Further evidence on the relation between historical changes in financial condition, future stock returns and the value/glamour effect

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1. Introduction

The basic premise behind traditional financial statement analysis (FSA)-based investment strategies, such as those advocated by Graham and Dodd (1934), is that sophisticated investors can use historical financial information to select profitable investment opportunities. Specifically, investors can earn returns in excess of that required for risk compensation by identifying undervalued or overvalued securities through an analysis of historical financial data. Such trading opportunities require that prices that do not fully reflect the future cash flow implications of historical information in a timely manner, resulting in equity prices that temporarily drift away from fundamental value for subsets of firms. Assuming no impediments to trade or arbitrage (e.g., Lamont and Thaler, 2003), long-term investors can profit through the capture of subsequent revisions of biased expecations and related price corrections. One example of such trading behavior would be a traditional value investing strategy.

This paper examines a simple, financial statement analysis-based investment strategy that separates firms with strong recent financial performance from firms with weak recent performance. If market participants systematically under-react to *changes* in firms' financial condition (i.e, underreact to the implied changes in expected future earnings and cash flow realizations signaled by these historical changes), then this historical categorization will be able to identify predictable revisions in future expectations, thereby successfully separating firms with strong future return performance from firms with weak future return performance. Given the predictive ability of the general strategy, the remainder of the paper explores the association between historical changes in financial condition and future returns conditional on various risk and misvaluation proxies, such as book-to-market ratios, firm size, and bankruptcy risk. Consideration of the joint evidence from these partitions is used to distinguish investment returns associated with risk compensation from market mispricing, to provide evidence on the types of firms that are generating the systematic variation in returns observed from traditional glamour versus value (i.e., book-to-market ratio-based) investment strategies, and to illustrate the contextual investment-related benefits of financial statement analysis.

To measure the strength and quality of historical performance trends, this paper uses an aggregate score based on an array of nine readily-available financial signals derived from traditional financial statement analysis sources (see Piotroski, 2000; Fama and French, 2004). The resultant measure, FSCORE, is not designed to identify the healthiest firms *per se*, but instead to identify firms with the strongest improvement in overall financial condition during the last fiscal year while meeting a minimum standard of financial performance. Every year, firms are rated and classified on the basis of these recent signals. "Strong" firms demonstrate distinct improvements along a variety of financial dimensions, while "weak" firms have deteriorating (and generally poor) fundamentals along these same dimensions. Investment portfolios are formed on the basis of these historical classifications using a broad spectrum of publicly traded firms with sufficient financial and price data between 1972 and 2001.

Distinguishing a recent change in financial condition from the overall level of financial health is central to this paper. Instead of identifying risk attributes and capturing the related expected return premium, the current methodology focuses on identifying those firms with likely predictable changes in valuation due to shifting cash flow expectations. As such, this paper jointly assumes and tests that (1) changes in current financial condition correspond to (i.e., are a leading indicator of) changes in future cash flow realizations and that (2) the market's initial price response does not fully incorporate the new information's implications about future earnings and cash flows innovations (i.e., historical information is correlated with errors in market expectations).

Consistent with market participants underreacting to significant changes in a firm's financial condition, firms with the strongest improvement in current fundamentals outperform firms with the strongest deterioration in fundamentals by approximately 13 percent in the one-year period following portfolio formation.[1] The strongest firms alone earn one-year ahead market-adjusted returns of approximately 8 percent. These relations confirm the contextual relation found in Piotroski (2000) for value firms, and the general relations documented in Fama and French (2004). Moreover, the distribution of realized returns earned by investors appears to be shifted to the right (left) for firms

[1] In this paper, the term "strongest" could also be written as the "broadest" improvement in financial performance, where a broad improvement means an improvement along many dimensions of performance

with strong (weak) current performance. This shift manifests itself in higher (lower) mean and median returns for the strongest (weakest) firms, and a greater (smaller) proportion of firms that earn positive one-year-ahead returns. The returns to this fundamental strategy are monotonic across historical performance classifications, and are robust to controls for size, book-to-market ratios, momentum, and bankruptcy risk.

Further tests investigate the predictive ability of historical changes in financial condition after partitioning the sample along size, book-to-market, and bankruptcy risk dimensions. The primary findings involve relations conditional on book-to-market portfolios. This analysis extends the contextual analyses of Piotroski (2000) and Mohanram (2004) for the value and glamour portfolio, respectively, by illustrating that a financial statement analysis-based strategy is an effective discriminating technique across all book-to-market portfolios. However, the *intensity* of the discriminatory power varies across book-to-market quintiles, with preliminary evidence suggesting that the predictive ability of FSCORE is significantly stronger in the two extreme BM portfolios. Moreover, the *directional effectiveness* of FSCORE varies systematically across BM regimes. Among glamour firms, FSCORE successfully identifies losers (i.e., firms with negative future market-adjusted returns), while among value firms, FSCORE successfully identifies future winners.

In both cases, the predictive pattern of FSCORE appears to be consistent with the *ex ante* bias traditionally attributed to each portfolio of securities. To the extent that the traditional low BM portfolio consists of firms with strong profitability and growth expectations, the glamour portfolio is likely to contain an over-representative share of over-valued securities (and an underrepresentation of undervalued securities) fueled by strong investor interest in growth companies. In contrast, to the extent that the value portfolio consists of firms with weak profitability and low growth expectations, the value portfolio is likely to contain an over-representative share of under-valued securities (and an underrepresentation of overvalued securities) in the presence of investor neglect. Essentially, if the market is slow to react to the shift in economic condition signaled by FSCORE, the relative benefits of trading on FSCORE should be concentrated among the 'contrarian firms' embedded within a

specific BM portfolio (i.e., where the expectatations implied by the BM ratio do not equate to the future performance outcomes implied by the firm's current FSCORE). This is the pattern observed.

Further tests examine relations within a given book-to-market portfolio conditional on firm size. Prior research suggests that strong investor interest in a security could delay the recognition of bad news and exacerbate the pricing of good news. To the extent that firm size proxies for the likely level of investor interest in the security, both the intensity of FSCORE's predictive ability as well as the type of directional effectiveness of FSCORE would be expected to vary systematically within these book-to-market / size portfolios. These tests show that identification of future winners in the value portfolio is concentrated among small and midsize firms, while large, strong value firms appears to generate a minimal market-adjusted return. This is consistent with those firms suffering the greatest amount of investor neglect being the most susceptible to the underpricing of strong recent performance. In contrast, among glamour firms, the ability of FSCORE to identify subsequent losers exists across all size portfolios, consistent with all glamour firms (with both high and low levels of investor interest) under-reacting to recent deterioration in fundamentals. Moreover, it is only among the smallest glamour firms (i.e, most neglected set of glamour firms) that the strong FSCORE portfolio is able to generate meaningfully positive market-adjusted returns. Together, the mosaic of results suggest that the book-to-market effect is an artifact of predictable valuation errors correlated with past financial data, and these errors are distribution within the respective book-to-market portfolios among those firms most susceptible to an over-reaction and under-reaction to historical information.

The final set of tests focus on the pattern of returns conditional on bankruptcy risk in an attempt to distinguish the return effects associated with FSCORE from those related to the firm's general level of health (as proxied by Ohlson's (1980) bankruptcy score). Conditional on Ohlson's bankruptcy score, FSCORE retains its predictive ability, with its greatest strength resting with the most financial distressed quintile of firms. The strength of this association is consistent with these firms being the most likely candidates for shareholders to exercise their implicit put options, where a small shift in economic condition is likely to have a significant effect on firm's equity value. Also,

these high bankruptcy risk firms are also likely to be the most neglected set of firms, thereby exacerbating the return effects associated with historical changes in financial condition.

Additional tests extend the analysis of Griffin and Lemmon (2002) by examining the predictive ability of FSCORE within book-to-market portfolios after controlling for distress risk. The most salient conclusion from Griffin and Lemmon's study is that, after controlling for the level of bankruptcy risk, there continues to exist a book-to-market effect in realized returns, and that the BM effect is most pronounced among the most distressed firms. This pattern is consistent with investor neglect in combination with the mispricing of subsequent revisions in performance. Moreover, because distressed firms are more likely to be associated with a general decline in overall performance, ceteris paribus, the relations between future returns, bankruptcy risk and book-to-market portfolios found in Griffin and Lemmon (2002) across BM portfolios could have been tainted by the presence of an omitted, yet correlated, performance relation. My tests indicate that after controlling for both the level of financial health and recent changes in financial condition, book-to-market ratios continue to predict future returns. Moreover, FSCORE retains its predictive ability, with the strongest hedge returns continuing to be concentrated in the high bankruptcy risk subportfolio. Finally, FSCORE appears to have systematically different directional predictive abilities across various bankruptcy risk and book-to-market partitions of the data.

This paper is organized as follows. Section 2 presents background information about the ability of financial statement analysis-based investment strategies tools to predict future returns. Section 3 presents the research design and outlines the nine financial signals from Piotroski (2000) used to categorize changes in a firm's financial condition. Sections 4 and 5 present the main empirical results. Section 6 concludes.

