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 percent 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 percent 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 under-reacts to the historical information. In particular, 1/6th 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; 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, this paper documents that less than 44 percent 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 from those with weak prospects. In the process, this paper discovers interesting regularities about the performance of the high BM portfolio and provides 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.

Moreover, 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 percent 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 the return distribution (i.e., 10^{th} percentile, 25^{th} 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 percent 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-

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[1] Through this paper, the term "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.

related evidence presented in Hong, Lim and Stein (1999), this paper finds 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 strong and weak value firms is greatest in these slow information processing / information flow 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 0.0409 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, Lakonishok, Shleifer and Vishny (1997). Moreover, approximately $1/6^{th}$ of total annual return difference between *ex ante* strong and weak firms is earned over just 12 trading days.

This study provides additional insight into the returns earned by small, financially distressed firms and the relation between these returns and their historical financial performance. This evidence is interesting given these firms' prominence in many of the "anomalies" documented in the current literature (see Fama, 1998). The results suggest that a portfolio of small, thinly-followed firms need not underperform the market; instead, strong performers are distinguishable from eventual underperformers through the utilization of past 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, Lakonishok, Shleifer and Vishny, 1997).

Ironically, as an investment strategy, analysts do not recommend high BM firms when forming their buy/sell recommendations. Stickel (1998) documents that analysts favor recommending firms with strong recent performance (low BM "glamour" companies and strong positive momentum firms). 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. A second explanation is that analysts have incentives to recommend firms with strong recent performance.

From a fundamental analysis 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 non-financial 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) and an assessment of these fundamental characteristics is most readily accomplished through a careful study of historical financial statements. To the extent that investors can use financial statement analysis to identify strong value companies, a firm-specific, high-return investment strategy based on the BM effect can be created.

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 the 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, 1999). Therefore, a forecast-based approach, such as Frankel and Lee (1998), has limited application for differentiating value stocks. By contrast, financial reports are likely to represent the best and most relevant source of current information about future performance prospects of high BM firms.

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 various 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. One of the drawbacks of these two studies rests on the use of complex methodologies and a vast amount of historical information to make the necessary predictions. To overcome these calculation costs and avoid over-fitting 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 macro-economic 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 forecasts of future earnings. 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 of approximately 13.2 percent per year.

This paper contextualizes the prior research by using financial signals as a means of gauging the financial health and investment worthiness of individual firms. Instead of focusing on the return effects of individual signals, I aggregate the information contained in an array of performance measures and form portfolios on the basis of a firm's overall signal. This approach shifts the focus of the research towards the *ex ante* differentiation of individual firms. By examining value firms, the benefits to financial statement analysis 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.

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 simple logic is used to identify the financial statement signals incorporated in this paper.

The nine fundamental signals chosen measure three areas of the firm's financial condition: profitability, financial leverage / liquidity and operating efficiency.[2] The signals used are easy to interpret, easy to implement and have broad appeal as summary performance statistics. In this paper, each firm's signal realization is classified as either "good" or "bad"

[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.

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). The aggregate signal measure, F_SCORE, is 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 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 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 some 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.

Three variables are used to measure these performance-related factors: ROA, CFO and ΔROA. ROA and CFO equal 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, the dummy variable F_ROA (F_CFO) equals one, zero otherwise.[3] ΔROA is equal to the current year's ROA less the prior year's ROA. If ΔROA > 0, the dummy variable F_ΔROA will equal one, zero otherwise.

Finally, the relationship between earnings and cash flow levels should be 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, while net negative accruals are good signals about future prospects. 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). The variable ACCRUAL equals current year's net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets. F_ACCRUAL equals one if CFO > ROA, zero otherwise.[4]

2.3.2 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, it is assumed that an increase in leverage, deterioration of liquidity or the use of external financing is a bad signal about financial risk.

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[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 non-trivial 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.

[4] The measure employed in this paper includes depreciation as a negative accrual. An alternative specification that adjusts for deprecation expense reduces the number of firms with a negative signal yet yields similar portfolio-level return results.

ΔLEVER captures changes in the firm's long-term debt levels. Measured as the historical change in the ratio of total long-term debt to average total assets, an increase (decrease) in financial leverage is viewed 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. The dummy variable F_ΔLEVER is one (zero) if the firm's leverage ratio fell (rose) in the year preceding portfolio formation.

ΔLIQUID measures the historical change in the firm's current ratio between the current and prior year, where the current ratio is defined as the ratio of current assets to current liabilities at fiscal year end. An improvement in liquidity (i.e., ΔLIQUID > 0) is assumed to be good signal about the firm's ability to service current debt obligations. The dummy variable F_ΔLIQUID equals one if the firms liquidity improved, zero otherwise.[5]

EQ_OFFER is a dummy variable equal to 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.

[5] An alternative specification is to consider a deterioration in liquidity a negative signal only if the firm's current ratio is near one. A specification where the current ratio cutoff equals 1.5 yields stronger return results than the liquidity metric and aggregate score used in the paper.

2.3.3 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 DuPont decomposition of return on assets.

ΔMARGIN is defined 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 dummy variable F_ ΔMARGIN equals one if ΔMARGIN is positive, zero otherwise.

ΔTURN is defined 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 dummy 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, this paper examines 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.[6] 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, F_SCORE equals the sum of the individual binary signals, or

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

where a low F_SCORE represents a firm with very few good signals while a high F_SCORE indicates the firm has mostly good fundamental signals. Given the nine underlying signals, F_SCORE can range from a low of 0 to a high of 9. As an aggregate measure of historical performance, F_SCORE is expected 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

[6] 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 carryforward position for tax purposes (due to their poor historical performance), thereby limiting the information content of Lev and Thiagarajan’s effective tax rate variable.

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. The binary signal approach was adopted because it is simple and easy to implement. An alternative specification would be to aggregate continuous representations of these nine factors. For robustness, the main results of this paper are also presented using an alternative method where the firms are classified based on the sum of annually ranked signals.

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. Several alternative measures are investigated. In particular, the high BM portfolio is split along dimensions of financial distress (as measured by Altman's z-statistic), historical change in profitability and a decomposition of ΔROA into changes in gross margins and changes in asset turnover. These tests will illustrate the robustness of using fundamental analysis techniques for identifying strong firms and document the benefits of aggregating multiple pieces of financial information when evaluating these companies.

