Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis

Partha S. Mohanram

Columbia Business School
605-A Uris Hall,
3022 Broadway
New York, NY 10027
pm2128@columbia.edu

Current Draft: April 2004

I would like to thank Jeff Abarbanell, Sudhakar Balachandran, Eli Bartov, Doron Nissim, Stephen Penman, Joe Piotroski, Richard Sloan, Doug Skinner, Shyam V. Sunder, and seminar participants at Columbia University, Harvard Business School (Information, Organizations, and Markets Conference 2003) New York University, and University of California at Berkeley for their help and comments. All data used is from publicly available sources.

Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis

ABSTRACT

This paper tests whether a strategy based on financial statement analysis of low book-to-market (growth) stocks is successful in differentiating between winners and losers in terms of future stock performance. I create an index (G_SCORE) based on a combination of traditional fundamentals such as earnings and cash flows and measures appropriate for growth firms such as the stability of earnings and growth and the intensity of R&D, capital expenditure and advertising. A strategy based on buying high G_SCORE firms and shorting low G_SCORE firms consistently earns significant excess returns. The results are robust across partitions based on size, stock price, analyst following, exchange listing and prior performance and are not affected by the inclusion or omission of IPO firms. The excess returns persist after controlling for well documented risk and anomaly factors such as momentum, book-to-market, accruals and size. The stock market in general and analysts in particular are much more likely to be positively surprised by firms whose growth oriented fundamentals are strong, indicating that the stock market fails to grasp the future implications of current fundamentals. Further, the results do not support a risk based explanation for the book-to-market effect as the strategy returns positive returns in all years, and firms that ex-ante appear less risky have better future returns. To conclude, one can use a modified fundamental analysis strategy to identify mispricing and earn substantial abnormal returns.

KEYWORDS: Fundamental Analysis, Financial Statement Analysis, Growth Firms, Low Book-to-Market Firms.

1 Introduction

This paper examines whether applying financial statement analysis can help investors earn excess returns on a broad sample of growth, or low book-to-market (BM) firms. The BM effect is well documented in research in finance. On average, firms with low BM earn significant negative excess returns, while firms with high BM earn significant positive excess returns. Low BM firms, also referred to as growth or glamour stocks, have experienced very strong stock performance in prior periods, while high BM firms, also referred to as value stocks, have typically underperformed in prior periods. There is considerable disagreement amongst researchers as to the cause of the book-to-market effect. Fama and French (1992) claim that unobserved risk factors cause the book-to-market effect, while Lakonishok, Shleifer and Vishny (1994) attribute the effect to mispricing.

Financial statement analysis attempts to identify ex-post winners and losers on the basis of information in the financial statements that are not completely or perfectly impounded in prices. Ex-ante, it is unclear whether financial statement analysis will be effective for low BM firms, even if they are mispriced, for the following reasons. First, low BM firms tend to be growth stocks that attract the attention of sophisticated market intermediaries such as analysts and institutional investors. Second, such firms are likely to have many sources of disclosure other than financial statements. Third, the rapid growth in many low BM firms potentially makes current fundamentals less important than other non-financial measures. Counterbalancing this is the fact that many of these stocks may be overvalued in departure from their fundamentals because of the hype or excitement surrounding their recent strong stock market performance. Further, while traditional fundamental analysis may have limited applicability for growth firms, other information from the financial statements can be potentially useful.

Researchers have shown that the stock market tends to naively extrapolate current fundamentals of growth stocks (e.g. La Porta (1996), Dechow and Sloan (1997)), or ignore the implications of conservative accounting for future earnings (e.g. Penman and Zhang (2002)). In this paper, I use financial statement information to create signals relating to naïve extrapolation and conservatism and augment traditional fundamental analysis of earnings and cash flow profitability. I then test the ability of these growth oriented fundamentals to identify winners and losers in terms of ex-post stock returns.

The results indicate that financial statement analysis, appropriately tailored for growth firms, is very successful in differentiating between ex-post winners and losers. The entire Low BM group earned mean size-adjusted annual returns of -6.0% and -4.2% for the first and second year after portfolio formation. The firms that are fundamentally soundest earned a size-adjusted 3.3% and 2.4% in the two years, while the weakest firms earned excess returns of –17.9% and –13.3% respectively. A strategy of buying firms with the strongest "growth fundamentals" and selling or shorting the weakest firms earns very significant abnormal returns. The results are robust across a variety of partitions including size, analyst following and exchange listing and also hold when recent IPO firms are excluded. In addition, the strategy works even if one focuses solely on fast growing firms or high technology firms. The strategy is also robust across time, earning positive returns in all years in the sample.

The success of the growth fundamentals strategy is linked to future performance. Firms with stronger growth fundamentals have better future realizations of earnings and are less likely to delist for reasons related to poor performance. Strong firms are more likely to beat earnings forecasts and earn positive abnormal returns around future earnings announcements, indicating that the market ignores the implications of growth fundamentals for future performance. Finally, there is no support for risk based explanations for the success of the strategy.

The results of this paper indicate that financial statement analysis can be suitably modified to be very successful for growth firms. Specifically, this paper introduces a number of simple and easy to implement tools, based solely on financial statement information, which can help separate future winners from losers in terms of stock performance.

The rest of this paper is organized as follows. Section 2 discusses prior research on the BM effect, financial statement analysis, conservatism and naïve extrapolation. Section 3 uses the insights gained from prior research to develop fundamental signals designed specifically for low BM firms. Section 4 discusses the data and provides summary statistics. Section 5 presents the results to the growth fundamentals strategy, including a variety of partition and sensitivity analyses. Section 6 analyzes the relationship between the growth fundamentals and future performance. Section 7 concludes the paper.

2 Literature Review

In this section, I summarize results from relevant papers. I classify the papers according to the following three groupings – i) the book-to-market effect, ii) fundamental analysis, and iii) growth, conservatism, and naïve extrapolation.

2.1 The Book-to-Market Effect

The book-to-market effect has been demonstrated in a variety of papers from Fama and French (1992) to Lakonishok, Shleifer and Vishny (1994). Both these papers show that the book-to-market ratio of a firm is strongly positively correlated to future stock performance. This correlation has been attributed to both risk and mispricing. The risk explanation offered by Fama and French (1992) argues that high BM stocks earn excess returns compared to most firms because of their greater risk, as many high BM firms are in financial distress. Vassalou and Xing (2004) identify that the book-to-market risk essentially proxies for default risk in high BM firms. However, Griffin and Lemmon (2002) show that firms with high distress risk exhibit the largest return reversals around earnings announcements, inconsistent with a risk based explanation.

This explanation is less satisfying for low BM firms, as there are few ex-ante reasons to believe that these firms, largely growth firms, are less risky than the entire population of firms. Lakonishok et al (1994) claim that mispricing is at the core of the BM effect. They show that the stock market is overly optimistic about low BM "glamour" stocks by over-extrapolating from currently strong earnings and earnings growth. As this optimism unravels with time, these firms earn negative excess returns. La Porta (1996) and Dechow and Sloan (1997) clarify that the naïve extrapolation occurs because the stock market does not adjust for the bias in analysts forecasts of long term growth. Further, La Porta et al (1997) show that low BM stocks are more likely to have negative earnings surprises. However, Doukas, Kim, and Pantzalis (2002) fail to document any support for the naïve extrapolation hypothesis when they examine analyst forecasts

Recent papers supporting mispricing include Bartov and Lee (2002) who demonstrate that the BM effect is stronger when one considers the accounting related reasons for low BM ratios, and Ali et al (2003) who show that the book-to-market effect is greater for stocks with higher idiosyncratic return volatility, higher transaction costs and lower investor sophistication.

2.2 Fundamental analysis

Many papers have focused on the usefulness of financial statement analysis in predicting future realizations of both earnings and returns. Ou and Penman (1989) demonstrate that certain financial ratios can be useful in predicting future changes in earnings. Lev and Thiagarajan

(1993) analyze 12 financials signals that are used by financial analysts and show that these signals are directly correlated to contemporaneous returns. Abarbanell and Bushee (1997) show that developing an investment strategy based on these signals earn significant abnormal returns. There has also been a stream of research that focuses on abnormal returns that can be earned on the basis of certain financial signals. Bernard and Thomas (1989) highlight the post earnings announcement drift, while Sloan (1996) shows that firms with a higher proportion of accruals in their earnings underperform in the future.

Piotroski (2000) applies the tools of financial statement analysis to develop an investment strategy for high BM firms. He argues that high BM or value firms are ideal candidates for the application of financial statement analysis as financial analysts generally neglect such firms. He demonstrates that within the high BM sample firms with the strongest fundamentals earn excess returns that are over 20% greater than firms with the weakest fundamentals.

Beneish, Lee and Tarpley (2001) use a two-stage approach towards financial statement analysis. In the first stage, they use market based signals to identify likely extreme performers. In the second stage, they use fundamental signals to differentiate between winners and losers among the firms identified as likely extreme performers in the first stage. Their results indicate the importance of carrying out fundamental analysis contextually. In a similar vein, Soliman (2003) demonstrates that one can improve the performance of the traditional Dupont analysis for ROA decomposition by industry adjusting profit margin and asset turnover.

2.3 Growth, Conservatism and Naïve Extrapolation

Many papers have also studied subsets of growth firms such as technology firms, research and development (R&D) intensive firms and Internet firms. Lev and Sougiannis (1996) study the value relevance of R&D and find that R&D intensive firms earn excess returns in future periods.

Chan, Lakonishok and Sougiannis (2001) confirm this and also find that advertising expenses are associated with excess returns in the future. Penman and Zhang (2002) demonstrate that the stock market does not understand the hidden reserves caused by conservative accounting for items such as R&D and advertising, which leads to excess returns in the future. To summarize, the literature indicates accounting conservatism is associated with future abnormal returns. A sample of growth firms is likely to have a substantial number of firms with such conservative accounting. Given that low BM stocks as a whole underperform, separating out the "low B" firms is likely to improve the success of any investment strategy.

Papers have also looked at the effect of predictability as well as naïve extrapolation of earnings and earnings growth. Huberts and Fuller (1995) show that firms with less predictable earnings underperform in terms of stock returns in future periods. As discussed earlier, La Porta (1996) and Dechow and Sloan (1997) demonstrate that the market's reliance on biased analyst long term growth forecasts is responsible for a substantial portion of the poor returns to low BM stocks. These papers may help separate out the "High M" firms that are more likely to underperform in the future amongst the population of low BM stocks.

Finally, a number of papers have looked at the importance of non-financial indicators for the valuation of growth stocks. For instance, Trueman, Wong and Zhang (2000) illustrate the importance of web traffic in the valuation of internet stocks. However, Bartov, Mohanram and Seethamraju (2002) show that the financial information in the IPO prospectus is value relevant for both internet as well as non-internet technology firms, with earnings mattering only for non-internet firms and cash flows and sales being more relevant for non-internet firms. Further, while non-financial indicators may be correlated with current valuation, financial statement information may have implications for *future* valuation and hence returns. As the rise and fall of

Internet stocks demonstrates, if the valuation of growth stocks eventually revert to fundamentals, firms with the strongest fundamentals are more likely to outperform or least likely to severely underperform in terms of stock market returns.