2. Background and motivation

2.1 The relation between changes in economic condition and future stock returns

Evidence that market participants underreact to future cash flow news abounds in the extant literature, and spans a host of likely correlated research settings. For example, market participants

underreact to corporate events that signal shifts in expected future cash flows, such as seasoned equity offerings (Loughran and Ritter, 1995; Spiess and Affleck-Graves, 1995), convertible and straight debt issues (Lee and Loughran, 1998; Spiess and Affleck-Graves, 1999; Dichev and Piotroski, 1999), share repurchases (Ikenberry, Lakonishok, and Vermaelen, 1995), and stock splits (Ikenberry, Rankine and Stice, 1996). Similarly, market participants appear to underreact to explicit signals of changes in financial performance, such as bond ratings downgrades (Dichev and Piotroski, 2001) and changes in analyst recommendations (Womack, 1996). In all cases, both the sign of the initial price response and the subsequent long-run return performance are correlated with the direction of the underlying news event. Moreover, in each aforementioned case, the observable "event" is the result of a more fundamental change in the firm's economic condition.

Similar patterns of underreaction have been observed with respect to the market's interpretation of financial accounting information. Examples include an underreaction to the autocorrelation structure of quarterly earnings innovations (Bernard and Thomas, 1989; 1990), the reversing nature of extreme accrual realizations (Sloan, 1996), the level of net financing activities (Bradshaw, Richardson and Sloan, 2004), and a host of different financial statement analysis-based ratios (Abarbanell and Bushee, 1998). Closer in the spirit to this paper, composite measures reflecting an aggregation of multi-dimensional performance and financial risk attributes are also predictive of future returns, consistent with the market underreacting to shifts in the underlying economic performance of these firms (e.g., Ou and Penman, 1989; Beneish, Lee and Tarpley, 2001; Piotroski, 2000; Mohanram, 2004).

This study incorporates the financial-statement analysis-based strategy developed in Piotroski (2000) for value firms, and applies this methodology across the full spectrum of publicly traded firms with sufficient accounting and price data. The first objective of the paper is to illustrate that market prices appear to underreact to fundamental changes in the firm's historical economic condition (and the implications these changes signal about future firm performance). The second objective is to use observed variation in the magnitude and direction of this predictive ability to better understand the source of returns to traditional value versus growth investment strategies.

2.2 Background on Piotroski (2000) and the predictive ability of the FSCORE statistic

Piotroski (2000) uses historical financial statement data to classify high book-to-market (i.e., value) firms into those firms with strong current financial performance and those with weak financial performance. Piotroski shows that this classification (FSCORE), which is an aggregation of nine binary signals about the firm's current financial condition and trends, is capable of predicting future returns within the high book-to-market portfolio. His results are consistent with the market failing to identify and price the improving performance prospects of a subset of these traditionally distressed and neglected value firms in a timely manner. The effect is more pronounced for firms without analyst coverage, yet fairly robust across firm size classifications.

Whereas Piotroski (2000) argues that the source of the association between future returns and historical performance is likely due to the market's temporary mispricing of the change in expected future performance conveyed by these shifting fundamentals, Fama and French (2004) suggest that FSCORE (labeled PT in their paper) is a proxy for expected future growth and profitability attributes that should have a positive association with expected returns. Using the residual income valuation model (Ohlson, 1995), Fama and French argue that holding the book-to-market ratio constant (i.e., for a given BM ratio), greater expected growth and profitability implies a higher implied discount rate (i.e., expected return) for those securities. As such, in the cross-section, a positive association between realized returns and any proxy for expected future growth/profitability, such as FSCORE, should be expected.

Fama and French (2004) provide empirical evidence consistent with this growth-related explanation for the predictive success of FSCORE.[2] First, Fama and French show that FSCORE is associated with both future profitability and asset growth across the complete sample of CRSP/Compustat firms. As such, FSCORE is a reasonable proxy for (or leading indicator of) future

[2] To test their general argument about a potential positive relation between expected growth and expected returns, Fama and French examine an array of accounting and return variables that could be correlated with future growth and profitability. The analysis included examining various lagged accounting fundamentals (e.g., lagged profitability, sales growth, accruals (+/-), the presence of negative earnings, the presence of dividends), lagged stock returns, analyst earnings forecasts for year t+1, and composite measures of firm strength (Piotroski (2000) and Ohlson (1980)).

performance. This relation is not surprising, since Piotroski finds (among value firms) a positive relation between FSCORE and subsequent profitability and a negative relation between FSCORE and the frequency of performance-related delistings. Second, Fama and French (2004) show that realized returns are positively associated with FSCORE, and that this relation is robust to their three factor model, as well as controls for other dimensions of lagged firm performance. They remain agnostic regarding whether this positive relation between expected returns and expected performance (unconditional, or conditional on a given BM ratio) is due to irrational mispricing or rational risk-compensation behavior.

An important interpretational issue raised by Fama and French (2004)'s arguments and analysis relates to the use of the term "expected returns." Traditionally, expected return refers to the implicit rate of return embedded in the security's price designed to compensate an investor for the investment's level of non-diversifiable risk. In contrast, given their neutrality on issue of rational versus irrational pricing, Fama and French (2004) are articulating a different concept of "expected returns." Specifically, their definition of expected return has been expanded to reflect any predictable return to the investor given the risk and performance expectations of the firm conditional on current price (i.e., the implied internal rate of return of the security as priced). As such, firms whose prices are too low for a given set of performance expectations and risk are "expected" to generate an above-average return. This argument is at the core of Graham and Dodd's value investment strategy, and represents the implicit trading assumption behind Frankel and Lee's (1998) value-to-price statistic and Easton's (2004) use of the PEG ratio to infer "expected" returns for a given level of forecasted earnings.

This paper embraces this broader definition of implied expected return, where "expected return" is synonymous with the expected price appreciation (decline) associated with the purchase of an undervalued (overvalued) security given the firm's current price and fundamentals. However, unlike Fama and French (2004), an additional goal of this paper is to try to differentiate the success of FSCORE between a growth-driven, risk-based explanation and a systematic mispricing explanation. This differentiation is accomplished by looking at the association between FSCORE

and future returns across various portfolios of stocks, with special emphasis placed on the association across book-to-market portfolios (both before and after controlling for other dimensions of value and glamour stocks).

3. Research design

3.1 Financial performance signals

To identify and classify trends in each firm's financial condition, this paper adopts the aggregate statistic, FSCORE, utilized in Piotroski (2000) and Fama and French (2004). This aggregate statistic is based on nine financial signals designed to measure three different dimensions of the firm's financial condition: profitability, financial leverage/liquidity and operational efficiency. The signals used are easy to interpret and implement, and have broad appeal as summary performance statistics.[3] Each firm's signal realization is classified as either "good" or "bad," depending on the signals implication for future profitability, cash flows and prices. An indicator variable for the signal is equal to one (zero) if the signal's realization is good (bad). The aggregate signal measure, FSCORE, is defined as the sum of the nine binary signals. The aggregate signal is designed to measure the overall quality, or strength, of the change in the firm's financial position. The following sections present the variables and signals used in Piotroski (2000).

3.1.1 Financial performance signals: Profitability

Current operating profits and cash flow realizations provide information about the firm's ability to internally generate funds, invest in value-creating assets and, ultimately, pay dividends to shareholders. Similarly, a positive earnings trend is suggestive of an improvement in the firm's underlying ability to generate positive future cash flows, while profits associated with current operating cash flow is a signal of strong earnings quality.

[3] It is important to note that these nine signals represent only one potential set of variables that could be used to assess changes in economic condition. Subsequent tests will examine the robustness of the main results to alternative performance statistics.

Piotroski uses four variables to measure these performance-related factors: NI, CFO, ΔNI and ACCRUAL. Net income (NI) is defined as net income before extraordinary items. CFO is defined as cash flow from operations. If the firm's NI is positive, the indicator variable F_NI equals one, zero otherwise. Similarly, if the firm's CFO is positive, the indicator variable F_CFO equals one, zero otherwise. These two variables are used to determine whether the firm meets a minimum level of financial performance, such as the ability of the firm's operations to cover operating costs, financing costs and necessary investments in productive assets (similar to the ideas discussed in Graham and Dodd, 1934).

The overall trend in profitability is measured by the annual change in net income. Change in net income (ΔNI) is defined as current year NI less the prior year's NI realization. If ΔNI is greater than zero, the indicator variable F_ΔNI equals one, zero otherwise.[4]

Finally, the relation between the level of earnings and cash flow is also considered. Sloan (1996) shows that earnings driven by positive accrual adjustments are a bad signal about future profitability and returns. To the extent that a firm's profits are not being converted into corresponding cash flow, this earnings innovation should be viewed suspiciously. The variable ACCRUAL is defined as current year's net income before extraordinary items less cash flow from operations, scaled by average total assets. The indicator variable F_ACCRUAL equals one if ACCRUAL is greater than zero, zero otherwise.

3.1.2 Financial performance signals: Changes in financial leverage/liquidity

Three of the nine signals are designed to measure changes in the firm's capital structure and ability to meet future debt service obligations: ΔLEVER, ΔLIQUID and ISSUANCE. Although increasing leverage can reduce agency costs (e.g., Harris and Raviv 1990) and decreasing liquidity can represent better utilization of working capital, Piotroski (2000) assumes that an increase in

[4] The various dimensions of firm performance (NI, CFO and ΔNI) are compared against zero benchmark for ease of implementation and to eliminate measurement errors associated with the use of non-zero benchmarks. Other benchmarks, such as a firm or industry-specific required rate of return hurdles or industry-level averages could be employed. Although such benchmarks have the potential to increase predictive power (see Soliman 2004), they also increase the complexity of the evaluating firms and implementing this investment heuristic.

financial leverage, a deterioration of liquidity, or the use of external financing is a bad signal about financial risk and future cash flows (e.g., Myers and Majlif 1984; Miller and Rock 1985).

