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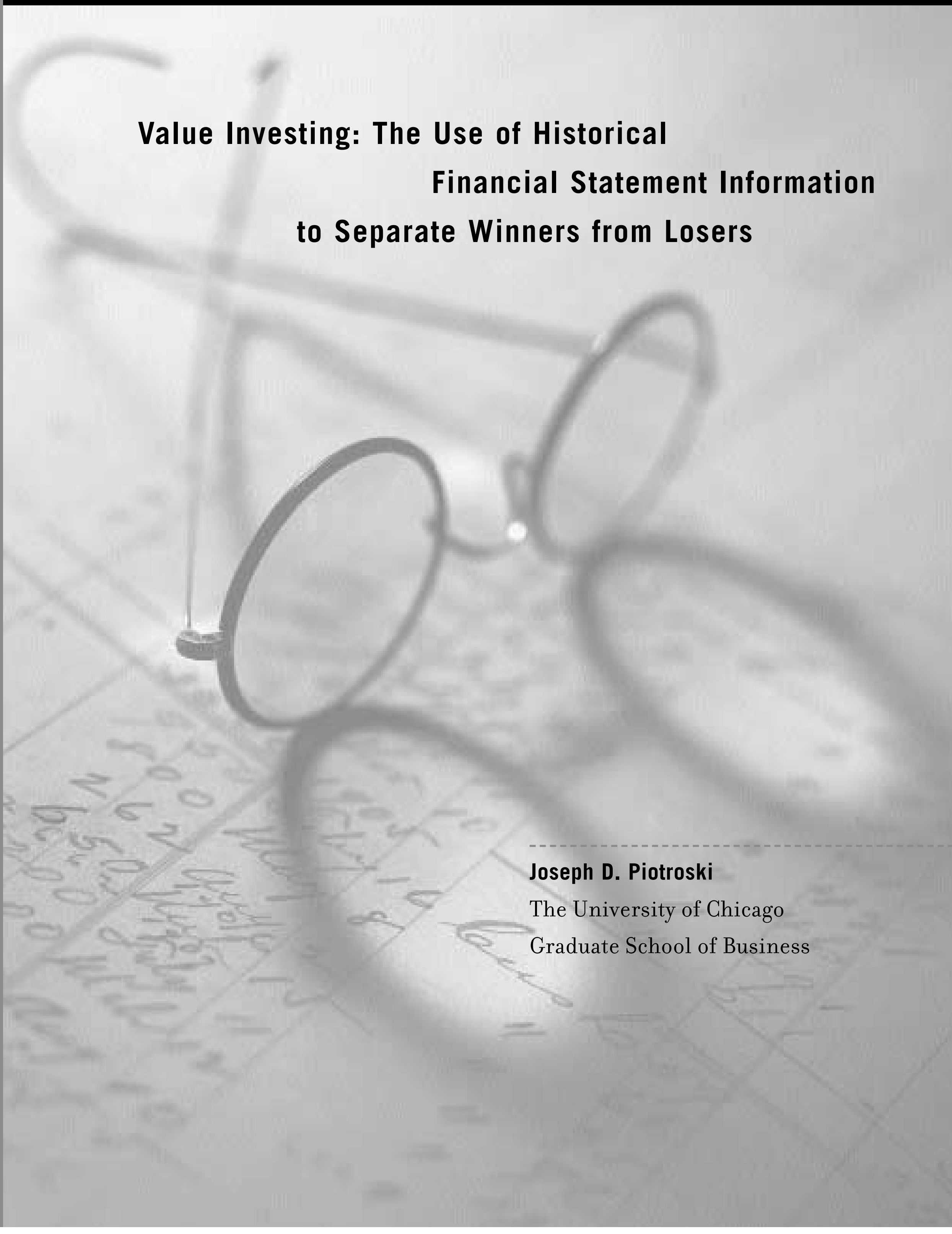
Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers



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Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers

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Abstract

This paper examines whether a simple accounting-based fundamental analysis strategy, when applied to a broad portfolio of high book-to-market firms, can shift the distribution of returns earned by an investor. I show that the mean return earned by a high book-to-market investor can be increased by at least 7½% annually through the selection of financially strong high BM firms while the entire distribution of realized returns is shifted to the right. In addition, an investment strategy that buys expected winners and shorts expected losers generates a 23% annual return between 1976 and 1996, and the strategy appears to be robust across time and to controls for alternative investment strategies. Within the portfolio of high BM firms, the benefits to financial statement analysis are concentrated in small and medium-sized firms, companies with low share turnover, and firms with no analyst following, yet this superior performance is not dependent on purchasing firms with low share prices. A positive relationship between the sign of the initial historical information and both future firm performance and subsequent quarterly earnings announcement reactions suggests that the market initially underreacts to the historical information. In particular, ⅙ of the annual return difference between *ex ante* strong and weak firms is earned over the four three-day periods surrounding these quarterly earnings announcements. Overall, the evidence suggests that the market does not fully incorporate historical financial information into prices in a timely manner.

Section 1: Introduction

This paper examines whether a simple accounting-based fundamental analysis strategy, when applied to a broad portfolio of high book-to-market (BM) firms, can shift the distribution of returns earned by an investor. Considerable research documents the returns to a high book-to-market investment strategy (e.g., Rosenberg, Reid, and Lanstein 1984; Fama and French 1992; and Lakonishok, Shleifer, and Vishny 1994). However, the success of that strategy relies on the strong performance of a few firms, while tolerating the poor performance of many deteriorating companies. In particular, I document that less than 44% of all high BM firms earn positive market-adjusted returns in the two years following portfolio formation. Given the diverse outcomes realized within that portfolio, investors could benefit by discriminating, *ex ante*, between the eventual strong and weak companies. This paper asks whether a simple, financial statement–based heuristic, when applied to these out-of-favor stocks, can discriminate between firms with strong prospects and those with weak prospects. In the process, I discover interesting regularities about the performance of the high BM portfolio and provide some evidence supporting the predictions of recent behavioral finance models.

High book-to-market firms offer a unique opportunity to investigate the ability of simple fundamental analysis heuristics to differentiate firms. First, value stocks tend to be neglected. As a group, these companies are thinly followed by the analyst community and are plagued by low levels of investor interest. Given this lack of coverage, analyst forecasts and stock recommendations are unavailable for these firms. Second, these firms have limited access to most "informal" information dissemination channels, and their voluntary disclosures may not be viewed as credible given their poor recent performance. Therefore, financial statements represent both the most reliable and accessible source of information about these firms. Third, high BM firms tend to be "financially distressed"; as a result, the valuation of these firms focuses on accounting fundamentals such as leverage, liquidity, profitability trends, and cash flow adequacy. These fundamental characteristics are most readily obtained from historical financial statements.

This paper's goal is to show that investors can create a stronger value portfolio by using simple screens based on historical financial performance.[1] If effective, the differentiation of eventual "winners" from "losers" should shift the distribution of the returns earned by a value investor. The results show that such differentiation is possible. First, I show that the mean return earned by a high book-to-market investor can be increased by at least 7½% annually through the selection of financially strong high BM firms. Second, the entire distribution of realized returns is shifted to the right. Although the portfolio's mean return is the relevant benchmark for performance evaluation, this paper also provides evidence that the left tail of

[1] Throughout this paper, the terms "value portfolio" and "high BM portfolio" are used synonymously. Although other value-based, or contrarian, strategies exist, this paper focuses on a high book-to-market ratio strategy.

the return distribution (i.e., 10th percentile, 25th percentile, and median) experiences a significant positive shift after the application of fundamental screens. Third, an investment strategy that buys expected winners and shorts expected losers generates a 23% annual return between 1976 and 1996. Returns to this strategy are shown to be robust across time and to controls for alternative investment strategies. Fourth, the ability to differentiate firms is not confined to one particular financial statement analysis approach. Additional tests document the success of using alternative, albeit complementary, measures of historical financial performance.

Fifth, this paper contributes to the finance literature by providing evidence on the predictions of recent behavioral models (such as Hong and Stein 1999; Barbaris, Shleifer, and Vishny 1998; and Daniel, Hirshleifer. and Subrahmanyam 1998). Similar to the momentum-related evidence presented in Hong, Lim, and Stein (2000), I find that the positive market-adjusted return earned by a generic high book-to-market strategy disappears in rapid information-dissemination environments (large firms, firms with analyst following, high share-turnover firms). More importantly, the effectiveness of the fundamental analysis strategy to differentiate value firms is greatest in slow information-dissemination environments.

Finally, I show that the success of the strategy is based on the ability to predict future firm performance and the market's inability to recognize these predictable patterns. Firms with weak current signals have lower future earnings realizations and are five times more likely to delist for performance-related reasons than firms with strong current signals. In addition, I provide evidence that the market is systematically "surprised" by the future earnings announcements of these two groups. Measured as the sum of the three-day market reactions around the subsequent four quarterly earnings announcements, announcement period returns for predicted "winners" are 0.041 higher than similar returns for predicted losers. This one-year announcement return difference is comparable in magnitude to the four-quarter "value" versus "glamour" announcement return difference observed in LaPorta et al. (1997). Moreover, approximately 1/6 of total annual return difference between *ex ante* strong and weak firms is earned over just 12 trading days.

The results of this study suggest that strong performers are distinguishable from eventual underperformers through the contextual use of relevant historical information. The ability to discriminate *ex ante* between future successful and unsuccessful firms and profit from the strategy suggests that the market does not efficiently incorporate past financial signals into current stock prices.

The next section of this paper reviews the prior literature on both "value" investing and financial statement analysis and defines the nine financial signals that I use to discriminate between firms. Section 3 presents the research design and empirical tests employed in the paper, while section 4 presents the basic results about the success of the fundamental analysis strategy. Section 5 provides robustness checks on the main results, while section 6 briefly examines alternative methods of categorizing a firm's historical performance and financial condition. Section 7 presents evidence on the source and timing of the portfolio returns, while section 8 concludes.

Section 2: Literature Review and Motivation

2.1 High book-to-market investment strategy

This paper examines a refined investment strategy based on a firm's book-to-market ratio (BM). Prior research (Rosenberg, Reid, and Lanstein 1984; Fama and French 1992; Lakonishok, Shleifer, and Vishny 1994) shows that a portfolio of high BM firms outperforms a portfolio of low BM firms. Such strong return performance has been attributed to both market efficiency and market inefficiency. In Fama and French (1992), BM is characterized as a variable capturing financial distress, and thus the subsequent returns represent a fair compensation for risk. This interpretation is supported by the consistently low return on equity associated with high BM firms (Fama and French 1995; Penman 1991) and a strong relation between BM, leverage, and other financial measures of risk (Fama and French 1992; Chen and Zhang 1998). A second explanation for the observed return difference between high and low BM firms is market mispricing. In particular, high BM firms represent "neglected" stocks where poor prior performance has led to the formation of "too pessimistic" expectations about future performance (Lakonishok, Shleifer, and Vishny 1994). This pessimism unravels in the future periods, as evidenced by positive earnings surprises at subsequent quarterly earnings announcements (LaPorta et al. 1997).