Section 3: Research Design

3.1 Sample selection

Each year between 1976 and 1996, firms with sufficient stock price and book value data are identified on COMPUSTAT. For each firm, the market value of equity and BM ratio are calculated at fiscal year end.[7] Each fiscal year (i.e., financial report year), all firms with sufficient data are ranked 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.[8] Similarly, a firm's size classification (small, medium or large) is determined using the prior fiscal year's distribution of market capitalizations. After the BM quintiles are formed, firms in the highest BM quintile with sufficient financial statement data to calculate the various financial performance signals are retained. This approach yields the final sample of 14,043 high BM firms across the 21 years (see Appendix 1).[9]

3.2 Calculation of returns

Returns are measured 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, the delisting return is assumed to be zero. The fifth month was chosen to ensure that

[7] Fiscal year end prices were 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.

[8] Since each firm's book-to-market ratio is calculated at a different point in times (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.

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

the necessary annual financial information is available to investors at the time of portfolio formation. Market-adjusted returns are defined 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 firms aggregate score (F_SCORE). Firms with the lowest aggregate signals (F_SCORE equals 0 or 1) are classified as *low F_SCORE firms* and are expected to have 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*. These firms should have the best subsequent return performance given the strength and consistency of their fundamental signals. The tests in this paper are designed 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, firms are randomly selected from the complete portfolio of high BM firms and are assigned 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 1448 and 396 respectively). Second, the difference between the mean returns of these two pseudo-portfolios is calculated and represents an observation under the null of no difference in mean return performance. Third, this process is repeated 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, differences in pseudo-portfolio returns are also calculated for six different portfolio return measures: mean returns, median returns, 10^{th} percentile, 25^{th} percentile, 75^{th} percentile and 90^{th} 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, a pseudo-portfolio of high F_SCORE firms is randomly formed, 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. This process is repeated 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. These empirical results are discussed in the next section.

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 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 the one 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 book-to-market firms earn positive market-adjusted returns in the one and two year period following portfolio formation. However, despite the strong mean performance of this portfolio, a majority of the firms (approximately 57 percent) earn negative market-adjusted returns over the one and two year windows. These characteristics indicate that 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 shown in the table, F_SCORE has a significant positive correlation with both one-year and two-year future returns (0.1207 and 0.1299, respectively). For comparison, the two strongest individual explanatory variables are ROA and CFO; however, these variables only have a correlation of 0.0862 and 0.0965, respectively, with one-year ahead market-adjusted returns. Thus, the aggregate F_SCORE is likely to outperform a simple strategy based on current profitability or cash flows alone.

Table 3 presents the returns to the fundamental investment strategy. Panel B presents one-year market-adjusted returns; inferences and results are similar using raw returns (Panel A) and a two-year investment horizon (Panel C). 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, 1448 observations can be 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). As discussed earlier, these extreme portfolios will be used to test the ability of fundamental analysis to differentiate between future winners and losers.[10]

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 B, high F_SCORE firms significantly outperform low F_SCORE firms in the year following portfolio formation (mean market-adjusted returns of 0.1342 versus -0.0956, respectively). The mean return difference of 0.2298 is significant at the one percent 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 0.1342 versus 0.0595 for the entire BM quintile.

[10] 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

This difference of 0.0747 is also statistically significant at the one-percent level using an empirically derived bootstrap distribution of high F_SCORE returns and traditional test statistics.[11]

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 10^{th} percentile, 25^{th} percentile, median, 75^{th} percentile and 90^{th} 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, portfolio results are presented where firms are classified using the sum of annually ranked signals. Specifically, the individual signal realizations (i.e., ROA, CFO, ΔROA, etc.) are ranked each year between zero and one, and these ranked representations are used to form the aggregate measure. RANK_SCORE equals the sum of the firm's ranked realizations and quintile portfolios are formed using the cutoffs determined by the prior fiscal year's RANK_SCORE distribution.

F_SCORE portfolio). Results and inferences using this alternative definition are qualitatively similar to those presented throughout the paper.

[11] It is important to note that the bootstrap procedures do not control for firm-specific factors (such as firm size or momentum effects) when creating the pseudo-portfolios. The impact of these other variables on the primary results reported in Table 3 are addressed in subsequent sections of the paper.

Panel D documents that the use of ranked information can also differentiate strong and weak value firms; the mean (median) one-year market adjusted return difference between the highest and lowest RANK_SCORE quintile is 0.0918 (0.1127), both significant at the one-percent level. However, the benefits from using the continuous data are not overwhelming. Most of the loss in efficiency appears to arise from the mechanical ranking of the signals irrespective of the nature (i.e., sign) of the underlying news.[12] Additional specifications that control for these sign effects yield stronger results.

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, all firms with the necessary COMPUSTAT data to compute the fundamental signals are ranked annually into three size portfolios (independent of their book-to-market ratio). Size is defined as the firm's market capitalization at the prior fiscal year-end. Compustat yielded a total of approximately 75,000 observations between 1976 to 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 0.2703, significant at the one percent level).

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[12] For example, the median ΔMARGIN signal is negative while the median ΔTURN signal is positive. These median realizations have different implications for future performance, yet both receive the same relative ranking.

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 percent more than all medium size firms and 17.3 percent 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 five or ten percent level. Thus, the improvement in returns is isolated to firms in the bottom 2/3 of market capitalization.[13]

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, two other partitions of the sample are examined: share price and trading volume.

Similar to firm size, companies were placed 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 firms have lower share prices and are more thinly traded than the average firm on COMPUSTAT. However, approximately 48.4 percent of the firms could be classified as having medium or large share prices and 45.4 percent can be classified as having medium to high share turnover. These proportions allow for tests to compare the effectiveness of fundamental analysis across these partitions.[14]

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[13] 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 non-existent for larger firms. Similarly, Hong, Lim and Stein (1999) show that momentum strategies are strongest in small firms.

[14] Only high F_SCORE firm minus low F_SCORE firm return differences were 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.

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 0.2462 and 0.2582 respectively, the high share price portfolio also yields a significant positive difference of 0.1317. Similar significant positive return differences exist in median returns as well. The robustness of these results across share price partitions and return metrics 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 (1999), 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 0.1013. 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, one of the largest returns to fundamental analysis is in the low volume portfolio. However, similar to the share price results, the fundamental analysis strategy is successful across all levels of trading volume. Whereas the difference between high minus low F_SCORE firms is 0.2392 in the low volume portfolio, the return difference in the high volume partition is 0.2059 (both differences are significant at the one-percent 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. As such, 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 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 percent, 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.[15] Consistent with slow information-processing for neglected firms, the superior returns earned by a generic high BM portfolio appear to be concentrated in firms without analyst coverage. High BM firms without analyst coverage significantly outperform the value-weighted market index by 0.1012, 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 0.2767 for the firms without analyst following compared to 0.1145 for the firms with analyst coverage. Together, these results are consistent with the information-dissemination and processing predictions of Hong and Stein (1999).

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 under-followed 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.