3 Research Design

3.1 Financial Statement Analysis for Growth Firms

It is a well known empirical phenomenon that low BM stocks underperform in the period(s) after portfolio formation. However, there is considerable variation in stock performance amongst the low BM firm. The aim of this paper is to apply *financial statement analysis* to the sample of growth or low book-to-market stocks in an attempt to separate likely winners from losers. The portfolio strategy outlined in this paper relies entirely on publicly available historical financials, without using market based indicators or other information such as analyst forecasts that may rely implicitly on non-financial or private sources of information

The signals used in this paper to separate the low BM firms into categories of potential winners and losers can be classified into three groups. The first consists of traditional fundamental signals pertaining to a firm's profitability and cash flow performance. The second category of signals tries to separate out those firms that are likely to be in the low BM category because their market valuation appears to be high from others, by utilizing insights from research that has focused on the tendency of markets to extrapolate naively from the present. The third category of signals attempts to identify the firms that have low BM because of conservative accounting. I refer to the signals developed in this paper as "growth" fundamental signals, as they measure the fundamental strength of these firms in a context appropriate for growth firms.

The maintained assumption implicit in the selection of these signals is that the BM effect for low BM firms is a mispricing effect and not a risk effect. The success or failure of the strategy will, in a large part, be determined by whether or not this is a valid assumption. What this implies is that the success of failure of this strategy also addresses whether the BM effect for low BM firms is caused by risk or mispricing.

3.2 Category 1: Signals based on Earnings and Cash Flow Profitability

The first three signals used in this paper are based on profitability, measured either in terms of earnings or cash flows. Firms that are currently profitable are likely to be fundamentally strong and maintain their fundamental strength in the future if current profits have any implications for future profits.

Profitability is measured in two ways. The first measure of profitability is Return on Assets (ROA), defined as the ratio of net income before extraordinary items scaled by beginning total assets[1]. I compare the ROA of a given firm to the ROA of all other low BM firms in the same 2 digit SIC code at the same time. This signal, and all signals used in this paper, will be based on industry contextual information, consistent directly with Soliman (2003) who illustrates the importance of industry adjustment in Dupont analysis, and indirectly with Beneish, Lee and Tarpley (2001) who highlight the importance of context in fundamental analysis. I define the first growth signal, *G1, to equal 1 if a firm's ROA is greater than the contemporaneous industry median and 0 otherwise.*

Earnings may be less meaningful than cash flows for early stage firms which are likely to be relatively over-represented among low BM firms. This may especially be true because of large depreciation or amortization charges that firms making large investments in fixed or intangible assets. Hence, I also use an additional measure of profitability by calculating ROA with cash

[1] Adding back after tax interest expense has a minimal effect on ROA and on the results.

from operations instead of net income[2]. I define the second growth signal, *G2, to equal 1 if a firm's cash flow ROA exceeds the contemporaneous industry median and 0 otherwise.*

Sloan (1996) and others have shown the importance of accruals by demonstrating that firms with a greater accrual component in their earnings generally underperform in the future, potentially because of the lower quality of their earnings. Accordingly, *G3 is defined to equal 1 if a firm's cash flow from operations exceeds net income and 0 otherwise.*[3]

Ex-ante, it is unclear as to how well these three signals will perform for the sample of low BM firms. Conventional wisdom indicates that these signals may not be as effective as they would be in the general population of firms, as growth firms are less likely to be in a state where the current financials have important implications for the future. Further, it is unclear in the accrual anomaly will manifest itself at the aggregate level for growth firms, which are likely to have large negative accruals because of their rapid growth. However, a counter argument can be made that if some of the firms are temporarily overvalued, then current fundamentals may help separate the solid growth firms from firms that are overvalued because of hype. The effectiveness of G1:G3 is hence an open question.

3.3 Category 2: Signals Related to Naïve Extrapolation

Consider two firms – firm A and firm B. Assume that both firms are growth firms in a market that is functionally fixated and extrapolates naively. If these firms had similar strong earnings performance, then both of them would potentially be valued similarly. Now suppose we know that firm A has very stable earnings, but firm B has unstable earnings. Then, the odds that

[2] For the years prior to 1988, cash from operations is estimated using the funds from operations and change in working capital.

[3] The choice of a signal based on total accruals can be improved by focusing not just on the magnitude of the accrual, but the quality or reliability of the accruals (see e.g. Richardson et al (2004)). I however use total accruals to make the signal as easy to construct as possible.

the current strong performance of firm B are just a lucky high realization are much higher than for firm A. Firm B is hence much more likely to provide disappointing earnings and hence poor returns in the future than firm A.

Empirically, Barth, Elliott and Finn (1999) show that the stock market eventually rewards firms with stable prior earnings, as these firms are more likely to have better earnings performance in the future. Huberts and Fuller (1995) demonstrate that firms with greater predictability in their earnings perform better than firms with less predictable earnings.

For low BM stocks, stability of earnings may help distinguish between firms with solid prospects and firms that are overvalued because of hype or glamour. I measure earnings variability as the variance of a firm's Return on Assets in the past five years.[4] I then compare the firm to other low BM firms in the same 2 digit SIC code at the same point in time. *G4 is defined to equal 1 if a firm's earnings variability is less than the contemporaneous industry median and 0 otherwise*.

The second signal in this category relates to the stability of growth and is motivated by the results from Lakonishok, Shleifer and Vishny (1994), La Porta (1996) and Dechow and Sloan (1997) that highlight the naïve extrapolation of current growth to predict future growth. As for the prior signal, a firm that has stable growth is less likely to have had a lucky high realization, and therefore less likely to disappoint in terms of future growth. In designing this signal, I focus on sales growth as opposed to earnings growth, as earnings growth is difficult to conceptualize for negative earnings, which many low BM growth stocks have[5]. As before, I compare the firm

---

[4] I ensure that there is at least three years of information to calculate this ratio. If a firm does not have enough past data, it is given a value of 0 for this signal. This is the equivalent of a fund manager deciding not to buy a stock when he does not have enough information to determine the firm's track record.

[5] Damodaran (2001) argues in his book entitled "The Dark Side of Valuation" (page 150) that revenue growth tends to be more persistent and predictable than earnings growth because accounting choices have less of an effect on revenues.

to other low BM firms in the same 2 digit SIC code at the same point in time. *G5 is defined to equal 1 if a firm's sale growth variability is less than the contemporaneous industry median and 0 otherwise*.

3.4 Category 3: Signals Related to Accounting Conservatism

The final three growth signals are based on actions that firms take that may depress current earnings and book values, but may boost future growth – R&D, capital expenditures and advertising. High levels of R&D, advertising and capital expenditures may boost future sales and earnings growth and make the firms more likely to meet the market's lofty expectations. Further, conservatism in accounting standards makes firms expense outlays such as R&D and advertising even if these items create intangible assets. These unrecorded intangible assets depress book values, making it more likely that a firm has a low BM ratio for accounting reasons as opposed to over-valuation. Accordingly, I define *G6, G7 and G8 to equal 1 if a firm's R&D, capital expenditure and advertising intensity are greater than the contemporaneous industry medians of the corresponding variables and 0 otherwise*. The intensity of R&D, capital expenditure and advertising are measured by deflating these variables by beginning assets.

4 Data

4.1 Sample Selection

I start with all firms in COMPUSTAT for which price and book value information is available between 1979 and 1999. I obtain return information from CRSP, including delisting returns to make adjustments where required. I then calculate the book-to-market ratios for all firms and divide the sample into quintiles in each year. I focus on the quintile with the lowest

BM ratio, including firms that have negative BM ratios. I do not eliminate the firms for which insufficient prior information is available. A large portion of the low BM sample (around 22%) consists of firms that have been recently gone public. Eliminating such firms potentially reduces the representativeness of the sample. However, as later partition results indicate, the results are robust to the exclusion of such firms. The final low BM sample consists of 20,866 firm-years.

Panel A of Table 1 presents descriptive statistics for the sample firms. For comparison, descriptive statistics for firms across all BM categories is also presented. Low BM firms have significantly greater market value and lower book value than the universe of firms. They also have far fewer assets and slightly less sales than all firms. Interestingly their mean net income is comparable to the population. Medians for most financials are significantly smaller than means indicating the presence of some very large firms. Low BM firms have lower ROA than the population, but higher ROE because of their smaller equity. They grow at a much faster rate than other firms with a mean annual sales growth rate of 30.8% as opposed to 17.3% for the entire sample. Low BM firms are also much have greater R&D Intensity (6.3% vs. 3%) and have a much greater proportion of recent IPOs (22% vs. 12%) compared to the universe of firms.

4.2 Calculation of Returns

Firm level returns are computed as the buy-and-hold returns for two consecutive one-year periods starting from four months after the fiscal year end to ensure that the current financials are publicly available. The returns are size-adjusted by subtracting the returns in the same period for the same capitalization decile as the firm, as available on CRSP[6]. Firm delistings are adjusted for

[6] In addition, the tests are also computed using the value weighted index. The results are essentially unchanged. I report results using size-adjusted returns because the large variability in size amongst low BM firms makes adjusting for size more appropriate than using a broad market index as a benchmark.

using the methodology suggested by Shumway (1997) [7].

Panel B of Table 1 presents the distribution of returns. Low BM firms earn mean size-adjusted returns of -6.0% and -4.2% in the first and second year after portfolio formation. The 25th percentile has highly negative size-adjusted returns of –47% and –43% for the first and second year respectively. The median size-adjusted returns are also negative. However, the market-adjusted returns of the 75% percentile are positive. Any strategy that identifies the firms in the two tails of the distribution and tries to profit from the differences between these firms is hence likely to succeed. In the tests ahead, I will test whether portfolios of firms with strong growth fundamentals outperform portfolios of firms with weak growth fundamentals.

4.3 Correlation between Signals

Table 2 presents the correlations between the eight growth fundamental signals (G1:G8). In addition to the obvious high correlation between earnings and cash flows, some interesting patterns are observed. Profitable firms (G1 or G2 using cash flows) are likely to have stable earnings (G4) and sales growth (G5). Also stable earnings (G4) and sales growth (G5) are positively correlated. Interestingly, the signals pertaining to conservatism – high R&D (G6), capital intensity (G7) and advertising intensity (G8) show weak correlations amongst each other and with other signals. Hence, if they are individually effective in predicting future returns, using them together may be fruitful because of their apparent orthogonality.

4.4 Returns to Individual Signals

To provide preliminary evidence as to whether the signals are effective, I analyze the relationship between the individual signals and the return realizations. The results are presented

[7] Shumway (1997) suggests using the CRSP delisting return where available. If not available, he uses -30% if the delisting is for performance reasons and 0 otherwise.

in Table 3. Panel A analyzes the one year size-adjusted returns ($SRET_1$), by comparing the mean returns for firms which met the signal's criteria (1) to those that did not (0). As the results indicate, the differences in returns are positive for all eight signals, and this difference is strongly significant for all signals, with the exception of capital intensity. Panel B analyzes the size-adjusted returns for the second year after portfolio formation ($SRET_2$). Here too, all return differences are positive. Advertising Intensity (G8) is no longer significant, while capital intensity now shows a significant return difference (G7). Presumably, advertising has shorter lived benefits, while the effects of high capital intensity occur with a time lag.

