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

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Abstract. This paper combines traditional fundamentals, such as earnings and cash flows, with measures tailored for growth firms, such as earnings stability, growth stability and intensity of R&D, capital expenditure and advertising, to create an index – GSCORE. A long–short strategy based on GSCORE earns significant excess returns, though most of the returns come from the short side. Results are robust in partitions of size, analyst following and liquidity and persist after controlling for momentum, book-to-market, accruals and size. High GSCORE firms have greater market reaction and analyst forecast surprises with respect to future earnings announcements. Further, the results are inconsistent with a risk-based explanation as returns are positive in most years, and firms with lower risk earn higher returns. Finally, a contextual approach towards fundamental analysis works best, with traditional analysis appropriate for high BM stocks and growth oriented fundamental analysis appropriate for low BM stocks.

Keywords: capital markets, market efficiency, financial statement analysis, growth, value, book-to-market, risk, mispricing

JEL Classification: G12, G14, M41

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

Financial statement analysis (or fundamental analysis) attempts to separate ex-post winners from losers on the basis of information from financial statements that is not correctly impounded in prices. A commonly used technique is the Dupont analysis of return on assets (ROA) and its decomposition into asset turnover and profit margin, coupled with an analysis of risk factors related to liquidity and solvency. Piotroski (2000) argues that such analyses will be especially effective in high BM (value) firms which are often ignored by market participants. He indeed finds that financial statement analysis effectively separates winners from losers in this setting.

Ex-ante, it is unclear whether financial statement analysis will be effective for low BM firms, even if they are mispriced, for the following reasons. First, low BM firms tend to be growth stocks that attract the attention of sophisticated market intermediaries such as analysts and institutional investors. Second, such firms are likely to have many sources of disclosure other than financial statements. Third, the rapid growth in many low BM firms potentially makes current fundamentals less important than other non-financial measures. Counterbalancing this is the fact that many of these stocks may be overvalued in departure from their fundamentals because of the hype or excitement surrounding their recent strong stock market performance. Further, while traditional fundamental analysis may have limited applicability for growth firms, there may be other information in the financial statements that can be potentially useful.

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

The results indicate that financial statement analysis, appropriately tailored for growth firms, is successful in differentiating between ex-post winners and losers. Firms with the highest GSCORE earned a mean size-adjusted return of 3.1% in the first year after portfolio formation, while firms with the lowest GSCORE earned −17.5%, indicating that a long–short strategy based on GSCORE can earn significant abnormal returns. Similar results are seen for a 2-year period after portfolio formation. The strategy is also robust across time, earning positive returns in all years in the sample. However, most of the returns to this strategy are earned on the downside, indicating that the ability to short stocks is crucial. I partition the sample in a variety of ways that attempt to address issues related to implementation. I find strong results in all partitions – including large firms, well followed firms, firms with put options and firms with high levels of liquidity. This mitigates the potential hurdles to implementing a long–short strategy.

The success of the GSCORE strategy is linked to future performance. High GSCORE firms are more likely to beat earnings forecasts and earn abnormal returns around future earnings announcements, indicating that the market ignores the implications of growth fundamentals for future performance. Furthermore, firms that have the lowest *a priori* levels of systematic, unsystematic and ex-ante risk earn the highest returns, ruling out a risk based explanation in favor of market mispricing as the reason for the success of the GSCORE strategy.

Does the GSCORE analysis work equally well in high BM firms? Tests indicate that the GSCORE strategy is less effective in high BM firms than in low BM firms. Similarly, the FSCORE strategy identified by Piotroski (2000) is less successful in low BM firms than for high BM firms. These results reinforce the importance of context for fundamental analysis.

To summarize, the results of this paper indicate that financial statement analysis can be successfully modified to develop a strategy for making investment choices in low BM firms. Specifically, this paper introduces a number of simple and easy to implement tools, based solely on financial statement information, to help separate winners from losers in terms of future stock performance.

The rest of this paper is organized as below. Section 1 discusses prior research on the BM effect, fundamental analysis, conservatism and naïve extrapolation. Section 2 builds on prior research to develop fundamental signals tailored for low BM firms. Section 3 discusses the data and summary statistics. Section 4 presents the results to the GSCORE strategy, including a variety of partition and sensitivity analyses. Section 5 attempts to distinguish between risk based and mispricing based explanations for the success of the GSCORE strategy. Section 6 demonstrates the importance of context in fundamental analysis. Section 7 concludes the paper.

1. Literature Review

In this section, I summarize results from relevant papers, classified into the following three groupings – (i) the BM effect, (ii) fundamental analysis, and (iii) growth, conservatism, and naïve extrapolation.

1.1. The BM Effect

Fama and French (1992) and Lakonishok et al. (1994), amongst others, show that the BM ratio of a firm is strongly positively correlated to future stock performance. However, these papers differ in their explanation for the BM effect.

The risk explanation offered by Fama and French (1992) argues that high BM firms earn excess returns compared to most firms because of their greater risk, as many high BM firms are in financial distress. Vassalou and Xing (2004) conclude that the BM risk essentially proxies for default risk in high BM firms. However, Griffin and Lemmon (2002) show that firms with high distress risk exhibit the largest return reversals around earnings announcements, inconsistent with a risk based explanation.

The risk explanation is less satisfying for low BM firms, as there are few ex-ante reasons to believe that these firms, largely growth firms, are less risky than the entire population of firms.[1] Lakonishok et al. (1994) argue that mispricing is at the core of the BM effect. They show that investors are overly optimistic about low BM "glamour" firms and over-extrapolate from currently strong earnings and earnings growth. As this optimism unravels over time, these firms earn negative excess returns. La Porta (1996) and Dechow and Sloan (1997) clarify that the naïve extrapolation occurs because the stock market does not adjust for the bias in analysts' forecasts of long term growth. Further, La Porta et al. (1997) show that low BM firms are more likely to have negative earnings surprises. However, Doukas et al. (2002) fail to document any support for the naïve extrapolation hypothesis when they examine analyst forecasts.

Recent papers supporting mispricing include Bartov and Kim (2004), who demonstrate that the BM effect is stronger when one considers the accounting related reasons for low BM ratios, and Ali et al. (2003) who show that the BM effect is greater for stocks with higher idiosyncratic return volatility, higher transaction costs and lower investor sophistication.

1.2. Fundamental Analysis

Many papers have focused on the usefulness of financial statement analysis in predicting future realizations of both earnings and returns. Ou and Penman (1989) demonstrate that certain financial ratios can be useful in predicting future changes in earnings. Lev and Thiagarajan (1993) analyze 12 financial signals that are used by financial analysts, and show that these signals are directly correlated to contemporaneous returns. Abarbanell and Bushee (1997) show that developing an investment strategy based on these signals earns significant abnormal returns. There has also been a stream of research focusing on abnormal returns that can be earned on the basis of particular financial signals. Bernard and Thomas (1989) highlight the post earnings announcement drift, while Sloan (1996) shows that firms with a higher proportion of accruals in their earnings underperform in the future.

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

Beneish et al. (2001) use a two-stage approach towards financial statement analysis. First, they use market based signals to identify likely extreme performers; then they use fundamental signals to differentiate between winners and losers among these firms. Their results indicate the importance of carrying out fundamental analysis contextually. In a similar vein, Soliman (2004) demonstrates that one can improve the performance of the traditional Dupont analysis for ROA decomposition by industry-adjusting both profit margin and asset turnover.

1.3. Growth, Conservatism and Naïve Extrapolation

Many papers have also studied subsets of growth firms such as technology firms, research and development (R&D) intensive firms and internet firms. Lev and Sougiannis (1996) study the value relevance of R&D and find that R&D intensive firms earn excess returns in future periods. Chan et al. (2001) confirm this and also find that advertising expenses are associated with excess returns in the future. Penman and Zhang (2002) demonstrate that the stock market does not understand the hidden reserves caused by conservative accounting for items such as R&D and advertising, which leads to excess returns in the future. To summarize, the literature indicates that accounting conservatism is associated with future abnormal returns. A sample of growth firms is likely to have a substantial number of firms with such conservative accounting. Given that low BM firms as a whole underperform, separating out the "low B" firms is likely to improve the success of any investment strategy.

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

Finally, a number of papers have looked at the importance of non-financial indicators for the valuation of growth stocks. For instance, Trueman et al. (2000) illustrate the importance of web traffic in the valuation of internet firms, while Rajgopal et al. (2003) show that leading indicators of future performance such as order backlog impact valuation. However, Bartov et al. (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 internet firms. Further, while non-financial indicators may be correlated with current valuation, financial statement information may have implications for *future* valuation and hence returns. As the rise and fall of internet firms demonstrates, if the valuation of growth firms eventually reverts to fundamentals, firms with the strongest fundamentals are more likely to outperform, or least likely to severely underperform, in terms of stock market returns.

2. Research Design

2.1. Financial Statement Analysis for Growth Firms

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

This paper's focus is on low BM firms, defined as firms with BM ratios equal to, or below, the 20th percentile for the entire market. The signals used in this paper to separate low BM firms into categories of potential winners and losers can be classified into three groups. The first consists of traditional fundamental signals pertaining to a firm's profitability and cash flow performance. The second category of signals tries to separate out those firms that have low BM ratios because they appear to be overvalued, by utilizing insights from research that has focused on the tendency of markets to extrapolate naively from current fundamentals. The third category of signals attempts to identify the firms that are in the low BM category because of conservative accounting. I refer to the signals developed in this paper as "growth fundamentals", as they measure the fundamental strength of these firms in a context appropriate for growth firms.

While the signals used in this paper largely do not conform to traditional notions of financial statement analysis, they have many aspects in common. All the information utilized is obtained from financial statements. This information pertains to aspects of the "nature" of low BM firms that analysts and other market participants commonly either ignore or misinterpret. This paper tries to see if there is something predictable about this that can be identified and implemented in a strategy, which is what the traditional analysis of profitability and risk essentially does.

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

2.2. Category 1: Signals based on Earnings and Cash Flow Profitability

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

Profitability is measured in two ways. The first measure is ROA, defined as the ratio of net income before extraordinary items scaled by average total assets.[2] I compare the ROA of a given firm to the ROA of all other low BM firms in the same two-digit SIC code at the same time. This signal, like most signals used in this paper, is based on industry contextual information, consistent with Soliman (2004) who illustrates the importance of industry-adjustment in Dupont analysis, and indirectly with Beneish et al. (2001), who highlight the importance of context in fundamental analysis. I define the first growth signal, *G1, to equal 1 if a firm's ROA is greater than the contemporaneous median ROA for all low BM firms in the same industry and 0 otherwise*.

Earnings may be less meaningful than cash flows for early stage firms, which are likely to be relatively over-represented among low BM firms. This may be especially true in certain industries, because of large depreciation or amortization charges by firms making large investments in fixed or intangible assets. Hence, I also use an additional measure of profitability by calculating ROA with cash from operations instead of net income.[3] I define the second growth signal, *G2, to equal 1 if a firm's cash flow ROA exceeds the contemporaneous median for all low BM firms in the same industry and 0 otherwise*.