Ironically, as an investment strategy, analysts do not recommend high BM firms when forming their buy/sell recommendations (Stickel 1998). One potential explanation for this behavior is that, on an individual stock basis, the typical value firm will underperform the market and analysts recognize that the strategy relies on purchasing a complete portfolio of high BM firms.

From a valuation perspective, value stocks are inherently more conducive to financial statement analysis than growth (i.e., glamour) stocks. Growth stock valuations are typically based on long-term forecasts of sales and the resultant cash flows, with most investors heavily relying on nonfinancial information. Moreover, most of the predictability in growth stock returns appears to be momentum driven (Asness 1997). In contrast, the valuation of value stocks should focus on recent changes in firm fundamentals (e.g., financial leverage, liquidity, profitability, and cash flow adequacy). The assessment of these characteristics is most readily accomplished through a careful study of historical financial statements.

2.2 Prior fundamental analysis research

One approach to separate ultimate winners from losers is through the identification of a firm's intrinsic value and/or systematic errors in market expectations. The strategy presented in Frankel and Lee (1998) requires investors to purchase stocks whose prices appear to be lagging fundamental values. Undervaluation is identified by using analysts' earnings forecasts in conjunction with an accounting-based valuation model (e.g., residual income model), and the strategy is successful at generating significant positive returns over a three-year investment window. Similarly, Dechow and Sloan (1997) and LaPorta (1996) find that systematic errors in market expectations about long-term earnings growth can partially explain the success of contrarian investment strategies and the book-to-market effect, respectively.

As a set of neglected stocks, high BM firms are not likely to have readily available forecast data. In general, financial analysts are less willing to follow poor performing, low- volume, and small firms (Hayes 1998; McNichols and O'Brien 1997), while managers of distressed firms could face credibility issues when trying to voluntary communicate forward-looking information to the capital markets (Koch 1999; Miller and Piotroski 2002). Therefore, a forecast-based approach, such as Frankel and Lee (1998), has limited application for differentiating value stocks.

Numerous research papers document that investors can benefit from trading on various signals of financial performance. Contrary to a portfolio investment strategy based on equilibrium risk and return characteristics, these approaches seek to earn "abnormal" returns by focusing on the market's inability to fully process the implications of particular financial signals. Examples of these strategies include, but are not limited to, post–earnings announcement drift (Bernard and Thomas 1989, 1990; Foster, Olsen, and Shevlin 1984), accruals (Sloan 1996), seasoned equity offerings (Loughran and Ritter 1995), share repurchases (Ikenberry, Lakonishok, and Vermaelen 1995), and dividend omissions/decreases (Michaely, Thaler, and Womack 1995).

A more dynamic investment approach involves the use of multiple pieces of information imbedded in the firm's financial statements. Ou and Penman (1989) show that an array of financial ratios created from historical financial statements can accurately predict future changes in earnings, while Holthausen and Larcker (1992) show that a similar statistical model could be used to successfully predict future excess returns directly. A limitation of these two studies is the use of complex methodologies and a vast amount of historical information to make the necessary predictions. To overcome these calculation costs and avoid overfitting the data, Lev and Thiagarajan (1993) utilize 12 financial signals claimed to be useful to financial analysts. Lev and Thiagarajan (1993) show that these fundamental signals are correlated with contemporaneous returns after controlling for current earnings innovations, firm size, and macroeconomic conditions.

Since the market may not completely impound value-relevant information in a timely manner, Abarbanell and Bushee (1997) investigate the ability of Lev and Thiagarajan's (1993) signals to predict future changes in earnings and future revisions in analyst earnings forecasts. They find evidence that these factors can explain both future earnings changes and future analyst revisions. Consistent with these findings, Abarbanell and Bushee (1998) document that an investment strategy based on these 12 fundamental signals yields significant abnormal returns.

This paper extends prior research by using context-specific financial performance measures to differentiate strong and weak firms. Instead of examining the relationships between future returns and particular financial signals, I aggregate the information contained in an array of performance measures and form portfolios on the basis of a firm's overall signal. By focusing on value firms, the benefits to financial statement analysis (1) are investigated in an environment where historical financial reports represent both the best and most relevant source of information about the firm's financial condition and (2) are maximized through the selection of relevant financial measures given the underlying economic characteristics of these high BM firms.

2.3 Financial performance signals used to differentiate high BM firms

The average high BM firm is financially distressed (e.g., Fama and French 1995; Chen and Zhang 1998). This distress is associated with declining and/or persistently low margins, profits, cash flows, and liquidity and rising and/or high levels of financial leverage. Intuitively, financial variables that reflect changes in these economic conditions should be useful in predicting future firm performance. This logic is used to identify the financial statement signals incorporated in this paper.

I chose nine fundamental signals to measure three areas of the firm's financial condition: profitability, financial leverage/liquidity, and operating efficiency.[2] The signals used are easy to interpret and implement, and they have broad appeal as summary performance statistics. In this paper, I classify each firm's signal realization as either "good" or "bad," depending on the signal's implication for future prices and profitability. An indicator variable for the signal is equal to one (zero) if the signal's realization is good (bad). I define the aggregate signal measure, F_SCORE, as the sum of the nine binary signals. The aggregate signal is designed to measure the overall quality, or strength, of the firm's financial position, and the decision to purchase is ultimately based on the strength of the aggregate signal.

It is important to note that the effect of any signal on profitability and prices can be ambiguous. In this paper, the stated *ex ante* implication of each signal is

[2] The signals used in this study were identified through professional and academic articles. It is important to note that these signals do not represent, nor purport to represent, the optimal set of performance measures for distinguishing good investments from bad investments. Statistical techniques such as factor analysis may more aptly extract an optimal combination of signals, but such an approach has costs in terms of implementability.

conditioned on the fact that these firms are financially distressed at some level. For example, an increase in leverage can, in theory, be either a positive (e.g., Harris and Raviv 1990) or negative (Myers and Majluf 1984; Miller and Rock 1985) signal. However, for financially distressed firms, the negative implications of increased leverage seem more plausible than the benefits garnered through a reduction of agency costs or improved monitoring. To the extent the implications of these signals about future performance are not uniform across the set of high BM firms, the power of the aggregate score to differentiate between strong and weak firms will ultimately be reduced.

2.3.1 Financial performance signals: Profitability

Current profitability and cash flow realizations provide information about the firm's ability to generate funds internally. Given the poor historical earnings performance of value firms, any firm currently generating positive cash flow or profits is demonstrating a capacity to generate funds through operating activities. Similarly, a positive earnings trend is suggestive of an improvement in the firm's underlying ability to generate positive future cash flows.

I use four variables to measure these performance-related factors: ROA, CFO, ΔROA, and ACCRUAL. I define ROA and CFO as net income before extraordinary items and cash flow from operations, respectively, scaled by beginning of the year total assets. If the firm's ROA (CFO) is positive, I define the indicator variable F_ROA (F_CFO) equal to one, zero otherwise.[3] I define ΔROA as the current year's ROA less the prior year's ROA. If $\Delta ROA > 0$, the indicator variable F_ΔROA equals one, zero otherwise.

The relationship between earnings and cash flow levels is also considered. Sloan (1996) shows that earnings driven by positive accrual adjustments (i.e., profits are greater than cash flow from operations) is a bad signal about future profitability and returns. This relationship may be particularly important among value firms, where the incentive to manage earnings through positive accruals (e.g., to prevent covenant violations) is strong (e.g., Sweeney 1994). I define the variable ACCRUAL as current year's net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets. The indicator variable F_ACCRUAL equals one if $CFO > ROA$, zero otherwise.

2.3.2 Financial performance signals: Leverage, liquidity, and source of funds

Three of the nine financial signals are designed to measure changes in capital structure and the firm's ability to meet future debt service obligations: ΔLEVER, ΔLIQUID, and EQ_OFFER. Since most high BM firms are financially constrained, I assume that an increase in leverage, a deterioration of liquidity, or the use of external financing is a bad signal about financial risk.

[3] The benchmarks of zero profits and zero cash flow from operations were chosen for two reasons. First, a substantial portion of high BM firms (41.6%) experience a loss in the prior two fiscal years; therefore, positive earnings realizations are nontrivial events for these firms. Second, this is an easy benchmark to implement since it does not rely on industry, market-level, or time-specific comparisons. An alternative benchmark is whether the firm generates positive industry-adjusted profits or cash flows. Results using "industry-adjusted" factors are not substantially different than the main portfolio results presented in Table 3.

ΔLEVER captures changes in the firm's long-term debt levels. I measure ΔLEVER as the historical change in the ratio of total long-term debt to average total assets, and view an increase (decrease) in financial leverage as a negative (positive) signal. By raising external capital, a financially distressed firm is signaling its inability to generate sufficient internal funds (e.g., Myers and Majluf 1984, Miller and Rock 1985). In addition, an increase in long-term debt is likely to place additional constraints on the firm's financial flexibility. I define the indicator variable F_ΔLEVER to equal one (zero) if the firm's leverage ratio fell (rose) in the year preceding portfolio formation.

The variable ΔLIQUID measures the historical change in the firm's current ratio between the current and prior year, where I define the current ratio as the ratio of current assets to current liabilities at fiscal year-end. I assume that an improvement in liquidity (i.e., $\Delta LIQUID > 0$) is a good signal about the firm's ability to service current debt obligations. The indicator variable F_ΔLIQUID equals one if the firm's liquidity improved, zero otherwise.

I define the indicator variable EQ_OFFER to equal one if the firm did not issue common equity in the year preceding portfolio formation, zero otherwise. Similar to an increase in long-term debt, financially distressed firms that raise external capital could be signaling their inability to generate sufficient internal funds to service future obligations (e.g., Myers and Majluf 1984; Miller and Rock 1985). Moreover, the fact that these firms are willing to issue equity when their stock prices are likely to be depressed (i.e., high cost of capital) highlights the poor financial condition facing these firms.

2.3.3 Financial performance signals: Operating efficiency

The remaining two signals are designed to measure changes in the efficiency of the firm's operations: ΔMARGIN and ΔTURN. These ratios are important because they reflect two key constructs underlying a decomposition of return on assets.

I define ΔMARGIN as the firm's current gross margin ratio (gross margin scaled by total sales) less the prior year's gross margin ratio. An improvement in margins signifies a potential improvement in factor costs, a reduction in inventory costs, or a rise in the price of the firm's product. The indicator variable F_ ΔMARGIN equals one if ΔMARGIN is positive, zero otherwise.

I define ΔTURN as the firm's current year asset turnover ratio (total sales scaled by beginning of the year total assets) less the prior year's asset turnover ratio. An improvement in asset turnover signifies greater productivity from the asset base. Such an improvement can arise from more efficient operations (fewer assets generating the same levels of sales) or an increase in sales (which could also signify improved market conditions for the firm's products). The indicator variable F_ΔTURN equals one if ΔTURN is positive, zero otherwise.