The variable ΔLEVER captures changes in the firms long-term debt levels. Piotroski defines ΔLEVER as the change in the ratio of long-term debt to total assets, and view an increase (decrease) in financial leverage as a negative (positive) signal. By raising external capital, the firm may be signaling its inability to generate sufficient internal funds. In addition, an increase in long-term debt is likely to place additional constraints on the firm's overall financial flexibility. The indicator variable F_ΔLEVER equals one if the firm's leverage ratio fell in the year preceding portfolio formation or if the firm has no long-term debt at both the beginning and the end of the fiscal year, zero otherwise.

The variable 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 is assumed to be a good signal about the firm's ability to service current debt obligations. The indicator variable F_ΔLIQUID equals one if the firm's liquidity improved, zero otherwise.

The indicator variable ISSUANCE equals one if the firm did not issue common equity in the fiscal year preceding portfolio formation, zero otherwise. Similar to an increase in long-term debt, raising external equity capital could be signaling the firm's inability to generate sufficient internal funds to service future obligations. Consistent with these assumptions, prior research documents that both of these external capital events convey, on average, bad economic news (cite event studies on SEO and bond issues).

3.1.3 Financial performance signals: Operating efficiency

The remaining two signals are designed to measure changes in the efficiency of the firm's underlying operations: Change in gross margin (ΔMARGIN) and asset turnover (ΔTURN). These two ratios reflect two key dimensions of performance underlying a traditional decomposition of return on assets.

The variable ΔMARGIN is defined as the firm's current gross margin ratio less the prior year's gross margin ratio. An improvement in margin signifies a potential improvement in factor costs, a reduction in inventory costs, a rise in the selling price of the firm's product, or a change in product mix toward more profitable line items, geographic regions and/or customers. The indicator variable F_ΔMARGIN equals one if ΔMARGIN is positive, zero otherwise.

The variable ΔTURN is defined as the difference between the firm's current and prior year asset turnover ratio, where the asset turnover ratio is measured as total sales scaled by average total assets during the respective fiscal year. An improvement in asset turnover tends to signal greater productivity from the asset base, more efficient operations or an increase in sales (which could also signify improved conditions for the firm's products. Such improvements in asset turnover tend to be persistent and strong predictors of future earnings performance. The indicator variable F_ΔTURN equals one if ΔTURN is positive, zero otherwise.

3.1.4 Aggregate score of recent financial performance

The aggregate fundamental score, FSCORE, is defined as the sum of the individual binary signals, or

$$\text{FSCORE} = \text{F\_NI} + \text{F\_CFO} + \text{F\_}\Delta\text{NI} + \text{F\_ACCRUAL} + \text{F\_}\Delta\text{LEVER}$$
$$+ \text{F\_}\Delta\text{LIQUID} + \text{ISSUANCE} + \text{F\_}\Delta\text{MARGIN} + \text{F\_}\Delta\text{TURN}$$

Given the nine underlying signals, FSCORE can range from a low of zero to a high of nine, where a low (high) FSCORE represents a firm with very few (mostly) good signals about the firm's financial condition. Given that FSCORE predicts future fundamentals, if the market underreacts to historical changes in performance, then I would expect FSCORE to be positively associated with future firm performance and stock returns. The investment strategy investigated in Piotroski (2000) and utilized in this paper is based on selecting firms with high FSCORE realizations. This is in contrast to previous FSA-based strategies where portfolio choices are either based on the relative realization of a particular signal (such as accruals), a complex hedge portfolio scheme based on the relative weighting of an array of financial ratios (e.g., Abarbanell and Bushee, 1998), or the output of

a first-stage probability models to identify candidate firms (Ou and Penman, 1989; Beneish, Lee and Tarpley, 2001).

Finally, as stated in Piotroski (2000), these nine signals do not purport to represent an optimal set of metrics to assess changes in the firm's financial condition. Whereas statistical techniques could be implemented to "identify" optimal ratios and signals using out-of-sample data, this approach represents a "step-back" to a simple, firm-specific analysis using absolute benchmarks to classify trends in financial condition. Each ratio (and related performance benchmark) chosen is only one from a set of numerous alternative ratios and related benchmarks designed to measure the same underlying construct. However, despite appearing "ad hoc," these ratios are intuitive, easy-to-construct and commonly used in financial statement analysis. To the extent this simple array of financial signals have predictive ability, this approach and related return benefits are likely to only represent a lower bound to the benefits of using financial statement analysis tools for investment purposes.

3.2 Calculation of returns

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

3.3 Sample Selection

Each fiscal year between 1972 and 2001, I identify firms with sufficient stock price and financial statement data on CRSP and COMPUSTAT, respectively. For each firm, I calculate the market value of equity, book-to-market ratio and financial performance signals at fiscal-year end.

Any firm-year observation lacking sufficient data to estimate these nine financial signals, the firm's preceding six month return, and subsequent twelve month buy-and-hold return is deleted from the sample. This selection procedure yields the final sample of 105,465 firm-year observations across the 30 fiscal years.

Each fiscal year, all firms with sufficient data are ranked to identify cutoffs to form three book-to-market and size portfolios and five six-month-return momentum and bankruptcy score portfolios. The prior fiscal year's distributions are used to classify firms into their respective book-to-market, size, momentum, and bankruptcy risk portfolios.

3.4 Description of the main empirical tests

The primary methodology of the paper is to form portfolios based on the firm's aggregate fundamental score (FSCORE). Firms with the poorest signals (FSCORE less than or equal to 3) have the strongest deterioration in fundamentals and are classified as low FSCORE firms, and are expected to have the worst subsequent stock return performance. Alternatively, firms receiving the highest score (FSCORE greater than or equal to 7) have the strongest improvement in fundamentals and are classified high FSCORE firms. I expect these firms to have the best subsequent performance given the strength and consistency of the underlying fundamental signals. I design the tests in this paper to examine whether a high FSCORE portfolio outperforms other portfolios drawn from the full sample of firms and across various size, book-to-market and bankruptcy risk portfolios.[5] Given concerns surrounding the use of parametric test statistics in long-run return settings (see Kothari and Warner 1997; Barber and Lyon 1997), the primary results will be tested using both traditional t-statistics as well as ultimately implementing a bootstrapping approach to test for differences in portfolio returns (not reported in current draft).

[5] In order to increase the number of observations allocated to the high and low FSCORE portfolios, the definitions of strong and weak firms have been expanded to encompass a broader range of scores than those used in Piotroski's original study. This procedure tends to diminish the apparent returns to a given high or low FSCORE portfolio, and related hedge portfolio returns; however, these larger sample sizes allow for more meaningful statistical tests across different partitions and sub-partitions of the data.

Section 4: Empirical results

4.1 Returns to financial statement analysis-based investment strategy

4.1.1 Univariate evidence

Table 1 presents descriptive evidence on the complete sample of firm-year observations. Table 2 presents one-year-ahead returns to Piotroski's (2000) fundamental investment strategy when applied to all available firm-year observations with sufficient historical accounting and stock price data between fiscal years 1972 and 2001. Panel A presents one-year-ahead buy-and-hold raw returns; Panel B presents one-year market-adjusted returns.

Consistent with the hypothesis that the market underreacts to changes in financial condition, the nine point scale is able to discriminate firms with subsequent strong return performance from firms with subsequent weak performance. First, one-year ahead return performance is monotonically increasing in FSCORE, as reflected in mean returns, median returns and the percentage of firms with positive returns. This pattern exists for both raw and market-adjusted returns. Second, firms with strongest improvement in fundamentals (FSCORE ≥7) earn a mean raw annual return of 20.60 percent compared with a mean return of 7.33 percent for firms with weakest fundamentals (FSCORE ≤ 3); median returns are 10.32 percent versus –9.09 percent, respectively. In terms of market-adjusted returns, the high FSCORE portfolio earns a mean (median) market-adjusted return of 7.80 (-1.27) percent while the low FSCORE portfolio generates a mean (median) market-adjusted return of -5.48 (-21.06) percent. Differences in mean (median) portfolio returns of high versus low FSCORE firms are significant at the one percent level using two-sample t-tests (sign ranked wilcoxon tests).

Third, the distribution of returns appears to be shifted to the right (left) for high (low) FSCORE firms. Whereas 42.86 percent of the firm-year observations in the full sample are associated with positive market-adjusted returns, nearly one-half (48.56 percent) of the high FSCORE firms generate positive one-year ahead returns, while the proportion of low FSCORE firms with positive market-adjusted returns is only 33.91 percent (approximately one-third). Differences in these proportions are all significant at the one percent level using binomial tests of proportions. Similar results and inferences emerge using raw returns.

It is important to stress that the apparent benefits of this strategy are not confined to hedge portfolios or short positions. Given the costs and implementation issues surrounding short positions (e.g., Thaler and Lamont, 2003, among others), a strategy where profitability arises through the capture of downside price movements should be viewed with skepticism. As such, these and subsequent tables purposefully highlight the raw and market-adjusted return to the high FSCORE portfolio alone, and report tests regarding whether the high FSCORE portfolio returns exceed the value-weighted market index. As indicated in Table 2, high FSCORE firms earn a mean, one-year ahead raw return of 20.60 percent and a market-adjusted return of 7.80 percent (both significantly different than zero at the one percent level). These portfolio returns are also significantly larger than the mean raw and market-adjusted returns earned by the full sample (15.42 percent and 2.66 percent, respectively) over the same time period. Similar patterns exist in median returns and proportion statistics. Thus, high FSCORE firms appear to have a greater probability of generating a positive return for an investor, and as a portfolio, appear to generate above-average returns.

