad d_2 = d_1 - \sigma_A \sqrt{T} \tag{3.1}$$

In equation 3.1, r is the risk-free rate, X is the strike price, V_E is the value of the firm's equity, V_A is the value of the firm's assets, σ_A is the volatility of the firm's assets, T is the maturity of the firm's debt and N is the cumulative density function of the standard normal distribution. In accordance with Vassalou and Xing (2004) and Gharghori et al. (2006b), the time to maturity T is set to one year and the strike price X set to the book

value of current liabilities plus one-half of non-current liabilities. Consistent with the calculation of B/M, the book values of current liabilities and non-current liabilities are obtained from the company's latest balance sheet in the twelve months prior to June 30. As in Gharghori et al. (2006b), the risk-free rate r is the 180-day bank bill rate from the Reserve Bank of Australia website. The value of equity V_E is the firm's market capitalisation, as defined above, and the values of V_A and σ_A are determined using an iterative procedure as follows.

The annualised standard deviation of the daily equity values V_E from the previous twelve months are used as initial estimates of each firm's σ_A. The initial value of σ_A is then plugged into equation (3.1) to yield daily estimates of V_A, which are then used to estimate a new value of σ_A. The new value of σ_A is then plugged into equation (3.1) to yield a new estimate of V_A. This process is repeated until the value of σ_A converges to within 0.0001, in accordance with Gharghori et al. (2006b). The DD is then defined according to equation 3.2:

$$DD = \frac{\ln\left(\frac{V_A}{X}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \qquad (3.2)$$

In equation (3.2) μ is the instantaneous drift in the value of the firm's underlying assets V_A under an assumed Geometric Brownian Motion. Following Vassalou and Xing (2004) it is calculated as the mean of the daily change in ln (V_A). Unlike Vassalou and Xing (2004) and Gharghori et al. (2007) the default probabilities implied by DD are not

computed. As default probability is a monotonic function of DD, the ranking of firms by default probability is the same as the ranking by DD.

DD is calculated at the end of November each year, employing data from the same set of financial statements as used in the calculation of B/M, E/P and C/P. DD cannot be observed as instantaneously as market capitalisation because of the additional computational effort required, and therefore, DD is calculated one month before portfolio formation to conservatively allow time for its computation based on relatively recent data. The daily market capitalisation data span the period from December 1st in the previous year until November 30th in the current year. As portfolios are formed at the end of December, a potential investor would thus have easily been able to compute DD (and the valuation ratios) at the time of portfolio formation.

Individual stock returns are the total monthly returns including capital gains and dividend yield. Portfolios are formed by ranking stocks on the above variables at December 31st each year, and held for the following 12 months. Portfolio returns are calculated each month on both an equally-weighted and a value-weighted basis. The equally-weighted return is the arithmetic average return of all stocks in the portfolio. The value-weighted return is the market capitalisation-weighted average return of all stocks in the portfolio. As portfolios are formed on December 31st each year, the portfolio weights are set proportional to market capitalisations on this date, with the weights at the end of the months from January to November adjusted to reflect capital gains and dividend reinvestment. The value-weighted return of a portfolio is thus the actual return that would be realised by an investor who forms the portfolio on December 31st each year by allocating capital to stocks in proportion to their market capitalisation,

who reinvests dividends in the same stock, and who makes no other changes until the end of the subsequent year. Where a return is not able to be calculated for a particular stock in a portfolio, it is replaced by the equally-weighted average return of the portfolio.

For the tests of mispricing, three asset pricing models are employed: the CAPM, the Fama-French three-factor model, and the Carhart four-factor model. The market risk premium for these models is the monthly value-weighted market return less the risk-free rate from the AGSM SPPR database. The SMB and HML factors are computed in accordance with Fama and French (1993) with the exception that portfolios are formed in December rather than June each year. Stocks above and below the median market capitalisation are classified as 'big' and 'small' respectively. Firms in the top 30%, middle 40% and bottom 30% by B/M are classified as 'high', 'middle' and 'low' respectively. Six portfolios are then constructed at the intersections of the size and B/M classifications, and the monthly value-weighted returns of each portfolio are calculated. SMB is then calculated as the average return of the three small portfolios minus the average return of the three big portfolios. HML is calculated as the average of the two high (B/M) portfolios minus the average return of the two low (B/M) portfolios. The PR1YR factor is calculated in accordance with Carhart (1997). Stocks are ranked each month on their previous 11-month return lagged by one month. PR1YR for the following month is then the equal-weighted average return of the top 30% of firms minus the equal-weight average return of the bottom 30% of firms.

3.5 Results

3.5.1 Returns and Pricing Errors from One-Way Sorts

In this section, portfolios are formed by sorting on one variable at a time, and then the raw returns and pricing errors of each portfolio computed. The return differential between extreme portfolios and its statistical significance are then computed, to determine whether the variable has a relationship with stock returns. Finally, the alphas of each portfolio are computed using the Fama-French three-factor model; these alphas will be of use in Section 3.5.2 where they will be compared with the three-factor alphas of double-sorted portfolios. Table 3.1 presents the results of this analysis.

Table 3.1 shows no evidence of a premium for small size in the sample. In fact there is a monotonic *increase* in equal-weighted returns from the smallest to the largest size portfolio; however this effect is much weaker for value-weighted returns and statistically insignificant for both equal-weighted and value-weighted returns. From this point on size is excluded from the analysis, as there are no intuitive reasons to retain this variable. In contrast, the results show an economically and statistically significant value premium, regardless of whether value and growth are differentiated by B/M, E/P or C/P and regardless of whether returns are equal-weighted or value-weighted. Table 3.1 also shows some evidence of a negative default risk premium, as equal-weighted returns increase monotonically with DD and the return differential between extreme portfolios is statistically significant. However, this result is substantially weaker and statistically insignificant for value-weighted returns.

The alphas of each portfolio from the Fama-French three-factor model are shown in the lower half of Table 3.1. There are no significant three-factor alphas for any of the portfolios sorted B/M, and thus the three-factor model appears to adequately explain the B/M effect. The low E/P and low C/P portfolios have significantly negative three-factor alphas if returns are equal-weighted, while the high E/P and high C/P portfolios have significantly positive alphas if returns are value-weighted. Thus, the three-factor model does not adequately explain the returns of all portfolios sorted by E/P and C/P. Finally, the relationship between DD and returns is not totally explained by the three-factor model, as the two extreme equal-weighted portfolios and the high DD value-weighted portfolio all have significant alphas. The next section will refer to the three-factor alphas in Table 3.1, where they will be compared with those of double sorted portfolios. Attention now turns to the main emphasis of the study: whether valuation ratios that are too high or too low relative to default risk are consistent with mispricing.

Table 3.1: Returns and Three-Factor Alphas of Large Capitalisation Portfolios formed from One-Way Sorts

All stocks within the top 300 by Market Capitalisation excluding property trusts, foreign companies, investment trusts, preference shares and partly-paid shares are sorted into quintile portfolios by Size (Market Capitalisation), book-to-market (B/M), earnings-to-price (E/P), cash flow-to-price (C/P) and distance-to-default (DD) at December 31st each year from 1995 to 2007. Monthly returns $r_{p,t}$ are calculated for each portfolio for the following 12 months after each portfolio formation date. Three-Factor Alphas are the intercept terms from the time series regression $\left(r_{p,t} - r_{f,t}\right) = \alpha_p + \beta_p (r_{m,t} - r_{f,t}) + s_p SMB_t + h_p HML_t + \varepsilon_t$; $r_{f,t}$ is the risk-free rate from the SPPR monthly database, $r_{m,t}$ is the return of the SPPR value-weighted market portfolio, and SMB_t and HML_t are calculated in accordance with Fama and French (1993). Significance levels of t-statistics are indicated by *** (1%), ** (5%) and * (10%).

	Equal-weighted returns						Value-weighted returns				
	Size	B/M	E/P	C/P	DD		Size	B/M	E/P	C/P	DD
Low	0.37%	0.29%	0.14%	0.10%	0.28%		0.54%	0.42%	0.25%	0.39%	0.61%
2	0.61%	0.44%	0.62%	0.77%	0.54%		0.84%	0.69%	0.64%	0.53%	0.74%
3	0.72%	0.73%	0.93%	0.73%	0.51%		0.96%	0.85%	0.82%	0.83%	0.89%
4	0.76%	0.78%	1.14%	1.05%	0.76%		0.97%	0.93%	1.07%	1.06%	0.89%
High	0.76%	1.02%	0.89%	0.98%	1.06%		0.75%	1.15%	1.26%	1.32%	0.86%
High-Low	0.38% (1.392)	0.73% (2.439***)	0.75% (2.738***)	0.88% (3.206***)	0.78% (2.355***)		0.21% (0.73)	0.73% (1.98**)	1.01% (2.91***)	0.93% (2.57***)	0.25% (0.68)

Table 3.1: Returns and Three-Factor Alphas of Large Capitalisation Portfolios formed from One-Way Sorts (continued)

	Three-Factor Alphas (equal-weighted portfolios)						Three-Factor Alphas (value-weighted portfolios)				
Low	-0.42% (-1.730*)	-0.34% (-1.313)	-0.80% (-2.404**)	-0.72% (-2.248**)	-0.60% (-2.086**)		-0.23% (-1.000)	-0.06% (-0.314)	-0.38% (-1.085)	-0.21% (-0.625)	-0.05% (-0.171)
2	-0.15% (-0.585)	-0.21% (-1.122)	-0.32% (-1.741*)	-0.04% (-0.224)	-0.21% (-0.991)		0.07% (0.310)	0.16% (1.052)	-0.11% (-0.534)	-0.18% (-0.976)	0.09% (0.540)
3	0.01% (0.040)	-0.02% (-0.100)	0.22% (1.422)	-0.06% (-0.395)	-0.21% (-1.028)		0.25% (1.338)	0.19% (1.304)	0.27% (1.782*)	0.04% (0.266)	0.08% (0.399)
4	0.01% (0.052)	0.08% (0.391)	0.29% (1.813*)	0.25% (1.480)	0.09% (0.536)		0.23% (1.387)	0.14% (0.684)	0.37% (1.824*)	0.28% (1.436)	0.13% (0.701)
High	0.07% (0.819)	0.05% (0.275)	0.15% (0.696)	0.14% (0.602)	0.38% (2.286**)		0.09% (1.273)	0.07% (0.236)	0.48% (2.104**)	0.46% (1.729*)	0.32% (1.808*)

3.5.2 Analysis of Portfolios formed from Two-Way Sorts

In this section, portfolios are formed by double sorting on default risk and value. The main aim is to test for mispricing when valuation ratios are either too high or too low relative to default risk. Specifically, the analysis tests for overvaluation amongst growth stocks with high default risk and for undervaluation amongst value stocks with low default risk. Growth stocks are defined as those with B/M, E/P and C/P in the bottom third of stocks in the sample and value stocks as those with B/M, E/P and C/P in the top third of stocks in the sample. Similarly, high default risk stocks are defined as those with DD in the bottom third of stocks in the sample and low default risk stocks as those with DD in the top third of stocks in the sample. There are thus three sorting procedures carried out to form portfolios: First by sorting on B/M and DD, second by sorting on E/P and DD, and finally by sorting on C/P and DD. Table 3.2 presents the characteristics of the portfolios formed in each of the three procedures.

The restrictions imposed on the sample (top 300 by market capitalisation, fully-paid ordinary shares only, no property or investment trusts and no foreign companies) result in a relatively small sample compared with other similar studies. Despite the relatively small number of stocks allocated to nine portfolios, each portfolio contains at least 11.5 stocks on average. The portfolios with the largest number of stocks are those where the valuation ratio is aligned with default risk; namely those consisting of either low default risk growth stocks, high default risk value stocks, or stocks with intermediate default risk and classified as neither value nor growth. For example, the low B/M, high DD (i.e. low default risk growth) portfolio contains on average 35.8 stocks.

In contrast, portfolios of stocks where the valuation rather appears misaligned with default risk contain relatively fewer stocks. For example, the high B/M, low DD (i.e. high default risk growth) portfolio contains on average only 13.0 stocks. These results suggest that most stocks have valuation ratios which reflect default risk, for example high B/M stocks generally have high default risk.

Panels C, D and E demonstrate the similarity of three valuation ratios when they are used to classify value and growth stocks. Value stocks generally have higher B/M, E/P and C/P than growth stocks, regardless of whether the value/growth classification is carried out using B/M, E/P or C/P. Thus it could be argued that the three valuation ratios are consistent with one another in their ability to differentiate value and growth stocks. Not surprisingly, however, the greatest spread in portfolio valuation ratios occurs when the same valuation ratio is used in the portfolio sorting process; for example the greatest spread in portfolio average B/M ratios occurs with portfolios sorted by B/M and DD. Thus, the three valuation ratios each contain incremental ability relative to the others to differentiate between value and growth stocks.

Table 3.3 presents the average equal-weighted returns and pricing errors of portfolios formed by sorting large capitalisation stocks on DD and each of the valuation ratios. Table 3.4 following immediately after is similar except the returns and pricing errors are based upon value-weighted returns. Tables 3.3 and 3.4 are both divided horizontally into three sections, each of which corresponds to one valuation ratio. The section headed B/M refers to the results for portfolios sorted by B/M and DD, the section headed E/P refers to the results for portfolios sorted by E/P and DD, and the section headed C/P refers to the results for portfolios sorted by C/P and DD. The results of most

interest are those for portfolios of high default risk growth stocks and of low default risk value stocks; the cells referring to these portfolios are shaded for ease of reference.

The average portfolio returns in Panel A tell a story that is incompatible with a risk-based explanation of stock returns. Regardless of the choice of valuation ratio, the average equal-weighted monthly return of high default risk growth stocks is negative over the sample period: -0.59% for low B/M, low DD stocks; -0.27% for low E/P, low DD stocks; and -0.32% for low C/P, low DD stocks. The corresponding value-weighted returns are -0.22%, -0.18% and -0.08% respectively. Thus, investors in these types of stocks were penalised severely rather than rewarded for holding assets that are risky. Consistent with arguments proposed by Griffin and Lemmon (2002), these results suggest overvaluation of high default risk growth stocks even before adjusting for risk.

Table 3.2: Characteristics of Large-Capitalisation Portfolios Sorted by Valuation Ratios and Distance-to-Default, 1996-2008
All stocks excluding property trusts, foreign companies, investment trusts, preference shares and partly-paid shares are ranked independently on distance-to-default (DD), book-to-market (B/M), earnings-to-price (E/P) and cash earnings-to-price (C/P) at December 31st each year from 1995 to 2007. Each stock is independently assigned to both a DD category and a category based upon B/M, E/P or C/P, and nine portfolios are formed from the intersections of the DD and B/M, E/P or C/P categories.

The number of stocks in each portfolio and the average DD, B/M, E/P and C/P of the stocks in each portfolio are determined at each portfolio formation date. The respective figures quoted are the time-series averages of these computations.

		B/M			E/P			C/P		
		Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel A: Average Number of Stocks										
DD	Low	13.0	23.0	35.2	24.6	17.5	29.7	18.7	19.4	33.7
	Mid	22.5	29.2	19.9	20.1	24.3	27.6	18.7	26.2	27.1
	High	35.8	19.6	16.9	27.1	30.2	15.0	34.4	26.4	11.5
Panel B: Average Market Value ($ millions)										
DD	Low	254,130	535,870	141,830	160,120	347,400	357,960	222,240	597,480	145,430
	Mid	291,500	368,610	295,490	223,170	300,470	415,560	213,920	418,700	305,740
	High	316,200	275,680	168,390	244,970	285,920	286,580	184,780	342,040	363,740
Panel C: Average B/M										
DD	Low	0.256	0.517	1.088	0.690	0.701	0.807	0.581	0.616	0.902
	Mid	0.258	0.522	0.928	0.412	0.523	0.672	0.380	0.491	0.722
	High	0.216	0.510	0.909	0.348	0.495	0.584	0.408	0.455	0.615

Table 3.2: Characteristics of Large-Capitalisation Portfolios Sorted by Valuation Ratios and Distance-to-Default, 1996-2008 (continued).

		B/M			E/P			C/P		
		Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel D: Average E/P										
DD	Low	0.028	0.061	0.052	-0.023	0.055	0.106	-0.029	0.054	0.090
	Mid	0.038	0.060	0.081	0.011	0.054	0.097	0.015	0.057	0.090
	High	0.038	0.057	0.064	0.021	0.054	0.090	0.029	0.058	0.089
Panel E: Average C/P										
DD	Low	0.058	0.108	0.147	0.040	0.104	0.190	0.001	0.086	0.201
	Mid	0.063	0.100	0.148	0.041	0.094	0.153	0.030	0.086	0.165
	High	0.056	0.089	0.086	0.035	0.079	0.126	0.037	0.086	0.144
Panel F: Average DD										
DD	Low	4.02	3.83	3.46	3.48	3.87	3.73	3.52	3.82	3.69
	Mid	6.70	6.59	6.41	6.58	6.60	6.56	6.69	6.60	6.48
	High	10.82	10.71	12.42	11.83	11.17	9.90	12.40	10.22	9.58

Table 3.3: Monthly Equal-Weighted Returns and Alphas of Portfolios sorted by Valuation Ratios and Distance-to-Default, 1996-2008
All stocks excluding property trusts, foreign companies, investment trusts, preference shares and partly-paid shares are ranked independently on distance-to-default (DD), book-to-market (B/M), earnings-to-price (E/P) and cash earnings-to-price (C/P) at December 31st each year from 1995 to 2007. Each stock is independently assigned to both a DD category and a category based upon B/M, E/P or C/P, and nine portfolios are formed from the intersections of the DD and B/M, E/P or C/P categories.

Monthly returns $r_{p,t}$ are calculated for each portfolio for the following 12 months after each portfolio formation date. One-Factor Alphas are the intercept terms from the time series regression $(r_{p,t} - r_{f,t}) = \alpha_p + \beta_p (r_{m,t} - r_{f,t}) + \varepsilon_t$; Three-Factor Alphas are the intercept terms from the time series regression $(r_{p,t} - r_{f,t}) = \alpha_p + \beta_p (r_{m,t} - r_{f,t}) + s_p SMB_t + h_p HML_t + \varepsilon_t$; Four-Factor Alphas are the intercept terms from the time-series regression $(r_{p,t} - r_{f,t}) = \alpha_p + \beta_p (r_{m,t} - r_{f,t}) + s_p SMB_t + h_p HML_t + p_p PR1YR_t + \varepsilon_t$; $r_{f,t}$ is the risk-free rate from the SPPR monthly database; $(r_{m,t} - r_{f,t})$ is the market risk premium, calculated as the return of the SPPR value-weighted market portfolio less the risk-free rate; SMB_t and HML_t are calculated in accordance with Fama and French (1993), and $PR1YR_t$ is calculated in accordance with Carhart (1997). Significance levels of t-statistics are indicated by *** (1%), ** (5%) and * (10%).

		B/M			E/P			C/P		
		Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel A: Raw Returns										
DD	Low	-0.59%	0.45%	0.73%	-0.27%	0.65%	0.83%	-0.32%	0.60%	0.78%
	Mid	-0.22%	0.70%	1.12%	-0.39%	0.74%	1.03%	-0.44%	0.68%	1.09%
	High	0.86%	0.94%	1.12%	0.48%	1.12%	1.36%	0.71%	1.07%	1.45%
Panel B: One-Factor Alphas and t-statistics										
DD	Low	-1.49% (-3.315***)	-0.31% (-1.297*)	-0.07% (-0.278)	-1.13% (-3.248***)	-0.10% (-0.389)	0.05% (0.211)	-1.21% (-3.285***)	-0.13% (-0.571)	-0.01% (-0.039)
	Mid	-1.04% (-2.661***)	-0.03% (-0.169)	0.41% (2.088**)	-1.22% (-2.685***)	0.01% (0.032)	0.31% (1.676**)	-1.28% (-2.919***)	-0.03% (-0.161)	0.35% (1.751**)
	High	0.11% (0.611)	0.22% (1.263)	0.46% (2.721***)	-0.29% (-1.235)	0.46% (3.240***)	0.67% (3.307***)	-0.04% (-0.206)	0.40% (2.549***)	0.76% (3.483***)

Table 3.3: Monthly Equal-Weighted Returns and Alphas of Portfolios sorted by Valuation Ratios and Distance-to-Default, 1996-2008 (continued)

		B/M			E/P			C/P		
		Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel C: Three-Factor Alphas and t-statistics										
DD	Low	-1.27% (-2.840***)	-0.28% (-1.095)	-0.28% (-1.142)	-0.99% (-2.887***)	-0.31% (-1.128)	-0.04% (-0.144)	-1.05% (-2.933***)	-0.26% (-1.046)	-0.12% (-0.437)
	Mid	-0.79% (-2.093**)	-0.01% (-0.049)	0.37% (1.787**)	-1.00% (-2.216**)	0.04% (0.245)	0.32% (1.646*)	-1.03% (-2.433***)	-0.04% (-0.209)	0.36% (1.705**)
	High	0.23% (1.240)	0.16% (0.873)	0.46% (2.531***)	-0.16% (-0.664)	0.46% (3.064***)	0.61% (2.868***)	0.05% (0.233)	0.41% (2.497***)	0.66% (2.883***)
Panel D: Four-Factor Alphas and t-statistics										
DD	Low	-1.08% (-2.470***)	-0.14% (-0.573)	-0.04% (-0.179)	-0.79% (-2.427***)	-0.09% (-0.365)	0.14% (0.610)	-0.88% (-2.535***)	-0.08% (-0.339)	0.09% (0.367)
	Mid	-0.74% (-1.932**)	0.06% (0.305)	0.43% (2.130**)	-0.88% (-1.955**)	0.11% (0.602)	0.37% (1.906**)	-0.97% (-2.272**)	0.03% (0.165)	0.40% (1.873**)
	High	0.25% (1.325*)	0.12% (0.652)	0.51% (2.827***)	-0.15% (-0.621)	0.49% (3.262***)	0.62% (2.850***)	0.06% (0.301)	0.43% (2.582***)	0.66% (2.885***)

Table 3.4: Monthly Value-Weighted Returns and Alphas of Portfolios sorted by Valuation Ratios and Distance-to-Default, 1996-2008
All details are identical to Table 3.3, except portfolio returns are value-weighted rather than equal-weighted.

		B/M			E/P			C/P		
		Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel A: Raw Returns										
DD	Low	-0.22%	0.66%	1.22%	-0.18%	0.96%	0.85%	-0.08%	0.92%	1.04%
	Mid	0.52%	1.09%	1.04%	0.61%	0.65%	1.25%	0.26%	0.70%	1.38%
	High	0.86%	0.90%	1.17%	0.38%	1.19%	1.46%	0.70%	1.00%	1.40%
Panel B: One-Factor Alphas and t-statistics										
DD	Low	-1.00% (-2.450***)	-0.08% (-0.296)	0.49% (1.872**)	-1.05% (-2.743***)	0.26% (1.033)	0.16% (0.640)	-0.96% (-2.502***)	0.22% (0.870)	0.32% (1.263)
	Mid	-0.28% (-0.917)	0.34% (1.518*)	0.31% (0.999)	-0.21% (-0.584)	-0.10% (-0.495)	0.51% (1.964**)	-0.56% (-1.649*)	-0.01% (-0.065)	0.61% (2.093**)
	High	0.17% (1.053)	0.20% (0.796)	0.49% (2.328**)	-0.36% (-1.685**)	0.54% (3.041***)	0.77% (2.514***)	-0.04% (-0.186)	0.36% (1.822**)	0.69% (1.955**)

Table 3.4: Monthly Value-Weighted Returns and Alphas of Portfolios sorted by Valuation Ratios and Distance-to-Default, 1996-2008 (continued)

		B/M			E/P			C/P		
		Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel C: Three-Factor Alphas and t-statistics										
DD	Low	-0.67% (-1.584*)	-0.03% (-0.093)	0.30% (1.107)	-0.87% (-2.160**)	0.11% (0.427)	0.21% (0.810)	-0.72% (-1.793**)	0.17% (0.657)	0.33% (1.225)
	Mid	0.08% (0.265)	0.25% (1.068)	0.01% (0.046)	-0.05% (-0.140)	-0.01% (-0.027)	0.36% (1.373*)	-0.30% (-0.869)	0.04% (0.192)	0.36% (1.236)
	High	0.34% (2.039**)	0.24% (0.919)	0.53% (2.361***)	-0.19% (-0.863)	0.67% (3.741***)	0.81% (2.498***)	0.10% (0.490)	0.49% (2.444***)	0.67% (1.802**)
Panel D: Four-Factor Alphas and t-statistics										
DD	Low	-0.64% (-1.503*)	0.13% (0.461)	0.47% (1.850**)	-0.68% (-1.740**)	0.20% (0.782)	0.29% (1.150)	-0.59% (-1.477*)	0.25% (0.973)	0.41% (1.573*)
	Mid	0.06% (0.201)	0.33% (1.407*)	-0.06% (-0.184)	-0.09% (-0.243)	-0.02% (-0.112)	0.41% (1.576*)	-0.28% (-0.803)	0.06% (0.277)	0.37% (1.252)
	High	0.28% (1.688**)	0.18% (0.662)	0.53% (2.327**)	-0.23% (-1.051)	0.69% (3.809***)	0.71% (2.211**)	0.04% (0.176)	0.50% (2.463***)	0.60% (1.605*)

In contrast, the average monthly equal-weighted returns of low default risk value stocks were exceptionally high over the sample period: 1.12% for high B/M, high DD stocks; 1.36% for high E/P, high DD stocks and 1.45% for high C/P, high DD stocks. The corresponding value-weighted returns are 1.17%, 1.46% and 1.40% respectively. For each of the three valuation ratios, no other portfolio displayed higher average returns than the low default risk value stock portfolio (although the value-weighted portfolios exhibit one exception to this observation). Thus, contrary to risk-based explanations for stock returns and consistent with mispricing, investors are rewarded for holding assets with low levels of default risk.

Panel B presents the alphas of the portfolios after adjusting for risk using the CAPM. In the case of high default risk growth stocks, the equal-weighted CAPM alphas are all large, negative and statistically significant at the 1% level. As expected, the alphas are larger in absolute value than the raw returns: -1.49% for low B/M, low DD stocks; -1.13% for low E/P, low DD stocks and -1.21% for low C/P, low DD stocks. The corresponding alphas for value weighted returns are -1.00%, -1.05% and -0.96%. Thus risk-adjustment using the CAPM strengthens the case for overpricing of high default risk growth stocks and weakens the case for a risk-based explanation.

In the case of low default risk value stocks, the equal-weighted CAPM alphas are large, positive and statistically significant: 0.46% for high B/M, high DD stocks; 0.67% for high E/P, high DD stocks and 0.76% for high C/P, high DD stocks. All the equal-weighted alphas are statistically significant at the 1% level. The corresponding value-weighted alphas are 0.49%, 0.77% and 0.69% respectively, and are statistically significant at the 5%, 1% and 5% levels respectively.

Panels C and D provide similar evidence in favour of mispricing based upon the Fama-French three-factor model and the Carhart four-factor model. Using equal-weighted returns, the results are similar to those obtained in Panel B. All the high default risk growth portfolios have monthly alphas close to -1% and all are statistically significant at the 1% level. All the low default risk value portfolios have monthly alphas close to 0.5% and all are statistically significant at the 1% level.

The evidence that high default risk growth stocks are overpriced is somewhat weaker in the case of value-weighted returns. For low B/M, low DD portfolios the hypothesis of no mispricing can only be rejected (in favour of overpricing) at the 10% level of significance, using either the Three-Factor or Four-Factor Model. However, the alphas of low E/P, low DD portfolios are negative and statistically significant at the 5% level in both models. For low default risk value portfolios, the hypothesis of no mispricing can be rejected (in favour of underpricing) at the 5% level or better except in the case of the high C/P, high DD portfolio where it can be rejected at the 10% level. Using either the Three-Factor or Four-Factor model, the monthly value weighted alphas of high default risk growth stocks are all in the range -0.87% to -0.59%, while the monthly value-weighted alphas of low default risk value stocks are all in the range 0.53% to 0.81%.

The pricing errors of low default risk value stocks and of high default risk growth stocks are not due solely to the value premium or to the effect of default risk; the combined effect of both DD and the relevant valuation ratio is required to generate pricing errors of the magnitude shown in Tables 3.3 and 3.4. For example, the three-factor alpha of the

low B/M, low DD portfolio (-1.27% equal weighted and -0.67% value-weighted) is larger in absolute value than the three-factor alphas of the low B/M quintile in Table 3.1 (-0.34% equal-weighted and -0.06% value-weighted) and the low DD quintile (-0.60% equal-weighted and -0.05% value-weighted). Similarly, the three-factor alphas of the high B/M, high DD portfolio (0.46% equal-weighted and 0.53% value-weighted) are larger than the three-factor alphas of the high B/M quintile (0.05% equal-weighted and 0.07% value-weighted) and the high DD quintile (0.38% equal-weighted and 0.32% value-weighted). This result holds for all three valuation ratios and applies equally well to a comparison of the t-statistics of the alphas. Thus, the anomaly is not a de-facto value premium or default risk effect; it requires the interaction of both value and default risk.

In summary, the evidence presented in this section is consistent with the mispricing of large capitalisation Australian stocks when valuation ratios are either too high or too low relative to default risk. Even before adjusting for risk using any of the three asset-pricing models, the negative average returns of high default risk growth portfolios defies explanation on a reward-for-risk basis, and is thus consistent with overvaluation. Following risk-adjustment using the above three models, the evidence is still consistent with the overvaluation of high default risk growth stocks and the undervaluation of low default risk value stocks. However, it must be borne in mind that the evidence based upon the alphas from any asset pricing model might equally well indicate model misspecification. This particular concern is addressed in the next section.

3.5.3 Inconsistency with Rational Pricing and Market Efficiency

In this section, additional evidence is presented to determine whether the results in Section 3.5.2 are most likely attributable to mispricing or to asset pricing model misspecification. First, the pricing of portfolio risk rather than default risk is examined as a possible explanation for the raw returns and pricing errors observed for high default risk growth stocks and low default risk value stocks. An observation that high default risk growth stocks have lower portfolio risk than low default risk value stocks would be consistent with rational pricing, and thus strengthen the case that the significant pricing errors reported in Section 3.5.2 are due to model misspecification rather than to mispricing. This section therefore compares high default risk growth and low default risk value portfolios on the basis of reward-to-risk (Sharpe Ratio), volatility and residual volatility from the CAPM, and conducts F-tests of equality of the latter two. Table 3.5 presents the results.

The Sharpe ratio is the excess return of a portfolio per unit of total risk (standard deviation). However, expressing portfolio performance on a per-unit of total risk basis provides no support for a rational pricing explanation of the results of this study. The low default risk value portfolios all have Sharpe ratios far in excess of the Sharpe Ratio for the market, while the high default risk growth portfolios all have large negative Sharpe ratios. Similarly, there is no evidence in Table 3.5 that low default risk value portfolios have higher risk than high default risk growth portfolios, whether risk is measured as total volatility or as residual volatility from a market model. On the contrary, the high default risk growth portfolios are uniformly riskier than the low default risk value portfolios, a result that applies to both total volatility and to residual

volatility, to all of the valuation ratios, and to both equal-weighted and value-weighted returns. In most cases, the difference in portfolio risk between high default risk growth stocks and low default risk value stocks is statistically significant, the exception being value-weighted returns where C/P is the valuation ratio. In summary, rational pricing of portfolio risk cannot explain the large positive returns and pricing errors of low default risk value portfolios or the large negative returns and pricing errors of high default risk growth stocks.

Table 3.5: Risk and Performance Measures for High Default Risk Growth and Low Default Risk Value Portfolios
All stocks excluding property trusts, foreign companies, investment trusts, preference shares and partly-paid shares are ranked independently on distance-to-default (DD), book-to-market (B/M), earnings-to-price (E/P) and cash earnings-to-price (C/P) at December 31st each year from 1995 to 2007. Each stock is independently assigned to both a DD category and a category based upon B/M, E/P or C/P, and nine portfolios are formed from the intersections of the DD and B/M, E/P or C/P categories. The following table shows portfolio performance and risk measures for the high default risk growth and the low default risk value portfolios, based on equal-weighted returns (Panel A) and value-weighted returns (Panel B). The F-statistics test the equality of the applicable volatility measures of the high default risk growth and low default risk value portfolios, based on a given valuation ratio (either B/M, E/P or C/P).

Panel A: Equal-Weighted Returns

	Market	Low B/M Low DD	High B/M High DD	Low E/P Low DD	High E/P High DD	Low C/P Low DD	High C/P High DD
Sharpe Ratio	0.076	-0.128	0.195	-0.103	0.226	-0.103	0.238
Annualised Volatility	12.12%	28.12%	11.89%	24.02%	14.06%	25.87%	14.58%
F-statistic (p-value)		2.3654 (0.000)		1.7080 (0.000)		1.7737 (0.000)	
Annualised Residual Volatility	-	19.35%	7.33%	14.96%	8.73%	15.96%	9.33%
F-statistic (p-value)		2.6405 (0.000)		1.7129 (0.000)		1.7096 (0.000)	

Panel B: Value-Weighted Returns

	Market	Low B/M Low DD	High B/M High DD	Low E/P Low DD	High E/P High DD	Low C/P Low DD	High C/P High DD
Sharpe Ratio	0.076	-0.099	0.181	-0.085	0.205	-0.072	0.171
Annualised Volatility	12.12%	23.31%	13.80%	25.53%	17.10%	25.73%	19.29%
F-statistic (p-value)		1.6892 (0.001)		1.4927 (0.007)		1.3338 (0.037)	
Annualised Residual Volatility	-	17.60%	9.12%	16.53%	13.14%	16.59%	15.16%
F-statistic (p-value)		1.9304 (0.000)		1.2578 (0.077)		1.0940 (0.288)	

Next, evidence is examined that determines whether the pricing error results are consistent with market inefficiency. Given that a high DD score implies the information in recent share prices is relatively favourable, the high returns of high DD value stocks imply return continuation and therefore underreaction. Similarly, as a low DD score implies unfavourable information embedded in recent share prices, the low returns of low DD growth stocks are also consistent with underreaction. The main testable hypotheses in this analysis are therefore that high DD value stocks do indeed have previous good price performance and favourable information relative to other value stocks, while low DD growth stocks do indeed have previous poor price performance and unfavourable information relative to other growth stocks. This section therefore compares the previous returns and earnings-related information of firms sorted by default risk and valuation ratios. All of the dependent variables in this analysis are computed at June 30th each year, six months before portfolio formation, thus the information represented by these variables is information *prior* to classification by value and default risk. Table 3.6 presents the results of this comparison.

It is immediately apparent from Panel A in Table 3.6 that prior returns vary inversely with each valuation ratio, and thus growth stocks in general have higher recent returns than value stocks. However, returns also increase with DD across all B/M, E/P and C/P categories, and thus high DD value stocks have higher prior returns than other value stocks, and low DD growth stocks have lower prior returns than other growth stocks. Therefore, the stocks argue to be undervalued (low default risk value stocks) have high returns before (as well as after) portfolio formation relative to other value stocks, consistent with underreaction. Similarly, the stocks argued to be overvalued (high

default risk growth stocks) have low returns before (as well as after) portfolio formation relative to other growth stocks, also consistent with underreaction.

Panel B presents the prior change in earnings-per-share (EPS), deflated by share price. Within each B/M, E/P and C/P category (except for the intermediate B/M category), the change in EPS increases monotonically with DD. Thus high DD firms have EPS that are increasing at a faster rate than low DD firms. The difference between low DD growth stocks and high DD value stocks is particularly striking. High DD value stocks have the largest prior increase in EPS than any other category including high DD growth stocks, a result that holds regardless of whether B/M, E/P or C/P is the valuation ratio. Similarly, low DD growth stocks have the largest prior decrease in EPS of any category when E/P or C/P is the valuation ratio; stocks with low DD and low B/M have a change in EPS that is statistically indistinguishable from that of stocks with low DD and high B/M. In any event, the results from Panel B support the contention that low default risk value stocks have improving earnings relative to other stocks, while high default risk growth stocks have deteriorating earnings relative to other stocks.

Panel C presents the variation in profitability, measured by return on assets (ROA), across portfolios. Consistent with Fama and French (1995), profitability is inversely related to B/M. As E/P and C/P are both computed from current earnings, the increase in profitability that Panel C displays with respect to these two variables is unremarkable. However, of more interest is the observation that ROA increases monotonically with DD in each B/M, E/P and C/P category, a result that is highly statistically significant. Thus, low default risk value stocks are more profitable than other value stocks and high default risk growth stocks are less profitable than other

growth stocks. However, when value/growth is measured using E/P and C/P the evidence of underreaction from Panel C is much stronger – high default risk growth stocks have the lowest ROA of *any* other category and low default risk value stocks have the highest ROA of *any* other category. Thus, the high returns of undervalued (low default risk value) stocks can be viewed as a delayed reaction to high profitability, whilst the low returns of overvalued (high default risk growth) stocks can be viewed as delayed reaction to low profitability.

