Is Fundamental Analysis Effective for Growth Stocks?

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Current Draft: March 2003

I would like to thank Shyam V. Sunder, Eli Bartov and seminar participants at Columbia University, New York University and the University of California at Berkeley for their comments.

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ABSTRACT

Piotroski (2000) demonstrates that a strategy based on fundamental analysis of value stocks is successful in differentiating between winners and losers in terms of future stock performance. In this paper, I test whether such a strategy works for low book-to-market growth stocks. I create an index (FG_SCORE) based on a combination of traditional fundamentals such as 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 FG_SCORE firms and shorting low FG_SCORE firms consistently earns significant excess returns. The results are robust across partitions based on size, stock price, analyst following and E/P ratios 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 current fundamentals are strong, indicating that the stock market fails to consider the implications of current fundamentals for future fundamentals. Hence, suitably modified, fundamental analysis can be effective even in growth firms. Further, the results do not support a risk based explanation for the Book-to-Market effect as firms that ex-ante appear less risky have better future returns.

1 Introduction

This paper examines whether applying an accounting based fundamental analysis strategy can help investors earn excess returns on a broad sample of low book to market (BM) firms. The BM effect is well documented in research in finance. Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994) amongst others show that BM is highly positively related to future returns. Firms with low BM earn significant negative excess returns, while firms with high BM earn significant positive excess returns. Low BM firms are referred to as growth or glamour stocks, which have experienced very strong stock performance in prior periods, while high BM firms are referred to as value stocks, which have typically underperformed in prior periods.

Firms within each BM category are hardly homogenous. For instance high BM stocks include both undervalued firms with good prospects as well as weak firms with poor prospects. Piotroski (2000) applies fundamental analysis to a sample of high BM (value) stocks to identify the firms that are fundamentally sound and ex-ante have good prospects. He focuses on accounting fundamentals such as profitability, leverage, liquidity and cash flow adequacy. He demonstrates that one can earn significantly greater returns by using such an approach to differentiate between the "winners" and the "losers". He also establishes the link between future financial performance and returns by showing that the stock market is systematically positively surprised by the future earnings of fundamentally strong firms.

In this paper, I use a similar fundamental analysis approach, but on a sample of low BM or growth/glamour stocks. This is potentially a stronger test for the efficacy of fundamental analysis for the following reasons. First, growth stocks are highly covered by analysts and institutional investors. Second, such firms are likely to have many sources of disclosure other than the financial statements. Third, many of these firms are growing rapidly which potentially makes current fundamentals less important as opposed to other measures based on non-financial information. 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 the recent strong stock market performance of these firms.

The results indicate that fundamental analysis, appropriately modified for growth firms, is very successful in differentiating between firms that are likely to perform well in the future and those that are likely to perform very poorly. Low BM stocks as a whole earned a 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 2.1% and 0.9% in the two years, while the weakest firms earned excess returns of –18.2% and –12.3% respectively. A strategy of buying firms with the strongest 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 stock price, and also hold when recent IPO firms are excluded. The success of the strategy is also robust across time, earning positive returns in all years in the sample.

The fundamental analysis strategy is related to firms' expected future performance. Like Piotroksi (2000), firms with stronger fundamentals are much more likely to have better realizations of earnings and much less likely to delist for performance related reasons. The stock market is much more likely to be surprised positively by future earnings announcements of fundamentally strong firms and indicates that the stock markets ignores the implications of current fundamentals for future earnings. Further, analysts are much more likely to be systematically pessimistic (optimistic) for firms whose current fundamentals are strong (weak).

The results of this paper provide an interesting corroboration of Piotroski (2000) in a vastly different sample. They indicate that fundamental analysis, suitably modified can be very successful even for growth firms. More generally, it indicates that fundamental analysis is likely to succeed in much more broad settings that it is normally confined to.

The rest of this paper is organized as follows. Section 2 discusses prior research both on the BM effect as well as on fundamental analysis. Section 3 presents the research design and describes the fundamental signals used in this paper. Section 4 discusses the data and provides summary statistics. Section 5 presents the results to the fundamental analysis strategy. Section 6 analyzes the relationship between fundamental analysis and future accounting performance. Section 7 concludes the paper.

2 Literature Review

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. Similar risk based explanations are also provided in more recent papers by Vassalou (2002) and Doukas, Kim, and Pantzalis (2002). This explanation is less satisfying for low BM firms, as there are few ex-ante reasons to believe that these growth firms are less risky than the stock market as a whole. Lakonishok et al (1994) claim that mispricing is at the core of the BM effect. They show that low BM stocks are glamour stocks that the stock market is too optimistic about. As this optimism unravels with time, these firms earn negative excess returns. This is supported by LaPorta et al (1997) who show that low BM stocks are more likely to have negative earnings surprises. Recent research by Griffin and Lemmon (2002) and Ali et al. (2002) also support a mispricing story. Bartov and Lee (2002) demonstrate that the BM effect is stronger when one considers the accounting related reasons for low BM ratios.

2.2 Fundamental Analysis

Many papers have focused on the usefulness of fundamental analysis using financial statement information 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 (1998) show that developing an investment strategy based on these signals earn significant abnormal returns. Nissim and Penman (2001) provide a rigorous paradigm for carrying out fundamental analysis, using ratios systematically to project future streams of abnormal earnings and free cash flow.

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 fundamental 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 fundamental analysis as financial analysts generally neglect such firms. He argues that historical financial statements the best source of information for analyzing value firms, which makes it more likely that a fundamental approach will lead to success. 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.

This paper essentially replicates Piotroski's approach for growth or low BM firms. While high BM firms may be ideal candidates for fundamental analysis because of their information environment, low BM firms can also be considered as viable candidates for fundamental analysis for the following reasons. First, many of these firms are likely to be valued at the time of their classification as low BM stocks on the basis of something other than fundamentals. This can be the case even despite their having substantial analyst following as the rise and fall of Internet stocks demonstrates. If the valuation of these stocks eventually revert to fundamentals, firms with the strongest fundamentals are least likely to severely underperform in terms of stock market returns. Second, the sample of low BM stocks is not uniform. They can consist of small hyped up stocks with no track record, as well as large established firms that have a low BM ratio because a substantial portion of their asset base lies in unrecorded intangible assets. Fundamental analysis can potentially help us differentiate between these different kinds of firms and identify those firms that are least likely to underperform in the future.

2.3 Growth Firms

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. There has also been a growing stream of papers that have looked at the usefulness of non-financial information for valuation and predicting future performance. Trueman, Wong and Zhang (2000) demonstrate 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.

Beneish, Lee and Tarpley (2001) use a two-stage approach towards fundamental 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 demonstrate the potential efficacy of fundamental analysis for growth firms, as their sample of extreme performers is over-weighted with growth firms as opposed to the general population of firms. The one crucial difference between their approach and the one in this paper is the complete reliance on only financial statement information in this paper. The research design of this paper allows me to directly test the efficacy of fundamental analysis for the entire sample of low BM firms.

3 Research Design

I now identify the financial signals used to separate the low BM firms into categories of potential winners and losers. I consider two categories of signals. The first consists of traditional fundamental signals pertaining to a firm's profitability, cash flow performance, operating efficiency and liquidity, as identified by Piotroski (2000). The second category consists of a set of signals that may add value specifically for growth firms, given that traditional fundamentals may not be as successful in this setting. These signals include measures for the stability of earnings, stability of growth as well as factors related to future growth such as R&D, capital expenditure and advertising expenditure.

The methodology used in codifying these signals and applying them in the analysis is very similar to Piotroski (2000). I first replicate his analysis by creating a composite score using the same signals for the sample of growth firms. Portfolios are formed on the basis of the composite scores and their performance is compared over a two year span after portfolio formation. I also analyze the performance of each of these signals for growth firms and differentiate between the signals that are effective and ineffective for this sample. I then combine the effective signals with new signals that may add value for growth firms and create a new composite score. The performance of this new composite score is then analyzed in terms of portfolio returns.

3.1 Traditional Fundamental Signals

Piotroski identifies nine fundamental signals in his paper. They can be broadly classified into the following four categories – profitability, cash flow profitability, operating efficiency and liquidity. The traditional fundamental signals used in this paper - F1:F9 are defined identically as Piotroski (2000). While this is one of many modes of fundamental analysis, it has the advantage of being simple to execute, comprehensive, and correlating well to how stock screens are typically used in practice for stock picking.

The first two signals are based on profitability, measured on the basis of Return on Assets (ROA). ROA is defined as the ratio of net income before extraordinary items scaled by beginning total assets[1]. I focus on two aspects of profitability – being profitable, and showing an increasing trend of profitability. 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. Further, even if a firm is not currently profitable, if it shows a trend of increasing profitability (or reducing losses), it is potentially more likely to be profitable in the future. Accordingly I define the following two signals. F1 equals 1 if a firm has positive ROA and equals 0 otherwise. F2 equals 1 if a firm's ROA exceeds the ROA of the prior year, and equals 0 otherwise.

The next two signals are defined on the basis of ROA using cash flow from operations instead of net income[2]. Cash flows provide a different, though related, measure of performance than net income. F3 is defined to equal 1 if a firm's cash flow ROA is positive and 0 otherwise. Further, 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, F4 is defined to equal 1 if a firm's cash flow from operations exceeds net income and 0 otherwise.