4.1.2 Multivariate evidence on the relation between FSCORE and future returns

The preceding analysis fails to control for known risk factors and other determinants of realized returns. Although the preceding return patterns appear to contradict a simple risk story, such effects cannot be ruled out. For example, firms with the weakest (strongest) historical performance are more likely to see improvements (deterioration) in financial performance through the combination of competitive economic pressures, mean revision and survivorship (e.g., Penman, 1991).

To alleviate these concerns, the following models are estimated annually:

$$RET_i \text{ or } MARET_i = \alpha + \beta_1 MVEDEC_i + \beta_2 BMDEC_i + \beta_3 MOMDEC_i + \beta_4 FSCORE_i \quad (1)$$

$$RET_i \text{ or } MARET_i = \alpha + \beta_1 MVEDEC_i + \beta_2 BMDEC_i + \beta_3 MOMDEC_i + \beta_4 LOWSCORE_i + \beta_5 HIGHSCORE_i \quad (2)$$

where annual returns are measured either as the firm's one-year-ahead raw return (RET) or one-year-ahead market-adjusted return (MARET). The variables MVEDEC, BMDEC and MOMDEC are count variables (zero to nine) that equal the firm's size, book-to-market and momentum decile

ranking, minus one, respectively. The variable LOWSCORE in an indicator variable equal to one if the firm-year's FSCORE was less than or equal to three, zero otherwise. Analogously, HIGHSCORE in an indicator variable equal to one if the firm-year's FSCORE is greater than or equal to seven, zero otherwise. Table 3 presents average coefficients from 30 annual cross-sectional estimations of these models. Reported t-statistics and related standard errors are based on the empirically-derived distribution of the thirty annual coefficients.

Consistent with Fama and French (2004), FSCORE retains a positive relation with future returns both before and after controlling for size, book-to-market and momentum. The positive coefficients of 0.0233 (raw returns) and 0.0218 (market-adjusted returns) imply that each one unit increase in FSCORE is associated with an approximate two percent increase in both raw and market-adjusted returns, or an approximate hedge return of 19 percent, annually. The inclusion of FSCORE into these models results in an approximate 21 percent relative increase in the model's explanatory power, with only a minimal impact on the coefficients of the other three explanatory variables, consistent with FSCORE explaining an additional dimension of realized returns. Similar inferences about the predictive ability of FSCORE are obtained if the estimations are performed using log transformations of the underlying raw data in these estimations (see Table 3, panels C and D).

4.2 Returns to financial statement analysis-based investment strategy conditional on firm size

Firm size has been shown to be inversely related to future returns. More importantly, firm size is correlated with a host of firm attributes that influence the price formation process. For example, firm size is positively related to analyst coverage (Bhushan, 1989), institutional ownership (O'Brien and Bhushan, 1990), level of corporate disclosure (Lang and Lundholm, 1993), and market liquidity. As a result, large firms appear to have more informed prices, as reflected by prices that reflect annual earnings innovations earlier in the year (Collins Kothari and Rayburn, 1989), smaller earnings announcement period returns and earnings response coefficients (Collins and Kothari, 1987), and smaller returns to both accounting and return-based anomalies (e.g., Bernard and Thomas, 1989; Hong, Lim and Stein, 2000; Collins, Gong and Hribar, 2003). To the extent that an

underreaction to historical financial information is influenced by the existing information environment and arbitrage constraints, there should be cross-sectional variation in the ability of the FSCORE to predict future returns across size portfolios. Similarly, to the extent that a valuation bias with respect to growth firms or loss firms is induced or exacerbated by analyst coverage, or lack thereof, the direction of the predictive ability of FSCORE (i.e., identifying overvalued or undervalued firms) may also vary along the firm size dimension.

Table 4 presents these results. The most striking observation is that FSCORE has discriminatory power across all size partitions. Examining market-adjusted returns (panel B), it is apparent that the hedge returns to a financial statement analysis-based trading strategy is weakest in the portfolio of large firms (10.30%) and strongest among the portfolio of small firms (16.94%), consistent with the preceding information flow and investor interest arguments.[6] However, despite the weaker hedge and buy-side returns in the large firm quintile, there still are benefits accruing to the FSA-based strategy. Specifically, FSCORE demonstrates an ability to identify large, weak firms that will ultimately underperform both the market and similar-sized firms. As shown in panel B, the mean market-adjusted return to low FSCORE firms in the large firm portfolio is –7.29 percent. In contrast, the mean return associated with high FSCORE firms in that portfolio is only 3.01 percent.

Among mid-cap firms, FSCORE is successful at differentiating both winners and losers, as the market-adjusted returns are roughly symmetric between the returns of the hypothetical long and short positions (7.46% and -7.80%, respectively). Lastly, within the portfolio of small firms, the predictive power of FSA is tilted towards the identification of eventual winners. Specifically, the average high FSCORE firm in the small firm portfolio generates a one-year market adjusted return of 14.70%, while the average low FSCORE firm yields a -2.24% market-adjusted annual return.

Together, the results conditional on firm size yield several interesting insights. First, the magnitude of potential gains associated with trading on the basis of historical financial information is

[6] This relation is interesting given the results in Mohanram (2004) with respect to the pricing of expected growth proxies. These results, when combined, suggests that the incorporation of information about financial health (i.e., traditional FSA-based ratios) are incorporated fairly quickly for large firms, except when the financial information signaling a potential deterioration in growth or growth rates. This combination is suggestive of a complex behavior bias with respect to the impounding of growth-related information for heavily followed firms.

diminishing in firm size. This finding is consistent with results in other settings, and suggests that less frequent trading on the part of informed investors slows the incorporation of news into prices for small firms. Second, to the extent that the market return is a reasonable proxy for the opportunity cost of investors' capital, these combined results suggest that the directional benefits accruing to financial statement analysis systematically vary across these firm size/investor interest regimes. Specifically, FSA is successful at identifying large firms that subsequently underperform the market and small firms that significantly outperform the market; the benefits of FSA appear to be fairly balanced for the mid-cap portfolio of firms. To the extent that the prices of followed firms are more likely to overweight good news and/or reflect the optimistic forecasts of analysts, the benefits from FSA should be expected to accrue to the identification of overvalued firms; in contrast, if neglected firms overweight bad news (and the implied pessimism driving the lack of coverage), the benefits of FSA would be likely to accrue to the identification of undervalued firms. The results across firm size portfolios support this investor interest/neglect interpretation. Finally, after controlling for historical changes in financial condition, a size effect still exists in returns, consistent with large firms being significantly less risky than small firms. And, similar to the general size effect, the small firm portfolio return is driven by greater skewness in returns (i.e., several extreme positive return winners) vis-à-vis the portfolio of large firms.

4.3 Returns to FSA strategy conditional on book-to-market portfolios

Fama and French (1992), among others, document that realized returns are increasing in the firm's book-to-market (BM) ratio. Fama and French (1992) suggest that the BM factor captures financial distress risk. Consistent with this argument, Penman (1996) shows using the residual income valuation framework that a high book-to-market ratio implies that market prices generally reflects poor expected performance (i.e., low return on equity realizations) and low expected growth in book values. In other words, a high book-to-market firm is expected to be a poor performer and therefore quite risky. In contrast, a firm with a low book-to-market ratio is expected to have strong return on equity performance and strong growth in book values. Consistent with this interpretation

of book-to-market ratios, Fama and French (1995) document that earnings (ROE) patterns across BM portfolios are consistent with this poor performance and risk explanation. Similarly, Chen and Zhang (1998) provide evidence relating book-to-market ratios to leverage. Taken together, these papers suggest that high book-to-market firms are indeed more financially distressed than low book-to-market firms, and therefore some, if not all, of the documented return performance is an artifact of expected returns for financial risk factors.

In contrast, Lakonishok, Shleifer and Vishny (1994), among others, claim that the subsequent returns to the book-to-market strategy represent a reversal of past valuation errors. For example, Lakonishok, Shleifer and Vishny (1994) argue that investors over-extrapolate past performance trends; in subsequent periods, overly optimistic and pessimistic expectations reverse as the market receives actual earnings news. As such, the poor (strong) returns to glamour (value) firms reflect a reversal in expectations. Consistent with this argument, LaPorta (1996) and Dechow and Sloan (1997) find that systematic errors in market expectations about long-term earnings growth can partially explain the success of the book-to-market effect and contrarian investment strategies, respectively, while LaPorta, Lakonishok, Shleifer and Vishny (1997) document that the future, one-year ahead-earnings announcement period returns to glamour firms are negative, while value firms generate positive earnings announcement period returns.[7] Lastly, Rozeff and Zaman (1998) show that insiders are more likely to sell (buy) shares in glamour (value) firms, consistent with insiders trading against potential biases in expectations.[8]

It is important to recognize that the risk and misvaluation explanations for the book-to-market effect are not mutually exclusive. Lakonishok, Shleifer and Vishny's extrapolation story hinges on the fact that the underlying financial performance of value and glamour firms is fundamentally different. Value firms are financially distressed (with low profitability, slow growth, and high leverage) and tend to be neglected by the market. In contrast, glamour firms tend to have high profitability, high growth rates and lower leverage, and tend to be heavily followed by investors

[7] In contrast, Doukas, Kim and Pantzalis (2002) examine analyst forecast errors conditional on BM portfolios and find little evidence supporting systematically biased expectations across these portfolios.
[8] Interestingly, evidence in Fama and French (1995) also show mean reversion in performance for both value and glamour firms.

and the analyst community. In extreme cases, it is possible that the current level of financial condition of the firm could taint the price formation process, leading to an over-reliance on past financial condition of the firm. This over-reliance could cause investors to both underweight new financial data that contradicts this history and overlook the mean reverting tendencies of financial ratios and performance. Moreover, given the variation in investor interest across these book-to-market portfolios, the nature of the bias (past overreaction) could systematically vary across these regimes.

