Do Value Stocks Offer Higher Returns and Lower Risks than Growth Stocks?

Xin Kai Shao

A Thesis
In
The John Molson School of Business

Presented in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Administration (Finance) at
Concordia University
Montréal, Quebec, Canada

May 2007

Your file Votre référence
ISBN: 978-0-494-34458-3
Our file Notre référence
ISBN: 978-0-494-34458-3

Abstract

Do Value Stocks Offer Higher Returns and Lower Risks than Growth Stocks?

Xin Kai Shao

Many papers have shown evidence that suggests that value stocks outperform growth stocks. Value stocks, in general, refer to stocks with a low price-earnings ratio (P/E), a high book to market ratio (B/M), low sales growth, small size and exhibit financial distress. Growth stocks, in contrast, are larger in size, have a higher P/E, a lower B/M, have higher growth rate and are more sound financially. If markets are efficient, all stocks should offer the same risk-adjusted returns. If value stocks outperform growth stocks, where do the premium returns come from? Is this due to higher risk or from mispricing? This paper tests to see if high book to market stocks have higher risks to compensate for their higher returns. In an effort to measure risk, various metrics are employed including bankruptcy rates, standard deviations, betas, historical Value at Risk (VAR) and extreme loss statistics. Results show that although high book to market ratio portfolios offer higher returns, they appear to have lower risks. Therefore, the evidence offered in this paper tends to support the notion that mispricing is the driving force behind the observed findings.

Acknowledgements

I would like to express my sincerest appreciation to my supervisor, Dr. Ian Rakita, for his excellent instructions, suggestions, careful editing and encouragement throughout this thesis.

I would also like to thank my committee members, Dr. Latha Shanker and Dr. Khaled Soufani, for their support and help.

TABLE OF CONTENTS

Do Value Stocks Offer Higher Returns and Lower Risks than Growth Stocks?

1. Introduction

During the period comprising the twentieth century, investors witnessed dramatic variations in stock market valuations. At one extreme the stock market hit an all time low with a book to market (B/M) ratio of 1.76 in 1932. At the other extreme, the bull market of the 1990's drove price multiples to unprecedented levels. The 1999 aggregate B/M ratio of 0.24 is historically unmatched. The use of the B/M ratio as a stock selection criterion has been a source of debate for a long time. Graham and Dodd (1934) have argued that an investment strategy of buying stocks with low price relative to earnings and book values subsequently leads to high returns. Thereafter, Chan, Hamao and Lakonishok (1991), and Fama and French (1992), show that the B/M ratio has a strong role in explaining the cross section of average returns. Currently the belief that high B/M firms earn significantly higher returns has received considerable support. However, there is considerable disagreement among researchers as to the factors, which cause this B/M effect. Fama, French (1992) and Chan (1991) believe that the return premium of high B/M firms is compensation for the risk of financial distress since most high B/M firms are small, have low earnings, low growth rates and high bankruptcy possibilities. Another group of researchers believe that high returns of high B/M firms are due to mispricing. They argue that high B/M firms tend to be followed by fewer financial analysts and that the past low growth rate of high B/M firms also causes naïve investors to believe the return will persist in the future.

If the return premium is due to higher risk, a portfolio constructed from firms with high book to market ratios (high B/M firms) should show higher risk than a portfolio with low book to market ratios (low B/M firms). Risk can be defined and measured in a few different ways. 1) Because high B/M firms are more likely to exhibit financial distress, they would tend to have a high bankruptcy rate and would be more likely to be delisted due to their negative performance. Thus, the bankruptcy or performance-related delisting rate can be used as a measure of risk. This approach has been applied by Griffin and Lemmon (2000) to test the risk difference between high B/M and low B/M firms. The main shortfall of this method is that it only considers the risk of individual stocks instead of stocks within a portfolio. A firm's specific financial events should typically be well diversified in the formation of a portfolio. Therefore, the profile of a well-diversified portfolio may not be seen as being particularly risky even it is constructed from some small firms with high failure rates. 2) Standard deviations and Betas are two of the most commonly used methods to measure risk. Both standard deviation and Beta are based on an underlying assumption that returns follow a normal distribution. However, such is usually not the case in the real world. The distribution of returns is generally fat-tailed and left skewed. Thus, a standard deviation method will tend to underestimate the actual risk. 3) Value at Risk (VAR) can overcome the shortfalls of diversification and distribution. The historical VAR method is not tied to any particular distribution assumptions. Major financial events are also reflected in the historical price of securities, which, in turn, will be detected from VAR statistics. Some financial events have such a strong impact that the return distribution will fall outside of the VAR probability level.

Extreme loss, considered as a supplement of VAR, can be used to detect actual losses when these events occur.

2. Literature Review

2.1 A Rational Explanation of Book to Market Effects

If a financial market is efficient, every stock in the market should be priced based on its underlying value. If high B/M firms offer a higher return than low B/M firms, the return premium should represent compensation for added risk. Therefore, high B/M firms should have some disadvantage compared to low B/M firms. The disadvantage could come from financial distress, lack of capability to generate enough earnings, a heavy debt burden or the inefficiency of the management team and/or an unfavorable industry sector. Adjusted for risk, the performance between high B/M and low B/M firms should not be different. Many studies have shown evidence that high B/M firms outperform low B/M firms on a consistent basis. Whether or not the excess returns come from a risk premium as suggested by market efficiency theory or from mispricing remains an open question.

Chan, Hamao and Lakonishok(1991) find that the book-to-market ratio and the cash flow-to-price ratio play strong roles in explaining the cross section of average returns on Japanese stocks.

Fama and French (1992) develop a three-factor model that works quite well when it comes to explaining stock returns. The three factors are: 1) the excess market return; 2) the difference in returns between portfolios of small stocks and large stocks; 3) the difference in returns between portfolios of high and low B/M firms. In contrast to evidence found in previous studies, they found that beta and the P/E ratio are no longer significant when adding elements of size and the B/M ratio. In other words, beta and P/E ratios themselves can be explained by size and the B/M ratio. The belief is that the B/M ratio is the primary determining factor. However, what accounts for the difference in returns between high and low B/M portfolios remains uncertain.

Some papers support the rational price hypothesis. Fama and French (1995) found that markets understand and make unbiased forecasts of earnings growth. This evidence supports rational pricing. They argue that if markets are rational, higher returns from high B/M ratios and size of firm must be related to a common risk factor, such as long-term earnings. They found high B/M firms have persistently poor earnings. Specifically, they found there existed low ratios of earnings to book value of equity for at least 11 years following portfolio formation. Conversely, low B/M is associated with sustained strong profitability.

Chan shows that small firms tend to be riskier than large firms due to their low profitability, low cash flow and high financial leverage. High B/M firms have much smaller size on average than low B/M firms, and will therefore have similar characteristics of small firms and higher risk compared with low B/M firms. Taken together the evidence is consistent with the view that return premiums on high B/M firms represent compensation for the risk emanating from financial distress and low profitability.

Doukas, Kim, and Pantzalis (2002) found that high B/M firms have high positive earning errors and large downward forecast revisions. Compared to forecasts for low B/M firms, analysts are more likely to overestimate future earnings of high B/M firms and revise their forecast down later. This finding is inconsistent with the extrapolation hypothesis. According to the extrapolation hypothesis, the earnings of high B/M firms should be underestimated and will tend to be revised upwards. Therefore, this finding undermines the extrapolation hypothesis (explained in greater detail in the following paragraph) and indirectly supports the rational price hypothesis.

2.2 Extrapolation hypothesis

The underlying assumption of the extrapolation hypothesis is that financial markets are not efficient and people are not rational when they make investment decisions. When a firm has sustained growth, naïve investors may believe the firm will continue to grow at its past growth rate, and they account for the expected growth rate in the stock price. However, high growth rates can not last forever. For example, when an industry sector enjoys a high profit margin, new entrants will likely come in. Competition intensifies, and profit margins will likely decline. Additionally, when a company grows beyond its optimal level in term of economic scale, marginal costs increase and profitability drops. Finally, for many companies, growth depends on patents or the development of new technology. When patents expire or technology is copied by others, a firm's competitive advantage will evaporate. As a consequence, growth slows. When actual growth does not match expected growth, there is downward pressure on prices and returns tend to fall. On the other hand, if the industry experiences a low-growth rate, companies will exit that sector. Due to pressure from financial distress, restructuring and aggressive cost-cutting strategies would likely be applied and margins should improve. Firms with low or negative historical growth rates are more likely to have higher growth rates in the future. Several studies listed below have supported this mean-reverting earnings growth pattern.