To summarize, all eight signals show a statistically significant ability to separate out firms in terms of ex-post returns, in at least one of the two years. In the tests going forward, I aggregate G1:G8 into a single index called G_SCORE.[8] While this is one of many ways one can implement a portfolio strategy using the information in these signals, it has the advantage of being simple to execute and correlating well to how stock screens are typically used in practice for stock picking.[9] This methodology is akin to having a checklist of screens for deciding to invest in stocks and rating stocks on the basis of how many screens they passed. Prior research has also used such a methodology; for instance Piotroski (2000) investigates the efficacy of traditional fundamental analysis for value firms by defining binary signals and aggregating them additively.

[8] While Capital Intensity (G7) and Advertising Intensity (G8) are clearly weak signals, I do include them as excluding them would impose a look-ahead bias – i.e. we know that these are weak signals only by peeking ahead and realizing that these signals perform poorly. The poor performance of capital intensity as a signal is consistent with the inefficient over-investment documented in Richardson and Sloan (2004).

[9]For instance, one could use continuous values instead of binary screens, or assigns weights while adding the individual screens. While such methods may be more powerful, they may implicitly induce a look-ahead bias if the ability of these signals to differentiate between winners and losers is used to calculate the weights assigned, or may need additional data to conduct these tests on holdout samples.

5 Results: Future Returns

5.1 Returns to a Growth Fundamentals Driven Strategy (G_SCORE)

As G_SCORE consists of eight signals, it can have nine values from zero to eight. Table 4 presents the returns to the nine portfolios based on the levels of the G_SCORE index. Panels A and B present raw and size-adjusted returns for the first year after portfolio formation.

For the entire low BM sample, the mean raw (size-adjusted) return is 8.2% (–6.0%). However, the return shows a very strong and almost perfectly monotonic relationship with G_SCORE. For instance, the mean raw return for the "0" G_SCORE portfolio is -12.6%, while the mean raw return for the "8" G_SCORE portfolio is 31.1%. This indicates that a portfolio strategy of going long in high G_SCORE firms and shorting low G_SCORE firms may be very effective. However, very few firms are in the two extreme portfolios (589 across 21 years for G_SCORE=0, and 72 across 9 years for F_SCORE=8), and this number is especially small for high G_SCORE as the distribution of G_SCORE is left skewed[10]. I group the two lowest portfolios (0, 1) into the low group and the highest three portfolios (6, 7, 8) into the high group. This ensures that over 2000 firm-years or on average, over 100 firms per year are in both the high and the low groups to allow one to develop feasible hedge strategies.

The mean raw returns for the low group are -4%, as opposed to 17.4% for the high group, a difference of 21.4%. In addition, similar significant differences between the groups are seen in medians (8% for high vs. -19.3% for low), as well as the proportion of firms with positive returns (60% for high vs. 34.4% for low). This indicates that a high minus low hedge strategy based on G_SCORE is very effective in the aggregate. The tables also present returns for firms at the 10th

[10] G_SCORE has a left skewed distribution because far fewer firms have a value of 1 for the growth signals. The reason for this is two-fold. First, some of the signals (variance of ROA and sales growth) require at least three years of past information, which means that fewer firms will qualify. Second, some of the signals are based on items that are often zero for many firms (R&D, capital expenditures and advertising expenditures).

percentile, 25th percentile, median, 75th percentile and 90th percentile. In general, the returns are lower at each of these percentiles for the low G_SCORE portfolios and higher for the high G_SCORE portfolios. This indicates that G_SCORE helps shift the distribution of returns to the left for lower score portfolios and to the right for higher score portfolios.

Panel B presents size-adjusted returns. The return differences are very similar, but one clear trend emerges. Firms in the high group earn positive but small size-adjusted returns (mean 3.3%), while firms in the negative group earn large negative size-adjusted returns (mean -17.9%). Hence, the strategy is more effective in identifying potential losers or torpedo stocks (see e.g. Skinner and Sloan (2002)), than in identifying winners. This may place a crucial caveat to the success of the strategy, especially if restrictions on short selling make a high minus low strategy tough to implement. However, in terms of separation from the sample mean (-6%), the shift in mean returns is almost symmetric. The high group earns a mean return that is 9.3% higher than the sample mean (3.3% vs. -6.0%), while the low group earns 11.9% lower (-17.9% vs. -6.0%). We will examine this issue in greater depth, by analyzing the portfolio's performance across different partitions in the sub-section to follow.

Panels C and D presents the raw and size-adjusted returns respectively in the second year after portfolio formation. As the results indicate, the return differences persist strongly in the second year. For instance, the mean size-adjusted return is 2.4% for the high group and –13.3% for the low group, a significant difference of 15.8%. Similar significant differences are observed in medians and in the proportion of positive size-adjusted returns. Hence, a G_SCORE based strategy is very effective in picking winning stocks beyond the first year.

5.2 Partition Analysis

One concern with a strategy that identifies extreme performers is that the returns may be concentrated in a peculiar subset of firms, for instance small firms or firms that are not followed by analysts or are thinly traded. This may cause difficulties in the implementation of a strategy based on buying stocks with high G_SCORE and selling stocks with low G_SCORE. This is especially the case because the poor performance of low G_SCORE firms is crucial to the success of the strategy and if most of these firms belong to subsets that have great illiquidity or trading restrictions, the strategy will be difficult to implement. Further, the composition of low BM firms is not homogeneous and while it is likely overweighted with growth firms, it also includes other firms. This may pose implementation problems for those focusing solely on growth firms. To address these issues, I compare the performance of the growth fundamentals strategy across different partitions. The results are presented in Table 5. For brevity, the partition analysis is conducted only for one year ahead returns.[11]

<u>Size Partition</u>

I first partition the sample into three equal partitions based on size, defined as market capitalization of equity (Table 5 - Panel A).[12] The BM effect is strongest for small firms and gets progressively weaker as firm size increases. Small firms earn an average excess return of -8.9%, compared to –7.0% for medium sized firms and -2.1% for large firms.

The effectiveness of a strategy based on G_SCORE is not influenced by firm size. For small firms, the separation in mean excess returns between low and high portfolios is 22.8%. For

---

[11] As the analysis will indicate, the High-Low strategy is effective across all partitions. A similar trend is seen across all partitions for $SRET_2$, the two-year ahead size-adjusted returns.

[12] Similar results are found if instead of forming three equal groups, external information is used to form the groups – e.g. market capitalization deciles using data on all firms.

medium firms, the mean separation is 23.1%, while for large firms the separation is 19.8%. All three return differences are highly significant at better than 1%. A similar trend is seen for median returns. The strong result for large firms is crucial as such firms are also least likely to have illiquid stocks or restrictions on short-selling.[13]

Analyst Following Partition

I next partition the sample of low BM firms into three groups – firms with no analyst following, firms with limited analyst following and firms with extensive analyst following. Analyst following is calculated as the number of I/B/E/S analysts who followed the firm at the time of portfolio formation. Almost half the sample does not have analyst following (9301 out of 20,866 firm-years). For the remaining firms, I compare their analyst following to other firms in the same 2 digit SIC code at the same point in time. Firms with following equal to or above the median following are classified as having extensive following and the rest are classified as having limited following. The results are presented in Panel B of Table 5.

In all three categories, there is a substantial difference between high G_SCORE firms and low G_SCORE firms. The mean return difference is 21.3% for firms without analyst following, 16.3% for firms with limited following and 18.1% for firms with extensive following. Interestingly, the difference is marginally greater for firms with extensive following than for firms with limited following. This indicates that even sophisticated users of financial information, such as analysts, can be susceptible to ignoring the implications of factors such as profitability and conservatism and to naive extrapolation.[14]

[13] In addition, when stock price is used as a partition instead of size, very similar results are obtained.

[14] G_SCORE is also clearly associated with analyst following. There are far more low G_SCORE observations amongst firms with no following and limited following and far more high G_SCORE observations amongst firms with extensive following, indicating that analysts tend to gravitate towards stronger firms.

Exchange Listing Partition

The ability to buy, sell and short a stock with the least possible trading costs is affected by its exchange listing status. To identify if this affects the results, I next partition the sample based on exchange listing status. Firms are classified as either NYSE/AMEX firms or NASDAQ firms. Results are presented in the left most columns of Panel C of Table 5.

Return differences are significant for both groups of firms, but much stronger for NASDAQ firms. The return difference is 12.7% for NYSE firms (1.8% for high vs. -10.9% for low), and 26.4% for NASDAQ firms (5.5% for high vs. -21% for low). This has two interesting implications. First – the strategy is effective in identifying the torpedoes (stocks likely to perform very poorly) mostly in the NASDAQ. Second – by going long on high firms in the NASDAQ, and shorting NYSE/AMEX firms, one can earn a hedge return of around 16.4% (5.5% vs. -10.9%), which maybe an interesting option if shorting NASDAQ stocks is difficult.

IPO Partition

Given the large proportion of recent IPOs (firms that have gone public less than one year before portfolio formation) amongst low BM firms (22%), I now test whether the strategy is driven by the inclusion or exclusion of IPO firms. This ensures that the strategy is doing more than merely shorting IPO firms, thereby taking advantage of the well documented underperformance of IPOs. Further, such firms typically have lower liquidity and are extremely difficult to short. The results are presented in right most columns of Panel C of Table 7.

By construction, IPO firms have lower G_SCORE as they do not meet the data requirements for some of the signals such as ROA variability and sales growth variability (G4 and G5). No IPO firm scores higher than 6, and only 21 firms had a G_SCORE of 6. However, the G_SCORE strategy is clearly helpful in identifying torpedo stocks amongst IPO firms (e.g.

mean size-adjusted return of -28.7%, -17.3% and -12.7% respectively for G_SCORE=0, 1 and 2).

When one excludes IPO firms and constructs portfolios with only non-IPO firms, the G_SCORE strategy continues to be effective. The return difference for non-IPO firms is a robust 19.5%. This compares favorably with the 21.2% return difference seen for the entire sample. The poor performance of the low group across both IPO and non-IPO firms explains why the return differences stay at close to the same levels. Among the IPO firms, 1402 observations belonged to the low G_SCORE group and earned -19.9 % mean size-adjusted returns in the next year. For non-IPO firms, 1839 firms were in the low group, and earned -16.5%. Hence, the success of the G_SCORE strategy is not dependent on the avoidance/shorting of IPO firms.

“Real Growth Firms” vs. Rest

Our final two partitions separates out the entire population of low BM stocks into those that are more likely to truly be “growth” stocks and those that are classified as low BM for other reasons. This is a potentially important partition, especially for investors who are interested in or constrained to invest only in growth stocks. As the definition of what constitutes a growth stock is rather unclear, I consider two partitions. First, I separate out the truly fast growing firms from the rest, by comparing the firms’ sales growth to other low BM firms in the same 2 digit SIC code. Second, I isolate high technology firms which are likely to be growth firms. The results are presented in Panel D of Table 7.