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

[2] For the years prior to 1988, cash from operations is estimated using the funds from operations and change in working capital. Cash from Operations includes the add-back of depreciation. No adjustment is made for this, consistent with Piotroski (2000) and depreciation is hence treated as a negative accrual. Excluding depreciation from cash from operations reduces the number of firms for which the cash flow based signals (F3 and F4) are positive, but does not affect the results.

The next two signals pertain to firms' operating efficiency. Asset turnover and operating margin are the two components that drive ROA and are an integral part of the well known Dupont framework in financial statement analysis. Asset turnover is defined as the ratio of sales to beginning of period assets. Operating margin is defined as the ratio of gross margin to sales. Asset turnover focuses on a firm's ability to generate sales from its assets, while operating margin measures the success of the firm in generating profits from these sales. The changes in these ratios represent the direction in which firms' fundamentals are potentially headed. Accordingly, F5 is defined to equal 1 if a firm's profit margin is higher than in the previous year, and equals 0 otherwise. F6 equals 1 if a firm's asset turnover exceeds the asset turnover of the prior year, and equals 0 otherwise.

The final three signals pertain to firms' liquidity and cash generation. Myers and Majluf (1984) posit in their pecking order theory that internally generated funds are the most valuable and are firms' preferred financing option. Firms with the strongest fundamentals will rely on internally generated funds, while weaker firms will resort to using debt markets or as a last resort, equity markets to generate funds. Accordingly, the following three signals are defined to identify the strongest firms. F7 is defined to equal 1 if a firm's leverage (measured as the ratio of debt to market value of equity) declines from the prior year, and 0 otherwise. F8 is defined to equal 1 if a firm's current ratio (ratio of current assets to current liabilities) increases from the prior year, and 0 otherwise. F9 is defined to equal 1 if a firm does not issue any equity in a given year and 0 otherwise.

It is an open empirical question as to how effective the traditional fundamental signals will be for growth firms. Such firms are typically at an early stage of their life cycle, which may reduce the predictive ability of measures like earnings as well as ratios such as asset turnover and profit margin. Further, given the fact that many of these firms are not necessarily profitable and have large cash burn rates, cash flow and liquidity measures may assume additional importance.

3.2 Growth Oriented Fundamentals

As discussed above, traditional fundamental analysis can be challenging and potentially unsuccessful for growth firms. However, there may be other sources of information in the financial statements that may have implications for future performance for growth firms. I now attempt to identify signals based on financial statement information that may be useful to identify growth firms with better future prospects.

The first growth signal focuses on the stability of earnings. Prior research by Barth, Elliott and Finn (1999) among others has shown that the stock market eventually rewards firms with stable earnings performance, as these firms are more likely to have better earnings performance in the future. 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 the variability of earnings by calculating the variance of a firm's Return on Assets in the past five years.[3] I then compare the firm to other low BM firms in the same 2 digit SIC code at the same point in time. G1 is defined to equal 1 if a firm's earnings variability is less than the industry median and 0 otherwise.

The second signal relates to the stability of growth. Lakonishok, Shleifer and Vishny (1994) attribute the underperformance of low BM stocks on the overoptimism of the stock markets and the mistaken belief that current strong performance will persist. LaPorta

[3] 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.

(1996) shows that one reason for this is the naïve extrapolation of current growth to predict future growth. Firms that exhibit stable growth are potentially more like to show stable future growth as well, making them less likely to underperform in the future. I measure the variability of sales growth by calculating the standard error of a firm's annualized sales growth 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. G2 is defined to equal 1 if a firm's sale growth variability is less than the industry median and 0 otherwise.

The third growth signal compares the growth in earnings to the growth in revenues. Growth from a valuation perspective refers to the growth in earnings. However, in practice, revenue growth is often used as a proxy for earnings growth, because earnings are often negative making earnings growth difficult to compute.[5] This gives an incentive for managers to maximize revenue growth, even if it comes at the expense of earnings growth. This is exacerbated in the case of growth stocks, which quite often are not profitable and are hence valued on the basis of revenue and revenue growth multiples. To identify firms that are growing profitability, I define G3 to equal 1 if a firm's earnings growth rate is equal to or greater than its sales growth rate and 0 otherwise.[6]

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

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[4] Just as for Earnings Variability, 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.

[5] Damodaran 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. This argument has been considerably weakened by the spate of revenue recognition scandals in technology firms such as Microstrategy, Priceline, Computer Associates and Lucent to name a few.

[6] I calculate the growth in earnings as the change in earnings divided by the absolute value of previous period earnings. This allows me to compute earnings growth rates for firms which have negative earnings. Loss making firms that have narrowing losses will have positive earnings growth. One may question the comparability of such earnings numbers to sales growth. Focusing on firms that have positive starting earnings in computing earnings growth reduces the number of firms for which this signal equals 1, but has an insignificant impact on the results.

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. Future, 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 G4, G5 and G6 to equal 1 if a firm's R&D, capital expenditure and advertising intensity are greater than the medians of the corresponding variables for low BM firms in the same two-digit SIC code 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 initially 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. Unlike, Piotroski (2000), I do not eliminate the firms for which insufficient prior information is available. A large portion of the low BM sample consists of firms that have been recently gone public. Eliminating such firms potentially reduces the representativeness of the sample. Consequently, my sample size is significantly larger than

Piotroski who had around 14,000 firm-years in his high BM sample from 1976 to 1996. The final low BM sample consists of 20,866 firm-years.

Panel A of Table 1 presents the descriptive statistics of the firms in the sample. For comparison, the descriptive statistics for firms across all BM categories is also presented. Low BM firms have much greater market values and much lower book values than the universe of firms. Low BM firms also have far less assets and slightly less sales than all firms. Interestingly their mean net income is around the same as the sample. The 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[7]. Firm delistings are adjusted for using the methodology suggested by Shumway (1997) [8].

[7] In addition, the tests are also computed using the value weighted index as Piotroski(2000) does. 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.

[8] 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. The results are unaffected if I use the assumption of zero delisting returns as Piotroski (2000) does.

Panel B of Table 1 presents the descriptive statistics for returns. The low BM portfolio earns mean negative size-adjusted returns of -6.0% and -4.2% in the first and second year after portfolio formation. The 25^{th} 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 which firms end up in the two tails of the distribution and tries to profit from the differences between these firms is likely to be successful. In the tests ahead, I will test whether portfolios of firms with strong fundamentals outperform portfolios of firms with weak fundamentals.

4.3 Correlation between Signals

Table 2 presents the correlation matrix between the nine traditional fundamental signals (F1:F9) and the six growth fundamental signals. (G1:G6). In addition to the obvious high correlation between earnings and cash flow based measures, some interesting patterns can be observed. Profitable firms (F1, or F3 when measured using cash flows) are likely to have more stable earnings (G1). Firms with increasing profitability (F2) are likely to have improving operating margin (F5) and asset turnover (F6), demonstrating the effectiveness of the traditional Dupont framework. Also stable earnings (G1) and stable sales growth (G2) are positively correlated.

5 Results: Future Returns

5.1 Returns to a Traditional Fundamentals Driven Strategy (F_SCORE)

The nine traditional fundamental signals F1:F9 are aggregated to construct an index, F_SCORE, on the basis of which portfolios are formed. Table 3 presents the returns on the ten portfolios constructed on the levels of F_SCORE. Panel A presents the one-year ahead size adjusted returns $SRET_1$ for the portfolios.

For the entire low BM sample, the mean $SRET_1$ is –6.0%. The relationship between F_SCORE and $SRET_1$, while not monotonic, appears to be positive. Very few firms are in the two extreme portfolios (F_SCORE=0 and F_SCORE=9). I group the lowest four portfolios (0,1,2 and 3) into the low group and the highest three portfolios (7,8,9) into the high group. The composition of the high and low group ensures that at least 3000 observations or approximately 15% of the entire sample are in each group to allow one to develop meaningful hedge strategies.

$SRET_1$ had a mean value of 0.2% for the high group, as compared to –8.4% for the low group, a difference of 8.6% that is statistically very significant. Similar trends are also seen for the medians (-21.4% for low group and –7.4% for the high group) as well as the proportion of firms that earn positive size adjusted returns (32.4% vs. 42.6%). The results, while statistically significant, are not very strong, especially when compared to the return differences in the 20% range documented by Piotroski (2000) for value firms.

Panel B presents the size-adjusted returns in the second year after portfolio formation ($SRET_2$).[9] The mean return difference between the two groups completely disappears in the second year. The mean $SRET_2$ was –1.3% for the high group and –4.0% for the low group, an insignificant difference. The relation between F_SCORE and $SRET_2$ is hardly monotonic. The high F_SCORE group does earn significantly greater median returns and has a greater proportion of positive size-adjusted returns, but these differences are weaker than those seen in year 1. Hence, an F_SCORE based strategy is not very effective in

[9] The 2nd year returns in this paper cannot be directly compared to Piotroski (2000) who reports buy and hold returns for the entire 24 month period. The returns here are the returns in months 13 to 24 after portfolio formation and are presented in this fashion to isolate what happens in the 2nd year.

picking winning stocks beyond the first year after portfolio formation, indicating that traditional fundamentals only add value in the short run and have weaker long-term implications for growth stocks.