[15] This result is consistent with Stickel (1998), Hayes (1998) and McNichols and O'Brien (1997).

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 be driving 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 (see Table 6) is not likely to account for a 22 percent 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, under-reaction 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. Given the significant differences documented in Table 6, 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.[16] All other variables are as previously defined. Consistent with the strategies originally proposed for each of these explanatory variables, MOMENT and ACCRUAL are assigned into a decile portfolio based on the prior annual distribution of each variable for all Compustat firms, and this portfolio rank (1 to 10) is used for model estimation.[17] Panel A of Table 7 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 two and a half to three percent 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 and Figure 1 illustrate the robustness of the fundamental analysis strategy over time. Due to small sample sizes in any given year, firms where a majority of the

[16] 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.
[17] Results and inferences using the raw values of the explanatory variables MOMENT and ACCRUAL are similar to those presented in the text and tables.

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.[18] Over the 21 years in this study, the average market-adjusted return difference is positive (0.0974) and statistically significant (t-statistic = 5.059). The strategy is successful in 18 out of 21 years, with the largest negative mean return difference being only -0.0363 in 1989 (the other two negative return differences are –0.0042 and –0.0013). 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 investigates potential information-based explanations for the observed return patterns.

Section 6: 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 8 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, each firm is classified as having either a high, medium or low level of financial distress

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

and historical change in profitability. These categorizations are based on the preceding fiscal year's cutoffs from the entire Compustat database during the sample period (using those firms with sufficient financial data). As shown in Panels A and B of Table 8, nearly half of all high book-to-market firms can be classified as having high levels of financial distress or poor trends in profitability. These distributions are consistent with the previous descriptive evidence presented in the paper.

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 0.1029 versus 0.0422, respectively).[19] This relationship is consistent with Dichev (1998), who documents an inverse relationship between measures of financial distress and stock returns for those firms with 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 (0.1073 versus 0.0367).[20] 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 –0.2454), yet demonstrates limited power to separate the strongest firms from the whole portfolio. For

[19] The difference in mean returns of 0.0607 is significant at the ten percent level (two-sample t-statistic = 1.826)

“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 changes in return on assets: change in asset turnover and change in gross margins.

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. Strong (weak) value firms are defined as those observations in the three cells below (above) the off-diagonal of the matrix (i.e., firms with the highest (lowest) 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

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[20] The differences in mean and median returns (0.0706 and 0.0363, respectively) are significant at the one-percent level (two-sample t-statistic = 3.270; signed rank wilcoxon p-value = 0.0008)

two groups of firms (mean difference = 0.1022, median difference = 0.0672) are both significant at the one-percent level.

The evidence presented in Table 8 clearly demonstrates that the ability to discriminate winners from losers is not driven by a single, specific metric. Instead, the future returns to a high BM strategy are predictable by conditioning on the past performance of the firm. The use of an aggregate performance metric, 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. The next section 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 9 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 9, there is a significant positive relation between F_SCORE and future profitability; the mean (median) spread in future ROA (one-year ahead) realizations is over 10 (12) percent (both differences are significant at the one-percent level). 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. Delisting data for the firms was gathered through CRSP, and a performance-related delisting is as defined in Shumway (1997).[21] 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 F_SCORE portfolios. Although close to 2 percent 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 one-percent level using a binomial test. The combined evidence in Table 9 suggests that F_SCORE can successfully discriminate between strong and weak future firm performance.[22]

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 9 shows that portfolios of the healthiest value firms yield *both* higher returns and stronger subsequent financial performance then the most financially distressed firms. The

[21] 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.

[22] It should be noted that including delisting returns in the measurement of firm-specific returns would not alter the inferences gleaned from Table 2 through Table 10. 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 the interpretation proposed by Fama and French. In contrast, the evidence is consistent with a market that slowly incorporates the good news imbedded in the strong value firms' financial statements. The next section examines whether the market is systematically surprised at subsequent earnings announcements.

7.2 Subsequent earnings announcement returns conditional on the fundamental signals

Table 10 examines market reactions around subsequent earnings announcements conditional on the historical information. LaPorta, Lakonishok, Shleifer and Vishny (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, Lakonishok, Shleifer and Vishny (1997), the average "value" firm (i.e., high BM 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.[23] However, when the

[23] For comparative purposes, LaPorta, Lakonishok, Shleifer and Vishny report first year earnings announcement returns of 0.0353 for their high BM firm sample. 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

value portfolio is partitioned by the aggregate score (F_SCORE), returns during the subsequent quarterly earnings' announcement windows appear to reflect an under-reaction to historical information. In particular, firms with strong prior performance (high F_SCORE) earn approximately 0.0486 over the subsequent four quarterly earnings announcement windows, while the firms with weak prior performance (low F_SCORE) only earn 0.0077 over the same four quarters. This difference of 0.0409 is statistically significant at the one-percent level and is comparable in magnitude to the one-year "value" versus "glamour" firm announcement return difference observed in LaPorta, Lakonishok, Shleifer and Vishny (1997). More incredibly, over $1/6^{th}$ of total annual return difference between high and low F_SCORE firms is earned over just 12 trading days (less than $1/20^{th}$ 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 low share turnover firms. For small firms, the four quarter earnings announcement return difference is 5.1 percent, which represents nearly one-fifth of the entire one-year return difference; conversely, there is no significant difference in announcement returns for large firms (see Panel B for summary of small firm results).

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

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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.

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, it convincingly demonstrates that investors can use past 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 percent 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 percent 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 under-reacts to the historical information. In particular, $1/6^{th}$ 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 the financial markets slowly incorporates 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 (1999). 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 fundamental analysis could be a useful technique to separate late-stage momentum losers (so-called "recovering dogs") from early-stage momentum losers.

Whether the market behavior documented in this paper equates to inefficiency or is the result of rational bayesian pricing strategies is a subject for future research.

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Appendix 1
Returns to a Fundamental Analysis Strategy by Year

This appendix documents one-year market adjusted returns by calendar year to a hedge portfolio taking a long position in firms receiving a good 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 in Table 2.