The left most columns separate out fast growing firms from the rest. The fast growing firms had mean and median sales growth of 62% and 48% respectively, as opposed to 2% mean and 6% median for the other firms. As the results indicate, the return differences are almost identical in both groups. Hence, even if one focuses only on growth stocks and excludes other low BM stocks, this strategy is very successful.

I use the classification proposed by Field and Hanka (2001) to identify hi-tech firms.[15] As the results indicate, even if one focuses on hi-tech firms alone, the return difference between the high and low group is 17.8%. Also, the mean return for the high group is 5.2%, slightly higher than for the entire population. Hence, the strategy appears to be successful not just in identifying potential losers but in identifying winners as well amongst hi-tech firms.

5.3 Robustness of Results across Time

In this section, I examine the robustness of the G_SCORE strategy across time to ensure that the results are not driven by extreme or unusual return patterns at some points in time or time clustering of observations. Table 6 presents the size-adjusted returns for the high and low groups of firms for each of the years (1979 to 1999). The strategy is remarkably robust across time. In all 21 years, the strategy paid positive returns, and in 16 out of the 21 years, the return difference was statistically significant. In 17 years, the return difference was greater than 10%. Further, in 15 out of the 21 years (every year after 1984), there were more than 100 firms in both the low as well as the high groups. This indicates that the strategy would not suffer from potential implementation problems in some years because of too few firms. The success of the strategy in avoiding negative performance over a relatively long time series of 21 years also lends credence to a market mispricing explanation as opposed to a risk based explanation.

[15] Field and Hanka (2001) categorize all firms with primary three-digit SIC codes in computer and office equipment (357), electronic components and accessories (367), miscellaneous electrical machinery equipment and supplies (369), measuring and controlling devices (382), medical instrument and supplies (384), and computer and data processing services (737) as hi-tech firms.

5.4 Controlling for Risk Factors

The G_SCORE strategy could potentially be correlated with other well documented risk factors and anomalies. First, though the sample consists of low BM firms, it is possible that low G_SCORE firms have much lower BM ratios than high G_SCORE firms. Second, one of the components of G_SCORE is the signal G3, which chooses firms with greater cash flows than earnings. This picks up on the accrual effect documented by Sloan (1996). Third, many of the momentum strategies are based on behavioral explanations rooted in the market's under-reaction or improper extrapolation of historical information, as demonstrated by Chan, Jegadeesh and Lakonishok (1996). Finally, even though returns are size-adjusted returns, this adjustment may be less than perfect because of variation in size within a given decile. I add these controls to ensure that the benefits from the modified fundamentals strategy go beyond these well documented effects.

I run a regression for $SRET_1$ using the following control variables; SIZE measured by log of market capitalization; LBM - log of the BM ratio; MOM - size-adjusted buy-and-hold return for the six month period prior to portfolio formation, ACCR – a dummy variable equal to 1 if net income exceeds cash from operations, and EQ_OFF – a dummy variable equal to 1 if a firm issues equity in the year before portfolio formation.

Panel A of Table 7 presents results from pooled regressions. The base regression includes only SIZE, LBM and MOM. Adding G_SCORE to the regression increases the adjusted R^2 from 0.87% to 1.45%. The coefficient on G_SCORE is a highly significant 0.039, indicating that a one point increase in G_SCORE is associated with a size-adjusted return of 3.9%. SIZE is no longer significant, indicating the positive correlation between G_SCORE and size because of the over-representation of large firms in the high G_SCORE group. LBM and MOM are still significant.

Hence, G_SCORE adds value even after controlling for size, book-to-market and momentum. Similar results are observed when controls for accruals and equity offering are added.

Panel B of Table 7 presents the summary results from annual regressions. The t-statistics are calculated from the distribution of coefficients from 21 annual regressions, adjusting for autocorrelation as in Bernard (1995). G_SCORE continues to very significant confirming the robustness of this strategy across time, corroborating the results from Table 8. The mean adjusted R^2 is higher at 3.67%. The coefficient on G_SCORE is around 0.037 in all the specifications. The economic implication of this is that a one point increase in G_SCORE is associated with a 3.7% increase in abnormal returns.

The mean values of G_SCORE for the low and high groups are 0.82 and 6.30 respectively. This implies a return difference of 3.7 % * (6.30-0.82), or approximately 20.3% between the high and low groups, as compared to the 21.2% difference reported in Table 4. Hence, the effectiveness of the strategy persists after controlling for factors such as momentum, size, book-to-market and the accrual anomaly.

5.5 Other Sensitivity Tests

One potential problem with grouping together all firms in a given fiscal year is that different firms have different fiscal years, which means that the financial information for some firms is available before others causing a potential look-ahead bias. Further, the return compounding periods are different across firms and could differ on average across the high and low groups. To ensure that this does not obfuscate the results, I repeat the analysis for the subgroup of firms with December fiscal year ends. While earnings for these firms will also not be available at the identically same time, the time range is likely to be significantly smaller and the time period for compounding future returns is identical. When this analysis is conducted on December fiscal year firms alone (11,153 firm-years out of 20,866), virtually identical results are obtained. For instance, the high group earned a size-adjusted excess return of 3.0%, while the low group earned a size-adjusted -18.0%, a difference of 21%.

Another potential issue is using contemporaneous industry medians implicitly uses information that is not yet available, i.e. the information for firms with later fiscal year ends. When the analysis is repeated by using lagged industry medians, virtually identical results are obtained. For instance, the high group earned a size-adjusted excess return of 3.8%, while the low group earned a size-adjusted -15.3%, a difference of 19.1%.

Finally, it is possible that some firms delay the release of financial statements, especially if there are some accounting issues or problems facing the firm. Earnings announcement dates were available for 16,865 firms out of the sample of 20,866. Of these, 15,842 released financials within three months of the fiscal year end. When the analysis is repeated on this subgroup, very similar results are observed. The high group earns +3.2%, while the low group earns -16.4%, a difference of 19.6%. To summarize, the results are not impacted by differing fiscal year ends, use of contemporaneous industry median information or differing time lags between fiscal year end and earnings announcement dates.

6 Results: Future Earnings Performance

6.1 Realizations of Earnings In Future Periods

The results in the Section 5 indicate that firms with high G_SCORE earn significantly greater returns than firms with low G_SCORE. This return difference persists after controlling for documented risk factors and anomalies. For market mispricing to explain the success of G_SCORE, it must be the case that the stock market does not fully impound the future implications of current growth fundamentals. Future fundamentals are likely to be stronger for high G_SCORE firms, and the stock market is unable to draw the correlation between current growth fundamentals and future fundamentals.

In this section, I test the first link in this hypothesis by examining future earnings realizations. Table 8 presents the future earnings performance in terms of Return on Assets for the entire sample for which information was available[16]. There is an almost monotonic relationship between ROA and G_SCORE. Firms in the low G_SCORE group had mean one-year ahead ROA of –8.5% as opposed to 11.9% for firms in the high group, a highly significant difference of 20.5%.

An analysis of the number of observations for the high and low group indicates that a lot of firms have missing one-year-ahead ROA information for the low group. This hints at a large number of performance related delistings. I next analyze the relationship between G_SCORE and the frequency of delisting for reasons related to poor performance. I use a methodology similar to Piotroksi (2000) to identify poor performance related delisting. Table 8 also analyzes the relationship between delisting and G_SCORE. Here too, an almost monotonic relationship is observed; while 3.6% of all firms were delisted in the first year for poor performance, this proportion was 7.4% for the low G_SCORE firms and only 0.3% for the high G_SCORE firms.

The results indicate that the future earnings fundamentals of high (low) G_SCORE firms are related to their currently strong (weak) growth fundamentals. The pattern of excess returns documented earlier however suggests that the market is potentially unaware of this link, and must be surprised when earnings realizations of high (low) G_SCORE firms are indeed high (low). To test this more precisely, I examine the stock market's reaction to future earnings realizations.

[16] ROA was winsorized at 1% and 99% to reduce the impact of outliers. Information was available for 17,053 firms.

6.2 Stock Market Reaction to Earnings Realizations

I analyze the stock market reaction to future earnings estimates in two ways. First, I examine the extent to which analysts are surprised by future realizations of earning. Second, I study the stock market's reaction around the window of quarterly earnings announcements. Both analyses are performed for the four quarters following portfolio formation. The results are presented in Table 9.

I measure analyst forecast surprise as the difference between the latest consensus EPS estimate on or before the end of the fiscal quarter as obtained from I/B/E/S and the realization of EPS, scaled by price at the beginning of the period. To ensure consistency, all information is obtained from I/B/E/S. I restrict the sample to include firms only if information for all four quarters is available. Slightly more than half the sample had analyst following (11,565 out of 20,866) and 7493 observations had valid information for all four quarters.[17] Panel A of Table 9 compares the forecast surprise across the firms based on their G_SCORE.

The results indicate that analysts' surprises were generally much more negative for low G_SCORE firms and neutral to less negative for high G_SCORE firms. An analysis of the trend across quarters is also interesting. The difference between the high and low group surprise is only 0.06% in the first quarter after portfolio formation, but rises to 0.13%, 0.25% and 0.80% over the next three quarters. This represents a complete unraveling in performance on the part of the low G_SCORE firms as time progresses. The total difference in mean surprise across the four quarters is 1.23%. This may seem like a small number, but one has to remember that price has been used as a deflator. The median P/E ratio for this sample is around 40, which means that as a percentage of earnings, the difference in surprise can be very substantial.

[17] The constraint of data availability for all four quarters was imposed to allow comparability across the quarters and to sum the surprise/return across the quarters. The results are very similar when no such constraint is imposed.

Using the announcement dates obtained from COMPUSTAT, I examine the reaction around quarterly earnings announcements in the first year after portfolio formation. Buy-and-hold returns are computed for a three-day window (-1 to +1) around earnings announcements. The return on the capitalization decile in the same period is subtracted to obtain size-adjusted returns. Return information was available for all four quarters for 11,945 out of the 20,866 observations. Results are presented in Panel B of Table 9.

For comparison, the one-year ahead size-adjusted returns ($SRET_1$) are also presented. The return difference between the high and low portfolios is only 15.8% for this sub-sample as opposed to 21.2% for the entire sample. This is probably because of the elimination of firms delisted for performance reasons, which would have lowered the returns in the low portfolios until the time of their delisting. The stock market reaction is generally more negative for the low G_SCORE firms and more positive for the high G_SCORE portfolios. The summed quarterly announcement excess returns are 2.17% for the high group and –0.95% for the low group, a significant difference of 3.12%. This difference is almost a fifth of the total annual return difference of 15.8% between the two groups. This indicates that a significant proportion of the underperformance of the low groups and superior performance of the high groups occurs in the 12 trading days around the announcements of future fundamentals. This supports the conjecture that the stock market fails to impound the implications of current fundamentals for future fundamentals for growth firms and is surprised at the realization of future fundamentals.

6.3 Risk vs. Mispricing: Evidence from Risk Factors

The evidence thus far is more consistent with a mispricing based explanation for the return performance of low BM stocks, especially the results that the market fails to impound the information in the current growth fundamentals. To corroborate these results, I compare the portfolios based on G_SCORE on the basis of their risk. I measure risk in two ways – systematic risk as measured by β, and total return variability. The results are presented in Table 10.