5.2 Returns to a Growth Fundamentals Driven Strategy (G_SCORE)

The six growth fundamental signals G1:G6 are aggregated to construct an index, G_SCORE, on the basis of which portfolios are formed. Table 4 presents the returns to the seven portfolios constructed on the levels of G_SCORE. Panel A presents the one-year ahead size adjusted returns $SRET_1$ for the portfolios. The relationship between G_SCORE and $SRET_1$ is almost strictly monotonically increasing. SRET1 increases from -16.2% for firms with a G_SCORE of 0, to +7.6% for firms with a G-SCORE of 6.

G_SCORE has a left skewed distribution with very few firms having high G_SCORE and many firms having low G_SCORE[10]. The high group is defined to include firms with G_SCORE of 4,5 or 6, while the low group is defined to include G_SCORE values of 0 to ensure that any strategy based on buying high G_SCORE firms and shorting low G_SCORE firms has enough observations. Firms in the high group earned a mean size adjusted return of 1.9% as compared to –16.2% for the low group, a difference that is statistically very significant. Similar trends are also seen for the medians (-26.3% for low group and –4.9% for the high group) as well as the proportion of firms that earn positive size adjusted returns (44.2% vs. 29.2%). The return differences are much greater than that for the F_SCORE portfolios (mean difference of 18.1% vs. 8.6%)

[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).

Panel B presents the size-adjusted returns in the second year after portfolio formation ($SRET_2$). For the G-SCORE portfolios, the return differences persist into the second year. The mean $SRET_2$ was 0.9% for the high group and –10.3% for the low group, a significant difference of 11.2%. 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.

5.3 Returns to Individual Signals

In order to understand why an investment strategy based on traditional fundamentals is relatively ineffective, especially when compared to a strategy based on growth fundamentals, I analyze the relationship of each of the signals and the return realizations. The results are presented in Table 5.

Panel A analyze the fundamental signals, F1:F9, and provides the following insights into why F_SCORE is only weakly effective. First, earnings are far less useful than cash flows for predicting future returns for low BM firms. The cash flow signal (F3) is much stronger than the ROA signal (F1) in both years, especially for second year returns, where F1 is completely ineffective. Firms with positive change in ROA (F2=1) actually underperform in the second year (-5.5% vs. –2.2%), indicating possible mean reversion in change in ROA. Firms with greater cash flows than earnings (F4=1) also earn significantly greater returns in both years. Second, signals based on operating ratios such as profit margin and asset turnover (F5 and F6) are ineffective. Third, only the change in leverage is successful in picking well performing stocks amongst the liquidity signals (F7). Firms with increasing current ratio (F8) actually underperform in both years, illustrating the problems with the current ratio.[11] Issuing equity does not seem to affect a firm's returns.

To summarize, only three out of the nine signals are effective in both years – F3 (cash flow ROA > 0), F4 (cash flow ROA > ROA) and F7 (decrease in leverage). The other signals either add noise or detract from the success of a portfolio based on F_SCORE. These results resonate with the findings of Bartov, Mohanram and Seethamraju (2002) who find that cash flows are much more value relevant for the valuation of internet IPOs.

Panel B of Table 5 analyzes the relationship between the growth signals (G1:G6) and $SRET_1$ and $SRET_2$. The results provide a stark contrast to Panel A. With the exception of capital expenditure intensity, all the other signals are effective in picking winners in both years. To illustrate, firms with positive industry-adjusted R&D intensity (G4=1) earned 8.4% more than other firms in year 1, and a further 7.6% in year 2. The strong individual performance of these signals contributes to the success of the G_SCORE index.

5.4 Returns to a Modified Fundamentals Based Strategy

I aggregate the six growth fundamentals (G1:G6) along with the three effective traditional fundamental signals (F3, F4 and F7) to create an index FG_SCORE. FG_SCORE combines aspects of traditional fundamental analysis with signals that specifically add value for growth firms. FG_SCORE has 10 levels from 0 to 9. Table 6 presents the results of a strategy based on FG_SCORE, which is referred to as a modified fundamentals based strategy.

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[11] Inventory buildup because of a firm's inability to sell will be lead to in higher current ratios. One alternative is to use the quick ratio which excludes inventory. This does not solve the problem completely as firms with a buildup in receivables because of collection problems will have increasing quick ratios. When the signal is defined on the basis of quick ratio, the difference between the two groups is insignificant.

Panel A presents the one-year ahead size-adjusted returns ($SRET_1$). The mean $SRET_1$ has a perfect monotonic relationship with FG_SCORE, increasing from –23.9% to +22.1% as FG_SCORE goes from 0 to 9. A similar monotonic relationship is observed for medians and for the proportion of firms that earned positive size-adjusted returns.

FG_SCORE has a left skewed distribution with very few firms having high FG_SCORE and many firms having low FG_SCORE. The high group is defined to include firms with FG_SCORE of 6, 7, 8 or 9, while the low group is defined to include FG_SCORE values of 0 or 1. The difference between the high group and the low group is 20.3% in means and 24.5% in medians. While over 44% of the firms in the high group outperformed their size decile, only 28% of the low group earned positive size-adjusted returns. The strong relationship between FG_SCORE and future returns continues into year 2. The difference in $SRET_2$ between the high and low groups is 13.2% in means and 19.7% in medians. Around 45% of the high group earned positive size-adjusted returns as opposed to 31.6% for the low group. The results are qualitatively similar to what Piotroski (2000) finds in his sample of high BM stocks, and the return differences are in fact stronger. This indicates that fundamental analysis, suitably modified, can be successful for growth stocks.

The tables also present returns for firms at the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile. In general, the returns are lower at each of these percentiles for the low FG_SCORE portfolios and higher for the high FG_SCORE portfolios. This indicates that FG_SCORE helps shift the distribution of returns to the left for lower score portfolios and to the right for higher score portfolios. Interestingly, the difference between the low group and the mean for the entire population of low BM stocks is much greater than the difference between the high group and the population mean. For instance, the low group earned –18.2% in the first year, which is 12.2% below the –6% mean for the entire population. The high group earned +2.1%, which was only 8.1% higher than the population mean. The shift in distribution is also much more pronounced for the lower percentiles than the higher percentiles. This indicates that the FG_SCORE strategy is dependent more on identifying losers to avoid or short than in picking winners to invest in.

A comparison of the return differences between G_SCORE and FG_SCORE indicates that FG_SCORE slightly outperforms G_SCORE. The mean return differences between the high and low groups are 20.3% for FG_SCORE as opposed to 18.1%. This may appear to be an insignificant increase, but this increase is despite the fact that the high and low groups for FG_SCORE portfolios have more observations (3722 High, 2635 Low) than for the G_SCORE portfolios (2934 High, 2464 Low). Similar increases are seen at the median level and for the second year. Thus, the three fundamental signals add value to the six growth signals and the FG_SCORE portfolios will be used for the remainder of the paper.

5.5 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 FG_SCORE and selling stocks with low FG_SCORE. This is especially the case because the poor performance of low FG_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. I now compare the performance of the modified fundamental analysis strategy across different partitions. The results are presented in Table 7. For brevity, the partition analysis is conducted only for one year ahead returns.[12]

I first partition the sample into three equal partitions based on size, defined as market capitalization of equity (Panel A). 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 FG_SCORE is influenced by firm size, but is strong across all groups of firms. For small firms, the separation in mean excess returns between low and high portfolios is 20.6%. For medium firms, the separation is 22.3%, while for large firms the separation is 13.5%. All three return differences are significant at better than 1%. A similar trend is seen for median returns. While the return differences are lower for the largest firms, such firms are also least likely to have illiquid stocks or restrictions on short-selling.

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 (9679 out of 21,284 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 7.

[12] 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.

In all three categories, there is a substantial difference between high FG_SCORE firms and low FG_SCORE firms. The mean return difference is 20.1% for firms without analyst following, 15.3% for firms with limited following and 22.0% for firms with extensive following. Interestingly, the difference is 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 fundamentals of a firm. FG_SCORE is also clearly associated with analyst following. There are far more low FG_SCORE observations amongst firms with no following and limited following and far more high FG_SCORE observations amongst firms with extensive following, indicating that analysts tend to gravitate towards stronger firms.

The next partition is stock price. Firms with low stock prices are more likely to be illiquid, increasing transaction costs associated with any strategy that involves buying, selling or shorting such stocks. Further, recent research by Bartov and Kim (2002) indicates that the book to market effect is much weaker once firms with stock prices below $10 are excluded. I divide our sample into three equal partitions based on a firm's stock price at the time of portfolio formation. The results are presented in Panel C of Table 7. The results are similar to those for the size partitions, which is not surprising because firm size and stock price are highly correlated. The difference in returns between high and low FG_SCORE portfolios is 22.5% for firms with low stock price, 24.2% for firms with medium stock price and 13.7% for firms with high stock price. All three return differences are highly statistically significant. Hence, the success of the FG_SCORE strategy persists for all categories of stock price.

The partitions considered thus far – size, analyst following and stock price – all relate to a firm's information environment. The strength of the results across all partitions indicates that any High - Low portfolio strategy based on FG_SCORE is unlikely to be seriously affected by restrictions on shorting stocks or illiquidity concerns.

The BM ratio of a firm is affected by both valuation as well as conservatism. Using another valuation metric such as the E/P ratio may isolate firms that have low BM ratios because of high valuations. Among firms with low BM ratios, those with low EP ratios as well are more likely to be overvalued and hence may see greater reversals in future periods.[13] To test if this is the case, I partition the sample into three groups based on the E/P ratio at the time of portfolio formation. The results are presented in Panel D of Table 7.