Year	Top F_SCORE Mkt.-adj. Returns	Bottom F_SCORE Mkt.-adj. Returns	Top – Bottom Return Difference	Number of observations
1976	0.3368	0.3410	-0.0042	383
1977	0.1952	0.1275	0.0677	517
1978	-0.0405	-0.1047	0.0642	531
1979	0.1842	-0.0394	0.2236	612
1980	0.1430	0.0582	0.0848	525
1981	0.3072	0.2016	0.1056	630
1982	0.2489	0.2219	0.0270	473
1983	0.0999	-0.2491	0.3490	257
1984	-0.0695	-0.2003	0.1308	807
1985	-0.0194	-0.0809	0.0615	468
1986	0.0506	0.0294	0.0212	728
1987	-0.0079	-0.1053	0.0974	1,007
1988	-0.0487	-0.2172	0.1685	684
1989	-0.0991	-0.0628	-0.0363	765
1990	0.2758	0.1194	0.1564	1,256
1991	0.3195	0.1542	0.1653	569
1992	0.2734	0.2026	0.0708	622
1993	0.0294	0.0093	0.0201	602
1994	-0.0084	-0.0071	-0.0013	1,116
1995	-0.0159	-0.1416	0.1257	876
1996	0.0693	-0.0784	0.1477	715
Average	0.1059	0.0085	0.0974	-
(t-stat)	(3.360)	(0.243)	(5.059)	

Figure 1
One-year Market Adjusted Returns to a Fundamental Analysis Strategy

This figure documents one-year market adjusted returns by calendar year to a hedge portfolio taking a long position in firms receiving a good 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 returns is defined as in Table 2.

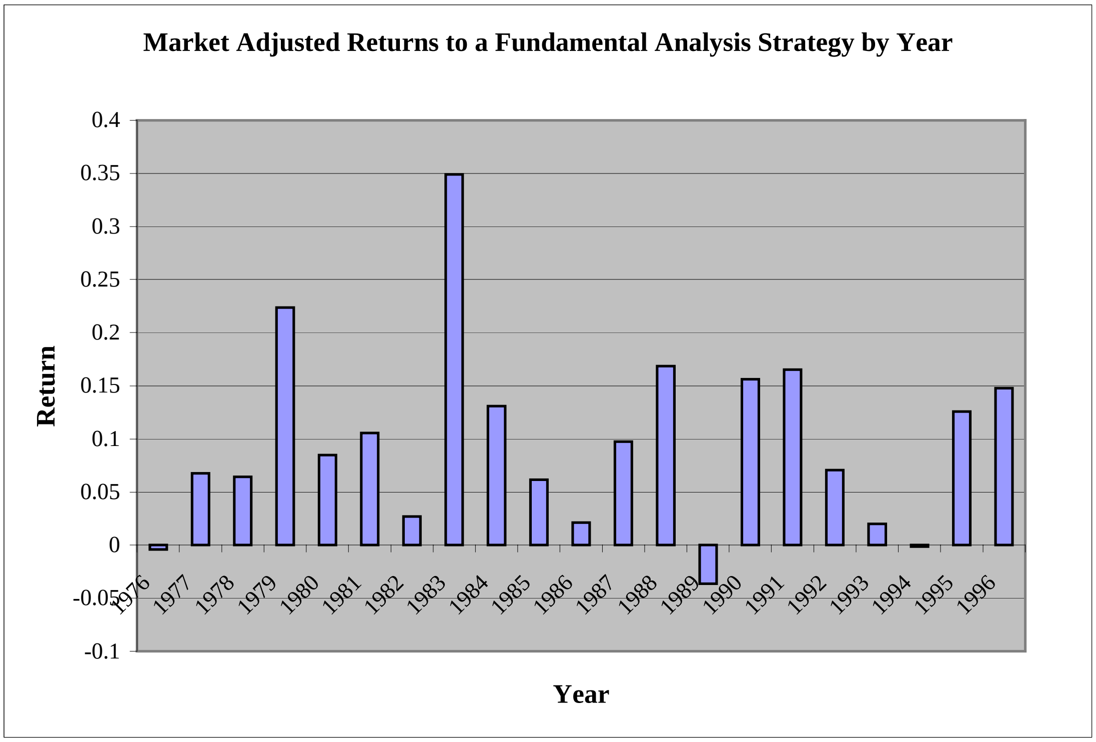

Table 1
Characteristics of High Book-to-Market Firms

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

Variable Definitions:

Note: All variables are measured as of the fiscal year-end prior to portfolio formation (year t)

MVE equals the 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 equals total assets reported at the end of the fiscal year t.
BM equals the firm's book value of equity at the end of fiscal year t, scaled by MVE.
ROA equals net income before extraordinary items for the fiscal year preceding portfolio formation scaled by total assets at the beginning of year t.
ΔROA equals the 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 equals the firms 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 equals cash flow from operations scaled by the beginning of year t total assets.
ΔLIQUID equals the 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.
ΔLEVERAGE equals the 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 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.
ACCRUAL is defined as net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets.

Table 1 (Continued)
Characteristics of High Book-to-Market Firms

Panel B: Buy-and-Hold Returns from a High Book-to-Market Strategy [c]

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Percent Positive
One-year returns							
Raw[a]	0.2394	-0.3913	-0.1500	0.1053	0.4381	0.9017	0.6100
Market-Adj.[b]	0.0595	-0.5597	-0.3170	-0.0605	0.2550	0.7082	0.4369
Two-year returns							
Raw[a]	0.4788	-0.5172	-0.1786	0.2307	0.7500	1.5793	0.6457
Market-Adj.[b]	0.1271	-0.8715	-0.5174	-0.1112	0.3943	1.2054	0.4322

[a] One-year (two-year) raw returns are calculated as the twelve (twenty-four) month buy-and-hold return of the firms starting at the beginning of the fifth month after fiscal year end. Return compounding ends the earlier of one year (two years) or the last day of CRSP reported trading. If the firm delisted, the delisting return is assumed to be zero.
[b] A market-value adjusted return equals the firm's buy-and-hold return less the buy-and-hold return on the value-weighted market index over the same investment horizon.
[c] The number of observations (years 1975 through 1995) equals 14,043. See Appendix 1 for the distribution of these high BM firm observations across the 21 years.

Table 2
Correlation Analysis

This table presents spearman correlations between realized one-year and two-year returns, the nine binary signals and the composite signal score (F_SCORE). An individual factor equals one if the underlying performance signal is good, zero otherwise. 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 are as defined in Table 1.