Lakonishok, Shleifer and Vishny (1994) find that firms with a high B/M, a high cash flow to price ratio, a low P/E ratio and historically low sales growth rates have higher returns than firms with the opposite set of characteristics. The paper supports the extrapolation hypothesis. La Porta (1996) uses the expected earnings growth rate of financial analysts to test the extrapolation hypothesis. He finds that the average return of low B/M firms is 20.9% higher than that of high B/M firms. In the year following portfolio formation, analysts sharply increase their expectations about both future earnings and growth rates for low growth firms. La Porta, Lakonishok, Shleifer, and Vishny (1997) use earnings announcements to test the extrapolation hypothesis. They find that firms with low prior sales growth and low expected earnings growth have cumulative returns of 3.5% in the 3-day period following earnings announcements. On the other hand, firms with high growth expectations have negative cumulative returns of -0.5% in the same period. The difference represents one third of the total difference in first year return between value and growth portfolios. Griffin and Lemmon (2000) use the Ohlson Score[1] to test for the level of financial distress. They find that in every level of financial distress that is represented by an associated Ohlson Score, high B/M firms outperform low B/M firms. The largest difference in terms of returns between high B/M and low B/M firms occurs in the most distressed group. In addition, they also find that in the most distressed group the delisting rate of high B/M firms is lower than that of low B/M firms. Therefore, when firms have similar levels of financial distress, high B/M firms offer higher returns. Their findings suggest that the return premium of high B/M firms can not be explained by risk factors alone.

[1] The Ohlson Score predicts company's financial health based on nine variables: Size, TLTA (Total Liabilities divided by Total Assets), WCTA (Working Capital divided by Total Assets), CLCA (Current Liabilities divided by Current Assets), OENEG (One if total liabilities exceeds total assets, zero otherwise), NITA (Net Income divided by Total Assets), FUTL (Funds provided by operations divided by Total Liabilities), INTWO (one if Net Income was negative for the last two years, zero otherwise), and CHIN (Net Income for the most recent period)

Ideally, to identify return premiums between low B/M and high B/M firms, we would have to compare the risk factors through an appropriate empirical study. If our results show that high B/M portfolios are riskier than low B/M portfolios, we can support the rational hypothesis that the return premium is due to higher risk. Otherwise, we indirectly support the extrapolation hypothesis.

3. Risk Measurement

3.1 Financial distress

It seems clear that firms facing financial distress have a higher probability of going bankrupt. Bankruptcy rates can therefore be used to measure risk. However the drawback of this method is that it does not take the diversification effect into account. Default or bankruptcy is only a specific event for an individual firm. This represents a type of unsystematic risk that will generally be diversified away when forming a reasonably large portfolio of stocks. Therefore, the probability of financial bankruptcy may not, on its own, be a good indictor of portfolio risk.

3.2 Standard deviation

In the pre-Markowitz era, financial risk was considered as a correcting factor of expected return. The correcting factor is the difference between the actual outcome and the expected value. Markowitz proposed instead to measure the total risk associated with a portfolio of investments by the value-weighted variance of each risky asset in the portfolio and the associated covariance between all pairs of these same investments. Basically, risk is measured by the standard deviation of risky assets. However, this method fails to distinguish between systematic risk and unsystematic risk. Unsystematic risk can be diversified away when forming a well-constructed portfolio but is also considered as a part of total risk. As a consequence, the approach includes a component of risk that investors should not be compensated for.

3.3 Beta

In the early 1960s, the concept of beta was introduced. The measure of linear dependence between the return of each security and that of the market (i.e., beta) led to the development of two now well-known pricing models, namely the CAPM, and APT. The beta concept considers only systematic risk as being true risk. All risk caused by poor diversification is not integrated into the asset-pricing model to generate the associated required compensation for the risk that is borne. The CAPM is deemed to be the appropriate model for portfolios that are well diversified. But the model makes several unrealistic assumptions leading to its ineffective use in the real world. For example, the CAPM assumes that stock returns must follow a normal distribution. In reality it has been observed that the distribution of stock returns is fat-tailed and negatively skewed. Moreover, beta is not necessarily stable and in fact, tends to vary noticeably over time. Finally the model is sensitive to the choice of a proxy for the market portfolio and this in turn leads to possible differences in estimated beta values.

3.4 VAR

Value at risk (VAR) is the maximum loss of a portfolio given a predefined probability. The typical VAR probability levels are 95 percent and 99 percent. VAR allows institutions to measure their market risk on an aggregate level, taking portfolio diversification and leverage into account. VAR not only measures risk, but also considers the magnitude of potential losses under normal market conditions. VAR does not rely on the assumption of a normal distribution for returns. In addition, VAR can be measured as a dollar value in order to facilitate comparisons. Philippe Jorion (2003) in his publication the "Financial Risk Manager Handbook" uses three ways to measure VAR including: 1) mean variance VAR; 2) historical VAR and 3) simulation VAR. In this study, we will use historical VAR as a measure of risk. Historical VAR assumes that history will repeat itself in the future. A 5% historical VAR considers the consequence of an event occurring in the fifth worst percentile. For example, if there are 100 daily returns, the fifth lowest return will be the 5% one-day historical VAR.

In most situations, stock returns will not follow a normal distribution. Normally the distribution of returns is fat-tailed and exhibits negative skewness. This indicates that returns have a greater chance of taking on extreme values than would otherwise be predicted under the assumption of a normal distribution. In addition, when markets are bearish, correlations among securities increase. Large losses occur more frequently than do large gains.

A simple mean-variance VAR from a normal distribution may substantially underestimate the extreme loss value. When using historical returns to test VAR, a distribution assumption is not required. There were many extreme financial events that occurred during the decade of the 1990s. The Mexican currency crisis in 1994–1995, the East Asian crisis in 1997–1998, the Russian debt and the LTCM Hedge fund crises in 1998, the Brazil crisis in 1999[2], and the turbulence arising from Argentina in 2001[3] are

---

[2] After the Russian debt crisis in August 1998, fears spread among investors concerning returns in emerging markets. When the Brazil government on Jan 13, 1999 announced a 90-day moratorium on debt payments, foreign capital moved out, and the Real depreciated. By February 3rd more than two billion US dollars had left the country, and the Real had tumbled by 32% against the dollar.

[3] Due to a military dictatorship that existed for many years, huge debt was issued and much of this money was later lost in different unfinished projects. The state eventually became unable to pay the interest on this debt. In the 1980s, inflation began to increase significantly. To stop the inflation, the government implemented a new policy to peg Argentina's currency to the dollar, and capital was then allowed to move freely out of the country. In 2001, after the Brazil crisis, people fearing the worst began withdrawing large sums of money from their bank accounts, converting the domestic currency into dollars and sending the money abroad. This caused a run on the banks. The government then froze all bank accounts for twelve

only a few examples. All but the LTCM Hedge Fund Crisis occurred outside U.S, but most of them had a strong impact on the U.S stock market due to the integration of global financial markets. Financial crises cause unusually large losses. The assumption of a normal distribution or even a fat-tailed distribution could not be expected to properly mirror these events. With historical VAR, financial crises are considered. If history does in fact repeat itself, historical data will be useful in predicting future outcomes.

The VAR level cited is only a benchmark associated with a given probability. The actual loss may be much worse. The historical method uses actual historical returns. Bali and Cakici (2004) use stock size, liquidity and historical VAR to predict the cross sectional variation in expected returns. They find that VAR in both individual stock levels and portfolio levels has the ability to capture expected returns after controlling for size and the book-to-market ratio. High VAR firms tend to have higher returns than low VAR firms. These authors also conducted a time series study. They started with the Fama and French three-factor model and added an additional factor, namely the difference in historical VAR. To be more specific, this last factor is determined as the difference between the returns of low VAR portfolios less the returns of high VAR portfolios. Unfortunately, their model had a major drawback. To form a VAR portfolio, they obtain the VAR of each individual firm value. This is similar to the Fama and French method. But a group of large-sized firms will obviously be composed of large firms by value while a group of large VAR firms might not have a large VAR when viewed from a portfolio perspective. Ideally, VAR should not be studied at the individual firm level and should not be included into a Fama and French three-factor model.

---

months, allowing for only minor sums of cash to be withdrawn. People became enraged and reacted violently. The economy collapsed.