E/P is highly correlated with FG_SCORE. Low E/P firms are far more likely to have low FG_SCORES (1409 observations) as opposed to high FG_SCORES (179). The exact opposite is the case for the sub-group with high E/P ratios (2090 high scores vs. 428 low scores). The BM effect is also the strongest in the low E/P group with mean excess returns of -12.0%, followed by -5.2% for the medium group. The BM effect is non-existent for the high EP group, with mean excess returns of only -0.8%. The FG_SCORE strategy is the most effective in firms that have relatively higher valuations (low and medium E/P groups), with highly significant return differences of 16.7% and 25.1% for the low and medium E/P groups respectively.[14] The strategy is less effective for high E/P stocks. One explanation for this could be the fact that many of the firms in this group are more likely to resemble value stocks (given their modest valuations) as opposed to growth stocks.

[13] The E/P ratio and BM ratio are highly correlated with a rank-order correlation of 0.45, but there is considerable variation in the E/P ratio within the sample.

[14] The weaker effect in low E/P firms may be attributable to the fact that very few low E/P firms have high FG_SCORE (only 2 each with FG_SCORE of 8 and 9).

However, for the subset of firms that have the highest valuations (the “true” glamour stocks), the FG_SCORE strategy works the best.

Given the large proportion of IPO firms in the low BM (25%), I now test to see whether the strategy is driven by the inclusion or exclusion of IPO firms (firms that have gone public less than one year before portfolio formation). This is to ensure that the strategy is doing more than merely avoiding IPO firms, and thereby avoiding the well documented underperformance of IPOs. The results are presented in Panel E of Table 7.

By construction, IPO firms have lower FG_SCORE because they do not meet the data requirements for some of the signals such as ROA variability and sales growth variability (G1 and G2). No IPO firm scores higher than 6, and only 5 firms had an FG_SCORE of 6. This means that within the IPO sample, an FG_SCORE strategy is not useful. However, when one excludes IPO firms and constructs portfolios with only non-IPO firms, the strategy continues to be effective. The return difference for non-IPO firms is a robust 19.5%. This compares favorably with the 20.3% 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, 1596 observations belonged to the low FG_SCORE group and earned -18.8% mean size adjusted returns in the next year. For non-IPO firms, 1039 firms were in the low group, and earned -17.4%. Hence, while the low group is dominated by IPO firms (1596 out of 2635 or 60%), the non-IPO firms in the low group do almost as poorly as the IPO firms. Hence, the success of the FG_SCORE strategy is not dependent on the avoidance of IPO firms.

5.6 Robustness of Results across Time

In this section, I examine the robustness of the FG_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 8 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, 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

The strength of the return differences across time compares favorably with Piotroksi (2000) who finds positive return differences in 19 out of 21 years and return difference greater than 10% in only 9 out of the 21 years in his analysis of value firms.

5.7 Controlling for Risk Factors

The FG_SCORE strategy is potentially correlated with other well documented risk factors and anomalies. First, though the sample consists of low BM firms, it is possible that low FG_SCORE firms have much lower BM ratios than high FG_SCORE firms. Second, one of the components of FG_SCORE is the signal F4, which chooses firms with greater cash flows than earnings. This may pick up the accrual effect documented by Sloan (1996) amongst others. 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.[15]

Panel A of Table 9 presents the results of pooled regressions. The first regression includes only SIZE, LBM and MOM. All three are highly significant. Adding FG_SCORE to the regression increases the adjusted R^2 from 0.87% to 1.38% and the coefficient on FG_SCORE is highly significant. SIZE is no longer significant, indicating the positive correlation between FG_SCORE and size because of the over-representation of large firms in the high FG_SCORE groups. LBM and MOM are still significant. Hence, FG_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 to the model.

Panel B 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). FG_SCORE continues to very significant confirming the robustness of this strategy across time, corroborating the results from Table 8. The

[15] I include EQ_OFF despite it not being one of our signals for consistency with Piotroski (2000).

mean adjusted R^2 is higher at 3.54%, and FG_SCORE adds almost 0.8 % in terms of incremental explanatory power.

The coefficient on FG_SCORE is around 0.033 in all the specifications. The economic implication of this is that a one point increase in FG_SCORE is associated with a 3.3% increase in abnormal returns. The mean values of FG_SCORE for the low and high groups are 0.75 and 6.45 respectively. This implies a return difference of 3.3 %*(6.45-0.75), or approximately 18.8% between the high and low groups, as compared to the 20.3% difference reported in Table 6. Hence, the effectiveness of the strategy persists after controlling for factors such as momentum, size, book to market and the accrual anomaly.

6 Results: Future Earnings Performance

6.1 Realizations of Earnings In Future Periods

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

In this section, I test the first link in this hypothesis by examining the future realizations of earnings. Table 10 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 FG_SCORE. Firms in the low FG_SCORE group had mean one-year ahead ROA of –5.9% as opposed to 10.9% for firms in the high group. Like Piotroski (2000), I analyze the relationship between FG_SCORE and the frequency of delisting for reasons related to poor performance. 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 6.2% for the low FG_SCORE firms and only 0.8% for the high FG_SCORE firms.

The results indicate that the future fundamentals of high FG_SCORE firms are much stronger than those of low FG_SCORE firms. This may appear to be trivial and entirely expected, unless one recalls that future excess returns are also much higher for high FG_SCORE firms. Hence, the stock market must be surprised that the fundamentals of these firms are indeed stronger when they are realized. I now examine the stock market's reaction to future earnings realizations.

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 11.

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

[16] ROA was winsorized at 1% and 99% to reduce the impact of outliers. Information was available for 16,098 firms.

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 11 compares the forecast surprise across the firms based on their FG_SCORE.

The results indicate that analysts' surprises were generally much more negative for low FG_SCORE firms and neutral to less negative for high FG_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 0.15%, 0.27% and 0.94% over the next three quarters. This represents a complete unraveling in performance on the part of the low FG_SCORE firms as time progresses. The total difference in mean surprise across the four quarters is 1.42%. 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.

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 14,437 out of the 20,866 observations. Results are presented in Panel B of Table 11.

[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.

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 13.4% for this sub-sample as opposed to 20.3% 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 FG_SCORE firms and more positive for the high FG_SCORE portfolios. The summed quarterly announcement excess returns are 1.80% for the high group and –1.42% for the low group, a significant difference of 3.22%. This difference is almost a quarter of the total annual return difference of 13.4% 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.

Compared to Piotroski (2000), the announcement return differences are a little lower for this sample (3.2%) than what he finds for his sample of high BM firms (5.1%). One potential explanation is that this sample consists of firms in superior information environment, because of which information, good or bad, is more continuously available.

7 Conclusions

In this paper, I test whether one can apply a fundamentals driven strategy on a sample of low Book-to-Market growth stocks to differentiate between winners and losers in terms of future stock market performance. I use an approach similar to that used by Piotroski

(2000), which I modify to take into account the unique characteristics of growth stocks. I create an index, FG_SCORE that includes both traditional fundamental signals related to cash flows and leverage as well as measures based on the stability of earnings and growth, and the levels of R&D, capital expenditures and advertising expenses. I create portfolios based on FG_SCORE and compare the performance of these portfolios with a one-year and two-year horizon.

The results indicate that the modified fundamental strategy is able to differentiate between future winners and losers. Firms with high FG_SCORE had substantially higher size adjusted returns than firms with low FG_SCORE. The results were robust across partitions based on firm size, stock price, analyst following, valuation in terms of E/P and did not depend on the inclusion or exclusion of IPO firms. FG_SCORE is also strongly positively associated with future returns after controlling for well documented risk factors and anomalies such as book to market, accruals, momentum and equity issuance.

I find that future earnings realizations are strongly correlated to current fundamentals, and that the stock market in general and analysts in particular are surprised positively for high FG_SCORE firms and negatively for low FG_SCORE firms. This indicates that the stock market does not understand the correlation between current fundamentals and future fundamentals. This is an interesting contrast to the results of papers like LaPorta (1996) who finds that the stock market often puts too much of a weight on current growth and naively extrapolates this into the future. I find that the stock market appears to ignore the fundamentals and then gets surprised when fundamentally strong firms continue to stay strong and weak firms continue their weak performance.

This paper contributes to the growing literature on fundamental analysis by showing that it can be effective 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 fundamental analysis.

This paper also contributes to the debate as to whether the book to market effect is a risk effect or a mispricing effect. Within a sample of low BM firms, I consider firms that differ considerably in their fundamentals. The low FG_SCORE firms are potentially riskier as by construction, they are likely to be loss making, have worsening operating performance and have more variable earnings and sales growth. Conversely, the high FG_SCORE firms are potentially less risky. In spite of their lower risk, the high FG_SCORE firms deliver higher returns in the future.

The results also corroborate the findings of Beneish, Lee and Tarpley (2001) who find that fundamental analysis is useful after extreme performers are identified using market based signals. The results here indicate that amongst growth firms, extreme performers can be identified from financial statement information itself. In addition to the traditional fundamentals, factors related to the stability and sustainability of growth and future oriented activities such as R&D and advertising add value in picking future winners.