The same conclusion applies when considering the change in ROA (ΔROA) from the previous year, rather the actual level of ROA (Panel D). ΔROA measures the historical change in profitability. As was the case with ROA, ΔROA also increases monotonically with DD in each B/M, E/P and C/P category, and this variation is statistically significant for all stocks except those with high B/M. Thus, high DD firms have a larger ΔROA than other firms in the same value/growth category. Amongst the portfolios sorted by E/P and C/P, low default risk value firms have the largest ΔROA of any category, and high default risk growth firms have the smallest ΔROA of any category (a result similar to that in Panel C). Thus, Panel D supports the contention that the high returns of undervalued stocks are a delayed reaction to an increase in profitability, whilst the low returns of overvalued stocks are a delayed reaction to a decrease in profitability.

In summary, the results of this section demonstrate that high default risk growth stocks have relatively poor price and earnings performance prior to portfolio formation, while low default risk value stocks have relatively good price and earnings performance prior

to portfolio formation[25]. The fact that the poor (good) price performance of high default risk growth (low default risk value) stocks continues after portfolio formation is consistent with an underreaction to earnings-related information.

[25] At the very least, it is confirmed that DD effectively captures an element of financial distress related to profitability.

Table 3.6: Other Characteristics of Portfolios Sorted by Valuation Ratios and Distance-to-Default, 1996-2008
Stocks are assigned to portfolios based upon their ranking by DD, B/M, E/P and C/P as per Table 3.2. Prior Six-Month Return is the return over the six months from January to June in the year of portfolio formation. Price-Deflated Change in Earnings-per-Share (EPS) is earnings-per-share from the latest financial statement as at June 30th in the year of portfolio formation, less earnings-per-share from the previous fiscal year divided by share price at June 30th. Return on Assets (ROA) is net income divided by total assets from the latest financial statement as at June 30th in the year of portfolio formation; the Change in ROA is ROA from the latest financial statement as at June 30th in the year of portfolio formation, less ROA from the previous fiscal year. KW χ^2 is the Kruskal-Wallis test statistic of equality of group medians, with figures in parenthesis denoting the p-value of a test that the group medians are identical.

		B/M				E/P				C/P			
		Low	Mid	High	KW χ^2	Low	Mid	High	KW χ^2	Low	Mid	High	KW χ^2
Panel A: Median Prior Six-Month Return													
DD	Low	7.74%	0.77%	-7.39%	45.65 (0.000)	-4.92%	-1.19%	-1.75%	16.19 (0.000)	1.63%	2.32%	-6.15%	18.78 (0.000)
	Mid	9.96%	11.75%	5.35%	13.67 (0.001)	11.25%	9.67%	8.58%	5.87 (0.053)	13.60%	8.96%	7.83%	8.71 (0.013)
	High	15.68%	12.66%	6.94%	35.46 (0.000)	14.36%	11.78%	9.59%	0.65 (0.724)	14.25%	9.78%	12.02%	18.64 (0.000)
	KW χ^2	112.09 (0.000)	90.44 (0.000)	17.46 (0.000)		89.79 (0.000)	68.06 (0.000)	94.55 (0.000)		142.79 (0.000)	45.28 (0.000)	42.99 (0.000)	
Panel B: Median Price-Deflated Change in Earnings-per-Share													
DD	Low	0.00002	0.00010	-0.00001	3.39 (0.184)	-0.00018	0.00007	0.00013	29.25 (0.000)	-0.00005	0.00009	0.00007	13.58 (0.001)
	Mid	0.00011	0.00010	0.00006	2.49 (0.288)	-0.00000	0.00010	0.00021	73.83 (0.000)	0.00002	0.00011	0.00016	28.89 (0.000)
	High	0.00011	0.00010	0.00023	15.81 (0.000)	0.00007	0.00012	0.00033	106.00 (0.000)	0.00009	0.00011	0.00034	38.31 (0.000)
	KW χ^2	42.28 (0.000)	2.32 (0.314)	15.26 (0.000)		14.35 (0.001)	10.56 (0.005)	80.20 (0.000)		25.38 (0.000)	5.43 (0.066)	75.54 (0.000)	

Table 3.6: Other Characteristics of Portfolios Sorted by Valuation Ratios and Distance-to-Default, 1996-2008 (continued)

Panel C: Median Return on Assets (ROA)													
DD	Low	4.46%	3.17%	2.83%	161.82 (0.000)	0.79%	3.05%	4.91%	92.08 (0.000)	0.55%	2.61%	4.28%	27.29 (0.000)
	Mid	6.91%	5.08%	4.29%	29.30 (0.000)	2.49%	5.05%	6.67%	177.99 (0.000)	2.68%	5.34%	6.02%	103.72 (0.000)
	High	9.15%	6.47%	4.47%	6.62 (0.036)	4.90%	7.00%	8.56%	274.21 (0.000)	5.88%	7.36%	7.37%	224.86 (0.000)
	KW χ^2	120.47 (0.000)	120.53 (0.000)	74.06 (0.000)		129.59 (0.000)	234.91 (0.000)	157.34 (0.000)		109.87 (0.000)	246.59 (0.000)	196.97 (0.000)	
Panel D: Median Change in ROA (ΔROA)													
DD	Low	0.00%	-0.03%	-0.24%	3.23 (0.199)	-1.30%	-0.02%	0.12%	16.90 (0.000)	-0.67%	-0.05%	0.09%	9.99 (0.007)
	Mid	0.18%	0.11%	0.17%	1.50 (0.472)	-0.65%	0.16%	0.47%	50.54 (0.000)	-0.42%	0.08%	0.45%	34.85 (0.000)
	High	0.66%	0.42%	0.22%	3.63 (0.163)	0.25%	0.29%	0.93%	70.53 (0.000)	0.24%	0.38%	0.85%	29.59 (0.000)
	KW χ^2	17.87 (0.000)	13.37 (0.001)	1.25 (0.535)		11.16 (0.004)	14.33 (0.001)	27.87 (0.000)		16.26 (0.000)	24.67 (0.000)	24.96 (0.000)	

3.6 Summary and Conclusion

This study has made three contributions to the Australian asset-pricing literature. First, the absence of a size effect and the existence of a large and statistically significant value premium amongst large-capitalisation stocks are documented. Second, and more importantly, all of the static asset-pricing models tested (the CAPM, Fama-French three-factor model and Carhart four-factor model) are rejected when confronted with a hypothesis that high default risk growth stocks are overvalued while low default risk value stocks are undervalued. Finally, evidence is presented that the rejection of the above models is most likely due to market inefficiency, in the form of underreaction to earnings-related information. Each of these three contributions is now discussed in more detail.

3.6.1 Cross-sectional Determinants of the Returns of Large Australian Stocks

A relatively minor contribution of this study is to examine the cross-sectional determinants of stock returns specifically amongst large capitalisation stocks. Whilst Halliwell et al. (1999) and Gaunt (2004) study the role of size and B/M in the returns of Australian stocks, they do so for the whole market-capitalisation spectrum, and the relevance of their inferences to a specific large capitalisation universe is somewhat diminished. For example, whilst both of these studies argue the evidence for a value premium in Australia is weak, it is clear that this conclusion is due to small stocks. Both studies tabulate a direct relationship between B/M and returns *amongst the largest size quintiles* but no relationship between B/M and returns amongst the smallest size quintiles. Both studies also report a return premium for small size, but only for the

smallest size quintiles. This study also finds similar patterns of returns in the sample tested (1996-2008) by sorting the full market capitalisation spectrum on size and each of the valuation ratios (B/M, E/P and C/P), but these results are confined to Appendix 3A to conserve space.

However, when one-way sorts are conducted on size, B/M, E/P and C/P based on a large-capitalisation universe, this study finds no statistically significant evidence that size plays a role in stock returns, but does find evidence of a value premium that is economically and statistically significant. This contrasts with the conclusions of Halliwell et al. (1999) and Gaunt (2004) that evidence of a value premium in Australia is weak. Based on the sorts on DD, this study also finds evidence of a negative default risk premium if returns are equal-weighted, (consistent with Campbell et al., 2008), however this evidence is not statistically significant for value-weighted returns (consistent with Gharghori et al., 2007).

3.6.2 Value, Default Risk and Stock Returns

The main contribution is the study of mispricing as a function of valuation ratios and default risk amongst large Australian stocks. The contention that high default risk growth stocks are overvalued whilst low default risk value stocks are undervalued is supported by the pattern of raw returns amongst value and default risk sorted portfolios, and by the tests of the CAPM, Fama-French three-factor model and Carhart four-factor model. In the sample tested, high default risk growth stocks have negative returns on average, whilst low default risk value stocks have very high returns on average. Whilst conventional tests of asset pricing models test the hypothesis that portfolio alphas are zero against a null that the alphas are non-zero, the alternative hypothesis of this study

imposes a constraint on the sign of the alpha (namely negative in the case of high default risk growth stocks and positive in the case of low default risk value stocks). Consistent with this hypothesis, the alphas of low default risk value stocks are indeed all positive, while the alphas of high default risk growth stocks are indeed all negative. This result holds regardless of whether B/M, E/P or C/P are used to form portfolios, regardless of whether returns are equal-weighted or value-weighted, and regardless of the choice of asset pricing model. In all but a small number of these variations, the alphas are significant at the 5% level or better. The alphas that are not significant at the 5% level are significant at the 10% level. The tests thus overwhelmingly reject all of the asset pricing models in favour of the mispricing hypothesis. The finding that high default risk growth stocks are overvalued is thus consistent with Griffin and Lemmon (2002), while the finding of that low default risk value stocks are undervalued is consistent with Piotroski (2000).

The conclusions on the adequacy of the above asset pricing models differ somewhat from Gharghori et al. (2007), who argue that the Fama-French three-factor model adequately explains the returns of portfolios sorted by size, B/M and default risk. Gharghori et al. (2007) report a significantly positive three-factor alpha for their large, low default risk value portfolio which is consistent with the findings of this study, but they also report an insignificant three-factor alpha for their large, high default risk growth portfolio which is inconsistent with the results of this study. However, there are a number of key methodological differences between the current study and theirs. This study follows Fama and French (1992) and other related studies by excluding property trusts, investment trusts and the shares of foreign companies, for which the B/M calculation may be problematical, and by calculating the book value of equity as the

actual book value from each company's balance sheet less preference capital and including balance sheet taxes. In contrast, Gharghori et al. (2007) do not exclude property trusts, investment trusts and the shares of foreign companies, and employ Net Tangible Assets for book equity. Furthermore, Gharghori et al. (2007) conduct three-by-three-by-three sorts on default risk, B/M and size, whereas this study conducts three-by-three sorts on default risk and each respective valuation ratio, but limits the sample to large stocks only.

3.6.3 Inconsistency with Rational Pricing and Market Efficiency

Whilst all of the asset pricing models tested are rejected, the possibility cannot be rejected that the results in this regard are due to model misspecification, and not to mispricing. However, the results are inconsistent with the rational pricing of risk and therefore present substantial problems to alternative model specifications, at least of the static kind[26]. The portfolios of overvalued (high default risk growth) stocks not only have high default risk, but also have high portfolio risk; in contrast, the portfolios of undervalued (low default risk value) stocks not only have low default risk, but also have low portfolio risk. The difference in risk between overvalued and undervalued portfolios is statistically significant and applies to both total risk and idiosyncratic risk. Therefore, an alternative rational asset pricing model needs to explain why it has been possible in this study to form portfolios with high risk and low returns and portfolios with low risk and high returns. On the other hand, Shleifer and Vishny (1997) argue that the presence of idiosyncratic risk poses a substantial deterrent to arbitrageurs and is therefore an important reason why some types of mispricing persist. The results of this study are therefore consistent with the Shleifer and Vishny (1997) thesis with regard to high

[26] It is left as a task for future research to determine whether conditional asset pricing models (see for example, Durack et al., 2004) can explain the results of this study.

default risk growth stocks, and demonstrate it is extremely difficult to form well-diversified portfolios of these types of stocks.

The results are also inconsistent with market efficiency because they imply a *gross* underreaction to information. For example, overvalued (high default risk growth) stocks exhibit poor prior returns and declining earnings. Their low DD score indicates that investors responded *somewhat* to the prior poor performance, as DD incorporates information in recent share prices. However, the poor returns continue after the portfolio formation date, indicating the initial market reaction was an underreaction. Similarly, the high post portfolio-formation returns of undervalued (low default risk value) stocks are a continuation of their prior earnings and return performance. Low default risk value stocks in the sample have increasing earnings and prior returns that are higher than that of other value stocks, and their high DD score indicates that investors responded *somewhat* to the relatively good prior performance.

The fact that the returns of mispriced stocks generally maintain the same direction before and after portfolio formation suggests an important role for underreaction and momentum in the value premium. The results are therefore consistent with Bird and Casavecchia (2007b), who find that momentum is a key variable in the identification of overvalued growth stocks and of undervalued value stocks, and contrasts with some behavioural finance theories that attempt to model the value premium as an overreaction (Barberis et al., 1998; Hong and Stein, 1999; Barberis and Shleifer, 2003). It is therefore plausible that the high default risk growth stocks and low default risk value stocks in this study correspond respectively to high trading-volume losers and low trading-volume winners in the momentum life cycle of Lee and Swaminathan (2000). In the

momentum life cycle, high trading-volume losers were once high trading-volume winners that became expensive growth stocks, while low volume winners were once low volume losers that became neglected value stocks. However, momentum is not the driving force behind the results of this study, as the evidence of mispricing withstands the Carhart four-factor model which includes momentum as a factor. In concluding, the study of mispricing and behavioural explanations of the value premium still offers fruitful opportunities for further research, particularly with regard to the previously-underemphasised role of underreaction.

APPENDIX 3A

Returns of Portfolios Formed by Two-Way Sorts on Size (Market Capitalisation) and Value (Book-To-Market, Earnings-To-Price and Cash Flow-To-Price), Based on All Listed Stocks

Table 3A.1: Returns and Characteristics of Portfolios Sorted by Book-to-Market and Size, 1996-2008

All stocks excluding property trusts, foreign companies, investment trusts, preference shares, partly-paid shares and negative book-equity firms are ranked independently on market capitalisation (size) and book-to-market (B/M) at December 31st each year from 1995 to 2007. Each stock is independently assigned to both a size quintile and a B/M quintile, and 25 portfolios are formed from the intersections of the size and B/M quintiles. Market capitalisation is calculated as the product of share price and number of shares outstanding. The size variable is the market capitalisation as at December 31st. Book-to-market is the ratio of the book value of equity to market capitalisation as at June 30th. Book value of equity is balance sheet shareholders' equity excluding preference shares and including balance sheet provisions for deferred taxes, taken from the latest balance sheet available in the 12 months ending June 30th in the year of portfolio formation. Equal-weighted and value-weighted monthly returns are calculated for each portfolio for the following 12 months after each portfolio formation date. Panels A and B are based on the time-series averages of these monthly returns. Panels C to E are based on the pooled time-series and cross-sectional average of the characteristic. One-sided significance levels of t-statistics are indicated by *** (1%), ** (5%) and * (10%).

Panel A: Average Monthly Equal-Weighted Returns

	Low B/M	2	3	4	High B/M	High-Low	t-statistic
Small	3.26%	4.29%	4.05%	3.73%	3.95%	0.69%	1.201
2	1.00%	0.63%	1.11%	1.35%	1.25%	0.25%	0.421
3	-0.76%	0.74%	0.70%	0.53%	1.20%	1.96%	3.997***
4	-0.68%	0.20%	0.36%	0.81%	0.88%	1.56%	3.809***
Big	0.16%	0.52%	0.79%	0.77%	1.70%	1.54%	4.321***
Small-Big	3.10%	3.78%	3.26%	2.96%	2.26%		
t-statistic	3.665***	3.639***	4.138***	3.698***	2.970***		

Panel B: Average Monthly Value-Weighted Returns

	Low B/M	2	3	4	High B/M	High-Low	t-statistic
Small	2.45%	3.90%	3.55%	2.45%	2.50%	0.05%	0.066
2	0.18%	0.17%	0.91%	0.78%	0.97%	0.79%	1.319
3	-0.77%	1.01%	0.79%	0.73%	1.30%	2.07%	4.109***
4	-0.07%	0.47%	0.64%	1.17%	1.14%	1.21%	2.843***
Big	0.72%	0.70%	0.94%	0.91%	2.16%	1.45%	2.950***
Small-Big	1.73%	3.20%	2.62%	1.54%	0.34%		
t-statistic	1.664**	2.792***	2.730***	1.711*	0.402		

Table 3A.1: Returns and Characteristics of Portfolios Sorted by Book-to-Market and Size, 1996-2008 (continued).

Panel C Average Number of Stocks

	Low B/M	2	3	4	High B/M
Small	32.3	24.8	30.7	44.3	77.7
2	31.9	37.8	42.7	52.1	60.4
3	41.5	45.4	46.1	48.6	47.9
4	54.8	50.1	51.6	48.0	27.5
Big	65.3	67.8	54.9	32.8	13.0

Panel D Average Market Capitalisation ($ millions)

	Low B/M	2	3	4	High B/M
Small	345	381	371	367	350
2	1,062	1,099	1,044	1,022	1,022
3	2,735	2,917	2,805	2,681	2,577
4	9,644	9,521	9,339	9,295	8,913
Big	254,553	383,027	287,630	161,185	93,265

Panel E: Average B/M

	Low B/M	2	3	4	High B/M
Small	0.188	0.454	0.690	1.045	2.778
2	0.197	0.442	0.701	1.051	2.408
3	0.201	0.435	0.684	1.043	2.381
4	0.196	0.437	0.693	1.031	1.729
Big	0.200	0.454	0.676	0.986	1.643

Table 3A.2: Returns and Characteristics of Portfolios Sorted by Earnings-to-Price and Size, 1996-2008

All stocks excluding property trusts, foreign companies, investment trusts, preference shares and partly-paid shares are ranked independently on market capitalisation (size) and earnings-to-price (E/P) at December 31st each year from 1995 to 2007. Each stock is independently assigned to both a size quintile and an E/P quintile, and 25 portfolios are formed from the intersections of the size and E/P quintiles. Market capitalisation is calculated as the product of share price and number of shares outstanding. The size variable is the market capitalisation as at December 31st. Earnings-to-price is the ratio of earnings before abnormal items to market capitalisation as at June 30th. Earnings before abnormal items excludes outside equity interests and preference dividends, and is taken from the latest profit and loss statement available in the 12 months ending June 30th in the year of portfolio formation. Equal-weighted and value-weighted monthly returns are calculated for each portfolio for the following 12 months after each portfolio formation date. Panels A and B are based on the time-series averages of these monthly returns. Panels C to E are based on the pooled time-series and cross-sectional average of the characteristic. One-sided significance levels of t-statistics are indicated by *** (1%), ** (5%) and * (10%).

Panel A: Average Monthly Equal-Weighted Returns

	Low E/P	2	3	4	High E/P	High-Low	t-statistic
Small	4.27%	3.51%	4.01%	2.06%	3.39%	-0.88%	-1.172
2	0.91%	1.03%	1.42%	0.93%	0.83%	-0.08%	-0.148
3	-0.40%	0.18%	0.38%	0.92%	1.36%	1.75%	3.201***
4	0.21%	-0.88%	-0.30%	0.31%	1.00%	0.79%	1.347*
Big	n/a	-0.84%	-0.17%	0.87%	0.94%	n/a	n/a
Small-Big	n/a	4.35%	4.18%	1.19%	2.45%		
t-statistic	n/a	4.813***	5.662***	1.323*	3.988***		

Panel B: Average Monthly Value-Weighted Returns

	Low E/P	2	3	4	High E/P	High-Low	t-statistic
Small	2.71%	2.47%	3.76%	1.64%	2.40%	-0.31%	-0.380
2	0.29%	0.54%	0.85%	0.77%	0.70%	0.41%	0.743
3	-0.50%	0.15%	0.63%	0.95%	1.59%	2.09%	3.708***
4	0.15%	-0.60%	0.37%	0.54%	1.25%	1.10%	1.836**
Big	n/a	-0.79%	0.20%	0.92%	1.21%	n/a	n/a
Small-Big	n/a	3.26%	3.56%	0.72%	1.19%		
t-statistic	n/a	3.359***	3.921***	0.768	1.665**		

Table 3A.2: Returns and Characteristics of Portfolios Sorted by Earnings-to-Price and Size, 1996-2008 (continued).

Panel C Average Number of Stocks

	Low E/P	2	3	4	High E/P
Small	113.2	59.2	26.6	8.4	26.2
2	71.6	72.9	41.7	14.1	33.5
3	35.5	62.1	55.9	27.9	52.8
4	11.7	32.6	58.3	59.9	71.4
Big	1.6	7.1	51.6	123.6	50.5

Panel D Average Market Capitalisation ($ millions)

	Low E/P	2	3	4	High E/P
Small	339	358	386	397	354
2	972	1,057	1,081	1,113	1,127
3	2,577	2,615	2,807	2,937	2,888
4	7,383	8,877	9,323	10,235	9,343
Big	37,330	67,048	189,923	300,212	347,017

Panel E: Average E/P

	Low E/P	2	3	4	High E/P
Small	-1.016	-0.128	-0.022	0.054	0.499
2	-0.849	-0.123	-0.020	0.053	0.590
3	-0.762	-0.114	-0.016	0.057	0.164
4	-0.629	-0.104	-0.010	0.057	0.136
Big	-0.712	-0.088	0.012	0.054	0.112

Table 3A.3: Returns and Characteristics of Portfolios Sorted by Cash Flow-to-Price and Size, 1996-2008

All stocks excluding property trusts, foreign companies, investment trusts, preference shares and partly-paid shares are ranked independently on market capitalisation (size) and cash flow-to-price (C/P) at December 31st each year from 1995 to 1997. Each stock is independently assigned to both a size quintile and a C/P quintile, and 25 portfolios are formed from the intersections of the size and C/P quintiles. Market capitalisation is calculated as the product of share price and number of shares outstanding. The size variable is the market capitalisation as at December 31st. Cash flow-to-price is the ratio of cash earnings to market capitalisation as at June 30th. Cash earnings is earnings before abnormal items, depreciation and amortisation and excludes outside equity interests and preference dividends, taken from the latest profit and loss statement available in the 12 months ending June 30th in the year of portfolio formation. Equal-weighted and value-weighted monthly returns are calculated for each portfolio for the following 12 months after each portfolio formation date. Panels A and B are based on the time-series averages of these monthly returns. Panels C to E are based on the pooled time-series and cross-sectional average of the characteristic. One-sided significance levels of t-statistics are indicated by *** (1%), ** (5%) and * (10%).

Panel A: Average Monthly Equal-Weighted Returns

	Low C/P	2	3	4	High C/P	High-Low	t-statistic
Small	4.34%	3.45%	3.33%	3.24%	3.42%	-0.93%	-1.203
2	0.69%	1.43%	0.96%	0.64%	1.07%	0.38%	0.679
3	-0.72%	0.27%	0.36%	0.90%	1.50%	2.22%	4.123***
4	-0.06%	-0.94%	-0.07%	0.60%	0.84%	0.90%	1.440*
Big	n/a	-0.15%	0.12%	0.82%	0.98%	n/a	n/a
Small-Big	n/a	3.60%	3.21%	2.42%	2.44%		
t-statistic	n/a	4.134***	4.039***	2.969***	3.690***		

Panel B: Average Monthly Value-Weighted Returns

	Low C/P	2	3	4	High C/P	High-Low	t-statistic
Small	2.72%	2.66%	3.14%	2.75%	2.32%	-0.40%	-0.484
2	-0.03%	0.90%	0.51%	0.33%	0.88%	0.91%	1.717**
3	-1.08%	0.18%	0.67%	1.03%	1.81%	2.88%	5.530***
4	-0.31%	-0.86%	0.42%	0.87%	1.17%	1.48%	2.391***
Big	n/a	-0.06%	0.37%	0.94%	1.23%	n/a	n/a
Small-Big	n/a	2.72%	2.77%	1.81%	1.09%		
t-statistic	n/a	2.917***	2.512***	1.876**	1.500*		

Table 3A.3: Returns and Characteristics of Portfolios Sorted by Cash Flow-to-Price and Size, 1996-2008 (continued).

Panel C Average Number of Stocks

	Low C/P	2	3	4	High C/P
Small	112.1	56.6	24.2	11.4	29.3
2	73.4	71.1	34.0	15.9	39.4
3	35.1	61.6	49.6	31.9	55.9
4	11.6	35.6	60.6	63.5	62.6
Big	1.3	8.9	65.7	111.3	47.2

Panel D Average Market Capitalisation ($ millions)

	Low C/P	2	3	4	High C/P
Small	341	358	390	377	348
2	975	1,058	1,120	1,071	1,098
3	2,572	2,640	2,893	2,980	2,746
4	7,567	8,468	9,618	10,156	9,306
Big	39,007	57,991	218,472	343,985	249,129

Panel E: Average C/P

	Low C/P	2	3	4	High C/P
Small	-0.863	-0.098	0.003	0.099	1.577
2	-0.719	-0.092	0.003	0.104	0.661
3	-0.625	-0.087	0.006	0.101	0.291
4	-0.426	-0.073	0.017	0.100	0.245
Big	-0.528	-0.057	0.038	0.092	0.208

CHAPTER 4: ANALYST OPTIMISM AND THE ERRORS-IN-EXPECTATIONS HYPOTHESIS: AUSTRALIAN EVIDENCE ON THE ROLE OF DEFAULT RISK

4.1 Abstract

Contrary to the errors-in-expectations hypothesis, a previous study by Doukas et al. (2002) reports an inverse relationship between analyst earnings forecast optimism (that is, forecast errors) and book-to-market (B/M) that is highly statistically significant. This study confirms a similar but substantially weaker relationship in Australian data over the period from 1995 to 2007. However this relationship is completely subsumed by a much stronger relationship between analyst optimism and default risk. Similarly, little variation is found in forecast errors with either earnings-to-price (E/P) or cash flow-to-price (C/P) independent of default risk, with the exception of very large forecast errors for firms with negative E/P and C/P. It is also confirmed that consensus earnings forecasts are more optimistic for high default risk growth stocks than they are for low default risk value stocks; a result not inconsistent with the errors-in-expectations hypothesis considering the evidence in Chapter 3 that these two groups of stocks are overvalued and undervalued respectively. However, the results of this study in general support *underreaction* to financial distress (in the form of either high default risk or negative earnings) and not the overreaction to or extrapolation of previous earnings growth as posited by Lakonishok et al. (1994), and are somewhat consistent with the momentum life cycle of Lee and Swaminathan (2000).

4.2 Introduction

The errors-in-expectations hypothesis states that investors are overly optimistic regarding the future prospects of, and consequently pay prices that are too high for, growth stocks. Lakonishok et al. (1994) argue that the expected future growth rates implied by valuation multiples (with which value and growth stocks are commonly defined) are not only unrealistic, but bear little resemblance to actual growth rates realised after the measurement of the multiples, a contention supported by evidence that earnings growth itself is extremely difficult, if not impossible, to predict (La Porta, 1996; Chan et al., 2003). Similarly, evidence that a substantial proportion of the value premium occurs close to company announcement dates is consistent with the idea that investors are informed by earnings surprises that their initial growth expectations might be too optimistic (La Porta et al., 1997; Skinner and Sloan, 2002).

Whilst the evidence from long-term growth rates and from announcement period returns supports the errors-in-expectations hypothesis, some conflicting evidence has emerged from analysts' *current year earnings* forecasts. Specifically, the errors-in-expectations hypothesis predicts that these forecasts should be more optimistic for growth stocks than for value stocks, but the actual data from analysts' forecasts contradicts this prediction. In particular, Doukas et al. (2002) find that the forecast error (the amount by which forecast earnings-per-share (EPS) exceeds actual EPS) *increases* directly with B/M, the *opposite* result predicted by the errors-in-expectations hypothesis. Mian and Teo (2004) also find analysts' earnings forecasts appear to be more optimistic for value stocks than for growth stocks in Japan. Thus, there appears to be consistent evidence that analysts' current-year earnings forecasts are systematically more optimistic for value stocks than for growth stocks, a conclusion inconsistent with the errors-in-

expectations hypothesis. These results have not yet been confirmed for the Australian stock market, and this is the first objective of the study.

However, a potentially important variable omitted from the above studies is financial distress, because high B/M stocks generally have higher default risk and other measures of distress relative to low B/M stocks (Fama and French, 1995; Dichev, 1998; Chen and Zhang, 1998; Piotroski, 2000). Whilst Doukas et al. (2002) control for size in their experiments and Chan and Chen (1991) argue that size is a proxy for distress, the Fama and French (1995) evidence indicates that distress is more closely related to B/M than to size. Thus, it could be argued that the relationship between analyst optimism and B/M uncovered in Doukas et al. (2002) does not adequately control for distress. There are two reasons why the failure to adequately control for distress might be a critical oversight in tests of the errors-in-expectations hypothesis that are based on analysts' forecast errors.

First, evidence from the analyst inefficiency literature suggests that analyst optimism might be directly related to distress. Analysts' forecasts are widely conjectured to be inefficient with regard to the incorporation of relevant *public* information, as forecast errors have been shown to be correlated with variables such as prior changes in EPS and prior returns (Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999; Abarbanell and Lehavy, 2003; Cohen and Lys, 2003). Analyst inefficiency makes it highly plausible that analysts' forecasts do not adequately reflect a firm's state of financial health or distress, and that forecast errors are correlated with distress-risk. Consequently, the relationship between forecast errors and B/M reported in Doukas et

al. (2002) might arise because of analyst inefficiency in recognising financial distress and because of the relationship between B/M and financial distress.

Second, studies have found significant cross-sectional variation in returns when stocks are sorted by distress/financial health indicators and valuation ratios such as B/M. In particular, evidence in Piotroski (2000), Griffin and Lemmon (2002), Mohanram (2005), and Bird and Casavecchia (2007a) suggests that financially healthy value stocks are undervalued while distressed growth stocks are overvalued. Chapter 3 confirmed this result for Australian stocks sorted by default risk and each of three valuation ratios (B/M, E/P and C/P). As the errors-in-expectations hypothesis is a model of mispricing it is therefore most relevant to mispriced stocks, which on the basis of the above studies include distressed growth stocks and financially healthy value stocks. Thus, to the extent that mispricing is related to financial distress and B/M, tests of the errors-in-expectations hypothesis should be conditioned on *both* of these variables. This argument is similar to that used by Bartov and Kim (2004), but they identify mispriced stocks in terms of B/M and accruals rather than in terms of B/M and distress. The main purpose of the study is therefore to determine how the distribution of analysts' forecast errors varies with valuation ratios (including B/M, E/P and C/P) and distress (which is measured in terms of default risk). This study is therefore the first, to the author's knowledge, to test the errors-in-expectations hypothesis using analysts' earnings forecasts *and* controlling for distress.

This study investigates how analysts' forecast errors, and by implication analyst forecast optimism, vary with distress and valuation ratios. The main predictions of the study are that forecast errors increase with distress, and consequently that analysts'

earnings forecasts are more optimistic for overvalued (that is, distressed growth) stocks than they are for undervalued (that is, financially healthy value) stocks, a result not inconsistent with the errors-in-expectations hypothesis. In the course of the analysis the manner in which forecast errors vary with valuation ratios whilst simultaneously controlling for distress is also investigated. Following Chapter 3, three valuation measures are employed for robustness purposes, namely B/M, E/P and C/P; and distress is defined in terms of default risk. As was the case in Chapter 3, the default risk indicator is distance-to-default (DD), developed by Moody's KMV and previously used in value premium studies by Vassalou and Xing (2004) and Gharghori et al. (2007). DD is arguably a more accurate predictor of default risk than models based upon accounting ratios such as Altman's z-score or Ohlson's O-score, and is otherwise preferable because it implicitly emphasises the information in current market values rather than historical data (Vassalou and Xing, 2004; Gharghori et al., 2006b).

The sample consists of the largest 300 stocks listed on the Australian Stock Exchange (ASX); the study is therefore the first, to the author's knowledge, to test the errors-in-expectations hypothesis employing Australian consensus earnings forecasts. Although analyst forecasts are generally available only for large stocks, the sample is explicitly limited to the largest 300 stocks for consistency with Chapter 3. The tests of mispricing in Chapter 3 were based on the largest 300 ASX-listed stocks primarily because, amongst this group of stocks, size (market capitalisation) was found to be a relatively unimportant determinant of stock returns whilst the value premium was found to be economically and statistically significant. As was discussed in Chapter 3, a benefit of limiting the sample to large stocks is an improvement in the overall accuracy of the calculation of DD because thinly traded stocks are excluded from the sample. Another

benefit is the exclusion of size from the tests, allowing the analysis to concentrate solely on the effects of valuation ratios and default risk.

The results of this study can be summarised as follows. As expected, analysts' earnings forecasts are overly optimistic for high default risk firms; however overly-optimistic forecasts are also observed for firms with negative values of E/P and C/P (in other words for loss-reporting firms); two findings that are consistent with analyst underreaction to distress. A similar but much weaker relationship is found between forecast errors and B/M than that reported by Doukas et al. (2002); however this (weak) relationship is completely subsumed by that between forecast errors and default risk. Similarly, there is little or no relationship between forecast errors and *positive* values of either E/P or C/P that cannot be explained by underreaction to default risk. Statistically significant evidence is also provided that analysts' earnings forecasts are more optimistic for high default risk growth stocks than for low default risk value stocks; a result not inconsistent with the errors-in-expectations hypothesis, given the results of Chapter 3 showing distressed growth-stocks to be overvalued and healthy value stocks to be undervalued. However, this finding appears to be a consequence of the main finding of analyst *underreaction* to distress, and is somewhat more difficult to explain in terms of extrapolation of or overreaction to past earnings growth. As was the case in Chapter 3, the results are argued to be more consistent with the momentum life cycle proposed by Lee and Swaminathan (2000) than with overreaction-based explanations of the value premium.

Analysts' forecast errors are found to be much smaller and the results much weaker in the second half of the sample period than in the first. However, this observation is

attributable to the generally lower default risk observed in the latter part of the sample period, and the fact that firms classified as *high default risk* by an annual sorting procedure over this time are actually lower in default risk than similarly classified firms in the first half of the sample period. Taking into account the inter-year variation in the general level of default risk however, a very strong relationship between forecast error and default risk is still observed; furthermore, loss-making firms have large forecast errors throughout the sample period. Therefore the main finding that analysts underreact to distress is relatively unaffected by sub-sample variation.

The rest of the chapter proceeds as follows. Section 4.3 discusses the data and methodology. Section 4.4 presents the empirical results. The results are discussed in detail in Section 4.5 and Section 4.6 concludes.

4.3 Data and Methodology

The data for this study are from five sources. Financial data are sourced from the Aspect Huntley Datalink database, from which are calculated book value of equity, earnings, cash earnings and debt. Monthly market data are sourced from the AGSM SPPR database, from which market capitalisation, used in the computation of the valuation ratios and to measure size, and stock returns are calculated. Daily market capitalisation data are sourced from SIRCA[27], which is used in the calculation of DD. The Reserve Bank of Australia website is used to obtain short-term interest rate data for the calculation of DD. Finally, analyst earnings forecast data is obtained from the I/B/E/S

[27] Data supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of the Australian Securities Exchange.

international summary database[28]. The financial data span the period from July 1994 till June 2006, the daily market capitalisation data span the period from November 1994 till November 2007, and the monthly market data span the period from January 1996 till December 2008. The I/B/E/S data covers forecast issued in the period from 1995 to 2006, and the earnings forecasts themselves are for fiscal year-ends covering the period from 1996 to 2007. The first four data sources are identical to the data sources used in Chapter 3, namely the Aspect Huntley Datalink database, the AGSM SPPR database, SIRCA and the Reserve Bank of Australia website. To be included in the sample, firms must have fully-paid ordinary shares listed on the ASX and be ranked in the top 300 by market capitalisation. From the resulting list of companies, property trusts, investment trusts and shares of foreign or dual-listed companies are excluded.