Sloan (1996) and others have shown the importance of accruals by demonstrating that firms with a greater accrual component in their earnings generally underperform in the future, potentially because of the lower quality of their earnings. Accordingly, *G3 is defined to equal if a firm's cash flow from operations exceeds net income and 0 otherwise*.[4]

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

2.3. Category 2: Signals Related to Naïve Extrapolation

Consider two firms – firm A and firm B. Assume that both are growth firms in a market that is functionally fixated and extrapolates naively. If these firms had similar strong earnings performance, then both of them would presumably be valued similarly. Now suppose we know that firm A has relatively stable earnings, but firm B has unstable earnings. Thus, the odds that the current strong performance of firm B is just a lucky high realization are much higher than for firm A. Firm B is hence much more likely to provide disappointing earnings and hence poor returns in the future.

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

For low BM firms, stability of earnings may help distinguish between firms with solid prospects and firms that are overvalued because of hype or glamour. I compare the firm to other low BM firms in the same two-digit SIC code at the same point in time. *G4 is defined to equal 1 if a firm's earnings variability is less than the contemporaneous median for all low BM firms in the same industry and 0 otherwise*.

The second signal in this category relates to the stability of growth and is motivated by the results from Lakonishok et al. (1994), La Porta (1996) and Dechow and Sloan (1997) that highlight the naïve extrapolation of current growth to predict future growth. As for the prior signal, a firm that has stable growth is less likely to have had a lucky high realization, and therefore less likely to disappoint in terms of future growth. In designing this signal. I focus on sales growth as opposed to earnings growth, as earnings growth is difficult to conceptualize for negative earnings, which many low BM firms have.[5] As before, I compare the firm to other low BM firms in the same two-digit SIC code at the same point in time. *G5 is defined to equal 1 it a firm's sale growth variability is less than the contemporaneous median for all low BM firms in the same industry and 0 otherwise.*

2.4. Category 3: Signals Related to Accounting Conservatism

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

3. Data

3.1. Sample Selection

I start with all firms in COMPUSTAT between 1978 and 2001. Using appropriate quarterly financial information, I create year-to-date annual financials for firms as of or closest to the end of December. All firms in the sample hence have financial information for the period ending at the end of December, November or October.[6] If adequate quarterly information is not available, the information from the latest fiscal year prior to December is used. This ensures that there is no look-ahead bias in the computation of the signals, even if it means that the data may sometimes be dated.

Firms with negative BM ratios are deleted. The distribution from the prior year is used to calculate the cutoffs for groups of firms based on the BM. The primary focus of this paper is on the firms in the lowest quintile of BM ratios (growth firms). In later tests, I also analyze firms in the highest quintile of BM (value firms).

Since the calculation of many of the signals used in the GSCORE metric requires comparison with industry medians, I require that a firm have at least three other firms in the same industry (defined by two-digit SIC code) in the same year. In addition, I obtain information about returns from CRSP, including delisting returns to make adjustments where necessary. I impose a constraint that earnings and cash flow information be available. Cash flows are inferred from the funds flow statement for periods prior to 1988. The final sample consists of 21,724 firm-years.

The signals relating to profitability and cash flows (G1:G3) as well as those related to conservatism (G6:G8) are created using the annualized financials. The two signals related to naïve extrapolation, i.e. earnings variability and sales growth variability (G4,G5) are generated from quarterly financials of the past 4 years, with the constraint that at least six quarters information be available. I measure earnings variability as the variance of a firm's ROA in the past 4 years using quarterly information. While quarterly information might induce variability owing to seasonality, the industry adjustment should mitigate this. I measure growth variability as the variance of a firm's year over year sales growth (Q_0 compared to Q_{-4}) over the past 4 years using quarterly information. If these data are missing, the observations are not deleted, but the signals are coded as zeroes. This is the equivalent of a fund manager deciding not to buy a stock unless enough information is available to determine the firm's track record.

Table 1 presents descriptive statistics for the sample firms. For comparison, descriptive statistics for the universe of firms as well as high BM firms are also presented. Low BM firms have significantly greater market value and lower book value than the universe of firms. They also have far fewer assets and slightly less sales than all firms. Interestingly, their mean net income is comparable to that of the entire population. Medians for most financials are significantly smaller than means indicating the presence of some very large firms. Low BM firms have lower mean ROA than the population, and this difference is amplified in terms of ROE because of their smaller equity. They grow at a much faster rate than other firms, with a mean annual sales growth rate of 61% as opposed to 30% for the entire sample. Low BM firms also have greater R&D intensity (6.5% vs. 2.8%) and a greater proportion of recent IPOs (12% vs. 6%) compared to the universe of firms. Low BM firms also provide an interesting contrast to high BM firms. Low BM firms have similar assets and slightly higher book value of equity, but have significantly greater market values. As expected, they grow much faster and have greater R&D intensity compared to high BM firms.

3.2. Calculation of Returns

Firm level returns are computed as the buy-and-hold returns for the 12-month and 24-month period starting on the 1st of May of the year after portfolio formation, to ensure that the most recent financials included in the signals are publicly available. The returns are size-adjusted by subtracting the returns in the same period for the same capitalization decile as the firm on CRSP.[7] Firm delistings are adjusted for using the methodology suggested by Shumway (1997).[8] The size and delisting adjusted return measures for the 12 and 24 month periods are denoted as SRET_1 and SRET_{12} respectively.

Table 1. Descriptive statistics.

Variable	Low BM firms (22,361 observations)			High BM firms (22,406 observations)			All firms (113,395 observations)		
	Mean	Median	Standard deviation	Mean	Median	Standard deviation	Mean	Median	Standard deviation
Market value of equity ($ million)	2647.2	137.6	14974.7	200.4	24.6	1057.8	1266.2	87.7	7998.5
Book value of equity ($ million)	380.5	25.3	1911.2	270.2	37.6	1428.2	485.8	52.3	2165.8
BM ratio	0.210	0.187	0.587	1.874	1.452	4.300	0.815	0.613	2.040
Assets ($ million)	1477.7	55.4	13420.7	1426.9	98.6	8196.4	2437.7	127.8	17591.8
Sales ($ million)	1035.8	48.0	5373.4	615.1	68.9	3628.6	1120.1	101.5	5261.4
Net income ($ million)	76.0	1.7	494.6	9.1	0.6	158.3	55.7	3.2	416.0
Return on assets	−5.1%	4.8%	27.8%	−2.3%	0.7%	12.1%	−0.6%	3.0%	17.1%
Return on equity	−14.3%	12.8%	67.8%	−4.5%	2.9%	26.3%	−1.3%	9.3%	39.9%
Sales growth	61.2%	23.7%	125.9%	14.5%	3.3%	70.6%	30.0%	10.9%	86.4%
R&D as a % of assets	6.5%	0.0%	15.4%	1.1%	0.0%	4.1%	2.8%	0.0%	9.0%
Proportion of IPO firms	12.2%			2.9%			6.2%		

Financial statement information used in the analysis is based on Year to Date annual financial statements created from quarterly financial statements on or closest to and before December 31st of each year. The time period covered is from 1979 to 2001. Firms with negative book value and firms without at least 2 years of financial information have been deleted. Firms that have BM ratios above the 80th percentile using prior year distributions are classified as high BM, while firms with BM ratios below the 20th percentile using prior year distributions are classified as low BM firms. ROA, Return on Equity and Sales growth have been winsorized at 1% and 99%.

Table 2. Correlations amongst fundamental signals for low BM firms.

	$SRET_1$	$SRET_{12}$	GSCORE	G1	G2	G3	G4	G5	G6	G7	G8
$SRET_1$	1.000	0.625	0.086	0.059	0.064	−0.019	0.063	0.067	0.032	0.017	0.019
$SRET_{12}$	0.732	1.000	0.101	0.069	0.079	−0.010	0.073	0.073	0.044	0.022	0.034
GSCORE	0.188	0.216	1.00	0.593	0.675	0.184	0.586	0.609	0.142	0.408	0.322
G1: $ROA_t \geq$ ind. median ROA_t	0.156	0.176	0.601	1.000	0.569	−0.274	0.394	0.331	−0.142	0.103	0.074
G2: $CFROA_t \geq$ ind. median $CFROA_t$	0.160	0.184	0.689	0.569	1.000	0.069	0.362	0.337	−0.142	0.087	0.059
G3: $CFROA_t \geq ROA_t$	−0.043	−0.035	0.162	−0.274	0.069	1.000	−0.120	−0.060	0.087	−0.012	−0.041
G4: $VARROA_t \leq$ ind. median $VARROA_t$	0.166	0.182	0.593	0.394	0.362	−0.120	1.000	0.459	−0.171	0.064	0.039
G5: $VARSGR_t \leq$ ind. median $VARSGR_t$	0.169	0.186	0.616	0.331	0.337	−0.060	0.459	1.000	−0.107	0.079	0.080
G6: $RDINT_t \geq$ ind. median $RDINT_t$	−0.026	−0.031	0.119	−0.142	−0.142	0.087	−0.171	−0.107	1.000	0.093	−0.033
G7: $CAPINT_t \geq$ ind. median $CAPINT_t$	0.022	0.028	0.399	0.103	0.087	−0.012	0.064	0.079	0.093	1.000	0.016
G8: $ADINT_t \geq$ ind. median $ADINT_t$	0.047	0.064	0.307	0.074	0.059	−0.041	0.039	0.080	−0.033	0.016	1.000

The above correlation table provides correlations between the GSCORE index, the individual signals and future stock returns for the 21,724 low BM firms in the sample. Note that the number of observations is slightly different from Table 1, because of the requirement here that earnings and cash flow information be available. GSCORE is the sum of eight fundamental signals, G1:G8, tailored for growth firms. G1:G8 have a default value of 0 and equal 1 if the following criteria are met respectively. G1: ROA ≥ ind. median, G2: CFROA ≥ ind. median, G3: CFROA ≥ ROA, G4: VARROA ≤ ind. median, G5: VARSGR ≤ ind. median, G6: RDINT ≥ ind. median, G7: CAPINT ≥ ind. median, G8: ADINT ≥ ind. median. ROA is Net Income scaled by average assets. CFROA is cash from operations scaled by average assets. VARROA and VARSGR are the variance of ROA and SGR respectively measured over the past 4 years using quarterly data. RDINT is R&D scaled by total assets. CAPINT is capital expenditure scaled by total assets. ADINT is advertising expenses divided by total assets. Industry medians are calculated at the two-digit SIC level within low BM firms. Returns are size-adjusted by subtracting the returns for the same capitalization decile in the same period. $SRET_1$ and $SRET_{12}$ are the size-adjusted buy-and-hold returns respectively, for 1-year and 2-year periods starting May 1st for the year after portfolio formation. When a firm delists, delisting returns are used as in Shumway (1997). Coefficients above the diagonal are Pearson and those below diagonal are Spearman rank-order correlations. Between dummy variables, Spearman rank-order correlations and Pearson correlations are the same.