In an ongoing extension, I am calculating ex-ante measures of risks using the methodology outlined in Gebhardt, Lee and Swaminathan (2001), Ohlson and Juettner (2002) and Gode and Mohanram (2002). If, low FG_SCORE firms have higher ex-ante risk and still deliver lower return, this would provide further support for the mispricing argument for the Book-to-Market Effect in low BM firms as opposed to the risk argument.

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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

	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: Buy and Hold Returns

Returns	Mean	10th percentile	25th Percentile	Median	75% Percentile	90th Percentile	Proportion Positive
One Year							
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							
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

F1:F9 are 9 traditional fundamental signals and G1:G6 are 6 growth fundamental signals. The signals are dummy variables that have a default value of 0 and equal 1 if ROA_t>0 (F1), if ROA_t>ROA_{t-1} (F2), if $CFROA_t$>0 (F3), if $CFROA_t$>ROA_t (F4), if $Margin_t$ > $Margin_{t-1}$ (F5), if $Turn_t$ > $Turn_{t-1}$ (F6), if Lev_t < Lev_{t-1} (F7), if Liq_t > Liq_{t-1} (F8), if EQ_OFF=0 (F9), if VARROA<Industry Median (G1), if VARSGR< Industry Median (G2), if EGR>SGR (G3), if RDINT > Industry Median (G4), if CAPINT > Industry Median (G5), if ADINT > Industry Median (G6). 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, Margin is Net Income divided by Sales, Turn is Sales divided by beginning of period assets, Lev is Debt divided by market value of equity, Liq is Current Assets divided by Current Liabilities. EQ_OFF equals 1 if a firm issues equity in the past year, and 0 otherwise. 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. EGR is annual growth in Net Income. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. As all variables are dummy variables, spearman rank-order correlations and pearson correlations are the same. N = 20865

	F1	F2	F3	F4	F5	F6	F7	F8	F9	G1	G2	G3	G4	G5	G6
F1: ROA_t > 0	1.00	0.23	0.46	-0.26	0.10	-0.11	0.13	0.07	0.04	0.55	0.22	0.29	-0.16	0.07	0.05
F2: ROA_t > ROA_{t-1}	0.23	1.00	0.03	-0.16	0.45	0.31	-0.04	0.27	-0.06	0.01	-0.06	0.28	-0.01	-0.01	0.01
F3: $CFROA_t$ > 0	0.46	0.03	1.00	0.28	0.03	-0.08	0.15	-0.04	0.05	0.36	0.21	0.24	-0.12	0.10	0.00
F4: $CFROA_t$ > ROA_t	-0.26	-0.16	0.28	1.00	-0.06	0.01	0.04	-0.14	0.01	-0.07	0.02	-0.03	0.00	0.06	-0.07
F5: $Margin_t$ > $Margin_{t-1}$	0.10	0.45	0.03	-0.06	1.00	0.21	-0.10	0.24	-0.09	-0.06	-0.03	0.19	0.01	-0.01	-0.01
F6: $Turn_t$ > $Turn_{t-1}$	-0.11	0.31	-0.08	0.01	0.21	1.00	-0.13	0.08	-0.02	-0.21	-0.10	-0.22	0.03	-0.02	-0.01
F7: Lev_t < Lev_{t-1}	0.13	-0.04	0.15	0.04	-0.10	-0.13	1.00	-0.18	0.01	0.24	0.18	0.29	-0.01	0.00	0.02
F8: Liq_t < Liq_{t-1}	0.07	0.27	-0.04	-0.14	0.24	0.08	-0.18	1.00	-0.12	-0.11	-0.14	-0.07	0.01	-0.03	0.00
F9: EQ_OFF=0	0.04	-0.06	0.05	0.01	-0.09	-0.02	0.01	-0.12	1.00	0.05	-0.02	0.03	-0.15	-0.08	0.02
G1: VARROA < Median	0.55	0.01	0.36	-0.07	-0.06	-0.21	0.24	-0.11	0.05	1.00	0.39	0.38	-0.09	0.10	0.02
G2: VARSGR < Median	0.22	-0.06	0.21	0.02	-0.03	-0.10	0.18	-0.14	-0.02	0.39	1.00	0.23	-0.03	0.10	0.02
G3: EGR > SGR	0.29	0.28	0.24	-0.03	0.19	-0.22	0.29	-0.07	0.03	0.38	0.23	1.00	-0.03	-0.01	0.01
G4: RDINT > Median	-0.16	-0.01	-0.12	0.00	0.01	0.03	-0.01	0.01	-0.15	-0.09	-0.03	-0.03	1.00	0.05	0.03
G5: CAPINT > Median	0.07	-0.01	0.10	0.06	-0.01	-0.02	0.00	-0.03	-0.08	0.10	0.10	-0.01	0.05	1.00	0.01
G6: ADINT > Median	0.05	0.01	0.00	-0.07	-0.01	-0.01	0.02	0.00	0.02	0.02	0.02	0.01	0.03	0.01	1.00

TABLE 3

Returns to an Investment Strategy Based on Traditional Fundamental Signals

F_SCORE is the sum of 9 binary signals defined as follows. The 9 fundamental signals are dummy variables that have a default value of 0 and equal 1 if $ROA_t>0$ (F1), if $ROA_t>ROA_{t-1}$ (F2), if $CFROA_t>0$ (F3), if $CFROA_t>ROA_t$ (F4), if $Margin_t > Margin_{t-1}$ (F5), if $Turn_t > Turn_{t-1}$ (F6), if $Lev_t < Lev_{t-1}$ (F7), if $Liq_t > Liq_{t-1}$ (F8), if EQ_OFF=0 (F9). ROA is Net Income scaled by beginning of period assets, CFROA is cash from operations scaled by beginning of period assets, Margin is Net Income divided by Sales, Turn is Sales divided by beginning of period assets, Lev is Debt divided by market value of equity, Liq is Current Assets divided by Current Liabilities. EQ_OFF equals 1 if a firm issues equity in a given year, and 0 otherwise. 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. z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

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

F_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	76	-14.1%	-81.0%	-61.2%	-17.9%	4.1%	54.0%	26.3%
1	469	-21.0%	-90.1%	-64.2%	-35.9%	-0.1%	50.3%	24.9%
2	1396	-11.2%	-80.4%	-56.2%	-23.0%	11.0%	60.4%	31.4%
3	2433	-4.3%	-76.4%	-51.5%	-18.1%	14.8%	66.6%	34.6%
4	4015	-8.0%	-78.1%	-50.4%	-17.6%	14.1%	61.8%	34.1%
5	4987	-9.1%	-78.0%	-49.6%	-18.4%	13.5%	60.0%	34.6%
6	3773	-2.8%	-67.1%	-41.1%	-10.9%	19.1%	58.1%	40.0%
7	2805	-0.4%	-63.3%	-37.3%	-8.2%	21.3%	62.7%	42.2%
8	823	2.9%	-61.0%	-32.5%	-5.1%	24.6%	68.2%	44.2%
9	89	-7.8%	-59.5%	-33.3%	-8.2%	8.9%	40.1%	39.3%
ALL	20866	-6.0%	-74.3%	-47.2%	-15.0%	15.9%	61.4%	36.4%
HIGH (7,8,9)	3717	0.2%	-63.0%	-36.3%	-7.4%	21.7%	63.2%	42.6%
LOW (0,1,2,3)	4374	-8.4%	-78.7%	-54.7%	-21.9%	12.4%	62.8%	32.4%
HIGH - LOW		8.6%			14.4%			10.2%
t statistic/ z statistic		4.82***			12.11***			9.51***

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

F_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	52	-17.3%	-77.7%	-54.9%	-28.6%	6.0%	45.5%	32.7%
1	342	-9.9%	-81.6%	-55.8%	-28.1%	7.4%	59.6%	29.8%
2	1077	-2.7%	-80.9%	-49.5%	-19.7%	17.0%	62.9%	33.7%
3	1914	-3.3%	-71.1%	-45.3%	-15.3%	16.8%	65.5%	36.6%
4	3199	-4.0%	-71.8%	-45.0%	-13.3%	16.0%	63.4%	37.2%
5	4107	-6.3%	-71.8%	-43.8%	-13.5%	15.6%	58.1%	36.9%
6	3249	-4.6%	-65.1%	-40.3%	-10.6%	17.8%	56.8%	39.3%
7	2477	-2.3%	-64.4%	-38.5%	-8.6%	19.2%	57.5%	41.5%
8	730	2.5%	-51.8%	-30.5%	-5.5%	22.1%	61.5%	41.5%
9	80	-3.0%	-56.0%	-32.4%	-10.3%	17.3%	49.1%	40.0%
ALL	17228	-4.2%	-69.2%	-42.8%	-12.4%	17.0%	59.7%	37.8%
HIGH (7,8,9)	3717	-1.3%	-61.5%	-36.9%	-7.9%	19.6%	58.1%	41.5%
LOW (0,1,2,3)	4374	-4.0%	-74.6%	-48.3%	-18.3%	15.5%	63.4%	34.9%
HIGH - LOW		2.7%			10.4%			6.5%
t statistic/ z statistic		1.33			7.38***			5.52***

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 six growth fundamental signals (G1:G6). The 6 signals are dummy variables that have a default value of 0 and equal 1 if VARROA<Industry Median (G1), if VARSGR< Industry Median (G2), if EGR>SGR (G3), if RDINT > Industry Median (G4), if CAPINT > Industry Median (G5), if ADINT > Industry Median (G6). 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. EGR is annual growth in Net Income. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. ROA is Net Income scaled by beginning of period assets. 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. z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