Consistent with Doukas et al. (2002), analyst optimism is measured by the error in the consensus current year earnings forecast, or simply the ‘forecast error’. The forecast error is the standardised (that is, deflated) difference between a company’s actual EPS and the consensus EPS forecast for the same fiscal year-end issued prior to the earnings announcement. Consistent with similar research, for example Skinner and Sloan (2002) and Doukas et al. (2002), the median EPS forecast is taken as the consensus. The median is used rather than the mean because it is less sensitive to the influence of outliers. Skinner and Sloan (2002) and Doukas et al. (2002) report their main results in terms of price-standardised forecast errors, although Doukas et al. (2002) also report results for other deflators, including the absolute value of the median forecast. As Mian and Teo (2004) point out, deflating by share price has the disadvantage of biasing the forecast errors of growth stocks towards zero relative to the forecast errors of value

[28] I/B/E/S Summary History data accessed via the Wharton Research Data Services (WRDS) website, Wharton School, University of Pennsylvania.

stocks, owing to the fact that growth stocks tend to have higher price-to-earnings ratios than value stocks. Therefore, for robustness purposes, the analysis is performed firstly using price-deflated forecast errors (FE/P) and secondly using forecast errors deflated by the absolute value of the consensus forecast (FE/|F|), defined respectively by equations (4.1) and (4.2). However, the tenor of the results is unaffected by the choice of forecast error variable.

$$\mathrm{FE/P} = \frac{\left(\mathrm{FEPS}_{y,y-m} - \mathrm{AEPS}_{y}\right)}{\mathrm{P}_{y-m}} \tag{4.1}$$

$$\mathrm{FE}/\left|\mathrm{F}\right| = \frac{\left(\mathrm{FEPS}_{y,y-m} - \mathrm{AEPS}_{y}\right)}{\left|\mathrm{FEPS}_{y,y-m}\right|} \tag{4.2}$$

In equations (4.1) and (4.2), $\mathrm{FEPS}_{y,y-m}$ is the consensus forecast EPS for fiscal year-end y available m months prior to fiscal year-end y; AEPS_{y} is the actual EPS for fiscal year-end y; and P_{y-m} is the stock price at the time of the forecast, which is obtained from the I/B/E/S dataset. The calculation follows Doukas et al. (2002) by using the consensus forecast available eight months prior to the fiscal year-end, in other words with m=8, in order to ensure that analysts had access to the previous year's annual report when issuing their forecasts and to ensure that the results are not affected by look-ahead bias. Whilst Doukas et al. (2002) standardise forecast errors using the stock price at the beginning of the fiscal year, the calculation here deviates slightly by using the stock price at the time of the forecast to calculate FE/P. This is done because it results in a slightly larger number of forecast error observations than would have been possible had the beginning-of-year stock price been used. To ensure the forecast used is a consensus,

only forecast observations where three or more analysts contributed estimates are employed.

The method for calculation of the control variables (B/M, E/P, C/P and DD) is as described in Section 3.4, with the exception of the timing of the calculations. In this study all the control variables are calculated at the end of every month, in order to sort stocks into value/growth and default risk categories at the end of each month. The ranking is performed each month because fiscal year-ends vary amongst companies. Although all firms are included in the monthly sorts, the relevant value/growth and default risk classification assigned to a particular forecast error observation is the classification that was current at the end of the fiscal year preceding the forecast, in other words four months prior to the date of the forecast. For January year-end firms, the relevant value/growth and default risk classifications are those that were current as at January in the year preceding the forecast. For February year-end firms, the relevant B/M and default risk classification are those that were current as at February in the year preceding the forecast, and so on. Similarly, each firm's ranking by market capitalisation is also determined at the end of the fiscal year preceding the forecast; the ranking by market capitalisation being used to determine the firms included in the sample.[29]

The financial data for B/M, E/P, C/P and DD (book value of equity, earnings, cash flow and current and non-current liabilities respectively) are taken from the latest financial statements up until the month of calculation. The value of market capitalisation used in

[29] The classification methodology is similar in spirit to that used by Doukas et al. (2002), although the latter is somewhat confusing and impractical to follow exactly *as specified*. The authors state that "the sorting procedure was conducted *annually* at the end of the fiscal year preceding the analysts' forecasts" (italics added, p.2149). As not all firms have the same fiscal year end, it is technically impossible to sort all firms on an annual basis at the end of the fiscal year.

the denominator of B/M, E/P and C/P is the ordinary share price times the number of shares outstanding at the end of the month of calculation, while the daily market capitalisation data used for the calculation of DD cover the 12-month period up until the end of the month of calculation. As there is a four-month lag between the timing of calculation of all control variables and the relevant analyst forecast for a company, analysts will have had sufficient time to observe and react to these variables and to the data underlying their calculation.

For robustness purposes, the analysis is repeated after splitting the sample into two roughly equal sub-periods. The first sub-period contains all forecast error observations for fiscal year-ends that fall in the years 1996 to 2001, while the second sub-period contains all forecast error observations for fiscal year-ends that fall in the subsequent years. As the forecasts used in this study are taken from eight months prior to fiscal year-end, the first sub-period pertains to forecasts that were current on or before April 2001. The second sub-period thus pertains to forecasts that were current on or after May 2001, which are for fiscal year-ends that fall in the period from 2002 onwards.

4.4 Results

4.4.1 Properties of Analysts' Forecast Errors

Table 4.1 presents some summary statistics for analysts' forecast errors over the full sample period and the two (non-overlapping) sub-periods. Regardless of whether forecast errors are standardised by stock price or by the absolute value of the consensus forecast, both the mean and median forecast errors are greater than zero, consistent with a tendency of analysts to overestimate current year earnings. The distributions of the

two forecast error variables are also highly skewed to the left and fat-tailed, and the Jarque-Bera statistic rejects the hypothesis of normality at better than a 0.1% level of significance. It is apparent that the mean forecast error is influenced by outliers (even after winsorising at the 99.5 percentiles), as its value is always close to or greater than the 75th percentile. The analysis to follow therefore concentrates on median values rather than mean values (as did Doukas et al., 2002), as medians are not influenced by the magnitude of outliers.

It is also apparent from Table 4.1 that analysts' current year forecasts were less optimistic in the second half of the sample period. The median FE/P fell from 0.0041 in the first sub-period to 0.0002 in the second, while the median FE/|F| fell from 0.0642 to 0.0032. In both cases, the Kruskal-Wallis χ^2 statistic rejects the null hypothesis that the sub-period medians are equal at better than a 0.1% level of significance.

The inter-quartile range also narrowed from 0.0242 to 0.0149 (a decrease of 38%) for FE/P and from 0.0372 to 0.02513 (a decrease of 33%) for FE/|F|. The distribution of forecast errors thus became narrower in the second sub-period, a result due to a large decrease in the number of large positive forecast errors: the 75th percentile decreased from 0.0210 to 0.0089 and from 0.3181 to 0.1459 for FE/P and FE/|F| respectively. There were, however, a greater number of large negative forecast errors, as the 25th percentile decreased from -0.0032 to -0.0060 and from -0.0591 to -0.1054 for FE/P and FE/|F| respectively. Thus, analysts' forecasts became less optimistic in the latter half of the sample period, as forecast errors became closer to zero; and somewhat more accurate as forecast error distributions became more tightly dispersed around the median.

The final three columns of Table 4.1 relate to analyst dispersion (the coefficient of variation of consensus forecasts, *not* the dispersion of forecast errors). Analyst dispersion is a widely-used measure of analyst disagreement regarding a company's future earnings. It is apparent that analyst dispersion decreased substantially in the second sub-period, from a median value of 0.0888 to 0.0634, a decrease of nearly 30%. The 25th and 75th percentile values also decreased by a similar proportion, and therefore the decrease in dispersion generally applies to the whole cross-section of companies covered by analysts. Thus, not only were forecasts less optimistic and more accurate over the second sub-period, there was lower dispersion in consensus forecasts; in other words there was less disagreement amongst analysts.

Table 4.1: Summary Statistics of Forecast Errors

Forecast errors and analyst dispersion are calculated from consensus earnings-per-share (EPS) forecasts made eight months prior to each company's fiscal year-end where at least three analysts have contributed estimates. FE/P is the difference between the median EPS forecast and reported EPS deflated by the share price at the time of the forecast, while FE/|F| is the difference between the median EPS forecast and reported EPS deflated by the absolute value of the median forecast. Analyst dispersion is the standard deviation of EPS forecasts for a company divided by the absolute value of the median EPS forecast. The Kruskal-Wallis χ^2 statistic and associated p-value test the null hypothesis that the median value of each variable is identical over the two sub-periods. The first sub-period corresponds to forecasts issued during or before April 2001 and the second sub-period corresponds to forecasts issued during or after May 2001. The number of observations in each classification is denoted by 'n'.

	FE/P			FE/|F|			Analyst Dispersion		
	All	1995-2001:4	2001:5-2007	All	1995-2001:4	2001:5-2007	All	1995-2001:4	2001:5-2007
n	1805	936	869	1805	936	869	2054	1006	1048
Mean	0.0199	0.0229	0.0166	0.2753	0.3170	0.2304	0.1405	0.1667	0.1153
Median	0.0015	0.0041	0.0002	0.0254	0.0642	0.0032	0.0749	0.0888	0.0634
25th percentile	-0.0046	-0.0032	-0.0060	-0.0822	-0.0591	-0.1054	0.0461	0.0561	0.0394
75th percentile	0.0155	0.0210	0.0089	0.2297	0.3181	0.1459	0.1357	0.1579	0.1141
Inter-quartile range	0.0201	0.0242	0.0149	0.3119	0.3772	0.2513	0.0896	0.1018	0.0747
Standard Deviation	0.0995	0.0929	0.1062	1.4456	1.3078	1.5801	0.2914	0.3192	0.2597
Skewness	7.49	7.24	7.62	7.23	6.95	7.30	7.75	6.73	9.34
Kurtosis	68.99	68.72	67.74	64.88	66.39	61.33	72.95	56.04	102.84
Jarque-Bera statistic (p-value)	344378 (0.0000)	176637 (0.0000)	160156 (0.0000)	303749 (0.0000)	164234 (0.0000)	130904 (0.0000)	439337 (0.0000)	125505 (0.0000)	450529 (0.0000)
Kruskal-Wallis χ^2 (p-value)		39.53 (0.0000)			40.20 (0.0000)			96.41 (0.0000)	

4.4.2 Results Based Upon One-Way Sorts

Table 4.2 presents the median price-deflated forecast errors of portfolios formed by sorting stocks on each of the four variables: B/M, E/P, C/P and DD. Focusing attention on the results for the B/M-sorted portfolios, the results are somewhat consistent with Doukas et al. (2002). Ignoring the small number of negative B/M firms, forecast errors increase with B/M; this observation is evident over the full sample period and most pronounced in the first sub-period. However, the variation amongst portfolio medians is not statistically significant and much smaller (along with the magnitudes of the median forecast errors) in the second sub-period. Although the relationship between B/M and forecast errors is much weaker in the sample used in this study than in Doukas et al. (2002), the results nevertheless fail to support the errors-in-expectations hypothesis, as analysts' current year forecasts are not more optimistic for low B/M firms than for high B/M firms.

The median forecast errors of E/P and C/P-sorted portfolios in Table 4.2 exhibit one dominant feature: the very large forecast errors of firms with negative E/P and C/P. The median forecast errors of these portfolios are generally an order of magnitude larger than the median forecast errors of positive E/P and C/P portfolios. For example, the median forecast error of the negative E/P portfolio over the full sample period is 0.0360, 18 times larger than the next largest median (0.0020 for the low E/P portfolio). Similarly, the median forecast error of the negative C/P portfolio of 0.0512 is nearly 15 times larger than the next largest C/P portfolio median. The finding that negative E/P and C/P portfolios have much larger forecast errors than all other portfolios applies to the full sample period as well as to

each of the two sub-periods. Thus, analysts tend to be too optimistic for loss-reporting firms, a result consistent with the finding of Easterwood and Nutt (1999) that analysts tend to underreact *specifically* to poor earnings performance.

Apart from the large forecast errors of negative E/P and C/P firms, there is some weak evidence of a U-shaped pattern in median (price-deflated) forecast errors. The median FE/P decreases from 0.0020 for the low E/P portfolio to 0.0008 for E/P portfolio three, and then increases to 0.0018 for the high E/P portfolio. A similar pattern is observed for the portfolios sorted by C/P. The U-shape is somewhat disrupted by the high E/P portfolio in the first sub-period (Panel B); and consistent with Table 4.1 the median FE/P of all the positive E/P and C/P portfolios are much closer to zero in the second sub-period (Panel C) than in the first. The variation in median FE/P across positive E/P portfolios is statistically significant at 10%, while across positive C/P portfolios it is statistically significant at 5%. The variation is not statistically significant in the first sub-period for positive C/P portfolios and not statistically significant in the second sub-period for positive E/P portfolios. Thus, the evidence of variation in FE/P with E/P and C/P excluding negative E/P and C/P firms is not strong; in any event this evidence is not consistent with the errors-in-expectations hypothesis as the relationship between FE/P and either E/P or C/P is not monotonic.

Finally, there is a clear inverse relationship in Table 4.2 between DD and forecast errors, evident over the full-sample period (Panel A) and the first sub-period (Panel B). Median FE/P decreases from 0.0039 for the low DD portfolio to the 0.0000 for the high DD portfolio in Panel A and from 0.0088 to 0.0000 in Panel B. Thus, there is evidence that analysts' earnings forecasts are more optimistic for high default risk firms than they are for

low default risk firms. In Panel C however, the variation in median FE/P across DD portfolios is not statistically significant if the small number of negative DD firms are excluded; a result consistent with the result from Table 4.1 that forecast errors in general were much closer to zero in the second sub-period. Thus, the relationship between default risk and analyst optimism is much stronger in the first sub-period (when analyst optimism was relatively high) than in the second sub-period (when analyst optimism was relatively low).

The above discussion and Table 4.2 relate to the variation in median forecast errors across various portfolios, where forecast errors were deflated by stock price. However, as Mian and Teo (2004) point out, the choice of stock price as a deflator might potentially bias the forecast errors of growth stocks downward relative to those of value stocks, because growth (value) stocks generally have high (low) stock prices relative to book value and earnings. Therefore, the analysis of Table 4.2 is repeated using the second forecast error variable, namely forecast errors deflated by the absolute value of the consensus forecast. The results are presented in Table 4.3.

The only material difference between the results from Table 4.2 and those from Table 4.3 pertains to portfolios sorted by E/P. In Table 4.3 the median FE/|F| of the low (positive) E/P portfolio is quite large relative to the median FE/|F| of the other positive E/P portfolios. Thus, there is some evidence that analysts' current year earnings forecasts are more optimistic for growth stocks than for value stocks, consistent with the errors-in-expectations hypothesis. This result is not as clear in the second sub-period (Panel C) where the median FE/|F| of the high E/P portfolio exceeds that of the low E/P portfolio; and not

evident amongst the C/P-sorted portfolios where once again a U-shaped pattern in FE/|F| is found. Other results from Table 4.3 are consistent with Table 4.2; namely a direct but statistically insignificant relationship between forecast errors and B/M, a fairly strong inverse relationship between DD and forecast errors, and fairly large forecast errors observed for negative E/P and C/P portfolios.

In summarising, the main findings in this section are that analysts overestimate current year earnings for negative E/P and C/P firms, and that analyst optimism increases with default risk. Although a direct relationship is observed between B/M and forecast errors consistent with Doukas et al. (2002), this relationship is not statistically significant. Excluding negative E/P and C/P firms, there is no conclusive evidence that analyst optimism is greater for low E/P and low C/P firms than it is for high E/P and high C/P firms.

Table 4.2: Medians of Forecast Errors Deflated by Stock Price (FE/P) for Portfolios sorted by Book-to-Market, Earnings-to-Price, Cash Flow-to-Price and Distance-to-Default

This table shows the variation in price-deflated forecast errors (FE/P) with book-to-market (B/M), earnings-to-price (E/P), cashflow-to-price (C/P) and distance-to-default (DD). FE/P is calculated as per Table 4.1; B/M, E/P, C/P and DD are calculated each month according to Section 4.3. For each independent variable (B/M, E/P, C/P and DD), companies are either assigned to a negative (<0) portfolio if the variable is negative or else sorted into quintile portfolios if the variable is positive. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios; when annotated with '(+ive classifications)' the test excludes observations in the negative (<0) portfolio. The number of observations in each classification is denoted by 'n'.

Panel A: Full Sample

Portfolio	Independent Variable							
	B/M		E/P		C/P		DD	
	Median	n	Median	n	Median	n	Median	n
<0	0.0117	6	0.0360	88	0.0512	41	0.1051	14
Low	0.0004	286	0.0020	276	0.0021	235	0.0039	385
2	0.0005	366	0.0009	307	0.0000	325	0.0022	370
3	0.0017	416	0.0008	363	0.0006	410	0.0030	373
4	0.0018	405	0.0010	389	0.0027	384	0.0010	354
High	0.0036	326	0.0018	381	0.0035	409	0.0000	292
Kruskal-Wallis χ^2 (p-value)	4.59 (0.4678)		60.83 (0.0000)		55.78 (0.0000)		29.88 (0.0000)	
Kruskal-Wallis χ^2 (+ive classifications) (p-value)	3.83 (0.4295)		8.17 (0.0857)		11.16 (0.0249)		23.39 (0.0001)	

Panel B: 1995-2001:4

	B/M		E/P		C/P		DD	
	Median	n	Median	n	Median	n	Median	n
<0	0.0609	2	0.0266	51	0.0446	19	0.0000	9
Low	0.0014	138	0.0062	147	0.0036	129	0.0088	195
2	0.0029	187	0.0025	167	0.0023	161	0.0064	196
3	0.0043	234	0.0028	182	0.0035	217	0.0064	191
4	0.0070	200	0.0058	189	0.0044	194	0.0039	181
High	0.0066	175	0.0018	199	0.0079	215	0.0000	153
Kruskal-Wallis χ^2 (p-value)	8.01 (0.1556)		26.19 (0.0001)		16.66 (0.0052)		27.25 (0.0001)	
Kruskal-Wallis χ^2 (+ive classifications) (p-value)	5.27 (0.2606)		10.09 (0.0390)		3.28 (0.5120)		27.48 (0.0000)	

Table 4.2 Medians of Forecast Errors Deflated by Stock Price (FE/P) for Portfolios sorted by Book-to-Market, Earnings-to-Price, Cash Flow-to-Price and Distance-to-Default (continued)

Panel C: 2001:5-2007

	B/M		E/P		C/P		DD	
	Median	n	Median	n	Median	n	Median	n
<0	-0.0012	4	0.0435	37	0.0726	22	0.6382	5
Low	0.0001	148	0.0006	129	0.0007	106	0.0016	190
2	-0.0004	179	0.0000	140	-0.0010	164	0.0002	174
3	0.0000	182	0.0000	181	-0.0012	193	0.0000	182
4	0.0004	205	-0.0010	200	0.0011	190	-0.0007	173
High	0.0017	151	0.0018	182	0.0010	194	0.0000	139
Kruskal-Wallis χ^2 (p-value)	3.79 (0.5796)		43.17 (0.0000)		45.13 (0.0000)		19.38 (0.0016)	
Kruskal-Wallis χ^2 (+ive classifications) (p-value)	3.82 (0.4312)		4.71 (0.3179)		12.85 (0.0120)		5.49 (0.2406)	

Table 4.3: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Portfolios (FE/|F|) sorted by Book-to-Market, Earnings-to-Price, Cash Flow-to-Price and Distance-to-Default

This table shows the variation in forecast errors deflated by the absolute value of the median forecast (FE/|F|) with book-to-market (B/M), earnings-to-price (E/P), cashflow-to-price (C/P) and distance-to-default (DD). FE/|F| is calculated as per Table 4.1; all other details are as per Table 4.2. The number of observations in each classification is denoted by 'n'.

Panel A: Full Sample

Portfolio	Independent Variable							
	B/M		E/P		C/P		DD	
	Median	n	Median	n	Median	n	Median	n
<0	0.0833	6	0.6411	88	0.7216	41	0.6396	14
Low	0.0125	286	0.0665	276	0.0584	235	0.0581	385
2	0.0096	366	0.0171	307	0.0000	325	0.0313	370
3	0.0284	416	0.0148	363	0.0096	410	0.0435	373
4	0.0263	405	0.0133	389	0.0332	384	0.0194	354
High	0.0541	326	0.0232	381	0.0448	409	0.0000	292
Kruskal-Wallis χ^2 (p-value)	2.79 (0.7320)		63.15 (0.0000)		51.91 (0.0000)		27.80 (0.0000)	
Kruskal-Wallis χ^2 (+ive classifications) (p-value)	2.79 (0.5943)		12.19 (0.0160)		10.94 (0.0272)		22.21 (0.0002)	

Panel B: 1995-2001:4

	B/M		E/P		C/P		DD	
	Median	n	Median	n	Median	n	Median	n
<0	0.1157	2	0.4918	51	0.4152	19	0.0000	9
Low	0.0428	138	0.1842	147	0.0800	129	0.0940	195
2	0.0473	187	0.0476	167	0.0510	161	0.0983	196
3	0.0659	234	0.0443	182	0.0492	217	0.0934	191
4	0.0921	200	0.0669	189	0.0639	194	0.0632	181
High	0.0877	175	0.0200	199	0.0723	215	0.0000	153
Kruskal-Wallis χ^2 (p-value)	3.55 (0.6163)		33.43 (0.0000)		13.05 (0.0229)		24.62 (0.0002)	
Kruskal-Wallis χ^2 (+ive classifications) (p-value)	3.46 (0.4846)		16.60 (0.0023)		2.62 (0.6234)		24.76 (0.0001)	

Table 4.3 Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Portfolios (FE/|F|) sorted by Book-to-Market, Earnings-to-Price, Cash Flow-to-Price and Distance-to-Default (continued)

Panel C: 2001:5-2007

	B/M		E/P		C/P		DD	
	Median	n	Median	n	Median	n	Median	n
<0	-0.0519	4	0.8220	37	1.0979	22	0.8220	5
Low	0.0021	148	0.0130	129	0.0264	106	0.0229	190
2	-0.0064	179	0.0007	140	-0.0193	164	0.0028	174
3	0.0002	182	0.0000	181	-0.0202	193	0.0000	182
4	0.0058	205	-0.0152	200	0.0178	190	-0.0097	173
High	0.0262	151	0.0232	182	0.0169	194	0.0000	139
Kruskal-Wallis χ^2 (p-value)	3.56 (0.6150)		39.04 (0.0000)		43.81 (0.0000)		17.36 (0.0039)	
Kruskal-Wallis χ^2 (+ive classifications) (p-value)	3.47 (0.4818)		3.38 (0.4967)		11.76 (0.0193)		4.96 (0.2914)	

4.4.3 Results Based Upon Two-Way Sorts on B/M and DD

The forecast errors of portfolios sorted by both value and default risk will now be analysed. In this section the results obtained from sorting on B/M and DD and for FE/P are discussed; the results for FE/|F| are qualitatively similar and are therefore consigned to Appendix 4A (Table 4A.1) for brevity. Given the relatively small numbers of negative B/M firms, the convention of similar studies is followed by excluding these observations. Given the small number of negative DD firms, a departure is made from Tables 4.2 and 4.3 by not creating a separate portfolio grouping for these observations[30].

Table 4.4 presents the results for the sorts on B/M and DD. If the effect of DD is ignored, there is somewhat stronger evidence of a direct relationship between B/M and FE/P in Table 4.4 (with three B/M portfolios) than in Tables 4.2 and 4.3 (with five B/M portfolios). Reading across the 'Total' rows, the variation in FE/P with B/M is only marginally statistically insignificant at the 10% level in Panel A and only marginally statistically insignificant at the 5% level in Panel B. Thus, the statistical significance of the relationship between FE/P and B/M appears to be sensitive to the number of B/M portfolios. However, any variation in Table 4.4 is largely due to the three cells that lie on the off diagonal and which have relatively large numbers of observations: the low DD high B/M portfolio, the mid DD mid B/M portfolio, and the high DD low B/M portfolio. As default risk increases with B/M across these portfolios and given the results from Tables 4.2 and 4.3, it is likely

[30] The number of observations is not the same in Table 4 as in Tables 2 and 3 because negative B/M firms are excluded and because DD is undefined for some observations.

that the variation in FE/P with B/M is mostly attributable to the variation in FE/P with default risk (that is, with DD). This assertion will now be tested.

Reading across the rows corresponding to the 'Low', 'Mid' and 'High' DD portfolios, the variation in FE/P with B/M after controlling for DD can be ascertained. Amongst the low DD portfolios in Panel A, the largest median FE/P occurs for the low B/M portfolio (0.0071) while the lowest occurs for the mid B/M portfolio (0.0011). In contrast, the largest median FE/P amongst the mid DD portfolios occurs for the mid B/M portfolio (0.0034) while the lowest occurs for the high B/M portfolio (0.0005). Thus, there is no consistent relationship between FE/P and B/M after controlling for default risk using DD. Furthermore, the variation in FE/P with B/M is statistically significant only in the row corresponding to the low DD portfolios, and not in the rows corresponding to the mid DD portfolio, the high DD portfolio and the 'Total' category. Panels B and C similarly fail to reveal any consistent relationship between FE/P and B/M after controlling for default risk.

Reading down each column in Table 4.4, the variation in FE/P with DD after controlling for B/M can be ascertained. Here there is clearer evidence of systematic variation in FE/P. In the low B/M, high B/M and Total columns (Panel A), the largest median FE/P occurs for the low DD portfolios (0.0071, 0.0058 and 0.0039 respectively). In the low B/M, mid B/M and Total columns, the smallest median FE/P occurs for the high DD portfolios (0.0000, 0.0001 and 0.0001 respectively), whilst in the high B/M column the mid and high DD portfolios have similar median FE/P (0.0005 and 0.0011 respectively). Therefore with one or two exceptions the median FE/P is inversely related to DD (and thus directly related to default risk) after controlling for B/M.

The variation in FE/P with DD is much stronger over the first sub-period (Panel B) than the second (Panel C) and highly statistically significant in both the full sample (Panel A) and the first sub-period. Unlike Panel A, FE/P decreases monotonically with DD (that is, increases with default risk) in *every* B/M column in Panel B. However, there is relatively little variation in FE/P in Panel C, consistent with the earlier result from Table 4.1 that forecast errors were generally much closer to zero in the second sub-period than in the first.

The median forecast errors of overvalued and undervalued firms will now be compared. Based on the results of Chapter 3, overvalued firms include growth stocks with high default risk whilst undervalued firms include value stocks with low default risk. Thus the low DD low B/M portfolio in Table 4.4 contains overvalued firms while the high DD high B/M portfolio contains undervalued firms. Panel A demonstrates that the median FE/P of overvalued firms (0.0071) is greater than the median FE/P of undervalued firms (0.0011) over the full sample period. The Mann-Whitney rank-sum statistic confirms that this difference is statistically significant at the 5% level. The difference is more pronounced in the first sub-period (Panel B) but not evident in the second sub-period (Panel C), consistent with the general decrease in forecast errors in this sub-period noted earlier in the study. Thus, the conjecture that analysts are more optimistic towards overvalued growth stocks than they are towards undervalued value stocks is confirmed in Panels A and B, but not in Panel C.

Table 4.4: Medians of Forecast Errors Deflated by Stock Price (FE/P) for Book-to-Market- and Distance-to-Default- Sorted Portfolios

This table shows the variation in price-deflated forecast errors (FE/P) amongst different combinations of book-to-market (B/M) and distance-to-default (DD) classifications. FE/P is calculated as per Table 4.1; B/M and DD are calculated each month according to Section 4.3. Companies sorted into three portfolios by B/M and independently into three portfolios by DD. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios. The Mann-Whitney rank sum statistic tests the null hypothesis that the median forecast error of the low B/M, low DD portfolio equals that of the high B/M, high DD portfolio. The number of observations in each classification is denoted by 'n'.

Panel A: Full Sample

DD Portfolio	B/M Portfolio								Kruskal-Wallis χ^2 (p-value)
	Low		Mid		High		Total		
	Median	n	Median	n	Median	n	Median	n	
Low	0.0071	60	0.0011	216	0.0058	339	0.0039	618	7.03 (0.0297)
Mid	0.0017	172	0.0034	282	0.0005	181	0.0020	637	4.57 (0.1020)
High	0.0000	284	0.0001	179	0.0011	69	0.0001	533	0.81 (0.6657)
Total	0.0004	516	0.0015	677	0.0033	589	0.0015	1788	4.46 (0.1075)
Kruskal-Wallis χ^2 (p-value)	14.85 (0.0006)		9.29 (0.0096)		13.02 (0.0015)		28.22 (0.0000)		40.68 (0.0000)

Mann-Whitney Rank Sum Statistic

Low DD Low B/M vs. High DD High B/M z=2.2052 p-value 0.0274

Table 4.4 Medians of Forecast Errors Deflated by Stock Price for Book-to-Market- and Distance-to-Default- Sorted Portfolios (continued)

Panel B: 1995 to 2001:4

DD Portfolio	B/M Portfolio								Kruskal-Wallis χ^2 (p-value)
	Low		Mid		High		Total		
	Median	n	Median	n	Median	n	Median	n	
Low	0.0212	30	0.0059	108	0.0114	180	0.0091	319	5.73 (0.0571)
Mid	0.0048	83	0.0055	161	0.0062	83	0.0055	328	0.65 (0.7224)
High	0.0000	150	0.0018	92	-0.0002	36	0.0002	278	2.17 (0.3373)
Total	0.0014	263	0.0041	361	0.0076	299	0.0040	925	5.82 (0.0545)
Kruskal-Wallis χ^2 (p-value)	21.95 (0.0000)		6.55 (0.0378)		7.76 (0.0206)		33.00 (0.0000)		40.25 (0.0000)

Mann-Whitney Rank Sum Statistic
Low DD Low B/M vs. High DD High B/M z=2.8203 p-value 0.0048

Table 4.4 Medians of Forecast Errors Deflated by Stock Price for Book-to-Market- and Distance-to-Default- Sorted Portfolios (continued)

Panel C: 2001:5 to 2007

DD Portfolio	B/M Portfolio								Kruskal-Wallis χ^2 (p-value)
	Low		Mid		High		Total		
	Median	n	Median	n	Median	n	Median	n	
Low	0.0018	30	0.0000	108	0.0035	159	0.0010	299	2.47 (0.2915)
Mid	0.0003	89	0.0008	121	-0.0017	98	-0.0005	309	2.99 (0.2246)
High	-0.0001	134	-0.0019	87	0.0020	33	0.0000	255	4.85 (0.0886)
Total	0.0001	253	-0.0003	316	0.0010	290	0.0003	863	1.90 (0.3860)
Kruskal-Wallis χ^2 (p-value)	0.82 (0.6642)		3.32 (0.1900)		7.53 (0.0232)		5.88 (0.0529)		14.62 (0.0670)

Mann-Whitney Rank Sum Statistic
Low DD Low B/M vs. High DD High B/M z=0.1307 p-value 0.8960

4.4.4 Results Based Upon Two-Way Sorts on E/P and DD

Attention is now turned towards the pattern of price-deflated forecast errors amongst portfolios sorted on E/P and DD. The tenor of the results is unaffected by the choice of E/P or C/P and by whether forecast errors are deflated by stock price or by the absolute value of the consensus forecast. For brevity, only the results based upon E/P and FE/P are presented and discussed here; further results are presented in Appendix 4A based upon FE/|F| (Table 4A.2) and upon C/P (Tables 4A.3 and 4A.4).

Table 4.5 presents the median forecast errors of portfolios sorted by E/P and DD, with negative E/P firms segregated because the earlier results of this study show negative E/P firms to have much larger forecast errors than positive E/P firms[31]. This result is now demonstrated to still hold after controlling for default risk. In every DD category the highest median forecast error occurs for the negative E/P portfolio, a result evident in all three panels. Amongst the low DD firms in Panel A, the median FE/P of the negative E/P portfolio (0.0503) is eight times larger than the median FE/P of the low E/P portfolio (0.0062), while amongst the mid DD firms, the median FE/P of the negative E/P portfolio (0.0196) is five times larger than the median FE/P of the low E/P portfolio (0.0037). A similar disparity is observed in Panels B and C and amongst high DD firms, although (not surprisingly) there are only a small number of firms with negative earnings and high DD (that is, low default risk).

[31] There are relatively few firms with negative earnings in the sample of the 300 largest companies compared with smaller firms. Around 10% of firms in the top 300 have negative earnings; while over 60% of firms outside the top 300 have negative earnings.

Excluding negative E/P firms, Table 4.5 also reveals some evidence that analysts' forecasts are relatively optimistic for low E/P stocks, *provided* they have high default risk. In Panels A and B, the highest median forecast error for positive E/P firms occurs for the low DD low E/P portfolio. The median FE/P for this portfolio in Panel A (0.0062) is twice as large as the next largest median FE/P (0.0031) amongst positive E/P portfolios with low DD, and 68% larger than the next largest median FE/P (0.0037) amongst all the positive E/P portfolios. The variation in FE/P with E/P (amongst positive E/P firms) is more pronounced in Panel B and statistically significant in both panels, but not evident in Panel C (a result consistent with the earlier result that forecast errors were generally lower in the second sub-period). Consistent with the results from Table 4.4, the evidence suggests that analysts are overly optimistic towards growth stocks with high default risk.

Apart from negative E/P, the most important factor in forecast errors evident in Table 4.5 is default risk; a result consistent with Tables 4.2, 4.3 and 4.4. In Panels A and B, median forecast errors are inversely related to DD in the low E/P, mid E/P and total columns. In the high E/P column, the smallest median FE/P occurs for the high DD portfolio (-0.0002 in both Panel A and Panel B). Therefore the direct relationship between default risk and FE/P is preserved (in Panels A and B) after controlling for E/P. As was the case with the earlier results, there appears little variation in forecast errors with default risk in the second sub-period (Panel C).

Finally, the major prediction in this study, that analysts are more optimistic towards overvalued firms than they are towards undervalued firms is once again directly tested. As before, undervalued stocks are value stocks with low default risk; in this case, stocks with

high DD and high E/P. Overvalued stocks are growth stocks with low default risk, however in this case two categories are considered: (i) stocks with low DD and negative E/P and (ii) stocks with low DD and low E/P. Comparing the median FE/P of the low DD low (positive) E/P portfolio (0.0062) with that of the high DD high E/P portfolio (-0.0002), the Mann-Whitney statistic (-3.4633) rejects the hypothesis of equal medians at better than a 0.1% level of significance. Similarly, the hypothesis of equality between the median FE/P of the low DD negative E/P portfolio (0.0503) and that of the high DD high E/P portfolio (-0.0002)[32] is also rejected. Thus, the conjecture that analysts are more optimistic towards overvalued firms than they towards undervalued firms is confirmed.

Similar results are evident in Panel B. The median FE/P of the low DD low (positive) E/P portfolio (0.0226) exceeds that of the high DD high E/P portfolio (-0.0002), and the null hypothesis of equality between the two medians is rejected at better than a 0.1% level of significance. Similarly, the null hypothesis of equality between the median FE/P of the low DD negative E/P portfolio (0.0446) and the high DD high E/P portfolio (-0.0002) can also be rejected. Consistent with the earlier results in this study, there is no significant variation in FE/P amongst the positive E/P portfolios in the second sub-period (Panel C), and thus the conjecture that forecast errors are greater for overvalued firms than they are for undervalued firms is not confirmed for this sub-period. It is possible, however, to reject the null hypothesis of equality between the median FE/P of the low DD negative E/P portfolio (0.0652) and that of the high DD high E/P portfolio (0.0005) at better than a 0.1% level of significance.

[32] The difference between the median FE/P of the low DD negative E/P portfolio and that of the low DD low (positive) E/P is also statistically significant.

In summarising, the dominant factor in analysts' forecast errors in Table 4.5 is the incidence of prior losses (that is, negative E/P), followed by default risk. Consistent with the errors-in-expectations hypothesis however, growth firms with positive E/P do indeed have large forecast errors, *provided* they have high default risk.

Table 4.5: Medians of Forecast Errors Deflated by Stock Price for Earnings-to-Price and Distance-to-Default Sorted Portfolios
This table shows the variation in price-deflated forecast errors (FE/P) amongst different combinations of earnings-to-price (E/P) and distance-to-default (DD) portfolio classifications. FE/P is calculated as per Table 4.1; E/P and DD are calculated each month according to Section 4.3. Companies are either sorted into a negative (<0) E/P portfolio if E/P is negative or into three portfolios E/P portfolio if E/P is positive; companies are also independently sorted into three portfolios by DD. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios; when annotated with '(E/P>0)' the test excludes observations in the negative (<0) E/P portfolio. The Mann-Whitney rank sum statistics test the null hypothesis of that the median forecast errors are equal for the pairs of portfolios indicated. The number of observations in each classification is denoted by 'n'.