I measure β using monthly returns, ensuring that at least 30 months of information is available. This reduces the size of the sample to just over 13,000 observations. As the table indicates, the mean β of the high and low group is virtually identical. The low group has a mean β of 1.26, while the high group has an insignificantly different mean β of 1.30. Even if one assumes a high market premium of 7.5%, this only potentially explains a return difference of 7.5%*0.04, or 0.3%. In contrast, the difference in returns between the high and low group is over 18%.

I measure return variability as the standard deviation of daily returns from the most recent past year, ensuring that at least 100 trading days of information were available. There is a strong negative relationship between G_SCORE and return variability. Firms with low G_SCORE had a mean return variability of 5.03%, almost double that of the low G_SCORE firms. This relationship is probably driven by the fact that earnings and sales growth stability, which are important components of G_SCORE, are strongly correlated with return variability. Hence, one sees an inverse relationship between G_SCORE and return variability, as opposed to a strong positive relationship between G_SCORE and ex-post returns.

To summarize, the ex-post performance of the G_SCORE portfolios in conjunction with an analysis of their riskiness lends credence to the mispricing story over the risk story for the book-to-market effect, at least as far as low BM stocks are concerned.[18]

[18] In an ongoing extension, I compute ex-ante measures of risk using the methodology outlined in Gebhardt, Lee and Swaminathan (2001) and Gode and Mohanram (2003). If, low G_SCORE firms have higher ex-ante risk and high G_SCORE firms have lower ex-ante risk, this would provide further support for the mispricing argument.

7 Conclusions

In this paper, I test whether a fundamentals driven strategy can separate out ex-post winners and losers amongst low book-to-market or growth stocks. I use an approach that combines three aspects into a portfolio strategy that uses financial statement information – earnings and cash flow based fundamentals, factors related to the stock market's naïve extrapolation of current fundamentals and factors that capture the impact of conservatism on the book-to-market ratio. I combine eight signals related to these factors into an index, G_SCORE, and compare the performance of portfolios based on G_SCORE.

The results indicate that the growth oriented fundamental strategy is able to strongly differentiate between future winners and losers. Firms with high G_SCORE earn substantially higher size-adjusted returns than firms with low G_SCORE. The results are robust across partitions based on firm size, analyst following and exchange listing and do not depend on the inclusion or exclusion of IPO firms. In addition, the strategy works even if one focuses solely on fast growing firms or high technology firms. G_SCORE is also strongly positively associated with future returns after controlling for well documented risk factors and anomalies such as book-to-market, accruals and momentum.

I further find that future earnings realizations are strongly correlated to current growth fundamentals, and that the markets in general and analysts in particular are surprised relatively positively for high G_SCORE firms and negatively for low G_SCORE firms. This indicates that the market does not understand the correlation between current growth fundamentals and future fundamentals. This provides an interesting insight into the results of papers like La Porta (1996) that identify naïve extrapolation on the part of stock markets. My result indicates that the market fails to consider a firm's historical earnings and growth variability in determining whether the firm will be able to maintain its current performance or not.

This paper contributes to the growing literature on financial statement analysis by showing that its effectiveness even for growth firms. Traditionally, the focus for growth firms has been on non-fundamental aspects of their operations. Analysts have looked outside the financial statements in search for drivers of future value. The growth signals outlined in this paper add considerable value in lieu of traditional financial statement analysis. In particular, the signals pertaining to the stability of earnings and growth help identify stocks that are less likely to be overvalued because of naïve extrapolation by stock markets.

This paper also contributes to the debate as to whether the book-to-market effect is caused by risk or mispricing. Firms with high G_SCORE ratings have virtually identical systematic risk and much lower return volatility than low G_SCORE firms and yet they significantly outperform low G_SCORE firms. Further, the G_SCORE strategy returns positive returns in all 21 years analyzed. This is inconsistent with a risk based explanation and provides support for a mispricing based explanation for the book-to-market effect for low BM firms.

References

Abarbanell, J., and B. Bushee, "Financial statement analysis, Future Earnings and Stock Prices", Journal of Accounting Research (35), 1997, 1-24.

Ali, A., L. Hwang, and M.Trombley, "Arbitrage Risk and the Book-to-Market Anomaly", Journal of Financial Economics (69-2), 2003, 355-373.

Barth, M., J. Elliott and M. Finn, "Market Rewards Associated with Patterns of Increasing Earnings", Journal of Accounting Research (37-2), 1999, 387-413.

Bartov, E. and M. Kim, "Risk Mispricing and Value Investing", Working Paper, New York University/University of Missouri-Columbia, 2002.

Bartov, E., P. Mohanram and C. Seethamraju, "Valuation of Internet Firms: An IPO Perspective", Journal of Accounting Research (40-2), 2002, 321-346.

Beneish, M.D., C.M. Lee and R.L.Tarpley, "Contextual Financial statement analysis through the Prediction of Extreme Returns", Review of Accounting Studies (6), 2001, 165-189.

Bernard, V, "The Feltham-Ohlson Framework: Implications for Empiricists", Contemporary Accounting Research (11-2), 1995, 733-747.

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

Chan, L., N. Jegadeesh and T. Sougiannis, "Momentum Strategies", Journal of Finance (51), 1996, 1681-1713.

Chan, L., J. Lakonishok and T. Sougiannis, "The Stock Market Valuation of Research and Development Expenditures", Journal of Finance (56), 2001, 2431-2456.

Damodaran, A., "The Dark Side of Valuation", Prentice Hall (2001) – pp 479.

Dechow, P. and R. Sloan, "Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses", Journal of Financial Economics (43), 1997, 3-27.

Doukas, J.A., C.F. Kim, and C. Pantzalis, "A test of the error-expectations explanation of the value/glamour stock returns performance: Evidence from analysts' forecasts", Journal of Finance (57), 2002, 2143 - 2166.

Fama, E., and K. French, "The Cross-Section of Expected Stock Returns", Journal of Finance (47), 1992, 427-465.

Field, L., and G. Hanka, "The Expiration of IPO Share Lockups", Journal of Finance (56-2), 2001, 471-500.

Gebhardt, W., C. Lee, and B. Swaminathan, "Toward an Implied Cost of Capital", Journal of Accounting Research (39-1), 2001, 135-176.

Gode, D. and P. Mohanram, "Inferring the Cost of Capital Using the Ohlson–Juettner Model", Review of Accounting Studies (8), 2003, 399-431.

Griffin, J., and M. Lemmon, “Book-to-Market Equity, Distress Risk, and Stock Returns”, Journal of Finance (57), 2002, 2317 - 2336.

Huberts, L. and R. Fuller, “Predictability Bias in the U.S. Equity Market”, Financial Analysts Journal (March-April), (1995), 12-28.

Lakonishok, J., A. Shleifer and R. Vishny, “Contrarian Investment, Extrapolation and Risk”, Journal of Finance (44), 1994, 1541-1578.

La Porta, R., “Expectations and the Cross Section of Stock Returns”, Journal of Finance (51), 1996, 1715-1742.

La Porta, R., J. Lakonishok, A. Shleifer and R. Vishny, “Good News for Value Stocks: Further Evidence on Market Efficiency”, Journal of Finance (52), 1997, 859-874.

Lev B. and R. Thiagarajan, “Fundamental Information Analysis”, Journal of Accounting Research (31), 1993, 190-214.

Lev B. and T. Sougiannis, “Capitalization, Amortization and Value-Relevance of R&D”, Journal of Accounting and Economics (21-1), 1996, 107-139.

Ou, J. and S. Penman, “Accounting Measures, Price-Earnings Ratio and the Information Content of Security Prices”, Journal of Accounting Research (27), 1989, 111-143.

Penman, S. and X. Zhang, “Accounting Conservatism, the Quality of Earnings, and Stock Returns” The Accounting Review (77-2), 2002, 237-264.

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

Richardson, J., R. Sloan, M. Soliman and I. Tuna, “Accrual Reliability, Earnings Persistence and Stock Prices”, Working Paper, University of Pennsylvania/ University of Michigan, 2004.

Richardson, J. and R. Sloan, “External Financing, Capital Investment and Future Stock Returns”, Working Paper, University of Pennsylvania/University of Michigan, 2004.

Shumway, T, “The Delisting Return Bias in CRSP Data”, Journal of Finance (52), 1997, 327 - 340.

Skinner, D. and R. Sloan, “Earnings Surprises, Growth Expectations, and Stock Returns or Don't Let an Earnings Torpedo Sink Your Portfolio”, Review of Accounting Studies (7), 2002, 289-312.

Sloan, R., “Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings”, The Accounting Review (71), 1996, 289-316.

Soliman, M., “Using Industry-Adjusted Dupont Analysis to Predict Future Profitability”, Working Paper, Stanford University, 2004.

Trueman, B., F. Wong and X. Zhang, “The Eyeballs Have It: Searching for the Value in Internet Stocks”, Journal of Accounting Research (38-2), 2000, 137-162.

Vassalou, M. and Y. Xing, “Default risk in equity returns”, Journal of Finance (59-2), 2004, 831-868.

TABLE 1

Descriptive Statistics for Low Book-to-Market Firms between 1979 and 1999

In this table below, accounting ratios such as Return on Assets, Return on Equity and Sales growth have been winsorized at 1% and 99%. Returns are size-adjusted by subtracting the returns for the same capitalization decile in the same period. Returns are calculated as the buy-and-hold returns for two consecutive one-year periods starting 4 months after fiscal year end. When a firm delists, delisting returns are used as in Shumway (1997). Observations are lower for the second year as some firms delist in year 1 (17,228 as opposed to 20,866 for year 1).