3.5 Extreme value

In using the VAR approach, we stop at a predefined level such as 95 percent or 99 percent. However we don't investigate further as to what happens in the remaining five percent or one percent probability since this outside the VAR cutoff. The information ignored in using the VAR approach can potentially be very important in risk management. Although this is associated with a low probability event, when it does in fact occur, the loss will normally be huge. For example, the terrorist attack on September 11, 2001 caused the Dow Jones Industrial Average to tumble by more than 15% in 7 trading days from September 10 to 21 (Trade was halted for several days due to the attack). The loss was too large to be represented by either 95% VAR or 99% VAR. If we don't investigate the extreme loss, this event would normally be ignored. Thus the study beyond the VAR level can be important.

4. Data selection

The sample period covered in this study extends from March 1993 to March 2003. The portfolios are formed every year starting at the beginning of 1993 based on prior year reporting.

All stocks from the NYSE, NASDAQ, and AMEX are selected from CRSP and daily returns are obtained. To be included in the sample set, four conditions must be met: 1) A firm must have a positive book to market ratio; 2) A firm's fiscal year and calendar year must be the same to avoid lags between book-to-market ratio data and year-end financial statement data. The condition is practical in the real world since managers often construct portfolios with stocks that have comparable financial reporting time frames; 3) Stocks selected from CRSP must also have all required data appearing on COMPUSTAT. Required data include common equity, numbers of outstanding shares, and closing price at year end. We first obtained return data from CRSP, then for all companies with return data, we use their CUSIP numbers to obtain their accounting information from COMPUSTAT. Therefore, only firms with data in both CRSP and COMPUSTAT databases will be included; 4) Reporting data must be provided to CRSP at the beginning of the study period. New portfolios are formed every year. For a firm to be included in a portfolio it must have a return value at the beginning of the year, but might not have return data at the end of the year. The problem of missing values will be discussed later.

4.1 Book to market ratio

A basic financial statement equation is:

$$\text{Book value} = \text{common equity} + \text{deferred tax}$$

If firms continue to grow, deferred tax can be treated as equity since a firm' asset pool is getting bigger and deferred tax from depreciation and amortization will not be realized. Most previous studies, including Fama and French, use this relationship to arrive at a firm's book value. For completeness, if deferred tax is missing or not defined, we assign zero to the value. Another basic equation reads:

Market value of equity = number of outstanding shares × closing price at year end

Information regarding common equity, deferred taxes and number of outstanding shares are drawn from the year-end balance sheet obtained from COMPUSTAT. Firms must have all data, except possibly deferred tax, to be included in the sample set.

4.2 Returns

Returns are the daily returns that are extracted for the period from April 1 each year to March 31 of the following year in CRSP. For example, a portfolio is formed based on the book to market ratio from balance sheet information at the end of 1991. The portfolio returns are the daily-adjusted returns from April 1, 1992 to March 31, 1993. For purposes of clarity, this portfolio is referred to as "Year 1993". A three-month lag of returns to book value data is assumed to ensure that all necessary accounting information is available. The choice of the lag time varies in the literature. Fama and French use a six-month lag, while Lakonishok, Vishny, and Shleifer (1994) use three-month. The total number of returns is approximately 3,000,000 (10years × 1200 firms × 250 trading days/year). Daily returns are compounded to produce annualized returns and accordingly:

Annual return = (1+ R1) × (1+R2) ×... (1+Rt) –1, where Rt is the return on day t.

4.3 Missing Values

There are many possible reasons for missing values. They include mergers, acquisitions, halts during the trading day, and performance related delistings. Missing values for all reasons other than performance related delistings are assigned a value zero. CRSP performance-related delistings include the failure to meet minimum exchange requirements, failure to pay fees, failure to file reports, and bankruptcy (corresponding to delisting codes 500, 520-584). Although stocks delisted due to performance no longer trade on the three major U.S. stock markets, many of them are still active on the OTC market. Therefore, their market values and returns are not negative 100 percent even though they are delisted. Shumway (2001) finds that these performances related delisted stocks are on average associated with a negative 30% return. A negative 30% return is equivalent to -0.143% daily return. In this paper we assign a -0.143% daily return for each of performance related missing value.

To convert negative 30% returns at the end of the year to a daily return, we use the following adjustment, and fill in blank cells of performance related missing values with these computed daily returns.

$$\text{Daily return} = (1-0.3)^{(1/D)} - 1$$

Where D is the number of days counted from the delisting date to the end of the year.

4.4 Beta

Beta is used to gauge the level of each portfolio's systematic risk. The S&P 500 is the most commonly used index to compute beta. The S&P 500 may well reflect price fluctuations of large sized firms, but may not work well when used to calculate betas for small sized firms. Since high B/M firms tend to be smaller in size compared to low B/M firms, high B/M firms are expected to have lower correlation with the S&P 500 Index. To reduce the potential bias caused by size, we use two indices to measure beta, the S&P 500, and the Russell Broad Market 3000. According to the excess return version of the CAPM model:

$$(R_i - R_f) = \alpha + \beta \times (R_m - R_f) + \varepsilon$$

R_f is the risk free rate and when converted to daily values, it is much smaller than the volatility of daily stock price movements. The effect of the risk free rate can be therefore ignored and the model simplifies to:

$$R_i = \alpha + \beta \times R_m + \varepsilon$$

4.5 VAR

4.5.1 Mean-variance VAR

We assume daily portfolio returns follow a normal distribution, so the mean-variance VAR is $\alpha \times$ standard deviation of daily returns, where α is the predefined probability of the maximum loss level allowed. The 95% VAR will be $1.65 \times$ SD. The value 1.65 is the one tail 0.05 probability in the normal distribution. In order to be consistent with the 95% level of the historical VAR value, we used $1.65 \times$ SD to measure mean-variance VAR instead of using SD.

A VAR obtained from the mean-variance approach may underestimate the actual loss because of fat-tailed or skewness features of the distribution.

4.5.2 Historical VAR

The 95% historical VAR is the maximum loss occurring during a given period 95 percent of the time. For example, with 250 trading days each year, 95% VAR represents the 13^{th} largest daily loss during the year.

4.5.3 Choosing VAR days

Empirical studies suggest that stock prices are mean reverting with a long term mean return trend, i.e. a stochastic movement. A short term return such as a return measured over one hour or one day might be just white noise instead of a meaningful return. To apply VAR, the VAR time span examined has to be long enough to avoid the volatility noise and short enough to permit a response when a threshold is reached. Since most banks and other financial institutions apply 10-day VAR to determine their required capital reserve when controlling internal risk, we will use the 10-day VAR in this study. Meanwhile, we also used 3-day VAR. We coded a Visual Basic program to obtain the VAR value. For 3-day VAR, there are approximately 250 trading days each year. The program first calculates compounded returns for any three consecutive days. There should be 248 three-day returns (There is no three-day compounded return for the first two days). We considered the lowest return as the largest loss, and then deleted the three daily returns that are used to obtain the lowest compound return. The series of steps form a "loop". The loop should be repeated until there are no three consecutive days remaining in the sample pool. For example, in a sample of 10 trading days, to obtain 3-day VAR, we calculate compound returns. There will be eight 3-day compound returns starting from day 3, which is compounded from daily returns of day 1, day 2 and day 3. If the worst outcome is from the compound returns of day 5, daily return of day 3, day 4, and day 5 will be removed before the next loop. The next loop will not use daily returns of day 1 and day 2 either since there are no 3 consecutive days with them. The loop will continue to find the second largest loss and so on. The worst return, which is in day 6, in the 10 day sample is the 10% VAR. For the sample of 250 trading days each year, the 13th worst outcome will be the 95% VAR. Finally we can determine the following VAR outcomes:

$$\text{Mean variance 10-day VAR} = (\text{one-day VAR} \times 10)^{1/2}$$

Historical 10 day VAR is the 13th largest loss of 10 day compounded returns in a given year.

4.6 Extreme loss

By using the VAR approach, we stop at a predefined level, such as 95 percent or 99 percent. According to this approach we will be ignoring what happens in the remaining five percent or one percent tail of the return distribution beyond the VAR level. The missing information caused by using the VAR approach can be very important for risk management.

To study extreme losses, we will check the mean, median, skewness, and total value of extreme values, and compare high and low B/M groups. The group experiencing extreme losses more frequently and more severely will be considered as being riskier.