Panel A: Full Sample

DD Portfolio	E/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (E/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.0503	54	0.0062	129	0.0031	151	0.0011	284	0.0039	618	44.18 (0.0000)	7.17 (0.0278)
Mid	0.0196	24	0.0037	135	0.0013	240	0.0019	236	0.0020	635	10.85 (0.0126)	4.77 (0.0919)
High	0.0284	6	-0.0001	197	0.0002	221	-0.0002	110	0.0001	534	4.55 (0.2079)	0.62 (0.7326)
Total	0.0365	84	0.0015	461	0.0010	612	0.0011	630	0.0015	1787	57.95 (0.0000)	4.52 (0.1044)
Kruskal-Wallis χ^2 (p-value)	5.49 (0.0642)		16.39 (0.0003)		8.56 (0.0139)		2.80 (0.2466)		27.74 (0.0000)		86.87 (0.0000)	30.80 (0.0002)

Mann-Whitney Rank Sum Statistics
Low DD Low E/P vs. High DD High E/P z=-3.4633 p-value 0.0005
Low DD E/P<0 vs. High DD High E/P z=6.5451 p-value 0.0000
Low DD E/P<0 vs. Low DD Low E/P z=4.4749 p-value 0.0000

Table 4.5 Medians of Forecast Errors Deflated by Stock Price for Earnings-to-Price and Distance-to-Default Sorted Portfolios (continued)

Panel B: 1995-2001:4

DD Portfolio	E/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (E/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.0446	31	0.0226	67	0.0052	73	0.0059	148	0.0091	319	23.27 (0.0000)	9.67 (0.0080)
Mid	0.0201	14	0.0067	69	0.0044	136	0.0067	107	0.0055	326	4.29 (0.2315)	2.83 (0.2433)
High	0.0036	4	0.0002	108	0.0006	107	-0.0002	60	0.0002	279	1.44 (0.6962)	1.13 (0.5684)
Total	0.0322	49	0.0041	244	0.0030	316	0.0035	315	0.0040	924	21.04 (0.0001)	3.10 (0.2119)
Kruskal-Wallis χ^2 (p-value)	3.55 (0.1695)		26.29 (0.0000)		4.89 (0.0868)		6.20 (0.0451)		32.24 (0.0000)		60.37 (0.0000)	40.18 (0.0000)

Mann-Whitney Rank Sum Statistics

Low DD Low E/P vs. High DD High E/P z=-4.1990 p-value 0.0000

Low DD E/P<0 vs. High DD High E/P z=4.6017 p-value 0.0000

Low DD E/P<0 vs. Low DD Low E/P z=2.0550 p-value 0.0399

Table 4.5 Medians of Forecast Errors Deflated by Stock Price for Earnings-to-Price and Distance-to-Default Sorted Portfolios (continued)

Panel C: 2001:5-2007

DD Portfolio	E/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (E/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.0652	23	0.0004	62	0.0027	78	0.0000	136	0.0010	299	26.30 (0.0000)	3.24 (0.1977)
Mid	0.0177	10	0.0012	66	-0.0015	104	-0.0009	129	-0.0005	309	9.73 (0.0210)	3.94 (0.1398)
High	1.0210	2	-0.0007	89	0.0000	114	0.0005	50	0.0000	255	5.90 (0.1166)	0.02 (0.9918)
Total	0.0435	35	0.0002	217	0.0001	296	-0.0004	315	0.0003	863	38.81 (0.0000)	1.58 (0.4542)
Kruskal-Wallis χ^2 (p-value)	6.96 (0.0308)		1.91 (0.3841)		8.35 (0.0154)		0.13 (0.9378)		5.88 (0.0529)		49.36 (0.0000)	10.57 (0.2271)

Mann-Whitney Rank Sum Statistics
Low DD Low E/P vs. High DD High E/P z=0.5941 p-value 0.5525
Low DD E/P<0 vs. High DD High E/P z=4.6252 p-value 0.0000
Low DD E/P<0 vs. Low DD Low E/P z=4.1398 p-value 0.0000

4.4.5 Yearly Variation in the Relationship between Default Risk and Forecast Errors

The full-sample results thus far are consistent with analyst underreaction to negative earnings and default risk; however the sub-period analysis finds no significant relationship between forecast errors and DD in the second half of the sample period, and therefore no evidence of underreaction to default risk in that period. A possible explanation is that analysts might be inefficient in processing default risk *in general*, but analyst efficiency *appears* to increase in years when there are fewer high default risk firms. Although there is inter-year variation in DD within both sub-periods, DD is generally higher and therefore default risk generally lower in the second sub-period than in the first. Therefore the observation that forecast errors are much closer to zero and lack any discernible pattern (for companies with positive earnings) in the second period might still be consistent with underreaction to default risk; the underreaction might be less evident in the second-sub-period simply because there are fewer high default risk firms, and relatively more firms are misclassified as high default risk based on an *annual sorting procedure*.

To shed further light on this issue, firms are reclassified into high and low default risk categories based upon *constant* DD breakpoints, namely the 20^{th} and 80^{th} percentiles of all (pooled) forecast error observations. The use of constant DD breakpoints to classify firms means that the analysis is not sensitive to the inter-year variation in default risk. Moreover, the median forecast errors of the high and low default risk groups are not materially affected by the use of constant rather than annual breakpoints; the major difference between using constant rather than annual breakpoints is the number of firms classified as high

default risk. The low and high quintile breakpoints based on the pooled sample are 3.9694 and 9.8337 respectively; therefore firms with a DD less than 3.9694 are classified as high default risk and those with a DD greater than 9.8337 are classified as low default risk. Table 4.6 and Figure 4.1 show the resulting inter-year variation in forecast errors of high and low default risk firms.

It is apparent from Table 4.6 and Figure 4.1 that median forecast errors were greater for high default risk firms than for low default risk firms in every year of the sample period, except the four years where there were 21 or fewer high default risk firms (1996 and 2004 to 2006). In 1999 and 2003 the median forecast error of both groups was negative but still larger for high default risk stocks. The above observations are more readily apparent in Figure 4.1. The final column of Table 4.6 reveals that the four years where median forecast errors were not greater for high default risk stocks than for low default risk stocks (1996 and 2004 to 2006) are the years of highest median DD (lowest default risk) in the sample. Therefore, the evidence relating analyst forecast optimism and default risk is stronger when there are a larger number of high default risk firms. The *lack of evidence* in the second sub-period of a direct relationship between forecast errors and default risk is thus directly attributable to the smaller number of high default risk firms therein, particularly over 2004 to 2006.

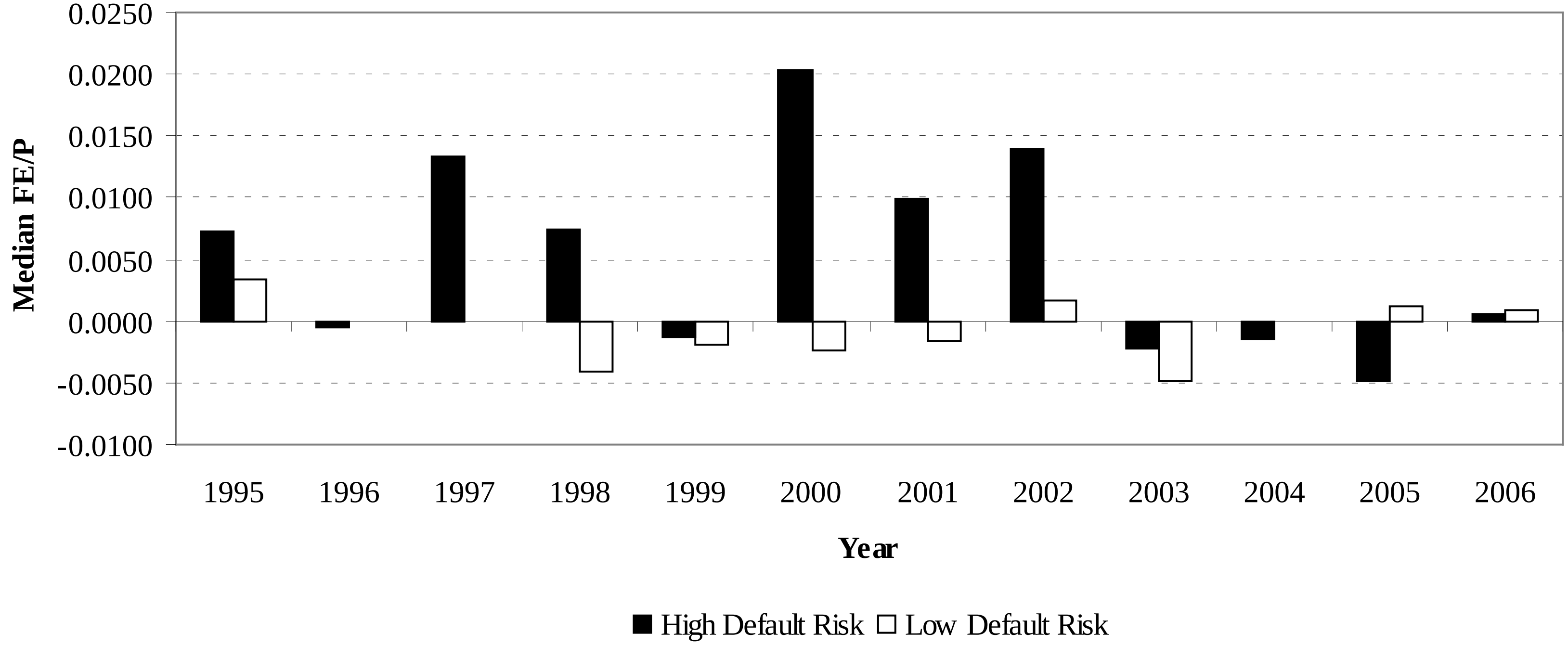
In summary, the results from Table 4.6 and Figure 4.1 confirm that the previous sub-period results are sensitive to inter-year variation in default risk. After taking this variation into account there remains a strong relationship between DD and forecast errors that is consistent with analyst underreaction to default risk.

Table 4.6: Median Price-Deflated Forecast Errors of High and Low Default Risk Portfolios and Sample Median DD by Forecast Year; Constant DD Portfolio Breakpoints

This table shows the variation in price-deflated forecast errors (FE/P) amongst high default risk and low default risk portfolios as well as the median DD of the whole sample by the calendar year in which the forecast was made (the forecast year). Stocks are classified as high default risk if their DD was less than the 20th percentile of the pooled sample, or 3.9694 at the end of the fiscal year preceding the forecast. Stocks are classified as low default risk if their DD was greater than the 80th percentile of the pooled sample, or 9.8337 at the end of the fiscal year preceding the forecast. The sample median DD in each year includes all stocks in the sample. The number of observations in each classification is denoted by 'n'.

Forecast Year	High Default Risk Portfolio (DD<3.9694)		Low Default Risk Portfolio (DD>9.8337)		Sample Median DD
	Median FE/P	n	Median FE/P	n	
1995	0.0073	35	0.0034	16	6.3005
1996	-0.0005	21	0.0000	36	7.5815
1997	0.0133	25	-0.0001	35	7.1047
1998	0.0074	68	-0.0040	7	4.7436
1999	-0.0012	43	-0.0019	18	5.6884
2000	0.0203	64	-0.0024	9	5.0243
2001	0.0100	54	-0.0016	20	5.7091
2002	0.0140	32	0.0017	8	5.7658
2003	-0.0023	32	-0.0049	18	6.4864
2004	-0.0014	8	0.0000	54	8.6423
2005	-0.0049	3	0.0012	28	8.1519
2006	0.0006	17	0.0010	27	7.4395

Figure 4.1: Yearly Variation in Price-Deflated Forecast Errors for High and Low Default Risk Portfolios
This figure plots the median price-deflated forecast errors of high and low default-risk portfolios by the year in which the forecast was made (the forecast year). The data and computation details are as per Table 4.6.



4.5. Interpretation of Results

Relationship between Forecast Errors and the Variables B/M, E/P, C/P and DD

Default risk is a pertinent factor in tests conditioned upon B/M such as Doukas et al. (2002) because high B/M firms generally also have high default risk. This assertion is confirmed by the observation that a relatively large number of stocks are classified as high default risk value and as low default risk growth by the independent sorts on B/M and DD, whilst relatively few are classified as low default risk value and high default risk growth. In the absence of a control for default risk the results of this study are consistent with Doukas et al. (2002) in that a direct relationship is found between analysts' forecast errors and B/M that runs counter to the errors-in-expectations hypothesis. In the sample tested, this relationship is not statistically significant based on quintile B/M portfolios but is somewhat stronger when stocks are sorted into groups of three by B/M, a by-product of the two-way sorts on B/M and DD. However, as expected the weak relationship observed between B/M and forecast errors is completely subsumed by a much stronger relationship between forecast errors and DD. The fact that forecast errors tend to be high for stocks with high default risk, *measured before the forecast*, is consistent with analyst inefficiency in recognising, in other words underreaction to, default risk. Thus, analysts appear to be more optimistic towards high B/M stocks than towards low B/M stocks because default risk tends to increase with B/M and analysts are inefficient in recognising default risk. This inference is consistent with an extensive literature documenting analyst inefficiency, for example Klein (1990), Lys and Sohn (1990), Abarbanell (1991), Abarbanell and Bernard (1992), Frankel and Lee (1998), Easterwood and Nutt (1999) and Abarbanell and Lehavy (2003).

The variation of forecast errors with E/P and C/P is different from the variation with B/M. The biggest difference is the observation that firms with negative E/P and C/P have very large forecast errors; a result indicating that analysts are overly optimistic towards loss-making firms and consistent with the finding in Easterwood and Nutt (1999) that analysts underreact to poor earnings performance. Earnings performance is a contributing factor in default risk, as demonstrated by the observation that most of the loss-making firms in Table 4.5 are in the low DD category. Thus, the optimism that analysts display towards both loss-making firms and high default risk firms appears to be essentially the same phenomenon, an underreaction to financial distress in general.

Amongst firms with positive E/P and C/P, there is no consistent pattern in forecast errors with either variable. Based upon one-way quintile sorts, price-deflated forecast errors display a U-shaped pattern with the smallest values for intermediate values of E/P and C/P, while forecast errors deflated by the absolute value of the forecast are actually quite high for low E/P firms, a result consistent with the errors-in-expectations hypothesis. However, this pattern is not evident for C/P sorted portfolios. The U-shape is not evident in Table 4.5 where positive E/P stocks are classified into three groups by E/P. Instead the finding is that forecast errors appear to vary inversely with E/P, a result consistent with the errors-in-expectations hypothesis. However, this observation is driven by low E/P firms with high default risk and overall, the message from the two-way sorts involving either E/P or C/P is that with the exception of negative values, neither variable is as important a factor for forecast errors as default risk or prior losses.

Analyst Optimism and Mispricing

The observation that forecast errors (and by implication analyst optimism) are relatively high for high default risk and loss-making firms has a direct bearing on analyst forecast-based tests of the errors-in-expectations hypothesis, because of evidence that firms with valuation ratios misaligned with default risk are mispriced. Chapter 3 finds that, in Australia, growth stocks with high default risk have relatively low returns while value stocks with low default risk have relatively high returns; a finding that applies to both raw and risk adjusted returns. These findings and those of other similar studies (for example Piotroski, 2000; Griffin and Lemmon, 2002) are consistent with overvaluation of distressed growth stocks and undervaluation of financially healthy value stocks. Thus, on the argument that not all growth stocks are overvalued and not all value stocks are undervalued, the finding in Doukas et al. (2002) that analyst forecast optimism is not greater for growth stocks than for value stocks says very little about the relationship between analyst optimism and mispricing.

The results of this study show that analysts' earnings forecasts are far more optimistic for overvalued (that is, distressed growth) stocks than they are for undervalued (that is, financially healthy value) stocks. In particular, analysts' earnings forecasts are excessively optimistic for growth stocks with high default risk, a finding that is not dependent upon whether growth is defined by B/M, E/P or C/P, and that applies to growth stocks with both low *and* negative values of E/P or C/P. Thus, analyst optimism reflects the direction of mispricing amongst portfolios sorted by value and default risk, and hence the results are consistent with the errors-in-expectations hypothesis *amongst mispriced firms*. This finding is consistent with Bartov and Kim (2004) who find that

analyst optimism reflects mispricing amongst portfolios sorted by B/M and accruals, and thus also consistent with the errors-in-expectations hypothesis.

However, as noted above the results of this study are driven by analyst *underreaction* to financial distress, and are therefore not consistent with the postulated extrapolation or overreaction behaviour underpinning the errors-in-expectations hypothesis, as expounded in Lakonishok et al. (1994). The default risk measure employed in this study DD incorporates the information in current share prices, and thus a low (high) DD score implies that the market has *to some extent* already recognised a firm's deteriorating (improving) financial health. Nevertheless, analysts' earnings forecasts are still too high for low DD firms, despite the fact that at the time of the forecast distress-related information is already evident in share prices and, by implication, DD. Thus, the relationship observed between analyst forecast optimism and DD can only be consistent with analyst underreaction to default risk as well as to the information in share prices.

The underreaction in analysts' earnings forecasts is consistent with the underreaction conclusion in Chapter 3, whereby high default risk growth stocks have poor recent (six-month) price performance *both before and after* portfolio formation, while low default risk value stocks have relatively good recent price performance *both before and after* portfolio formation. Furthermore, Chapter 3 showed that high default risk growth stocks have relatively poor recent (prior year) earnings before portfolio formation while low default risk value stocks have relatively good or improving recent earnings performance. The overall picture that emerges is one where both analysts and share prices respond slowly to earnings news, in other words market inefficiency.

Consistency with the Momentum Life Cycle

The evidence presented in this study supporting underreaction suggests that momentum plays an important role in the value premium, and thus the results are somewhat consistent with the momentum life cycle postulated by Lee and Swaminathan (2000), according to which stocks go through periods of favouritism and neglect. Parallels between the momentum life cycle and this study can be drawn because the two key variables in the momentum life cycle, trading volume and momentum, are related to the control variables in this study, namely valuation ratios and DD. DD is related to momentum because it increases with the drift in asset values (μ in equation 4), and trading volume is related to valuation ratios in that Lee and Swaminathan (2000) find that trading volume is greater for growth stocks than for value stocks. The low default risk value stocks in this study are therefore similar to the 'low-volume winners' in the momentum life cycle, which are previously-neglected stocks subject to improving sentiment. The fact that low default risk value stocks are no worse than low default risk growth stocks at meeting analyst expectations is consistent with their initial undervaluation and subsequent (postulated) improvement in sentiment. Both groups of stocks, namely the low default risk value stocks in Chapter 3 and the low volume winners in Lee and Swaminathan (2000), are identified as the most likely to deliver high future returns.

Furthermore, the high default risk growth stocks in this study are similar to the 'high-volume losers' in the momentum life cycle, which are subject to increasing unpopularity and neglect and are the most likely stocks to disappoint investors. Consistent with this view, high default risk growth stocks fail to meet analyst expectations at a similar level

to high default risk value stocks, consistent with their initial overvaluation and subsequent (postulated) decline in popularity. Both groups of stocks, namely the high default risk growth stocks in Chapter 3 and the high volume losers in Lee and Swaminathan (2000), are identified as the most likely to deliver *low* future returns.

4.6 Conclusion

This chapter has investigated the relationship between the errors in Australian analyst earnings forecasts and a number of variables; including B/M, E/P, C/P and DD. The study contributes to the literature by being the first Australian study to directly test the errors-in-expectations hypothesis using analysts' forecast errors, and also by being the first to investigate the role of default risk in this context. Consistent with Doukas et al. (2002) and Mian and Teo (2004), the findings of this study are that earnings forecast optimism does not vary with valuation ratios in a manner that supports the errors-in-expectations hypothesis. However, the results of this study show that default risk and prior losses (negative earnings) are far more important determinants of forecast errors than B/M, positive values of E/P or positive values of C/P, and are consistent with analyst underreaction to financial distress (evident as either losses or high default risk). The conclusion that analysts underreact to distress is consistent with a number of previous studies on analyst inefficiency, and in this regard is consistent with Doukas et al. (2002) who also attribute their results to underreaction.

However, the results of this study help to explain why Doukas et al. (2002) find a *highly statistically significant* direct relationship between forecast optimism and B/M. This relationship is counterintuitive because returns increase with B/M, and forecast optimism implies negative earnings surprises and, consequently, poor returns.

Underreaction to distress explains why analysts tend to over-estimate earnings for high B/M stocks in general, because B/M tends to increase with distress. Consistent with this explanation, there is no apparent optimistic bias in analysts' earnings forecasts for high B/M stocks with low default risk, and there is little or no variation in forecast errors with B/M independent of default risk. Similarly, there is little or no variation in forecast errors with E/P or C/P, independent of default risk and *over positive values* of these variables.

For firms where the valuation ratio (either B/M, E/P or C/P) appears misaligned with default risk, the pattern of forecast errors closely reflects the pattern of mispricing found in Chapter 3: analysts forecasts are more optimistic for overvalued (high default risk growth) stocks than they are for undervalued (low default risk value) stocks, and in this sense the results are actually consistent with the errors-in-expectations hypothesis. Bartov and Kim (2004) make a similar case arguing that relatively few value and growth firms are actually mispriced, and they too find that analyst forecast errors for mispriced firms reflect errors-in-expectations. However, the results of this study appear entirely due to underreaction (to distress) and consequently do not support the argument of Lakonishok et al. (1994) that extrapolation of past earnings is the source of errors-in-expectations. On the other hand, the results of this study appear to be consistent with the momentum life-cycle of Lee and Swaminathan (2000); especially as meaningful analogies are able to be drawn between low default risk value stocks and the low volume winners in the momentum life cycle, and between high default risk growth stocks and the high volume losers in the momentum life cycle.

There are at least two unresolved issues from this study that deserve mention. First, this study of analysts' forecast errors is consistent with others such as Doukas et al. (2002) and Mian and Teo (2004) which fail to support errors-in-expectations *based upon extrapolation of past earnings*. However, evidence from studies of analysts' forecast *long-term* growth rates is more supportive of this hypothesis (La Porta, 1996; Dechow and Sloan, 1997) as is evidence that valuation ratios are directly related to past earnings growth but not to future earnings growth (Lakonishok et al., 1994; Chan et al., 2003). A potentially fruitful area of future research might therefore be to reconcile the difference in the relative optimism of *short-term* earnings forecasts and *longer-term* growth expectations of value and growth stocks. Relative errors in short-term earnings forecasts might not reflect errors in long term growth expectations because of the sluggishness of mean-reversion in earnings growth (see for example Lakonishok et al., 1994; Haugen, 1999), or because of manipulation of current earnings by managers, in order to delay bad news and to sustain positive investor sentiment (see Chan, Chan, Jegadeesh and Lakonishok, 2006b).

The second unresolved issue from the analysis of this chapter pertains to the relationship between analysts' forecast errors and stock returns, and how this relationship is affected by B/M and default risk. As is well known, returns increase with B/M while the findings here show that forecast errors, and by implication the incidence of negative earnings surprises, increase with default risk. Therefore, an important question is why aren't high default risk value stocks punished by the market for their high forecast errors? Chapter 3 demonstrates that high default risk *growth* stocks have very low returns and negative portfolio alphas, consistent with a strong market reaction to negative earnings surprises. However, the chapter also demonstrates that high default

risk *value* stocks do not have particularly low returns or statistically significant negative alphas, despite the fact that they exhibit a similar level of forecast error as high default risk growth stocks. This latter observation is consistent with a relatively muted market reaction to negative earnings surprises. This discrepancy in apparent market reactions to earnings surprises will be explored in greater depth in the next chapter.

APPENDIX 4A

Additional Results Omitted from Chapter 4

Table 4A.1: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Book-to-Market- and Distance-to-Default-Sorted Portfolios

This table shows the variation in forecast errors deflated by the absolute value of forecast (FE/|F|) amongst different combinations of book-to-market (B/M) and distance-to-default (DD) classifications. FE/|F| is calculated as per Table 4.1; B/M and DD are calculated each month according to Section 4.3. Companies are sorted into three portfolios by B/M and independently into three portfolios by DD. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios. The Mann-Whitney rank sum statistic tests the null hypothesis that the median forecast error of the low B/M, low DD portfolio equals that of the high B/M, high DD portfolio. The number of observations in each classification is denoted by ‘n’.

Panel A: Full Sample

DD Portfolio	B/M Portfolio								Kruskal-Wallis χ^2 (p-value)
	Low		Mid		High		Total		
	Median	n	Median	n	Median	n	Median	n	
Low	0.1127	60	0.0189	216	0.0794	339	0.0585	618	5.12 (0.0775)
Mid	0.0318	172	0.0569	282	0.0078	181	0.0297	637	6.80 (0.0334)
High	0.0000	284	0.0023	179	0.0182	69	0.0014	533	1.58 (0.4536)
Total	0.0072	516	0.0233	677	0.0514	589	0.0252	1788	3.11 (0.2109)
Kruskal-Wallis χ^2 (p-value)	16.14 (0.0003)		10.13 (0.0063)		11.86 (0.0027)		27.68 (0.0000)		41.51 (0.0000)

Mann-Whitney Rank Sum Statistic

Low DD Low B/M vs. High DD High B/M z=1.9856 p-value 0.04708

Table 4A.1: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Book-to-Market- and Distance-to-Default-Sorted Portfolios (continued)

Panel B: 1995 to 2001:4

DD Portfolio	B/M Portfolio								Kruskal-Wallis χ^2 (p-value)
	Low		Mid		High		Total		
	Median	n	Median	n	Median	n	Median	n	
Low	0.3942	30	0.0757	108	0.1587	180	0.1293	319	4.22 (0.1215)
Mid	0.0941	83	0.0869	161	0.0717	83	0.0867	328	2.01 (0.3667)
High	0.0000	150	0.0321	92	-0.0017	36	0.0029	278	2.30 (0.3163)
Total	0.0350	263	0.0632	361	0.1008	299	0.0631	925	4.13 (0.1267)
Kruskal-Wallis χ^2 (p-value)	22.39 (0.0000)		6.12 (0.0468)		6.65 (0.0360)		30.29 (0.0000)		38.74 (0.0000)

Mann-Whitney Rank Sum Statistic

Low DD Low B/M vs. High DD High B/M z=2.5498 p-value 0.0108

Table 4A.1: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Book-to-Market- and Distance-to-Default-Sorted Portfolios (continued)

Panel C: 2001:5 to 2007

DD Portfolio	B/M Portfolio								Kruskal-Wallis χ^2 (p-value)
	Low		Mid		High		Total		
	Median	n	Median	n	Median	n	Median	n	
Low	0.0468	30	0.0002	108	0.0576	159	0.0189	299	1.98 (0.3712)
Mid	0.0096	89	0.0114	121	-0.0246	98	-0.0070	309	3.28 (0.1942)
High	-0.0010	134	-0.0315	87	0.0310	33	0.0000	255	4.35 (0.1136)
Total	0.0014	253	-0.0032	316	0.0173	290	0.0041	863	1.45 (0.4831)
Kruskal-Wallis χ^2 (p-value)	1.23 (0.5400)		4.05 (0.1318)		6.74 (0.0343)		5.41 (0.0669)		14.02 (0.0814)

Mann-Whitney Rank Sum Statistic
Low DD Low B/M vs. High DD High B/M z=0.1032 p-value 0.9178

Table 4A.2: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Earnings-to-Price- and Distance-to-Default-Sorted Portfolios

This table shows the variation in forecast errors deflated by the absolute value of forecast (FE/|F|) amongst different combinations of earnings-to-price (E/P) and distance-to-default (DD) portfolio classifications. FE/|F| is calculated as per Table 4.1; E/P and DD are calculated each month according to Section 4.3. Companies are either sorted into a negative (<0) E/P portfolio if E/P is negative or into three portfolios E/P portfolio if E/P is positive; companies are also independently sorted into three portfolios by DD. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios; when annotated with '(E/P>0)' the test excludes observations in the negative (<0) E/P portfolio. The Mann-Whitney rank sum statistics test the null hypothesis of that the median forecast errors are equal for the pairs of portfolios indicated. The number of observations in each classification is denoted by 'n'.

Panel A: Full Sample

DD Portfolio	E/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (E/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.5503	54	0.1364	129	0.0521	151	0.0144	284	0.0585	618	41.08 (0.0000)	11.47 (0.0032)
Mid	1.0899	24	0.0771	135	0.0214	240	0.0257	236	0.0295	635	19.11 (0.0003)	8.47 (0.0145)
High	0.5127	6	-0.0015	197	0.0030	221	-0.0018	110	0.0019	534	4.47 (0.2145)	0.34 (0.8419)
Total	0.7463	84	0.0370	461	0.0180	612	0.0133	630	0.0251	1787	59.02 (0.0000)	7.43 (0.0243)
Kruskal-Wallis χ^2 (p-value)	0.24 (0.8885)		17.94 (0.0001)		8.97 (0.0113)		2.54 (0.2806)		27.63 (0.0000)		89.67 (0.0000)	38.46 (0.0000)

Mann-Whitney Rank Sum Statistics

Low DD Low E/P vs. High DD High E/P z=-3.6955 p-value 0.0003

Low DD E/P<0 vs. High DD High E/P z=6.0132 p-value 0.0000

Low DD E/P<0 vs. Low DD Low E/P z=3.4193 p-value 0.0006

Table 4A.2: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Earnings-to-Price- and Distance-to-Default-Sorted Portfolios (continued)

Panel B: 1995-2001:4

DD Portfolio	E/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (E/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.7216	31	0.4719	67	0.0708	73	0.0637	148	0.1293	319	28.03 (0.0000)	16.27 (0.0003)
Mid	0.8910	14	0.1181	69	0.0605	136	0.0717	107	0.0867	326	8.57 (0.0356)	5.67 (0.0586)
High	0.0849	4	0.0045	108	0.0095	107	-0.0026	60	0.0031	279	1.37 (0.7118)	0.99 (0.6088)
Total	0.7216	49	0.0925	244	0.0464	316	0.0354	315	0.0628	924	25.66 (0.0000)	7.30 (0.0260)
Kruskal-Wallis χ^2 (p-value)	2.06 (0.3575)		26.26 (0.0000)		4.92 (0.0853)		6.08 (0.0479)		30.36 (0.0000)		65.95 (0.0000)	47.11 (0.0000)

Mann-Whitney Rank Sum Statistics

Low DD Low E/P vs. High DD High E/P z=-4.5805 p-value 0.0000

Low DD E/P<0 vs. High DD High E/P z=4.2667 p-value 0.0000

Low DD E/P<0 vs. Low DD Low E/P z=1.5813 p-value 0.1138

Table 4A.2: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Earnings-to-Price- and Distance-to-Default-Sorted Portfolios (continued)

Panel C: 2001:5-2007

DD Portfolio	E/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (E/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.5399	23	0.0088	62	0.0444	78	0.0002	136	0.0189	299	21.89 (0.0001)	3.93 (0.1398)
Mid	1.2344	10	0.0205	66	-0.0218	104	-0.0129	129	-0.0070	309	12.42 (0.0061)	4.32 (0.1152)
High	14.5450	2	-0.0175	89	0.0000	114	0.0059	50	0.0000	255	5.91 (0.1159)	0.03 (0.9844)
Total	0.8221	35	0.0060	217	0.0020	296	-0.0041	315	0.0041	863	35.84 (0.0000)	1.40 (0.4960)
Kruskal-Wallis χ^2 (p-value)	3.16 (0.2060)		1.98 (0.3724)		7.95 (0.0188)		0.11 (0.9466)		5.41 (0.0669)		46.40 (0.0000)	11.16 (0.1930)

Mann-Whitney Rank Sum Statistics
Low DD Low E/P vs. High DD High E/P z=-0.5941 p-value 0.5525
Low DD E/P<0 vs. High DD High E/P z=4.1265 p-value 0.0000
Low DD E/P<0 vs. Low DD Low E/P z=3.4078 p-value 0.0007

Table 4A.3: Medians of Forecast Errors Deflated by Stock Price for Cash Flow-to-Price- and Distance-to-Default- Sorted Portfolios

This table shows the variation in price-deflated forecast errors (FE/P) amongst different combinations of cash flow-to-price (C/P) and distance-to-default (DD) classifications. FE/P is calculated as per Table 4.1; C/P and DD are calculated each month according to Section 4.3. Companies sorted into three portfolios by C/P and independently into three portfolios by DD. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios. The Mann-Whitney rank sum statistics test the null hypothesis of that the median forecast errors are equal for the pairs of portfolios indicated. The number of observations in each classification is denoted by 'n'.

Panel A: Full Sample

DD Portfolio	C/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (C/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.1031	24	0.0050	90	0.0002	190	0.0064	314	0.0039	618	44.28 (0.0000)	11.19 (0.0037)
Mid	0.0189	11	0.0020	127	0.0019	250	0.0019	247	0.0020	635	4.73 (0.1929)	0.68 (0.7122)
High	0.0512	3	-0.0002	218	0.0010	223	-0.0006	90	0.0001	534	7.41 (0.0598)	2.92 (0.2318)
Total	0.0582	38	0.0006	435	0.0010	663	0.0027	651	0.0015	1787	48.17 (0.0000)	3.25 (0.1974)
Kruskal-Wallis χ^2 (p-value)	6.16 (0.0459)		16.35 (0.0003)		3.17 (0.2047)		11.54 (0.0031)		27.74 (0.0000)		84.44 (0.0000)	36.11 (0.0000)

Mann-Whitney Rank Sum Statistics

Low DD Low C/P vs. High DD High C/P z=3.6534 p-value 0.0003

Low DD C/P<0 vs. High DD High C/P z=6.3112 p-value 0.0000

Low DD C/P<0 vs. Low DD Low C/P z=4.6151 p-value 0.0000

Table 4A.3: Medians of Forecast Errors Deflated by Stock Price for Cash Flow-to-Price- and Distance-to-Default- Sorted Portfolios (continued)

Panel B: 1995-2001:4

DD Portfolio	C/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (C/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.0962	10	0.0178	45	0.0026	90	0.0098	174	0.0091	319	20.54 (0.0001)	10.19 (0.0061)
Mid	0.0212	5	0.0042	71	0.0059	134	0.0052	116	0.0055	326	2.58 (0.4604)	0.26 (0.8766)
High	0.0263	2	0.0000	113	0.0021	118	-0.0003	46	0.0002	279	3.47 (0.3244)	1.79 (0.4081)
Total	0.0512	17	0.0021	229	0.0038	342	0.0059	336	0.0040	924	18.93 (0.0003)	2.75 (0.2527)
Kruskal-Wallis χ^2 (p-value)	1.55 (0.4600)		22.83 (0.0000)		8.17 (0.0169)		6.23 (0.0444)		32.24 (0.0000)		58.63 (0.0000)	41.49 (0.0000)

Mann-Whitney Rank Sum Statistics

Low DD Low C/P vs. High DD High C/P z=-3.6396 p-value 0.0003

Low DD C/P<0 vs. High DD High C/P z=4.0440 p-value 0.0001

Low DD C/P<0 vs. Low DD Low C/P z=2.0622 p-value 0.0392

Table 4A.3: Medians of Forecast Errors Deflated by Stock Price for Cash Flow-to-Price- and Distance-to-Default- Sorted Portfolios (continued)

Panel C: 2001:5-2007

DD Portfolio	C/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (C/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.1195	14	0.0001	45	-0.0011	100	0.0037	140	0.0010	299	27.61 (0.0000)	4.13 (0.1268)
Mid	0.0127	6	0.0007	56	-0.0008	116	-0.0008	131	-0.0005	309	4.86 (0.1823)	2.33 (0.3123)
High	0.2859	1	-0.0004	105	0.0003	105	-0.0015	44	0.0000	255	5.08 (0.1659)	2.22 (0.3303)
Total	0.0652	21	0.0000	206	-0.0004	321	0.0010	315	0.0003	863	32.19 (0.0000)	2.33 (0.3126)
Kruskal-Wallis χ^2 (p-value)	7.21 (0.0271)		1.73 (0.4220)		1.29 (0.5251)		5.08 (0.0788)		5.88 (0.0529)		43.66 (0.0000)	11.43 (0.1785)

Mann-Whitney Rank Sum Statistics
Low DD Low C/P vs. High DD High C/P z=-1.6453 p-value 0.0999
Low DD C/P<0 vs. High DD High C/P z=4.8607 p-value 0.0000
Low DD C/P<0 vs. Low DD Low C/P z=4.2851 p-value 0.0000

Table 4A.4: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Cash Flow-to-Price- and Distance-to-Default-Sorted Portfolios

This table shows the variation in forecast errors deflated by the absolute value of forecast (FE/|F|) amongst different combinations of cash flow-to-price (C/P) and distance-to-default (DD) classifications. FE/|F| is calculated as per Table 4.1; C/P and DD are calculated each month according to Section 4.3. Companies sorted into three portfolios by C/P and independently into three portfolios by DD. The relevant portfolio grouping for a forecast error observation is the one that was current at the end of the fiscal year preceding the forecast. Kruskal-Wallis χ^2 statistics and associated p-values test the null hypothesis of no variation in median forecast error amongst portfolios. The Mann-Whitney rank sum statistics test the null hypothesis of that the median forecast errors are equal for the pairs of portfolios indicated. The number of observations in each classification is denoted by ‘n’.