As expected, several of the signals used in this paper overlap with constructs tested in Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997, 1998). However, most of the signals used in this paper do not correspond to the financial signals used in prior research. Several reasons exist for this difference. First, I examine smaller, more financially distressed firms and the variables were chosen to measure profitability and default risk trends relevant for these companies. Effects from signals such as LIFO/FIFO inventory choices, capital expenditure decisions, effective tax rates, and qualified audit opinions would likely be second-order relative to broader variables capturing changes in the overall health of these companies.[4] Second, the work of Bernard (1994) and Sloan (1996) demonstrates the importance of accounting returns and cash flows (and their relation to each other) when assessing the future performance prospects of a firm. As such, variables capturing these constructs are central to the current analysis. Finally, neither Lev and Thiagarajan (1993) nor Abarbanell and Bushee (1997, 1998) purport to offer the optimal set of fundamental signals; therefore, the use of alternative, albeit complementary, signals demonstrates the broad applicability of financial statement analysis techniques.

2.3.4 Composite score

As indicated earlier, I define F_SCORE as the sum of the individual binary signals, or

$$\text{F\_SCORE} = \text{F\_ROA} + \text{F\_}\Delta\text{ROA} + \text{F\_CFO} + \text{F\_ACCRUAL} + \text{F\_}\Delta\text{MARGIN} + \text{F\_}\Delta\text{TURN} + \text{F\_}\Delta\text{LEVER} + \text{F\_}\Delta\text{LIQUID} + \text{EQ\_OFFER}.$$

Given the nine underlying signals, F_SCORE can range from a low of 0 to a high of 9, where a low (high) F_SCORE represents a firm with very few (mostly) good signals. To the extent current fundamentals predict future fundamentals, I expect F_SCORE to be positively associated with changes in future firm performance and stock returns. The investment strategy discussed in this paper is based on selecting firms with high F_SCORE signals, instead of purchasing firms based on the relative realization of any particular signal. In comparison to the work of Ou and Penman (1989) and Holthausen and Larker (1992), this paper represents a "step-back" in the analysis process—probability models need not be estimated nor does the data need to be fitted on a year-by-year basis when implementing the investment strategy. Instead, the investment decision is based on the sum of these nine binary signals.

This approach represents one simple application of fundamental analysis for identifying strong and weak value firms. In selecting this methodology, two issues arise. First, the translation of the factors into binary signals could potentially eliminate useful information. I adopted the binary signal approach because it is simple and easy to implement. An alternative specification would be to aggregate

[4] For example, most of these firms have limited capital for capital expenditures. As a result, Lev and Thiagarajan's capital expenditure variable displays little cross-sectional variation in this study. Similarly, most of these high BM firms are likely to be in a net operating loss carry-forward position for tax purposes (due to their poor historical performance), thereby limiting the information content of Lev and Thiagarajan's effective tax rate variable.

continuous representations of these nine factors. For robustness, the main results of this paper are also presented using an alternative methodology where the signal realizations are annually ranked and summed.

Second, given a lack of theoretical justification for the combined use of these particular variables, the methodology employed in this paper could be perceived as *ad hoc.* Since the goal of the methodology is to merely separate strong value firms from weak value firms, alternative measures of financial health at the time of portfolio formation should also be successful at identifying these firms. I investigate several alternative measures in section 6.

Section 3: Research Design

3.1 Sample selection

Each year between 1976 and 1996, I identify firms with sufficient stock price and book value data on COMPUSTAT. For each firm, I calculate the market value of equity and BM ratio at fiscal year-end.[5] Each fiscal year (i.e., financial report year), I rank all firms with sufficient data to identify book-to-market quintile and size tercile cutoffs. The prior fiscal year's BM distribution is used to classify firms into BM quintiles.[6] Similarly, I determine a firm's size classification (small, medium, or large) using the prior fiscal year's distribution of market capitalizations. After the BM quintiles are formed, I retain firms in the highest BM quintile with sufficient financial statement data to calculate the various financial performance signals. This approach yields the final sample of 14,043 high BM firms across the 21 years (see appendix 1).[7]

3.2 Calculation of returns

I measure firm-specific returns as one-year (two-year) buy-and-hold returns earned from the beginning of the fifth month after the firm's fiscal year-end through the earliest subsequent date: one year (two years) after return compounding began or the last day of CRSP traded returns. If a firm delists, I assume the delisting return is zero. I chose the fifth month to ensure that the necessary annual financial information is available to investors at the time of portfolio formation. I define market-adjusted returns as the buy-and-hold return less the value-weighted market return over the corresponding time period.

3.3 Description of the empirical tests (main results section)

The primary methodology of this paper is to form portfolios based on the firm's aggregate score (F_SCORE). I classify firms with the lowest aggregate signals (F_SCORE equals 0 or 1) as *low F_SCORE firms* and expect these firms to have

[5] Fiscal year-end prices are used to create consistency between the BM ratio used for portfolio assignments and the ratio used to determine BM and size cutoffs. Basing portfolio assignments on market values calculated at the date of portfolio inclusion does not impact the tenor of the results.

[6] Since each firm's book-to-market ratio is calculated at a different point in time (i.e., due to different fiscal year-ends), observations are grouped by and ranked within financial report years. For example, all observations related to fiscal year 1986 are grouped together to determine the FY86 size and book-to-market cutoffs. Any observation related to fiscal year 1987 (regardless of month and date of its fiscal year-end) is then assigned to a size and BM portfolio based on the distribution of those FY86 observations. This approach guarantees that the prior year's ratios and cutoff points are known prior to any current year portfolio assignments.

[7] Since prior year distributions are used to create the high BM

the worst subsequent stock performance. Alternatively, firms receiving the highest score (i.e., F_SCORE equals 8 or 9) have the strongest fundamental signals and are classified as *high F_SCORE firms*. I expect these firms to have the best subsequent return performance given the strength and consistency of their fundamental signals. I design the tests in this paper to examine whether the high F_SCORE portfolio outperforms other portfolios of firms drawn from the high BM portfolio.

The first test compares the returns earned by high F_SCORE firms against the returns of low F_SCORE firms; the second test compares high F_SCORE firms against the complete portfolio of all high BM firms. Given concerns surrounding the use of parametric test statistics in a long-run return setting (e.g., Kothari and Warner 1997; Barber and Lyon 1997), the primary results are tested using both tradition t-statistics as well as implementing a bootstrapping approach to test for differences in portfolio returns.

The test of return differences between the high and low F_SCORE portfolios with bootstrap techniques is as follows: First, I randomly select firms from the complete portfolio of high BM firms and assign them to either a pseudo–high F_SCORE portfolio or a pseudo–low F_SCORE portfolio. This assignment continues until each pseudo-portfolio consists of the same number of observations as the actual high and low F_SCORE portfolios (number of observations equals 1,448 and 396, respectively). Second, I calculate the difference between the mean returns of these two pseudo-portfolios and this difference represents an observation under the null of no difference in mean return performance. Third, I repeat this process 1,000 times to generate 1,000 observed differences in returns under the null, and the empirical distribution of these return differences is used to test the statistical significance of the actual observed return differences. Finally, to test the effect of the fundamental screening criteria on the properties of the entire return distribution, I also calculate differences in pseudo-portfolio returns for six different portfolio return measures: mean returns, median returns, 10th percentile, 25th percentile, 75th percentile, and 90th percentile returns.

The test of return differences between high F_SCORE firms and all high BM firms is constructed in a similar manner. Each iteration, I randomly form a pseudo-portfolio of high F_SCORE firms, and the returns of the pseudo-portfolio are compared against the returns of the entire high BM portfolio, thereby generating a difference under the null of no-return difference. I repeat this process 1,000 times, and the empirically derived distribution of return differences is used to test the actual difference in returns between the high F_SCORE portfolio and all high BM firms. I discuss these empirical results in the next section.

portfolio (in order to eliminate concerns about a peek-ahead bias), annual allocations to the highest book-to-market portfolio do not remain a constant proportion of all available observations for a given fiscal year. In particular, this methodology leads to larger (smaller) samples of high BM firms in years where the overall market declines (rises). The return differences documented in section 4 do not appear to be related to these time-specific patterns.

Table 1: Financial and Return Characteristics of High Book-to-Market Firms
(14,043 firm-year observations between 1975 and 1995)

Panel A: Financial Characteristics

Variable	Mean	Median	Standard Deviation	Proportion with Positive Signal
MVE	188.500	14.365	1015.39	n/a
ASSETS	1043.99	57.561	6653.48	n/a
BM	2.444	1.721	34.66	n/a
ROA	−0.0054	0.0128	0.1067	0.632
ΔROA	−0.0096	−0.0047	0.2171	0.432
ΔMARGIN	−0.0324	−0.0034	1.9306	0.454
CFO	0.0498	0.0532	0.1332	0.755
ΔLIQUID	−0.0078	0	0.1133	0.384
ΔLEVER	0.0024	0	0.0932	0.498
ΔTURN	0.0119	0.0068	0.5851	0.534
ACCRUAL	−0.0552	−0.0481	0.1388	0.780

Panel B: Buy-and-Hold Returns from a High Book-to-Market Investment Strategy

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Percent Positive
One-year returns							
Raw	0.239	−0.391	−0.150	0.105	0.438	0.902	0.610
Market-Adj.	0.059	−0.560	−0.317	−0.061	0.255	0.708	0.437
Two-year returns							
Raw	0.479	−0.517	−0.179	0.231	0.750	1.579	0.646
Market-Adj.	0.127	−0.872	−0.517	−0.111	0.394	1.205	0.432

Section 4: Empirical Results

4.1 Descriptive evidence about high book-to-market firms

Table 1 provides descriptive statistics about the financial characteristics of the high book-to-market portfolio of firms, as well as evidence on the long-run returns from such a portfolio. As shown in panel A, the average (median) firm in the highest book-to-market quintile of all firms has a mean (median) BM ratio of 2.444 (1.721) and an end-of-year market capitalization of 188.50 (14.37) million dollars. Consistent with the evidence presented in Fama and French (1995), the portfolio of high BM firms consists of poor performing firms; the average (median) ROA realization is –0.0054 (0.0128), and the average and median firm saw declines

Table 1 (continued)

Variable definitions

MVE	Market value of equity at the end of fiscal year t. Market value is calculated as the number of shares outstanding at fiscal year-end times closing share price.
ASSETS	Total assets reported at the end of the fiscal year t.
BM	Book value of equity at the end of fiscal year t, scaled by MVE.
ROA	Net income before extraordinary items for the fiscal year preceding portfolio formation scaled by total assets at the beginning of year t.
ΔROA	Change in annual ROA for the year preceding portfolio formation. ΔROA is calculated as ROA for year t less the firm's ROA for year t-1.
ΔMARGIN	Gross margin (net sales less cost of good sold) for the year preceding portfolio formation, scaled by net sales for the year, less the firm's gross margin (scaled by net sales) from year t-1.
CFO	Cash flow from operations scaled by total assets at the beginning of year t.
ΔLIQUID	Change in the firm's current ratio between the end of year t and year t-1. Current ratio is defined as total current assets divided by total current liabilities.
ΔLEVER	Change in the firm's debt-to-assets ratio between the end of year t and year t-1. The debt-to-asset ratio is defined as the firm's total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets.
ΔTURN	Change in the firm's asset turnover ratio between the end of year t and year t-1. The asset turnover ratio is defined as net sales scaled by average total assets for the year.
ACCRUAL	Net income before extraordinary items less cash flow from operations, scaled by total assets at the beginning of year t.
1yr (2yr) Raw Return	12- (24-) month buy-and-hold return of the firm starting at the beginning of the fifth month after fiscal year-end. Return compounding ends the earlier of one year (two years) after return compounding started or the last day of CRSP reported trading. If the firm delisted, the delisting return is assumed to be zero.
Market-adjusted Return	Buy-and-hold return of the firm less the buy-and-hold return on the value-weighted market index over the same investment horizon.

in both ROA (–0.0096 and –0.0047, respectively) and gross margin (–0.0324 and –0.0034, respectively) over the last year. Finally, the average high BM firm saw an increase in leverage and a decrease in liquidity over the prior year.