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

G_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	2464	-16.2%	-85.2%	-60.8%	-26.3%	7.2%	55.3%	29.2%
1	5436	-10.5%	-82.7%	-55.6%	-23.7%	12.2%	62.4%	32.0%
2	5786	-4.5%	-74.5%	-48.4%	-16.5%	16.8%	68.8%	36.3%
3	4246	-1.8%	-65.5%	-38.9%	-9.0%	18.4%	59.0%	41.2%
4	2203	1.8%	-53.2%	-30.7%	-6.4%	20.6%	56.7%	43.0%
5	636	1.6%	-50.3%	-25.6%	-2.4%	22.2%	55.0%	46.2%
6	95	7.6%	-39.0%	-15.9%	3.2%	30.1%	52.5%	56.8%
ALL	20866	-6.0%	-74.3%	-47.2%	-15.0%	15.9%	61.4%	36.4%
HIGH (4,5,6)	2934	1.9%	-51.7%	-29.1%	-4.9%	21.0%	56.1%	44.2%
LOW (0)	2464	-16.2%	-85.2%	-60.8%	-26.3%	7.2%	55.3%	29.2%
HIGH - LOW		18.1%			21.4%			15.0%
t statistic/ z statistic		9.40***			17.27***			11.57***

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

G_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	1874	-10.3%	-81.6%	-52.8%	-20.4%	14.0%	57.5%	34.0%
1	4285	-7.2%	-77.8%	-50.4%	-18.3%	14.4%	66.7%	34.2%
2	4761	-3.6%	-69.3%	-45.1%	-14.4%	17.7%	63.4%	36.9%
3	3647	-1.8%	-60.1%	-35.7%	-9.5%	18.1%	56.9%	40.3%
4	1975	1.2%	-52.3%	-30.2%	-4.0%	21.0%	53.9%	45.1%
5	593	0.3%	-48.9%	-23.8%	-3.8%	18.0%	50.5%	44.7%
6	92	-2.0%	-45.8%	-23.5%	-8.8%	18.3%	37.3%	45.7%
ALL	17228	-4.2%	-69.2%	-42.8%	-12.4%	17.0%	59.7%	37.8%
HIGH (4,5,6)	2934	0.9%	-51.4%	-28.0%	-4.0%	19.7%	52.6%	45.0%
LOW (0)	2464	-10.3%	-81.6%	-52.8%	-20.4%	14.0%	57.5%	34.0%
HIGH - LOW		11.2%			16.4%			11.0%
t statistic/ z statistic		5.02***			11.65***			7.57***

TABLE 5

Relation between Individual Signals and Future Returns

F1:F9 are 9 traditional fundamental signals and G1:G6 are 6 growth fundamental signals. 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, Margin is Net Income divided by Sales, Turn is Sales divided by beginning of period assets, Lev is Debt divided by market value of equity, Liq is Current Assets divided by Current Liabilities. EQ_OFF equals 1 if a firm issues equity in a given year, and 0 otherwise. 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. EGR is annual growth in Net Income. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. 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. z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

Panel A: Fundamental Signals

	$SRET_1$ (One Year Ahead Size Adjusted Returns)						**$SRET_2$ (**Two Year Ahead Size Adjusted Returns)					
SIGNAL	(0)		(1)				(0)		(1)			
	N	Mean	N	Mean	(1) – (0)	T Stat	N	Mean	N	Mean	(1) – (0)	T Stat
F1: $ROA_t > 0$	7444	-10.6%	13421	-3.4%	7.2%	5.71***	5175	-4.0%	12053	-4.2%	-0.2%	-0.10
F2: $ROA_t > ROA_{t-1}$	8692	-5.6%	12173	-6.2%	-0.6%	-0.55	7045	-2.2%	10183	-5.5%	-3.3%	-2.76***
F3: $CFROA_t > 0$	8005	-13.1%	12860	-1.5%	11.6%	9.90***	6062	-7.4%	11166	-2.4%	5.0%	3.78***
F4: $CFROA_t > ROA_t$	8666	-8.8%	12199	-4.0%	4.8%	4.66***	7547	-6.9%	9681	-2.0%	4.9%	4.22***
F5: $Margin_t > Margin_{t-1}$	6953	-6.7%	13912	-5.6%	1.1%	0.96	5665	-2.8%	11563	-4.8%	-2.0%	-1.55
F6: $Turn_t > Turn_{t-1}$	7551	-6.3%	13314	-5.8%	0.5%	0.48	6426	-5.0%	10802	-3.6%	1.4%	1.25
F7: $Lev_t < Lev_{t-1}$	13143	-7.4%	7722	-3.6%	3.8%	3.59***	10661	-5.0%	6567	-2.8%	2.2%	1.89*
F8: $Liq_t < Liq_{t-1}$	9494	-3.8%	11371	-7.8%	-4.0%	-3.70***	7782	-2.8%	9446	-5.3%	-2.5%	-2.15**
F9: EQ_OFF=0	16434	-6.2%	4431	-5.4%	0.8%	0.66	13598	-4.2%	3630	-3.8%	0.4%	0.35

Panel B: Growth Signals

	$SRET_1$ (One Year Ahead Size Adjusted Returns)						**$SRET_2$ (**Two Year Ahead Size Adjusted Returns)					
SIGNAL	(0)		(1)				(0)		(1)			
	N	Mean	N	Mean	(1) – (0)	T Stat	N	Mean	N	Mean	(1) – (0)	T Stat
G1: VARROA<Ind. Median	12743	-8.8%	8122	-1.6%	7.2%	7.04***	9993	-5.7%	7235	-2.0%	3.7%	3.46***
G2: VARSGR < Ind. Median	13763	-7.5%	7102	-3.1%	4.4%	4.22***	11034	-5.9%	6194	-1.1%	4.8%	4.21***
G3: EGR > SGR	12935	-8.9%	7930	-1.3%	7.6%	7.20***	10372	-4.9%	6856	-3.0%	1.9%	1.77*
G4: RDINT > Ind. Median	15085	-8.3%	5782	0.1%	8.4%	6.03***	12515	-6.2%	4713	1.4%	7.6%	5.02***
G5: CAPINT > Ind. Median	10202	-6.7%	10663	-5.3%	1.4%	1.31	8267	-5.1%	8961	-3.3%	1.8%	1.53
G6: ADINT > Ind. Median	16922	-6.7%	3943	-3.1%	3.6%	2.98***	13806	-4.4%	3422	-3.3%	1.1%	0.88

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

TABLE 6

Returns to an Investment Strategy Based on Modified Fundamental Signals

FG_SCORE is the sum of 9 binary signals – six growth fundamental signals (G1:G6) and three traditional fundamental signals (F3, F4, F7). The 9 signals are dummy variables that have a default value of 0 and equal 1 if VARROA<Industry Median (G1), if VARSGR< Industry Median (G2), if EGR>SGR (G3), if RDINT > Industry Median (G4), if CAPINT > Industry Median (G5), if ADINT > Industry Median (G6), if $CFROA_t>0$ (F3), if $CFROA_t>ROA_t$ (F4), if $Lev_t < Lev_{t-1}$ (F7). 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. EGR is annual growth in Net Income. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. ROA is Net Income scaled by beginning of period assets, CFROA is cash from operations scaled by beginning of period assets, Lev is Debt divided by market value of equity. 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. z-statistics are for wilcoxon sign-rank test for medians and can be interpreted the same way as t-statistics.

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

FG_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	671	-23.9%	-87.3%	-62.5%	-29.2%	2.0%	51.6%	28.5%
1	1964	-16.3%	-87.3%	-64.1%	-28.8%	5.0%	56.1%	26.6%
2	3553	-10.5%	-83.0%	-57.4%	-26.0%	9.7%	65.1%	30.4%
3	4128	-7.2%	-78.6%	-51.0%	-18.7%	15.5%	65.8%	34.7%
4	3611	-3.5%	-68.6%	-43.8%	-13.7%	16.7%	62.2%	37.1%
5	3217	-1.6%	-63.9%	-37.6%	-8.2%	19.7%	61.5%	42.0%
6	2223	-0.4%	-58.6%	-33.1%	-7.1%	19.2%	56.9%	42.1%
7	1168	5.2%	-52.7%	-27.0%	-2.1%	24.8%	63.7%	47.7%
8	285	6.2%	-41.0%	-21.4%	1.8%	25.7%	58.8%	50.5%
9	46	22.1%	-44.3%	-23.2%	5.8%	30.1%	52.5%	63.0%
ALL	20866	-6.0%	-74.3%	-47.2%	-15.0%	15.9%	61.4%	36.4%
HIGH (6,7,8,9)	3722	2.1%	-55.2%	-30.0%	-4.7%	21.1%	58.4%	44.6%
LOW (0,1)	2635	-18.2%	-87.3%	-63.5%	-29.2%	4.6%	55.6%	28.0%
HIGH - LOW		20.3%			24.5%			16.6%
t statistic/ z statistic		10.92^{***}			19.51^{***}			13.86^{***}