Panel A: Full Sample

DD Portfolio	C/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (C/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.5503	24	0.1152	90	0.0025	190	0.0736	314	0.0585	618	33.58 (0.0000)	12.75 (0.0017)
Mid	2.0435	11	0.0648	127	0.0275	250	0.0254	247	0.0295	635	11.45 (0.0095)	2.57 (0.2763)
High	0.9254	3	-0.0039	218	0.0182	223	-0.0088	90	0.0019	534	8.55 (0.0358)	2.70 (0.2598)
Total	0.7718	38	0.0129	435	0.0182	663	0.0325	651	0.0251	1787	43.00 (0.0000)	2.06 (0.3562)
Kruskal-Wallis χ^2 (p-value)	0.13 (0.9362)		19.69 (0.0001)		3.56 (0.1685)		11.68 (0.0029)		27.63 (0.0000)		80.95 (0.0000)	39.79 (0.0000)

Mann-Whitney Rank Sum Statistics
Low DD Low C/P vs. High DD High C/P z=3.8594 p-value 0.0001
Low DD C/P<0 vs. High DD High C/P z=5.6856 p-value 0.0000
Low DD C/P<0 vs. Low DD Low C/P z=2.8150 p-value 0.0049

Table 4A.4: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Cash Flow-to-Price- and Distance-to-Default-Sorted Portfolios (continued)

Panel B: 1995-2001:4

DD Portfolio	C/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (C/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.3847	10	0.4445	45	0.0529	90	0.1297	174	0.1293	319	18.89 (0.0003)	14.09 (0.0009)
Mid	2.0435	5	0.1008	71	0.0929	134	0.0597	116	0.0867	326	3.97 (0.2646)	1.04 (0.5948)
High	0.5127	2	-0.0008	113	0.0311	118	-0.0037	46	0.0031	279	4.27 (0.2333)	1.52 (0.4669)
Total	0.4152	17	0.0584	229	0.0573	342	0.0605	336	0.0628	924	12.97 (0.0047)	0.80 (0.6695)
Kruskal-Wallis χ^2 (p-value)	0.31 (0.8582)		25.05 (0.0000)		8.38 (0.0152)		6.33 (0.0422)		30.36 (0.0000)		56.42 (0.0000)	44.19 (0.0000)

Mann-Whitney Rank Sum Statistics
Low DD Low C/P vs. High DD High C/P z=3.9175 p-value 0.0001
Low DD C/P<0 vs. High DD High C/P z=3.5305 p-value 0.0004
Low DD C/P<0 vs. Low DD Low C/P z=0.4474 p-value 0.6546

Table 4A.4: Medians of Forecast Errors Deflated by the Absolute Value of Forecast for Cash Flow-to-Price- and Distance-to-Default-Sorted Portfolios (continued)

Panel C: 2001:5-2007

DD Portfolio	C/P Portfolio										Kruskal-Wallis χ^2 (p-value)	Kruskal-Wallis χ^2 (C/P>0) (p-value)
	<0		Low		Mid		High		Total			
	Median	n	Median	n	Median	n	Median	n	Median	n		
Low	0.6914	14	0.0023	45	-0.0163	100	0.0559	140	0.0189	299	21.70 (0.0001)	3.57 (0.1674)
Mid	2.0613	6	0.0130	56	-0.0152	116	-0.0109	131	-0.0070	309	8.55 (0.0360)	2.44 (0.2953)
High	8.9268	1	-0.0115	105	0.0060	105	-0.0217	44	0.0000	255	4.61 (0.2029)	1.74 (0.4193)
Total	0.9494	21	0.0000	206	-0.0041	321	0.0156	315	0.0041	863	31.42 (0.0000)	1.85 (0.3971)
Kruskal-Wallis χ^2 (p-value)	1.36 (0.5057)		2.09 (0.3515)		0.82 (0.6629)		4.66 (0.0972)		5.41 (0.0669)		40.34 (0.0000)	10.48 (0.2331)

Mann-Whitney Rank Sum Statistics
Low DD Low C/P vs. High DD High C/P z=-1.7110 p-value 0.0871
Low DD C/P<0 vs. High DD High C/P z=4.4609 p-value 0.0000
Low DD C/P<0 vs. Low DD Low C/P z=3.4477 p-value 0.0006

CHAPTER 5: THE MARKET RESPONSE TO EARNINGS SURPRISE, CONDITIONAL UPON BOOK-TO-MARKET, DEFAULT RISK AND ANALYST AGREEMENT

5.1 Abstract

This study uses Australian data and long horizon (240 trading day) returns to examine variation in the market's reaction to earnings surprises across value/growth, default risk and analyst agreement categories. Consistent with prior literature, the findings demonstrate that this market reaction is inversely related to a firm's book-to-market (B/M) ratio and directly related to the degree of analyst agreement regarding expected (forecast) earnings. In other words, the market reaction is relatively strong for growth stocks and for earnings forecasts with a high degree of analyst agreement, and relatively muted for value stocks and for earnings forecasts with a relatively low level of analyst agreement. Controlling for B/M and analyst agreement, there appears no residual effect of default risk in this context, a finding which contributes to the relatively sparse literature on the effects of default risk on the market reaction to earnings surprises

The data support a model of the return-earnings relationship with a slope (or earnings response coefficient, ERC) that is increasing in analyst agreement (consistent with prior literature) and with an asymmetric intercept term that captures the effects of an earnings torpedo, in other words the large negative returns attributable to even a marginally negative surprise. Consistent with Skinner and Sloan (2002) this asymmetric intercept term is larger for low B/M stocks than for high B/M stocks. When the asymmetric intercept term was not explicitly modelled, the slope was also found to vary inversely

with B/M; a result consistent the ERC literature. However, when the regression tests allowed for variation in both the intercept and slope, no statistically significant variation between high and low B/M stocks was found in the slope term.

The findings are applied to a conundrum posed by the findings of Doukas et al. (2002), whereby high B/M stocks are observed to have larger, more negative earnings surprises than low B/M stocks, despite that fact that high B/M stocks are observed to have higher returns than low B/M stocks. This conundrum is *not* explained by differences in analyst agreement between value and growth stocks, despite the observation that analyst agreement affects the severity of the market reaction to earnings surprise and that value stocks generally possess lower analyst agreement than growth stocks. The best explanation for the conundrum that can be offered by this study is that value stocks remain relatively unpunished by the market for missing earnings expectations while growth stocks are heavily punished for missing earnings expectations. Although this result is known from previous studies (Skinner and Sloan, 2002; Chan et al., 2006a), a major contribution is to show that the effect exists independently from differences in analyst agreement and default risk.

5.2 Introduction

In this study, Australian data are employed to measure the market reaction to earnings surprises, and how this reaction varies with B/M, default risk and analyst forecast dispersion. All three variables above have been the subject of studies in the earnings response coefficient (ERC) literature, and therefore the effect of each of these variables is of interest in its own right (the ERC is the slope of the relationship between unexpected returns and unexpected earnings). However, there are few if any studies in

this literature that examine all three variables in this context simultaneously; a seemingly worthwhile endeavour because B/M, default risk and forecast dispersion are all correlated. In addition, further results are provided based on asymmetric slope and intercept terms of the unexpected return-earnings surprise relationship, including the ‘earnings torpedo’ and its relationship with B/M as documented by Skinner and Sloan (2002). This study thus provides Australian evidence regarding the determinants of the ERC as well as on the importance of the earnings torpedo for growth stocks.

The study is motivated by recent results in the value premium literature. Whilst it is by now a well known empirical result that stock returns increase with B/M (see for example Fama and French, 1992), earnings surprises have been found to be more negative for high B/M stocks than for low B/M stocks (Bauman and Miller, 1997; Doukas et al., 2002). This result is counterintuitive because in general it implies an inverse relation between stock returns and earnings surprises[33]. At first glance, a simple explanation is that growth stocks merely respond more than value stocks to unexpected earnings, a result not inconsistent with prior results in the literature (for example Collins and Kothari, 1989; Skinner and Sloan, 2002). However, this story fails to explain why returns are *directly* related to B/M but earnings surprises are *inversely* related to B/M, unless the ERC is negative or value-relevant information is missed in comparisons of average earnings surprises and returns of B/M-sorted portfolios. An examination involving the three variables in this study is intended to shed light on the discrepancy noted above between the average returns and earnings surprises of B/M sorted

[33] According to Doukas et al. (2002), analysts tend to issue earnings forecasts which are more upwardly biased for high B/M stocks than for low B/M stocks. The median earnings surprises implied by their results are -0.0026 for bottom quintile of stocks by B/M stocks and -0.0118 for the top quintile of stocks by B/M. In a study that uses the same study period (1976 to 1997), Ali et al. (2003) report average annual returns of 13% and 21.9% for the bottom and top quintile of stocks by B/M.

portfolios. The primary objective, however, is to determine the relative importance of each of the variables to the market reaction to earnings surprises.

The importance of B/M to the market reaction to unexpected earnings has long been recognised. As pointed out by Collins and Kothari (1989) a low B/M ratio is indicative of either or both of two characteristics, the presence of growth opportunities and earnings persistence, each of which increase the importance of unexpected earnings news to a firm's valuation and which therefore imply an inverse relationship between B/M and ERC. The inverse relationship between B/M and ERC is confirmed in Collins and Kothari (1989) and Biddle and Seow (1991). Moreover, an inverse relationship between B/M and ERC is also implied in valuation models that recognise the importance of *both* book value *and* earnings to equity value, for example Ohlson (1995) and Burgstahler and Dichev (1997). In particular, Burgstahler and Dichev (1997) argue that current earnings are relatively more important to firm valuation when book values are low relative to earnings (indicating that the firm's assets are being productively utilised) rather than when book values are high relative to earnings (indicating that the firm's assets might be adapted to alternative, more productive uses).

In the finance literature B/M is often used to distinguish between value and growth stocks, for example in Fama and French (1992). The market reaction to earnings surprises and the variation of this reaction with B/M (and other valuation measures) has been of interest to finance researchers in tests of the errors-in-expectations hypothesis. This hypothesis states that investors' expectations of future growth in earnings are more optimistic towards growth stocks than towards value stocks, resulting in overvaluation

of growth stocks relative to value stocks[34]. Whilst the errors-in-expectations hypothesis is couched in terms of erroneous future growth expectations (for example in Lakonishok et al., 1994, and La Porta, 1996), some empirical studies of the hypothesis have examined the effects of actual earnings announcements (for example La Porta et al., 1997[35]) and earnings surprises on returns. In particular, Skinner and Sloan (2002) find that low B/M stocks suffer large negative returns as a consequence of negative earnings surprises; a result they argue is consistent with the downward revision of growth expectations and therefore with the errors-in-expectations hypothesis. In contrast, high B/M stocks are less affected by negative surprises. Similar results were also obtained by Levis and Liodakis (2001) and Chan et al. (2006a)[36].

In contrast to the ERC literature, Skinner and Sloan (2002) and Chan et al. (2006a) base most of their inferences upon regressions of returns upon dummy variables intended to capture the *sign*, rather than the *magnitude*, of the earnings surprise. Implicit in this particular return-earnings surprise specification is the effect of the 'earnings torpedo', whereby the act of missing analysts' forecasts by *even a small margin* is more relevant to the market reaction than the actual magnitude of the earnings surprise. In effect, modelling of the earnings torpedo introduces a discontinuity of the return-earnings surprise relationship at the zero level of earnings surprise. Both studies cited above find that the effect of the earnings torpedo is greater for low B/M stocks than for high B/M stocks, and therefore imply that the intercept in the return-earnings surprise relationship for negative surprises is lower (more negative) for growth than for value stocks. In this

[34] The opposing view in the literature is that growth stocks are not overvalued, but rather earn lower returns than value stocks because they are less risky (Fama and French, 1992, 1993).
[35] La Porta et al. (1997) find that a disproportionate amount of the annual value premium occurs in the 12 days surrounding the quarterly earnings announcements of US firms, suggesting the arrival of predominantly bad news for growth stocks and of a downward revision of growth expectations, and therefore consistent with the errors-in-expectations hypothesis.
[36] Dreman and Berry (1995) also compare value and growth stocks for their reaction to positive and negative surprises, but differentiate value and growth on the basis of earnings-to-price rather than B/M.

study, allowance is made for variation in both the slope and intercept terms of the return-earnings surprise with B/M; however the results are generally supportive of the growth stock earnings torpedo reported by Skinner and Sloan (2002).

Default risk is considered in the analysis for two reasons. First, Dhaliwal and Reynolds (1994) point out that default risk may represent a form of priced risk not adequately reflected in observed equity betas, but relevant to the expected rate of return required by shareholders, and therefore also relevant to the discounted value of expected future cash flows and to the observed ERC[37]. Consistent with this line of reasoning Dhaliwal and Reynolds (1994) observe an inverse relationship between ERC and default risk, measured in terms of either bond ratings or debt-to-equity ratios, after controlling for equity beta. On the other hand, Billings (1999) argues that both measures of default risk used by Dhaliwal and Reynolds (1994) are correlated with expected earnings growth, and therefore the inverse relation between ERC and default risk is merely capturing the association between ERC and growth. Billings (1999) finds that the relation between bond ratings and ERC disappears when he controls for expected growth, measured as either the I/B/E/S long term growth forecast or as return-on-equity. However, he still finds a negative relation between debt-to-equity ratios and ERC after controlling for growth, suggesting that the effect of default risk on the ERC may not be completely subsumed by that of growth. The results of this study provide additional evidence on

[37] Theoretically, the ERC is underpinned by an assumption that current earnings are directly related to expected future cash flows, and by a valuation model linking expected future cash flows to current share price (Collins and Kothari, 1989). If the Capital Asset Pricing Model (CAPM) is valid, the rate at which expected future cash flows are discounted is proportional to equity beta and consequently, the ERC is inversely related to equity beta. However, equity beta is directly related to the riskiness of a firm's debt and hence to default risk; put differently, equity holders may demand a higher return on equity for investing in companies with higher default risk. Dhaliwal and Reynolds (1994) point out that if the equity beta is measured without error and the CAPM is valid, the effect of default risk is subsumed by the effect of equity beta. If the equity beta is measured with error or the CAPM is not valid, however, the expected return demanded by shareholders may appear to increase with default-risk, and hence the ERC will be inversely related to default-risk.

this issue, particularly as an alternative measure of default risk is used, namely the distance-to-default (DD) measure developed by Moody's KMV and discussed in Crosbie and Bohn (2003). DD is arguably a cleaner measure of default risk than ratios or statistical models upon which bond ratings are based, because it captures equity market participants' ex ante assessment of the solvency of each firm (Vassalou and Xing, 2004; Gharghori et al., 2006b).

The second reason default risk is considered here is because it is correlated with B/M (Fama and French, 1995; Dichev, 1998), and therefore may provide some intuition regarding the discrepancy between the returns and earnings surprises of B/M sorted portfolios. An inverse relation between default risk and the market reaction to earnings surprise would at least partially explain why high B/M stocks are not punished by the market for failing to meet analysts' forecasts. However, such an inverse relationship also implies that growth stocks with high default risk are also likely to escape punishment for negative earnings surprises. It is argued that this is an unlikely outcome, particularly as evidence in Griffin and Lemmon (2002) shows that the poor returns of growth stocks are actually concentrated in high default risk growth stocks (a result confirmed for Australian stocks in Chapter 3). Furthermore, the weight of recent evidence suggests that default risk is not priced in equity market (see for example Dichev, 1998; Gharghori et al., 2007; Campbell et al., 2008). It is therefore expected that default risk plays a relatively unimportant role in the market reaction to earnings surprises after controlling for B/M and forecast dispersion, and the results of this study generally support this conjecture.

Forecast dispersion (the coefficient of variation of analysts' earnings-per-share forecasts) is considered because this variable has been demonstrated empirically to be an important determinant of the magnitude of earnings response coefficients (Imhoff and Lobo, 1992; Kinney et al., 2002) and because Doukas et al. (2004) find that high B/M stocks have relatively high forecast dispersion. This observation alone might therefore explain the discrepancy between the returns and earnings surprises of B/M sorted portfolios. Kinney et al. (2002) argue that high forecast dispersion implies that a firm's earnings are difficult to predict, and consequently investors pay less attention to earnings surprises when dispersion is large. Similarly, Doukas et al. (2006) argue that investors view low dispersion forecasts as more reliable than high dispersion forecasts. In support of this view, they find that the degree to which prices reflect forecast changes in earnings is inversely related to forecast dispersion. The results of this study strongly support the inverse relationship between forecast dispersion and the market reaction to earnings surprise. As it turns out however, this relationship unfortunately sheds little light on the discrepancy between returns and earnings surprises of B/M sorted portfolios.

The principal findings of the study are as follows. As expected default risk, which is measured using DD, has little impact upon the market reaction to earnings surprise after controlling for B/M and forecast dispersion. In contrast, both B/M and forecast dispersion are important. Consistent with Imhoff and Lobo (1992) and Kinney et al. (2002), the slope of the return-earnings relation (or ERC) is found to be inversely related to forecast dispersion; however the effect of B/M is somewhat more complicated. When the return-earnings relation is modelled without an earnings torpedo the slope (ERC) is inversely related to B/M, consistent with Collins and Kothari (1989)

and the valuation models of Ohlson (1995) and Burgstahler and Dichev (1997). However, upon including asymmetric intercept terms that vary with B/M, no statistically significant evidence is found that the slope increases with B/M, but evidence is found consistent with the growth stock torpedo effect of Skinner and Sloan (2002). Finally, it is shown that the discrepancy between the returns and earnings surprises of B/M sorted portfolios is confined to negative surprises, and is consistent with both the growth stock torpedo effect and a marked lack of market response to value stocks' negative surprises.

The results of this study are robust to a number of changes in experimental design, including the definition of unexpected returns, the exclusion of losses, the use of only June year-end companies, and the use of earnings-to-price (E/P) rather than B/M. The study also addresses concerns raised in Payne and Thomas (2003) that the growth-stock earnings torpedo arises because of a rounding error in I/B/E/S.

The remainder of the chapter is structured as follow. Section 5.3 lays out the empirical framework for the study. The data and methodology is discussed in Section 5.4. Section 5.5 presents the results, which are interpreted and analysed graphically in Section 5.6. Section 5.6 also applies the results to an analysis of the discrepancy discussed above between the returns and earnings surprises of B/M sorted portfolios. Section 5.7 concludes.

5.3 Empirical Framework

The main research question of this study asks whether the market reaction to earnings surprise varies with B/M, default risk and forecast dispersion. In the context of the ERC literature, this question asks whether the slope of the unexpected return-earnings surprise varies with the three variables. However, the analysis also includes an earnings torpedo or asymmetric intercept term, and the question is therefore slightly more complicated: whether the slope *and* intercept terms vary with B/M, default risk and forecast dispersion. The picture is made even more complicated by the fact that a flatter slope is observed for negative surprises generally, and further allowances are therefore required for this asymmetry.

To keep the analysis tractable and avoid confusing the reader, the analysis is divided into three sections. With each progressive section, a layer of complexity is added to the return-earnings relation. In the first section, a simple ERC specification is considered which allows the slope of the return-earnings relation to vary with each of the three control variables:

$$UR=\beta_0+\beta_1 ES+\beta_2 G*ES+\beta_3 DR*ES+\beta_4 AA*ES+\varepsilon \qquad (5.1)$$

In equation (5.1), UR is the unexpected return, ES is the earnings surprise or unexpected return, and G, DR and AA are indicator variables[38]. G takes on the values 0, 1, and 2 for

[38] To make the results easier to interpret, the three variables (B/M, default risk and forecast dispersion) are expressed as indicator or categorical variables which are also employed as regression dummy variables. To this end, default risk is converted into a categorical variable of the same name (DR). B/M is converted into to a growth score (G) with high B/M stocks having a low value of G and vice-versa. Forecast dispersion is converted into an 'analyst agreement' score (AA) with high forecast dispersion stocks having a low value of AA and vice-versa. The order of magnitude for G and AA are reversed

stocks which are classified respectively as high B/M, intermediate B/M and low B/M; thus G=2 for growth stocks and G=0 for value stocks. Similarly, DR takes on the values 0, 1, and 2 for stocks which are classified as low, intermediate and high default risk respectively. AA, for 'analyst agreement', takes on the values 0, 1, and 2 for stocks classified respectively as high, intermediate and low forecast dispersion; thus AA=0 for high forecast dispersion (low analyst agreement) stocks and AA=2 for low forecast dispersion (high analyst agreement) stocks. Variation in the ERC (or market reaction to earnings surprise) with B/M, default risk and forecast dispersion is tested by examining the coefficients β_2, β_3 and β_4 respectively. To illustrate the interpretation of equation (5.1), the ERC of value stocks equals β_1, the ERC of intermediate B/M stocks is $\beta_1+\beta_2$, and the ERC of growth stocks is $\beta_1+2\beta_2$. The approach adopted for the indicator variables is similar to that adopted by Skinner and Sloan (2002) in defining their GROWTH variable, except they employ five B/M categories while this study employs only three, partly to avoid overly constraining the parameter values and partly because the sample used here is much smaller.

Next, allowance is made for asymmetric slope coefficients between positive and negative surprises as follows:

$$\begin{aligned} UR &= \beta_0 + \beta_1 ES + \beta_2 BAD * ES + \beta_3 G * ES + \beta_4 G * BAD * ES \\ &+ \beta_5 DR * ES + \beta_6 DR * BAD * ES + \beta_7 AA * ES + \beta_8 AA * BAD * ES + \varepsilon \end{aligned} \tag{5.2}$$

because, based on the literature discussed in the introduction, the market reaction to earnings surprise is expected to be an increasing function of G and AA.

Equation (5.2) introduces the BAD indicator variables, which takes on the value of 1 if ES<0 and 0 otherwise. Thus, value stocks with low DR and AA have an ERC of β_1 for positive surprise and $\beta_1+\beta_2$ for negative surprises; growth stocks with low DR and AA have an ERC of $\beta_1+\beta_2+2\beta_3$ for positive surprises and $\beta_1+\beta_2+2\beta_3+2\beta_4$ for negative surprises. The results show that β_2 is generally statistically significant and therefore the term BAD*ES is included in all subsequent analyses. Variation in the ERC (or market reaction to earnings surprise) with B/M, default risk and forecast dispersion is tested by testing the coefficients β_3, β_5 and β_7 respectively. Further tests examine whether the *incremental effect* of these variables is different for negative surprises, via the coefficients β_4, β_6 and β_8 respectively. Fortunately, this task is made easier by the fact that none of the terms β_4, β_6 or β_8 is statistically significant, and to avoid clutter the terms G*BAD*ES, DR*BAD*ES and AA*BAD*ES are omitted from the remaining discussion and equations in this section.

Next, allowance is made for asymmetric intercept terms, without mixed terms involving G, DR or AA:

$$UR = \beta_0 + \beta_1 G + \beta_2 BAD + \beta_3 G * BAD + \beta_4 ES + \beta_5 BAD * ES + \beta_6 G * ES + \varepsilon \qquad (5.3a)$$

$$UR = \beta_0 + \beta_1 DR + \beta_2 BAD + \beta_3 DR * BAD + \beta_4 ES + \beta_5 BAD * ES + \beta_6 DR * ES + \varepsilon \qquad (5.3b)$$

$$UR = \beta_0 + \beta_1 AA + \beta_2 BAD + \beta_3 AA * BAD + \beta_4 ES + \beta_5 BAD * ES + \beta_6 AA * ES + \varepsilon \qquad (5.3c)$$

Equations (5.3a), (5.3b) and (5.3c) include asymmetric intercept terms which vary with the sign of the surprise (β_0 and β_2), the categorisation of each stock by G, DR or AA

(β_1) and the interaction of the sign of the surprise with the categorisation by G, DR or AA (β_3). Thus equation (5.3a) for example gives us an estimate of the intercepts for value and growth stocks; value stocks have intercept terms of β_0 for positive surprises and $\beta_0+\beta_2$ for negative surprises while growth stocks have intercept terms of $\beta_0+\beta_1$ for positive surprises and $\beta_0+2\beta_1+\beta_2+2\beta_3$ for negative surprises. Note that Skinner and Sloan (2002) find β_3 to be a large negative number, implying a torpedo effect that is particularly strong for growth stocks, and $\beta_1=0$ implying that there is no residual value premium after taking the growth-earnings torpedo into account.

Finally, the most significant terms from equations (5.3a), (5.3b) and (5.3c) are combined; in other words the terms involving G, DR and AA are finally mixed in a regression specification that allows for asymmetric slope and intercept terms.

5.4 Data and Methodology

5.4.1 Data

The data for this study are from five sources and is identical to the data used in Chapter 4. Financial data are sourced from the Aspect Huntley Datalink database, from which are calculated book value of equity, earnings, cash earnings and debt. Monthly market data are sourced from the AGSM SPPR database, from which market capitalisation, used in the computation of the valuation ratios and to measure size, are calculated. Daily market capitalisation data are sourced from SIRCA[39], which is used in the calculation of DD. Analyst earnings forecast data is obtained from the I/B/E/S international summary

[39] Data supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of the Australian Securities Exchange.

database[40]. The financial data span the period from July 1994 till June 2006, the daily market capitalisation data span the period from November 1994 till November 2007, and the monthly market data span the period from January 1996 till December 2008. The I/B/E/S data covers forecast dates from 1995 to 2006, and the earnings forecasts themselves are for fiscal year-ends covering the period from 1996 to 2007. To be included in the sample, firms must have fully-paid ordinary shares listed on the Australian Stock exchange and be ranked in the top 300 by market capitalisation. As was the case in Chapter 4 and for consistency with Doukas et al. (2002), the ranking by market capitalisation is determined at the end of the fiscal year prior to the relevant earnings forecast. From the resulting list of companies, property trusts, investment trusts and shares of foreign or dual-listed companies are excluded.

5.4.2 Calculation of Unexpected Returns

Following Chan et al. (2006a), size-adjusted buy and hold abnormal returns (BHAR) are employed as a measure of unexpected returns, calculated over a return window which covers the period from 180 trading days before to 60 trading days after the earnings announcement date. This return window always commences after the forecast date, and makes allowances for the post-earnings announcement drift documented in Chan et al. (2006a). Observations where the announcement date occurs more than six months after the fiscal year end are excluded. Following Skinner and Sloan (2002) and Chan et al. (2006a), all abnormal returns are size-adjusted, computed as the buy-and-hold stock return less the equally-weighted return on a size-matched portfolio. As in Chan et al. (2006a) size-based quintiles on the top 500 ASX-listed stocks are formed. Each stock is matched to a size quintile at the end of the month immediately before the

[40] I/B/E/S Summary History data accessed via the Wharton Research Data Services (WRDS) website, Wharton School, University of Pennsylvania.

return measurement period. The size-adjusted return is the stock return over the period from 180 trading days prior to the earnings announcement date to 60 trading days after the announcement date, minus the return of the size-matched portfolio over the same period. For robustness purposes abnormal returns are also computed as stock returns less the equal-weighted return of the top 500 stocks over the same holding period[41].

5.4.3 Definition of Earnings Surprise

In this study, unexpected earnings are measured as the price-deflated difference between actual earnings-per-share (EPS) for a company and the consensus analyst forecast from the I/B/E/S database, in other words the earnings surprise (ES). For consistency with Doukas et al. (2002) and Chapter 4, the consensus forecast is defined as the median forecast issued eight months prior to fiscal year end, where three or more analysts have contributed forecasts[42]. The earnings surprise is deflated by the I/B/E/S stock price at the forecast date to calculate ES.

As is well known, deflating earnings surprises by stock price creates a number of extreme outliers (Abarbanell and Lehavy, 2003; Cohen and Lys, 2003). To circumvent the influence of such outliers, the analysis follows similar research by excluding earnings surprise observations outside the 1st and 99th percentiles.

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[41] Unlike a number of papers in the ERC literature, Cumulative Abnormal Returns (CARS) are not used because errors in risk adjustment are amplified over return windows as long as the one used in this study, and because the correct model of expected returns is uncertain (Kothari and Warner, 2006).

[42] The earnings surprise is minus one times the forecast error defined in Doukas et al. (2002); however this definition is conventional in that a ‘positive’ (‘negative’) earnings surprise implies that a company has beaten (failed to meet) the consensus forecast.

5.4.4 Definition of Indicator Variables G, DR and AA

The indicator variables G, DR and AA are based respectively on rankings of the underlying variables B/M, DD and forecast dispersion; for one of the robustness checks G is also obtained from a firm's ranking by E/P rather than from its ranking by B/M. Firms are assigned a value of 0 if they are ranked in the top third of the sample by the underlying variable and a value of 2 if they are ranked in the bottom third of the sample by the underlying variable; otherwise a value of 1 is assigned. As was the case in Chapter 4, B/M, E/P and DD are computed at the end of *each* month in the sample period, and the ranking performed at the end of *each* month (AA is discussed below). The ranking is performed each month because fiscal year-ends vary amongst companies. Although all firms are included in the monthly sorts, the relevant G and DR classifications assigned to a particular earnings surprise observation is the classification that was current at the end of the fiscal year preceding the forecast, in other words four months prior to the date of the forecast. For January year-end firms, the relevant G and DR classifications are those that were current as at January in the year preceding the forecast. For February year-end firms, the relevant G and DR classification are those that were current as at February in the year preceding the forecast, and so on.

Unfortunately, there is a maximum of one earnings surprise observation per company per year, and thus a maximum of one forecast dispersion observation per company per year. The situation is unfortunate because fiscal year ends vary by company, and thus it is not possible to include every company simultaneously in the monthly sorts. For AA therefore, stocks are grouped by the calendar year in which the forecast was issued, and the ranking is therefore based on calendar year rather than month. As most companies in

Australia have June year-ends, the analysis is later repeated using only June year-end companies, with the dispersion calculation and ranking carried out the same time every year (namely in October, as eight-month forecasts are used). The results do not materially differ for this restricted sample, and the results are therefore not sensitive to the original method of combining firms with the same forecast year to determine AA.

5.4.5 Calculation of B/M, E/P, DD and Forecast Dispersion

The method for calculation of B/M, E/P and DD is as described in Section 3.4 with the exception of the timing of the calculations. In this study B/M, E/P and DD are calculated at the end of every month, in order to perform the monthly sorts required for the calculation of G and DR as described above. Thus, the timing of the calculation of B/M, E/P and DD is consistent with Chapter 4, the other empirical chapter in this thesis that is based upon analysts' earnings forecasts. Forecast dispersion is defined as the standard deviation of EPS forecasts for a company at the forecast date, divided by the absolute value of the mean forecast for the company at the forecast date. The absolute value of the mean forecast is used in the denominator rather than the mean forecast to avoid artificially assigning low dispersion rankings to forecasts which have a negative mean.

5.5 Results

5.5.1 Preliminary Data Analysis

Table 5.1 presents some descriptive statistics for the sample data. Of particular interest are the rank correlation coefficients in Panel B and the characteristics of portfolios implied by the categorical variables G, DR and AA. First, Panel B shows that B/M and DD are negatively correlated; confirming the earlier assertion in Section 5.2 that B/M and default risk are correlated. Similarly, forecast dispersion is positively correlated with B/M, confirming the results of Doukas et al. (2004), and negatively correlated with DD (in other words, positively correlated with default risk). The correlation between forecast dispersion and earnings surprise is especially noteworthy. Note that the correlation is large and positive when earnings surprise is expressed in absolute value. This result implies that high forecast dispersion is associated with large earnings surprises of either sign, and confirms a similar result in Kinney et al. (2002). A consequence of this result is that differences in dispersion are expected to add more explanatory power over the ERC for larger earnings surprises, where the slope of the returns-earnings relation is generally flatter, than for earnings surprises close to zero where the slope is generally steeper (as previously documented in Freeman and Tse, 1992, and others).

Panel C illustrates the stock characteristics implied by the levels of each the three categorical variables used to measure the effect of B/M, default risk and forecast dispersion on the market reaction to earnings surprise. The levels range from 0 (lowest) to 2 (highest). Of particular interest are the average earnings surprises (ES) and buy-

hold abnormal returns (BHAR) of stocks grouped by G. B/M increases from 0.2524 for the high G portfolio to 0.9764 for the low G portfolio; similarly BHAR increases from -0.05 to 0.0447, consistent with the direct relationship between returns and B/M. However, notice that the average ES for the low G portfolio is large and negative (-0.0179) while the average ES for the high G portfolio (-0.0091) whilst still negative is not as large in absolute value. Consistent with the results of Doukas et al. (2002), this pattern reflects the direct relationship between forecast optimism and B/M, and as discussed in Section 5.2 forms the motivation for the study.

Table 5.1: Summary Statistics and Correlations

The following table shows summary statistics and correlations of the main variables in this study, and characteristics of portfolios formed by grouping stocks by the indicator variables G, DR and AA. ES is the price-deflated earnings surprise based on analysts' consensus median earnings-per-share (EPS) forecast issued eight months prior to fiscal year end. BHAR is the size-adjusted buy and hold abnormal return over the period from 180 trading days prior to the earnings announcement date to 60 trading days after the announcement date. B/M is the book-to-market ratio calculated as the book value of equity from the company's latest balance sheet divided by market capitalisation at the end of the fiscal year prior to the forecast. DD is the distance-to-default calculated in accordance with Section 5.4.5. Dispersion is the standard deviation of EPS forecasts for a company at the forecast date, divided by the absolute value of the mean forecast for the company at the forecast date. Analyst Coverage is the number of analysts who contributed forecasts as part of the consensus forecast. Market capitalisation is the market capitalisation of the company which is the subject of the EPS forecast, at the end of the fiscal year prior to the forecast. G, DR and AA are based respectively on rankings of the underlying variables B/M, DD and dispersion with values of 0, 1 and 2 assigned if firm is ranked in the top, middle and bottom thirds of the sample respectively, by the underlying variable. The number of observations in each classification is denoted by 'n'.

Panel A: Descriptive Statistics of Raw Variables

	ES	BHAR	B/M	DD	Dispersion	Analyst Coverage	Market Capitalisation ($millions)
n	1651	1651	1651	1635	1651	1651	1651
Minimum	-0.4521	-1.1223	0.0149	-0.42	0.0055	3.00	75
Maximum	0.0720	5.7302	3.3251	24.83	30.0000	20.00	101,376
Mean	-0.0117	0.0009	0.5891	6.64	0.1357	8.74	3,345
Median	-0.0017	-0.0245	0.5211	6.33	0.0731	9.00	901
Standard Deviation	0.0442	0.3949	0.3797	3.41	0.7647	3.78	7,361
25th Percentile	-0.0152	-0.2152	0.3440	4.27	0.0453	6.00	389
75th Percentile	0.0047	0.1694	0.7443	8.54	0.1253	11.75	2,920
Skewness	-4.78	2.86	1.96	0.78	36.35	0.31	5.13
Kurtosis	36.29	34.66	10.45	4.29	1411.59	2.29	39.71

Panel B: Rank Correlation Coefficients

	DD	Dispersion	BHAR	ES	|ES|
B/M	-0.373	0.217	0.100	-0.057	0.209
DD		-0.313	0.035	0.135	-0.266
Dispersion			-0.084	-0.155	0.402
BHAR				0.372	-0.077
ES					-0.329

Table 5.1 Summary Statistics and Correlations (continued)

Panel C: Characteristics of Stocks Grouped by Indicator Variables

Variable	Category	n	B/M	DD	Dispersion	ES	BHAR
	0	537	0.9764	4.9742	0.1332	-0.0179	0.0447
G	1	624	0.5201	6.4580	0.1115	-0.0085	0.0031
	2	490	0.2524	8.4730	0.1693	-0.0091	-0.0500
	0	500	0.3917	10.3220	0.0779	-0.0041	-0.0035
DR	1	586	0.5585	6.4209	0.1681	-0.0100	-0.0193
	2	549	0.8032	3.5138	0.1526	-0.0206	0.0272
	0	512	0.7029	5.5074	0.3065	-0.0213	-0.0187
AA	1	561	0.5878	6.5251	0.0792	-0.0102	-0.0022
	2	578	0.4895	7.5646	0.0392	-0.0048	0.0213

5.5.2 Response Coefficients with simple slope dummy variables

Table 5.2 presents the results for the analyses in which the unexpected return-earnings surprise relation is modelled as a linear function, but with the slope of the function allowed to vary with B/M, default risk and analyst agreement. As in Kinney et al. (2002), estimates over progressively narrower ranges about zero of ES are included to observe the effect of non-linearity on the results. The well known S-shape is manifest in the increase in slope as |ES| approaches zero.