4.7 The delisting rate

If we found evidence that high B/M firms have higher failure rates than low B/M firms, it would partially explain high B/M firms' return premium. The delisting rate is more appropriately used for small investors who only hold a few stocks.

5. Empirical Results

5.1 Descriptive statistics

Table 1 presents data for the sample of firms for each year and also the total average value for 10 years. The total average mean and median of firm size for high B/M firms are $558 million and $62 million respectively. The size for low B/M firms are $4.616 billion and 445 million respectively. Low B/M firms are significantly larger in terms of market value of equity than high B/M firms. In addition, the mean of both high and low B/M firms are much larger than the median, indicating the presence of some very large firms in both groups. High (low) B/M firms have an average book-to-market ratio of 1.48 (0.24). The total number of firms in the sample is 22,195 with 11,036 high B/M firms and 11,159 low B/M firms. A single firm can be included more than once as long as the book-to-market value falls into the 30 percentile range in any given year.

5.2 Correlation between size and book to market ratio

Fama and French (1992) show that the log of size and B/M ratio are negative correlated, and the correlation coefficient is -0.21. Table 2 suggests that the correlation between the log of market size and B/M ratio is -0.375, which is significantly more negative than the result of Fama and French. The correlation is significant at the 1% level. Because book-to-market ratio and size show strong negative correlations, when comparing any different results from high B/M and low B/M firms, size factors need to be considered in tests of robustness.

5.3 Returns

As stated previously, analyzed returns are annual returns compounded from daily returns. All portfolios are constructed based on an equally weighted approach. This method is commonly used in most studies that consider book-to-market ratio topics and assigns the same weight to each stock regardless of size. Results are separated by years.

Table 3 shows the mean and the standard deviation of daily returns. For all years except 1999, high B/M firms offered higher returns with lower standard deviations. The results are significant in six of ten years at the 5% level.

Table 4 and Graph 1 indicate that high B/M firms outperform low B/M firms in all years except 1999. The average annual compound return of high B/M firm is 38%, and of low B/M firms is 16%. The difference between average annual returns for high B/M firms compared to low B/M firms is 22%. The result is consistent with previous findings that high B/M firms outperform low B/M firms. The results are also statistically significant at the 10% level. The yearly average difference between these two groups is 23.1%. Both high and low B/M firms have similar exposure to common economic events. This suggests that a strategy of investing one dollar in each stock of a high B/M firm and short selling a value of one dollar in each stock of a low B/M firm will earn an investor an average return of 23.1% in an average year with no associated beta-risk. This is contradictory to the tenets of modern asset pricing theory.

5.4 The delisting rate

The CRSP database indicates that delisting codes between 500 and 600 refer to performance related delisting firms. The delisting rate is calculated as:

Delisting rate = % of delisted firms divided by the total number of firms

Small firms tend to have a higher probability of bankruptcy. High B/M firms tend to be small. There is a potential multicolinearity problem. High B/M groups have a higher bankruptcy rate. This may be caused by their small size rather than the book to market ratio. To mitigate this problem, we separate high and low B/M firms each into five size groups, and compare the delisting rate in each size group.

From Table 5 and Graph 2, we see that as the size of firm increases, the likelihood of bankruptcy is significantly reduced. Indeed, 71% of defaults are from firms classified as being in the smallest 20 percent category. High B/M firms have an average yearly delisting rate of 1.514% which is 50% higher than low B/M firms of 1.0%. However, the difference is mainly due to many more small size firms in high B/M group. This incidence of high default rate is caused by a large number of small firms in the high B/M groups. Interestingly, in the smallest size group, in which delisting events most likely happen, the high B/M portfolio has a relatively low default rate of 3.43% compared to a default rate of 8.79% in the low B/M portfolio.

5.5 Systematic risk

When growth stocks (low B/M firms) outperform value stocks (high B/M firms), a bull markets appears to be more likely. The only year that growth beats value during the period under study is from 1999 to 2000 when the stock markets were very bullish prior to the start of a significant correction. If the negative relation between value-style performance and total market movement does exist, it implies that value stocks give lower betas and higher returns. This finding would tend to undermine the rational hypothesis. Investors expect high growth companies to continue to grow at a high rate. If the market is doing well, investors will become more optimistic, pushing stock prices even higher. When total market performance does not meet expectations, investors will revise their outlook, resulting in a market decline. On the other hand, value stocks tend to be defensive, and therefore have low betas. When market performance is poor, value stocks will not fall as much as growth stocks since their high book values will act as a buffer to slow down or stop the decline as market prices approach book values.

Prices of value stocks are mainly determined by their tangible asset value rather than their opportunity for growth. Value stocks tend to be more defensive and have low systematic risk. We use both the S&P 500 index and the Russell 3000 as a proxy for the market to run a regression to explain the difference in returns between high B/M and low B/M firms.

$R_i = a + b \times R_m + \varepsilon$, where R_i is the expected daily return of an individual stock

5.6 Regression results

Table 6 shows that high B/M portfolios have much lower betas than low B/M portfolios, which indicates the systematic risk of high B/M portfolios is lower. The results are consistent for data examined year by year. The overall beta for a 10-year period of high B/M and low B/M portfolios is 0.36 and 0.89, respectively, when using the S&P 500 as the market index. Benchmarking with the Russell 3000 arrives at much the same conclusion. The reason that the Russell 3000 was used is to avoid size bias. The S&P index comprises the 500 largest firms that trade on the New York Stock Exchange. It may show high correlation to low B/M firms due to the relatively large size of these firms. The results suggest that an arbitrage opportunity may be available. If we form a hedge fund portfolio by buying high B/M firms and shorting low B/M firms the yearly return difference is 23% ignoring liquidation and transaction costs. The systematic risk measured by beta should be negative because we are buying a low beta portfolio and shorting a high beta portfolio.

5.7 Total risk

Total risk includes both systematic risk and unsystematic risk and is measured by the standard deviation of returns. We found that high B/M portfolios have significantly lower total risk compared to low B/M portfolios. The mean of the standard deviation of daily returns of high and low B/M firms are 0.0047 and 0.01 respectively. The difference is significant at the 99% level.

Table 7 and Graph 3 show that not only do high B/M portfolios have lower systematic risk but also lower total risk. This implies that investors who possess either diversified portfolios or portfolios that are not well diversified will both reduce risk by investing in high B/M portfolios.

5.8 Historical VAR

Next we measure 10-day VAR at the 95 percent level. There are approximately 250 trading days each year. Out of 10,000 returns the 125th largest loss will be the VAR at the 95% level.

$$95\%\ \text{VAR} = 1^{st}\ \text{largest loss} \times 0.75 + 2^{nd}\ \text{largest loss} \times 0.25$$

Table 8 and Graph 4 indicate that the means of high B/M and low B/M stocks are -5.24% and -10.46% respectively. The 10-day VAR of high B/M portfolios is significantly lower than that of low B/M portfolios. The p-value is 0.002. It implies that there is 5 percent probability that high B/M firms will experience a maximum loss of

5.24% in a 10 consecutive day period, while the loss of low B/M firms will be 10.46%. We also tested 3-day VAR, and the conclusions are similar to that for 10 days. For 250 trading days each year, the 3-day VAR at the 95% level should correspond to the following value: $250 / 3 \times 0.05 = 4.16$. Then the appropriate VAR calculation is:

$$\text{VAR} = \text{4th largest} \times 0.84 + \text{5th largest} \times 0.16$$

5.9 Extreme value

When using the VAR method to measure risk, we can determine the maximum level of loss for a given probability level. If, for example, we set the probability to 5 percent, we have no further information regarding the losses that can be incurred in the lower tail of the distribution. Additional risk exposure information can be obtained by analyzing the extreme values of high and low B/M firms. We computed the 3-day VAR for all years, and chose the largest 5 percent as extremes. The sample size for each high B/M and low B/M group is 40, which is obtained as follows:

$$\text{250 business days} \times \text{10 years} \times \text{1/3 days} \times 5\% = 41$$

Table 9 shows that the average extreme value of high B/M firms and low B/M firms for each year were -0.031 and -0.056, respectively. The extreme value of high B/M firms is significantly smaller than that of low B/M firms with a p-value of less than 0.01. When considering a large loss beyond 5 percent, high B/M firms are still less risky than low B/M firms. We also used the 41 data points to obtain a best fit for the distribution. From Graph 5, we can see the high B/M extreme distribution is more flat and left-skewed than the low B/M extreme distribution. If their means were the same, the high B/M firms would have a greater likelihood of experiencing a huge loss.