Panel A: Firm Characteristics (in the year of portfolio formation)

	Low BM Firm (20,866 observations)			All Firms (104,327 observations)		
Variable	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Market Value of Equity	1965.4	123.6	11371.4	1084.8	80.5	6581
Book Value of Equity	266.7	18.5	1402.2	452.3	46.5	2062
Book-to-Market Ratio	0.086	0.177	0.464	0.791	0.614	0.731
Assets	1069.6	54.9	9891.2	2161.4	117.1	14281
Sales	871.9	51.1	4484.3	1068.2	96.8	5047
Net Income	54.6	1.9	364.3	51.1	3.3	313
Return on Assets	-1.3%	7.4%	24.7%	2.3%	5.7%	15.3%
Return on Equity	13.1%	15.7%	157.5%	3.0%	9.9%	43.3%
Sales Growth	30.9%	19.5%	49.8%	17.3%	10.1%	38.2%
R&D as a % of Assets	6.3%	0.1%	14.1%	3.0%	0%	8.4%
Proportion of IPO Firms	22.3%			11.9%		

Panel B: Distribution of Annual Buy-and-hold Returns

Returns	Mean	10^{th} percentile	25^{th} Percentile	Median	75% Percentile	90^{th} Percentile	Proportion Positive
One Year Ahead							
Raw Return	8.2%	-63.1%	-36.4%	-3.6%	31.5%	82.2%	45.7%
Size-adjusted	-6.0%	-74.3%	-47.2%	-15.0%	15.9%	61.4%	36.4%
Two Year Ahead							
Raw Return	9.8%	-57.1%	-31.4%	-1.4%	31.4%	79.2%	47.8%
Size-adjusted	-4.2%	-69.2%	-42.8%	-12.4%	17.0%	59.7%	37.8%

TABLE 2

Correlations amongst Fundamental Signals

G1:G8 are 8 fundamental signals tailored for growth firms. These signals have a default of 0, and equal 1 if some criteria are met. The criteria for each signal are presented on the table itself. The signals are based on the following ratios. ROA is Net Income scaled by beginning of period assets, CFROA is cash from operations scaled by beginning of period assets. VARROA is the variance of ROA measured over the past 3-5 years. VARSGR is the variance of annual sales growth measured over the past 3-5 years. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. Industry medians are calculated at the 2 digit SIC code amongst low book-to-market firms. As all variables are dummy variables, Spearman rank-order correlations and Pearson correlations are the same. N = 20866

	G1	G2	G3	G4	G5	G6	G7	G8
G1: ROA_t > Ind. Median ROA_t	1.000	0.450	-0.185	0.294	0.175	-0.083	0.090	0.031
G2: $CFROA_t$ > Ind. Median $CFROA_t$		1.000	0.295	0.259	0.218	-0.053	0.132	0.002
G3: $CFROA_t$ > ROA_t			1.000	-0.006	0.073	-0.007	0.054	-0.070
G4: $VARROA_t$< Ind. Median $VARROA_t$				1.000	0.361	-0.083	0.091	0.001
G5: $VARSGR_t$< Ind. Median $VARSGR_t$					1.000	-0.053	0.040	0.028
G6: $RDINT_t$ > Ind. Median $RDINT_t$						1.000	0.052	0.033
G7: $CAPINT_t$ > Ind. Median $CAPINT_t$							1.000	0.011
G8: $ADINT_t$ > Ind. Median $ADINT_t$								1.000

TABLE 3

Relation between Individual Signals and Future Returns

G1:G8 are 8 fundamental signals tailored for growth firms. These signals have a default of 0, and equal 1 if some criteria are met. The criteria for each signal are presented on the table itself. The signals are based on the following ratios. ROA is Net Income scaled by beginning of period assets, CFROA is cash from operations scaled by beginning of period assets. VARROA is the variance of ROA measured over the past 3-5 years. VARSGR is the variance of annual sales growth measured over the past 3-5 years. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. Industry medians are calculated at the 2 digit SIC code amongst low book-to-market firms. Returns are size-adjusted by subtracting the returns for the same capitalization decile in the same period. $SRET_1$ is the size-adjusted buy-and-hold returns for one-year periods starting 4 months after fiscal year end. $SRET_2$ is the size-adjusted buy-and-hold returns for one-year period following $SRET_1$. When a firm delists, delisting returns are used as in Shumway (1997). Observations are lower for $SRET_2$ as some firms delist in year 1. t- statistics for the mean differences are from 2 sample t-tests.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

Panel A: $SRET_1$ (One-Year Ahead Size-adjusted Returns)

SIGNAL	(0)		(1)			
	N	Mean	N	Mean	(1) – (0)	T Stat
G1: ROA_t >= Ind. Median ROA_t	11017	-9.8%	9849	-1.7%	8.1%	7.68***
G2: $CFROA_t$ >= Ind. Median $CFROA_t$	10968	-11.0%	9898	-0.4%	10.7%	10.04***
G3: $CFROA_t$ >= ROA_t	8668	-8.3%	12198	-4.3%	4.0%	3.73***
G4: $VARROA_t$<= Ind. Median $VARROA_t$	12632	-8.3%	8234	-2.5%	5.8%	5.70***
G5: $VARSGR_t$<= Ind. Median $VARSGR_t$	13795	-8.3%	7071	-1.5%	6.8%	6.62***
G6: $RDINT_t$ >= Ind. Median $RDINT_t$	15084	-8.3%	5782	0.1%	8.4%	6.02***
G7: $CAPINT_t$ >= Ind. Median $CAPINT_t$	10202	-6.7%	10664	-5.3%	1.4%	1.30
G8: $ADINT_t$ >= Ind. Median $ADINT_t$	16924	-6.7%	3942	-3.1%	3.6%	3.00***

Panel B: $SRET_2$ (Two-Year Ahead Size-adjusted Returns)

SIGNAL	(0)		(1)			
	N	Mean	N	Mean	(1) – (0)	T Stat
G1: ROA_t >= Ind. Median ROA_t	9109	-6.2%	9254	-2.3%	3.9%	3.50***
G2: $CFROA_t$ >= Ind. Median $CFROA_t$	9235	-7.8%	9128	-0.7%	7.1%	6.38***
G3: $CFROA_t$ >= ROA_t	7771	-7.1%	10592	-2.2%	5.0%	4.46***
G4: $VARROA_t$<= Ind. Median $VARROA_t$	10673	-6.2%	7690	-1.7%	4.5%	4.21***
G5: $VARSGR_t$<= Ind. Median $VARSGR_t$	11902	-5.5%	6461	-2.1%	3.4%	3.27***
G6: $RDINT_t$ >= Ind. Median $RDINT_t$	13232	-6.3%	5131	0.9%	7.2%	5.00***
G7: $CAPINT_t$ >= Ind. Median $CAPINT_t$	8821	-5.3%	9542	-3.3%	1.9%	1.75*
G8: $ADINT_t$ >= Ind. Median $ADINT_t$	14889	-4.5%	3474	-3.3%	1.1%	0.96

Significant at *** 1% level ** 5% level * 10% level using a 2 tailed test

TABLE 4
Returns to an Investment Strategy Based on Growth Fundamental Signals

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. G1:G8 have a default value of 0 and equal 1 if the following criteria are met respectively. G1: ROA > Ind. Median, G2: CFROA > Ind. Median, G3: CFROA > ROA, G4: VARROA< Ind. Median, G5: VARSGR< Ind. Median, G6: RDINT > Ind. Median, G7: CAPINT > Ind. Median, G8: ADINT > Ind. Median. ROA is Net Income scaled by beginning of period assets, CFROA is cash from operations scaled by beginning of period assets. VARROA is the variance of ROA measured over the past 3-5 years. VARSGR is the variance of annual sales growth measured over the past 3-5 years. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. Industry medians are calculated at the 2 digit SIC level. Returns are size-adjusted by subtracting the returns for the same capitalization decile in the same period. RET_1 and $SRET_1$ are the raw and size-adjusted buy-and-hold returns respectively, for one-year periods starting 4 months after fiscal year end. RET_2 and $SRET_2$ are the raw and size-adjusted buy-and-hold returns respectively, for one-year period following $SRET_1$. When a firm delists, delisting returns are used as in Shumway (1997). Observations are lower for $SRET_2$ as some firms delist in year 1. t-statistics for the mean differences are from 2 sample t-tests. z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

Panel A: Distribution of RET_1 (One-Year Ahead Raw Returns)

G_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	589	-12.6%	-76.7%	-57.4%	-23.7%	12.5%	65.2%	30.4%
1	2706	-2.1%	-75.0%	-51.6%	-18.4%	15.4%	71.4%	35.2%
2	4430	5.1%	-70.0%	-45.2%	-11.2%	26.3%	87.8%	40.0%
3	4514	7.8%	-63.5%	-39.3%	-6.4%	32.2%	87.3%	43.7%
4	3590	11.6%	-55.4%	-30.5%	0.0%	35.9%	84.7%	48.8%
5	2747	16.5%	-47.7%	-21.4%	5.4%	38.6%	84.0%	56.1%
6	1667	15.6%	-39.8%	-14.7%	6.9%	35.6%	75.4%	58.8%
7	551	21.1%	-27.5%	-10.7%	11.2%	40.2%	77.7%	61.5%
8	72	31.1%	-14.1%	0.4%	20.1%	39.7%	64.6%	76.4%
ALL	20866	8.2%	-63.1%	-36.4%	-3.6%	31.5%	82.2%	45.7%
HIGH (6,7,8)	2290	17.4%	-37.1%	-13.5%	8.0%	37.0%	75.2%	60.0%
LOW (0,1)	3295	-4.0%	-75.0%	-52.0%	-19.3%	15.0%	70.0%	34.4%
HIGH - LOW		21.4%			27.3%			25.7%
t-stat/z-stat		10.71***			21.51***			19.52***

Panel B: Distribution of $SRET_1$ (One-Year Ahead Size-adjusted Returns)

G_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	589	-26.5%	-90.6%	-68.8%	-32.7%	1.9%	44.1%	26.1%
1	2706	-16.0%	-87.1%	-61.7%	-29.4%	3.7%	52.7%	27.8%
2	4430	-9.0%	-82.7%	-55.7%	-23.7%	12.1%	66.0%	32.0%
3	4514	-6.3%	-74.9%	-49.0%	-18.2%	17.4%	64.9%	35.9%
4	3590	-2.8%	-67.4%	-41.7%	-10.7%	19.3%	64.4%	39.3%
5	2747	1.7%	-58.1%	-33.0%	-6.0%	20.6%	61.5%	43.4%
6	1667	1.4%	-50.3%	-27.5%	-4.6%	19.0%	54.1%	44.4%
7	551	7.3%	-39.5%	-21.6%	-0.2%	25.6%	57.7%	49.7%
8	72	16.8%	-32.9%	-8.2%	4.7%	28.4%	49.7%	59.7%
ALL	20866	-6.0%	-74.3%	-47.2%	-15.0%	15.9%	61.4%	36.4%
HIGH (6,7,8)	2290	3.3%	-47.5%	-25.7%	-3.3%	20.9%	55.4%	46.2%
LOW (0,1)	3295	-17.9%	-87.5%	-62.8%	-30.4%	3.6%	50.8%	27.5%
HIGH - LOW		21.2%			27.0%			18.7%
t-stat/z-stat		11.07***			20.99***			14.38***

Panel C: Distribution of RET_2 (Two-Year Ahead Raw Returns)

G_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	479	-12.3%	-71.9%	-53.6%	-21.4%	12.5%	56.7%	31.1%
1	2179	3.2%	-69.0%	-44.4%	-12.2%	22.5%	78.5%	38.4%
2	3725	6.2%	-65.0%	-41.7%	-9.1%	27.3%	85.7%	42.0%
3	3934	10.0%	-57.1%	-34.1%	-4.2%	31.4%	85.0%	45.7%
4	3255	10.9%	-54.1%	-28.7%	-0.6%	31.9%	77.0%	48.5%
5	2596	12.6%	-44.2%	-20.5%	4.4%	33.8%	72.0%	55.1%
6	1594	13.7%	-36.1%	-14.3%	7.0%	33.7%	65.5%	59.1%
7	531	19.9%	-28.7%	-7.7%	9.3%	36.2%	69.6%	63.5%
8	70	10.7%	-27.8%	-12.0%	2.1%	32.6%	49.5%	55.7%
ALL	18363	9.0%	-57.6%	-31.9%	-2.0%	30.5%	78.1%	47.2%
HIGH (6,7,8)	2195	15.1%	-33.7%	-12.2%	7.4%	34.1%	66.5%	60.0%
LOW (0,1)	2658	0.4%	-69.6%	-46.2%	-13.7%	21.2%	75.5%	37.1%
HIGH - LOW		14.7%			21.1%			23.0%
t-stat/z-stat		7.21***			17.12***			16.34***