3.3. *Correlation between Signals*

Table 2 presents the correlations between the eight growth fundamental signals (G1:G8) and the return measures, $SRET_1$ and $SRET_{12}$, for the sample of low BM firms. In addition to the obvious high correlation between earnings and cash flows, some interesting patterns are observed. Profitable firms (G1 or G2 using cash flows) are likely to have stable earnings (G4) and sales growth (G5), which are also positively correlated with each other. Interestingly, the signals pertaining to conservatism – high R&D (G6), capital intensity (G7), and advertising intensity (G8), show weak correlations amongst each other and with other signals. Hence, if they are individually effective in predicting future returns, using them together may be fruitful because of their apparent orthogonality.

3.4. *Returns to Individual Signals*

To provide preliminary evidence as to whether the signals are effective, I analyze the relationship between the individual signals and the return realizations for the sample of low BM firms. The results are presented in Table 3. Panel A analyzes the one year size-adjusted returns ($SRET_1$), by comparing the mean returns for firms which met the signal's criteria (1) to those that did not (0). As the results indicate, the differences in returns are positive and strongly significant for seven of the eight signals, with the sole exception being the accruals signal (G3). Similar results are seen for the 2 year size-adjusted returns as well ($SRET_{12}$). The weak performance of the accruals signal may be related to errors in estimating annualized cash flows using quarterly information in the periods prior to 1988. An alternate explanation could be that accruals are not a negative signal for fast growing firms who may have increasing levels of depreciation, receivables and inventory in order to finance growth. Desai et al. (2004) claim that the accrual anomaly is essentially the BM effect (value-glamour) in disguise. Given that I am looking within a sample of low BM firms, it is not surprising that the accrual signal has little power.

In the tests going forward, I aggregate G1:G8 into a single index called GSCORE.[9] While this is one of many ways one can implement a portfolio strategy using the information in these signals, it has the advantage of being simple to execute and correlating well to how stock screens are typically used in practice for stock picking.[10] This methodology is akin to having a checklist of screens for deciding to invest in stocks and rating stocks on the basis of how many screens they pass. Prior research has also used such a methodology; for instance Piotroski (2000) investigates the efficacy of traditional fundamental analysis for value firms by defining binary signals and aggregating them additively.

Table 3. Relation between individual signals and future returns for low BM firms.

Signal	(0) *N*	(0) Mean	(1) *N*	(1) Mean	(1) − (0)	*t*-statistic
Panel A: $SRET_1$ (1-year size-adjusted returns)						
G1: $ROA_t \geq$ ind. median ROA_t	10650	−13.4%	11074	−4.3%	9.1%	8.70^{***}
G2: $CFROA_t \geq$ ind. median $CFROA_t$	10598	−13.8%	11126	−3.9%	9.9%	9.41^{***}
G3: $CFROA_t \geq ROA_t$	11919	−7.4%	9805	−10.3%	−2.9%	-2.72^{***}
G4: $VARROA_t \leq$ ind. median $VARROA_t$	11144	−13.4%	10580	−3.8%	9.7%	9.36^{***}
G5: $VARSGR_t \leq$ ind. median $VARSGR_t$	11893	−13.4%	9831	−3.1%	10.3%	10.13^{***}
G6: $RDINT_t \geq$ ind. median $RDINT_t$	15450	−10.3%	6274	−4.8%	5.5%	4.11^{***}
G7: $CAPINT_t \geq$ ind. median $CAPINT_t$	11061	−10.0%	10663	−7.4%	2.7%	2.56^{***}
G8: $ADINT_t \geq$ ind. median $ADINT_t$	15061	−9.7%	6663	−6.6%	3.1%	2.86^{***}
Panel B: $SRET_{12}$ (2-year size-adjusted returns)						
G1 :$ROA_t \geq$ ind. median ROA_t	10650	−23.9%	11074	−8.2%	15.7%	10.12^{***}
G2: $CFROA_t \geq$ ind. median $CFROA_t$	10598	−25.1%	11126	−7.2%	17.9%	11.59^{***}
G3: $CFROA_t \geq ROA_t$	11919	−14.8%	9805	−17.2%	−2.4%	−1.50
G4: $VARROA_t \leq$ ind. median $VARROA_t$	11144	−23.9%	10580	−7.4%	16.5%	10.81^{***}
G5:$VARSGR_t \leq$ ind. median $VARSGR_t$	11893	−23.4%	9831	−6.8%	16.6%	11.01^{***}
G6: $RDINT_t \geq$ ind. median $RDINT_t$	15450	−19.1%	6274	−8.0%	11.1%	5.37^{**}
G7: $CAPINT_t \geq$ ind. median $CAPINT_t$	11061	−18.4%	10663	−13.3%	5.1%	3.31^{***}
G8: $ADINT_t \geq$ ind. median $ADINT_t$	15061	−18.4%	6663	−10.1%	8.3%	4.93^{***}

The table above presents the mean 1-year and 2-year size adjusted returns for the two binary values of the individual signals for the sample of 21,724 low BM firms. For definitions of Gl:G8 as well as $SRET_1$ and $SRET_2$, please see the notes after Table 2. *t*-statistic for difference in means is from a two-sample *t*-test. */**/*** represent statistical significance using two tailed tests at 10%/ 5%/ 1% levels.

4. Returns to a Growth Fundamentals Driven Strategy

4.1. Basic Results

As GSCORE consists of eight signals, it can have nine values from zero to eight. The sample of low BM firms is sorted into nine portfolios based on their GSCORE levels. Table 4 presents the returns to these nine portfolios. Panels A and B present

Table 4. Returns to an investment strategy based on GSCORE for low BM firms.

Panel A: distribution of RET_1 (1-year raw returns)

GSCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	614	−9.2%	−73.6%	−56.8%	−30.0%	10.8%	84.2%	30.0%
1	2191	−3.7%	−74.5%	−54.3%	−24.2%	17.2%	76.5%	33.5%
2	4038	−1.8%	−75.0%	−54.5%	−22.7%	19.1%	82.4%	34.9%
3	4378	0.0%	−72.7%	−50.0%	−17.5%	24.4%	84.1%	37.4%
4	3974	5.1%	−64.0%	−38.3%	−6.7%	30.0%	80.9%	44.5%
5	3477	9.3%	−53.7%	−29.7%	−0.7%	32.2%	75.1%	49.6%
6	2139	12.4%	−47.9%	−23.3%	4.1%	32.9%	78.3%	54.3%
7	803	17.4%	−43.1%	−15.8%	7.1%	37.0%	78.3%	57.9%
8	110	20.3%	−46.7%	−15.5%	3.5%	39.3%	82.5%	56.4%
All	21724	3.4%	−67.5%	−43.1%	−10.0%	27.5%	80.0%	42.1%
High (6, 7, 8)	3052	14.0%	−47.1%	−21.5%	4.8%	34.7%	78.3%	55.3%
Low (0, 1)	2805	−4.9%	−74.4%	−54.7%	−25.6%	16.1%	77.8%	32.7%
High − Low		18.9%			30.4%			22.6%
t-statistic/z-statistic		9.14***			20.27***			17.87***
Bootstrap result		0/1000			0/1000			0/1000
p-Value		(0.000)			(0.000)			(0.000)

Panel B: distribution of $SRET_1$ (1-year size adjusted returns)

GSCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	614	−19.1%	−87.8%	−61.7%	−34.7%	2.7%	62.0%	26.2%
1	2191	−17.0%	−86.1%	−62.4%	−34.0%	5.0%	52.8%	27.4%
2	4038	−14.0%	−84.8%	−61.4%	−30.9%	7.6%	60.1%	28.6%
3	4378	−12.7%	−83.1%	−57.4%	−25.2%	10.8%	60.6%	31.3%
4	3974	−6.7%	−71.8%	−46.0%	−15.7%	16.9%	61.4%	36.4%
5	3477	−3.2%	−62.7%	−38.5%	−10.2%	18.3%	56.3%	39.7%
6	2139	1.3%	−54.0%	−31.2%	−5.1%	20.4%	57.6%	44.0%
7	803	6.8%	−49.7%	−23.9%	0.0%	23.3%	62.7%	49.9%
8	110	11.4%	−51.9%	−22.5%	−0.2%	21.1%	62.4%	50.0%
All	21724	−8.7%	−76.4%	−50.7%	−19.1%	14.3%	58.6%	34.6%
High (6, 7, 8)	3052	3.1%	−52.6%	−29.1%	−3.7%	21.1%	58.9%	45.8%
Low (0, 1)	2805	−17.5%	−86.3%	−62.1%	−34.0%	4.5%	54.7%	27.2%
High − Low		20.6%			30.3%			18.6%
t-statistic/z-statistic		10.41***			21.23***			15.12***
Bootstrap result		0/l000			0/1000			0/1000
p-Value		(0.000)			(0.000)			(0.000)

Table 4. Continued.

Panel C: distribution of RET_{12} (2-year raw returns)

GSCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	614	−14.5%	−88.1%	−72.2%	−44.6%	2.3%	80.6%	30.0%
1	2191	−9.2%	−86.7%	−70.8%	−37.3%	12.5%	93.5%	33.5%
2	4038	−2.4%	−87.5%	−69.5%	−34.0%	20.0%	99.3%	34.9%
3	4378	3.8%	−84.6%	−63.7%	−23.4%	32.2%	104.5%	37.4%
4	3974	15.7%	−77.8%	−49.9%	−7.1%	45.7%	118.8%	44.5%
5	3477	19.8%	−64.5%	−34.8%	2.0%	46.6%	108.8%	49.6%
6	2139	25.3%	−57.9%	−27.4%	8.9%	53.5%	111.2%	54.3%
7	803	37.4%	−52.7%	−21.1%	17.4%	66.7%	138.9%	57.9%
8	110	37.1%	−49.4%	−21.1%	13.7%	60.3%	153.4%	56.4%
All	21724	9.1%	−80.9%	−56.2%	−13.6%	38.3%	108.7%	42.1%
High (6, 7, 8)	3052	28.9%	−56.9%	−25.6%	11.2%	57.1%	121.2%	55.3%
Low (0, 1)	2805	−10.4%	−87.0%	−71.1.%	−39.6%	10.4%	87.2%	32.7%
High − Low		39.3%			50.8%			22.6%
t-statistic/z-statistic		14.52***			26.03***			17.90***
Bootstrap result		0/1000			0/1000			0/1000
p-Value		(0.000)			(0.000)			(0.000)

Panel D: distribution of $SRET_{12}$ (2-year size adjusted returns)

GSCORE	N	Mean	10%	25%	Median	75%	90%	% Positive
0	614	−36.1%	−120.8%	−92.5%	−58.1%	−10.6%	50.0%	26.2%
1	2191	−32.8%	−116.3%	−91.1%	−56.5%	−5.9%	60.1%	27.4%
2	4038	−26.4%	−114.4%	−88.6%	−54.2%	−1.9%	69.4%	28.6%
3	4378	−22.4%	−111.7%	−86.7%	−46.4%	7.5%	74.5%	31.3%
4	3974	−9.9%	−102.0%	−71.9%	−30.5%	21.4%	90.6%	36.4%
5	3477	−6.2%	−92.1%	−61.1%	−21.1%	22.3%	81.8%	39.7%
6	2139	0.9%	−81.0%	−49.3%	−11.8%	28.1%	82.9%	44.0%
7	803	13.4%	−73.1%	−41.2%	−1.7%	40.4%	108.3%	49.9%
8	110	15.5%	−64.1%	−38.4%	−4.3%	34.0%	121.7%	50.0%
All	21724	−15.9%	−106.5%	−77.2%	−36.1%	14.7%	79.1%	34.6%
High (6, 7, 8)	3052	4.7%	−77.5%	−46.9%	−8.8%	31.5%	89.6%	45.8%
Low (0, 1)	2805	−33.5%	−117.8%	−91.4%	−57.0%	−7.2%	58.2%	27.2%
High − Low		38.3%			48.2%			18.6%
t-statistic/z-statistic		14.25***			21.24***			15.12***
Bootstrap result		0/1000			0/1000			0/1000
p-Value		(0.000)			(0.000)			(0.000)

The above table presents the returns to portfolios based on the GSCORE index for the sample of 21,724 low BM firms. For a definition of GSCORE, $SRET_1$ and $SRET_2$, see the note to Table 2. Firms with GSCORE of 0 or 1 (6, 7, 8) are classified as low (high). RET_1 and RET_2 are raw buy-and-hold returns for 1-year period and 2-year period respectively, starting May 1st for the year after portfolio formation. t- statistic (z-statistic) for difference in means (medians) is from the two sample t-test (wilcoxon sign-rank test).