Piotroski's (2000) evidence for value firms suggests that investor neglect delays the impounding of good news for "value" firms. As such, historical changes in financial condition are capable to identifying firms with future strong and weak return performance among these neglected securities. Consistent with traditional information-related anomalies, this predictive ability is more pronounced for firms without analyst coverage.

Focusing on glamour firms, Mohanram (2004) classifies low book-to-market firms on the basis of growth-related financial-statement attributes. His classification variables, such as the relative level of R&D, capital expenditures, and advertising expenditures, and the relative volatility of sales and assets, are chosen over Piotroski's FSA ratios due to (1) the high-growth, low information content of earnings nature of high book-to-market firms and (2) the potential link between the poor performance of glamour firms and the naïve over-extrapolation of past growth-related attributes. Mohanram finds that weak glamour firms significantly underperform glamour firms with more sustainable growth rates, consistent with an underreaction to this historical information. This underreaction to information about the likelihood of a future 'torpedo' is found to be more pronounced among larger firms and firms with analyst coverage. The stronger effect among these large, covered firms suggests a behavioral explanation in this glamour stock setting that is different than the traditional information environment, information dissemination, and investor neglect arguments found for most accounting-based anomalies, and for the value stock portfolio. Given that the mispricing of growth-driven securities appears to be inversely correlated with investor neglect, such mispricing could be an artifact of behavior biases associated with fads or investor

overconfidence. Ultimately, the combined work of Piotroski (2000) and Mohanram (2004) suggest that different mechanisms could be behind the book-to-market effect, and that the benefits to an FSA-based strategy could vary according to the valuation and/or investor interest attributes of the firm.

Early studies documenting the book-to-market effect in realized returns implicitly assume homogeneity of the firms composing a specific BM portfolio by focusing on mean return realizations and average firm-level characteristics. However, the forementioned papers by Piotroski (2000) and Mohanram (2004), and other such as Griffin and Lemon (2002), provide evidence that the set of firms included in a typical book-to-market portfolio can exhibit considerable heterogeneity. In each of these studies, the author(s) partition firms within a specific BM portfolio by a given firm-level attribute and examine returns conditional on this sub-partition of the data. As such, each paper is exploiting the heterogeneity within given book-to-market portfolios to better understand the source of future returns to that portfolio and assessing whether the book-to-market effect is a manifestation of risk and/or mispricing effects.

This paper extends this logic by examining the predictive ability of Piotroski's FSCORE across all BM portfolios. To the extent that the BM effect is an artifact of expectation errors, both the nature of the underlying firm performance in advance of portfolio formation, as well as future returns conditional on this categorization, should vary across BM portfolios. Specifically, FSCORE's predictive ability is expected to display cross-sectional variation consistent with the ex *ante* valuation errors implied by these ratios. For example, if high (low) book-to-market firms tend to have overly pessimistic (optimistic) expectations, then the relative gains to this strategy should be tilted towards identifying undervalued (overvalued) firms in these portfolios. Examining FSCORE conditional on book-to-market portfolios will help identify these conditional relations, and observed variation can be used to either support or contradict the mis-valuation argument for the book-to-market effect.

Table 5 presents these results. The most striking observation is that FSCORE systematically distinguishes subsequent winners from losers across all three book-to-market portfolios. However, the nature of FSCORE's predictive ability varies across these portfolios. First, the ability to

distinguish weak from strong (i.e., the hedge return earned) through this strategy is significantly strongest among low book-to-market glamour firms. Given that high book-to-market firms tend to be growth firms, the enhanced performance of FSCORE in this portfolio (relative to its success in other BM portfolios) is consistent with Fama and French's 'expected growth' interpretation of FSCORE. This result is interesting given claims that the usefulness of accounting-related data and fundamentals is lower for high growth, high book-to-market firms.

Second, in terms of directional effectiveness, the benefits to FSA (relative to simple passive investment in the market index) are correlated with the *ex ante* bias in prices across these book-to-market portfolios. Consistent with Mohanram's findings, the benefits to financial statement analysis in the glamour portfolio are tilted towards the identification of overvalued securities that will subsequently underperform the market index (mean return to low FSCORE portfolio is -15.71%). In contrast, among value firms, the benefits are concentrated in identifying those firms with subsequent strong performance (mean return to high FSCORE portfolio is 13.25%). Buying glamour firms with a strong recent improvement in financial condition or shorting value stocks with a strong deterioration in financial condition yields portfolio returns that are not economically different than the market return (market-adjusted returns of 3.14% and 2.70%, respectively). The patterns of observed benefits, and lack thereof, are internally consistent with the market mispricing these extreme portfolios as a bundle of similar securities and overlooking the heterogeneous nature of the underlying financial condition of firms in each portfolio.

Relative to the opportunity cost of simply holding the market portfolio, FSCORE is very successful at finding undervalued winners in the high BM portfolio and overvalued losers in the low BM portfolio. In other words, it is very difficult for investors to systematically identify meaningfully underpriced (overpriced) glamour firms (value firms), consistent with the gains to financial statement analysis-based strategies corresponding to the expected bias imbedded in each book-to-market portfolio. When FSCORE corresponds to the expected performance of these firms (i.e., strong performance for glamour and poor performance for value firms), each respective portfolio earns near the market return. Effectively, financial signals confirming the expectations that are likely already

imbedded in price are assimilated into prices quickly, while contrarian signals are (generally) discounted until future confirmatory news is received. As a result, historical good news for glamour firms is unable to generate excess returns, while historical good news for value firms is a tradable opportunity, and vice-versa for trading opportunities conditional on bad news.

Interestingly, corroborating evidence suggestive of an asymmetric pricing of recent news exists. For example, Hong, Lim and Stein (2000) show that the recognition of bad news appears to be delayed for large, covered firms. Similarly, focusing on insider transactions, Piotroski and Roulstone (2005) show that insiders of value firms buy during periods of good, contemporaneous earnings news, while insiders of glamour firms are selling during periods of good, contemporaneous earnings news. Their results are consistent with insiders recognizing the relative speed with which good news is being impounded into their firm's security prices, and trade accordingly.

Whereas the market-adjusted returns in the extreme book-to-market portfolios display an asymmetry in directional performance, FSCORE portfolios in the middle book-to-market portfolio display a slightly more symmetrical return patterns -- predicted winners outperform the market and predicted losers underperform the market, consistent with errors in expectations being more randomly distributed across these portfolios. However, these errors still exist, although the nature and magnitude of the bias realized in subsequent returns is not nearly as strong as observed in the two extreme portfolios.

Lastly, the returns to the high or low FSCORE strategy within a given book-to-market portfolio are not driven by the extreme performance of a few winners or losers, but instead tends to reflect the shifting of the entire distribution of portfolio returns, as evidenced by the increasing proportion of firms with positive market-adjusted returns across these portfolios. Similarly, the book-to-market effect is still prevalent after controlling for recent changes in financial condition, suggesting that a risk-based explanation for a portion of the returns to the strategy is still a relevant consideration. Moreover, unlike firm size, the average returns to the various BM portfolios (and sub-portfolios after controlling for FSCORE) are also not driven by a few extreme winners or losers, but instead reflect a meaningful shift in the distribution of realized returns.

4.4 Returns to a financial statement analysis based strategy conditional on book-to-market and size portfolios

Interestingly, the directional effectiveness of FSCORE within both book-to-market and firm size portfolios is correlated with the likelihood of significant analyst coverage and general level of investor interest. To the extent that the book-to-market effect is an artifact of a complex interplay between expectation errors associated with historical changes in financial condition and varying degrees of investor interest/neglect, variation in the intensity and directional usefulness of FSCORE should systematically vary within a specific book-to-market portfolio conditional on firm size. Table 6 tabulates returns to FSCORE portfolios within the intersection of book-to-market and size portfolios.

These results reflect three interesting patterns. First, the book-to-market effect in returns is robust to controlling for the underlying changes in financial condition (FSCORE) and firm size. Second, the predictive ability of FSCORE is robust within each book-to-market and size portfolio, with the intensity of the predictive ability strongest among the smallest firms in each book-to-market portfolio. Third, the observed intensity and directional effectiveness of FSCORE within a given book-to-market portfolio is a function of investor interest, as proxied by firm size.

For example, within the value portfolio, the ability to identify subsequent winners is concentrated among small and midsize firms, with the market-adjusted portfolio returns to high FSCORE firms of 18.12 and 10.01 percent, respectively; in contrast, large value firms with strong fundamentals generate a market-adjusted return of only 4.69 percent. Thus, the above average return performance of the value portfolio appears to be driven by an underreaction to good news among firms most likely to suffer from investor neglect (as proxied by firm size).