6. Robustness tests

6.1 Why use grouping instead of regression to control for size and industry?

Fama and French and other researchers use regression to control for size when studying book to market effects. The method is valid when studying returns. However, risk must be considered at the portfolio level. In other words, 10 risky stocks might form a less-risky portfolio if their returns are either low or negatively correlated. Therefore, VAR needs to be considered for the relevant portfolios. Any cross-section regression for each stock to control for size or industry effects can not be applied. Since we can not use cross-section regression to control for size and industry, we will use the grouping approach to test for size and industry robustness.

6.2 Size

We know that high B/M firms are significantly smaller than low B/M firms. The Return premium under examination may be due to size effects instead of book-to-market effects. Fama and French use a three-factor model to show that size has significant negative correlation with returns. In this section we control for size effects to check for robustness. We divide size into five groups. First, in any given year, we extract all high and low B/M firms from the sample. We divide them into five groups by size percentile. For example, the top 20 indicates the largest 20 percent of firms. In each size group, the number of high and low B/M firms is not necessarily equal. The largest group by size (top 20) contains many more low B/M firms than high B/M firms. On the other hand, the smallest group by size (80-100) has more high B/M firms than low B/M firms. Details are shown in Table 10.

6.3 Results of the size robustness test

Our findings are consistent with the Fama and French paper. We found that the size factor does have an effect on returns. The smallest portfolios by size have the highest returns, and conversely the largest portfolios by size have the lowest returns. In addition large size portfolios have higher betas. When comparing high B/M with low B/M portfolios in each size group, the high B/M portfolios have significantly higher return in four of the five groups. Table 11 shows that only in the size group of 60-80, are low B/M portfolio returns marginally better. When looking at risk including standard deviation, beta, and VAR, in all five groups, high B/M portfolios have significantly lower risk. In general, the risk of high B/M firms is twice that of low B/M firms. We used the Paired Mean Comparison method to conduct an appropriate t-test. The finding is that small size portfolios have a pronounced book-to-market effect. In the smallest size group, the 10-day VAR difference between high B/M portfolios and low B/M portfolios is 4.4% with a p-value of 0.00 while in the largest size group the difference is 2% with a p-value of 0.04. In conclusion, firm size does have an effect on returns and VAR, but the book-to-market influence is still significant in each size group. Book-to-market effects appear to diminish as size increases.

6.4 Industry impact

Industry could be another factor that may cause differential performance. Size, the book-to-market ratio, and the debt-to-equity ratio vary across different industrial sectors. For example, the automotive industry tends to have large size companies with medium book-to-market ratios. Other firms in high growth industries such as the technology sector, health science sector and consumer production sector tend to have low book-to-market ratios. The difference in performance between high book-to-market portfolios and low book-to-market portfolios might be due to differences in performance between industry sectors. To resolve this potential problem, we used the same methodology to control for industry effects as we did to control for size. The sample is divided into three industry groups including: 1) the manufacturing sector (comprised of manufacturing, construction, and transportation), 2) the service sector (comprised of service, health care and technology), and 3) the retail and wholesale sector (comprised of firms in the retail and wholesale industries). The financial sector is not included in the study. Most firms in the finance industry are small and tend to have high book-to-market ratios. As a consequence, the total number of high B/M firms is fewer than the total number of low B/M firms.

6.5 Results of the industry robustness test

The results are still robust when grouping stocks by industry sector. We can see that from Table 13, in all three industrial sectors, firms with high book-to-market ratios have higher returns than those of low B/M firms. The results also show that high B/M firms have lower risk in terms of standard deviation, beta and VAR. The results are significant when using yearly differences as a variation to conduct t-tests within each industry group.

6.6 Comparison of different levels of book to market ratios

So far, we have used only a split of 30-40-30 B/M ratios to group our high B/M and low B/M firms. The method has been well-accepted since Fama and French used it in two often-cited articles (see Fama and French (1992) and (1995)). We also used 20-60-20 and

10-80-10 B/M ratios to evaluate the book-to-market ratio effects. We divided the book-to-market ratio into three levels in both high and low B/M groups. The highest B/M firms in high B/M group are compared to the lowest B/M firms in the low B/M group. The lowest B/M firms in the high B/M group are compared to the highest B/M firms in the low B/M group. According to the results shown in Table 15, high B/M firms have lower VAR in all three groups. The results are statistically significant. The largest difference occurs in the top group. VARs of high B/M firms and low B/M firms in the top group are 5.1% and 13.1% respectively. We observe a trend that in the low B/M group, as the book to market ratio increases, VAR declines. However, in the high B/M group, VAR is relatively stable as the book-to-market ratio changes.

7. Conclusions and suggestions for future research

The purpose of the study is to examine whether or not return premiums between high and low book-to-market ratio portfolios are due to risk. Risk is measured here as the default rate, the standard deviation, beta, 10-day historical VAR, and extreme value beyond VAR. Excluding the default rate, the study focuses on portfolio levels. All unsystematic risk and cross-section variance have been diversified away. Results show that return premiums from high B/M portfolios do exist. However, the high return premiums are not due to high risk. Excluding default risk, high B/M portfolios have significantly lower risk according to four of five risk indicators. Even default risk data suggest that both groups have no significant difference after adjusting for the size factor. Since the study relies heavily on the VAR approach, robustness tests for VAR were conducted to control for size and industry. The general results are unchanged. Overall results indicate that the high returns of high B/M firms can not be explained by high risk, at least at the portfolio level. This suggests that the result is due to mispricing, which is consistent with the extrapolating hypothesis.

Since high B/M firms tend to be small, and we use equally weighted portfolios, large transaction fees and liquidity costs might be associated when forming equally weighted portfolios in the real world. Further studies could integrate transaction costs and liquidity costs into the sample framework. Concurrently, a study using market weighted portfolios could be conducted. We leave this work for the future.

8. Tables and Graphs

TABLE 1

Descriptive Statitics ($ in millions)

	Year	Size		Book to Market ratio		# of firms
		Mean	Median	Mean	Median	
High B/M						
	1993	$542	$55	1.81	1.23	780
	1994	$490	$49	1.44	1.11	1024
	1995	$469	$49	1.40	1.16	1089
	1996	$595	$66	1.21	1.04	1043
	1997	$231	$61	0.87	0.74	1177
	1998	$819	$113	0.99	0.84	1195
	1999	$491	$72	1.41	1.14	1156
	2000	$548	$77	1.47	1.24	1211
	2001	$970	$44	2.12	1.51	1226
	2002	$897	$60	2.13	1.26	1135
	Average	$558	$62	1.48	1.15	1103
Low B/M						
	1993	$1,818	$193	0.24	0.24	769
	1994	$1,748	$197	0.23	0.24	997
	1995	$1,699	$192	0.26	0.27	1071
	1996	$2,384	$250	0.21	0.22	1117
	1997	$4,616	$454	0.45	0.44	1301
	1998	$3,955	$433	0.20	0.21	1233
	1999	$6,435	$558	0.20	0.20	1191
	2000	$8,228	$776	0.14	0.14	1192
	2001	$8,835	$787	0.21	0.21	1138
	2002	$6,731	$607	0.23	0.24	1150
	Average	$4,616	$454	0.24	0.23	1116

Size represents the total market value of firm.