*/**/*** represent statistical significance using two tailed tests at 10%/5%/1% levels.

raw and size-adjusted returns for the first year after portfolio formation. For the entire low BM sample, the mean raw (size-adjusted) return is 3.4% (−8.7%). However, the return shows a strong and almost perfectly monotonic relationship with GSCORE. For instance, the mean raw return for the "0" GSCORE portfolio is −9.2%, while the mean raw return for the "8" GSCORE portfolio is 20.3%. This indicates that a portfolio strategy of going long in high GSCORE firms and shorting low GSCORE firms may be especially effective. However, very few firms are in the two extreme portfolios (614 for GSCORE = 0, and 110 for GSCORE = 8, across 23 years), and this number is especially small for high GSCORE as the distribution of GSCORE is left skewed.[11] 1 group the two lowest portfolios (0, 1) into the low group and the highest three portfolios (6, 7, 8) into the high group. This ensures that around 3000 firm-years or on average, well over 100 firms per year are in both the high and the low groups to allow the development of feasible hedge strategies.

The mean raw returns for the low group are −4.9%, as opposed to 14.0% for the high group, a difference of 18.9%. In addition, similar significant differences between the groups are seen in medians (4.8% for high vs. −25.6% for low), as well as the proportion of firms with positive returns (55.3% for high vs. 32.7% for low). This indicates that a high minus low hedge strategy based on GSCORE is effective in the aggregate. The table also presents returns for the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile in each GSCORE portfolio. In general, the returns are lower at each of these percentiles for the low GSCORE portfolios and higher for the high GSCORE portfolios. This indicates that GSCORE helps shift the distribution of returns to the left for lower score portfolios and to the right for higher score portfolios. All differences are highly significant using both conventional as well as non-parametric tests.[12]

Panel B presents size-adjusted returns. The return differences are almost identical, but one clear trend emerges. Finns in the high group earn positive but small mean size-adjusted returns (3.1%), while firms in the low group earn large negative mean size-adjusted returns (−17.5%). Hence, the strategy is more effective in identifying potential losers or torpedo stocks (see Skinner and Sloan (2002)), than in identifying winners. This may hinder the success of the strategy, especially if short selling restrictions affect the implementation of a high minus low strategy. However, the shift in returns from the sample mean is slightly stronger for the high group. High firms earns mean returns 11.8% higher than the sample mean (3.1% vs. −8.7%), while the low group earns 8.8% lower (−17.5% vs. −8.7%). We will examine this in greater depth, by analyzing the portfolio's performance across different partitions in the sub-section to follow.

Panels C and D present the raw and size-adjusted returns, respectively, for the 2-year period after portfolio formation. The return differences are almost twice as big as the 1-year return differences, indicating that the strategy's success persists strongly in the second year. The mean size-adjusted return is 4.7% for the high group and −33.5% for the low group, a significant difference of 38.3%. Similar significant differences are observed in medians and in the proportion of positive size-adjusted returns. Hence, a GSCORE based strategy effectively separates out winners from losers beyond the first year.

Table 5. Returns to an investment strategy based on GSCORE in low BM firms by partitions.

Panel A: $SRET_1$ (1-year size adjusted returns) by size partitions

	Small firms			Medium firms			Large firms		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	7347	−12.0%	−29.5%	7192	−10.8%	−23.3%	7185	−3.2%	−7.7%
High (6, 7, 8)	275	−3.3%	−14.6%	736	3.0%	−7.7%	2041	4.0%	−1.5%
Low (0, 1)	1644	−15.9%	−36.6%	888	−19.5%	−32.5%	273	−20.8%	−27.1%
High − Low		12.5%	22.0%		22.5%	24.8%		24.8%	25.6%
t-statistic/*z*-statistic		2.63^{***}	5.56^{***}		6.38^{***}	8.84^{***}		6.92^{***}	9.48^{***}

Panel B: $SRET_1$ (1-year size adjusted returns) by analyst following partitions

	No following			Limited following			Extensive following		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	9928	−13.6%	−26.8%	4620	−10.0%	−24.6%	7176	−1.2%	−7.2%
High (6, 7, 8)	599	−3.1%	−7.6%	440	0.9%	−8.3%	2013	5.4%	−1.8%
Low (0, 1)	1996	−17.7%	−34.8%	554	−15.3%	−33.8%	255	−20.6%	−27.7%
High − Low		14.6%	27.2%		16.2%	25.5%		26.0%	26.0%
t-statistic/*z*-statistic		5.08^{***}	10.11^{***}		3.07^{***}	6.78^{***}		6.85^{***}	8.35^{***}

Panel C: $SRET_1$ (1-year size adjusted returns) by exchange listing/IPO partition

	NYSE/AMEX			NASDAQ			IPO firms			Non-IPO firms		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	7318	−4.0%	−8.5%	14406	−11.1%	−26.3%	2905	−17.8%	−32.1%	18819	−7.3%	−17.2%
High (6, 7, 8)	1469	2.2%	−0.3%	1583	4.0%	−7.7%	142	−1.4%	−6.5%	2910	3.3%	−3.7%
Low (0, 1)	557	−11.7%	−24.7%	2248	−18.9%	−36.1%	605	−23.5%	−37.9%	2200	−15.8%	−33.2%
High − Low		13.9%	24.4%		22.9%	28.4%		22.1%	31.3%		19.2%	29.5%
t-statistic/*z*-statistic		4.07^{***}	10.20^{***}		8.49^{***}	15.05^{***}		3.55^{***}	4.86^{***}		8.79^{***}	19.24^{***}

Table 5. Continued.

Panel D: $SRET_1$ (1-year size adjusted returns) by growth related partitions

	Fast growing firms			Slow growing firms			Hi-tech firms			Non-hi-tech firms		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	10190	−9.8%	−22.6%	11534	−7.8%	−16.0%	7504	−6.0%	−21.4%	14220	−10.2%	−18.0%
High (6, 7, 8)	1216	6.1%	−4.2%	1836	1.1%	−3.1%	1180	4.9%	−7.2%	1872	2.0%	−2.2%
Low (0, 1)	1396	−20.1%	−35.4%	1409	−14.8%	−33.3%	897	−11.3%	−34.3%	1908	−20.4%	−33.8%
High − Low		26.2%	31.1%		16.0%	30.2%		16.2%	27.0%		22.4%	31.6%
t-statistic/*z*-statistic		8.68***	13.88***		5.79***	15.45***		4.03***	10.12***		10.52***	19.02***

Panel E: $SRET_1$ (1-year size adjusted returns) by liquidity partitions

	Low Bid-Ask spreads			High Bid-Ask spreads			Low trading turnover			High trading turnover		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	8503	−8.1%	−19.3%	8491	−11.3%	−28.4%	10160	−5.7%	−13.2%	10172	−11.8%	−24.7%
High (6, 7, 8)	1202	2.8%	−5.8%	668	6.2%	−8.4%	1493	0.9%	−2.3%	1496	4.6%	−5.6%
Low (0, 1)	939	−16.0%	−31.3%	1611	−18.6%	−37.4%	1331	−12.8%	−30.3%	1266	−23.0%	−37.7%
High − Low		18.8%	25.4%		24.8%	29.0%		13.7%			27.6%	
t-statistic/*z*-statistic		5.23***	10.14***		11.30***	15.32***		5.22***	4.09***		9.44***	14.42***

Panel F: $SRET_I$ (1-year size adjusted returns) by trading volume partitions

	Low number of shares traded			High number of shares traded			Low dollar volume			High dollar volume		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	10158	−8.8%	−20.6%	10169	−8.7%	−16.6%	10158	−10.8%	−25.2%	10169	−6.7%	−12.8%
High (6, 7, 8)	864	−0.1%	−5.7%	2124	3.9%	−3.0%	586	−3.5%	−8.1%	2402	4.3%	−2.9%
Low (0, 1)	1605	−15.4%	−33.4%	992	−21.7%	−35.6%	1958	−16.3%	−34.8%	639	−22.2%	−33.2%
High − Low		15.2%	27.7%		25.6%	32.6%		12.8%	26.7%		26.5%	30.3%
t-statistic/*z*-statistic		5.46***	11.79***		9.36***	16.24***		4.29***	9.15***		9.90***	13.80***

Panel G: $SRET_1$ (1-year size adjusted returns) excluding low GSCORE NASDAQ firms without put options

	Exclude all Low GSCORE firms without put options			Exclude all Low GSCORE NASDAQ firms without put options			Exclude all Low GSCORE NASDAQ firms without put options prior to 1990		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
All	19148	−7.5%	−17.1%	19635	−7.5%	−17.3%	20694	−8.3%	−18.5%
High (6, 7, 8)	3052	3.1%	−3.7%	3052	3.1%	−3.7%	3052	3.1%	−3.7%
Low (0, 1)	229	−9.1%	−26.3%	711	−10.6%	−25.2%	1770	−17.3%	−35.5%
High − Low		12.2%	22.5%		13.7%	21.5%		20.5%	31.8%
t-statistic/*z*-statistic		2.24**	5.90***		6.38***	8.84***		6.92***	9.48***

The above table presents the 1-year ahead size-adjusted returns ($SRET_1$) to portfolios based on GSCORE for the sample of 21,724 low BM firms, within a variety of partitions. For a definition of GSCORE and $SRET_1$, see the note to Table 2. Firms with GSCORE of 0 or 1 (6, 7, 8) are classified as low (high). 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. Firms with following greater than or equal to the median in that year are classified as having extensive following. Exchange listing is based on the CRSP classification at the time of portfolio formation. IPO firms are those that went public within the previous year. Firms with annual sales growth rates in excess of the median amongst low BM firms in the same two-digit SIC code are classified as fast growing firms. Hi-Tech classification is based on Field and Hanka (2001) Bid ask spreads (Ask – Bid), trading turnover (shares traded/shares outstanding), number of shares traded, as well as dollar volume of trades are all obtained from CRSP by averaging daily data over the prior year; firms with values greater than or equal to (less than) the contemporaneous median for all low BM firms are classified as high (low). *t*-statistic (*z*-statistic) for difference in means (medians) is from the two sample *t*-test (wilcoxon sign-rank test).