Using all earnings surprise observations, Table 5.2 shows an ERC of around 2.7[43]. However, all three variables add explanatory power when introduced in isolation of one another. The difference in ERC between value and growth stocks, captured by the coefficient on G*ES, is statistically significant and large in economic terms, ranging from around 6 for all observations to 10 for |ES|<0.02. Using all observations, value stocks have an ERC close to zero (no reaction) while growth stocks have an ERC around 6 (2*3.0). However, the ERC for both value and growth stocks increases as the range of ES is narrowed. Default risk has an inverse relationship with the ERC, as

[43] An ERC of 2.7 implies that a change in price-deflated earnings surprise of 0.01 (i.e. a change in unexpected earnings-per-share of 1% of the share price) leads to 2.7% change in unexpected return.

evidenced by the negative coefficient on DR*ES. Using all observations, it is found that high DR stocks have an ERC of around 1.5 (6.606-2*2.577) while low DR stocks have an ERC of 6.6. In accordance with Kinney et al. (2002), the ERC appears to be positively related to AA, but only for large ES (also consistent with Kinney et al., 2002). Notice also that the incremental value stays around 3, until |ES| is restricted to less than 0.02.

With all three slope dummies present, the least significant variable is DR*ES. Thus, any explanatory power DR has over ERC appears to be due to its correlation with the other two variables. If DR is excluded, both G and AA are significant until |ES| is restricted to 0.02. In general, Table 5.2 shows ERC increasing as ES become smaller in absolute value (consistent with the S-shape), and increasing with both G and AA. Value stocks with low analyst agreement have an ERC close to zero based on all observations, or about 4 based on observation where |ES|<0.05. At the other extreme, growth stocks with high analyst agreement have an ERC of around 11 based on all observations, or 15 based on |ES|<0.05.

Table 5.2: Earnings Response Coefficients Conditional on Book-to-Market (G), Default Risk (DR) and Analyst Agreement (AA)

The following table displays the estimated coefficients from the regression equation $UR_{it} = \beta_0 + \beta_1 ES_{it} + \beta_2 G_{it} * ES_{it} + \beta_3 DR_{it} * ES_{it} + \beta_4 AA_{it} * ES_{it} + \varepsilon_{it}$, where UR_{it} is the size-adjusted buy and hold abnormal return (BHAR) of stock i in year t, and ES_{it} is the earnings surprise of stock i in year t, G_{it}, DR_{it} and AA_{it} are indicator variables based on B/M, DD and forecast dispersion as defined in Section 5.3.4. The coefficients are estimated using the Fama-MacBeth procedure; in other words they are the time-series averages from a series of 12 yearly cross-sectional regressions; the t-statistics (in parenthesis) are based upon the time-series of estimated coefficients. Significance levels are indicated by *** (1%), ** (5%) and * (10%).

Range |ES|<	Intercept	ES	G*ES	DR*ES	AA*ES	Average Adjusted R^2
All	0.027	2.669				6.4%
	(2.264**)	(5.698***)				
0.05	0.034	7.655				11.7%
	(2.254**)	(8.383***)				
0.02	0.023	11.937				9.3%
	(1.372)	(8.139***)				
All	0.028	0.814	2.967			11.0%
	(2.243**)	(1.007)	(4.116***)			
0.05	0.035	4.938	3.672			14.9%
	(2.297**)	(3.580***)	(2.469**)			
0.02	0.023	6.654	5.36			11.7%
	(1.312)	(1.992*)	(2.241**)			
All	0.027	6.606		-2.577		9.7%
	(2.131*)	(8.278***)		(-4.745***)		
0.05	0.034	9.78		-1.587		12.7%
	(2.184*)	(6.613***)		(-1.395)		
0.02	0.023	15.834		-3.976		10.4%
	(1.309)	(7.965***)		(-1.932*)		
All	0.024	1.949			2.845	9.1%
	(2.116*)	(4.197***)			(3.189***)	
0.05	0.033	5.909			2.724	13.1%
	(2.271**)	(4.921***)			(2.751**)	
0.02	0.019	8.907			3.433	11.6%
	(1.205)	(2.931**)			(1.016)	
All	0.027	1.896	1.819	-0.945	2.796	13.6%
	(2.162*)	(1.435)	(1.696)	(-1.635)	(3.883***)	
0.05	0.036	4.134	3.582	-0.145	2.019	16.3%
	(2.314**)	(2.688**)	(2.617**)	(-0.139)	(2.011*)	
0.02	0.022	7.031	3.487	-1.643	3.21	13.4%
	(1.270)	(1.884*)	(1.492)	(-1.026)	(0.898)	
All	0.028	0.138	2.34		2.986	13.0%
	(2.235**)	(0.136)	(2.526**)		(4.190***)	
0.05	0.035	3.676	3.275		2.394	16.1%
	(2.320**)	(2.827**)	(2.156*)		(2.518**)	
0.02	0.02	5.013	3.583		3.567	13.4%
	(1.239)	(1.631)	(1.306)		(1.017)	

5.5.3 Response Coefficients with asymmetric slope dummy variables

A further dummy variable is now introduced to account for the flatter slope of the return-earnings relation for negative ES (the flatter slope for negative ES is a consequence of shareholders' limited liability and the compounding of returns over a long window). The statistical significance of the incremental slope parameter (BAD*ES) is now studied as well as that of the interaction of BAD with each of the other three variables, G, DR and AA (G*BAD, DR*BAD and AA*BAD respectively). The interaction terms allow for the possibility that the incremental effect on ERC of a variable, for example G, is not the same for positive and negative surprises. In Table 5.3, the ERC for value and growth stocks with positive surprises are β_1 and $\beta_1+2\beta_3$ respectively, whilst for negative surprises they are $\beta_1+\beta_2$ and $\beta_1+\beta_2+2\beta_3+2\beta_4$ respectively. The coefficient on G*BAD*ES (β_4) thus allows the difference in ERC (slope term) between value and growth stocks to be greater or smaller for negative surprises than for positive surprises.

In Table 5.3, the coefficient on BAD*ES (β_2) is statistically significant in nearly all the cases except for cases where |ES|<0.02, confirming the overall flatter slope of the return-earnings relation over negative surprises. The adjusted R^2 values in Table 5.3 are higher by about 3% than those in Table 5.2 when the estimation includes all ES, but around the same for |ES|<0.02. Thus, allowing for a flatter slope for negative surprises adds explanatory power particularly for large earnings surprises. This result is intuitive because the limited liability of equity (returns cannot be less than -100%) is not likely to come into play for small earnings surprises, which are not indicative of catastrophic losses.

Note however that the inclusion of BAD*ES does not appear to affect the statistical significance of terms involving G*ES, DR*ES or AA*ES; the coefficients on these terms (β_3, β_5 and β_7) all remain highly statistically significant. The ERC of growth stocks is higher than that of value stocks by around 5 ($2\beta_3$). Similarly, the ERC of high default risk stocks is lower than that of high default risk stocks by around 4 ($2\beta_5$) and the ERC of high analyst agreement stocks is higher than that of low analyst agreement stocks by around 4 ($2\beta_7$).

There is little evidence in Table 5.3 that the term G*BAD*ES is significant. Therefore, although the ERC appears different for value and growth stocks, the difference in ERC is not affected by the sign of the earnings surprise. Similarly, neither DR*BAD*ES nor AA*BAD*ES are statistically significant. Thus, the incremental effect of both DR and AA on the ERC does not appear to vary between positive and negative surprises, although the unexpected return-earnings surprise relation is generally flatter for negative surprises than for positive surprises. Henceforth, the interaction terms G*BAD*ES, DR*BAD*ES and AA*BAD*ES are excluded from the analysis because they appear to add little explanatory power.

Finally, the initial three variables (G, DR and AA) and the BAD indicator variable are included without the interaction terms, with the conclusion from the previous section remaining unaltered. The coefficients of G*ES and AA*ES are statistically significant while that of DR*ES is not, suggesting DR adds explanatory power only because it is correlated with G and AA. Thus, the market response to earnings surprise depends on G and AA but not DR. The ERC estimates are higher by around 4 ($2\beta_3$) for growth stocks

than for value stocks, higher by around 5 ($2\beta_7$) for high analyst agreement stocks than for low analyst agreement stocks, and higher by around 8 (β_2) for positive than for negative surprises.

Table 5.3: Earnings Response Coefficients Conditional on Book-to-Market (G), Default Risk (DR) and Analyst Agreement (AA) and the Sign of Earnings Surprise (BAD)

The following table displays the estimated coefficients from the following regression equation.

$$UR_{it} = \beta_0 + \beta_1 ES_{it} + \beta_2 BAD_{it} * ES_{it} + \beta_3 G_{it} * ES_{it} + \beta_4 G_{it} * BAD_{it} * ES_{it} + \beta_5 DR_{it} * ES_{it} + \beta_6 DR_{it} * BAD_{it} * ES_{it}$$
$$+ \beta_7 AA_{it} * ES_{it} + \beta_8 AA_{it} * BAD_{it} * ES_{it} + \varepsilon_{it}$$

All variables are as per Table 5.2 with the exception of BAD_{it}, which takes the value of 1 if $ES_{it}<0$ and 0 otherwise. All other details are as per Table 5.2.

Range $\lvert ES \rvert <$	Intercept	ES	BAD*ES	G*ES	G*BAD*ES	DR*ES	DR*BAD*ES	AA*ES	AA*BAD*ES	Average Adjusted R^2
All	-0.022	9.290	-9.470	2.451						15.1%
	(-1.757)	(5.068***)	(-6.253***)	(3.503***)						
0.05	0.004	9.226	-6.464	3.519						16.9%
	(0.230)	(3.298***)	(-1.953*)	(2.435**)						
0.02	0.004	10.638	-6.624	5.258						11.7%
	(0.188)	(2.283**)	(-1.414)	(2.540**)						
All	-0.024	9.836	-10.001	1.944	0.431					16.2%
	(-1.890*)	(4.237***)	(-5.065***)	(0.782)	(0.167)					
0.05	0.006	10.712	-8.011	1.281	2.588					19.0%
	(0.309)	(3.358***)	(-2.389**)	(0.451)	(0.751)					
0.02	0.002	13.911	-14.186	1.762	6.630					15.5%
	(0.107)	(2.124*)	(-1.777)	(0.333)	(0.946)					
All	-0.019	13.217	-8.783			-1.957				13.8%
	(-1.342)	(7.507***)	(-4.220***)			(-3.292***)				
0.05	0.003	13.868	-6.557			-1.449				14.9%
	(0.144)	(4.248***)	(-1.820*)			(-1.218)				
0.02	0.009	19.391	-5.495			-4.122				11.0%
	(0.350)	(4.304***)	(-0.945)			(-2.065*)				
All	-0.020	14.253	-9.560			-2.098	-0.012			14.0%
	(-1.511)	(3.910***)	(-2.326**)			(-1.140)	(-0.006)			
0.05	0.005	12.564	-4.531			-0.393	-1.454			14.9%
	(0.257)	(3.718***)	(-1.285)			(-0.218)	(-0.846)			
0.02	0.012	16.474	0.635			-1.225	-5.641			12.1%
	(0.449)	(3.152***)	(0.093)			(-0.298)	(-1.179)			
All	-0.021	9.869	-8.846					2.161		12.6%

Range |ES|<	Intercept	ES	BAD*ES	G*ES	G*BAD*ES	DR*ES	DR*BAD*ES	AA*ES	AA*BAD*ES	Average Adjusted R^2
	(-1.979*)	(6.403***)	(-5.871***)					(3.818***)		
0.05	0.000	10.485	-7.126					2.556		15.0%
	(-0.025)	(3.870***)	(-2.203**)					(2.814**)		
0.02	0.003	12.603	-6.225					3.368		12.0%
	(0.108)	(4.719***)	(-1.138)					(1.018)		
All	-0.025	7.756	-6.639					6.459	-4.101	13.8%
	(-2.238**)	(4.470***)	(-3.450***)					(3.184***)	(-1.548)	
0.05	-0.004	8.902	-5.222					5.275	-3.089	16.1%
	(-0.217)	(3.097**)	(-1.319)					(3.229***)	(-1.072)	
0.02	-0.004	5.152	3.338					11.362	-10.530	14.5%
	(-0.171)	(1.580)	(0.482)					(2.139*)	(-1.727)	
All	-0.016	8.594	-8.476	1.718		-0.476		2.388		17.1%
	(-1.115)	(3.451***)	(-4.490***)	(1.730)		(-0.709)		(4.100***)		
0.05	0.003	8.429	-7.083	3.641		-0.019		1.882		18.2%
	(0.137)	(2.880**)	(-2.100*)	(2.845**)		(-0.015)		(1.858*)		
0.02	0.004	11.528	-6.543	3.280		-1.927		2.931		13.4%
	(0.162)	(3.586***)	(-1.342)	(1.654)		(-1.157)		(0.825)		
All	-0.017	7.815	-8.569	2.073				2.406		16.4%
	(-1.255)	(3.380***)	(-4.962***)	(2.182*)				(4.454***)		
0.05	0.002	8.132	-6.963	3.208				2.245		17.9%
	(0.100)	(3.056**)	(-2.223**)	(2.159*)				(2.497**)		
0.02	0.002	8.864	-6.529	3.503				3.501		13.4%
	(0.106)	(2.816**)	(-1.398)	(1.430)				(0.999)		

5.5.4 Response Coefficients with Asymmetric Intercepts

The analysis is now extended to cases where the intercept terms in the unexpected return-earnings surprise relationship vary with the three main variables (G, DR and AA) and also with the sign of the earnings surprise[44]. In order to keep the analysis and discussion tractable, this functional form is investigated separately for each of the main variables before a more complicated model is examined which includes all of the main variables. The simplified analysis, where the main variables are examined one at a time, is the subject of this section. Furthermore, as the asymmetric intercept terms capture much of the non-linearity associated with ES close to zero, attention is focused on regressions based on an unrestricted range of ES.

Asymmetric Intercepts and slopes conditional on G

The unexpected return-earnings surprise relationship is first estimated with asymmetric intercepts as a function of G only; the results are shown in Table 5.4. The intercept terms for positive surprises are β_0 for value stocks and $\beta_0+2\beta_1$ for growth stocks. The intercept terms for negative surprises are $\beta_0+\beta_2$ for value stocks and $\beta_0+2\beta_1+\beta_2+2\beta_3$ for growth stocks. The coefficient on G is not statistically significant in any of the specifications tested, indicating the absence of a residual value premium in the presence of the other explanatory variables.

[44] The effect of allowing the intercept to vary between positive and negative surprises introduces a point of discontinuity at ES=0 and permits incorporation of the 'Earnings Torpedo'. The Earnings Torpedo is the large negative price response to firms announcing earnings-per-share even marginally below analyst expectations. Skinner and Sloan (2002) argue that this effect is greater in growth than in value stocks and is an important factor in the value premium.

In contrast, the coefficient on BAD (β_2) is large and statistically significant in each of the specifications that include it as an explanatory variable, supporting the existence of an earnings torpedo effect (note however, that the earnings torpedo may merely be a manifestation of the steepness of the unexpected return-earnings surprise relationship around ES=0). The coefficient on G*BAD is also statistically significant in all the specifications that include it except when G is also included, in which case its t-statistic is larger than that of G. Thus, it can be inferred that the negative intercept term for negative surprises is much larger (in absolute value) for growth stocks than for value stocks, a result in accordance with Skinner and Sloan (2002).

The intercept terms implied by the various specifications support the same inference regarding the asymmetric effects of negative surprises on value and growth stocks. In the specification that includes all three of the terms G, BAD and G*BAD, the intercept term is -3.1% for value stocks with negative surprises and -12.7% for growth stocks with negative surprises[45]. The corresponding terms in the specification that includes only BAD and G*BAD are -3.2% and -12.6%[46]. Thus the torpedo effect is large in economic terms and especially so for growth stocks; in other words growth stocks are more heavily punished than value stocks for missing earnings forecasts.

In contrast, there is a smaller and statistically insignificant difference between value and growth stocks in the implied intercept terms for positive surprises. The difference between value and growth stocks in the intercept term for positive surprises is given by $2\beta_1$ and has a largest (absolute) value of 6.2%, which occurs in the specification that includes G and BAD but not G*BAD. However, the omission of G*BAD constrains the

[45] These terms are computed as (0.084 – 0.115) and (0.084 – 2(0.014) – 0.115 – 2(0.034)) respectively.
[46] These terms are computed as (0.064 – 0.096) and (0.064 – 0.096 – 2(0.047)) respectively.

value-growth differential to be the same for both positive and negative surprises, and the figure of 6.2% thus represents an average difference between value and growth stocks with both positive and negative surprises. The specifications that include G*BAD allow the value-growth differential to differ between positive and negative surprises, and in such cases, the difference in the positive intercept term ($2\beta_1$) is either -2.8% or +4.4%. Furthermore, β_1 is not statistically significant in any of the specifications tested. Thus the value-growth differential observed for positive surprises is inconsistent in sign, not statistically significant and much smaller in absolute value than the differential observed for negative surprises (which is around 9% or greater).

Table 5.4: Earnings Response Coefficients with Asymmetric Intercepts Conditional on Book-to-Market (G)

The following table displays the estimated coefficients from the following regression equation.

$$UR_{it} = \beta_0 + \beta_1 G_{it} + \beta_2 BAD_{it} + \beta_3 G_{it} * BAD_{it} + \beta_4 ES_{it} + \beta_5 BAD_{it} * ES_{it} + \beta_6 G_{it} * ES_{it} + \varepsilon_{it}$$

All variables are as defined in Tables 5.2 and 5.3.

Intercept	G	BAD	G*BAD	ES	BAD*ES	G*ES	Average Adjusted R^2
0.001 (0.024)	-0.022 (-0.932)			9.022 (5.270***)	-9.112 (-5.942***)	2.312 (3.202***)	16.6%
0.103 (2.201*)	-0.031 (-1.232)	-0.149 (-5.231***)		5.289 (2.833**)	-5.759 (-3.117***)	1.875 (2.408**)	18.9%
0.084 (1.624)	-0.014 (-0.433)	-0.115 (-2.986**)	-0.034 (-1.271)	5.759 (2.853**)	-6.071 (-3.172***)	1.488 (1.879*)	18.9%
0.012 (0.398)	0.022 (0.966)		-0.100 (-5.089***)	8.024 (4.826***)	-7.930 (-5.057***)	1.060 (1.244)	18.5%
0.064 (2.760**)		-0.141 (-5.714***)		5.960 (2.961**)	-6.579 (-3.741***)	2.061 (2.711**)	17.3%
0.031 (1.391)			-0.085 (-3.903***)	7.840 (4.037***)	-7.604 (-4.316***)	1.355 (1.693)	17.6%
0.064 (2.723**)		-0.096 (-4.852***)	-0.047 (-1.981*)	6.279 (3.241***)	-6.659 (-3.640***)	1.655 (1.996*)	18.1%

Asymmetric Intercepts and slopes conditional on DR

The results involving asymmetric intercepts and slopes conditioned on DR are presented in Table 5.5. As before, the BAD dummy variable is highly statistically significant in all specifications tested, supporting the existence of a general earnings torpedo effect (different intercept for positive and negative surprises).

The evidence in Table 5.5 suggests that of all the variables considered, DR and DR*BAD are redundant. When DR is included, it is quite small in magnitude and statistically insignificant, except when DR*BAD is included and BAD is omitted. Similarly, DR*BAD is quite small in magnitude and statistically insignificant except when BAD is excluded. The sign of the coefficient on DR*BAD is positive when BAD is included but negative when BAD is omitted. Given the strong evidence regarding the importance of BAD, it is therefore likely the estimate of DR*BAD is heavily biased by the omission of BAD. Similarly, the significance of DR in the fourth specification appears to be an over-compensation for the effect of DR*BAD. To see this, note that the implied intercept term for low DR firms in this specification is β_0 = -1.5% for *both* positive and negative surprises, a result which appears inconsistent with the fact that growth stocks are heavily represented amongst low DR firms, and that the earlier results confirm that growth stocks are heavily punished by the market for missing analyst expectations.

Table 5.5: Earnings Response Coefficients with Asymmetric Intercepts Conditional on Default Risk (DR)

The following table displays the estimated coefficients from the following regression equation.

$$UR_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 BAD_{it} + \beta_3 DR_{it} * BAD_{it} + \beta_4 ES_{it} + \beta_5 BAD_{it} * ES_{it} + \beta_6 DR_{it} * ES_{it} + \varepsilon_{it}$$

All variables are as defined in Tables 5.2 and 5.3.

Intercept	DR	BAD	DR*BAD	ES	BAD*ES	DR*ES	Average Adjusted R^2
-0.025 (-1.090)	0.006 (0.476)			13.186 (7.162***)	-8.805 (-4.077***)	-1.917 (-3.077**)	14.1%
0.057 (1.950*)	0.014 (1.032)	-0.146 (-5.682***)		8.685 (4.317***)	-5.757 (-2.557**)	-1.369 (-1.944*)	16.3%
0.065 (2.121*)	0.008 (0.323)	-0.159 (-4.600***)	0.010 (0.302)	8.329 (4.439***)	-5.887 (-2.514**)	-1.065 (-1.432)	16.3%
-0.015 (-0.644)	0.050 (2.522**)		-0.078 (-3.268***)	11.288 (5.573***)	-6.609 (-2.820**)	-2.290 (-4.078***)	15.2%
0.065 (2.665**)		-0.140 (-5.541***)		9.100 (4.537***)	-6.084 (-2.731**)	-1.454 (-2.201*)	15.9%
0.006 (0.297)			-0.040 (-2.434**)	12.581 (6.207***)	-7.984 (-3.304***)	-2.219 (-3.835***)	14.6%
0.066 (2.679**)		-0.159 (-5.508***)	0.018 (0.956)	8.688 (4.570***)	-6.037 (-2.675**)	-1.171 (-1.571)	16.3%

Asymmetric Intercepts and slopes conditional on AA

The intercept terms of the unexpected return-earnings surprise relation are now investigated for dependence upon AA. Table 5.6 shows little evidence that AA affects the intercept either for positive or negative surprises. AA and AA*BAD are significant only in the fourth specification where the two variables are included together and BAD, which is once again highly significant in the other specifications, is omitted. The estimated coefficients in this specification imply that the intercept term for firms with high AA and negative surprises is -6.3%[47]. This return is only slightly below the intercept term for low AA firms with either positive or negative surprises, which is β_0 = -5.9% in both cases. Therefore, the results based on this specification imply the unlikely scenario whereby high AA firms are not punished by the market any more severely for

[47] This value is computed as (-0.059 + 2(0.071) – 2(0.73)).

missing analysts' forecasts than low AA firms, or even low AA firms that beat analysts' forecasts. Therefore, the fourth specification is rejected, on grounds that the parameters appear biased due to the omission of BAD. Consequently it is concluded that the intercept terms in the unexpected return-earnings surprise relation are not dependent upon AA.

At first glance, the inference that the magnitude of the intercept term (or earnings torpedo effect) is unrelated to AA might seem unintuitive, as a high level of AA implies a lower level of uncertainty regarding the 'true' level of expected earnings and hence a greater degree of agreement that the earnings surprise variable is a 'true' measure of unexpected earnings. However, recall from Section 5.5.1 (see also Kinney et al., 2002) that the magnitude (or absolute value) of ES is itself related to AA, and thus *for small ES* AA does not add much new information already contained in ES. Put differently, high levels of AA are generally associated with *small* ES (of either sign), and there are proportionately fewer small ES associated with lower levels of AA. Thus, AA does not vary enough when |ES| is small for it to have an effect on the intercept term (or earnings torpedo).

Table 5.6: Earnings Response Coefficients with Asymmetric Intercepts Conditional on Analyst Agreement (AA)

The following table displays the estimated coefficients from the following regression equation.

$$UR_{it} = \beta_0 + \beta_1 AA_{it} + \beta_2 BAD_{it} + \beta_3 AA_{it} * BAD_{it} + \beta_4 ES_{it} + \beta_5 BAD_{it} * ES_{it} + \beta_6 AA_{it} * ES_{it} + \varepsilon_{it}$$

All variables are as defined in Tables 5.2 and 5.3.

Intercept	AA	BAD	AA*BAD	ES	BAD*ES	AA*ES	Average Adjusted R^2
-0.066 (-2.409**)	0.038 (1.523)			10.218 (6.481***)	-9.677 (-6.540***)	2.673 (5.514***)	15.4%
0.024 (0.925)	0.030 (1.213)	-0.128 (-5.096***)		6.878 (4.213***)	-6.622 (-4.402***)	2.094 (5.348***)	16.9%
0.011 (0.281)	0.038 (1.357)	-0.109 (-1.830*)	-0.016 (-0.413)	7.437 (3.681***)	-7.151 (-4.025***)	1.653 (3.078**)	17.2%
-0.059 (-2.286**)	0.071 (2.712**)		-0.073 (-4.761***)	9.456 (6.206***)	-8.808 (-6.256***)	1.446 (3.825***)	16.2%
0.060 (2.531**)		-0.130 (-4.708***)		6.807 (4.026***)	-6.153 (-3.547***)	1.602 (3.422***)	14.3%
-0.007 (-0.472)			-0.028 (-1.364)	9.659 (7.242***)	-8.611 (-7.296***)	1.642 (3.736***)	13.6%
0.060 (2.572**)		-0.160 (-2.908**)	0.025 (0.738)	6.499 (3.465***)	-6.291 (-3.720***)	2.013 (4.838***)	16.5%

5.5.5 Response Coefficients with slope dummy variables, asymmetric intercepts and multiple conditioning variables

Thus far, the analysis has separately investigated variation in the slope and intercepts of the unexpected return-earnings surprise relation. Variation in the slope was found to be explained by the control variables G, DR and AA and the negative surprise indicator BAD, although the explanatory power of DR is lower in the presence of the other two control variables. The most important explanatory variables for the intercept terms were found to be BAD and G*BAD. A more complete version of this relation is now estimated incorporating both asymmetric intercept and slope terms and the most significant of the variables from the preceding analyses.

Table 5.7 shows the results of estimation of various specifications of the unexpected return-earnings surprise relation. G is retained as a dummy variable for some of the

specifications because it represents a well-established empirical fact (the value premium), and hence its omission might bias the results. However, it is statistically insignificant in the presence of the other variables, whose parameter estimates and significance levels are largely unaffected by its presence. As was the case with the previous analyses, the indicator variable for negative surprises (BAD) remains significant by itself as a dummy variable for the intercept and when interacted with ES as a slope dummy variables. Thus, the return-earnings surprise relation for negative surprises is characterised by a negative intercept (generally around 5%) and a slope which is close to zero. As was the case in Table 5.4, the coefficient on G*BAD is generally statistically significant and of the order of around 0.05. Thus, the much larger negative intercept term for growth stocks remains in evidence and is of similar magnitude (around 10%).

The most remarkable feature of Table 5.7 is the coefficient of G*ES, which represents the incremental slope of the return-earnings surprise relation for growth stocks. This coefficient is always around 1.0 (implying an increase in ERC of around 2 for growth stocks relative to value stocks) but is not significantly significant. The result is remarkable because B/M is a proxy for both growth and persistence, which have been identified in the literature as important determinants of the ERC. The difference between Sections 5.5.2 and 5.5.3, where the coefficient G*ES is around 3.0 and statistically significant, and Table 5.7 is the presence of the asymmetric intercept terms BAD and G*BAD. Two of the specifications in Table 5.7 show that the importance of growth on the slope of the return-earnings relation is not revived by splitting its effect into positive and negative surprises (via the G*BAD*ES and G*GOOD*ES variables). The final specification in Table 5.7, which excludes G*ES, has a slightly lower adjusted

R^2 (17.2%) than the similar specification which includes G*ES (18.7%). Given previous results in the literature, the relatively small sample size (compared with US studies) and the fact that the t-statistic on G*ES is greater than 1, this study is reluctant to conclude that B/M has no effect whatsoever upon the slope of the return-earnings relationship. Nevertheless, the results suggest that B/M, as a proxy for either growth or earnings persistence, might not be as important a determinant of the *slope* of return-earnings relation as was previously thought.

The results pertaining to DR*ES and AA*ES are consistent with the results of Section 5.5.2. The coefficient of AA*ES of around 2 is slightly smaller than its value (around 3) in Tables 5.3 and 5.4, however it remains statistically significant. The coefficient of DR*ES is small (for a slope coefficient) and statistically insignificant. Thus, the most important variable that affects the *slope* of unexpected return-earnings surprise relation in this study is AA, a result consistent with Kinney et al. (2002).

Table 5.7: Earnings Response Coefficients with Asymmetric Intercepts and Multiple Conditioning Variables

The following table displays the estimated coefficients from the following regression equation.

$$UR_{it} = \beta_0 + \beta_1 G_{it} + \beta_2 BAD_{it} + \beta_3 G_{it} * BAD_{it} + \beta_4 DR_{it} * BAD_{it} + \beta_5 ES_{it} + \beta_6 BAD_{it} * ES_{it} + \beta_7 G_{it} * ES_{it} + \beta_8 DR_{it} * ES_{it} + \beta_9 AA_{it} * ES_{it}$$
$$\beta_{10} G_{it} * BAD_{it} * ES_{it} + \beta_{11} G_{it} * GOOD_{it} * ES_{it} + \varepsilon_{it}$$

All variables are as per Tables 5.2 and 5.3 with the exception of $GOOD_{it}$, which takes the value of 1 if ES_{it}>0 and 0 otherwise. All other details are as per Tables 5.2 and 5.3.

Intercept	G	BAD	G*BAD	DR*BAD	ES	BAD*ES	G*ES	DR*ES	AA*ES	G*BAD*ES	G*GOOD*ES	Average Adjusted R^2
0.075	-0.012	-0.075	-0.049	-0.005	5.623	-5.534	0.900	-0.296	1.683			20.8%
(1.459)	(-0.371)	(-2.826**)	(-3.055**)	(-0.193)	(2.301**)	(-2.589**)	(0.918)	(-0.361)	(3.019**)			
0.074	-0.011	-0.086	-0.047		6.108	-5.73	0.719	-0.5	1.703			20.2%
(1.424)	(-0.334)	(-2.239**)	(-2.093*)		(2.319**)	(-2.775**)	(0.740)	(-0.782)	(3.275***)			
0.059		-0.059	-0.059	-0.004	5.902	-6.011	1.056	-0.229	1.836			20.1%
(2.283**)		(-1.388)	(-2.004*)	(-0.166)	(2.383**)	(-2.937**)	(0.955)	(-0.264)	(3.081**)			
0.059		-0.071	-0.056		6.387	-6.186	0.882	-0.449	1.861			19.4%
(2.309**)		(-3.337***)	(-2.572**)		(2.562**)	(-3.141***)	(0.858)	(-0.693)	(3.356***)			
0.058		-0.076	-0.05		5.582	-6.352	1.355		1.905			18.7%
(2.421**)		(-4.248***)	(-2.137*)		(2.452**)	(-3.368***)	(1.247)		(3.759***)			
0.057		-0.076	-0.053		5.994	-6.683			1.538	1.052	1.029	19.4%
(2.318**)		(-5.097***)	(-2.504**)		(2.560**)	(-3.585***)			(3.326***)	(0.992)	(0.418)	
0.084	-0.021	-0.103	-0.032		5.000	-5.696			1.536	1.087	2.076	19.6%
(1.503)	(-0.631)	(-2.516**)	(-1.161)		(1.642)	(-2.269**)			(3.446***)	(1.030)	(0.940)	
0.060		-0.043	-0.084		6.739	-5.933			1.667			
(2.544***)		(-1.699)	(-3.288***)		(3.848***)	(-3.333***)			(3.821***)			17.2%

Table 5.8: Earnings Response Coefficients with Asymmetric Intercepts and Multiple Conditioning Variables (Robustness Tests)

The following table displays the estimated coefficients from the following regression equation.

$$UR_{it} = \beta_0 + \beta_1 G_{it} + \beta_2 BAD_{it} + \beta_3 G_{it} * BAD_{it} + \beta_5 ES_{it} + \beta_6 BAD_{it} * ES_{it} + \beta_7 G_{it} * ES_{it} + \beta_8 DR_{it} * ES_{it} + \beta_9 AA_{it} * ES_{it} + \varepsilon_{it}$$

All variables and details are as per Tables 5.2 and 5.3, with the exception of *G* in the cases of ‘Growth defined by E/P’ and ‘Growth defined by E/P+’ where G is based on ranking by earnings-to-price (E/P) and not book-to-market. In the case ‘Growth defined by E/P+’ stocks with E/P<0 are excluded from the ranking procedure.

Panel A: Estimation Based On Alternative Sample Selection Criteria

Case	Intercept	BAD	G*BAD	ES	BAD*ES	G*ES	DR*ES	AA*ES	Average Adjusted R^2
Excluding Losses [a]	0.058 (2.181*)	-0.066 (-2.043*)	-0.051 (-1.827*)	6.198 (2.477**)	-6.116 (-2.422**)	0.730 (0.580)	-0.154 (-0.284)	2.246 (2.428**)	18.5%
June Year End Companies [a]	0.080 (2.946**)	-0.083 (-3.838***)	-0.060 (-2.286**)	1.893 (0.600)	-3.128 (-1.445)	2.107 (1.361)	0.138 (0.154)	3.207 (2.738**)	22.8%
Excluding Small ES	0.082 (2.803**)	-0.098 (-3.850***)	-0.057 (-2.273**)	5.369 (2.085*)	-5.242 (-2.631**)	0.879 (0.815)	-0.407 (-0.624)	1.808 (3.218***)	20.2%

Panel B: Estimation Based On Alternative Variable Definitions

Case	Intercept	BAD	G*BAD	ES	BAD*ES	G*ES	DR*ES	AA*ES	Average Adjusted R^2
Market-Adjusted Returns	0.062 (1.870*)	-0.074 (-3.057**)	-0.057 (-2.558**)	6.317 (2.699**)	-6.283 (-3.453***)	0.958 (0.860)	-0.473 (-0.699)	1.979 (3.144***)	20.2%
Growth defined by E/P [b]	0.059 (2.346**)	-0.071 (-2.488**)	-0.064 (-2.308**)	8.041 (3.104**)	-6.171 (-2.951**)	0.048 (0.064)	-1.036 (-1.576)	1.478 (2.285**)	19.3%
Growth defined by E/P+ [b]	0.056 (2.309**)	-0.067 (-2.258**)	-0.058 (-2.008*)	7.936 (3.055**)	-6.379 (-2.770**)	-0.162 (-0.228)	-1.007 (-1.661)	1.925 (2.894**)	19.1%

Notes: In cases denoted by ‘a’, G*BAD is marginally statistically insignificant if the G dummy variable is included; in cases denoted by ‘b’, G*BAD is statistically insignificant if the G dummy variable is included. In all other cases, G*BAD is statistically significant if the G dummy variable is included.

5.5.6 Robustness Checks

A number of factors are now investigated that might affect the results. First, the lower information content of losses as documented by Hayn (1995) is accounted for by excluding loss-making firms from the sample. Second, the disparity in fiscal year ends might lead to erroneous rankings by B/M, DR and AA, and therefore the estimations are repeated using only June year-end companies (which comprise around two-thirds of the original sample). Third, the use of stock-split adjusted I/B/E/S data were shown by Payne and Thomas (2003) to lead to estimates of earnings surprise *erroneously close to zero*, which they argue is the explanation for the growth stock earnings-torpedo of Skinner and Sloan (2002). Potential biases of this type are accounted for by excluding observations where $|ES| < 0.001$ (which comprise about 9% of the original sample). Fourth, to ensure the results are not dependent upon the use of size-adjusted BHAR, the estimation is repeated using market-adjusted returns (stock return less the equal-weighted return of the largest 500 stocks). Finally, the G dummy variable is redefined in terms of E/P instead of B/M, both with and without negative E/P firms. The results are presented in Table 5.8.

Table 5.8 shows the results of re-estimating the third specification in Table 5.7 for each of the variations discussed above, with variations based on sample choice (that is, exclusion of losses, restriction to June year end companies, and exclusion of small earnings surprises) presented in Panel A and variations based on alternative variable definitions presented in Panel B. The third specification from Table 5.7 is re-estimated because it encapsulates the main results: the importance of G*BAD and AA*ES and the lack of significance of G*ES and DR*ES. The results in Table 5.8 do not alter the

conclusions in Section 5.5.5, and the parameter estimates and t-statistics are similar to those in Table 5.7. The intercept is around 6% for positive surprises and -7% for negative surprises (slightly larger in absolute value if small earnings surprises and non-June year end companies are excluded). The growth stock earnings torpedo is very large and significant: the difference in negative intercept between growth and value stocks is around -12% (2 X -0.06). The slope of the unexpected return-earnings surprise relation is positive for positive surprises but flat for negative surprises. The slope increases with AA but does not vary with either G or DR. For June year-end companies, the slope is statistically indistinguishable from zero (the coefficients on ES and BAD*ES are statistically insignificant) except for high AA companies.