	MA_RET	MA_RET2	F_ROA	F_ΔROA	F_ΔMARGIN	F_CFO	F_ΔLIQUID	F_ΔLEVER	F_ΔTURN	F_ACCRUAL	EQ_OFFER
RETURN	0.9456	0.6947	0.1059	0.0435	0.0392	0.1042	0.0269	0.0576	0.0494	0.0507	0.0121
MA_RET	1.0000	0.7273	0.0862	0.0375	0.0423	0.0965	0.0319	0.0554	0.0339	0.0527	0.0407
M_RET2	-	1.0000	0.0989	0.0392	0.0451	0.1129	0.0291	0.0674	0.0232	0.0635	0.0428
F_ROA	-	-	1.0000	0.2646	0.1713	0.3821	0.1275	0.1566	-0.0159	-0.0225	-0.0758
F_ΔROA	-	-	-	1.0000	0.4044	0.1192	0.1167	0.1368	0.1010	-0.0186	0.0402
F_ΔMARGIN	-	-	-	-	1.0000	0.0799	0.0832	0.0726	0.0038	-0.0002	0.0123
F_CFO	-	-	-	-	-	1.0000	0.1282	0.0944	0.0410	0.5729	-0.0346
F_ΔLIQUID	-	-	-	-	-	-	1.0000	-0.0060	0.0533	0.0710	-0.0181
F_ΔLEVER	-	-	-	-	-	-	-	1.0000	0.0814	0.0155	-0.0232
F_ΔTURN	-	-	-	-	-	-	-	-	1.0000	0.0621	0.0342
F_ACCRUAL	-	-	-	-	-	-	-	-	-	1.0000	-0.0149
F_SCORE	0.1207	0.1299	0.5124	0.5775	0.4832	0.5562	0.3948	0.3997	0.3507	0.3655	0.2320

Table 3
Buy and Hold Returns to a Value Strategy based on Fundamental Signals

Panel A: One-year Raw Returns[a]

	Mean	10th Prctl.	25th Prctl.	Median	75th Prctl.	90th Prctl.	% Positive	nobs
All Firms	0.2394	-0.3913	-0.1500	0.1053	0.4381	0.9017	0.6100	14,043
F_SCORE								
0	0.1118	-0.6379	-0.3023	0.0000	0.5112	1.0513	0.4912	57
1	0.0729	-0.5893	-0.2983	-0.0417	0.2533	0.7407	0.4543	339
2	0.1586	-0.5122	-0.2778	0.0244	0.3687	0.8977	0.5204	859
3	0.1594	-0.5128	-0.2500	0.0341	0.3684	0.8667	0.5352	1618
4	0.2023	-0.4118	-0.1806	0.0704	0.4118	0.8750	0.5731	2462
5	0.2341	-0.3750	-0.1458	0.1142	0.4474	0.9000	0.6161	2787
6	0.2935	-0.3333	-0.1071	0.1429	0.4695	0.9081	0.6514	2579
7	0.3045	-0.2941	-0.0703	0.1640	0.4868	0.9412	0.6811	1894
8	0.3044	-0.2651	-0.0658	0.1626	0.4826	0.9218	0.6753	1115
9	0.3408	-0.2718	-0.1015	0.1667	0.5063	1.2000	0.6607	333
Low Score	0.0785	-0.5893	-0.3003	-0.0275	0.2697	0.7727	0.4596	396
High Score	0.3127	-0.2667	-0.0736	0.1658	0.4836	0.9546	0.6720	1448
High – All	0.0733	0.1246	0.0764	0.0605	0.0455	0.0529	0.0620	-
t-stat/(p-value)	3.279	-	-	(0.000)	-	-	(0.0001)	-
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	0.2342	0.3226	0.2267	0.1933	0.2139	0.1819	0.2124	-
t-stat/(p-value)	5.594	-	-	(0.0001)	-	-	(0.0001)	-
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)	-	-

[a] A raw return is calculated as the twelve 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 or the last day of CRSP reported trading. If the firm delisted, the delisting return is assumed to be zero.
[b] F_SCORE is equal to the sum of the nine individual binary signals, where zero equals the least favorable set of signals and 9 equals the most favorable set of 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.
[c] T-statistics for portfolio means (p-value for medians) are from a two-sample t-test (signed rank wilcoxon test); 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.

Table 3 (Continued)
Buy and Hold Returns to a Value Strategy based on Fundamental Signals

Panel B: One-year Market-adjusted Returns[a]

	Mean	10th Prctl.	25th Prctl.	Median	75th Prctl.	90th Prctl.	% Positive	nobs
All Firms	0.0595	-0.5597	-0.3170	-0.0605	0.2550	0.7082	0.4369	14,043
F_SCORE								
0	-0.0605	-0.7097	-0.4501	-0.1047	0.3723	0.7660	0.3860	57
1	-0.1015	-0.7956	-0.4632	-0.2029	0.0866	0.4895	0.3068	339
2	-0.0198	-0.6855	-0.4405	-0.1507	0.1976	0.7317	0.3737	859
3	-0.0149	-0.6908	-0.4106	-0.1420	0.1862	0.6667	0.3752	1618
4	0.0263	-0.5811	-0.3507	-0.0996	0.2292	0.6913	0.4046	2462
5	0.0527	-0.5429	-0.3069	-0.0586	0.2545	0.7054	0.4378	2787
6	0.1121	-0.4927	-0.2778	-0.0239	0.2852	0.7101	0.4711	2579
7	0.1159	-0.4663	-0.2508	-0.0112	0.3009	0.7470	0.4889	1894
8	0.1268	-0.4619	-0.2261	0.0025	0.3094	0.7101	0.5040	1115
9	0.1589	-0.4595	-0.2645	-0.0125	0.3274	0.8846	0.4865	333
Low Score	-0.0956	-0.7811	-0.4601	-0.1999	0.1072	0.5475	0.3182	396
High Score	0.1342	-0.4619	-0.2356	-0.0002	0.3162	0.7567	0.5000	1448
High – All	0.0747	0.0978	0.0814	0.0603	0.0612	0.0485	0.0631	-
t-stat/(p-value)	3.140	-	-	(0.000)	-	-	(0.0001)	-
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	0.2298	0.3192	0.2245	0.1997	0.2090	0.2092	0.1818	-
t-stat/(p-value)	5.590	-	-	(0.0001)	-	-	(0.0001)	-
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)	-	-

[a] A market-value adjusted return equals the firm's twelve-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.
[b] All other variables and tests are as defined in Panel A.