TABLE 2

Correlation of BM ratio and Size

		LN(Size)
Person Correlation	B/M ratio	-0.375
Sig. (2-tailed)		0.000
N		22187

*** Correlation is significant at the 0.001 level (2-tailed).

TABLE 3

Daily Return -- Paired Samples Statistics

		High Book to Market Group		Low Book to Market Group			
Year	N	Mean	Std. Deviation	Mean	Std. Deviation	Difference	T-statistic
1993	245	0.0018	0.0034	0.0010	0.0051	0.0007	3.17***
1994	245	0.0011	0.0035	0.0005	0.0058	0.0007	2.80***
1995	245	0.0017	0.0032	0.0016	0.0058	0.0001	0.2696
1996	245	0.0013	0.0034	0.0004	0.0083	0.0009	2.46***
1997	245	0.0019	0.0052	0.0014	0.0070	0.0005	2.22***
1998	245	0.0001	0.0076	0.0001	0.0134	0.0000	-0.0198
1999	245	0.0018	0.0049	0.0022	0.0089	-0.0003	-0.5643
2000	245	0.0009	0.0061	-0.0017	0.0224	0.0026	2.31***
2001	245	0.0020	0.0072	0.0009	0.0144	0.0011	1.2261
2002	245	0.0004	0.0081	-0.0012	0.0152	0.0016	2.64***

Std. Deviation is cross-section Standard Deviation for all companies in a particular group in a given year
*** represents significance at the 1% level

TABLE 4

Yearly Return -- Paired Samples Statistics

Year	Returns of High B/M	Returns of Low B/M	Difference
1993	0.5315	0.2772	0.2543
1994	0.3225	0.1268	0.1957
1995	0.5062	0.4788	0.0274
1996	0.3744	0.1034	0.2710
1997	0.6117	0.4157	0.1960
1998	0.0137	-0.0201	0.0338
1999	0.5588	0.6793	-0.1205
2000	0.2456	-0.3574	0.6030
2001	0.6287	0.2196	0.4092
2002	0.0957	-0.3414	0.4371
Average	0.3889	0.1582	0.2307***
SD	0.2166	0.3350	
T-test			3.37

*** represents significance at the 1% level

GRAPH 1

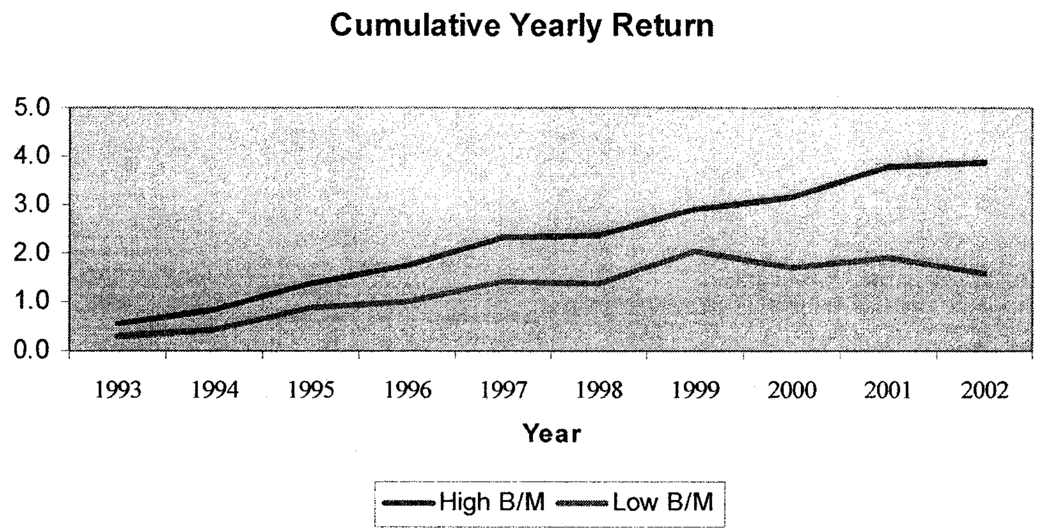


TABLE 5

Delisting Rate

Size Group	High B/M			Low B/M		
	Number of Firms	Default Frequency	Default Rate	Number of Firms	Default Frequency	Default Rate
Top 20	943	0	0.00%	3479	2	0.06%
20-40	1443	5	0.35%	2999	3	0.10%
40-60	2120	8	0.38%	2324	7	0.30%
60-80	2937	31	1.06%	1504	25	1.66%
80-100	3591	123	3.43%	853	75	8.79%
Overall	11034	167	1.51%	11159	112	1.00%

GRAPH 2

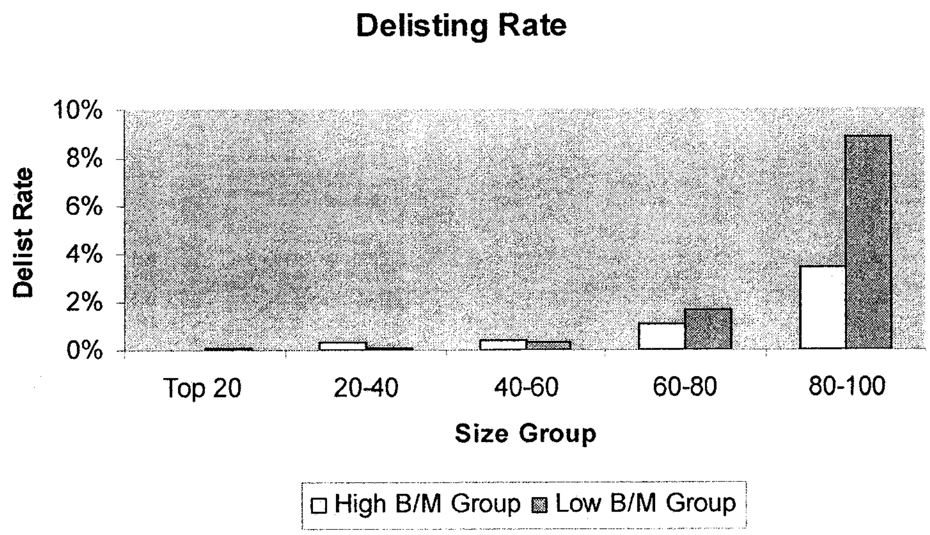


TABLE 6

Beta Comparison

Year	S&P 500			Russell 3000		
	high B/M	low B/M	Difference	high B/M	low B/M	Difference
1993	0.3654	0.7441	0.3787	0.3057	0.6358	0.3300
1994	0.4305	0.8006	0.3700	0.3907	0.7128	0.3221
1995	0.3551	0.7535	0.3984	0.3063	0.6410	0.3347
1996	0.3511	0.8792	0.5281	0.3053	0.7466	0.4413
1997	0.3452	0.6102	0.2651	0.2924	0.5418	0.2494
1998	0.4470	0.8806	0.4336	0.4084	0.8111	0.4027
1999	0.1976	0.6109	0.4133	0.1735	0.5414	0.3680
2000	0.3075	1.2768	0.9693	0.3022	1.2901	0.9879
2001	0.4394	1.0075	0.5681	0.4433	1.0093	0.5660
2002	0.3912	0.8229	0.4318	0.3717	0.7812	0.4096
Average	0.3623	0.8934	0.5310***	0.3299	0.7711	0.4412***
T-test			6.61			7.69

*** represents significance at the 1% level

TABLE 7

Standard Deviation Comparison

year	High B/M	Low B/M	Difference
1993	0.0026	0.0037	0.0012
1994	0.0026	0.0042	0.0016
1995	0.0023	0.0042	0.0019
1996	0.0025	0.0059	0.0034
1997	0.0033	0.0070	0.0038
1998	0.0076	0.0134	0.0058
1999	0.0049	0.0089	0.0040
2000	0.0061	0.0223	0.0162
2001	0.0072	0.0144	0.0072
2002	0.0081	0.0166	0.0085
Mean	0.0047	0.0101	0.005***
T-test			3.74

*** represents significance at the 1% level

GRAPH 3

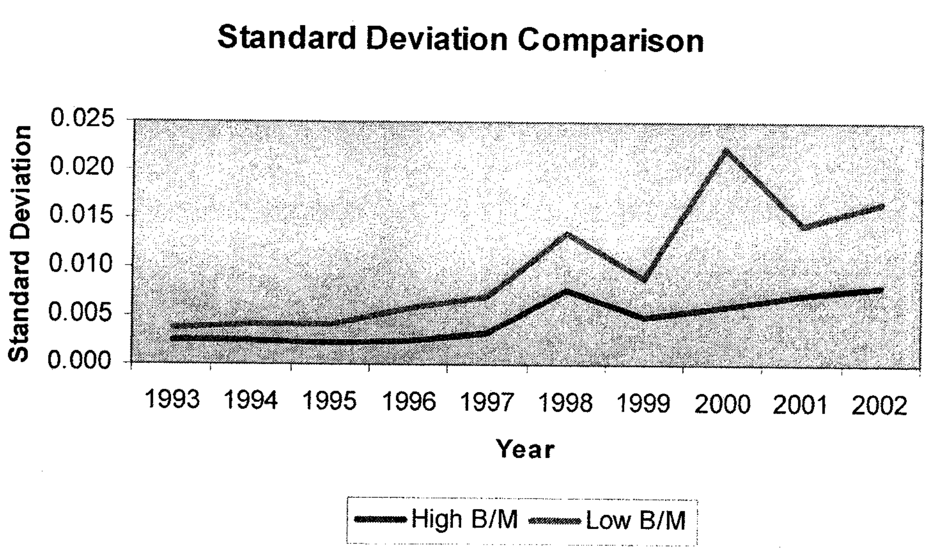


TABLE 8

VAR Comparison

	10-Day VAR			3-Day VAR		
	Low B/M	High B/M	Difference	Low B/M	High B/M	Difference
1993	0.0322	0.0112	0.0210	0.0223	0.0096	0.0127
1994	0.0557	0.0240	0.0317	0.0297	0.0116	0.0181
1995	0.0409	0.0102	0.0307	0.0309	0.0094	0.0215
1996	0.1183	0.0338	0.0845	0.0432	0.0105	0.0327
1997	0.0630	0.0462	0.0168	0.0256	0.0142	0.0114
1998	0.1724	0.1081	0.0643	0.0609	0.0335	0.0274
1999	0.0606	0.0306	0.0300	0.0413	0.0112	0.0301
2000	0.2202	0.0527	0.1675	0.0962	0.0228	0.0734
2001	0.1680	0.1104	0.0576	0.0525	0.0195	0.0330
2002	0.1141	0.0967	0.0174	0.0604	0.0301	0.0303
Mean	0.1045	0.0524	0.05215***	0.0463	0.0172	0.02906***
T-test			3.39			5.03