5.6 Interpretation and Graphical Representation of Results

The results in Table 5.7 suggest that the unexpected return-earnings surprise relation might parsimoniously be represented as a linear function with slope increasing in analyst agreement and with a discontinuity at zero (the earnings torpedo) which is greater for growth stocks than for value stocks. This representation is graphed in Figure 5.1, which plots earnings surprises versus unexpected returns, along with the fitted unexpected return-earnings surprise relation for value and growth stocks, and for low and high analyst agreement stocks. To form the portfolios, stocks are first allocated to the four groups Low AA Value, Low AA Growth, High AA Value and High AA Growth based on the indicator variables AA and G. Within each group, a maximum of 15 stocks are allocated to each portfolio by ranking on earnings surprise. Also plotted on this graph is the fitted relationship between unexpected returns and earnings surprise estimated by including (Panel A) and excluding (Panel B) the insignificant G*ES term.

A number of features are immediately apparent from Figure 5.1. First, the portfolios are more dispersed horizontally in the Low Analyst Agreement panel than in the High Analyst Agreement panel, which illustrates the earlier result that |ES| tends to increase with forecast dispersion. Second, the same difference is not observed in the vertical direction, in other words the relatively large variation in ES for Low Analyst Agreement stocks is not accompanied by an increase in variation of unexpected return. Put differently, a relatively small earnings surprise for a High Analyst Agreement stock results in the same magnitude unexpected return as a larger earnings surprise for a Low Analyst Agreement stock. This difference is modelled by the parameter AA*ES, and its effect is evident in the steeper slopes observed in the right hand panel.

Value stocks are relatively insensitive to negative earnings surprises

Regardless of the difference in analyst agreement, the value portfolios with negative surprises plot on either side of the horizontal (UR=0) axis. Thus the market does not systematically react to the negative earnings surprises of value stocks to the extent it reacts to the negative surprises of growth stocks or to positive surprises. If the slope of the fitted relationship is allowed to differ between value and growth stocks (Panel A), the ERC of value stocks with negative surprises and low analyst agreement is actually negative (-0.75=5.582–6.352); however a Wald test reveals that this value is statistically indistinguishable from zero, and the negative slope is not apparent if the relation is estimated without the insignificant G*ES term. The positive slope in the right hand panel for value stocks with negative surprises occurs solely by virtue of the coefficient on AA*ES, which says that the market response is greater for high analyst agreement stocks. Whilst the value portfolios in the right hand panel display an average UR that

trends upward with ES, two of the portfolios still have ES<0 and UR>0. Thus, there is relatively little market reaction to the negative earnings surprises of value stocks.

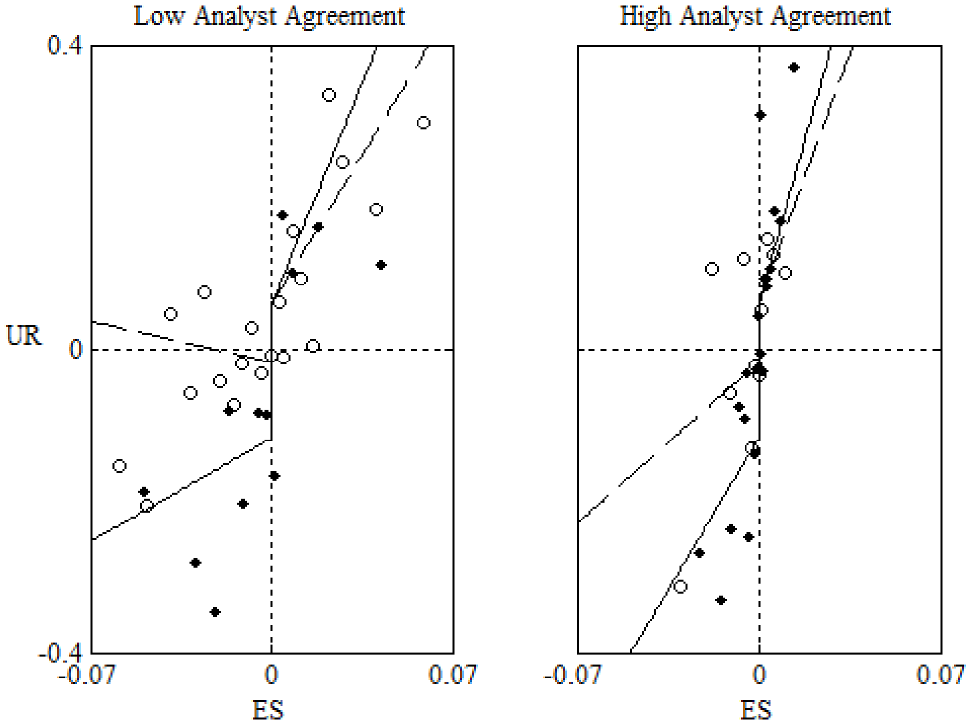
In contrast to negative earnings surprises, the value portfolios with positive surprises plot in the region one would expect them to if the market reacts to the news in earnings surprises; in other words UR>0 when ES>0 (with one exception). The unexpected return-earnings surprise relationship thus appears to slope upwards for value stocks with positive surprises. Therefore, although there appears to be no systematic market response to value stocks' negative earnings surprises, the market does respond favourably to value stocks' positive earnings surprises.

The Growth Stock Earnings Torpedo of Skinner and Sloan (2002)

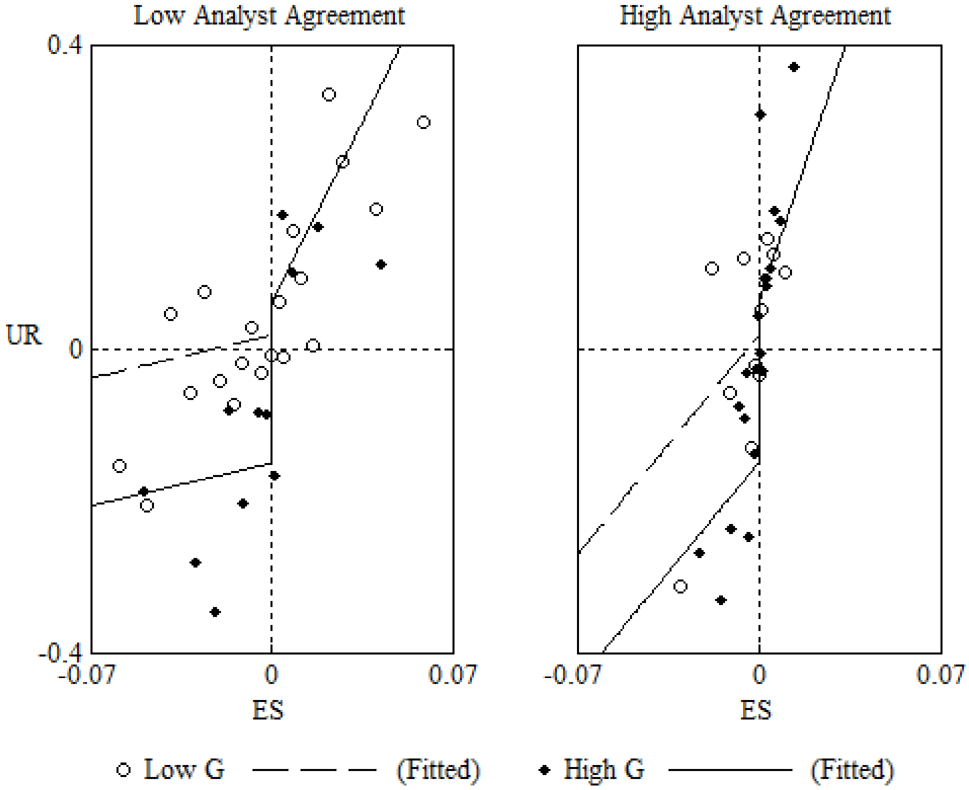
In contrast to the value portfolios, the growth portfolios with negative surprises plot much further below the horizontal axis, illustrating the importance of the earnings torpedo effect for growth stocks; an observation that is unaffected by the level of Analyst Agreement. The growth stock torpedo effect is evident in the fitted return-earnings surprise relation as the large discontinuity at ES=0 for the thick (growth stock) line, which occurs for both Low Analyst Agreement and High Analyst Agreement stocks. According to Skinner and Sloan (2002), it is this *growth stock-torpedo effect* that accounts for the difference in average returns of value and growth stocks. Notice also that the growth stock torpedo effect is present regardless of whether G*ES is included (Panel A) or excluded (Panel B); the omission of G*ES has the effect of increasing the size of the growth stock torpedo effect from -10% (= 2X-5.0%) to -16.8% (=2X-8.4%).

Figure 5.1: Fitted Unexpected Return-Earnings Surprise Relationships
The plots display the fitted unexpected return-earnings surprise relationship for the top 1/3 of stocks ranked by B/M (Low G) and those in the bottom 1/3 (High G). Low Analyst Agreement and High Analyst Agreement stocks are, respectively, those ranked in the top and bottom 1/3 by forecast dispersion.

(a) Fitted Relationship Including G*ES (Value and Growth have different Slopes)



(b) Fitted Relationship Excluding G*ES (Value and Growth have the same Slope)



Explaining the discrepancy between the returns and earnings surprises of B/M-sorted portfolios

According to Doukas et al. (2002), analysts tend to issue earnings forecasts which are more upwardly biased for high B/M stocks than for low B/M stocks. The median earnings surprises implied by their results are -0.0026 for the bottom quintile of stocks by B/M stocks and -0.0118 for the top quintile of stocks by B/M. It is well known that returns tend to increase with B/M; for example in a study that uses the same study period (1976 to 1997), Ali et al. (2003) report average annual returns of 13% and 21.9% for the bottom and top quintile of stocks by B/M. Thus, returns and earnings surprises have opposite relationships with B/M. The results above are now used to explain how this can occur. First however, the sample is dissected based on the sign of the earnings surprise, with the results shown in Table 5.9.

Comparing observations with positive ES, there appears to be little difference between high and low B/M stocks in terms of the average ES and the BHAR observed over the return window. The positive surprises and BHARS are larger for high B/M stocks than for low B/M stocks, but on the whole there is nothing extraordinary about these figures. The negative surprises are also larger (in absolute value) for high B/M stocks than for low B/M stocks. Notice however, that the BHARS of high B/M stocks are extraordinarily small in absolute value, while the BHARS of low B/M stocks are extraordinarily large in absolute value. In the regressions this discrepancy is largely captured by G*BAD, which accounts for 16.8% of the difference between value and growth stocks[48]. This finding is very similar to Skinner and Sloan (2002).

[48] Based on the return-earnings specification that omits G*ES. If G*ES is included, G*BAD accounts for only 10% of the discrepancy while G*ES accounts for 4 to 8%.

Table 5.9 Cross Sectional Differences in Earnings Surprises and Buy-Hold Abnormal Returns
The following table compares the average earnings surprises (ES) and buy-hold abnormal returns (BHAR) of observations for high and low book-to-market (B/M) stocks, for positive and negative earnings surprises, and across different categories of analyst agreement (AA). All variables are calculated as per Table 5.1. High B/M stocks are those ranked in top third of the sample each year by B/M; low B/M stocks are those ranked in bottom third of the sample each year by B/M. Low, Mid and High AA stocks respectively are those ranked in top, middle and bottom third of the sample each year by forecast dispersion. The number of observations in each classification is denoted by 'n'.

	Analyst Agreement	Positive Surprises		Negative Surprises	
		High B/M (G=0)	Low B/M (G=2)	High B/M (G=0)	Low B/M (G=2)
n	Low (AA=0)	93	47	135	78
	Mid (AA=1)	72	76	111	76
	High (AA=2)	52	109	74	104
	All	217	232	320	258
Average ES	Low (AA=0)	0.020	0.012	-0.058	-0.032
	Mid (AA=1)	0.013	0.007	-0.030	-0.026
	High (AA=2)	0.007	0.005	-0.022	-0.016
	All	0.014	0.007	-0.040	-0.023
Average BHAR	Low (AA=0)	14.06%	6.20%	-2.15%	-22.92%
	Mid (AA=1)	13.98%	13.71%	-4.06%	-23.12%
	High (AA=2)	21.48%	15.02%	-3.89%	-18.02%
	All	15.81%	12.80%	-3.21%	-21.00%

The issue of whether differences in analyst agreement can explain the discrepancy in BHARS described above is now addressed, as value stocks generally rate much lower on this score. In the regressions, the coefficient on AA*ES is positive and significant, implying a direct relationship between ERC and Analyst Agreement. However, this relationship *cannot* explain the discrepancy for two reasons. First, the discrepancy exists in all AA categories, including the Low AA category where AA=0 and the incremental effect of AA on the ERC plays no part. Second, negative surprises are larger in absolute value for high B/M stocks than for low B/M stocks. Thus, *larger negative* BHARS would be expected for high B/M stocks, for negative surprises in the high AA category. The average negative ES amongst high AA stocks is -0.022 for high B/M stocks and -0.016 for low B/M stocks. The coefficient on AA*ES (1.667) thus implies that BHARS

should be 2*1.667*0.006=2% *lower* (i.e. more negative) for high B/M stocks than for low B/M stocks. Therefore, the discrepancy in BHARS illustrated in Table 5.9 is actually *greater* by 2% for high AA stocks (and greater by 1% for mid AA stocks) after taking analyst agreement into account.

5.7 Conclusion

This study investigated variation in the market responses to earnings surprises of Australian stocks as a function of B/M, default risk and analyst forecast dispersion. This was achieved by estimating the incremental effects of these variables on both the slope and intercept terms of the unexpected return-earnings surprise relation. By examining variation in the slope of the relationship, this study contributed an understanding of the determinants of earnings response coefficients. By studying variation in the intercept terms of the relationship the study added to the knowledge of the implications of the growth-stock earnings torpedo reported by Skinner and Sloan (2002), particularly to the value premium literature.

In the context of the ERC literature, each of the variables examined (B/M, default risk and forecast dispersion) were found to be related *in isolation* to the slope of the unexpected return-earnings surprise relation (in other words, the ERC). However, the incremental effect of default risk on the ERC vanishes after controlling for B/M and forecast dispersion, and therefore it is concluded that default risk is not a determinant of the ERC. Furthermore, as the *intercept terms* of the unexpected return-earnings surprise are not related to default risk the more general conclusion is reached that the market reaction to earnings surprise is not related to default risk.

In contrast to the results for default risk, strong evidence is found that the market reaction to earnings surprise is related to both B/M and forecast dispersion. Consistent with Imhoff and Lobo (1992) and Kinney et al. (2002), the slope of the unexpected return-earnings surprise relation (ERC) is negatively related to forecast dispersion (or, equivalently, positively related to analyst agreement). The results with regard to B/M are, however, sensitive to the choice of functional form for the unexpected return-earnings surprise relationship. In the absence of asymmetric intercept terms, evidence is found that the slope increases with B/M, consistent with prior results in the ERC literature. When asymmetric intercept terms are included similar to the earnings torpedo modelled in Skinner and Sloan (2002), the results of this study are consistent with theirs in that B/M affects the *negative intercept* of the unexpected return-earnings surprise relationship (in other words, the earnings torpedo) more than the slope of the relationship. Thus, the market reaction to earnings surprises is inversely related to B/M, but particularly so for small negative surprises.

Although consistent with Skinner and Sloan (2002), the results are somewhat at odds with prior results in the ERC literature in that B/M is found to affect the earnings torpedo more than the slope of the unexpected return-earnings surprise relationship. A possible reason for the inconsistency is the rounding error in I/B/E/S documented by Payne and Thomas (2003), which they argue has the effect of making the earnings surprises of growth stocks appear closer to zero than the 'true' earnings surprise. However, this possibility is accounted for by re-running the tests without a substantial proportion (9%) of the sample with zero or near-zero earnings surprises, with similar results. Another explanation is that the earnings torpedo may in effect simply be a manifestation of the nonlinearity of the relationship; as is well known the relationship is

steepest in the vicinity of zero earnings surprises and flattens out for more extreme surprises (Freeman and Tse, 1992). Thus, it is possible a nonlinear functional form of the relationship may allow for both a steeper slope (larger ERC) for small earnings surprises as well as variation in the slope with B/M and at the same time obviate the need to include asymmetric intercept terms. An investigation of this possibility is beyond the scope of the current study and therefore left as a task for future research.

Regardless of the possible explanations behind the results of this study, they have implications for a discrepancy in the value premium literature alluded to previously. The discrepancy is between the inverse relationship between earnings surprises and B/M documented in Doukas et al. (2002) (which is also confirmed in this study), and the direct relationship between stock returns and B/M. In the sample used in this study, the discrepancy occurs *only* for negative surprises and is consistent with the growth stock earnings torpedo, and therefore might at first glance appear to be explainable by the results of Skinner and Sloan (2002). However the results of this study go further, because it is confirmed that the discrepancy does not appear to be otherwise explainable by differences in either default risk or forecast dispersion. These results suggest that there is no systematic reaction of high B/M stocks to negative earnings surprises, while low B/M stocks have a severe market reaction to negative earnings surprises.

CHAPTER 6: CONCLUSIONS, CONTRIBUTION TO KNOWLEDGE, LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

6.1 Summary of Findings

This thesis examined the role played by financial distress in behavioural explanations of the value premium in Australia. Behavioural explanations argue that the value premium is due to mispricing of value and growth stocks and not to differences in rationally-priced risk. One such explanation is the errors-in-expectations hypothesis, where the relative mispricing is due to investors' erroneous growth expectations of earnings growth; a hypothesis that has previously been tested and rejected using analysts' earnings forecasts by Doukas et al. (2002) and Mian and Teo (2004). The specific issues examined in this thesis are (i) whether mispricing exists in Australia as a function both of value/growth classification and of financial distress, (ii) whether the evidence contrary to the errors-in-expectations hypothesis is sensitive to financial distress, and (iii) the reconciliation of two apparently contradictory sets of observations: the observation that value stocks have higher returns than growth stocks (the value premium) and the observation that analysts' earnings forecasts are more optimistic for value stocks than for growth stocks.

The general research design follows the relevant literature by categorising stocks according to their relative value/growth orientation and their relative level of financial distress, and then testing for variation in a number of characteristics across the value/growth and financial distress categories. Value/growth orientation is measured

using the valuation ratios book-to-market (B/M), earnings-to-price (E/P) and cash flow-to-price (C/P) while financial distress is measured using distance-to-default (DD). The examination of issue (iii) involves further categorisation by analyst agreement, which is measured using analyst forecast dispersion. The characteristics of interest which correspond to the three issues are, respectively, (i) raw and risk-adjusted stock returns and changes in firm profitability, (ii) analysts' forecast errors and (iii) the market reaction to earnings surprises. The research issues were examined through a series of research questions, the findings for which will be discussed below. The analyses were performed on data covering the period from 1995 to 2008, for Australian stocks with fully-paid ordinary shares in the top 300 by market capitalisation with the exclusion of listed property trusts, investment trusts, and foreign or dual-listed companies.

Are Australian stocks mispriced when their valuation ratios (B/M, E/P or C/P) are either high or low relative to their level of default risk?

This research question addresses the first issue discussed above, regarding the existence of mispricing in Australia as a function both of value/growth classification and of financial distress, and was initially investigated by testing two hypotheses. These hypotheses are (i) that portfolios of stocks with high valuation ratios and high DD have positive alphas, and (ii) that portfolios of stocks with low valuation ratios and low DD have negative alphas. The portfolio alphas are defined in terms of empirical implementations of the capital asset pricing model (CAPM), the Fama-French three-factor model and the Carhart four-factor model. Hypothesis (i) is consistent with underpricing of value stocks with low financial distress, while hypothesis (ii) is consistent with overpricing of growth stocks with high financial distress. In addition to

the direct evidence based on the portfolio alphas, the discussion here will also consider the variation in raw portfolio returns.

The results of chapter 3 are consistent with the mispricing hypotheses. Average portfolio returns increase with valuation ratios and with DD, such that the highest portfolio returns are observed for low default risk value portfolios while the lowest returns are observed for high default risk growth portfolios. This pattern is also evident in the portfolio alphas: low default risk value portfolios have statistically-significant positive alphas while high default risk growth portfolios have statistically significant negative alphas. The results generally hold for each of the three valuation ratios, each of the three asset-pricing models and for both equal-weighted and value-weighted portfolio returns. The principal findings of chapter 3 can be summarised in Figure 6.1, which plots the equal-weighted returns and four-factor alphas as a function of (i) B/M and DD and (ii) E/P and DD. Figure 6.1 shows that low default risk value stocks, which are represented either by the high DD, high B/M or the high DD, high E/P cells, have relatively high average returns and positive portfolio alphas; a result consistent with the underpricing hypothesis (i). Figure 6.1 also shows that high default risk growth stocks, which are represented either by the low DD, low B/M or the by low DD, low E/P cells, have relatively low average returns and negative portfolio alphas; a result consistent with the overpricing hypothesis (ii). The findings are consistent with the tenor of overseas studies which have documented undervaluation of financially healthy value stocks and overvaluation of financially distressed growth stocks, for example Piotroski

(2000), Griffin and Lemmon (2002), Mohanram (2005) and Bird and Casavecchia (2007a)[49].

It is acknowledged that the findings to this point might be consistent with deficiencies in the asset pricing models used to risk-adjust returns (in other words, to compute the portfolio alphas). However it is argued that inadequacy of asset pricing models *which are based on the premise of rational pricing* is not the likely explanation for the results. To this end, chapter 3 also confirmed that both the raw returns and portfolio alphas are inversely related to other measure of risk not specifically included in the asset pricing models – namely portfolio volatility (both total and residual) and default risk itself. Thus, a rational asset pricing explanation for the results faces the difficulty of explaining this inverse relationship with alternative risk measures.

To further develop an understanding of the potential mechanisms by which mispricing might occur (for example underreaction and/or overreaction), chapter 3 also presented some evidence based on characteristics related to profitability and changes in profitability. This evidence is consistent with an underreaction mechanism. The findings show that low default risk value stocks are characterised by *improving* financial health while high default risk growth stocks are characterised by *declining* financial health. For example, the *rate of change* of return on assets is greater for low default risk value stocks than for high default risk growth stocks. Similarly, the (price-deflated) rate of change of earnings-per-share (EPS) is greater for low default risk value stocks than for high default risk growth stocks. Put differently, the *change in profitability* increases steadily with valuation ratios as well as with DD. It is pertinent to note that these trends

[49] The Mohanram (2005) findings are couched in terms of the portfolio selection of financially healthy growth stocks to deliver high future returns (relative to otherwise similar growth stocks); a similar finding to the relative underperformance of financially distressed growth stocks.

in financial performance, which were observed *prior* to portfolio formation, are matched by similar trends in stock returns *after* portfolio formation: low default risk value stocks continue to perform well while high default risk growth stocks continue to perform poorly. The findings are inconsistent with the overreaction behaviour postulated in some models as the mechanism behind the value premium, for example Barberis et al. (1998), Hong and Stein (1999) and Barberis and Shleifer (2003), but are consistent with the momentum life cycle postulated by Lee and Swaminathan (2000).

How do median analysts' forecast errors vary with valuation ratios and default risk?

This research question addresses the second issue discussed above, namely whether the evidence contrary to the errors-in-expectations hypothesis is sensitive to financial distress, and is the basis for the analysis in chapter 4. The errors-in-expectations hypothesis suggests that investors are overly optimistic regarding the future prospects of and consequently pay prices that are too high for growth stocks. Some evidence contrary to this hypothesis has emerged from empirical studies based on analysts' earnings forecasts (Bauman and Miller, 1997; Doukas et al., 2002; Mian and Teo, 2004). Most notably, Doukas et al. (2002) find that analysts' short term earnings forecasts exceed actual earnings numbers by greater amounts for value stocks than for growth stocks (in other words, analysts' forecasts appear to be more optimistic for value stocks than for growth stocks). Chapter 4 contains a similar analysis using Australian data, but unlike previous studies controls for financial distress, measured as above by DD.

The principal findings from chapter 4 are summarised by Figure 6.2. Forecast errors are the amounts by which analysts' EPS forecasts exceed subsequently announced EPS numbers; therefore large forecast errors imply overly optimistic forecasts. In univariate tests (not shown), a similar but weaker relationship to that reported by Doukas et al. (2002) is obtained between forecast errors and B/M. However, this relationship is completely subsumed by a much stronger relationship between forecast errors and DD. When portfolios are sorted by DD and B/M (as in the left-hand panel of Figure 6.2), the largest forecast errors are observed for low DD (in other words, high default risk) firms. Although there are some deviations, the variation in forecast errors with default risk is statistically significant and dominates the variation in forecast errors with B/M (which is not statistically significant).

A slightly different picture emerges when portfolios are sorted by E/P and DD (the right-hand panel of Figure 6.2) rather than by B/M and DD; however the conclusion is similar: the relationship between analysts' forecast errors and financial distress dominates the relationship between analysts' forecast errors and the valuation ratio (E/P in this case). There is some evidence in Figure 6.2 that forecast errors are inversely related to E/P. Thus, the pattern of forecast errors observed for portfolios sorted by E/P and DD is closer to that predicted by the errors-in-expectations hypothesis than the pattern observed for B/M and DD sorted portfolios. However, on closer inspection most of the variation in forecast error with E/P is due to the very large forecast errors of negative E/P firms. The variation in forecast errors with E/P is statistically significant if negative E/P firms are included in the sample, but if negative E/P firms are excluded the variation in forecast errors with E/P is statistically significant only amongst low DD firms. Within each E/P category, forecast errors generally vary inversely with DD (that

is, they vary directly with default risk), and this variation is statistically significant. Thus, the conclusion from the portfolios sorted by E/P and DD is similar to that obtained from the portfolios sorted by B/M and DD. Analysts' forecast errors are more strongly related to the firm's state of financial distress or health than to valuation ratios, where financial distress is indicated either by negative earnings or by a low DD score.

How does the market reaction to earnings surprises vary with valuation ratios, default risk and forecast dispersion?

This research question deals with issue (iii); in other words it attempts to increase our understanding of how earnings surprises for value stocks can be relatively large and more negative than those for growth stocks, while value stocks can continue to earn higher returns than growth stocks. To this end the final empirical study of this dissertation examined the market reaction to earnings surprises for variation across value/growth, default risk and forecast dispersion categories. Earnings surprises are incidences where companies announce earnings that are different from the market's expectations; measured in this dissertation similarly to the errors in consensus analysts' forecasts discussed above and in chapter 4. The market reaction to earnings surprise is generally manifest in terms of an 'unexpected' stock return or difference between a stock's return and the return of the market over the same period. As discussed in chapter 5, the severity of the market reaction to earnings surprises is measured by both the slope of the relationship between unexpected returns and earnings surprises as well as the intercept of this relationship. Both the slope and intercept are permitted to vary with a stock's B/M ratio, its level of default risk, and analyst agreement. Thus, a relatively severe market reaction to earnings surprises for a particular category of stocks might be

demonstrated by a relatively large slope (ERC) or a relatively large negative intercept for negative surprises.

Consistent with prior literature, the results of chapter 5 demonstrate that the market reaction to a firm's earnings surprise is inversely related to its B/M ratio and directly related to the degree of analyst agreement regarding expected (forecast) earnings. After controlling for B/M and analyst agreement however, there was no residual effect of default risk on the market reaction to earnings surprises. In other words, the market reaction is relatively strong for growth stocks and for earnings forecasts with a high degree of analyst agreement, and relatively muted for value stocks and for earnings forecasts with a relatively low level of analyst agreement[50]. The results of the analysis are illustrated in Figure 6.3, which shows the fitted relationship between unexpected (buy-hold abnormal) returns and earnings surprises.

Figure 6.3 illustrates a major difference between low B/M stocks and high B/M stocks regarding the returns-earnings relationship; namely the intercept term for negative earnings surprises. Consistent with Skinner and Sloan (2002), this intercept term is larger and more negative for low B/M stocks than for high B/M stocks, implying that growth stocks suffer a large, negative market reaction for negative earnings surprises regardless of the magnitude of the surprise. When the asymmetric intercept term was not explicitly modelled, the slope (earnings response coefficient) was also found to be larger for low B/M than for high B/M stocks; a result also consistent with prior results in the literature (Collins and Kothari, 1989; Biddle and Seow, 1991; Skinner and Sloan, 2002) and with valuation models discussed in Ohlson (1995) and Burgstahler and

[50] Although Collins and Kothari (1989) argue that B/M might be relevant to earnings response coefficients because it proxies for earnings persistence, the chapter 5 findings were also obtained using E/P instead of B/M.

Dichev (1997). However, when the regression tests allowed for variation in both the intercept and slope, no statistically significant variation between high and low B/M stocks was found in the slope term. Hence value and growth stocks plot along the same line in Figure 6.3 for positive surprises and differ only in the intercept for negative surprises.

Unlike B/M however, the effect of analyst agreement (on the relationship between unexpected returns and earnings surprises) is primarily observed through variation in the slope and not through variation in the intercept. This finding is illustrated by a comparison of the left and right panels in Figure 6.3. The slope of the relationship is steepest in the case of high analyst agreement (low dispersion) stocks, represented in the right-hand panel. Thus, high analyst agreement stocks have a greater market reaction to earnings surprises than low analyst agreement stocks. The incremental effect of analyst agreement on the slope applies to both high B/M and low B/M stocks, and to both positive and negative earnings surprises. Furthermore, the findings are consistent with prior literature that documents a direct relationship between earnings response coefficients and analyst agreement (Imhoff and Lobo, 1992; Kinney et al., 2002).

Whilst analyst agreement affects the severity of the market reaction to earnings surprise, it *does not explain* the conundrum behind issue (iii); namely the observation that analysts' earnings forecasts are more optimistic (earnings surprises are more negative) for value stocks than for growth stocks despite the fact value stocks have higher returns than growth stocks. The best explanation for this conundrum that can be offered following the analysis in chapter 5 is that value stocks remain relatively unpunished by the market for missing earnings expectations while growth stocks are heavily punished

for missing earnings expectations. Although this result is known from previous studies (Skinner and Sloan, 2002; Chan et al., 2006a), a major contribution of the analysis here is to show that the effect exists independently from differences in analyst agreement (and, as discussed above, default risk). Put differently, the finding that growth stocks are more heavily punished for negative surprises than value stocks holds for low analyst agreement stocks *as well as* for high analyst agreement stocks, and is not explained by differences in analyst agreement between value and growth stocks.

6.2 Contributions to Knowledge

This dissertation makes several contributions to the Asset Pricing Literature. The contributions increase knowledge in three general areas: (i) the pricing of default risk in equity markets, (ii) the existence of market inefficiencies and mispricing in the Australian equity market and (iii) behavioural explanations of cross-sectional stock return differences. The contributions to each of these three areas will now be discussed in detail.

6.2.1 Rational Pricing of Default Risk

As has been discussed previously, the weight of recent empirical evidence in the finance literature suggests that default risk is not priced in equity markets (Dichev, 1998; Gharghori et al., 2007; Campbell et al., 2008). The implications of this general finding are that stocks of distressed companies do not have higher expected returns than stocks of otherwise financially healthy companies, and therefore the HML factor in the Fama-French three-factor model is not a proxy for a priced financial distress risk factor. The findings in chapter 3 are consistent with and further support the weight of recent empirical evidence against a priced distress factor.

However, the findings in Chapter 3 go further than rejecting a positive default risk premium. On the contrary, the findings are consistent with a negative default risk premium as documented by Campbell et al. (2008) and others; and when a firm's level of default risk is at odds with (either too high or too low given) the firm's valuation ratios, the findings are consistent with mispricing rather than with rational pricing. Thus the results pertaining to the relationship between stocks returns, default risk and valuation ratios fail to support a rational pricing explanation for the value premium. The results are consistent with several recent studies finding evidence of overvaluation of distressed growth stocks and of undervaluation of financially healthy value stocks (Piotroski, 2000; Griffin and Lemmon, 2002; Mohanram, 2005; and Bird and Casavecchia, 2007a); the contributions made to this body of knowledge are: (i) in the use of a single variable to define a firm's state of financial distress or health, (ii) the robustness of the results across several valuation ratios (B/M, E/P and C/P) and (iii) the application of the analysis to large-capitalisation Australian stocks.

The finding that default risk does not appear to be rationally priced has implications for research that deals with the relationship between earnings and stocks returns, or that attempts to determine the factors determining the market reaction to earnings surprises. Theoretically the ERC, or slope of the relationship between unexpected returns and unexpected earnings, is inversely related to a firm's systematic risk, and if the CAPM is valid, to equity betas (Collins and Kothari, 1989; Easton and Zmijewski, 1989). Dhaliwal and Reynolds (1994) point out that if default risk represents a form of priced risk not adequately reflected in observed equity betas, then response coefficients will similarly be inversely related to default risk.

There is limited empirical evidence that directly tests the conjecture that response coefficients (or the market reaction to earnings surprises in general) vary with default risk. Dhaliwal and Reynolds (1994) observe an inverse relationship between ERC and default risk, measured in terms of either bond ratings or debt-to-equity ratios, after controlling for equity beta. Billings (1999), on the other hand, finds that the relationship between default risk and response coefficients is largely explained by the negative correlation between default risk and growth. The findings in Chapter 5 show that after controlling for growth and differences in analyst agreement, default risk is not a determinant of the market reactions to earnings surprises; a finding that further supports the earlier conclusion that default risk is not priced in equity markets. The main contributions in this regard are that the results in this thesis (i) control for analyst agreement and (ii) employ an alternative and arguably cleaner measure of default risk (DD) than ratios or statistical models upon which bond ratings are based (Vassalou and Xing, 2004; Gharghori et al., 2006b).

6.2.2 Market Inefficiency and Mispricing

This thesis contributes to the literature regarding market efficiency, primarily through the analysis of portfolio returns in chapter 3 and the analysis of analysts' forecast errors in chapter 4. The findings in this thesis are consistent with inefficiency, rather than efficiency, of the Australian stock market. Strong-form market efficiency postulates that all publicly-available information is reflected in security prices, such that it is not possible to earn abnormal returns by trading on the information in financial statements or in security prices. However, the findings of this thesis demonstrate that over the sample period tested, it was indeed possible to form portfolios with abnormally high

and abnormally low subsequent returns, using the information in financial statements and past security prices, a finding inconsistent with market efficiency. Furthermore, it was also demonstrated that over the sample period tested, analysts' earnings forecasts were overly optimistic for firms with high default risk and for firms with negative earnings; a finding that is consistent with analyst underreaction to distress and therefore also inconsistent with market efficiency. The conclusion that analysts underreact to distress is consistent with the majority of studies on analyst efficiency (Abarbanell and Bernard, 1992; Abarbanell and Lehavy, 2003; Cohen and Lys, 2003), and in particular with the findings of Easterwood and Nutt (1999) who find that analysts underreact to bad news (but not to good news).

Whilst there is a vast extant body of literature on market efficiency (with support for both the efficiency and inefficiency arguments), the main contribution of this thesis to knowledge of the subject stems from the use of DD to measure default risk. DD employs, in addition to the information in a firm's financial statements, recent share price information to infer the market's perception of the firm's default risk. Thus, the DD calculation implicitly (and not unreasonably) assumes that at the time of calculation, share prices have reacted to prior changes in each firm's economic fundamentals. However, the results of this thesis suggest that the reaction to prior changes in each firm's economic fundamentals is an *underreaction*, because the direction of price changes continues *after* the time of measurement of DD. For example, overvalued (high default risk growth) stocks exhibit poor prior returns and declining earnings, but also have low *future* returns. Similarly, analysts' earnings forecasts are *too high* for this group of firms (as they are for low DD and distressed firms in general), consistent with analyst underreaction to poor prior returns and declining earnings. Thus,

the findings also add to the accounting literature that deals specifically with analyst efficiency.