Panel D: Distribution of $SRET_2$ (Two-Year Ahead Size-adjusted Returns)

G_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	479	-26.1%	-89.1%	-61.5%	-34.5%	0.0%	45.8%	25.1%
1	2179	-10.5%	-84.7%	-56.4%	-23.0%	13.4%	60.9%	31.8%
2	3725	-7.1%	-77.5%	-51.8%	-20.9%	14.6%	68.1%	33.7%
3	3934	-3.5%	-69.8%	-44.0%	-14.6%	17.4%	66.6%	37.1%
4	3255	-2.0%	-64.6%	-39.6%	-10.1%	18.2%	58.1%	39.8%
5	2596	-0.6%	-56.1%	-32.1%	-6.6%	20.1%	54.8%	42.5%
6	1594	1.3%	-47.3%	-24.5%	-2.5%	19.1%	51.8%	46.7%
7	531	6.4%	-41.2%	-19.5%	0.0%	22.1%	50.5%	49.9%
8	70	-1.7%	-39.6%	-22.9%	-4.9%	17.9%	37.0%	44.3%
ALL	18363	-4.3%	-69.2%	-42.9%	-12.5%	16.9%	59.4%	38.0%
HIGH (6,7,8)	2195	2.4%	-45.9%	-22.9%	-2.1%	19.9%	51.1%	47.4%
LOW (0,1)	2658	-13.3%	-85.1%	-57.4%	-25.0%	11.3%	57.1%	30.6%
HIGH - LOW		15.8%			22.8%			16.8%
t-stat/z-stat		7.94***			16.85***			12.10***

TABLE 5

Returns to an Investment Strategy Based on Modified Fundamental Signals by Partitions

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. Details are at the top of Table 4. Size Partitions are based on market capitalization at time of portfolio formation. Analyst-following partitions are on the basis of most recent analyst following on IBES – groups are not of equal size because of the substantial number of firms without analyst following. Firms with annual sales growth rates in excess of the median amongst low BM firms in the same 2 digit SIC code are classified as fast growing firms. The Hi-Tech classification is based on Field and Hanka (2001) – see footnote 14 for details. $SRET_1$ is the size-adjusted buy-and-hold returns for one-year periods starting 4 months after fiscal year end. When a firm delists, delisting returns are used as in Shumway (1997). t- statistics for the mean differences are from 2 sample t-tests. z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

Panel A: One-Year Ahead Size-adjusted Returns by Size Partitions

G_SCORE	SMALL FIRMS			MEDIUM FIRMS			LARGE FIRMS		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
0	344	-27.2%	-35.9%	188	-26.0%	-26.9%	57	-24.1%	-30.3%
1	1423	-14.3%	-32.9%	886	-19.1%	-27.3%	397	-15.5%	-22.4%
2	2042	-6.7%	-25.4%	1600	-12.0%	-26.7%	788	-8.6%	-15.9%
3	1649	-7.9%	-24.4%	1666	-7.6%	-19.5%	1199	-2.3%	-10.0%
4	908	-7.3%	-17.2%	1316	-0.4%	-11.7%	1366	-2.1%	-7.3%
5	427	1.1%	-16.6%	803	4.5%	-6.8%	1517	0.4%	-3.6%
6	131	2.3%	-11.7%	395	1.4%	-5.3%	1141	1.3%	-3.9%
7	24	-4.6%	-12.0%	95	8.5%	-0.3%	432	7.7%	1.5%
8	2	370.4%	370.4%	12	2.8%	4.0%	58	7.5%	4.7%
ALL	6950	-8.9%	-25.1%	6963	-7.0%	-17.6%	6953	-2.1%	-7.0%
HIGH (6,7,8)	157	6.0%	-11.7%	502	2.8%	-2.8%	1631	3.2%	-2.9%
LOW (0,1)	1767	-16.8%	-33.7%	1074	-20.3%	-27.2%	454	-16.6%	-22.9%
HIGH - LOW		22.8%	21.9%		23.1%	24.4%		19.8%	20.0%
t-stat/z-stat		3.13^{***}	5.41^{***}		6.60^{***}	9.51^{***}		6.64^{***}	9.70^{***}

Panel B: One-Year Ahead Size-adjusted Returns by Analyst Following Partitions

G_SCORE	NO FOLLOWING			LIMITED FOLLOWING			EXTENSIVE FOLLOWING		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
0	422	-27.1%	-34.7%	128	-26.5%	-29.1%	39	-20.7%	-15.4%
1	1661	-17.8%	-30.9%	770	-13.6%	-29.0%	275	-12.5%	-21.7%
2	2303	-12.8%	-26.5%	1403	-3.8%	-21.7%	724	-6.8%	-16.2%
3	2137	-10.3%	-20.9%	1354	-3.6%	-19.8%	1023	-1.5%	-10.0%
4	1473	-6.8%	-15.0%	970	-2.6%	-10.0%	1147	2.2%	-5.7%
5	828	-0.7%	-9.1%	626	4.5%	-5.7%	1293	1.9%	-4.2%
6	355	0.4%	-5.6%	305	-0.6%	-5.8%	1007	2.4%	-3.7%
7	106	-1.2%	-5.1%	68	7.7%	-5.2%	377	9.6%	2.5%
8	16	46.6%	-1.5%	2	-16.2%	-16.2%	54	9.2%	6.2%
ALL	9301	-11.0%	-21.2%	5626	-4.2%	-16.8%	5939	0.1%	-6.7%
HIGH (6,7,8)	477	1.6%	-5.1%	375	0.8%	-5.8%	1438	4.5%	-1.8%
LOW (0,1)	2083	-19.6%	-31.8%	898	-15.5%	-29.0%	314	-13.5%	-21.6%
HIGH - LOW		21.3%	26.8%		16.3%	23.2%		18.1%	19.8%
t-stat/z-stat		6.19^{***}	10.76^{***}		4.35^{***}	7.86^{***}		3.58^{***}	8.39^{***}

Panel C: One-Year Ahead Size-adjusted Returns by Exchange Listing / IPO Partition

G_SCORE	NYSE/AMEX			NASDAQ		
	N	Mean	Median	N	Mean	Median
0	162	-17.5%	-19.2%	427	-29.9%	-39.1%
1	828	-9.6%	-16.3%	1878	-18.9%	-35.7%
2	1393	-4.6%	-15.2%	3037	-11.0%	-28.0%
3	1634	-1.8%	-9.9%	2880	-8.8%	-24.0%
4	1572	-2.1%	-6.7%	2018	-3.3%	-14.4%
5	1440	1.4%	-3.0%	1307	2.0%	-9.5%
6	961	0.6%	-3.9%	706	2.6%	-5.9%
7	343	4.6%	2.3%	208	11.7%	-3.7%
8	54	7.2%	4.7%	18	45.7%	4.0%
ALL	8387	-2.2%	-7.9%	12479	-8.5%	-22.3%
HIGH (6,7,8)	1358	1.8%	-2.4%	932	5.5%	-5.1%
LOW (0,1)	990	-10.9%	-16.5%	2305	-21.0%	-36.1%
HIGH - LOW		12.7%	14.2%		26.4%	31.0%
t-stat/z-stat		5.36**	9.74***		8.58*	15.32***

G_SCORE	IPO FIRMS			NON-IPO FIRMS		
	N	Mean	Median	N	Mean	Median
0	321	-28.7%	-35.6%	268	-23.9%	-30.4%
1	1081	-17.3%	-33.5%	1625	-15.2%	-26.2%
2	1443	-12.7%	-29.2%	2987	-7.2%	-21.2%
3	1078	-7.1%	-23.0%	3436	-6.0%	-16.7%
4	554	-8.7%	-13.8%	3036	-1.7%	-10.4%
5	152	8.9%	-8.0%	2595	1.3%	-5.7%
6	21	30.9%	16.9%	1646	1.1%	-4.8%
7	0			551	7.3%	-0.2%
8	0			72	16.8%	4.7%
ALL	4650	-12.2%	-26.7%	16216	-4.2%	-12.3%
HIGH (6,7,8)	21	30.9%	16.9%	2269	3.1%	-3.6%
LOW (0,1)	1402	-19.9%	-33.9%	1893	-16.5%	-26.7%
HIGH - LOW		50.8%	50.8%		19.5%	23.2%
t-stat/z-stat		4.47***	4.54***		8.62***	16.73***

Panel D: One-Year Ahead Size-adjusted Returns by Growth Related Partitions

G_SCORE	FAST GROWING FIRMS			SLOW GROWING FIRMS		
	N	Mean	Median	N	Mean	Median
0	135	-24.1%	-29.6%	133	-23.6%	-30.7%
1	769	-16.6%	-27.7%	856	-14.0%	-24.9%
2	1439	-10.8%	-25.3%	1548	-3.8%	-16.7%
3	1693	-6.1%	-17.7%	1743	-6.0%	-15.3%
4	1536	-0.4%	-11.2%	1500	-3.1%	-9.1%
5	1226	2.7%	-5.3%	1369	0.0%	-6.2%
6	711	0.8%	-6.5%	935	1.3%	-3.7%
7	249	7.1%	-2.9%	302	7.4%	1.3%
8	25	9.1%	13.9%	47	20.9%	4.0%
ALL	7783	-4.7%	-14.1%	8433	-3.7%	-10.8%
HIGH (6,7,8)	985	2.6%	-5.3%	1284	3.4%	-2.1%
LOW (0,1)	904	-17.7%	-28.0%	989	-15.3%	-26.0%
HIGH - LOW		20.3%	22.7%		18.7%	23.9%
t-stat/z-stat		6.50***	10.60***		5.67***	12.78***

G_SCORE	HI-TECH FIRMS			Non HI-TECH FIRMS		
	N	Mean	Median	N	Mean	Median
0	49	-17.4%	-18.1%	540	-27.3%	-34.1%
1	353	-12.0%	-35.0%	2353	-16.7%	-28.4%
2	625	-7.3%	-22.7%	3805	-9.3%	-24.1%
3	699	-7.8%	-20.0%	3815	-6.0%	-17.8%
4	574	1.1%	-10.8%	3016	-3.5%	-10.6%
5	452	6.7%	-10.4%	2295	0.7%	-4.8%
6	260	5.4%	-6.8%	1407	0.7%	-3.9%
7	118	5.5%	-3.5%	433	7.7%	1.2%
8	15	-0.3%	6.0%	57	21.3%	3.1%
ALL	3145	-3.0%	-17.0%	17721	-6.5%	-14.7%
HIGH (6,7,8)	393	5.2%	-5.6%	1897	2.9%	-2.7%
LOW (0,1)	402	-12.6%	-34.2%	2893	-18.7%	-29.6%
HIGH - LOW		17.8%	28.6%		21.6%	26.9%
t-stat/z-stat		2.56***	7.96***		11.06***	19.46***

TABLE 6

Performance of Hi-Low Strategy across Time

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. Details are at the top of Table 4. $SRET_1$ is the size-adjusted buy-and-hold returns for one-year periods starting 4 months after fiscal year end. When a firm delists, delisting returns are used as in Shumway (1997). t- statistics for the mean differences are from 2 sample t-tests.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