In contrast, within the glamour portfolio, large and medium firms with strong current performance (high FSCORE) do not generate significant market-adjusted returns. Only among the portfolio of small glamour firms, which are likely to be the least covered set of firms, is FSCORE able to identify future winners (portfolio returns of 7.27%). However, given these stocks current

pricing multiples, the gains are less than half of the gains to corresponding small firms in the value portfolio. Thus, there appears to be only limited instances where market participants underreact to an improvement in financial condition among glamour firms. As a result, the returns to the glamour portfolio as a whole are driven down by an underreaction to bad news; this underreaction to the deterioration in financial condition appears to be prevalent across all size portfolios.

Together, the patterns across these book-to-market portfolios suggest that the prices of glamour and value firms systematically incorporate concurrent information about strong and weak fundamental performance differently. These pricing biases appear to be concentrated as a function of the prevailing level of aggregate investor interest in the security, as proxied by firm size. Finally, within the middle book-to-market portfolio of firms, a similar (albeit less extreme) pattern of returns conditional on firm size/investor interest emerges. Specifically, among small firms, high FSCORE can identify firms that subsequently outperform the market, while among large firms, low FSCORE is better able to identify firms that subsequently underperform the market. Across the diagonal spanning corresponding expectations and prevailing level of investor coverage, the market-adjusted returns appear to be effectively zero.

Section 5 Returns to FSA strategy conditional on the firm's bankruptcy risk

The primary argument in this paper is that market prices do not fully reflect underlying changes in the firm's financial condition in a timely manner. Imbedded in this argument is a distinction between the firm's overall level of financial health and a change in financial condition. Discount rates and expectations about future cash flow are based on the firm's current financial condition. Absent changes in financial condition, expectations are static and realized returns should be a function of risk-based expected returns. These expected returns should be positively correlated with the firm's general level of financial distress. In contrast, events producing a change in the firm's underlying financial condition will alter prices through both the shifting of risk and revising of future cash flow expectations. It is the market's reaction to this dynamic event that I argue to be incomplete and a leading indicator of future price movements.

As discussed in Section 2, there is ample evidence that the market systematically underreacts to current changes in financial condition. However, the evidence between returns and the level of financial health is less clear. Using Ohlson's bankruptcy risk measure as a broader measure of financial health, Dichev (1998), Griffin and Lemmon (2002) and Fama and French (2004) document an inverse relation between the financial distress, as proxied by bankruptcy risk, and realized returns. In contrast, Shumway (1996), using a hazard model to assess bankruptcy risk, finds some evidence consistent with a positive relation between distress risk and realized returns. However, distress risk is unable to explain the book-to-market effect.

Fama and French (2004) show that Ohlson's bankruptcy score (OH) is a predictor of future growth and profitability, and conclude that this negative relation is due to OH's inverse relation with expected growth and profitability. As such, the predicted positive correlation between distress risk and future returns is likely to have been obscured by an negative correlation with future performance. Ironically, Fama and French treat FSCORE and the level of bankruptcy risk as measuring the same underlying construct: growth. Although these two variables are correlated, it is reasonable to assume that they are measuring different dimensions of a firm's financial condition. For example, Fama and French show that, individually, both FSCORE and OH predict both future profitability and asset growth. However, if both variables are considered together (along with other fundamental variables) in the same model, FSCORE only remains associated with future profitability, while OH is only associated with future asset growth. Given that these aggregate measures would seem to be measuring different constructs, display differences in forecasting ability, and themselves are likely to be inversely correlated, this section focuses on the predictive power of FSCORE conditional on the firm's level of bankruptcy risk at the end of the fiscal year, and vice versa.

To measure the firm's economic condition at year-end, I employ the probability of bankruptcy risk score outlined in Ohlson (1980). This measure of financial health is analogous to an Altman's (1968) z-score, and is used in Dichev (1998), Griffin and Lemmon (2002) and Fama and French (2004). To the extent that the market systematically underreactions to changes in these fundamental signals regardless of the level of financial health, FSCORE should have discriminatory

power across all ranges of financial risk. Moreover, after controlling for correlated changes in financial performance (i.e., FSCORE), it is possible that bankruptcy risk will display a positive risk-return relation in realized returns.

Table 7 presents these results. First, FSCORE retains its predictive ability across all bankruptcy risk quintiles; however, the hedge return between high and low FSCORE firms is significantly stronger in the high bankruptcy risk portfolio. This pattern is reasonable given that, for these firms, the smallest change in performance can have the largest ramification on shareholder payoffs.[9] Moreover, as argued in Griffin and Lemmon (2002), high bankruptcy risk firms are likely to be neglected by the market; as such, information processing and arbitrage activities are likely to be limited for these firms. Second, consistent with Griffin and Lemmon (2002) and Dichev (1998), firms in the highest quintile of bankruptcy risk experience the lowest returns; however, high bankruptcy risk firms with strong recent performance trends ultimately generate the largest portfolio return (12.53%), similar to high book-to-market securities experiencing a contemporaneous turnaround in financial condition. However, unlike the high book-to-market portfolio, those high-bankruptcy risk firms with the weakest change in fundamentals (low FSCORE firms) significantly underperform the market (mean return -9.25%), which is closer in characterization to the performance observed for fundamentally weak glamour firms.

The final set of tests extends the analysis of Griffin and Lemmon (2002) by examining the predictive ability of FSCORE within book-to-market portfolios after controlling for distress risk. Table 8 present these results. Griffin and Lemmon's study show that, after controlling for the level of bankruptcy risk, there continues to exist a book-to-market effect in realized returns, and that the BM effect is most pronounced among the most distressed firms. This pattern is consistent with investor neglect in combination with the mispricing of subsequent revisions in performance. Because distressed firms are more likely to be associated with a general decline in overall performance, ceteris paribus, the relations between future returns, bankruptcy risk and book-to-

[9] Such non-linearity in response to a change in economic condition has been in other settings. For example, both announcement period and long-run returns to bond rating changes are significantly stronger for non-investment grade debt as compared to investment grade securities (see Dichev and Piotroski, 2001).

market portfolios found across book-to-market portfolios could have been tainted by the presence of an omitted, yet correlated, performance relation.

These tests indicate that after controlling for both the level of financial health and recent changes in financial condition, book-to-market ratios continue to predict future returns. Moreover, FSCORE retains its predictive ability, with the strongest hedge returns continuing to be concentrated in the high bankruptcy risk subportfolio. Finally, FSCORE continues to have systematically different directional predictive abilities across various bankruptcy risk and book-to-market partitions of the data.

Section 6 Conclusion

The paper offers several contributions to the existing literature. First, the paper documents that the contextual underreaction to financial statement information documented in Piotroski (2000) and Mohanran (2004) is a general phenomena. These results are shown to be robust to controls for size, book-to-market ratios and financial distress risk, and are consistent with concurrent work by Fama and French (2004). Second, the paper documents that the intensity and directional effectiveness of this strategy is a function of the prevailing investor sentiment associated with a given set of securities. Specifically, evidence on cross-sectional variation in the usefulness of FSA for investing purposes across different size, book-to-market and bankruptcy risk portfolios suggests that the usefulness of financial statement analysis is tilted towards the identification of undervalued (overvalued firms) among thinly followed (heavily followed) firms.

Overall, the evidence clearly shows that historical accounting data signaling changes in the firm's financial condition have predictive ability with respect to future returns. These relations are consistent with a market that underreacts to financial information, resulting in predictable pricing corrections. Whether these relations are anomalous, or the result of an undetected risk factor, is an area for future research.

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Table 1
Descriptive Statistics

This presents descriptive statistics on the financial variables underlying the nine financial signals used to measure FSCORE, as well as firm size (total assets (ASSETS) and market value of equity (MVE)), book-to-market ratio (BM) and six month prior raw return (MOMENT). All variables (except MOMENT) are measured at the fiscal year end prior to portfolio formation. MOMENT is measured over the six months directly preceding portfolio investment. All financial signals are defined in Section 3 of the text.

	Mean	Std. Dev.	25th Pctl.	Median	75th Pctl.	Proportion with Positive Signal
ASSETS	837.057	3923.096	21.455	76.651	331.746	n/a
MVE	846.263	6323.764	13.800	55.110	273.669	n/a
BM	1.150	51.463	0.366	0.661	1.127	n/a
MOMENT	0.110	0.492	-0.141	0.049	0.266	n/a
ROA	0.004	0.198	-0.002	0.043	0.083	0.747
ΔROA	-0.026	0.288	-0.123	0.035	0.223	0.600
CFO	0.047	0.268	0.012	0.076	0.134	0.777
ACCRUAL	-0.041	0.232	-0.095	-0.041	0.013	0.703
ΔTURN	-0.020	0.357	-0.119	-0.002	0.098	0.492
ΔMARGIN	-0.031	0.232	-0.002	-0.000	0.019	0.495
ΔLEVER	0.002	0.103	-0.028	-0.001	0.024	0.618
ΔLIQUID	-0.128	9.989	-0.369	-0.029	0.276	0.468
ISSUANCE	11.725	94.179	0.000	0.118	2.032	0.345

Table 2
Returns to financial statement analysis-based investment strategy

This table presents returns to a fundamental analysis based investment strategy over the fiscal years 1972 to 2001. Panel A presents raw returns; panel B presents market-adjusted returns. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. A firm-year is classified as being in the low (high) portfolio if the firm's FSCORE is less than or equal to three (greater than or equal to seven). T-statistics (in parentheses) for differences in the mean (median) returns between high and low FSCORE portfolios are from a t-test of means (sign ranked wilcoxon test). T-statistics on the difference in proportion of firms with positive returns is from a binomial test of proportions.