Table 3 (Continued)
Buy and Hold Returns to a Value Strategy based on Fundamental Signals

Panel C: Two-year Market-adjusted Returns[a]

	Mean	10th Prctl.	25th Prctl.	Median	75th Prctl.	90th Prctl.	% Positive	nobs
All Firms	0.1271	-0.8715	-0.5174	-0.1112	0.3943	1.2054	0.4322	14,043
F_SCORE								
0	0.0644	-0.9387	-0.7722	-0.2876	0.1506	1.7850	0.2983	57
1	-0.1798	-1.0660	-0.7715	-0.3683	0.0899	0.7958	0.2773	339
2	0.0376	-1.0308	-0.7524	-0.2781	0.3285	1.1392	0.3667	859
3	0.0024	-1.0223	-0.6581	-0.2297	0.2859	1.1174	0.3653	1618
4	0.0961	-0.9034	-0.5584	-0.1584	0.3375	1.1452	0.4037	2462
5	0.1300	-0.8549	-0.5134	-0.1077	0.3945	1.1931	0.4385	2787
6	0.1637	-0.7784	-0.4637	-0.0596	0.4284	1.1830	0.4595	2579
7	0.1950	-0.7171	-0.3911	-0.0250	0.4658	1.3192	0.4857	1894
8	0.3092	-0.6653	-0.3763	0.0122	0.5068	1.4587	0.5094	1115
9	0.2129	-0.7730	-0.3878	-0.0106	0.6160	1.3424	0.4925	333
Low Score	-0.1446	-1.0587	-0.7718	-0.3668	0.1081	0.8286	0.2803	396
High Score	0.2871	-0.6900	-0.3771	0.0065	0.5323	1.4142	0.5055	1448

High – All	0.1600	0.1815	0.1403	0.1177	0.1380	0.2088	0.0733	-
t-stat/(p-value)	-2.639	-	-	(0.0001)	-	-	(0.0001)	-
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	0.4317	0.3687	0.3947	0.3733	0.4242	0.5856	0.2252	-
t-stat/(p-value)	-5.749	-	-	(0.0001)	-	-	(0.0001)	-
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 two-year raw returns is calculated as the twenty-four 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 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 twenty four-month buy-and-hold return less the buy-and-hold return on the value-weighted market index over the same investment horizon.
[b] All other variables and tests are as defined in Panel A.

Table 3 (Continued)
Buy and Hold Returns to a Value Strategy based on Fundamental Signals

Panel D: Portfolios formed on the Sum of Ranked Fundamental Signals[b]

	Mean	10th Prctl.	25th Prctl.	Median	75th Prctl.	90th Prctl.	% Positive	nobs
One-year Market-adjusted Returns [a]								
All Firms	0.0595	-0.5597	-0.3170	-0.0605	0.2550	0.7082	0.4369	14,043
RANK_SCORE Quintile [b]								
1	0.0047	-0.6770	-0.4067	-0.1332	0.2232	0.7204	0.3862	2892
2	0.0398	-0.5790	-0.3347	-0.0806	0.2498	0.6719	0.4210	2843
3	0.0611	-0.5254	-0.3142	-0.0590	0.2505	0.7115	0.4358	2708
4	0.0976	-0.4846	-0.2735	-0.0258	0.2787	0.7086	0.4680	2818
5	0.0965	-0.4900	-0.2666	-0.0204	0.2756	0.7366	0.4723	2788
High – All	0.0370	0.0697	0.0504	0.0401	0.0206	0.0284	0.0354	-
t-stat/(p-value)	1.979	-	-	(0.0001)	-	-	(0.0001)	-
High – Low	0.0918	0.1870	0.1401	0.1128	0.0524	0.0162	0.0861	-
t-stat/(p-value)	4.488	-	-	(0.0001)	-	-	(0.0001)	-
Two-year Market-adjusted Returns [a]								
All Firms	0.1271	-0.8715	-0.5174	-0.1112	0.3943	1.2054	0.4322	14,043
RANK_SCORE Quintile [b]								
1	0.0609	-1.0160	-0.6822	-0.2448	0.3329	1.1607	0.3748	2892
2	0.1043	-0.9031	-0.5473	-0.1257	0.4130	1.2488	0.4291	2843
3	0.1213	-0.8549	-0.4883	-0.1099	0.3769	1.1470	0.4291	2708
4	0.1660	-0.7583	-0.4424	-0.0509	0.4226	1.2186	0.4641	2818
5	0.1855	-0.7605	-0.4437	-0.0556	0.4364	1.2377	0.4659	2788
High – All	0.0584	0.1110	0.0737	0.0556	0.0421	0.0323	0.0337	-
t-stat/(p-value)	1.891	-	-	(0.0036)	-	-	(0.0001)	-
High – Low	0.1246	0.2555	0.2385	0.1892	0.1035	0.0770	0.0911	-
t-stat/(p-value)	2.461	-	-	(0.0001)	-	-	(0.0001)	-

[a] One and two year market-adjusted buy-and-hold returns are as defined in Panels B and C, respectively.
[b] Each year, the individual signal realizations (e.g., ROA, CFO, etc.) are independently ranked between zero and one. RANK_SCORE equals the sum of the firm's ranked realizations. Firms are assigned to quintile portfolios by RANK_SCORE; the quintile cutoffs are determined by the prior fiscal year's RANK_SCORE distribution.
[c] The High (Low) RANK_SCORE portfolio equals those firms in quintile five (one).

Table 4
Market-adjusted Buy and Hold Returns to a Value Strategy based on Fundamental Signals by Size Partition

This table presents the relationship between one-year market-adjusted returns and the aggregate performance score (F_SCORE) by size portfolio. 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 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.

	Small Firms			**Medium Firms**			**Large Firms**		
	Mean	**Median**	**nobs**	**Mean**	**Median**	**nobs**	**Mean**	**Median**	**nobs**
All Firms	0.0907	-0.0769	8302	0.0083	-0.0592	3906	0.0027	-0.0278	1835
F_SCORE									
0	0.0000	-0.0763	32	-0.1463	-0.2354	17	-0.1196	-0.0469	8
1	-0.1038	-0.2266	234	-0.0833	-0.2284	79	-0.1363	-0.0725	26
2	-0.0156	-0.1713	582	-0.0445	-0.1308	218	0.0309	-0.0761	59
3	0.0025	-0.1675	1028	-0.0487	-0.1082	429	-0.0362	-0.0682	161
4	0.0578	-0.1160	1419	-0.0241	-0.1044	687	-0.0023	-0.0230	356
5	0.0792	-0.0751	1590	0.0279	-0.0604	808	-0.0039	-0.0311	389
6	0.1831	-0.0299	1438	0.0285	-0.0406	736	0.0119	-0.0039	405
7	0.1822	0.0049	1084	0.0266	-0.0276	540	0.0282	-0.0146	270
8	0.1704	0.0013	671	0.0814	0.0239	312	0.0120	-0.0408	132
9	0.2044	-0.0171	224	0.0675	0.0315	80	0.0587	-0.0447	29
Low Score	-0.0913	-0.2093	266	-0.0944	-0.2319	96	-0.1324	-0.0655	34
High Score	0.1790	-0.0066	895	0.0786	0.0239	392	0.0204	-0.0446	161
High – All	0.0883	0.0703	-	0.0703	0.0831	-	0.0177	-0.0168	-
t-statistic / (p-value)	2.456	(0.000)	-	2.870	(0.000)	-	0.872	(0.203)	-
High – Low	0.2703	0.2027	-	0.1730	0.2558	-	0.1528	0.0209	-
t-statistic / (p-value)	4.709	(0.0001)	-	2.870	(0.0001)	-	1.884	(0.2241)	