*/**/*** represent statistical significance using two tailed tests at 10%/ 5%/ 1% levels.

4.2. *Partition Analysis*

One concern with a strategy that identifies extreme performers is that the returns may be concentrated in a peculiar subset of firms, for instance small firms or firms that are not followed by analysts or are thinly traded. This may cause difficulties in the implementation of a strategy based on buying stocks with high GSCORE and selling stocks with low GSCORE. The poor performance of low GSCORE firms is crucial to the success of the strategy, and if most of these firms belong to subsets that have great illiquidity or trading restrictions, the strategy will be difficult to implement. Further, the composition of low BM firms is not homogeneous and while the category is likely to be over-weighted with growth firms, it also includes other firms. This may pose implementation problems for those focusing solely on growth firms. To address these issues, I compare the performance of the growth fundamentals strategy across different partitions. The results are presented in Table 5. For brevity, the partition analysis is conducted only for 1 year ahead returns and only returns for the entire partition, high GSCORE and low GSCORE groups are presented.

4.2.1. *Size Partition*

I first partition the sample of low BM firms into three equal partitions based on size, defined as market capitalization of equity (Table 5 – Panel A).[13] The BM effect is strongest for small firms and gets progressively weaker as firm size increases. Small firms earn average excess returns of −12.0%, compared to −10.8% for medium sized firms and −3.2% for large firms.

The effectiveness of a strategy based on GSCORE is interestingly positively correlated with firm size. For small firms, the separation in mean excess returns between low and high portfolios is 12.5%. For medium firms, the mean separation is 22.5%, while for large firms the separation is 24.8%. All three return differences are highly significant at better than 1%. A similar trend is seen for median returns. The strong result for large firms is crucial, as such firms are also least likely to have illiquid stocks or restrictions on short-selling.[14] However, it must be noted that most high GSCORE firms in the sample are large firms (2041 out of 3052), while most low GSCORE firms are small firms (1644 out of 2805). This implies that partitions for liquidity and trading restrictions are still likely to be important.

4.2.2. *Analyst Following Partition*

I next partition the sample of low BM firms into three groups – firms with no analyst following, firms with limited analyst following and firms with extensive analyst following. Analyst following is calculated as the number of I/B/E/S analysts who followed the firm at the time of portfolio formation. Almost half the sample does not have analyst following (9928 out of 21,724 firm-years). For the remaining firms, I compare their analyst following to other firms in the same two-digit SIC code at the same point in time. Firms with analyst following equal to or above the median are classified as having extensive following and the rest are classified as having limited following. The results are presented in Panel B of Table 5.

In all three categories, there is a substantial difference between high and low GSCORE firms. The mean return difference is 14.6% for firms without analyst following, 16.2% for firms with limited following and 26.0% for firms with extensive following. Interestingly, the return difference is related positively to analyst following. This indicates that sophisticated users of financial information, such as analysts, are more susceptible to ignoring the implications of factors such as profitability and conservatism, and to naive extrapolation.[15] This offers an interesting contrast to the FSCORE strategy in Piotroski (2000), who finds strongest results in firms without analyst following, indicating that the success of the FSCORE strategy appears to be driven by investors ignoring the financial information of a class of firms. For low BM firms, at least a part of the success of the GSCORE strategy is driven not by investors ignoring the financial information but misinterpreting the financial information of this class of firms.

4.2.3. Exchange Listing Partition

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

Return differences are significant for both groups of firms, but much stronger for NASDAQ firms. The return difference is 13.9% for NYSE/AMEX firms (2.2% for high vs.−11.7% for low), and 22.9% for NASDAQ firms (4.0% for high vs. −18.9% for low). This has two interesting implications. First – the strategy is most effective in identifying the torpedoes (stocks likely to perform very poorly) among NASDAQ firms. Second – by going long on high firms in the NASDAQ, and shorting NYSE/AMEX firms, one can earn a hedge return of around 15.7% (4.0% vs. −11.7%), which maybe an interesting option if shorting NASDAQ stocks is difficult.

4.2.4. IPO Partition

Given the large proportion of recent IPOs (firms that have gone public less than one year before portfolio formation) amongst low BM firms (12%), I now test whether the strategy is driven by the inclusion or exclusion of IPO firms. This ensures that the strategy is doing more than merely shorting IPO firms, thereby taking advantage of the well documented underperformance of IPOs. Further, such firms typically have lower liquidity and are extremely difficult to short. The results are presented in the right columns of Panel C of Table 5.

By construction, IPO firms have a lower GSCORE, as they do not meet the data requirements for some of the signals, such as earnings variability and sales growth variability. Only 142 IPO firms were classified as high GSCORE firms, while 605 were classified as low. However, the GSCORE strategy is clearly helpful in identifying torpedo stocks amongst IPO firms, as the mean size-adjusted returns for the low group are −23.5%, while the returns for the high group are −1.4%, a difference of 22.1%. When one excludes IPO firms and constructs portfolios with only non-IPO firms, the GSCORE strategy continues to be effective; the return difference for non-IPO firms is a robust 19.2%. This compares favorably with the 20.6% return difference seen for the entire sample. Hence, the success of the GSCORE strategy is not dependent on the avoidance/shorting of IPO firms.

4.2.5. "Real Growth Firms" vs. Rest

The next two partitions separate out the entire population of low BM firms into those that are more likely to truly be "growth" firms and those that are classified as low BM for other reasons. This is a potentially important partition, especially for investors who are interested in or constrained to invest only in growth stocks. As the definition of what constitutes a growth stock is rather unclear, I consider two partitions. First, I separate out the truly fast growing firms from the rest, by comparing the firms' sales growth to other low BM firms in the same two-digit SIC code. Second, I isolate high technology firms which are likely to be growth firms. The results are presented in Panel D of Table 5.

The left columns separate out fast growing firms from the rest by partitioning firms at their contemporaneous industry medians. The mean and median sales growth for the fast growing partition was 62% and 48% respectively, as opposed to 2% mean and 6% median for the slow growing partition. As the results indicate, the return differences are significant in both groups and in fact stronger in the subset of fast growing stocks. Hence, even if one focuses only on growth stocks and excludes other low BM stocks, the GSCORE strategy provides strong returns.

I use the classification proposed by Field and Hanka (2001) to identify hi-tech firms.[16] As the results indicate, even if one focuses on hi-tech firms alone, the return difference between the high and low group is 16.2%. Also, the mean size-adjusted return for the high group is 4.9%, slightly higher than for the entire population of low BM firms. Hence, the strategy appears to be successful not just in identifying potential losers but in identifying winners as well amongst hi-tech firms.

4.2.6. Liquidity Partitions

To measure the potential impact of factors such as illiquidity and shorting restrictions that may affect the success of the strategy, I partition the sample using a number of different proxies for liquidity. The results are presented in Table 5, Panels E to F.

The left columns of Panel E partition the sample on the basis of bid-ask spread, using the average daily bid-ask spread from the previous year. This information is only available for a subset of the firms in the sample. The results indicate that the return differences are indeed stronger in the group with greater bid-ask spreads (24.8%), but also strongly significant for the group with lower bid-ask spreads (18.8%). The right columns partition the sample on the basis of share turnover (average shares traded daily divided by shares outstanding). Interestingly, the return differences are much greater for the partition with greater share turnover (27.6% vs. 13.7%). Panel F partitions the sample based on trading volume calculated either in terms of number of shares or in terms of dollar volume. Both partitions indicate that the results are stronger when trading volume is higher. This is probably related to the earlier finding that the results are in fact stronger in large firms. One can hence conclude that lack of liquidity is unlikely to be a severe constraint in the implementation of this strategy.

4.2.7. Partitions Based on the Ability to Buy Put Options

Finally, I incorporate information about the ability of investors to purchase put options into the analysis. Even if unable to short a stock, an investor could attain the same position by buying a put option. As this constraint applies only on the shorting side, it is only applied for firms in the low GSCORE group.

I obtain the data on option listing used in the analysis of the determinants of option listing by Mayhew and Mihov (2004). The results are presented in Table 5, Panel G. I first exclude all firms for which put options were not available. The return difference declines to 12.2% but is still significant. In the next analysis, I only exclude NASDAQ firms that did not have put options, as shorting NYSE/AMEX firms is relatively easier. The return difference rises to 13.7% and is much more significant.

In recent times, it has become easier and cheaper, in terms of transaction costs, to short NASDAQ stocks. For instance, Geczy et al. (2002) find "the loans of initial public offering (IPOs), DotCom, large-cap, growth and low-momentum stocks to be cheap relative to the strategies' documented profits." I repeat the analysis excluding only NASDAQ firms without put options prior to 1990, as shorting has become easier and less expensive in the past decade. The return difference obtained for this group is 20.5%, almost identical as that for the entire sample. These results indicate that the inability to short stocks was not too serious a constraint, as investors could buy puts and attain strong hedge returns to the GSCORE strategy.

4.3. Robustness of Results across Time

In this section, I examine the robustness of the GSCORE strategy across time to ensure that the results are not driven by extreme or unusual return patterns at some points in time or time clustering of observations. Table 6 presents the size-adjusted returns for the high and low groups of firms for each of the years (1979 to 2001). I

Table 6. Performance of the GSCORE strategy in low BM firms across time.

	High GSCORE		Low GSCORE			
Year	N	Mean $SRET_1$	N	Mean $SRET_1$	Difference	t-statistic
1979	155	13.0%	77	11.5%	1.5%	0.08
1980	167	−4.2%	196	−21.0%	16.8%	4.22***
1981	76	10.9%	98	−26.6%	37.4%	2.39**
1982	119	−13.0%	109	−28.7%	15.7%	3.90***
1983	164	−9.7%	167	−22.9%	13.1%	2.53**
1984	54	6.1%	95	−25.3%	31.4%	3.06***
1985	111	−1.8%	138	0.2%	−2.0%	−0.28
1986	117	−4.0%	149	−18.0%	14.1%	3.22***
1987	106	0.7%	146	−18.4%	19.1%	3.31***
1988	122	9.7%	133	−12.6%	22.4%	3.41***
1989	160	10.0%	119	−7.2%	17.2%	2.12**
1990	134	5.6%	81	9.5%	−3.9%	−0.23
1991	235	−9.7%	139	−20.3%	10.7%	1.45
1992	195	6.5%	110	−19.6%	26.1%	3.61***
1993	209	13.3%	146	−30.0%	43.4%	7.85***
1994	142	4.3%	132	−4.7%	9.0%	0.88
1995	191	−10.9%	207	−29.5%	18.6%	4.28***
1996	191	8.2%	188	−24.8%	32.9%	3.48***
1997	205	−3.0%	149	−7.2%	4.2%	0.58
1998	185	41.7%	324	29.0%	12.7%	0.83
1999	240	−10.1%	399	−45.6%	35.5%	7.60***
2000	153	−6.5%	209	−38.5%	32.0%	5.71***
2001	189	−2.8%	195	−27.0%	24.1%	5.36***
Mean (year by year)		2.4%		−16.4%	18.8%	7.27***

The above table presents the returns to a GSCORE strategy across time for the sample of 21,724 low BM firms, within a variety of partitions. For a definition of GSCORE and $SRET_1$, see the note to Table 2. To ensure that an adequate number of firms are available each year for the strategy, firms with GSCORE less than or equal to the 10th percentile in that year are classified as low GSCORE firms, while firms with GSCORE greater than or equal to the 10^{th} percentile in that year are classified as high GSCORE firms. t-statistics for differences in means for each year are from two-sample t-tests. t-statistics for the entire period are calculated from the time series of return differences from 1979 to 2001, corrected for auto-correlation as in Bernard (1995).