Panel A: One-year raw returns to fundamental investment strategy

	Mean	10^{th} Pctl.	25^{th} Pctl.	Median	75^{th} Pctl.	90^{th} Pctl.	% Positive	N
All firms:	0.1542	-0.4891	-0.2273	0.0456	0.3627	0.8033	0.5480	105,465
FSCORE:								
0	-0.0188	-0.7031	-0.5135	-0.1955	0.2130	0.7727	0.3442	215
1	-0.0026	-0.7273	-0.5284	-0.2091	0.2360	0.8300	0.3662	1,868
2	0.0721	-0.6890	-0.4444	-0.1212	0.2791	0.9065	0.4073	5,443
3	0.0893	-0.6263	-0.3778	-0.0571	0.3103	0.8528	0.4496	10,550
4	0.1221	-0.5471	-0.2799	0.0000	0.3321	0.8155	0.5042	16,395
5	0.1525	-0.4616	-0.2169	0.0471	0.3607	0.7880	0.5510	21,367
6	0.1817	-0.4059	-0.1667	0.0790	0.3759	0.7830	0.5898	22,371
7	0.2004	-0.3626	-0.1343	0.1000	0.3926	0.7988	0.6113	17,550
8	0.2094	-0.3383	-0.1154	0.1047	0.4004	0.7833	0.6268	8,097
9	0.2501	-0.3330	-0.1111	0.1270	0.4337	0.9000	0.6445	1,609
Low (0-3)	0.0733	-0.6624	-0.4190	-0.0909	0.2917	0.8605	0.4270	18,076
Med (4-6)	0.1551	-0.4674	-0.2163	0.0489	0.3602	0.7931	0.5527	60,133
High (7-9)	0.2060	-0.3532	-0.1276	0.1032	0.3969	0.80000	0.6179	27,256
High-Low	0.1327	0.3092	0.2914	0.1941	0.1052	-0.0605	0.1909	-
(t-statistic)	(16.84)	-	-	(42.83)	-	-	(40.51)	-

Table 2 (continued)
Returns to financial statement analysis-based investment strategy

Panel B: One-year market-adjusted returns to fundamental investment strategy

	Mean	10th Pctl.	25th Pctl.	Median	75th Pctl.	90th Pctl.	% Positive	N
All firms:	0.0266	-0.5934	-0.3349	-0.0690	0.2246	0.6641	0.4286	105,465
FSCORE:								
0	-0.1736	-0.8749	-0.6700	-0.3357	0.0609	0.5527	0.2605	215
1	-0.1362	-0.8614	-0.6372	-0.3264	0.0935	0.6840	0.2934	1,868
2	-0.0527	-0.7877	-0.5489	-0.2266	0.1560	0.7420	0.3265	5,443
3	-0.0390	-0.7324	-0.4883	-0.1793	0.1722	0.6931	0.3553	10,550
4	-0.0042	-0.6506	-0.3932	-0.1142	0.1944	0.6535	0.3928	16,395
5	0.0248	-0.5729	-0.3227	-0.0677	0.2194	0.6261	0.4278	21,367
6	0.0539	-0.5103	-0.2740	-0.0366	0.2353	0.6204	0.4586	22,371
7	0.0707	-0.4736	-0.2486	-0.0191	0.2522	0.6436	0.4786	17,550
8	0.0855	-0.4404	-0.2340	-0.0033	0.2731	0.6294	0.4953	8,097
9	0.1193	-0.4350	-0.2228	0.0124	0.3090	0.7276	0.5134	1,609
Low (0-3)	-0.0548	-0.7654	-0.5279	-0.2106	0.1586	0.7035	0.3391	18,076
Med (4-6)	0.0277	-0.5744	-0.3225	-0.0659	0.2201	0.6312	0.4297	60,133
High (7-9)	0.0780	-0.4633	-0.2427	-0.0127	0.2626	0.6443	0.4856	27,256
High-Low	0.1328	0.3021	0.2852	0.1979	0.1040	-0.0592	0.1465	-
(t-statistic)	(17.17)	-	-	(43.55)	-	-	(31.56)	-

Table 3
Returns to financial statement analysis-based investment strategy: Cross-sectional regressions

This panel presents average coefficients from 30 annual estimations of the following cross-sectional models:

$$RET_i \text{ or } MARET_i = \alpha + \beta_1 MVEDEC_i + \beta_2 BMDEC_i + \beta_3 MOMDEC_i + \beta_4 FSCORE_i$$

$$RET_i \text{ or } MARET_i = \alpha + \beta_1 MVEDEC_i + \beta_2 BMDEC_i + \beta_3 MOMDEC_i + \beta_4 LOWSCORE_i + \beta_5 HIGHSCORE_i$$

The count variables MVEDEC, BMDEC and MOMDEC equal the firm's size, book-to-market ratio and six-month return momemtum decile assignment, minus one, based on the preceding year's distribution of decile cutoffs. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. T-statistics (in parentheses) and related standard errors are based on the empirically-derived distribution of annual coefficients.

	Intercept	MVEDEC	BMDEC	MOMDEC	FSCORE	LOW SCORE	HIGH SCORE	Adj. R^2
Panel A1: Dependent variable: One-year ahead raw returns								
(1)	0.1096	-0.0070	0.0146	0.0061	-	-	-	0.0334
	(1.73)	(-1.53)	(3.61)	(1.75)	-	-	-	
(2)	0.0149	-0.0091	0.0134	0.0037	0.0226	-	-	0.0398
	(0.21)	(-2.10)	(3.36)	(1.08)	(7.76)	-	-	
(3)	0.1320	-0.0089	0.0136	0.0041	-	-0.0709	0.0399	0.0387
	(2.11)	(-2.03)	(3.40)	(1.20)	-	(-6.08)	(5.06)	
Panel A2: Dependent variable: One-year-ahead market adjusted returns								
(1)	-0.0262	-0.0072	0.0142	0.0095	-	-	-	0.0331
	(-0.51)	(-1.56)	(3.61)	(3.11)	-	-	-	
(2)	-0.1177	-0.0092	0.0130	0.0072	0.0218	-	-	0.0392
	(-2.03)	(-2.10)	(3.36)	(2.39)	(7.49)	-	-	
(3)	-0.0044	-0.0091	0.0132	0.0076	-	-0.0694	0.0382	0.0381
	(-0.09)	(-2.04)	(3.40)	(2.52)	-	(-5.94)	(5.03)	

Table 3 (continued)
Returns to financial statement analysis-based investment strategy: Cross-sectional regressions

This panel presents average coefficients from 30 annual estimations of the following cross-sectional models:

$$\text{Log(1+RET or MARET)} = \alpha + \beta_1 \log(\text{MVE}) + \beta_2 \log(1+\text{BM}) + \beta_3 \log(1+\text{MOM}) + \beta_4 \text{FSCORE} + \varepsilon$$

$$\text{Log(1+RET or MARET)} = \alpha + \beta_1 \log(\text{MVE}) + \beta_2 \log(1+\text{BM}) + \beta_3 \log(1+\text{MOM}) + \beta_4 \text{LOWSCORE} + \beta_5 \text{HIGHSCORE} + \varepsilon$$

The firm's market value of equity (MVE) is measured as the fiscal year-end (in millions), book-to-market ratio is measured as the book-value of equity at year end scaled by MVE, while short-term momentum (MOM) is measured as the preceding six-month market-adjusted return of the firm prior to portfolio formation (i.e., includes the last two months of the fiscal year plus the four months after fiscal year end before investment). All other variables are as defined in panel A.

	Intercept	Log(MVE)	Log(BM)	Log(MOM)	FSCORE	LOW SCORE	HIGH SCORE	Adj. R^2
Panel B1: Dependent variable: One-year ahead raw returns								
(1)	-0.2055	0.0229	0.2042	0.0852	-	-	-	0.0501
	(-3.33)	(3.95)	(6.54)	(3.43)	-	-	-	
(2)	-0.3530	0.0178	0.1892	0.0560	0.0342	-	-	0.0634
	(-4.90)	(3.33)	(6.30)	(2.38)	(10.53)	-	-	
(3)	-0.1718	0.0182	0.1909	0.0601	-	0.0559	-0.1142	0.0615
	(-2.93)	(3.37)	(6.34)	(2.54)	-	(8.67)	(-10.22)	
Panel B2: Dependent variable: One-year-ahead market adjusted returns								
(1)	-0.3540	0.0268	0.2128	0.1180		-	-	0.0470
	(-5.88)	(4.18)	(6.93)	(5.00)		-	-	
(2)	-0.5005	0.0217	0.1974	0.0890	0.0338	-	-	0.0579
	(-7.49)	(3.64)	(6.65)	(4.00)	(11.98)	-	-	
(3)	-0.3228	0.0221	0.1997	0.0933	-	0.0570	-0.1121	0.0561
	(-5.63)	(3.66)	(6.70)	(4.14)	-	(9.10)	(-10.39)	

Table 4
Returns to financial statement analysis-based investment strategy across traditional size portfolios

This table presents returns to a fundamental analysis based investment strategy over the fiscal years 1972 to 2001 conditional on firm size at the end of the fiscal year. Panel A presents raw returns; panel B presents market-adjusted returns. Firm size is measured as the firm's market value of equity at the end of the fiscal year prior to portfolio formation. Firms are assigned to size portfolios on the basis of the preceding year's distribution of MVE. Small, medium and large firms are classified as those firms below the 30th percentile, between the 40th and 70th percentiles and above the 70th percentile cutoffs from the preceding year's distribution. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. A firm-year is classified as being in the low (high) portfolio if the firm's FSCORE is less than or equal to three (greater than or equal to seven). T-statistics (in parentheses) for differences in the mean (median) returns between high and low FSCORE portfolios are from a t-test of means (sign ranked wilcoxon test). T-statistics on the difference in proportion of firms with positive returns is from a binomial test of proportions.