Table 5
Market-adjusted Buy-and-Hold Returns to a Value Strategy based on Fundamental Signals by Share Price, Trading Volume and Analyst Following

Panel A: Share Price[a]

	Small Price			Medium Price			Large Price		
	Mean	**Median**	**nobs**	**Mean**	**Median**	**nobs**	**Mean**	**Median**	**nobs**
All Firms	0.0919	-0.0945	7250	0.0176	-0.0458	4493	0.0654	0.0018	2300
Low Score	-0.0921	-0.2097	285	-0.0993	-0.1885	87	-0.1235	-0.1263	24
High Score	0.1541	-0.0158	749	0.1589	0.0439	485	0.0082	-0.0343	214
High–Low Diff.	0.2462	0.1939	-	0.2582	0.2324	-	0.1317	0.0920	-
t-stat / (p-value)	(4.533)	(0.0001)	-	(3.573)	(0.0001)	-	(1.852)	(0.0991)	-

Panel B: Trading Volume[b]

	Low Volume			Medium Volume			High Volume		
	Mean	**Median**	**nobs**	**Mean**	**Median**	**nobs**	**Mean**	**Median**	**nobs**
All Firms	0.1013	-0.0436	7661	0.0105	-0.0920	3664	0.0283	-0.0333	2718
Low Score	-0.0724	-0.1914	217	-0.1078	-0.2063	110	-0.1490	-0.2354	69
High Score	0.1668	0.0131	998	0.0666	-0.0204	280	0.0539	-0.0343	170
High–Low Diff.	0.2392	0.2045	-	0.1744	0.1859	-	0.2029	0.2011	-
t-stat / (p-value)	(4.417)	(0.0001)	-	(2.050)	(0.0008)	-	(2.863)	(0.0002)	-

Panel C: Analyst Following[c]

	With Analyst Following			No Analyst Following		
	Mean	**Median**	**nobs**	**Mean**	**Median**	**nobs**
All Firms	0.0016	-0.0654	5317	0.1012	-0.0438	8726
Low Score	-0.0934	-0.1690	159	-0.0971	-0.2089	237
High Score	0.0211	-0.0241	415	0.1796	0.0122	1033
High–Low Diff.	0.1145	0.1449	-	0.2767	0.2211	-
t-stat / (p-value)	(1.832)	(0.0002)	-	(5.298)	(0.0001)	-

[a] Share price equal the firm's price per share at the end of the fiscal year preceding portfolio formation.
[b] Trading volume is proxied by 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 is measured as 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).

Table 6
Descriptive Statistics for the Portfolios of High and Low F_SCORE Firms

This table presents descriptive statistics for the portfolios with high and low fundamental analysis scores (F_SCORES) as well as benchmark statistics for the complete high BM ratio portfolio.

Variable	All High BM Firms	High F_SCORE Firms	Low F_SCORE Firms	High minus Low Difference	t-stat (p-value)
MVE					
mean	188.50	178.38	81.44	96.94	2.388
median	14.37	11.41	11.96	-0.55	(0.4533)
BM ratio					
mean	2.444	2.079	2.000	0.079	1.141
median	1.721	1.856	1.709	0.147	(0.0095)
Leverage					
mean	0.2236	0.2106	0.2214	-0.0108	1.187
median	0.2058	0.1956	0.2029	-0.0073	(0.9760)
Momentum					
mean	0.0240	0.1292	-0.1049	0.2341	10.76
median	-0.0308	0.0655	-0.1440	0.2095	(0.0001)
Accruals					
mean	-0.0565	-0.0828	0.0509	-0.1337	25.99
median	-0.0491	-0.0687	0.0327	-0.1014	(0.0001)

Variable Definitions:

MVE equals the 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.
BM equals the firm's book value of equity at the end of fiscal year t, scaled by MVE.
LEVERAGE is measured by the firm's debt-to-assets ratio at the end of year t. The debt-to-asset ratio is defined as the firm total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets.
MOMENTUM is defined as the six-month market-adjusted buy-and-hold return over the six months directly preceding the date of portfolio formation.
ACCRUAL is defined as net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets.

Table 7
Cross-Sectional Regressions

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

$$MA\_RET_i = \alpha + \beta_1 \log(MVE_i) + \beta_2 \log(BM_i) + \beta_3 F\_SCORE_i$$

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

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. 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.

Panel A: Coefficients from Pooled Regressions

	Intercept	log(MVE)	log(BM)	Moment	Accrual	EQ_OFFER	F_SCORE	Adj. R^2
(1)	0.1007	-0.0296	0.0849	-	-	-	-	0.0096
	(5.597)	(-7.703)	(5.445)	-	-	-	-	
(2)	-0.0767	-0.0279	0.1032	-	-	-	0.0305	0.0146
	(-2.907)	(-7.060)	(6.051)	-	-	-	(8.175)	
(3)	0.1101	-0.0284	0.0834	0.0118	-0.0043	-0.0349	-	0.0119
	(5.894)	(-7.194)	(5.307)	(5.277)	(-1.811)	(-2.393)	-	
(4)	-0.0566	-0.0279	0.1029	0.0059	-0.0032	-0.0067	0.0273	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

	Intercept	log(MVE)	log(BM)	Moment	Accrual	EQ_OFFER	F_SCORE
(2)	-0.0299	-0.0274	0.1215	-	-	-	0.0307
	(-0.556)	(-3.779)	(4.809)	-	-	-	(7.062)
(4)	-0.0400	-0.0280	0.1271	-0.0001	0.0005	0.0077	0.0321
	(-0.669)	(-4.234)	(4.193)	(-0.035)	(0.141)	(0.731)	(5.889)

Variable Definitions:

MA_RET is the one-year market-adjusted return and equals 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.
MVE equals the 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.
BM equals the firm's book value of equity at the end of fiscal year t, scaled by MVE.
MOMENTUM is defined as the six-month market-adjusted buy-and-hold return over the six months directly preceding the date of portfolio formation.
ACCRUAL is defined as net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets.
EQ_OFFER equals one if the firm raised equity capital during the prior fiscal year, zero otherwise.

Table 8
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. The 33.3 and 66.7 percentile cutoffs are used to classify the value firms into high, medium and low portfolios. All other definitions and test statistics are as described in Table 3.