	High G_SCORE (G_SCORE=6,7,8)		Low G_SCORE (G_SCORE=0,1)			
Year	N	Mean $SRET_1$	N	Mean $SRET_1$	Difference	T Statistic
1979	60	29.8%	83	24.2%	5.6%	0.24
1980	54	-1.7%	116	-21.6%	19.9%	2.81***
1981	48	4.7%	131	-21.5%	26.2%	1.88*
1982	68	-5.3%	126	-24.4%	19.1%	3.66***
1983	62	-15.9%	144	-17.4%	1.6%	0.25
1984	83	-0.2%	136	-22.6%	22.5%	3.10***
1985	100	6.3%	120	-4.9%	11.2%	1.40
1986	114	0.8%	142	-11.2%	12.0%	2.22**
1987	133	-2.4%	165	-18.7%	16.2%	2.82***
1988	119	11.9%	133	-17.4%	29.4%	4.88***
1989	135	10.4%	129	-13.1%	23.6%	2.47**
1990	140	3.2%	118	-17.0%	20.1%	2.39**
1991	122	-3.1%	129	-28.7%	25.6%	3.71***
1992	111	1.5%	150	-8.2%	9.7%	1.23
1993	133	3.8%	196	-24.3%	28.0%	3.76***
1994	133	6.1%	228	-13.5%	19.6%	2.79***
1995	116	-15.1%	236	-35.6%	20.4%	4.74***
1996	125	-3.5%	233	-23.2%	19.7%	2.46**
1997	146	0.3%	208	-5.2%	5.4%	0.75
1998	140	26.1%	187	-5.1%	31.2%	2.20**
1999	148	5.1%	185	-38.9%	44.0%	3.91***
ALL YEARS	2290	3.3%	3295	-17.9%	21.2%	11.07***

TABLE 7

Cross-Sectional Regression for Annual Returns

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. Details are at the top of Table 4. The dependent variable is $SRET_1$, the size-adjusted buy-and-hold returns for one-year periods starting 4 months after fiscal year end. When a firm delists, delisting returns are used as in Shumway (1997). SIZE is measured as log of market capitalization. LBM is the log of the book-to-market ratio. MOM is the buy and old return for the six month period before portfolio formation. ACCR is a dummy that equals 1 if net income exceeds cash from operations. EQ_OFF is a dummy that equals 1 if a firm issued equity in the year prior to portfolio formation. Figures in brackets are t-statistics. For the year-by-year regressions, the figures presented are averages from 21 annual regressions from 1979 to 1999. The t-statistics are adjusted for auto-correlation using the method outlined in Bernard (1995). Number of observations is less than 20,866 because return momentum was not available for all firms, especially firms with IPOs in the past 6 months.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

MODEL	Intercept	SIZE	LBM	MOM	ACCR	EQ_OFF	G_SCORE	Adj. R^2
Panel A: Pooled Regressions (N=17,075)								
(1)	-0.026	0.016	0.069	0.116				0.87%
	(-1.16)	(5.41) ***	(6.84) ***	(9.40) ***				
(2)	-0.122	0.001	0.046	0.112			0.039	1.45%
	(-5.05) ***	(0.39)	(4.45) ***	(9.09) ***			(10.07) ***	
(3)	-0.019	0.016	0.071	0.116	-0.045	-0.006		0.88%
	(-0.76)	(5.43) ***	(6.96) ***	(9.44) ***	(-1.68) *	(-0.39)		
(4)	-0.126	0.001	0.046	0.112	0.003	0.006	0.039	1.44%
	(-4.70) ***	(0.34)	(4.37) ***	(9.08) ***	(0.10)	(0.38)	(9.92) ***	
Panel B: Year by Year Regressions (N varies from 653 in 1979 to 1212 in 1999)								
(1)	-0.113	0.002	0.045	0.172			0.031	2.86%
	(-2.64) ***	(0.61)	(1.60)	(4.26)*			(7.33)***	
(2)	-0.116	-0.001	0.045	0.162	0.004	-0.020	0.037	3.67%
	(-2.54) **	(-0.25)	(1.65) *	(4.41) ***	(0.05)	(-0.97)	(7.04) ***	

TABLE 8
Relation between G_SCORE and Future Earnings Performance

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. Details are at the top of Table 4. ROA_{t+1} is the realized Return on Assets for the year after portfolio formation, winsorized at 1% and 99%. Delisting information is for the first year after portfolio information and was obtained from CRSP. Firms were regarded as delisting for reasons of poor performance if the delisting code was 500 (reason unavailable), 520 (now trades on OTC), 551-573 and 580 (miscellaneous performance related reasons), 574 (bankruptcy) and 584 (failed to meet exchange specifications). Differences in proportions are tested with a binomial test. t-statistic is for pooled difference of means test for means and z-statistic is for the wilcoxon sign-rank test for medians.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

G_SCORE	N	ROA_{t+1} Mean	ROA_{t+1} Median	N	Performance Delisting (%)
0	469	-8.3%	0.9%	589	6.8%
1	2000	-8.6%	2.2%	2706	7.5%
2	3405	-7.7%	2.8%	4430	5.2%
3	3587	0.1%	6.7%	4514	4.1%
4	3012	6.1%	9.2%	3590	1.9%
5	2464	9.9%	10.7%	2747	0.9%
6	1526	11.5%	11.9%	1667	0.4%
7	521	12.7%	13.2%	551	0.4%
8	69	15.8%	15.1%	72	0.0%
ALL	17053	1.2%	7.7%	20866	3.6%
HIGH (6,7,8)	2116	11.9%	12.3%	2290	0.3%
LOW (0,1)	2469	-8.5%	1.9%	3295	7.4%
HIGH – LOW		20.5%	10.4%		-7.0%
t-stat/z-stat		32.25***	12.46***		-14.89***

TABLE 9

Relation between G_SCORE and Surprises/Returns around Future Earnings Announcements

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. Details are at the top of Table 4. Analyst forecast surprises are defined as the difference between actual realized EPS and the last consensus estimate on or before the end of a fiscal quarter, scaled by the price at the beginning of the quarter. Forecast surprises are winsorized at 1% and 99% to remove the influence of outliers. Returns are calculated in a three-day window around quarterly earnings announcement dates in the first year after portfolio formation. Returns are size-adjusted to ensure comparability with the returns for the entire year, by subtracting the return for the same capitalization decile in the same period. The return for All Quarters is the sum of the returns earned in the windows around each of the 4 quarterly announcements. Firms are included only if all four quarterly announcement dates and the returns for these dates were available. t-statistics for the mean differences are from 2 sample t-tests.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

Panel A: Mean Analyst Forecast Surprises

G_SCORE	N	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	All Quarters
0	65	-0.10%	-0.44%	-0.63%	-2.04%	-3.21%
1	460	-0.08%	-0.14%	-0.28%	-0.78%	-1.28%
2	1073	-0.10%	-0.18%	-0.34%	-0.72%	-1.34%
3	1384	-0.04%	-0.08%	-0.20%	-0.43%	-0.75%
4	1486	-0.02%	-0.09%	-0.20%	-0.39%	-0.71%
5	1489	-0.02%	-0.06%	-0.15%	-0.23%	-0.46%
6	1086	-0.02%	-0.04%	-0.08%	-0.13%	-0.28%
7	398	-0.03%	-0.04%	-0.08%	-0.19%	-0.34%
8	52	-0.04%	-0.03%	0.01%	-0.08%	-0.15%
ALL	7493	-0.04%	-0.09%	-0.19%	-0.40%	-0.73%
HIGH (6,7,8)	1536	-0.03%	-0.04%	-0.08%	-0.14%	-0.29%
LOW (0,1)	525	-0.08%	-0.17%	-0.32%	-0.94%	-1.52%
HIGH - LOW		0.06%	0.13%	0.25%	0.80%	1.23%
t statistic		1.70*	2.61***	3.45***	5.28***	5.59***

Panel B: Mean Returns around Earnings Announcement

G_SCORE	N	Entire Year	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	All Quarters
0	207	-19.92%	-0.44%	-2.36%	0.46%	-0.67%	-3.02%
1	1120	-11.76%	0.76%	-0.41%	-0.09%	-0.83%	-0.57%
2	2240	-6.13%	0.98%	-1.40%	-0.88%	-0.29%	-1.59%
3	2489	-2.56%	0.72%	-0.01%	-1.18%	-0.38%	-0.84%
4	2241	0.07%	0.74%	0.67%	-0.83%	-0.26%	0.32%
5	1913	2.61%	1.59%	1.02%	-0.46%	0.70%	2.86%
6	1247	1.43%	1.11%	1.16%	0.07%	0.16%	2.50%
7	436	6.14%	1.12%	-0.18%	-0.60%	1.17%	1.50%
8	52	5.14%	1.28%	-0.62%	0.97%	-1.61%	0.02%
ALL	11945	-2.30%	0.95%	0.06%	-0.65%	-0.11%	0.26%
HIGH (6,7,8)	1735	2.73%	1.12%	0.77%	-0.07%	0.36%	2.17%
LOW (0,1)	1327	-13.03%	0.57%	-0.71%	-0.01%	-0.81%	-0.95%
HIGH - LOW		15.76%	0.54%	1.48%	-0.07%	1.17%	3.12%
t statistic			0.86	2.38**	-0.10	1.77*	2.40**

TABLE 10
Relation between G_SCORE and Risk Measures

G_SCORE is the sum of 8 fundamental signals, G1:G8, tailored for growth firms. Details are at the top of Table 4. β is calculated using monthly returns, with the requirement that at least 30 observations be available. Return Variability is measured by STDRET, the standard deviation of daily returns in the past year, with the requirement that there at least 100 observations be available. $SRET_1$ mean size-adjusted one-year ahead return. $SRET_1$ is reported separately alongside both β as well as STDRET as the composition of firms that have enough information to calculate β and STDRET is different.

t-statistics for the mean differences are from 2 sample t-tests. . z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

Significance levels using 2 tailed tests are represented by *** 1% level ** 5% level * 10% level

	N	Mean $SRET_1$	Mean β	N	Mean $SRET_1$	Mean STDRET
0	258	-22.8%	1.31	539	-26.7%	5.23%
1	1374	-14.3%	1.25	2423	-13.9%	4.99%
2	2407	-5.3%	1.34	3928	-6.6%	4.71%
3	2677	-5.7%	1.39	4063	-4.6%	4.13%
4	2381	-1.1%	1.36	3279	-1.6%	3.54%
5	2138	1.8%	1.34	2553	2.4%	3.01%
6	1396	0.1%	1.29	1528	1.2%	2.64%
7	501	8.1%	1.33	516	7.5%	2.52%
8	70	17.9%	1.22	70	17.9%	2.21%
ALL	13202	-3.6%	1.34	18899	-4.5%	3.97%
HIGH (6,7,8)	1967	2.8%	1.30	2114	3.3%	2.60%
LOW (0,1)	1632	-15.6%	1.26	2962	-16.2%	5.03%
HIGH - LOW		18.4%	0.03		19.5%	-2.44%
t stat/z stat			1.57			-37.26***