Panel B presents one-year and two-year buy-and-hold returns for the complete portfolio of high BM firms, along with the percentage of firms in the portfolio with positive raw and market-adjusted returns over the respective investment horizon. Consistent with Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994), the high BM firms earn positive market-adjusted returns in the one-year and two-year periods following portfolio formation. Yet despite the strong mean performance of this portfolio, a majority of the firms (approximately 57%)

earn negative market-adjusted returns over the one- and two-year windows. Therefore, any strategy that can eliminate the left tail of the return distribution (i.e., the negative return observations) will greatly improve the portfolio's mean return performance.

4.2 Returns to a fundamental analysis strategy

Table 2 presents spearman correlations between the individual fundamental signal indicator variables, the aggregate fundamental signal score F_SCORE, and the one-year and two-year buy-and-hold market-adjusted returns. As expected, F_SCORE has a significant positive correlation with both one-year and two-year future returns (0.121 and 0.130, respectively). For comparison, the two strongest individual explanatory variables are ROA and CFO (correlation of 0.086 and 0.096, respectively, with one-year-ahead market-adjusted returns).

Table 3 presents the returns to the fundamental investment strategy. Panel A presents one-year market-adjusted returns; inferences, patterns and results are similar using raw returns (panel B) and a two-year investment horizon (panel C).

Table 2: Spearman Correlation Analysis between One- and Two-Year Market-Adjusted Returns, the Nine Fundamental Signals, and the Composite Signal (F_SCORE) for High Book-to-Market Firms

	ROA	ΔROA	ΔMARGIN	CFO	ΔLIQUID	ΔLEVER	ΔTURN	ACCRUAL	EQ_OFFER	F_SCORE
RETURN	0.106	0.044	0.039	0.104	0.027	0.058	0.049	0.051	0.012	0.124
MA_RET	0.086	0.037	0.042	0.096	0.032	0.055	0.034	0.053	0.041	0.121
M_RET2	0.099	0.039	0.045	0.113	0.029	0.067	0.023	0.064	0.043	0.130
ROA	1.000	0.265	0.171	0.382	0.127	0.157	−0.016	−0.023	−0.076	0.512
ΔROA	—	1.000	0.404	0.119	0.117	0.137	0.101	−0.019	0.040	0.578
ΔMARGIN	—	—	1.000	0.080	0.083	0.073	0.004	0.000	0.012	0.483
CFO	—	—	—	1.000	0.128	0.094	0.041	0.573	−0.035	0.556
ΔLIQUID	—	—	—	—	1.000	−0.006	0.053	0.071	−0.018	0.395
ΔLEVER	—	—	—	—	—	1.000	0.081	0.016	−0.023	0.400
ΔTURN	—	—	—	—	—	—	1.000	0.062	0.034	0.351
ACCRUAL	—	—	—	—	—	—	—	1.000	−0.015	0.366
EQ_OFFER	—	—	—	—	—	—	—	—	1.000	0.232

Note: The nine individual factors in this table represent indicator variables equal to one (zero) if the underlying performance measure was a good (bad) signal about future firm performance. The prefix ("F_") for the nine fundamental signals was eliminated for succinctness. One-year market-adjusted returns (MA_RET) and two-year market-adjusted returns (MA_RET2) are measured as the buy-and-hold return starting in the fifth month after fiscal year-end less the corresponding value-weighted market return over the respective holding period. All raw variables underlying the binary signals are as defined in Table 1. The sample represents 14,043 high BM firm-year observations between 1975 and 1995.

This discussion and subsequent analysis will focus on one-year market-adjusted returns for succinctness.

Most of the observations are clustered around F_SCORES between 3 and 7, indicating that a vast majority of the firms have conflicting performance signals. However, 1,448 observations are classified as high F_SCORE firms (scores of 8 or 9), while 396 observations are classified as low F_SCORE firms (scores of 0 or 1). I will use these extreme portfolios to test the ability of fundamental analysis to differentiate between future winners and losers.[8]

The most striking result in table 3 is the fairly monotonic positive relationship between F_SCORE and subsequent returns (particularly over the first year). As documented in panel A, high F_SCORE firms significantly outperform low F_SCORE firms in the year following portfolio formation (mean market-adjusted returns of 0.134 versus –0.096, respectively). The mean return difference of 0.230 is significant at the 1% level using both an empirically derived distribution of potential return differences and a traditional parametric t-statistic.

A second comparison documents the return difference between the portfolio of high F_SCORE firms and the complete portfolio of high BM firms. As shown, the high F_SCORE firms earn a mean market-adjusted return of 0.134 versus 0.059 for the entire BM quintile. This difference of 0.075 is also statistically significant at the 1% level.

The return improvements also extend beyond the mean performance of the various portfolios. As discussed in the introduction, this investment approach is designed to shift the entire distribution of returns earned by a high BM investor. Consistent with that objective, the results in table 3 show that the 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile returns of the high F_SCORE portfolio are significantly higher than the corresponding returns of both the low F_SCORE portfolio and the complete high BM quintile portfolio using bootstrap techniques. Similarly, the proportion of winners in the high F_SCORE portfolio, 50.0%, is significantly higher than the two benchmark portfolios (43.7% and 31.8%), where significance is based on a binomial test of proportions.

Overall, it is clear that F_SCORE discriminates between eventual winners and losers. One question is whether the translation of the fundamental variables into binary signals eliminates potentially useful information. To examine this issue, I re-estimate portfolio results where firms are classified using the sum of annually ranked signals [not tabulated]. Specifically, I rank the individual signal realizations (i.e., ROA, CFO, ΔROA, etc.) each year between zero and one, and these ranked representations are used to form the aggregate measure. I sum each of the firm's ranked realizations and form quintile portfolios using cutoffs based on the prior fiscal year's RANK_SCORE distribution. Consistent with the evidence in Table 3, I find that the use of ranked information can also differentiate strong and weak

[8] Given the *ex post* distribution of firms across F_SCORE portfolios, an alternative specification could be to define *low F_SCORE firms* as all high BM firms having an F_SCORE less than or equal to 2. Such a classification results in the low F_SCORE portfolio having 1,255 observations (compared to the 1,448 observations for the high F_SCORE portfolio). Results and inferences using this alternative definition are qualitatively similar to those presented throughout the paper.

Table 3: Buy-and-Hold Returns to a Value Investment Strategy Based on Fundamental Signals

This table presents buy-and-hold returns to a fundamental investment strategy based on purchasing high BM firms with strong fundamental signals. F_SCORE is equal to the sum of nine individual binary signals, or

$$\text{F\_SCORE} = \text{F\_ROA} + \text{F\_}\Delta\text{ROA} + \text{F\_CFO} + \text{F\_ACCRUAL} + \text{F\_}\Delta\text{MARGIN} + \text{F\_}\Delta\text{TURN} + \text{F\_}\Delta\text{LEVER} + \text{F\_}\Delta\text{LIQUID} + \text{EQ\_OFFER}$$

where each binary signal equals one (zero) if the underlying realization is a good (bad) signal about future firm performance. A F_SCORE equal to zero (nine) means the firm possesses the least (most) favorable set of financial signals. The low F_SCORE portfolio consists of firms with an aggregate score of 0 or 1; the high F_SCORE portfolio consists of firms with a score of 8 or 9.

Panel A: One-Year Market-Adjusted Returns[b]

	Mean	10%	25%	Median	75%	90%	%Positive	n
All Firms	0.059	−0.560	−0.317	−0.061	0.255	0.708	0.437	14,043
F_SCORE								
0	−0.061	−0.710	−0.450	−0.105	0.372	0.766	0.386	57
1	−0.102	−0.796	−0.463	−0.203	0.087	0.490	0.307	339
2	−0.020	−0.686	−0.440	−0.151	0.198	0.732	0.374	859
3	−0.015	−0.691	−0.411	−0.142	0.186	0.667	0.375	1618
4	0.026	−0.581	−0.351	−0.100	0.229	0.691	0.405	2462
5	0.053	−0.543	−0.307	−0.059	0.255	0.705	0.438	2787
6	0.112	−0.493	−0.278	−0.024	0.285	0.711	0.471	2579
7	0.116	−0.466	−0.251	−0.011	0.301	0.747	0.489	1894
8	0.127	−0.462	−0.226	0.003	0.309	0.710	0.504	1115
9	0.159	−0.459	−0.265	−0.012	0.327	0.885	0.486	333
Low Score	−0.096	−0.781	−0.460	−0.200	0.107	0.548	0.318	396
High Score	0.134	−0.462	−0.236	0.000	0.316	0.757	0.500	1448
High—All	0.075	0.098	0.081	0.061	0.061	0.049	0.063	—
t-stat/(p-value)	3.140	—	—	(0.000)	—	—	(0.000)	—
Bootstrap Rslt	2/1000	0/1000	0/1000	0/1000	2/1000	126/1000	—	—
(p-value)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.126)	—	—
High—Low	0.230	0.319	0.224	0.200	0.209	0.209	0.182	—
t-stat/(p-value)	5.590	—	—	(0.000)	—	—	(0.000)	—
Bootstrap Rslt	0/1000	0/1000	0/1000	0/1000	0/1000	18/1000	—	—
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	—	—

Table 3 (continued)

Panel B: One-Year Raw Returns[a]