*/**/*** represent statistical significance using two tailed tests at 10%/ 5%/ 1% levels.

define the high and low cutoffs as the GSCORE of the 90th and 10th percentiles of the distribution in a given year. This ensures that while the cutoff may not necessarily be the same in each year, there will be enough observations in each year (at least 10% in each group) for a meaningful hedge strategy.

The strategy is remarkably robust across time. In 21 out of 23 years, the strategy paid positive returns, and in 16 out of the 23 years, the return difference was statistically significant. In 18 years, the return difference was greater than 10%. Further, all but 4 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 certain years because of too few firms in the extreme groups. The success of the strategy in avoiding negative performance over a relatively long time series of 23 years also lends credence to a market mispricing explanation as opposed to a risk based explanation.

4.4. Controlling for Risk Factors

The GSCORE strategy could potentially be correlated with other well documented risk factors and anomalies. First, it is possible that within the sample of low BM firms, low GSCORE firms have much lower BM ratios than high GSCORE firms. Second, one of the components of GSCORE is the signal G3, which chooses firms with greater cash flows than earnings. This picks up on the accrual effect documented by Sloan (1996), although univariate tests indicate that this signal is ineffective in this setting. 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 et al. (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.

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 6 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. The regressions are run each year, and Table 7 presents the summary from the annual regressions. The *t*-statistics are calculated from the distribution of coefficients from 23 annual regressions, adjusting for autocorrelation as in Bernard (1995).

The first regression includes all the control variables, but excludes GSCORE. The proxies for size, BM and momentum all have significant positive coefficients. Neither the accrual variable nor the equity offering variable is significant. The regression has an average adjusted R^2 of just over 1%.

The second regression adds GSCORE to the control variables. The explanatory power of the regression increases fourfold, with an average adjusted R^2 of over 4%. The coefficient on GSCORE is a highly significant 0.034, indicating that a one point increase in GSCORE is associated with a size-adjusted return of 3.4%. SIZE is no longer significant, indicating the positive correlation between GSCORE and size because of the over-representation of large firms in the high GSCORE group. LBM and MOM are still significant. Hence, GSCORE adds value even after controlling for size, BM and momentum.

The mean values of GSCORE is 0.78 for the low group (614 and 2191 firm-years for GSCORE 0 and 1 respectively), and 6.34 for the high group (2139, 803 and 110 firm-years for GSCORE 6, 7 and 8 respectively), a difference of 5.56. If one extrapolates from the above regression, this implies a return difference of 5.56*3.4%, or approximately 18.9% between the high and low groups, as compared to the 20.6%

Table 7. Year by year regressions for annual returns.

Model	Intercept	SIZE	BM	MOM	ACCR	EQ_OFF	GSCORE	Adj.R^2
(1)	−0.063	0.012	0.044	0.023	−0.023	−0.009		1.06%
	(−1.50)	(3.58)***	(2.24)**	(2.32)**	(−0.70)	(−0.56)		
(2)	−0.138	−0.001	0.034	0.023	−0.052	−0.008	0.034	4.29%
	−(3.29)***	(−0.25)	(1.69)*	(2.46)**	(−1.42)	(−0.50)	(5.53)***	

The above table presents a regression of the 1-year ahead size adjusted return $SRET_1$ on GSCORE and other risk and anomaly factors, for the sample of low BM firms. For a definition of GSCORE and $SRET_1$, see the note to Table 2. SIZE is measured as log of market capitalization. BM is the BM ratio at the time of portfolio formation. MOM is the buy and old return for the 6 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 film issued equity in the year prior to portfolio formation. Figures in brackets are t-statistics. Of the 21,724 observations from 1979 to 2001, 21,253 had all the information required for the regressions. The figures presented are averages from 23 annual regressions from 1979 to 2001. The t-statistics are adjusted for auto-correlation using the method outlined in Bernard (1995). Number of observations varies from a low of 431 in 1982 to a high of 1485 in 1995.

*/**/*** represent statistical significance using two tailed tests at 10%/5%/1% levels.

difference reported in Table 4. Hence, the effectiveness of the strategy persists after controlling for factors such as momentum, size, BM and the accrual anomaly.

5. Risk or Mispricing?

The results in the previous section indicate that low BM firms with high GSCORE earn significantly greater returns than low BM firms with low GSCORE. This return difference persists after controlling for documented risk factors and anomalies. For market mispricing to explain the success of GSCORE, it must be the case that the stock market does not fully impound the future implications of current growth fundamentals. Future fundamentals are likely to be stronger for high GSCORE firms and weaker for low GSCORE firms, and the stock market is unable to draw the correlation between current growth fundamentals and future realization of fundamentals. In this section, I explore this in two ways – by analyzing forecast errors by analysts and stock market reaction to future earnings announcements. Further, I compare the risk characteristics of the different GSCORE portfolios to test the validity of risk based explanations.

5.1. Stock Market Reaction to Earnings Realizations

I analyze the stock market reaction to future earnings of low BM firms in two ways. First, I examine the extent to which analysts are surprised by future realizations of earnings. 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.

Analyst forecasts are obtained from I/B/E/S at or around May 1st of the year after portfolio formation to ensure that all financial information used in the construction of GSCORE has been released. Annual analyst forecast surprise is defined as the difference between actual realized EPS and the consensus EPS estimate for the first year after portfolio formation. In addition, forecast surprises are calculated for the four quarterly periods after May 1st. All forecast surprises are scaled by stock price as of May 1st. All information is obtained from I/B/E/S. The results are presented in Table 8.

Slightly less than half the sample of low BM firms had adequate information to calculate analyst forecast surprise. For the remainder, as shown in Panel A of Table 8, analysts' surprises were generally much more negative for low GSCORE firms and neutral to less negative for high GSCORE firms. Firms in the high GSCORE group have on average a forecast surprise of −0.5%, while the mean surprise for low GSCORE firms is −2.3%, with the difference being highly significant. The difference of 1.8% 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 is substantial. Further, there is a near monotonic relationship between GSCORE and the proportion of firms that report positive earnings surprises, with almost 50% of high GSCORE

Table 8. Relation between GSCORE and Surprises/Returns around future earnings announcements.

Panel A: Mean annual analyst forecast surprises

GSCORE	*N*	Year 1	% Positive	*N*	Year 2	% Positive
0	91	−2.9%	27.5%	67	−3.8%	23.9%
1	449	−2.2%	30.3%	307	−3.5%	20.5%
2	1207	−1.7%	37.8%	913	−3.2%	23.4%
3	1770	−1.3%	38.7%	1354	−2.7%	24.1%
4	2145	−1.0%	43.0%	1731	−2.2%	26.6%
5	2253	−0.7%	44.5%	1956	−1.6%	30.5%
6	1558	−0.5%	48.3%	1350	−1.3%	33.0%
7	632	−0.4%	51.3%	567	−1.0%	38.4%
8	95	−0.3%	50.5%	83	−1.0%	37.3%
All	10200	−1.0%	42.6%	8328	−2.1%	28.5%
High (6, 7, 8)	2285	−0.5%	49.2%	2000	−1.2%	34.8%
Low (0, 1)	540	−2.3%	29.8%	374	−3.6%	21.1%
High − Low		1.8%	19.4%		2.4%	13.6%
t-statistic		11.96***	8.69***		11.69***	5.76***

Panel B: Mean quarterly analyst forecast surprises

GSCORE	*N*	1st quarter	2nd quarter	3rd quarter	4th quarter	All quarters
0	20	−0.6%	−0.1%	−1.2%	−1.1%	−3.0%
1	133	−0.5%	−0.5%	−0.8%	−1.0%	−2.9%.
2	451	−0.3%	$_{7}$0.4%	−0.7%	−0.9%	−2.4%
3	690.	−0.3%	−0.4%	−0.6%	−0.7%	−1.9%
4	945	−0.1%	−0.3%	−0.4%	−0.5%	−1.3%
5	1189	−0.1%	−0.2%	−0.3%	−0.4%	−1.0%
6	926	−0.1.%	−0.1%	−0.2%	−0.3%	−0.7%
7	445	−0.1%	−0.1%	−0.2%	−0.2%	−0.5%
8	75	−0.1%	−0.1%	−0.1%	−0.2%	−0.5%.
All	4874	−0.2%	−0.3%	−0.4%	−0.5%	−1.3%
High (6, 7, 8)	1446	−0.1%	$_{7}$0.1%	−0.2%	−0.2%	−0.6%
Low (0, 1)	153	−0.5%	−0.5%	−0.9%	−1.0%	−2.9%
High − Low		0.5%	0.3%	0.7%	0.8%	2.3%
t-statistic		3.01***	2.51***	4.46***	4.62***	5.39***

Panel C: Mean returns around earnings announcement

GSCORE	*N*	$SRET_1$	1st quarter	2nd quarter	3rd quarter	4th quarter	All quarters
0	241	−15.3%	−0.4%	−0.3%	−0.2%	−0.6%	−1.5%
1	1011	−12.2%	−1.1%	−1.0%	0.2%	−0.4%	−2.3%
2	2256	−9.0%	1.1%	−0.8%	0.1%	−2.3%	−1.9%
3	3117	−10.0%	0.0%	−1.3%	−0.2%	−0.9%	−2.3%
4	3271	−4.6%	0.8%	−0.6%	0.1%	−0.4%	−0.1%
5	3181	−1.9%	0.8%	−0.2%	0.0%	−0.6%	0.0%
6	1922	0.6%	1.2%	−0.5%	0.6%	0.7%	1.9%
7	754	6.5%	2.1%	0.5%	2.6%	0.9%	6.1%
8	108	11.4%	2.6%	−2.4%	−0.7%	0.5%	0.1%
All	15861	−5.1%	0.7%	−0.7%	0.2%	−0.6%	−0.4%
High (6, 7, 8)	2784	2.6%	1.5%	−0.3%	1.1%	0.8%	3.0%

Table 8. Continued.