*** represents significance at the 1% level

GRAPH 4

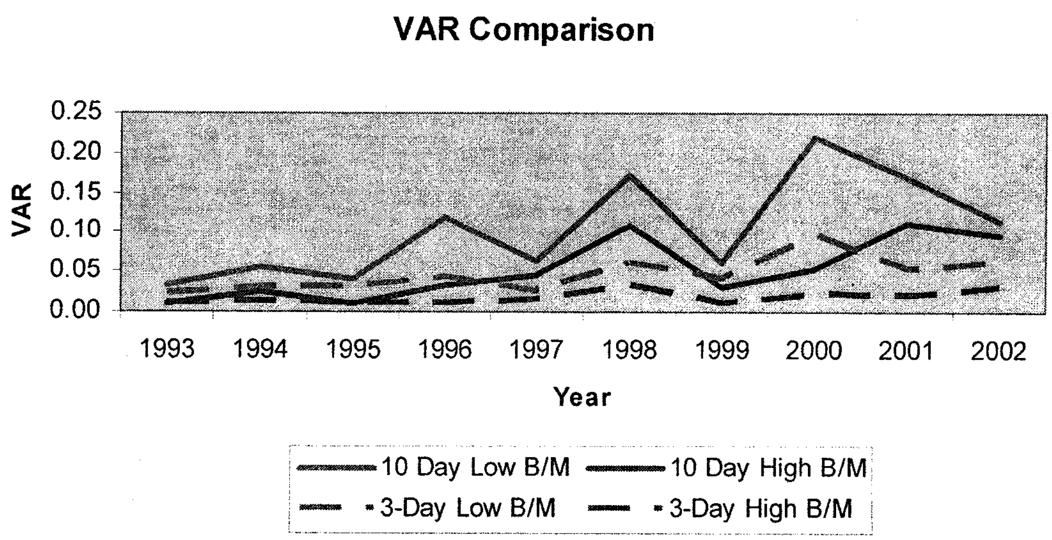


TABLE 9 Best fit of Extreme loss

Low B/M

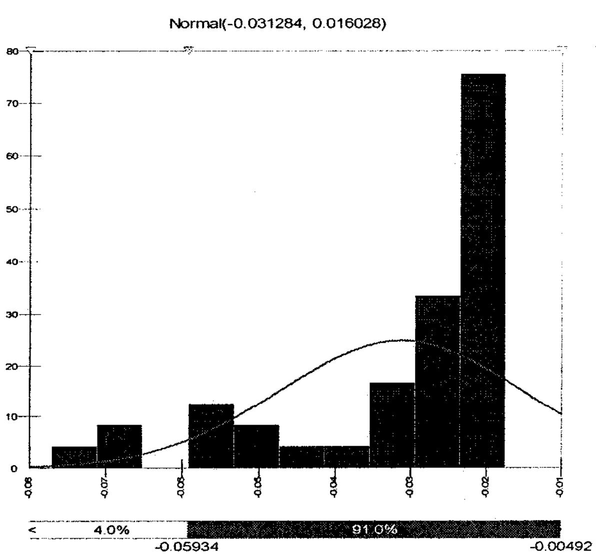
	Fit	Input
Minimum	N/A	-0.115735
Maximum	N/A	-0.034774
Mean	-0.056418	-0.056418
Mode	-0.056418	-0.052462 [est]
Median	-0.056418	-0.052381
Std. Deviation	0.019571	0.019571
Variance	0.00038304	0.00037347
Skewness	0	-1.0398
Kurtosis	3	3.5734

High B/M

	Fit	Input
Minimum	N/A	-0.077114
Maximum	N/A	-0.017566
Mean	-0.031284	-0.031284
Mode	-0.031284	-0.017669
Median	-0.031284	-0.024237
Std. Deviation	0.016028	0.016028
Variance	0.00025689	0.00025047
Skewness	0	-1.3844
Kurtosis	3	3.7955

GRAPH 5

LowB/M



HighB/M

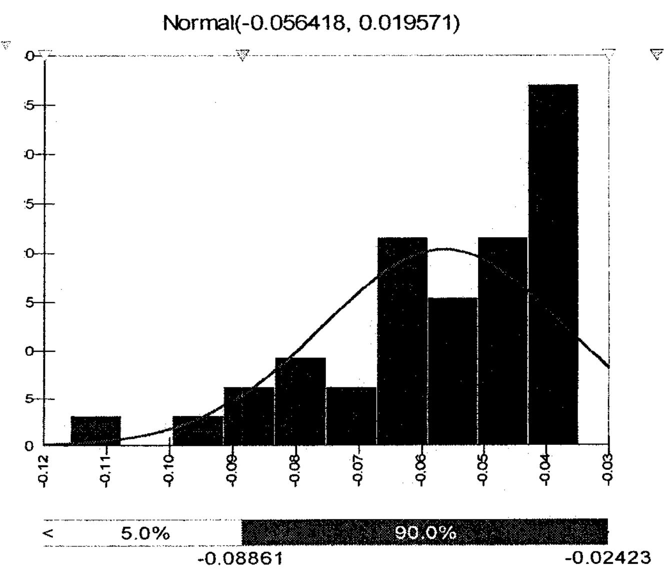


TABLE 10

Statistics of Size Group ($ in millions)

	Size Group	Size	Book to Market ratio	# of firms
High B/M				
	Top 20%	$4,931	1.08	943
	20% - 40%	$641	1.14	847
	40%-60%	$172	1.20	2119
	60%-80%	$55	1.31	2937
	80%-100%	$14	2.02	3591
	Average	$1,163	1.35	2087.4
Low B/M				
	Top 20%	$14,718	0.24	3479
	20% - 40%	$677	0.25	2999
	40%-60%	$185	0.24	2324
	60%-80%	$60	0.21	1505
	80%-100%	$17	0.22	851
	Average	$3,131	0.23	2231.6

Size represents the total market value of firm.