	Mean	10%	25%	Median	75%	90%	%Positive	n
All Firms	0.239	−0.391	−0.150	0.105	0.438	0.902	0.610	14,043
Low F_Score	0.078	−0.589	−0.300	−0.027	0.270	0.773	0.460	396
High F_Score	0.313	−0.267	−0.074	0.166	0.484	0.955	0.672	1448
High—All	0.074	0.124	0.076	0.061	0.046	0.053	0.062	—
t-stat/(p-value)	3.279	—	—	(0.000)	—	—	(0.000)	—
Bootstrap Rslt	1/1000	0/1000	0/1000	0/1000	16/1000	110/1000	—	—
(p-value)	(0.001)	(0.000)	(0.000)	(0.000)	(0.016)	(0.110)	—	—
High—Low	0.235	0.322	0.226	0.193	0.214	0.182	0.212	—
t-stat/(p-value)	5.594	—	—	(0.000)	—	—	(0.000)	—
Bootstrap Rslt	0/1000	0/1000	0/1000	0/1000	0/1000	28/1000	—	—
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.028)	—	—

Panel C: Two-Year Market-Adjusted Returns[c]

	Mean	10%	25%	Median	75%	90%	%Positive	n
All Firms	0.127	−0.872	−0.517	−0.111	0.394	1.205	0.432	14,043
Low Score	−0.145	−1.059	−0.772	−0.367	0.108	0.829	0.280	396
High Score	0.287	−0.690	−0.377	0.006	0.532	1.414	0.505	1448
High—All	0.160	0.182	0.140	0.117	0.138	0.209	0.073	—
t-stat/(p-value)	2.639	—	—	(0.000)	—	—	(0.000)	—
Bootstrap Rslt	0/1000	0/1000	0/1000	0/1000	0/1000	7/1000	—	—
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	—	—
High—Low	0.432	0.369	0.395	0.373	0.424	0.585	0.225	—
t-stat/(p-value)	5.749	—	—	(0.000)	—	—	(0.000)	—
Bootstrap Rslt	0/1000	0/1000	0/1000	0/1000	0/1000	0/1000	—	—
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	—	—

[a] A raw return is calculated as the 12-month buy-and-hold return of the firm starting at the beginning of the fifth month after fiscal year-end. Return compounding ends the earlier of one year after return compounding starts or the last day of CRSP reported trading. If the firm delisted, the delisting return is assumed to be zero.

[b] A market-adjusted return equals the firm's 12-month buy-and-hold return (as defined in panel A) less the buy-and-hold return on the value-weighted market index over the same investment horizon.

[c] A two-year raw return is calculated as the 24-month buy-and-hold return of the firm starting at the beginning of the fifth month after fiscal year end. Return compounding ends the earlier of two years after return compounding starts or the last day of CRSP reported trading. If the firm delisted, the delisting return is assumed to be zero. A two-year market-value adjusted return equals the firm's 24-month buy-and-hold return less the buy-and-hold return on the value-weighted market index over the same investment horizon.

[f] T-statistics for portfolio means (p-values for medians) are from two-sample t-tests (signed rank wilcoxon tests); empirical p-values are from bootstrapping procedures based on 1,000 iterations. P-values for the proportions are based on a binomial test of proportions.

value firms. Specifically, the mean (median) one-year market adjusted return difference between the highest and lowest ranked score quintile is 0.092 (0.113), both significant at the 1% level.

4.3 Returns conditional on firm size

A primary concern is whether the excess returns earned using a fundamental analysis strategy is strictly a small firm effect or can be applied across all size categories. For this analysis, I annually rank all firms with the necessary COMPUSTAT data to compute the fundamental signals into three size portfolios (independent of their book-to-market ratio). I define size as the firm's market capitalization at the prior fiscal year-end. Compustat yielded a total of approximately 75,000 observations between 1976 and 1996, of which 14,043 represented high book-to-market firms. Given the financial characteristics of the high BM firms, a preponderance of the firms (8,302) were in the bottom third of market capitalization (59.12%), while 3,906 (27.81%) and 1,835 (13.07%) are assigned to the middle and top size portfolio, respectively. Table 4 presents one-year market-adjusted returns based on these size categories.

Table 4 shows that the above-market returns earned by a generic high BM portfolio are concentrated in smaller companies. Applying F_SCORE within each size partition, the strongest benefit from financial statement analysis is also garnered in the small firm portfolio (return difference between high and low F_SCORE firms is 0.270, significant at the 1% level). However, the shift in mean and median returns is still statistically significant in the medium firm size portfolio, with the high score firms earning approximately 7% more than all medium-size firms and 17.3% more than the low F_SCORE firms. Contrarily, differentiation is weak among the largest firms, where most return differences are either statistically insignificant or only marginally significant at the 5% or 10% level. Thus, the improvement in returns is isolated to firms in the bottom two-thirds of market capitalization.[9]

4.4 Alternative partitions

When return predictability is concentrated in smaller firms, an immediate concern is whether or not these returns are realizable. To the extent that the benefits of the trading strategy are concentrated in firms with low share price or low levels of liquidity, observed returns may not reflect an investor's ultimate experience. For completeness, I examine two other partitions of the sample: share price and trading volume.

Similar to firm size, I place companies into share price and trading volume portfolios based on the prior year's cutoffs for the complete COMPUSTAT sample (i.e., independent of BM quintile assignment). Consistent with these firms' small market capitalization and poor historical performance, a majority of all high BM

[9] These results are consistent with other documented anomalies. For example, Bernard and Thomas (1989) show that the post-earnings announcement drift strategy is more profitable for small firms, with abnormal returns being virtually nonexistent for larger firms. Similarly, Hong, Lim, and Stein (2000) show that momentum strategies are strongest in small firms.

Table 4: One-Year Market-Adjusted Buy-and-Hold Returns to a Value Investment Strategy Based on Fundamental Signals by Size Partition

	Small Firms			Medium Firms			Large Firms		
	Mean	Median	n	Mean	Median	n	Mean	Median	n
All Firms	0.091	−0.077	8302	0.008	−0.059	3906	0.003	−0.028	1835
F_SCORE									
0	0.000	−0.076	32	−0.146	−0.235	17	−0.120	−0.047	8
1	−0.104	−0.227	234	−0.083	−0.228	79	−0.136	−0.073	26
2	−0.016	−0.171	582	−0.045	−0.131	218	0.031	−0.076	59
3	0.003	−0.168	1028	−0.049	−0.108	429	−0.036	−0.068	161
4	0.058	−0.116	1419	−0.024	−0.104	687	−0.002	−0.023	356
5	0.079	−0.075	1590	0.028	−0.060	808	−0.004	−0.031	389
6	0.183	−0.030	1438	0.029	−0.041	736	0.012	−0.004	405
7	0.182	0.005	1084	0.027	−0.028	540	0.028	−0.015	270
8	0.170	0.001	671	0.081	0.024	312	0.012	−0.041	132
9	0.204	−0.017	224	0.068	0.032	80	0.059	−0.045	29
Low Score	−0.091	−0.209	266	−0.094	−0.232	96	−0.132	−0.066	34
High Score	0.179	−0.007	895	0.079	0.024	392	0.020	−0.045	161
High–All	0.088	0.070	—	0.071	0.083	—	0.017	−0.017	—
t-statistic/(p-value)	2.456	(0.000)	—	2.870	(0.000)	—	0.872	(0.203)	—
High–Low	0.270	0.202	—	0.173	0.256	—	0.152	0.021	—
t-statistic/(p-value)	4.709	(0.000)	—	2.870	(0.000)	—	1.884	(0.224)	—

Note: Each year, all firms on COMPUSTAT with sufficient size and BM data are ranked on the basis of the most recent fiscal year-end market capitalization. The 33.3 and 66.7 percentile cutoffs from the prior year's distribution of firm size (MVE) are used to classify the high BM firms into small, medium, and large firms each year. All other definitions and test statistics are as described in table 3.

firms have smaller share prices and are more thinly traded than the average firm on COMPUSTAT. However, approximately 48.4% of the firms could be classified as having medium or large share prices and 45.4% can be classified as having medium to high share turnover. Table 5 examines the effectiveness of fundamental analysis across these partitions.[10]

4.4.1 Relationship between share price, share turnover, and gains from fundamental analysis

Contrary to the results based on market capitalization partitions, the portfolio results across all share price partitions are statistically and economically significant. Whereas the low and medium share price portfolios yield positive mean return differences of 0.246 and 0.258, respectively, the high share price portfolio also yields a significant positive difference of 0.132. The robustness of these results

[10] Only high F_SCORE firm minus low F_SCORE firm return differences are presented in this and subsequent tables for succinctness. Inferences regarding the return differences between high F_SCORE firms and all high BM firms are similar, except where noted in the text.

across share price partitions suggests that the positive return performance of this fundamental analysis strategy is not solely based upon an ability to purchase stocks with extremely low share prices.

Further evidence contradicting the stale price and low liquidity argument is provided by partitioning the sample along average share turnover. Consistent with the findings in Lee and Swaminathan (2000), this analysis shows that a majority of the high BM portfolio's "winners" are in the low share turnover portfolio. For these high BM firms, the average market-adjusted return (before the application of fundamental analysis screens) is 0.101. This evidence suggests, *ex ante*, that the greatest information gains rest with the most thinly traded and most out-of-favored stocks. Consistent with those potential gains, the low volume portfolio experiences a large return to the fundamental analysis strategy; however, the strategy is successful across all trading volume partitions. Whereas the difference between high minus low F_SCORE firms is 0.239 in the low volume portfolio, the return difference in the high volume partition is 0.203 (both differences are significant at the 1% level).

The combined evidence suggests that benefits to financial statement analysis are not likely to disappear after accounting for a low share price effect or additional transaction costs associated with stale prices or thinly traded securities. However, one caveat does exist: although the high minus low F_SCORE return differences for the large share price and high volume partitions are statistically significant, the return differences between the high F_SCORE firms and all high BM firms are not significant for these partitions. And, within the large share price partition, the mean and median return differences are (insignificantly) negative. These results, however, do not eradicate the claimed effectiveness of financial statement analysis for these subsamples. Despite an inability to identify strong companies, the analysis can successfully identify and eliminate firms with extreme negative returns (i.e., the low F_SCORE firms). Additional tests reveal that the two portfolios of low F_SCORE firms significantly underperform all high BM firms with the corresponding share price and trading volume attributes. Thus, within these partitions of the high BM portfolio, the benefits from fundamental analysis truly relate to the original motivation of this study: to eliminate the left-hand tail of the return distribution.