Panel C: Mean returns around earnings announcement

GSCORE	*N*	$SRET_1$	1st quarter	2nd quarter	3rd quarter	4th quarter	All quarters
Low (0, 1)	1252	−12.8%	−0.9%	−0.9%	0.1%	−0.4%	−2.1%
High − Low		15.4%	2.4%	0.5%	1.0%	1.2%	5.1%
t-statistic		5.43***	3.94***	0.81	1.24	1.78*	3.63%

The above table analyzes analyst forecast surprises and returns around earnings announcements for portfolios based on the GSCORE index for the subset of the sample of 21,724 low BM firms for which the relevant data were available. For a definition of GSCORE and $SRET_1$, see the note to Table 2. All IBES estimates are obtained at or around May 1st of the year after portfolio formation, to coincide with the return accumulation period. Analyst forecast surprises are defined as the difference between actual realized EPS and the mean consensus estimate, scaled by stock price. Forecast surprises are winsorized at 1% and 99% to remove the influence of outliers. For quarterly forecast surprises, firms are included only if the information is available for all four quarterly forecasts. The surprise for All Quarters is the sum of the scaled surprises for each of the four quarters. Returns are calculated in a 3-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 four quarterly announcements. Firms are included only if all four quarterly announcement dates and the returns for these dates were available. *t*-statistics for differences in means are from two-sample *t*-tests.

*/**/*** represent statistical significance using two tailed tests at 10%/5%/1% levels.

firms meeting or beating analyst expectations, as opposed to less than 30% for low GSCORE firms. Similar results are seen for 2 year ahead forecasts.

Panel B of Table 8 compares the quarterly forecast surprise across the firms based on their GSCORE. To analyze trends across time, only firms with information for all four quarters are analyzed, reducing the sample size to 4874.[17] The difference in forecast surprise between the high and low groups is only 0.5% in the first quarter after portfolio formation, and 0.3% in the second quarter, but rises to 0.7% and 0.8% over the next two quarters. This represents a significant unraveling in performance on the part of the low GSCORE firms as time progresses. The total difference in mean surprise across the four quarters is 2.3%.

Using announcement dates obtained from COMPUSTAT, I next examine the stock-market 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. Announcement date and return information was available for all four quarters for 15,861 out of the 21,724 observations. Results are presented in Panel C of Table 8.

For comparison, the 1-year ahead size-adjusted returns ($SRET_1$) are also presented. The return difference between the high and low portfolios is only 15.4% for this subsample as opposed to 20.6% 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 GSCORE firms and more positive for

Table 9. Relation between GSCORE and risk measures.

Panel A: Systematic and unsystematic risk

GSCORE	N	Mean $SRET_1$	Mean β	N	Mean $SRET_1$	Mean STDRET
0	328	−15.6%	1.427	562	−19.1%	84.0%
1	1178	−13.3%	1.518	2001	−15.9%	85.5%
2	2361	−11.3%	1.491	3682	−12.8%	81.8%
3	2710	−10.3%	1.526	4029	−11.5%	74.8%
4	2898	−6.4%	1.401	3782	−6.0%	64.2%
5	2746	−2.4%	1.302	3397	−3.1%	53.8%
6	1814	1.7%	1.261	2113	1.3%	50.5%
7	700	7.3%	1.259	796	6.9%	49.0%
8	100	13.6%	1.312	109	11.4%	49.4%
All	14835	−6.1%	1.405	20471	−7.8%	68.3%
High (6, 7, 8)	2614	3.7%	1.263	3018	3.2%	50.1%
Low (0, 1)	1506	−13.8%	1.498	2563	−16.6%	85.2%
High − Low		17.4%	−0.235		19.8%	−35.1%
t-statistic		6.98***	−9.61***		9.53***	−29.99***

Panel B: Ex-Ante risk

GSCORE	N	Mean $SRET_1$	Mean RP_{OJ}
0	67	−11.7%	14.2%
1	267	−14.3%	13.2%
2	708	−8.0%	12.2%
3	1182	−9.9%	11.5%
4	1761	−2.4%	10.9%
5	2113	−0.4%	10.2%
6	1536	2.6%	9.7%
7	632	8.7%	9.5%
8	94	15.1%	9.1%
All	8360	−1.9%	10.7%
High (6, 7, 8)	2262	4.8%	9.6%
Low (0, 1)	334	−13.8%	13.4%
High − Low		18.6%	−3.8%
t-statistic		4.93***	11.18***

The above table analyzes the risk characteristics for portfolios based on the GSCORE index for the subset of the sample of 21,724 low BM firms for which the relevant data were available. For a definition of GSCORE and $SRET_1$, see the note to Table 2 β is calculated using monthly returns, with the requirement that at least 24 observations be available. Return Variability is measured by STDRET, the standard deviation of daily returns in the past year, with the requirement that there at least 100 observations be available, annualized by multiplying by $\sqrt{252}$. $SRET_1$ is reported separately alongside both β as well as STDRET as the composition of firms that have enough information to calculate β and STDRET is different. Ex-ante risk is measured as the risk premium from the Ohlson–Juettner model ($RP_{OJ)}$ as implemented in Gode and Mohanram (2003). t-statistics for differences in means are from two-sample t-tests.

*/**/*** represent statistical significance using two tailed tests at 10%/5%/1% levels.

the high GSCORE portfolios. The summed quarterly announcement excess returns are 3.0% for the high group and −2.1% for the low group, a significant difference of 5.1%. This difference is almost a third of the total annual return difference of 15.4% between the two groups. This indicates that a significant proportion of the under-performance 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 current growth fundamentals for low BM firms, and is predictably surprised at future realizations.

5.2. *Risk vs. Mispricing: Evidence from Risk Factors*

The evidence thus far is more consistent with a mispricing based explanation for the return performance of low BM firms, especially the results showing that the market fails to impound the information in the firms' current growth fundamentals. However, to ensure that differences in risk do not drive the success of the GSCORE strategy, I compare the GSCORE portfolios on the basis of three measures of risk – systematic risk as measured by β, unsystematic risk as measured by total stock return variability, and ex-ante risk as measured by the implied risk premium from the Ohlson and Juettner-Nauroth (2005) model. The results are presented in Table 9.

Panel A of Table 9 presents the results for systematic and unsystematic risk. β is measured using monthly returns, ensuring that at least 30 months of returns are available. This reduces the size of the sample to just over 14,835 observations. As the table indicates, the mean β of the high GSCORE group at 1.26 is significantly lower than the mean β for the low GSCORE group at 1.5. This contradicts a systematic risk based explanation, given that high GSCORE firms in this sub-sample earn a size-adjusted 3.7% while low GSCORE firms earn −13.8%.

I measure return variability as the annualized standard deviation of daily returns from the most recent year, after ensuring that at least 100 trading days of information are available. Firms with low GSCORE had a mean return variability of 85%, almost twice that of the high GSCORE firms (50%). This strong negative relationship is probably driven by the fact that earnings and sales growth stability, which are important components of GSCORE, are strongly correlated with return variability. Hence, one sees an inverse relationship between GSCORE and return variability, as opposed to the strong positive relationship between GSCORE and ex-post returns.

In addition to conventional measures of systematic and unsystematic risk, I also measure risk using an ex-ante approach that infers the market's implied riskiness of a firm from its current valuation and expected future earnings or cash flows. Prior research has either used a residual income valuation (RIV) based approach towards the calculation of ex-ante risk or used approaches based on the price/earnings to growth (PEG) ratio. Given that the RIV method is based implicitly on the BM ratio, its interpretation can be confounding in the context of this paper. I hence use the PEG based approach outlined in the Ohlson and Juettner (2005) model as implemented in Gode and Mohanram (2003).[18] The ex-ante risk premium is calculated on the 1st of May of the year after portfolio formation for all firms for which necessary

Table 10. The importance of context in financial statement analysis.

Panel A: distribution of $SRET_1$ (1-year size adjusted returns) for GSCORE portfolios in high BM firms

GSCORE	*N*	Mean	10%	25%	Median	75%	90%	% Positive
0	396	−0.6%	−78.3%	−49.5%	−13.3%	22.0%	83.4%	48.0%
1	1640	3.9%	−76.2%	−49.0%	−14.7%	26.4%	86.5%	50.7%
2	3202	3.1%	−76.7%	−47.8%	−13.6%	24.8%	79.8%	49.3%
3	4077	5.6%	−70.0%	−42.0%	−9.4%	27.7%	81.6%	52.6%
4	3826	6.8%	−63.0%	−35.4%	−5.8%	28.1%	73.3%	56.5%
5	2762	5.2%	−59.4%	−32.8%	−4.6%	27.7%	75.8%	58.0%
6	1363	11.5%	−49.1%	−26.2%	1.2%	32.8%	78.4%	64.0%
7	294	8.2%	−54.2%	−29.5%	−2.9%	23.5%	65.0%	58.5%
8	33	13.9%	−50.2%	−27.7%	−16.2%	42.2%	97.4%	48.5%
ALL	17593	5.6%	−67.6%	−39.3%	−7.8%	27.4%	78.2%	54.4%
HIGH (6,7,8)	1690	11.0%	−50.3%	−27.5%	0.4%	31.8%	76.1%	62.7%
LOW(0, 1)	2036	3.0%	−76.3%	−49.1%	−14.7%	25.0%	86.5%	50.1%
High − Low		7.9%			15.0%			12.6%
t-statistic/*z*-statistic		2.75***			8.63***			7.78***
Bootstrap result		0/1000			0/1000			0/1000
p-Value		(0.000)			(0.000)			(0.000)

Panel B: distribution of $SRET_1$ (1-year size adjusted returns) for FSCORE portfolios in low BM firms

FSCORE	*N*	Mean	10%	25%	Median	75%	90%	% Positive
0	117	−20.7%	−97.0%	−73.7%	−33.6%	14.4%	69.6%	35.0%
1	1784	−9.6%	−87.9%	−59.1%	−28.6%	13.4%	79.4%	30.6%
2	2649	−17.4%	−86.0%	−60.6%	−30.2%	5.6%	59.4%	27.8%
3	3809	−12.8%	−81.8%	−57.8%	−27.3%	8.9%	59.0%	30.6%
4	4511	−9.3%	−76.2%	−50.7%	−19.6%	13.2%	53.6%	34.3%
5	3987	−5.9%	−72.2%	−46.0%	−14.3%	16.1%	59.2%	36.7%
6	2826	−3.0%	−65.2%	−39.9%	−10.6%	19.0%	58.4%	40.2%
7	1472	−1.3%	−56.8%	−32.9%	−6.9%	19.6%	53.5%	42.3%
8	513	2.2%	−56.4%	−31.8%	−5.1%	19.9%	62.7%	44.1%
9	56	−3.3%	−55.4%	−30.9%	−6.9%	19.6%	61.9%	46.4%
All	21724	−8.7%	−76.4%	−50.7%	−19.1%	14.3%	58.6%	34.6%
High (7,8,9)	2041	−0.5%	−56.8%	−32.7%	−6.7%	19.7%	55.5%	42.9%
Low (0, 1)	1901	−10.3%	−88.7%	−59.4%	−28.7%	13.5%	75.4%	30.9%
High − Low		9.8%			22.0%			12.0%
t-statistic/*z*-statistic		3.68***			12.18***			7.87***
Bootstrap result		0/1 000			0/1 000			0/1000
p-Value		(0.000)			(0.000)			(0.000)

GSCORE is the sum of eight fundamental signals, G1:G8, tailored for growth firms. For a definition of GSCORE and $SRET_1$, see the note to Table 2. FSCORE is the sum of nine traditional fundamental signals from Piotroski (2000). Firms with BM ratios above the 80th percentile using prior year distributions are classified as high BM (value) firms, while firms with BM ratios below the 20th percentile using prior year distributions are classified as low BM (growth) firms, *t* -statistic (*z*- statistic) for difference in means (medians) is from the two sample *t*-test (wilcoxon sign-rank test).