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

FG_SCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	534	-18.5%	-84.0%	-58.4%	-26.2%	9.9%	51.3%	30.3%
1	1502	-10.1%	-85.1%	-58.4%	-23.2%	13.5%	60.4%	32.0%
2	2723	-8.3%	-77.0%	-51.2%	-21.7%	13.4%	68.0%	33.1%
3	3299	-2.9%	-72.2%	-45.9%	-15.3%	16.7%	69.6%	36.0%
4	3008	-4.9%	-67.5%	-41.8%	-12.6%	16.9%	58.0%	37.7%
5	2813	-1.0%	-60.3%	-34.7%	-8.4%	18.3%	55.8%	41.0%
6	1988	-0.1%	-52.5%	-31.4%	-5.3%	20.8%	54.8%	44.2%
7	1050	2.7%	-52.6%	-26.8%	-2.2%	20.1%	57.3%	46.9%
8	266	2.7%	-45.4%	-23.6%	-4.3%	19.9%	50.5%	45.5%
9	44	-5.0%	-55.8%	-26.7%	-11.8%	24.8%	36.9%	36.4%
ALL	17228	-4.2%	-69.2%	-42.8%	-12.4%	17.0%	59.7%	37.8%
HIGH (6,7,8,9)	3348	0.9%	-52.0%	-29.1%	-4.4%	20.4%	54.4%	45.0%
LOW (0,1)	2036	-12.3%	-85.1%	-58.4%	-24.2%	12.8%	57.1%	31.6%
HIGH - LOW		13.2%			19.7%			13.5%
t statistic/ z statistic		5.89^{***}			14.23^{***}			10.03^{***}

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

TABLE 7
Returns to an Investment Strategy Based on Modified Fundamental Signals by Partitions

FG_SCORE is the sum of 9 binary signals – six growth fundamental signals (G1:G6) and three traditional fundamental signals (F3, F4, F7). Details are at the top of Table 6. 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. Stock Price partitions are on the basis of most recent stock price per share. E/P partitions are on the basis of most recent E/P ratio at time of portfolio formation and include loss-making firms. $SRET_1$ 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.

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

	SMALL FIRMS			MEDIUM FIRMS			LARGE FIRMS		
FG_SCORE	N	Mean	Median	N	Mean	Median	N	Mean	Median
0	364	-26.4%	-34.1%	212	-20.3%	-25.2%	95	-22.0%	-26.5%
1	1038	-16.2%	-31.8%	686	-19.6%	-28.2%	240	-7.2%	-17.3%
2	1706	-7.1%	-26.5%	1251	-13.1%	-28.1%	596	-14.5%	-19.7%
3	1675	-8.3%	-23.4%	1515	-7.8%	-19.6%	938	-4.4%	-11.2%
4	1122	-3.5%	-21.3%	1291	-3.3%	-15.1%	1198	-3.8%	-9.1%
5	618	-9.7%	-21.1%	1052	-0.8%	-11.6%	1547	1.1%	-3.3%
6	315	-1.8%	-17.0%	604	2.4%	-9.0%	1304	-1.3%	-5.3%
7	93	8.3%	-5.9%	286	1.5%	-6.9%	789	6.1%	-0.8%
8	15	-17.6%	-28.8%	56	7.4%	7.0%	214	7.5%	2.4%
9	4	202.9%	45.6%	10	4.3%	4.0%	32	5.0%	7.5%
ALL	6950	-8.9%	-25.1%	6963	-7.0%	-17.6%	6953	-2.1%	-7.0%
HIGH (6,7,8,9)	427	1.7%	-14.6%	956	2.5%	-7.3%	2339	2.1%	-3.0%
LOW (0,1)	1402	-18.9%	-32.7%	898	-19.8%	-26.6%	335	-11.4%	-21.0%
HIGH - LOW		20.6%	18.0%		22.3%	19.3%		13.5%	18.0%
t statistic/ z statistic		4.43***	6.58***		6.53***	9.02***		3.48***	7.14***

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

	NO FOLLOWING			LIMITED FOLLOWING			EXTENSIVE FOLLOWING		
FG_SCORE	N	Mean	Median	N	Mean	Median	N	Mean	Median
0	468	-25.2%	-32.2%	156	-20.3%	-24.6%	47	-22.3%	-30.9%
1	1202	-17.7%	-30.9%	583	-13.1%	-26.8%	179	-17.4%	-24.2%
2	1954	-14.1%	-27.4%	1101	-6.6%	-26.7%	498	-4.6%	-16.1%
3	2004	-12.1%	-21.0%	1332	-2.8%	-18.7%	792	-2.3%	-11.3%
4	1517	-7.1%	-19.2%	1004	-1.0%	-14.8%	1090	-1.0%	-8.5%
5	1147	-6.0%	-15.1%	733	-1.6%	-9.3%	1337	2.2%	-4.1%
6	671	-1.0%	-9.4%	464	-3.1%	-9.7%	1088	1.1%	-5.0%
7	270	1.9%	-6.4%	209	6.8%	-2.1%	689	5.9%	-0.8%
8	55	-4.9%	-12.3%	42	8.7%	-3.2%	188	8.8%	3.2%
9	13	52.9%	2.0%	2	62.9%	62.9%	31	6.5%	9.3%
ALL	9301	-11.0%	-21.2%	5626	-4.2%	-16.8%	5939	0.1%	-6.7%
HIGH (6,7,8,9)	1009	0.3%	-8.2%	717	0.6%	-7.0%	1996	3.6%	-2.7%
LOW (0,1)	1670	-19.8%	-31.4%	739	-14.6%	-25.6%	226	-18.4%	-25.5%
HIGH - LOW		20.1%	23.2%		15.3%	18.6%		22.0%	22.8%
T statistic/ z statistic		7.21***	11.73***		3.99***	7.13***		5.03***	7.66***

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

Panel C: One-Year Ahead Size adjusted Returns by Stock Price Partitions

	SMALL PRICE			MEDIUM PRICE			LARGE PRICE		
FG_SCORE	N	Mean	Median	N	Mean	Median	N	Mean	Median
0	354	-25.4%	-33.8%	229	-25.2%	-27.7%	88	-14.4%	-19.8%
1	1060	-15.6%	-32.9%	636	-19.5%	-26.7%	268	-11.7%	-17.1%
2	1723	-8.8%	-29.1%	1243	-10.8%	-24.2%	587	-14.6%	-20.0%
3	1726	-9.9%	-25.2%	1494	-6.4%	-17.5%	908	-3.5%	-10.1%
4	1120	-6.8%	-25.1%	1299	-3.6%	-14.0%	1192	-0.4%	-7.6%
5	614	-12.6%	-25.5%	1085	-0.7%	-8.5%	1518	2.3%	-3.6%
6	267	3.5%	-15.1%	628	2.6%	-8.8%	1328	-2.6%	-5.9%
7	78	0.9%	-20.6%	297	2.9%	-4.6%	793	6.4%	-0.2%
8	10	-13.4%	-21.2%	45	13.8%	-0.4%	230	5.5%	2.5%
9	3	249.7%	8.3%	6	3.4%	-1.7%	37	6.7%	9.3%
ALL	6955	-10.3%	-27.2%	6962	-6.2%	-15.8%	6949	-1.4%	-6.5%
HIGH (6,7,8,9)	358	4.5%	-15.7%	976	3.2%	-7.7%	2388	1.3%	-3.2%
LOW (0,1)	1414	-18.0%	-33.2%	865	-21.0%	-27.0%	356	-12.4%	-18.6%
HIGH - LOW		22.5%	17.5%		24.2%	19.2%		13.7%	15.3%
T statistic/ z statistic		4.20***	5.91***		7.18***	10.15		3.70***	6.36***

Panel D: One-Year Ahead Size adjusted Returns by E/P Partitions

	Low E/P			Medium E/P			High E/P		
FG_SCORE	N	Mean	Median	N	Mean	Median	N	Mean	Median
0	318	-30.4%	-36.0%	240	-21.7%	-26.2%	111	-9.4%	-16.4%
1	1091	-17.0%	-33.2%	556	-22.9%	-32.0%	317	-2.2%	-11.2%
2	1876	-10.0%	-30.0%	997	-14.5%	-26.5%	676	-5.8%	-15.4%
3	1902	-12.1%	-27.8%	1230	-4.2%	-16.9%	995	-1.7%	-8.8%
4	1087	-8.8%	-27.1%	1241	-1.3%	-11.2%	1283	-1.2%	-8.9%
5	493	-7.1%	-18.4%	1244	-0.4%	-10.1%	1480	-0.7%	-4.3%
6	150	-6.9%	-18.6%	876	-0.3%	-10.2%	1197	0.4%	-4.6%
7	25	-16.5%	-18.2%	450	7.6%	-5.1%	693	4.4%	0.4%
8	2	39.4%	39.4%	106	4.6%	-0.5%	177	6.8%	2.4%
9	2	381.4%	381.4%	21	8.6%	5.7%	23	3.1%	5.4%
ALL	6946	-12.0%	-28.5%	6961	-5.2%	-14.8%	6952	-0.8%	-6.3%
HIGH (6,7,8,9)	179	-3.3%	-18.1%	1453	2.6%	-7.7%	2090	2.3%	-2.4%
LOW (0,1)	1409	-20.0%	-34.2%	796	-22.5%	-29.7%	428	-4.1%	-13.0%
HIGH - LOW		16.7%	16.0%		25.1%	22.0%		6.4%	10.6%
t statistic/ z statistic		2.51**	4.24***		8.16***	10.79***		1.81*	4.63***