4.4.2 Relationship between analyst following and gains from fundamental analysis

A primary assumption throughout this analysis is that high BM firms are not heavily followed by the investment community. In such a setting, financial statement analysis may be a profitable method of investigating and differentiating firms. If the ability to earn above-market returns is truly driven by information-processing limitations for these companies, then (1) these high BM firms should display low levels of analyst coverage and (2) the ability to earn strong returns should be

Table 5: One-Year Market-Adjusted Buy-and-Hold Returns to a Value Investment Strategy Based on Fundamental Signals by Share Price, Trading Volume, and Analyst Following Partitions

Panel A: Share Price[a]

	Small Price			Medium Price			Large Price		
	Mean	Median	n	Mean	Median	n	Mean	Median	n
All Firms	0.092	−0.095	7250	0.018	−0.046	4493	0.065	0.002	2300
Low Score	−0.092	−0.210	285	−0.099	−0.189	87	−0.124	−0.126	24
High Score	0.154	−0.016	749	0.159	0.044	485	0.008	−0.034	214
High–Low Diff.	0.246	0.194	—	0.258	0.233	—	0.132	0.092	—
t-stat/(p-value)	4.533	(0.000)	—	3.573	(0.000)	—	1.852	(0.099)	—

Panel B: Trading Volume[b]

	Low Volume			Medium Volume			High Volume		
	Mean	Median	n	Mean	Median	n	Mean	Median	n
All Firms	0.101	−0.044	7661	0.011	−0.092	3664	0.028	−0.033	2718
Low Score	−0.072	−0.191	217	−0.108	−0.206	110	-0.149	−0.235	69
High Score	0.167	0.013	998	0.067	−0.020	280	0.054	−0.034	170
High–Low Diff.	0.239	0.204	—	0.175	0.186	—	0.203	0.201	—
t-stat/(p-value)	4.417	(0.000)	—	2.050	(0.001)	—	2.863	(0.000)	—

Panel C: Analyst Following[c]

	With Analyst Following			No Analyst Following		
	Mean	Median	n	Mean	Median	n
All Firms	0.002	−0.065	5317	0.101	−0.044	8726
Low Score	−0.093	−0.169	159	-0.097	−0.209	237
High Score	0.021	−0.024	415	0.180	0.012	1033
High–Low Diff.	0.114	0.145	—	0.277	0.221	—
t-stat/(p-value)	1.832	(0.000)	—	5.298	(0.000)	—

[a]Share price equals the firm's price per share at the end of the fiscal year preceding portfolio formation.

[b]Trading volume represents share turnover, defined as the total number of shares traded during the prior fiscal year scaled by the average number of shares outstanding during the year.

[c]Analyst following equals the number of forecasts reported on I/B/E/S during the last statistical period of the year preceding portfolio formation.

[d]Firms are classified into share price and trading volume portfolios in a manner similar to firm size (see table 4).

Note: High and low F_SCORE firms are as defined in table 3. Differences in mean (median) realizations between the high F_SCORE firms and low F_SCORE firms are measured; T-statistics for differences in means (p-values for medians) from two-sample t-tests (signed rank wilcoxon tests) are presented.

negatively related to the amount of analyst coverage provide. Table 5, panel C provides evidence on this issue.

Consistent with arguments of low investor interest, only 5,317 of the 14,043 firms in the sample, or 37.8%, have analyst coverage in the year preceding portfolio formation (as reported on the 1999 I/B/E/S summary tape). For the firms with coverage, the average (median) number of analysts providing a forecast at the end of the prior fiscal year was only 3.15 (2). Based on these statistics, it appears that the analyst community neglects most high BM firms. Consistent with slow information processing for neglected firms, the superior returns earned by a generic high BM portfolio are concentrated in firms without analyst coverage. High BM firms without analyst coverage significantly outperform the value-weighted market index by 0.101, while those firms with analyst coverage simply earn the market return. In addition, the gains from financial statement analysis are also greatest for the group of firms without analyst coverage. Although financial statement analysis can be successfully applied to both sets of firms, the average return difference between high and low F_SCORE firms is 0.277 for the firms without analyst following compared to 0.114 for the firms with analyst coverage.

In conclusion, the evidence suggests that financial statement analysis is fairly robust across all levels of share price, trading volume, and analyst following. The concentration of the greatest benefits among smaller, thinly traded and underfollowed stocks suggests that information-processing limitations could be a significant factor leading to the predictability of future stock returns. Section 7 will address this issue in detail.

Section 5: Other Sources of Cross-Sectional Variation in Returns

Despite all firms being selected annually from the same book-to-market quintile, one source of the observed return pattern could be different risk characteristics across F_SCORE rankings. Alternatively, a correlation between F_SCORE and another known return pattern, such as momentum, accrual reversal, or the effects of seasoned equity offerings, could drive the observed return patterns. This section addresses these issues.

Conceptually, a risk-based explanation is not appealing; the firms with the strongest subsequent return performance appear to have the smallest amount of *ex ante* financial and operating risk (as measured by the historical performance signals). In addition, small variation in size and book-to-market characteristics across the F_SCORE portfolios [not tabulated] is not likely to account for a 22% differential in observed market-adjusted returns.

In terms of F_SCORE being correlated with another systematic pattern in realized returns, there are several known effects that could have a strong relationship with F_SCORE. First, underreaction to historical information and financial events, which should be the ultimate mechanism underlying the success of F_SCORE, is also the primary mechanism underlying momentum strategies (Chan, Jegadeesh, and Lakonishok 1996). Second, historical levels of accruals (Sloan 1996) and recent equity offerings (Loughran and Ritter 1995, Spiess and Affleck-Graves 1995), both of which have been shown to predict future stock returns, are imbedded in F_SCORE and are thereby correlated with the aggregate return metric. As such, it is important to demonstrate that the financial statement analysis methodology is identifying financial trends above and beyond these other previously documented effects.

To explicitly control for some of these correlated variables, I estimate the following cross-sectional regression within the population of high book-to-market firms:

$$MA\_RET_i = \alpha + \beta_1 \log(MVE_i) + \beta_2 \log(BM_i) + \beta_3 MOMENT_i + \beta_4 ACCRUAL_i + \beta_5 EQ\_OFFER_i + \beta_6 F\_SCORE_i$$

where MA_RET is the one-year market-adjusted return, MOMENT equals the firm's six-month market-adjusted return prior to portfolio formation, ACCRUAL equals the firm's total accruals scaled by total assets, and EQ_OFFER equals one if the firm issued seasoned equity in the preceding fiscal year, zero otherwise.[11] All other variables are as previously defined. Consistent with the strategies originally proposed for each of these explanatory variables, I assign MOMENT and ACCRUAL into a decile portfolio based on the prior annual distribution of each variable for all Compustat firms, and I use this portfolio rank (1 to 10) for model estimation. Panel A of table 6 presents the results based on a pooled regression; panel B presents the time-series average of the coefficients from 21 annual regressions along with t-statistics based on the empirically derived time-series distribution of coefficients.

The coefficients on F_SCORE indicate that, after controlling for size and book-to-market differences, a one-point improvement in the aggregate score (i.e., one additional positive signal) is associated with an approximate 2½% to 3% increase in the one-year market-adjusted return earned subsequent to portfolio formation. More importantly, the addition of variables designed to capture momentum, accrual reversal, and a prior equity issuance has no impact on the robustness of F_SCORE to predict future returns.

Finally, appendix 1 illustrates the robustness of the fundamental analysis strategy over time. Due to small sample sizes in any given year, firms where a majority of the signals are good news (F_SCORES of 5 or greater) are compared against firms with a majority of bad news signals (F_SCORES of 4 or less) each year.[12] Over the 21 years in this study, the average market-adjusted return difference is positive (0.097) and statistically significant (t–statistic = 5.059). The strategy is successful

[11] Equity offerings were identified through the firm's statement of cash flows or statement of sources and uses of funds (through Compustat) for the year preceding portfolio formation.

[12] The use of this categorization throughout the paper does not alter the inferences reported about the successfulness of the F_SCORE strategy.

Table 6: Cross-Sectional Regression

This table presents coefficients from the following cross-sectional regression:

$$MA\_RET_i = \alpha + \beta_1 \log(MVE_i) + \beta_2 \log(BM_i) + \beta_3 MOMENT_i + \beta_4 ACCRUAL_i + \beta_5 EQ\_OFFER_i + \beta_6 F\_SCORE_i$$

Panel A presents coefficients from a pooled regression; panel B presents the time-series average coefficients from 21 annual regressions (1976–1996) where the t-statistic is based on the distribution of the estimated annual coefficients. MOMENT is equal to the firm's six month market-adjusted buy-and-hold return over the six months preceding the date of portfolio formation. For purposes of model estimation, the variables MOMENT and ACCRUAL were replaced with their portfolio decile ranking (1 through 10) based on annual cutoffs derived from the entire population of Compustat firms. (n=14,043)

Panel A: Coefficients from Pooled Regressions

	Intercept	log(MVE)	log(BM)	Moment	Accrual	EQ_OFFER	F_SCORE	Adj. R^2
(1)	−0.077	−0.028	0.103	—	—	—	0.031	0.0146
	(−2.907)	(−7.060)	(6.051)	—	—	—	(8.175)	
(2)	−0.057	−0.028	0.103	0.006	−0.003	−0.007	0.027	0.0149
	(−1.953)	(−6.826)	(5.994)	(2.475)	(−1.253)	(−0.432)	(6.750)	

Panel B: Time-Series Average of Coefficients from 21 Annual Regressions (1976–1996)

	Intercept	log(MVE)	log(BM)	Moment	Accrual	EQ_OFFER	F_SCORE
(1)	−0.030	−0.027	0.122	—	—	—	0.031
	(−0.556)	(−3.779)	(4.809)	—	—	—	(7.062)
(2)	−0.040	−0.028	0.127	−0.000	0.001	0.008	0.032
	(−0.669)	(−4.234)	(4.193)	(−0.035)	(0.141)	(0.731)	(5.889)

in 18 out of 21 years, with the largest negative mean return difference being only −0.036 in 1989 (the other two negative return differences are −0.004 and −0.001). This time series of strong positive performance and minimal negative return exposure casts doubt on a risk-based explanation for these return differences. Section 7 will investigate potential information-based explanations for the observed return patterns.

A second concern relates to the potential existence of survivorship issues, especially given the small number of observations in the low F_SCORE portfolios relative to the high F_SCORE portfolio. To the extent that there exists a set of firms with poor fundamentals that did not survive (and were *not* represented on Compustat), these missing low F_SCORE observations would have generated substantial negative returns. The omission of these firms from the study would bias upward the returns being earned by the current low F_SCORE portfolio. Therefore, the high minus low F_SCORE return differences reported in this paper could be *understating* the actual return performance associated with this investment strategy.

Alternatively, the high F_SCORE portfolio could consist of high BM firms recently added by Compustat due to their strong historical performance. Including firm observations from the early years of their "coverage" (i.e., back-filled historical data) could inflate the high F_SCORE portfolio returns because of the Compustat coverage bias. However, the data requirements of this paper should mitigate this concern. In particular, the variable ΔROA requires three years of historical data, so any firm-year observation associated with the first or second year of apparent Compustat "coverage" has insufficient data to calculate F_SCORE. Since Compustat adds three years of data when it initiates coverage, the first firm-year observation with sufficient data to be assigned to a portfolio equates to the first year the firm had "real time" coverage by Compustat. Thus, the financial information necessary to calculate F_SCORE existed at the time of portfolio formation, and the future performance of the firm (after year t) was not a factor in Compustat's decision to cover the firm.