GRAPH 6

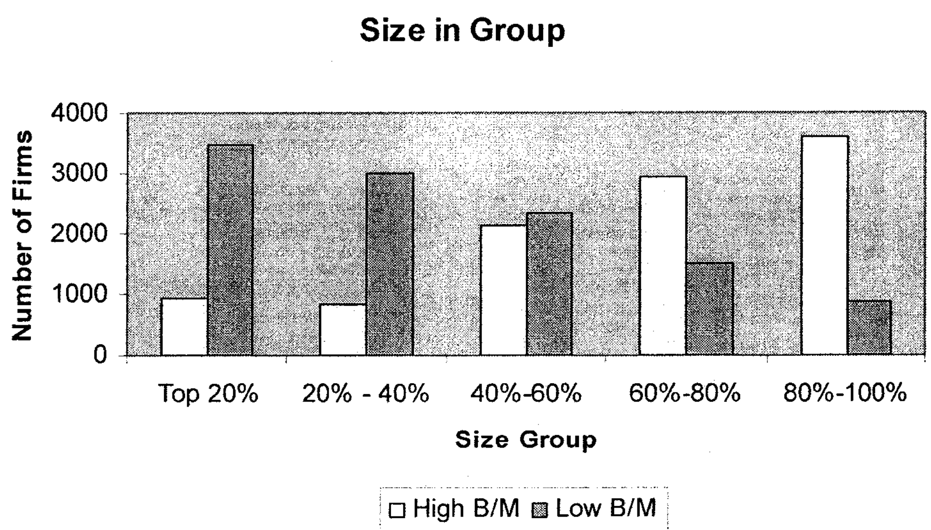


TABLE 11

Size Robustness Results

	Size Group	Return	10-Day SD	Beta	10-Day VAR	EV
High B/M						
	Top 20%	0.1324	0.0261	0.6387	0.0758	0.2326
	20% - 40%	0.1725	0.0237	0.5266	0.0769	0.2109
	40%-60%	0.2189	0.0204	0.4007	0.0669	0.1850
	60%-80%	0.3080	0.0166	0.2636	0.0419	0.1715
	80%-100%	0.7940	0.0191	0.1983	0.0561	0.1441
Low B/M						
	Top 20%	0.0746	0.0353	0.9355	0.0931	0.2966
	20% - 40%	0.1125	0.0385	0.8645	0.1140	0.3389
	40%-60%	0.1355	0.0414	0.6836	0.1475	0.3332
	60%-80%	0.3317	0.0335	0.5355	0.1077	0.3131
	80%-100%	0.6076	0.0409	0.3732	0.0957	0.3253

TABLE 12

VAR T-test of Size Robustness

Size Group	High B/M	Low B/M	Difference	T-statistic
Top 20%	0.0125	0.0168	0.2326**	1.75
20% - 40%	0.0113	0.0189	0.2109***	2.66
40%-60%	0.0096	0.0173	0.1850***	3.92
60%-80%	0.0075	0.0159	0.1715***	4.14
80%-100%	0.0067	0.0174	0.1441***	5.06

*** represents significance at the 1% level
** represents significance at the 5% level

TABLE 13

Statistics of Industry Group ($ in millions)

	Industry Group	Size	Book to Market Ratio	# of firms
High B/M				
	Manufacture	$454	1.3100	2049
	Service & Technology & Health Care	$227	1.3572	772
	Retail & Wholesale	$141	1.2597	452
	Average	$274	1.3090	1091
Low B/M				
	Manufacture	$4,063	0.2476	4558
	Service & Technology & Health Care	$1,822	0.1937	2107
	Retail & Wholesale	$1,648	0.2524	460
	Average	$2,511	0.2312	2375

Size represents the total market value of firm.

TABLE 14

Industry Robustness Results

	Industry Group	Return	10-Day SD	Beta	VAR	EV
High B/M						
	Manufacturing	0.4476	0.0221	0.3832	0.0653	0.1922
	Service & Technology & Health Care	0.5793	0.0310	0.4060	0.0753	0.2521
	Retail & Wholesale	0.4746	0.0291	0.3218	0.0724	0.2322
Low B/M						
	Manufacturing	0.1881	0.0361	0.8059	0.1095	0.3273
	Service & Technology & Health Care	0.2045	0.0424	0.8567	0.1304	0.3809
	Retail & Wholesale	0.1285	0.0360	0.6985	0.1033	0.3110

TABLE 15

Book to Market Ratio Robustness Results

	Year	High B/M 10-Day VAR	Low B/M 10-Day VAR	Difference
Top 33%				
	1993	0.0054	0.0438	0.0384
	1994	0.0172	0.0648	0.0476
	1995	0.0103	0.0551	0.0448
	1996	0.0340	0.1403	0.1063
	1997	0.0442	0.0840	0.0399
	1998	0.0964	0.1848	0.0885
	1999	0.0308	0.0692	0.0384
	2000	0.0678	0.2604	0.1926
	2001	0.1094	0.1816	0.0723
	2002	0.0949	0.2268	0.1320
	Average	0.0510	0.1311	0.0801***
	T-Test			4.95
Middle 33%				
	1993	0.0211	0.0304	0.0094
	1994	0.0318	0.0621	0.0302
	1995	0.0164	0.0461	0.0296
	1996	0.0329	0.1167	0.0838
	1997	0.0388	0.0738	0.0351
	1998	0.1008	0.1672	0.0664
	1999	0.0368	0.0644	0.0277
	2000	0.0482	0.1548	0.1067
	2001	0.1127	0.1624	0.0497
	2002	0.0979	0.1148	0.0169
	Average	0.0537	0.0993	0.0455***
	T-Test			4.63
Bottom 33%				
	1993	0.0178	0.0274	0.0096
	1994	0.0247	0.0482	0.0234
	1995	0.0154	0.0324	0.0170
	1996	0.0358	0.0935	0.0578
	1997	0.0523	0.0598	0.0075
	1998	0.1124	0.1594	0.0470
	1999	0.0339	0.0482	0.0143
	2000	0.0622	0.1247	0.0624
	2001	0.1094	0.1572	0.0478
	2002	0.1013	0.1185	0.0172
	Average	0.0565	0.0869	0.0304***
	T-Test			4.57

*** represents significance at the 1% level

9. References

Abarbanell, Jeffrey and Brian Bushee. "Fundamental Analysis, Future earnings, and Stock Prices." Journal of Accounting Research 35 (1997): 1-24.

Alexander, Gordon J. "A VaR-Constrained Mean-Variance Model: Implications for Portfolio Selection and the Basle Capital Accord." Working paper. 2001.

Argentine Economic Crisis. Wikipedia. 2002.
<http://www.en.wikipedia.org/wiki/Argentine_economic_crisis_(1999-2002)>

Bali, Turan and Nusret Cakici. "Value at Risk and Expected Stock Return." Financial Analysts Journal 60 (2004): 57-73.

Bernard, Victor L. and Jacob K. Thomas. "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?" Journal of Accounting Research 27 (1989): 1-36.

Bodie, Zvi et al. Investments. McGraw-Hill. 1999.

Chan, Louis K.C., Yasushi Hamao and Josef Lakonishok. "Fundamentals and Stock Returns in Japan." Journal of Finance 47 (1991): 1739-1774.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok. "Momentum Strategies." Journal of Finance 51 (1996): 1681-1713.

Doukas, John A., Chansog Kim, and Christors Pantzalis. "A test of the Errors-in-Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts." Working paper. 2002.

Fama, Eugene F. and Kenneth R French. "The Cross-Section of Expected Stock Returns." Journal of Finance 47 (1992): 427-465.

Fama, Eugene F. and Kenneth R French. "Size and Book-to-Market Factors in Earnings and Returns." Journal of Finance 50 (1995): 131-155.

Fama, Eugene F. and Kenneth R French. "Multifactor Explanations of Asset Pricing Anomalies." Journal of Finance 51 (1996): 55-84.

Fama, Eugene F. and Kenneth R French. "Value versus Growth: The International Evidence." Journal of Finance 53 (1998): 1975-1999.

Graham, Benjamin, and David L Dodd. *Security Analysis*. New York: McGraw-Hill. 1934.

Griffin, John M. and Michael L. Lemmon. "Does Book-to-Market Equity Proxy for Distress Risk or Overreaction?" Working paper. 2000.

Hull, John C.. Options, Futures, and Other Derivatives. Prentice Hall. 2000.

Jorion, Philippe and GARP (Global Association of Risk Professionals). Financial Risk Manager Handbook. Wiley Finance. 2003.

La Porta, Rafael. "Expectations and the Cross-Section of Stock Returns." Journal of Finance 51 (1996): 1715-1742.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer and Robert Vishny. "Good News for Value Stocks: Further Evidence on Market Efficiency." Journal of Finance 52 (1997): 859-874.

Lakonishok, Josef, Robert W. Vishny and Andrei Shleifer. "Contrarian Investment, Extrapolation, and Risk." Journal of Finance 49 (1994): 1541-1578.

Lev, Baruch and S. Ramu Thiagarajan. "Fundamental Information Analysis." Journal of Accounting Research 31 (1993): 190-215.

Langley, Suchada and Chris Bolling. "Brazil's Finanical Crisis & the Potential Afershocks." Economic Research Service. 1999. <http://www.ers.usda.gov/publications/agoutlook/mar1999/ao259c.pdf>.

Mohanram, Partha S. "Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis." Working paper. 2004.

Ohlson, James A.. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." Journal of Accounting Research 18 (1980): 109-131.

Piotroski, Joseph D.. "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers." Journal of Accounting Research 38 Supplement (2000): 1-41.

Shumway. "CRSP Delisting Returns." CRSP. 2001. <www.crsp.com>