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

Panel E: One-Year Ahead Size adjusted Returns by IPO Partition

FG_SCORE	IPO Firms N	IPO Firms Mean	IPO Firms Median	Non IPO Firms N	Non IPO Firms Mean	Non IPO Firms Median
0	477	-27.0%	-31.5%	194	-16.2%	-23.4%
1	1119	-15.3%	-32.2%	845	-17.6%	-25.5%
2	1609	-11.2%	-27.8%	1944	-9.9%	-24.1%
3	1078	-7.7%	-20.7%	3050	-7.1%	-17.9%
4	308	-0.3%	-11.0%	3303	-3.8%	-14.0%
5	54	-5.6%	-14.6%	3163	-1.5%	-8.2%
6	5	-5.3%	-11.7%	2218	-0.4%	-7.1%
7	0			1168	5.2%	-2.1%
8	0			285	6.2%	1.8%
9	0			46	22.1%	5.8%
ALL	4650	-12.2%	-26.7%	16216	-4.2%	-12.3%
HIGH (6,7,8,9)	5	-5.3%	-11.7%	3717	2.1%	-4.7%
LOW (0,1)	1596	-18.8%	-32.1%	1039	-17.4%	-25.4%
HIGH - LOW		13.5%	20.4%		19.5%	20.8%
t statistic/ z statistic		0.59	0.97		8.41***	12.74***

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

TABLE 8
Performance of Hi-Low Strategy across Time

FG_SCORE is the sum of 9 binary signals – six growth fundamental signals (G1:G6) and three traditional fundamental signals (F3, F4, F7). Details are at the top of Table 6. $SRET_1$ 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.

	High FG_SCORE (FG_SCORE=6,7,8,9)		Low FG_SCORE (FG_SCORE=0,1)			
Year	N	Mean $SRET_1$	N	Mean $SRET_1$	Difference	T Statistic
1979	140	23.87%	54	1.87%	22.0%	0.98
1980	125	-6.39%	93	-19.13%	12.7%	2.35^{**}
1981	98	-0.89%	109	-23.07%	22.2%	1.80^{*}
1982	119	-6.57%	97	-27.28%	20.7%	4.15^{***}
1983	103	-19.88%	134	-16.52%	-3.4%	-0.61
1984	138	-1.69%	115	-17.18%	15.5%	2.21^{**}
1985	159	0.54%	110	-10.05%	10.6%	1.67^{*}
1986	159	0.53%	138	-7.29%	7.8%	1.44
1987	193	-0.57%	144	-16.95%	16.4%	2.68^{***}
1988	190	8.85%	106	-11.29%	20.1%	2.45^{**}
1989	188	11.04%	93	-5.38%	16.4%	1.78^{*}
1990	193	4.39%	87	-14.88%	19.3%	1.83^{*}
1991	195	-3.19%	108	-26.17%	23.0%	2.95^{***}
1992	195	-3.94%	123	-8.52%	4.6%	0.68
1993	208	3.19%	150	-14.56%	17.7%	1.97^{**}
1994	220	7.43%	155	-15.96%	23.4%	3.03^{***}
1995	212	-6.30%	192	-30.67%	24.4%	4.73^{***}
1996	213	-1.04%	172	-25.08%	24.0%	3.54^{***}
1997	215	-0.90%	152	-1.64%	0.7%	0.09
1998	232	21.33%	143	-21.27%	42.6%	2.98^{***}
1999	227	-0.92%	160	-46.50%	45.6%	6.68^{***}
ALL YEARS	3722	1.5%	2635	-18.2%	20.3%	10.92^{***}

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

TABLE 9
Cross-Sectional Regression for Annual Returns

FG_SCORE is the sum of 9 binary signals – six growth fundamental signals (G1:G6) and three traditional fundamental signals (F3, F4, F7). Details are at the top of Table 6. 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.

MODEL	Intercept	SIZE	LBM	MOM	ACCR	EQ_OFF	FG_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)	-0.121	0.003	0.047	0.112			0.033	1.38%
	(-4.99) ***	(0.84)	(4.56) ***	(9.06) ***			(9.44) ***	
(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)	-0.124	0.002	0.048	0.111	0.001	0.003	0.033	1.37%
	(-4.58) ***	(0.81)	(4.48) ***	(9.05) ***	(0.05)	(0.21)	(9.28) ***	
Panel B: Year by Year Regressions (N varies from 653 in 1979 to 1212 in 1999)								
(1)	-0.112	0.001	0.041	0.165			0.030	3.54%
	(-2.26) **	(0.15)	(1.66) *	(5.59) ***			(6.12) ***	
(2)	-0.125	-0.002	0.040	0.155	0.015	-0.008	0.034	4.33%
	(-2.14) **	(-0.48)	(1.68) *	(5.71) ***	(0.24)	(-0.38)	(7.00) ***	

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

TABLE 10
Relation between FG_SCORE and Future Earnings Performance

FG_SCORE is the sum of 9 binary signals – six growth fundamental signals (G1:G6) and three traditional fundamental signals (F3, F4, F7). Details are at the top of Table 6. ROA_{t+1} is the realized Return on Assets for the year after portfolio formation. Delisting information is for the first year after portfolio information and was obtained from CRSP. Consistent with Piotroski (2000) 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.

FG_SCORE	N	ROA_{t+1} Mean	ROA_{t+1} Median	N	Performance Delisting (%)
0	409	-2.7%	3.7%	671	6.7%
1	1409	-7.1%	1.8%	1964	6.1%
2	2523	-7.2%	3.7%	3553	6.3%
3	3081	-1.7%	6.0%	4128	4.5%
4	2775	3.7%	8.2%	3611	3.3%
5	2631	7.9%	9.6%	3217	1.3%
6	1878	10.2%	11.0%	2223	1.0%
7	997	11.9%	12.1%	1168	0.4%
8	261	11.9%	13.3%	285	0.4%
9	44	15.2%	14.5%	46	0.0%
ALL	16098	1.9%	7.9%	20866	3.6%
HIGH (6,7,8,9)	3180	10.9%	11.5%	3722	0.8%
LOW (0,1)	1908	-5.9%	2.4%	2635	6.2%
HIGH – LOW		16.8%	9.2%		-5.4%
t statistic/ z statistic		25.04***	7.29***		11.06***

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

TABLE 11
Relation between FG_SCORE and Surprises/Returns around Future Earnings Announcements

FG_SCORE is the sum of 9 binary signals – six growth fundamental signals (G1:G6) and three traditional fundamental signals (F3, F4, F7). Details are at the top of Table 6. 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. 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.

Panel A: Mean Analyst Forecast Surprises

FG_SCORE	N	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	All Quarters
0	80	-0.11%	-0.16%	-0.38%	-1.46%	-2.10%
1	354	-0.05%	-0.21%	-0.38%	-1.06%	-1.70%
2	804	-0.07%	-0.15%	-0.30%	-0.65%	-1.18%
3	1171	-0.07%	-0.09%	-0.24%	-0.54%	-0.94%
4	1297	-0.08%	-0.13%	-0.25%	-0.43%	-0.89%
5	1517	-0.03%	-0.06%	-0.13%	-0.23%	-0.44%
6	1265	0.00%	-0.05%	-0.13%	-0.22%	-0.41%
7	764	-0.01%	-0.06%	-0.11%	-0.17%	-0.35%
8	211	0.03%	-0.02%	0.01%	-0.08%	-0.07%
9	30	-0.06%	-0.03%	0.07%	-0.08%	-0.10%
ALL	7493	-0.04%	-0.09%	-0.19%	-0.40%	-0.73%
HIGH (6,7,8,9)	2270	0.00%	-0.05%	-0.11%	-0.19%	-0.35%
LOW (0,1)	434	-0.06%	-0.20%	-0.38%	-1.13%	-1.77%
HIGH - LOW		0.06%	0.15%	0.27%	0.94%	1.42%
t statistic		1.62	2.69***	3.36***	5.20***	5.52***

Panel B: Mean Returns around Earnings Announcement

FG_SCORE	N	Entire Year	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	All Quarters
0	236	-19.76%	0.51%	-0.57%	-0.94%	-1.51%	-2.51%
1	811	-8.90%	1.26%	-1.49%	0.01%	-0.85%	-1.07%
2	1672	-3.28%	0.80%	-0.45%	-1.44%	-0.14%	-1.22%
3	2211	-4.85%	0.66%	0.02%	-0.76%	-0.70%	-0.78%
4	2135	1.38%	0.89%	0.02%	-0.56%	0.35%	0.70%
5	2141	-1.56%	1.21%	0.49%	-0.51%	0.16%	1.34%
6	1603	-0.41%	1.03%	0.71%	-0.97%	0.44%	1.22%
7	872	4.88%	1.36%	1.62%	0.31%	0.44%	3.73%
8	228	4.51%	0.42%	-0.59%	0.30%	-1.06%	-0.93%
9	36	6.51%	1.55%	0.72%	0.73%	0.96%	3.97%
ALL	11945	-2.30%	0.95%	0.06%	-0.65%	-0.11%	0.26%
HIGH (6,7,8,9)	2739	1.85%	1.08%	0.83%	-0.41%	0.30%	1.80%
LOW (0,1)	1047	-11.52%	1.08%	-1.27%	-0.22%	-1.01%	-1.42%
HIGH - LOW		13.36%	0.00%	2.10%	-0.19%	1.31%	3.22%
t statistic			0.01	3.57***	-0.31	2.03**	2.57***

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