Section 6: Sensitivity Tests: Use of Alternative Measures of Historical Financial Performance to Separate Winners from Losers

One potential criticism of this paper is the use of an *ad hoc* aggregate performance metric (F_SCORE) to categorize the financial prospects of the company at the time of portfolio formation. To mitigate this concern, table 7 presents results where the entire portfolio of high BM firms is split based on two accepted measures of firm health and performance: financial distress (Altman's z-score) and historical change in profitability (as measured by the change in return on assets). If these simple measures can also differentiate eventual winners from losers, then concerns about "metric-specific" results should be eliminated. In addition, I test whether the use of an aggregate measure such as F_SCORE has additional explanatory power above and beyond these two partitioning variables.

Similar to the methodology used for partitioning on firm size, share price, and trading volume, I classify each firm as having either a high, medium, or low level of financial distress and historical change in profitability. As shown in panels A and B of table 7, nearly half of all high book-to-market firms are classified as having high levels of financial distress or poor trends in profitability.

Table 7: Ability of Alternative Historical Financial Measures to Differentiate Winners from Losers

Panels A and B of this table present the relationship between one-year market-adjusted returns and two historical financial measures: financial distress and change in profitability. Each year, all firms on COMPUSTAT with sufficient financial statement data are ranked on the basis of the most recent fiscal year-end measures of financial distress (Altman's Z-score) and change in annual profitability (DROA). The 33.3 and 66.7 percentile cutoffs are used to classify the value firms into high, medium, and low portfolios. Financial distress is measure by Altman's z-statistic. Historical change in profitability is measured by the difference between year t and t-1 net income before extraordinary items scaled by beginning of year t and year t-1 total assets, respectively. All other definitions and test statistics are as described in table 3.

Panel A: Financial Distress

	High Distress			Medium Distress			Low Distress		
	Mean Return	Median Return	n	Mean Return	Median Return	n	Mean Return	Median Return	n
By financial distress partition:									
All Firms	0.042	−0.066	7919	0.073	−0.045	4332	0.103*	−0.072	1792
Differentiation based on F_SCORE:									
Low Score	−0.060	−0.065	270	−0.145	0.000	92	−0.245	−0.107	34
High Score	0.127	0.170	574	0.149	0.167	595	0.118	0.148	279
High–Low Diff.	0.187	0.235	—	0.294	0.167	—	0.363	0.255	—
t-stat/(p-value)	2.806	(0.000)	—	5.219	(0.000)	—	4.363	(0.000)	—

Panel B: Historical Change in Profitability

	High ΔROA			Medium ΔROA			Low ΔROA		
	Mean Return	Median Return	n	Mean Return	Median Return	n	Mean Return	Median Return	n
By profitability partition:									
All Firms	0.107**	−0.051	3265	0.057	−0.035	4391	0.037	−0.087	6387
Differentiation based on F_SCORE:									
Low Score	−0.181	−0.395	44	−0.021	−0.095	105	−0.040	−0.171	1106
High Score	0.127	−0.019	1520	0.109	−0.006	1462	0.171	0.024	320
High–Low Diff.	0.308	0.376	—	0.130	0.089	—	0.211	0.195	—
t-stat/(p-value)	2.634	(0.000)	—	2.151	(0.016)	—	4.814	(0.000)	—

** (*) Significantly different than the mean return of the low change in profitability portfolio (high financial distress portfolio) at the 1% (10%) level.

Table 7 (continued)

Panel C of this table presents one-year market-adjusted returns conditional on the interaction of two components of change in profitability: change in asset turnover and change in gross margins. Firms were assigned to portfolios in a manner consistent with panels A and B. Median returns are presented in parentheses below reported mean portfolio returns. Mean (median) return differences between strong/high signal and weak/low signal firms are tested using a two-sample t-tested (signed rank wilcoxon test). Strong (weak) firms are defined as the observations below (above) the off-diagonal of the matrix. ΔMARGIN equals the firm's gross margin (net sales less cost of good sold) for the year preceding portfolio formation, scaled by net sales for the year, less the firm's gross margin (scaled by net sales) from year t-1. ΔASSET_ TURN equals the change in the firm's asset turnover ratio between the end of year t and year t-1. The asset turnover ratio is defined as net sales scaled by average total assets for the year.

Panel C: Decomposition of ΔROA: Changes in Asset Turnover and Gross Margins[c]

		ΔTURN				
		Low	**Medium**	**High**	**Unconditional**	**High–Low**
ΔMargin	**Low**	-0.019	0.032	0.076	0.031	0.095
		(-0.125)	(-0.061)	(-0.092)	(-0.092)	(0.033)
		1726	1902	1912	5540	-
	Medium	-0.004	0.047	0.130	0.059	0.134
		(-0.102)	(-0.033)	(-0.003)	(-0.044)	(0.099)
		1331	1428	1452	4211	-
	High	0.098	0.057	0.137	0.096	0.039
		(-0.050)	(-0.036)	(-0.045)	(-0.042)	(0.005)
		1364	1530	1398	4292	-
	Unconditional	0.021	0.044	0.110	0.060	0.089[b]
		(-0.098)	(-0.044)	(-0.045)	(-0.061)	(0.053)[b]
		4421	4860	4762	-	-
	High–Low	0.117	0.025	0.061	0.065[a]	-
		(0.075)	(0.025)	(0.047)	(0.050)[a]	-

Portfolio-level returns:

	Mean	**10%**	**25%**	**Median**	**75%**	**90%**	**%Positive**	**n**
Strong Firms	0.107	-0.521	-0.290	-0.028	0.294	0.760	0.469	4380
Weak Firms	0.005	-0.586	-0.342	-0.095	0.206	0.605	0.402	4959
Strong–Weak	0.102	0.065	0.052	0.067	0.088	0.155	0.067	—
t-stat/(p-value)	5.683	—	—	(0.000)	—	—	(0.000)	—

[a] T-statistic = 3.579; signed rank wilcoxon p-value = 0.0001.
[b] T-statistic = 4.659; signed rank wilcoxon p-value = 0.0001.

Partitioning reveals a monotonic relationship between the measures of financial distress and historical profitability and mean one-year-ahead market-adjusted returns. First, firms with lower levels of financial distress earn significantly stronger future returns than high-distress firms (mean market-adjusted return of 0.103 versus 0.042, respectively).[13] This relationship is consistent with Dichev (1998), who documents an inverse relationship between measures of financial distress and stock returns among a set of CRSP firms facing a reasonable probability of default or bankruptcy. Second, high BM firms with the strongest historical profitability trends also earn significantly higher returns in the subsequent year (0.107 versus 0.037).[14] These results corroborate the evidence and inferences presented using F_SCORE as the conditioning "information" variable.

After controlling for financial distress and historical changes in profitability, F_SCORE still displays power to discriminate between stronger and weaker firms within each partition. However, the nature of the effectiveness depends upon the set of firms being examined. For the set of relatively healthy high BM firms (low financial distress), F_SCORE is extremely effective at identifying future poor performing firms (mean low F_SCORE return of −0.245), yet it demonstrates limited power to separate the strongest firms from the whole portfolio. For "troubled" firms (medium and high levels of financial distress), the usefulness of F_SCORE is more balanced, leading to both high and low F_SCORE portfolio returns that are significantly different from the returns of all firms in the respective financial distress partition. Similar patterns of effectiveness are demonstrated across the change in profitability partitions.

Despite the overall success of these individual metrics, they were unable to differentiate firms along other dimensions of portfolio performance. In particular, neither financial distress nor change in profitability alone was able to consistently shift the median return earned by an investor. The ability to shift the entire distribution of returns appears to be a result of aggregating multiple pieces of financial information to form a more precise "signal" of historical performance. To demonstrate the usefulness of aggregating alternative performance measures, panel C examines one-year market-adjusted returns conditioned on two variables that drive a change in return on assets: change in asset turnover and change in gross margin.

Partitioning ΔROA into its two fundamental components provides stronger evidence on the use of simple historical financial information to differentiate firms. First, unconditionally, both metrics provide some information about future performance prospects: firms with strong historical improvements in asset turnover and margins earn the strongest future returns. Second, a joint consideration of the metrics generates stronger predictions of future firm performance. I define strong (weak) value firms as those observations in the three cells below (above) the off-diagonal of the matrix (i.e., firms with the highest (lowest)

[13] The difference in mean returns of 0.061 is significant at the 10% level (two-sample t-statistic = 1.826).

[14] The differences in mean and median returns (0.070 and 0.036, respectively) are significant at the one-percent level (two-sample t-statistic = 3.270; signed rank wilcoxon p-value = 0.0008).

changes in asset turnover and gross margins). As shown, strong (weak) value firms consistently outperform (underperform) the other firms in the high book-to-market portfolio. The differences in returns between these two groups of firms (mean difference = 0.102, median difference = 0.067) are both significant at the 1% level.

The evidence presented in table 7 clearly demonstrates that the ability to discriminate winners from losers is not driven by a single, specific metric. Instead, future returns are predictable by conditioning on the past performance of the firm. The combined use of relevant performance metrics, such as F_SCORE or a DuPont-style analysis, simply improves the ability of an investor to distinguish strong companies from weak companies relative to the success garnered from a single, historical measure. Section 7 examines whether the slow processing of financial information is at least partially responsible for the effectiveness of this strategy.

Section 7: Association between Fundamental Signals, Observed Returns, and Market Expectations

This section provides evidence on the mechanics underlying the success of the fundamental analysis investment strategy. First, I examine whether the aggregate score successfully predicts the future economic condition of the firm. Second, I examine whether the strategy captures systematic errors in market expectations about future earnings performance.

7.1 Future firm performance conditional on the fundamental signals

Table 8 presents evidence on the relationship between F_SCORE and two measures of the firm's future economic condition: the level of future earnings and subsequent business failures (as measured by performance-related delistings). As shown in the first column of table 8, there is a significant positive relation between F_SCORE and future profitability. To the extent these profitability levels are unexpected, a large portion of the excess return being earned by the high F_SCORE firms over the low F_SCORE firms could be explained.

The second column presents evidence on the proportion of firms that ultimately delist for performance-related reasons (in the two years subsequent to portfolio formation) conditional on F_SCORE. I gather delisting data through CRSP and define a performance-related delisting as in Shumway (1997).[15] The most striking result is the strong negative relationship between a firm's *ex ante* financial strength (as measured by F_SCORE) and the probability of a performance-related delisting. With the exception of slight deviations in the delisting rate for the most extreme firms (F_SCORE equals 0 or 9), the relationship is nearly monotonic across

[15] Performance-related delistings comprise bankruptcy and liquidation delistings, as well as delistings for other poor performance–related reasons (e.g., consistently low share price, insufficient number of market makers, failure to pay fees, etc.) See Shumway (1997) for further information on performance-related delistings.