Panel A: Financial Distress[a]

	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	0.0422	-0.0660	7919	0.0733	-0.0452	4332	0.1029*	-0.0721	1792
Differentiation based on F_SCORE:									
Low Score	-0.0598	-0.0653	270	-0.1452	0.0000	92	-0.2454	-0.1066	34
High Score	0.1266	0.1703	574	0.1492	0.1667	595	0.1177	0.1481	279
High–Low Diff.	0.1864	0.2356	-	0.2944	0.1667	-	0.3631	0.2547	-
t-stat / (p-value)	2.806	(0.0001)	-	5.219	(0.0001)	-	4.363	(0.0001)	-

Panel B: Historical Change in Profitability[b]

	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	0.1073**	-0.0507	3265	0.0571	-0.0352	4391	0.0367	-0.0870	6387
Differentiation based on F_SCORE:									
Low Score	-0.1808	-0.3950	44	-0.0210	-0.0948	105	-0.0404	-0.1713	1106
High Score	0.1272	-0.0194	1520	0.1088	-0.0056	1462	0.1709	0.0236	320
High–Low Diff.	0.3080	0.3756	-	0.1298	0.0892	-	0.2113	0.1949	-
t-stat / (p-value)	2.634	(0.0001)	-	2.151	(0.0161)	-	4.814	(0.0001)	-

[a] Financial distress is measure by Altman's z-statistic.
[b] 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-1 total assets.
** (*) Significantly different than the mean return of the low change in profitability portfolio (high financial distress portfolio) at the one-percent (ten-percent) level.

Table 8 (Continued)
Ability of Alternative Historical Financial Measures to Differentiate Winners from Losers

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 profit margins. Firms were assigned to portfolios in a manner consistent with Panels A and B. Median returns are presented in parenthesis 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.

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

ΔMARGIN \ ΔASSET_TURN	Low	Medium	High	Unconditional	High – Low
Low	**-0.0192** **(-0.1249)** **1726**	**0.0320** **(-0.0614)** **1902**	0.0763 (-0.0916) 1912	0.0314 (-0.0920) 5540	0.0955 (0.0333) -
Medium	**-0.0042** **(-0.1018)** **1331**	0.0469 (-0.0333) 1428	**0.1300** **(-0.0027)** **1452**	0.0594 (-0.0436) 4211	0.1342 (0.0991) -
High	0.0977 (-0.0499) 1364	**0.0567** **(-0.0363)** **1530**	**0.1372** **(-0.0446)** **1398**	0.0959 (-0.0417) 4292	0.0395 (0.0053) -
Unconditional	0.0214 (-0.0975) 4421	0.0442 (-0.0439) 4860	0.1105 (-0.0449) 4762	0.0595 (-0.0605) -	0.0891[e] (0.0526)[e] -
High - Low	0.1169 (0.0750)	0.0247 (0.0251)	0.0609 (0.0470)	0.0645[d] (0.0503)[d]	- -

Portfolio-level returns:

	Mean	10th Prctl.	25th Prctl.	Median	75th Prctl.	90th Prctl.	% Positive	nobs
Strong Firms	0.1067	-0.5214	-0.2898	-0.0278	0.2943	0.7595	0.4687	4380
Weak Firms	0.0045	-0.5862	-0.3421	-0.0950	0.2057	0.6045	0.4023	4959
Strong - Weak	0.1022	0.0648	0.0540	0.0672	0.0886	0.1550	0.0664	-
t-stat/(p-value)	5.683	-	-	(0.0001)	-	-	(0.0001)	-

[c] ΔMARGIN equals the firms 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.
[d] T-statistic = 3.579; Signed rank wilcoxon p-value = 0.0001
[e] T-statistic = 4.659; Signed rank wilcoxon p-value = 0.0001

Table 9
Future Earnings Performance based on Fundamental Signals

This table presents the one-year ahead mean realizations of return on assets for the complete sample of high BM firms and by the firms aggregate fundamental analysis scores (F_SCORE). ROA equals income before extraordinary items scaled by beginning of the year total assets. The difference between the mean return on assets of the high and low F_SCORE firms is tested using a two-sample t-test. 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 delisting proportions between the high and low F_SCORE firms is tested using a t-statistic from a binomial test.

	Mean ROA_{t+1}	**Proportion of firms with Performance Delisting**	**nobs**
All firms	-0.014	0.0427	14,043
F_SCORE			
0	-0.080	0.0702	57
1	-0.079	0.1062	339
2	-0.065	0.0792	859
3	-0.054	0.0637	1618
4	-0.034	0.0524	2462
5	-0.010	0.0359	2787
6	0.006	0.0318	2579
7	0.018	0.0275	1894
8	0.028	0.0170	1115
9	0.026	0.0210	333
Low F_SCORE	-0.079	0.1010	396
High F_SCORE	0.027	0.0180	1448
High-Low Diff.	0.106	-0.0830	-
(t-statistic)	(15.018)	(-7.878)	-

Table 10
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. Quarterly earnings announcement dates are gathered from the Compustat Quarterly Industrial tape. 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 ahead market adjusted returns (MARET) for this sub-sample is presented for comparison purposes. Panel B presents summary data for the sample of small high BM firms.

Panel A: All High BM Firms

	1yr MARET	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	All Quarters
All value firms	0.0701	0.0088	0.0074	0.0102	0.0106	0.0370
F_SCORE						
0	-0.0390	0.0175	0.0055	-0.0183	0.0195	0.0238
1	-0.0751	-0.0024	0.0094	-0.0008	-0.0005	0.0048
2	0.0091	0.0059	0.0125	0.0113	0.0029	0.0293
3	0.0024	0.0086	0.0027	0.0049	0.0090	0.0231
4	0.0351	0.0094	0.0042	0.0060	0.0112	0.0282
5	0.0653	0.0097	0.0132	0.0132	0.0143	0.0457
6	0.1064	0.0087	0.0044	0.0101	0.0084	0.0291
7	0.1283	0.0092	0.0074	0.0120	0.0110	0.0371
8	0.1352	0.0076	0.0092	0.0197	0.0151	0.0469
9	0.1747	0.0191	0.0098	0.0117	0.0182	0.0543
Low SCORE	-0.0695	0.0007	0.0088	-0.0031	0.0025	0.0077
High SCORE	0.1442	0.0102	0.0093	0.0179	0.0158	0.0486
High-Low Diff.	0.2137	0.0095	0.0005	0.0210	0.0133	0.0409
(t-statistic)	(4.659)	(1.560)	(0.075)	(3.104)	(2.270)	(3.461)

Panel B: Small Firms:

	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	All Quarters
Low SCORE	-0.0017	0.0196	-0.0018	0.0038	0.0165
High SCORE	0.0159	0.0161	0.0229	0.0229	0.0681
High-Low Diff.	0.0176	-0.0035	0.0247	0.0267	0.0516
(t-statistic)	(1.750)	(0.396)	(2.559)	(2.146)	(3.000)