*/**/*** represent statistical significance using two tailed tests at 10%/ 5%/1% levels.

data is available, using the most recent consensus forecasts of 1-year ahead EPS, 2-year ahead EPS and long term growth from I/B/E/S. The results are presented in Panel B of Table 9.

The need for analyst forecasts and the model's requirement that the EPS forecasts be positive reduces the sample size to 8360. As the results indicate, there is a strong negative relationship between GSCORE and ex-ante risk premium, while there is a strong positive relationship between GSCORE and realized returns. This gives further credence to the mispricing argument over risk for the BM effect, at least as far as low BM firms are concerned.

6. Contextual Fundamental Analysis

The results presented thus far indicate that financial statement analysis, suitably tailored for low BM or growth firms, is effective in separating winners from losers. This provides an interesting complement to the results of Piotroski (2000), who demonstrates that traditional fundamental analysis (FSCORE strategy) is similarly effective when applied to high BM or value firms. The unresolved question is how important context is to the success of each of these strategies; how well does the GSCORE strategy work for high BM stocks and conversely, how well does the FSCORE strategy work for low BM stocks? Table 10 presents the results of this analysis.

Table 10, Panel A, applies the GSCORE methodology to a sample of high BM firms.[19] Firms in the highest quintile of BM are ranked by GSCORE and separated into portfolios. The return difference between the high (GSCORE = 6, 7, or 8) and low (GSCORE = 0 or 1) groups, though significant, is only 7.9%, as compared to the 20.7% documented earlier for low BM firms. The 7.9% return difference is also much lower than the return differences in excess of 20% that the FSCORE strategy produces in high BM firms as documented by Piotroski (2000).[20] Further, relatively fewer firms make it to the high and low groups, reducing the potential implementability of the strategy.

Table 10, Panel B, replicates the FSCORE methodology for low BM stocks. FSCORE is the sum of nine binary signals that are 1 if the following conditions are met and zero otherwise. F1: Firms is profitable, F2: Firm's ROA is larger than last years, F3: Firm has positive cash flows, F4: Firm's cash flows exceed net income, F5: Firm's operating margin is higher than the previous year, F6: Firm's asset turnover is higher than the previous year, F7: Firm's leverage is lower than the previous year, F8: Firm's current ratio is higher than the previous year, F9: Firm did not issue equity in the past year. Note one significant difference between FSCORE and GSCORE: most signals in FSCORE involve a time series comparison of a firm to itself in the previous year, while signals in GSCORE involve a contemporaneous cross-sectional comparison of a firm to industry peers. The results indicate that the FSCORE methodology does provide a return difference of 9.8% for low BM firms, but this pales in comparison to both the success of GSCORE in low BM stocks and the success of FSCORE in high BM stocks. Further, as with the GSCORE strategy in high BM stocks, not too many firms make it to the extreme groups, reducing the applicability of the strategy. These results validate the importance of context in financial statement analysis. Simple fundamental analysis, such as the Dupont time-series analysis of profitability, seems to work best in high BM value firms. The modified fundamental analysis proposed in this paper seems to work best in low BM growth firms.

The lack of success of traditional fundamental analysis in low BM stocks can be interpreted in one of two ways. It may be the case that traditional extrapolation of fundamentals over time does not work in rapidly growing firms that have yet to attain a semblance of steady state in their operations. However, it may also be the case that because of the greater visibility and analyst coverage of low BM firms, little mispricing exists with respect to traditional fundamentals, as these have already been impounded in prices. What is interesting is how successful a modified strategy can be in this sample. The modified strategy has three aspects – earnings and cash flow based fundamentals, factors related to naïve extrapolation of current fundamentals and factors related to accounting conservatism. The first aspect is common to both FSCORE and GSCORE. The stronger performance of GSCORE in low BM firms indicates that naïve extrapolation and conservatism potentially play an important role in this setting.

7. Conclusions

In this paper, I test whether a fundamentals driven strategy can separate out ex-post winners and losers amongst low BM or growth firms. I use an approach that combines the analysis of earnings and cash flow based fundamentals, factors related to the stock market's naïve extrapolation of current fundamentals and factors that capture the impact of conservatism on the BM ratio. I combine eight signals related to these factors into an index, GSCORE, assign the low BM firms into portfolios based on their GSCORE, and compare the performance of these portfolios.

The results indicate that the growth oriented fundamental strategy is able to strongly differentiate between future winners and losers. Firms with high GSCORE earn substantially higher size-adjusted returns than firms with low GSCORE. However, a substantial proportion of the success of the strategy is driven by the poor performance of low GSCORE firms. Admittedly, the strength of the strategy lies not in picking which stocks to buy, but in picking which stocks to avoid. To earn significant hedge returns from a GSCORE strategy, the ability to short such stocks is crucial. Partition results indicate that the results hold for a variety of partitions, including large, well followed, and liquid stocks, for which short selling would be less difficult. GSCORE is also strongly positively associated with future returns after controlling for well documented risk factors and anomalies such as BM, accruals and momentum, and is effective across a long time period (positive returns in 21 of 23 years).

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

The results of this paper providing an insightful contrast to the FSCORE strategy implemented in value firms by Piotroski (2000). The success of fundamental analysis in value firms appeared to be driven by investors ignoring a certain class of firms. In the low BM setting though, the success of the GSCORE strategy seems to be driven not by the ignorance of financial information, but by its potential misinterpretation. Further analysis highlights the importance of context in financial statement analysis. The GSCORE strategy does not work as well in value firms, and conversely, the FSCORE strategy does not work as well in growth firms.

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

Finally, this paper contributes to the debate as to whether the BM effect is caused by risk or mispricing. Firms with high GSCORE ratings significantly outperform low GSCORE firms, despite their lower systematic, unsystematic and ex-ante risk. Further, the GSCORE strategy returns positive returns in 21 years out of 23 years analyzed. Together, these are inconsistent with a risk based explanation and provide support for a mispricing based explanation for the BM effect for low BM firms.

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Notes

1. Admittedly, there are some low BM firms which will be less risky. Typically, these are firms whose high market values reflect an ability to generate ROEs in excess of the cost of capital and/or the ability to extract economic rents.

2. Adding back after tax interest expense has a minimal effect on ROA and on the results.
3. For the years prior to 1988, cash from operations is estimated using the funds from operations and change in working capital.
4. The choice of a signal based on total accruals can be improved by focusing not just on the magnitude of the accruals, but on their quality or reliability (see Richardson et al. (2004)). I however use total accruals to make the signal as easy to construct as possible.
5. Damodaran (2001) argues in his book entitled *The Dark Side of Valuation* (page 150) that revenue growth tends to be more persistent and predictable than earnings growth because accounting choices have less of an effect on revenues.
6. Out of the final sample of 21,724 firms used in the returns tests, 17,453 (80%) had financials ending 12/31, 1871 (9%) had financials ending 11/30, and 2400 (11%) had financials ending 10/31.
7. In addition, the tests are also computed using the value weighted index. The results are essentially unchanged. I report results using size-adjusted returns because the large variability in size amongst low BM firms makes adjusting for size more appropriate than using a broad market index as a benchmark.
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.
9. While the accrual proxy (G3) is clearly a weak signal, I do not exclude it, as this would impose a look-ahead bias – i.e., we know that this is a weak signal only by peeking ahead and realizing that it performs poorly.
10. For instance, one could use continuous values instead of binary screens, or assign weights while adding the individual screens. While such methods may be more powerful, they may implicitly induce a look-ahead bias if the ability of these signals to differentiate between winners and losers is used to calculate the weights assigned, or may need additional data to conduct these tests on holdout samples.
11. GSCORE has a left skewed distribution because far fewer firms have a value of 1 for the growth signals. The reason for this is twofold. First, some of the signals (variance of ROA and sales growth) require at least 3 years of past information, which means that fewer firms qualify. Second, some of the signals are based on items that are often zero for many firms (R&D, capital expenditures and advertising expenditures).
12. In addition to conventional tests of differences of means and medians, non-parametric bootstrap tests are conducted. Random pseudo-portfolios of sizes equal to the low and high group are created from the sample with replacement. The difference in mean returns between these groups is calculated. This procedure is repeated a thousand times to create a distribution of return differences. The number of generated differences that are less than the actual difference in the data is presented, and this provides a *p*-value for this test. As the table indicates, the results are highly significant as none of the generated differences exceed the empirically observed difference between the groups.
13. Similar results are found if instead of forming three equal groups, external information is used to form the groups – e.g., market capitalization deciles using data on all firms in the sample.
14. In addition, when stock price is used as a partition instead of size, similar results are obtained.
15. GSCORE is also clearly associated with analyst following. There are far more low GSCORE observations amongst firms with no following and limited following and far more high GSCORE observations amongst firms with extensive following, indicating that analysts tend to gravitate towards stronger firms.
16. Field and Hanka (2001) categorize all firms with primary three-digit SIC codes in computer and office equipment (357), electronic components and accessories (367), miscellaneous electrical machinery equipment and supplies (369), measuring and controlling devices (382), medical instrument and supplies (384), and computer and data processing services (737) as hi-tech firms.
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 similar when no such constraint is imposed.
18. The Ohlson–Juettner model determines a firm's ex-ante cost of capital as: $r_e = A + \sqrt{A^2 + \frac{\text{eps}_1}{P_0}(g_2 - (\gamma - 1))}$, where $A = \frac{1}{2}\left((\gamma - 1) + \frac{\text{dps}_1}{P_0}\right)$ and $g_2 = \frac{(\text{eps}_2 - \text{eps}_1)}{\text{eps}_1}$. My implementation is consistent with Gode and Mohanram (2003). P_0 is price as of the 1st of May of the year after portfolio formation. eps_1 and eps_2 are 1 and 2 year ahead forecasts, dps_1 is forecasted 1-year

ahead payout based on historical payout, γ is the long term growth rate of the economy, set to r_f–3%, where r_f is the risk free rate. Empirically, g_2 tends to be extremely noisy, and so the average of g_2 and IBES long term growth forecast is used instead. RP_{OJ} is obtained by subtracting r_f from r_e.

19. Note that the sample size for high BM stocks is smaller than for low BM stocks. This is partially because previous year's cutoffs were used to determine groupings and over time there was a trend towards lower BM ratios. Also, a greater proportion of high BM firms lacked adequate quarterly information to estimate year to date cash flows.
20. Replicating the FSCORE strategy for value stocks provides a return difference of 17.8%, where the low (high) group is defined as firms with FSCORE of 0 or 1 (7, 8 or 9). This is a little weaker than the returns in excess of 20% that Piotroski (2000) documents and may be related to the differences in methodology (using annualized financials vs. fiscal year financials) as well as the slightly different sample periods.

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