Table 8: Future Earnings Performance Based on Fundamental Signals

This table presents the one-year ahead mean realizations of return on assets and delisting propensity for the complete sample of high BM firms and by these firms' aggregate fundamental analysis scores (F_SCORE). Delisting information was gathered through CRSP for the two-year period subsequent to portfolio formation. A delisting is categorized as performance-related if the CRSP code was 500 (reason unavailable), 520 (moved to OTC), 551–573 and 580 (various reasons), 574 (bankruptcy) and 584 (does not meet exchange financial guidelines). See Shumway (1997) for further details on classification. The difference in ROA performance (delisting proportions) between the high and low F_SCORE firms is tested using a t-statistic from a two-sample t-test (binomial test).

	Mean ROA_{t+1}	Proportion of Firms with Performance Delisting	n
All firms	−0.014	0.0427	14,043
F_SCORE			
0	−0.080	0.070	57
1	−0.079	0.106	339
2	−0.065	0.079	859
3	−0.054	0.064	1618
4	−0.034	0.052	2462
5	−0.010	0.036	2787
6	0.006	0.032	2579
7	0.018	0.028	1894
8	0.028	0.017	1115
9	0.026	0.021	333
High-Low Diff.	0.106	−0.083	—
(t-statistic)	(15.018)	(−7.878)	—

F_SCORE portfolios. Although close to 2% of all high F_SCORE firms delist within the next two years, low F_SCORE firms are more than five times as likely to delist for performance-related reasons. These differences in proportions are significant at the 1% level using a binomial test. The combined evidence in table 8 suggests that F_SCORE can successfully discriminate between strong and weak future firm performance.[16]

These results are striking because the observed return and subsequent financial performance patterns are inconsistent with common notions of risk. Fama and French (1992) suggest that the BM effect is related to financial distress. However, the evidence in tables 3 through 8 shows that portfolios of the healthiest value firms yield *both* higher returns and stronger subsequent financial performance. This

[16] The inclusion of delisting returns in the measurement of firm-specific returns would not alter the inferences gleaned from table 2 through table 9. For those firms with an available delisting return on CRSP, low F_SCORE firms have an average delisting return of −0.0087, while high F_SCORE firms have an average delisting return of 0.0220.

inverse relationship between *ex ante* risk measures and subsequent returns appears to contradict a risk-based explanation. In contrast, the evidence is consistent with a market that slowly reacts to the good news imbedded within a high BM firm's financial statements. Section 7.2 examines whether the market is systematically surprised at subsequent earnings announcements.

7.2 Subsequent earnings announcement returns conditional on the fundamental signals

Table 9 examines market reactions around subsequent earnings announcements conditional on the historical information. LaPorta et al. (1997) show that investors are overly pessimistic (optimistic) about the future performance prospects of value (glamour) firms, and that these systematic errors in expectations unravel during subsequent earnings announcements. They argue that these reversals in expectations account for a portion of the return differences between value and glamour firms and lead to a systematic pattern of returns around subsequent earnings announcements. LaPorta (1996) and Dechow and Sloan (1997) show similar results regarding expectations about firm growth and the success (failure) of contrarian (glamour) investment strategies. This paper seeks to determine whether similar expectation errors are imbedded within the value portfolio *itself* when conditioning on the past performance of the individual firms.

Consistent with the findings in LaPorta et al. (1997), the average "value" firm earns positive raw returns (0.0370) around the subsequent four quarterly earnings announcement periods. These positive returns are indicative of an aggregate overreaction to the past poor performance of these firms.[17] However, when the value portfolio is partitioned by the aggregate score (F_SCORE), returns during the subsequent quarterly earnings' announcement windows appear to reflect an underreaction to historical information. In particular, firms with strong prior performance (high F_SCORE) earn approximately 0.049 over the subsequent four quarterly earnings announcement windows, while the firms with weak prior performance (low F_SCORE) only earn 0.008 over the same four quarters. This difference of 0.041 is statistically significant at the 1% level and is comparable in magnitude to the one-year "value" versus "glamour" firm announcement return difference observed in LaPorta et al. (1997). Moreover, approximately 1/6 of total annual return difference between high and low F_SCORE firms is earned over just 12 trading days (less than 1/20 of total trading days).

If these systematic return differences are related to slow information processing, then the earnings announcement results should be magnified (abated) when conditioned on small (large) firms, firms with (without) analyst following, and firms with low (high) share turnover. Consistent with the one-year-ahead results, the differences between the earnings announcement returns of high and low F_SCORE firms are greatest for small firms, firms without analyst following, and

[17] Earnings announcement returns are calculated as the three-day buy-and-hold return (-1, +1) around the quarterly earnings announcement date (date 0). Earnings announcement dates are gathered from Compustat. The annual earnings announcement period returns equals the sum of buy-and-hold returns earned over the four quarterly earnings announcement periods following portfolio formation.

Table 9: Relationship between F_SCORE and Subsequent Earnings Announcement Reactions

This table presents mean stock returns over the subsequent four quarterly earnings announcement periods following portfolio formation. Announcement returns are measured as the buy-and-hold returns earned over the three-day window (-1, +1) surrounding each earnings announcement (date 0). Mean returns for a particular quarter represents the average announcement return for those firms with returns available for that quarter. The total earnings announcement return for each firm (i.e., all quarters) equals the sum of the individual quarterly earnings announcement returns. If announcement returns are not available for all four quarters, the total announcement return equals the sum of announcement returns over the available dates. The mean "all quarters" return for each portfolio is the average of these firm-specific total earnings announcement returns. The difference between the mean announcement returns of the high and low F_SCORE firms is tested using a two-sample t-test. Earnings announcement dates were available for 12,426 of the 14,043 high BM firms. One-year market-adjusted returns (MARET) for this subsample are presented for comparison purposes.

	1year MARET	First Quarter	Second Quarter	Third Quarter	Fourth Quarter	All Quarters
All value firms	0.070	0.009	0.007	0.010	0.011	0.037
Low SCORE	−0.070	0.001	0.009	−0.003	0.003	0.008
High SCORE	0.144	0.010	0.009	0.018	0.016	0.049
High-Low Diff.	0.214	0.009	0.000	0.021	0.013	0.041
(t-statistic)	(4.659)	(1.560)	(0.075)	(3.104)	(2.270)	(3.461)

low share turnover firms. For small firms, the four quarter earnings announcement return difference is 5.1%, which represents nearly one-fifth of the entire one-year return difference; conversely, there is no significant difference in announcement returns for large firms [results not tabulated].

Overall, the pattern of earnings announcement returns, conditional on the past historical information (i.e., F_SCORE), demonstrates that the success of fundamental analysis is at least partially dependent on the market's inability to fully impound predictable earnings-related information into prices in a timely manner.

Section 8: Conclusions

This paper demonstrates that a simple accounting-based fundamental analysis strategy, when applied to a broad portfolio of high book-to-market firms, can shift the distribution of returns earned by an investor. Although this paper does not purport to find the optimal set of financial ratios for evaluating the performance prospects of individual "value" firms, the results convincingly demonstrate that investors can use relevant historical information to eliminate firms with poor future prospects from a generic high BM portfolio. I show that the mean return earned by a high book-to-market investor can be increased by at least 7½% annually through the selection of financially strong high BM firms and the entire distribution of realized returns is shifted to the right. In addition, an investment strategy that buys expected winners and shorts expected losers generates a 23% annual return between 1976 and 1996, and the strategy appears to be robust across time and to controls for alternative investment strategies.

Within the portfolio of high BM firms, the benefits to financial statement analysis are concentrated in small and medium-sized firms, companies with low share turnover, and firms with no analyst following and the superior performance is not dependent on purchasing firms with low share prices. A positive relationship between the sign of the initial historical information and both future firm performance and subsequent quarterly earnings announcement reactions suggests that the market initially underreacts to the historical information. In particular, ⅙ of the annual return difference between *ex ante* strong and weak firms is earned over the four three-day periods surrounding these earnings announcements.

Overall, the results are striking because the observed patterns of long-window and announcement-period returns are inconsistent with common notions of risk. Fama and French (1992) suggest that the BM effect is related to financial distress; however, among high BM firms, the healthiest firms appear to generate the strongest returns. The evidence instead supports the view that financial markets slowly incorporate public historical information into prices and that the "sluggishness" appears to be concentrated in low volume, small, and thinly followed firms. These results also corroborate the intuition behind the "life cycle hypothesis" advanced in Lee and Swaminathan (2000a, 2000b). They conjecture that early stage-momentum losers that continue to post poor performance can become subject to extreme pessimism and experience low volume and investor neglect (i.e., a late stage-momentum loser). Eventually, the average late stage-momentum loser does "recover" and becomes an early stage-momentum winner. The strong value firms in this paper have the same financial and market characteristics as Lee and Swaminathan's late stage-momentum losers. Since it is difficult to identify an individual firm's location in the life cycle, this study suggests that contextual fundamental analysis could be a useful technique to separate late stage-momentum losers (so-called recovering dogs) from early stage-momentum losers.

One limitation of this study is the existence of a potential data-snooping bias. The financial signals used in this paper are dependent, to some degree, on previously documented results; such a bias could adversely affect the out-of-sample predictive ability of the strategy. Whether the market behavior documented in this paper equates to inefficiency, or is the result of a rational pricing strategy that only appears to be anomalous, is a subject for future research.

Appendix 1

One-Year Market-Adjusted Returns to a Hedge Portfolio Taking a Long Position in Strong F_SCORE Firms and a Short Position in Weak F_SCORE Firms by Calendar Year

This appendix documents one-year market-adjusted returns by calendar year to a hedge portfolio taking a long position in firms with a strong F_SCORE (F_SCORE greater than or equal to 5) and a short position in firms with a poor F_SCORE (F_SCORE less than 5). Returns are cumulated over a one-year period starting four months after fiscal year-end. A market-adjusted return is defined as the firm's twelve-month buy-and-hold return less the buy-and-hold return on the value-weighted market index over the same investment horizon.

Year	Strong F_SCORE Mkt.-adj. Returns	Weak F_SCORE Mkt.-adj. Returns	Strong–Weak Return Difference	Number of Observations
1976	0.337	0.341	−0.004	383
1977	0.195	0.128	0.067	517
1978	−0.041	−0.105	0.064	531
1979	0.184	−0.039	0.223	612
1980	0.143	0.058	0.085	525
1981	0.307	0.202	0.105	630
1982	0.249	0.222	0.027	473
1983	0.100	−0.249	0.349	257
1984	−0.070	−0.200	0.130	807
1985	−0.019	−0.081	0.062	468
1986	0.051	0.029	0.022	728
1987	−0.008	−0.105	0.097	1,007
1988	−0.049	−0.217	0.168	684
1989	−0.099	−0.063	−0.036	765
1990	0.276	0.119	0.157	1,256
1991	0.320	0.154	0.166	569
1992	0.273	0.203	0.070	622
1993	0.029	0.009	0.020	602
1994	−0.008	−0.007	−0.001	1,116
1995	−0.016	−0.142	0.126	876
1996	0.069	−0.078	0.147	715
Average	0.106	0.009	0.097	—
(t-stat)	(3.360)	(0.243)	(5.059)	

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