This thesis also presented some findings consistent with the existence of mispricing in the Australian stock market, as summarised in Section 6.1. The specific hypothesis tested was that growth stocks with high default risk are overvalued while value stocks with low default risk are undervalued; a system of mispricing that is consistent with several recent studies such as (Piotroski, 2000; Griffin and Lemmon, 2002; Mohanram, 2005; Bird and Casavecchia, 2007a). There are two main contribution of this thesis to studies in this particular body of literature (and therefore also to the more general literature on return predictability). The first contribution pertains to the use and choice of a single variable, DD, to identify overvalued growth stocks and undervalued value stocks. In contrast, Piotroski (2000), Mohanram (2005) and Bird and Casavecchia (2007a) all employ dissimilar composite variables to define financial health, thus diminishing the external validity of these studies; Griffin and Lemmon (2002) employ Ohlson's O-score in a similar fashion to identify overvalued growth stocks. DD is arguably a more accurate and theoretically sound measure of financial health than the measures used in the above studies, and is now widely employed in both academic studies and in practice.

The second contribution of the thesis to the above body of literature (mispricing as a function of value/growth and financial health) pertains to the choice of sample. There are few studies of this specific form of mispricing in the Australian market, and to the best of the author's knowledge no published studies that focus specifically upon large capitalisation stocks. Two interpretations are offered here for the findings and their

support of mispricing amongst *large* stocks. First, it could be argued that the findings contradict the limits-to-arbitrage thesis of Shleifer and Vishny (1997), which argues that mispricing exists because it is costly for arbitrageurs to drive prices back to fundamental values. Arbitrage might reasonably be expected to be less costly for large stocks, because of greater analyst coverage (and therefore more information) and liquidity, and lower idiosyncratic volatility and bid-ask-spreads (Ali et al., 2003); therefore mispricing might reasonably be expected to be less prevalent amongst large stocks. Second, it could alternatively be argued that the findings imply that arbitrage is indeed costly (and inefficiency is prevalent) for the Australian market *in general* or for the firms specifically identified as being mispriced, relative to larger equity markets such as the American market. The costly-arbitrage argument is also supported by the observations that relatively few firms are indeed identified as mispriced and that the high default risk growth portfolios possess high residual volatility, making arbitrage difficult.

6.2.3 Behavioural Explanations of Cross-sectional Return Differences

It has already been argued that the findings of this thesis are inconsistent with market efficiency and with rational asset pricing. Furthermore, this thesis makes contributions to the alternative asset pricing paradigm, which involves behavioural explanations of cross-sectional stock return differences. The contributions specifically pertain to the errors-in-expectations hypothesis, the momentum life cycle, and the cognitive biases and other assumptions underlying various behavioural finance theories.

6.2.3.1 The Errors-in-Expectations Hypothesis

A number of previous studies have tested the errors-in-expectations by comparing the analysts' forecast errors of value and growth stocks. A noteworthy study is Doukas et al. (2002), because they find a relationship between forecast errors and B/M that is the

exact opposite of that predicted by the errors-in-expectations hypothesis. A major contribution of this thesis has been to demonstrate that, in the Australian sample used in the analysis, the relationship between B/M and analyst forecast errors is completely subsumed by the relationship between analyst forecast errors and distress. Thus, high B/M stocks have overly optimistic earnings forecasts because, as discussed earlier, such forecasts tend to be too high for distressed firms and because B/M is correlated with distress. The pattern of forecast errors that results from classifying firms according to value/growth as well as default risk is similar to the pattern of mispricing from the same classification; put differently overvalued firms have earnings forecasts that are more optimistic than those of undervalued firms. This specific finding is consistent with the predictions of errors-in-expectations hypothesis and similar to that obtained by Bartov and Kim (2004) who use the level of accruals in reported earnings rather than default risk to define mispriced value and growth firms. However, the driving factor behind the results here appears to be *analyst underreaction to distress*; a mechanism which is inconsistent with the *extrapolation* behaviour underpinning the errors-in-expectations hypothesis.

The analysis of market reactions to earnings surprises (Chapter 5) provides a further contribution to our understanding of analyst forecast-based tests of the errors-in-expectations hypothesis. Previous studies have demonstrated that growth stocks react more strongly to earnings surprises than value stocks, in particular it has been demonstrated that growth stocks are punished severely by the market for missing earnings expectations while value stocks are not (Skinner and Sloan, 2002; Chan et al., 2006a). The findings in this thesis not only confirm this result, but moreover

demonstrate that it is not due to differences in either default risk or forecast dispersion between value and growth stocks.

Skinner and Sloan (2002) argue that the extreme reaction of growth stocks to even marginally negative surprises is consistent with the errors-in-expectations hypothesis, because it demonstrates that investors are informed that their growth expectations are too optimistic and subsequently revise their expectations and valuations downwards following negative surprises. However, a different interpretation is offered here based upon the findings of both Chapter 4 and Chapter 5. Earnings forecasts for value stocks are more optimistic on average than those of growth stocks because most value stocks are distressed and because analysts underreact to the distress-related information in stock prices and earnings changes (Chapter 4). The application of analysts' earnings forecasts to tests of the errors-in-expectations hypothesis, which is based upon long-term *overreaction*, might therefore be invalid because such forecasts are subject to *underreaction*.

Furthermore, growth stocks are punished by the market for missing earnings forecasts while value stocks are not (Chapter 5), a corollary of which is that the over-optimistic earnings forecasts of value stocks are not instrumental in their low valuation (i.e. their low prices or their high B/M ratio). In other words, the market appears to disregard the earnings forecasts of value stocks relative to those of growth stocks, suggesting that differences in such forecasts might not be representative of differences in investors' growth expectations. In summary, a potential explanation offered here for the findings in Chapters 4 and 5 is that errors in analysts' earnings forecasts might not be valid as measures of the errors in investors' long-term growth expectations (*and therefore might*

conceivably be inadmissible in tests of the errors-in-expectations hypothesis), because (i) such forecasts are influenced by analyst short-term underreaction and (ii) they appear to be ignored by investors in value stocks.

6.2.3.2 The Momentum Life Cycle

The findings in this thesis contribute to an understanding of the momentum life cycle postulated by Lee and Swaminathan (2000). Lee and Swaminathan (2000) focus on the interaction between trading volume and momentum, but do however make analogies between trading volume and value/growth measures; namely that stocks with high trading volume possess many characteristics of growth stocks while stocks with low trading volume possess many characteristics of value stocks. They find that momentum appears to be strongest amongst stocks with high trading volume and poor recent returns (which continue to perform poorly), and amongst stocks with low trading volume and high recent returns (which continue to exhibit high returns). Lee and Swaminathan (2000) explain their results in terms of a model they refer to as the momentum life cycle.

According to the momentum life cycle, stocks go through periods of favouritism and neglect. High momentum stocks are argued to be experiencing a period of favouritism in their life cycle, beginning with a phase of low trading volume ('low volume winners'). Low volume winners are the most likely stocks to continue to deliver high returns. As sentiment towards a low volume winner increases, accompanied by high returns, trading volume increases. Eventually, the low volume winners become expensive growth stocks characterised by high trading volume and the tendency to subsequently disappoint investors with return reversals ('high volume winners'). From here, stocks become 'high volume losers', companies with poor recent returns and high

trading volume. High volume losers are the most likely companies to continue to deliver poor returns. Stocks in this stage of their momentum life cycle become increasingly unpopular and neglected, resulting in falling trading volume. Finally, the stocks become ‘low volume losers’, in other words companies that have had extended periods of poor returns accompanied by diminishing trading volume.

The overpriced growth stocks identified in Chapter 3 are characterised by relatively poor recent returns and lower profitability than other growth stocks. This group of companies are highly likely to deliver poor returns and, from the results of Chapter 4, to disappoint investors with an earnings torpedo. Thus, overpriced growth stocks share many of the characteristics of the high volume losers in the momentum life cycle. On the other hand, the underpriced value stocks identified in Chapter 3 are characterised by high recent returns and higher profitability than other value stocks. This group of companies are highly likely to deliver high returns and to pleasantly surprise investors with better-than-expected earnings. Thus underpriced value stocks share many of the characteristics of the low volume winners in the momentum life cycle.

The relevance of the findings of this thesis to the momentum life cycle is further illustrated by the link between DD and momentum. Stocks which rank highly on DD also tend to have high momentum by virtue of the drift term μ in the calculation; moreover the relationship between DD and momentum is intuitive because it implies that all else equal, changes in the market’s assessment of a firm’s default risk are reflected in movements in the firm’s stock price. However, DD encapsulates additional information besides momentum, as is evident from the alphas of low DD growth and high DD value portfolios calculated using the Carhart four-factor model. As the fourth

factor in this model represents momentum, the significance of the alphas of these portfolios demonstrates they are not merely de-facto low momentum growth and high momentum value portfolios respectively.

Given that DD and momentum are not merely proxies for one another, the contribution of this thesis to our understanding of the momentum life cycle can be stated as follows. Results similar to those of Lee and Swaminathan (2000) can be obtained using DD instead of momentum, and using value/growth measures instead of trading volume. Whilst Lee and Swaminathan (2000) confirm that trading volume is related to value/growth; the findings here are consistent with the idea that DD captures sentiment in the same manner as momentum in the momentum life cycle. Moreover, DD may be a more complete measure of market sentiment towards a stock than momentum because it includes capital structure-related information and theoretically at least, it directly measures the market's assessment of the firm's state of financial health.

6.2.3.3 Contributions to Behavioural Finance Theory

The findings of this thesis provide evidence regarding a number of behavioural finance theories which have been proposed to explain asset pricing anomalies such as momentum and long-term reversals, where the term 'long-term reversals' also includes the value premium. In particular, the findings are inconsistent with the model of Barberis et al. (1998) which treats the value premium as an overreaction and momentum as an underreaction. According to the model, investors are subject to a 'representativeness bias', whereby investors observing a series of earnings changes mistakenly infer that earnings follow a trend, when in fact earnings changes are random. The model also specifies that investors are subject to a 'conservatism bias', whereby investors who observe a single earnings change mistakenly infer that earnings are mean

reverting, and update their prior expectations (of future earnings) insufficiently. Thus, under the Barberis et al. (1998) model, the representativeness bias leads investors to overreact to consistently good performance, causing prices to overshoot their fundamental values; a mechanism consistent with the exposition of the errors-in-expectations hypothesis in Lakonishok et al. (1994), where investors extrapolate previous good performance too far into the future.

However, the findings in this thesis are difficult to reconcile with the model of Barberis et al. (1998), insofar as the investor behaviour underpinning the value premium. According to this model, the value premium is characterised as an overreaction while momentum is characterised as an underreaction. As discussed above, the findings within this thesis are not consistent with the characterisation of the value premium as an overreaction. Specifically, the value premium in Australia appears to be primarily attributable to two groups of stocks: overpriced growth stocks and underpriced value stocks. Overpriced growth stocks are stocks of companies whose fortunes have turned for the worse, with low profitability and poor returns. However, the market appears to be slow in recognising the distress of these companies, as prices are too high and analysts too optimistic relative to other growth stocks. Underpriced value stocks, on the other hand, have higher profitability and returns than other value stocks. Again, the market appears slow in recognising the improving fortunes of these companies, as prices are too low and analysts too pessimistic relative to other value stocks. This behaviour is more consistent with the conservatism bias, which Barberis et al. (1998) rely on to explain momentum, than with the representativeness bias.

It is pertinent to note that other studies are also inconsistent with explanations of the value premium that rely upon the representativeness bias. Dechow and Sloan (1997) argue that the value premium appears unrelated to investors' extrapolation of past earnings trends, arguing instead that it bears a very strong relationship to the biased growth forecasts of analysts. Chan et al. (2004) find that neither the consistency nor the trends in earnings performance are related to future stock returns. They do, however, find evidence of an underreaction to recent accounting performance which is consistent with a conservatism bias[51].

The findings in this thesis also constitute evidence regarding a number of other assumptions adopted in other behavioural finance theories. The delayed reaction of prices and analysts to public information embedded in prices and financial information is consistent with the slow diffusion of information assumption in Hong and Stein (1999), and also with the prediction of the Daniel et al. (1998) model that investors underreact to public information (a consequence of two separate cognitive biases, overconfidence and biased self-attribution). The findings of this thesis are consistent with the modelling of the value premium in Daniel et al. (1998) as a *gradual* correction of prices (in other words, an underreaction) following the arrival of public information, and therefore inconsistent with the modelling of the value premium as an overreaction in Barberis et al. (1998) and Hong and Stein (1999).

[51] Chan et al. (2004) argue that their rejection of the representativeness bias rules out the majority of behavioural finance theories of cross-sectional return patterns; however Daniel (2004) points out that this finding is only relevant to the model of Barberis et al. (1998) and not to other theories which do not specifically rely on the representativeness bias, such as Hong and Stein (1999), Daniel et al. (1998) and Daniel and Titman (2004) (the latter subsequently published as Daniel and Titman (2006)).

6.3 Limitations of the Research

A limitation of the thesis is the relatively small sample size, which consists of the largest 300 stocks on the Australian stock exchange minus property and investment trusts and foreign or dual-listed shares, and which covers a thirteen-year period. The limited time period suggests that robustness and business-cycle variation in the results might be tested in future studies through replication over longer or alternative time periods. The limited cross-section posed some difficulties for the portfolio-sorting procedures, resulting in relatively small portfolios representing the high default risk growth and low default risk value categories of stocks. The small number of stocks in the high default risk growth and low default risk value portfolios implies that disproportionately few stocks are indeed mispriced amongst the largest 300 stocks on the ASX. However, mispricing is less likely amongst large stocks than amongst small stocks (Ali et al., 2003), and therefore the fact that even a small number of mispriced securities could be identified in effect strengthens the arguments for mispricing and for inefficiency of the Australian stock market. Moreover, the fact that relatively few stocks are mispriced supports the costly arbitrage argument (Shleifer and Vishny, 1997) for the existence of mispricing, because it is difficult for arbitrageurs to form diversified hedge portfolios to exploit and therefore eliminate any mispricing.

A limitation of the tests of mispricing in chapter 3 are that they rely on static asset pricing models (the CAPM, the Fama-French three-factor model and the Carhart four-factor model) to risk-adjust returns. The analysis does not consider conditional asset pricing models (for example, Jagannathan and Wang, 1996, and Lettau and Ludvigson,

2001) which might capture time-variation in systematic risk or other models that attempt to relate variations in risk premiums with business-cycle variation. Although beyond the scope of this thesis, it is possible that a model of this type might explain the significant alphas of high default risk growth and low default risk value portfolios estimated from static models. However, any candidate rational asset pricing model faces the difficulty of explaining the negative default risk premium evident not just in the results of Chapter 3, but also in other studies such as Dichev (1998) and Campbell et al. (2008). It is therefore argued that a rational pricing explanation for the results of Chapter 3 will be difficult to arrive at; however the possibility can not be ruled out altogether.

A further limitation pertains to the external validity of the findings; in particular the findings from Chapter 4 dealing with the relationship between valuation ratios, default risk and analyst optimism. These findings are based on Australian data; however the prior studies which motivate the research are the US-based study by Doukas et al. (2002), and to a lesser extent the Japan-based study by Mian and Teo (2004). The findings from Chapter 4 support the contention that the direct relationship between B/M and analyst optimism documented by Doukas et al. (2002) is sensitive to default risk; however it remains to be seen whether these findings are confirmed in the US data upon which that study is based, or indeed in other overseas markets besides the US.

Similarly, the external validity of two specific findings from Chapter 5 might also be questioned. These findings are: (i) that default risk does not affect the market reaction to earnings surprises independently of B/M and dispersion, and (ii) that differences in dispersion are not responsible for the anomalous observation that analyst optimism

increases with B/M (the observation is anomalous because returns also increase with B/M). It is left as a task for future research to replicate these findings on other markets. The third important finding from Chapter 5 is that the anomalous relationship between analyst optimism and B/M is largely explainable by the lack of market response to value stocks' negative surprises. External validity is less of an issue for this particular finding because it is consistent with the US-based results of Skinner and Sloan (2002). External validity is also less of a limitation for Chapter 3, because the findings are generally consistent with overseas studies (Piotroski, 2000; Griffin and Lemmon, 2002; Mohanram, 2005; and Bird and Casavecchia, 2007a).

6.4 Extensions and Future Research

6.4.1 Value/growth, Default Risk and Mispricing

There are at least three potential extensions of the findings and analysis of Chapter 3, which dealt with mispricing as a function of value/growth and default risk. The first potential extension is an investigation of temporal variation in the portfolio alphas similar to the analysis in Lewellen (1999). Such an investigation might reveal temporal variation in mispricing (in other words, time variation of portfolio alphas) or perhaps an explanation of the findings consistent with rational pricing, for example time variation in risk factor loadings.

The second potential extension of Chapter 3 might be to more directly relate the findings to the momentum life cycle of Lee and Swaminathan (2000). Although the findings of this thesis are consistent with the momentum life cycle, there remain some

unaddressed issues. First, Lee and Swaminathan (2000) classify stocks according to trading volume and price momentum rather than value/growth and default risk; therefore it is worthwhile to replicate the study of Lee and Swaminathan (2000) using Australian data. Second, it is worthwhile to test whether low default risk value stocks are typically the same stocks as low volume winners and whether high default risk growth stocks are typically the same stocks as high volume winners. Whilst Lee and Swaminathan (2000) do investigate the link between trading volume and value/growth, an equally pertinent question might be how closely momentum and DD are related, and whether DD conveys additional information relevant to the momentum life cycle besides momentum.

The final potential extension of Chapter 3 is an examination of the differences between large capitalisation and small capitalisation stocks listed on the ASX. The findings of Chapter 3 suggest a large and statistically significant value premium specifically amongst large capitalisation Australian stocks. Whilst other studies have not emphasised this specific finding, it is readily apparent from the largest two size quintiles in the two-way sorts on size and B/M in both Halliwell et al. (1999) and Gaunt (2004), as well as from a similar analysis presented in Table 3A.1. However, both Halliwell et al. (1999) and Gaunt (2004) fail to find a significant value premium amongst the smaller size quintiles, a result also apparent in Table 3A.1; in other words, returns increase with B/M for large stocks on the ASX but not for small stocks on the ASX. Chapter 3 also reports that size (market capitalisation) does not appear to be related to returns for the largest 300 stocks on the ASX by market capitalisation. This result is also consistent with both Halliwell et al. (1999) and Gaunt (2004), who find a significant size effect only amongst the smallest size quintiles of ASX stocks, and little variation in returns

with size amongst the largest size quintiles. The findings of Chapter 3, along with those of Halliwell et al. (1999) and Gaunt (2004), therefore suggest that large and small stocks on the ASX behave differently: the largest stocks exhibit a value premium while the smallest stocks exhibit a size effect. A potentially fruitful area of research might be to explain this disparity between large and small ASX stocks, perhaps as a function of trading frequency, bid-ask bounce or other market microstructure effects.

6.4.2 Analyst Optimism

As discussed earlier, one of the limitations of the thesis is the external validity of the investigation of the role played by default risk in tests of the errors-in-expectations hypothesis based upon analyst optimism. It was previously stated that the relationship between analyst optimism and default risk (or financial distress more generally) completely subsumes any relationship between analyst optimism and B/M; however this finding is based upon Australian data rather than the US data employed by Doukas et al. (2002), who documented the strength and statistical significance of the latter relationship. Therefore, it is worthwhile to replicate the analysis using the same data as Doukas et al. (2002), in other words to validate the findings of Chapter 4 using US data.

The findings of Chapter 4 along with those of Doukas et al. (2002) and Mian and Teo (2004) show that analysts' forecast errors do not display biases consistent with errors-in-expectations based upon extrapolation of past earnings, although analyst optimism does appear to be related to the direction of mispricing. However, evidence based upon longer-term growth forecasts is more supportive of the errors-in-expectations hypothesis (La Porta, 1996; Dechow and Sloan, 1997) as is evidence that valuation ratios are directly related to past earnings growth but not to future earnings growth (Lakonishok et

al., 1994; Chan et al., 2003). A potentially fruitful area of future research might therefore be to explain the conflicting inferences resulting from short term earnings forecasts and longer term growth forecasts.

One reason why the relative errors in short-term earnings forecasts might not fully reflect the errors in long term growth expectations is because of the sluggishness of mean reversion in earnings growth. Fuller, Huberts and Levinson (1993) show that low E/P stocks continue to maintain higher earnings growth than high E/P stocks for periods up to eight years, however the growth differential is concentrated in the first two years and diminishes substantially after this period of time; this finding of a concentration of (and continuation of) the earnings growth differential in a relatively small number of years is also documented in Lakonishok et al. (1994). Therefore, the two-to-three year horizon typical of most analysts' earnings forecasts covers a period when growth stocks are likely to continue to experience substantially greater earnings growth than value stocks. Consequently, the errors in analysts' earnings forecasts might not capture the mean reversion in earnings growth that only occurs after several years have elapsed, a possibility that could potentially explain why evidence from forecast long-term growth rates is generally consistent with the errors-in-expectations hypothesis but evidence from (shorter-term) earnings forecasts is not. The relationship between the errors from both types of forecasts (earnings and long-term growth) and the value premium is beyond the scope of this thesis but warrants further investigation.

6.4.3 Market Reactions to Earnings Surprises

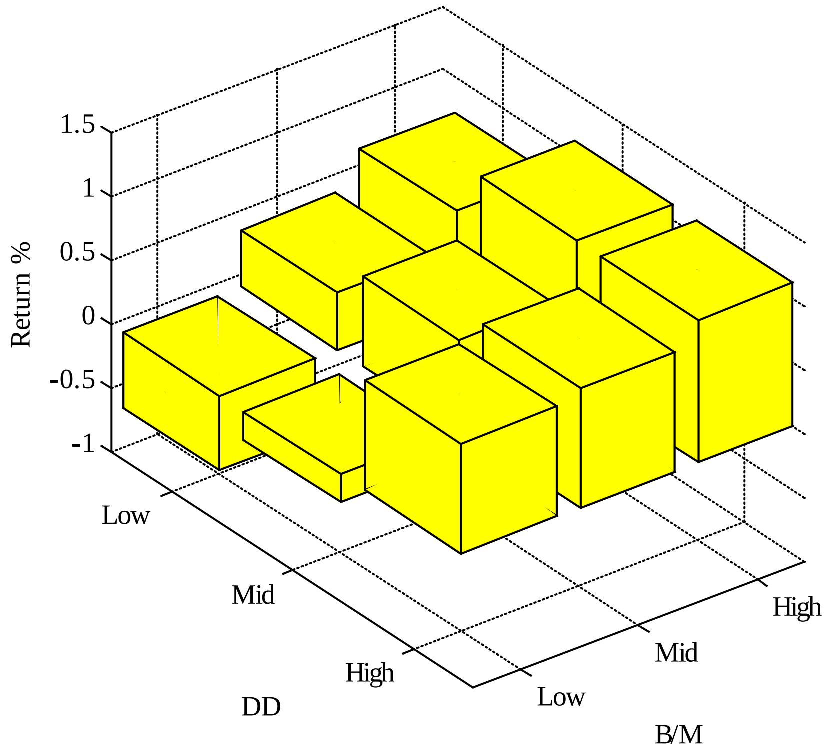
A potential area of future research might be the link between the 'earnings torpedo effect' (the large negative return associated with marginally negative earnings surprises)

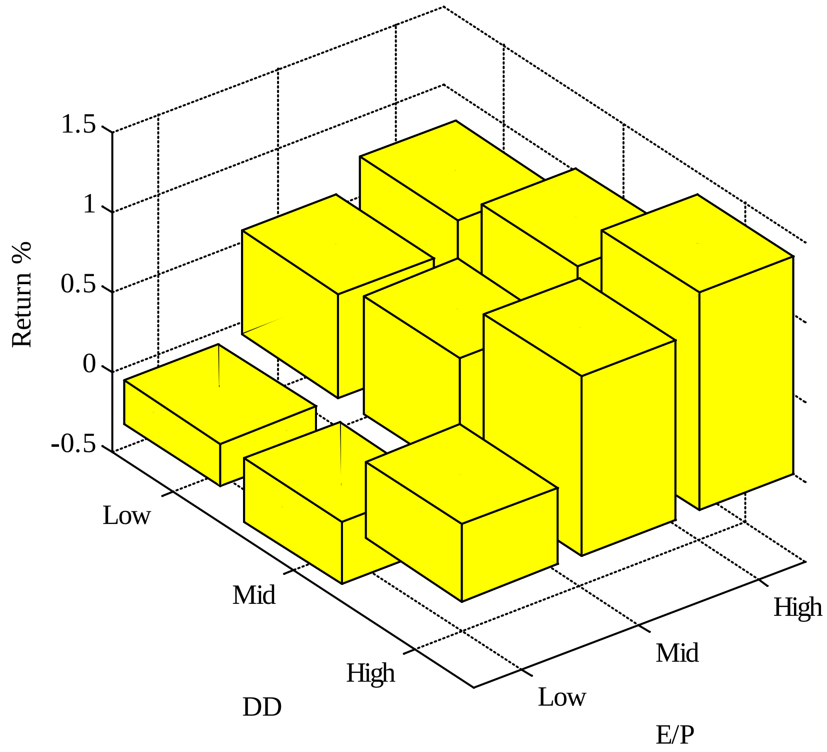
documented by Skinner and Sloan (2002) and the nonlinearity of the return-earnings surprise relationship. This relationship is well known in the ERC literature to be S-shaped, being steepest in the vicinity of zero earnings surprises and flattening out for more extreme surprises (Freeman and Tse, 1992). It is possible a nonlinear functional form such as the arctan function used in Freeman and Tse (1992) might fit the data better and more parsimoniously than a functional form that includes an asymmetric intercept term. Future research on the value premium might conceivably attempt to differentiate value and growth stocks by variation in one or two shape parameters of a nonlinear return-earnings surprise relationship, rather than variation in the large number of dummy variables necessary to capture asymmetric slope and intercept terms as in Skinner and Sloan (2002). The arctan function in Freeman and Tse (1992) contains one parameter for the intercept and two parameters to describe the S-shaped return-earnings relationship, and is therefore suitable for this purpose.

Having confirmed that default risk is a relatively unimportant factor in the market reaction to earnings surprises, the findings of this thesis warrant further investigation of the role of both value/growth and analyst dispersion in this regard. As discussed above, such an investigation might be more tractable using a nonlinear model of the return-earnings relationship with one or two parameters, rather than a linear model with a large number of dummy variables. It is plausible that the findings here and in Skinner and Sloan (2002) of a large and asymmetric intercept term for growth stocks might be masking a steep, but positively sloped, return-earnings relationship for growth stocks, particularly in the vicinity of relatively small earnings surprises. Such a steeply-sloped relationship might be due to the fact that growth stocks generally have lower dispersion than value stocks (Doukas et al., 2004), and might not be apparent in a linear model

with slope and intercept dummy variables. Thus, a potential research topic might be to employ a nonlinear return-earnings relationship to jointly model the effects of growth and analyst dispersion on earnings response coefficients.

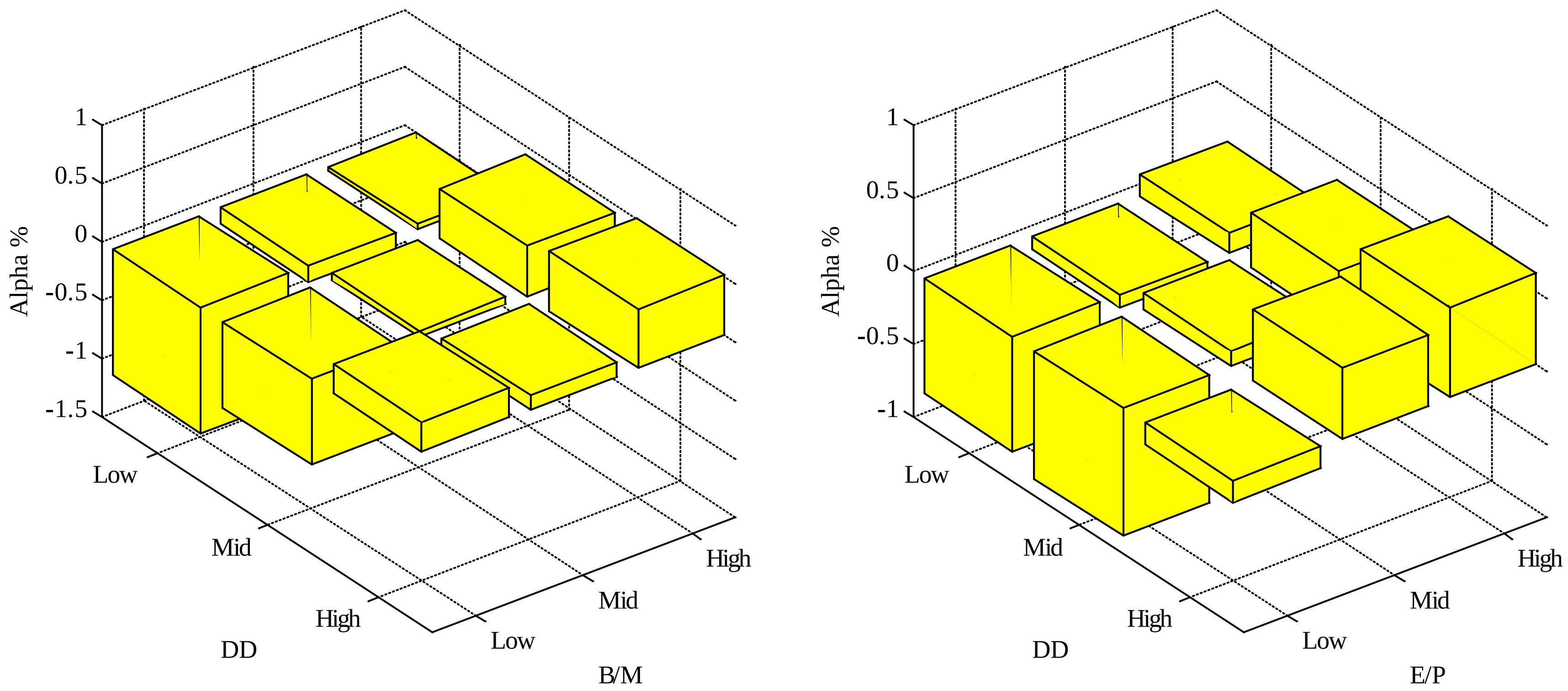
Figure 6.1: Returns and Four-Factor Alphas of Portfolios sorted by Value/Growth (B/M and E/P) and Distance-to-Default (DD)





Panel A: Returns

Figure 6.1: Returns and Four-Factor Alphas of Portfolios sorted by Value/Growth (B/M and E/P) and Distance-to-Default (DD) (continued)



Panel B: Four-Factor Alphas

Figure 6.2: Price-Deflated Analysts' Forecast Errors of Portfolios sorted by Value/Growth (B/M and E/P) and Distance-to-Default

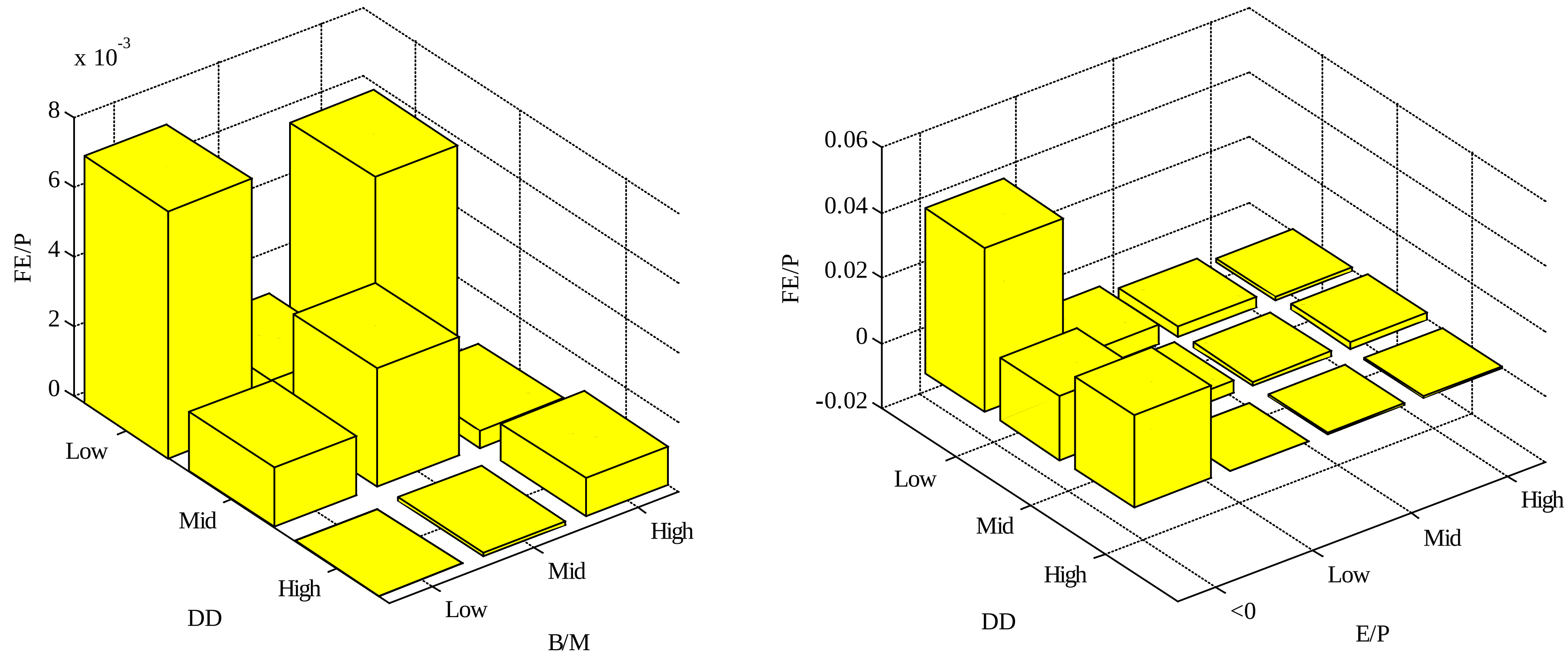
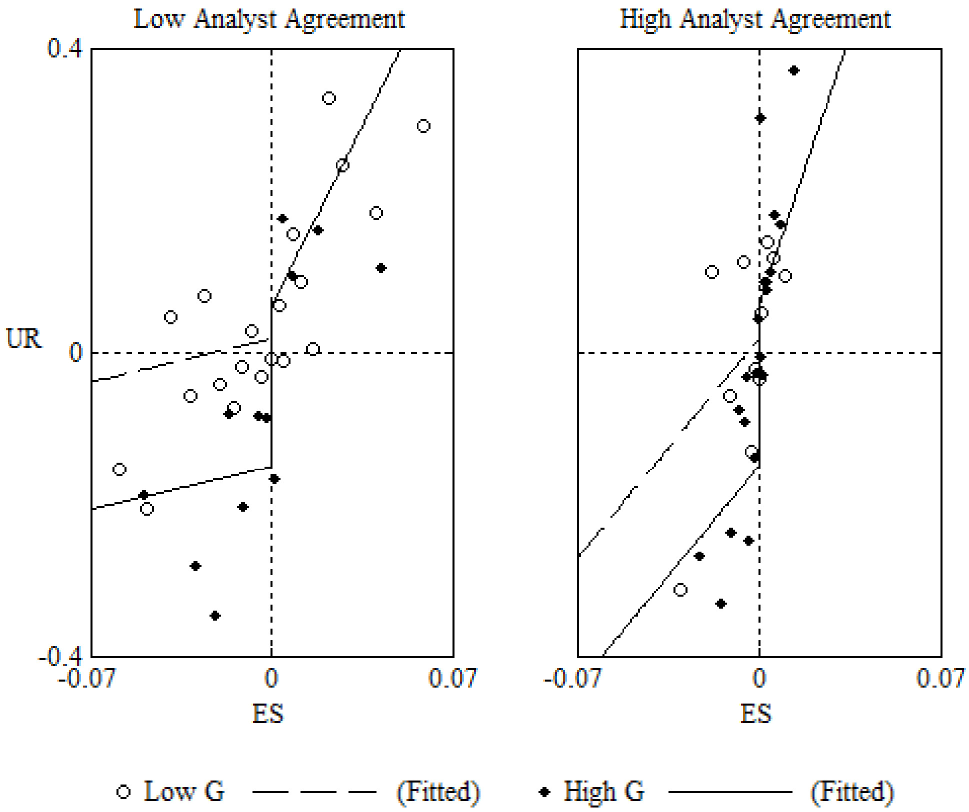


Figure 6.3: Fitted Unexpected Return-Earnings Surprise Relationships
The plots display the fitted unexpected return-earnings surprise relationship for the top 1/3 of stocks ranked by B/M (Low G) and those in the bottom 1/3 (High G). Low Analyst Agreement and High Analyst Agreement stocks are, respectively, those ranked in the top and bottom 1/3 by forecast dispersion. The plotted points are the average unexpected returns and earnings surprises of portfolios formed by sorting stocks on the size of the earnings surprise within each growth/analyst agreement classification.



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