Panel A: One-year ahead raw returns to FSA strategy across size portfolios

	Mean portfolio returns					Proportion with positive returns					Number of observations		
	Small MVE	Medium MVE	Large MVE	Large-Small Difference	(t-stat)	Small MVE	Medium MVE	Large MVE	Large-Small Difference	(t-stat)	Small MVE	Medium MVE	Large MVE
All firms:	0.2015	0.1404	0.1271	-0.0744	(11.93)	0.4980	0.5382	0.6074	0.1094	(27.95)	31,011	41,557	32,897
FSCORE:													
0	-0.0432	0.0169	-0.1177	-	-	0.3804	0.3084	0.3750	-	-	92	107	16
1	0.0858	-0.0517	-0.1650	-	-	0.3776	0.3743	0.2679	-	-	805	895	168
2	0.0954	0.0659	0.0147	-	-	0.3888	0.4166	0.4381	-	-	2366	2374	703
3	0.1328	0.0605	0.0666	-	-	0.4356	0.4345	0.5121	-	-	4031	4527	1992
4	0.1733	0.1031	0.0903	-	-	0.4660	0.5007	0.5547	-	-	5247	6693	4455
5	0.2119	0.1382	0.1213	-	-	0.5073	0.5386	0.6013	-	-	5772	8494	7101
6	0.2415	0.1858	0.1404	-	-	0.5356	0.5869	0.6264	-	-	5332	8482	8557
7	0.2820	0.1959	0.1533	-	-	0.5705	0.6025	0.6455	-	-	4247	6548	6755
8	0.2460	0.2070	0.1788	-	-	0.5633	0.6337	0.6773	-	-	2482	2888	2727
9	0.3026	0.2350	0.1908	-	-	0.5950	0.6630	0.6950	-	-	637	549	423
Low Score	0.1133	0.0489	0.0394	-0.0739	(-4.34)	0.4134	0.4206	0.4790	0.0656	(5.99)	7294	7903	2879
Med Score	0.2092	0.1453	0.1226	-0.0866	(-10.11)	0.5033	0.5452	0.6017	0.0984	(18.86)	16351	23669	20113
High Score	0.2717	0.2013	0.1619	-0.1098	(-9.74)	0.5702	0.6148	0.6563	0.0861	(11.51)	7366	9985	9905
High-Low	0.1584	0.1524	0.1225	-	-	0.1568	0.1942	0.1773	-	-			
(t-statistic)	(9.84)	(13.26)	(9.77)	-	-	(19.23)	(26.29)	(16.95)	-	-			

Table 4
Returns to financial statement analysis-based investment strategy across traditional size portfolios

Panel B: One-year ahead market-adjusted returns to FSA strategy across size quintiles

	Mean portfolio returns					Proportion with positive returns					Number of observations		
	Small MVE	Medium MVE	Large MVE	Large-Small Difference	(t-stat)	Small MVE	Medium MVE	Large MVE	Large-Small Difference	(t-stat)	Small MVE	Medium MVE	Large MVE
All firms:	0.0739	0.0117	0.0007	-0.0732	(-11.93)	0.4146	0.4244	0.4472	0.0326	(8.33)	31,011	41,557	32,897
FSCORE:													
0	-0.2131	-0.1272	-0.2574	-	-	0.2717	0.2523	0.2500	-	-	92	107	16
1	-0.0539	-0.1827	-0.2827	-	-	0.3230	0.2872	0.1845	-	-	805	895	168
2	-0.0335	-0.0587	-0.0968	-	-	0.3149	0.3290	0.3570	-	-	2366	2374	703
3	-0.0053	-0.0662	-0.0453	-	-	0.3597	0.3415	0.3775	-	-	4031	4527	1992
4	0.0454	-0.0261	-0.0296	-	-	0.3892	0.3855	0.4081	-	-	5247	6693	4455
5	0.0873	0.0070	-0.0047	-	-	0.4200	0.4216	0.4416	-	-	5772	8494	7101
6	0.1185	0.0559	0.0118	-	-	0.4533	0.4646	0.4560	-	-	5332	8482	8557
7	0.1532	0.0675	0.0220	-	-	0.4794	0.4817	0.4752	-	-	4247	6548	6755
8	0.1262	0.0865	0.0473	-	-	0.4617	0.5114	0.5086	-	-	2482	2888	2727
9	0.1866	0.0972	0.0467	-	-	0.4914	0.5301	0.5248	-	-	637	549	423
Low Score	-0.0224	-0.0780	-0.0729	-0.0505	(3.03)	0.3400	0.3304	0.3605	0.0205	(1.96)	7294	7903	2879
Med Score	0.0840	0.0152	-0.0032	-0.0872	(10.39)	0.4210	0.4268	0.4403	0.0193	(3.71)	16351	23669	20113
High Score	0.1470	0.0746	0.0301	-0.1169	(10.67)	0.4715	0.4929	0.4865	0.0150	(1.57)	7366	9985	9905
High-Low	0.1694	0.1526	0.1030	-	-	0.1315	0.1625	0.1260	-	-	-	-	-
(t-statistic)	(10.69)	(13.55)	(8.50)	-	-	(16.73)	(22.32)	(12.27)	-	-	-	-	-

Table 5
Returns to financial statement analysis-based investment strategy across traditional size portfolios

This table presents returns to a fundamental analysis based investment strategy over the fiscal years 1972 to 2001 conditional on firm size at the end of the fiscal year. Panel A presents raw returns; panel B presents market-adjusted returns. Book-to-market ratios are measured as the firm's book value of equity to market value of equity at the end of the fiscal year prior to portfolio formation. Firms are assigned to book-to-market portfolios on the basis of the preceding year's distribution of BM. Low, medium and high BM firms are classified as those firms below the 30th percentile, between the 40th and 70th percentiles and above the 70th percentile cutoffs from the preceding year's distribution. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. A firm-year is classified as being in the low (high) portfolio if the firm's FSCORE is less than or equal to three (greater than or equal to seven). T-statistics (in parentheses) for differences in the mean (median) returns between high and low FSCORE portfolios are from a t-test of means (sign ranked wilcoxon test). T-statistics on the difference in proportion of firms with positive returns is from a binomial test of proportions.

Panel A: One-year ahead raw returns to FSA strategy across book-to-market portfolios

	Mean portfolio returns					Proportion with positive returns					Number of observations		
	Glamour Low BM	Med BM	Value High BM	High-Low Difference	(t-stat)	Glamour Low BM	Med BM	Value High BM	High-Low Difference	(t-stat)	Glamour Low BM	Med BM	Value High BM
All firms:	0.0836	0.1581	0.2224	0.1388	(22.14)	0.4816	0.5755	0.5810	0.0994	(25.39)	32,783	41,086	31,596
FSCORE:													
0	0.0209	-0.0890	0.0090	-	-	0.3378	0.2571	0.4366	-	-	74	70	71
1	-0.1197	0.0607	0.0960	-	-	0.2929	0.4113	0.4218	-	-	758	586	524
2	-0.0264	0.1124	0.1399	-	-	0.3247	0.4345	0.4710	-	-	1,925	1,779	1,739
3	-0.0071	0.0998	0.1703	-	-	0.3727	0.4737	0.4985	-	-	3,397	3,576	3,577
4	0.0479	0.1211	0.1960	-	-	0.4334	0.5251	0.5483	-	-	5,021	6,245	5,129
5	0.0930	0.1515	0.2191	-	-	0.4845	0.5824	0.5818	-	-	6,817	8,336	6,214
6	0.1238	0.1786	0.2554	-	-	0.5326	0.6111	0.6248	-	-	7,127	9,260	5,984
7	0.1395	0.2025	0.2625	-	-	0.5621	0.6312	0.6350	-	-	5,328	7,261	4,961
8	0.1745	0.1840	0.2673	-	-	0.5872	0.6380	0.6422	-	-	2,013	3,384	2,700
9	0.1677	0.2434	0.2941	-	-	0.6161	0.6537	0.6499	-	-	323	589	697
Low Score	-0.0267	0.0975	0.1528	0.1795	(10.43)	0.3474	0.4535	0.4828	0.1354	15.23	6,154	6,011	5,911
Med Score	0.0927	0.1541	0.2248	0.1321	(16.03)	0.4891	0.5785	0.5867	0.0976	18.73	18,965	23,841	17,327
High Score	0.1499	0.1991	0.2667	0.1168	(10.80)	0.5710	0.6344	0.6386	0.0676	8.75	7,664	11,234	8,358
High-Low	0.1766	0.1016	0.1139	-	-	0.2236	0.1809	0.1558	-	-	-	-	-
(t-statistic)	(13.10)	(8.19)	(7.48)	-	-	(26.95)	(23.00)	(18.63)	-	-	-	-	-

Table 5
Returns to financial statement analysis-based investment strategy across traditional book-to-market portfolios

Panel B: One-year ahead market-adjusted returns to FSA strategy across book-to-market portfolios

	Mean portfolio returns					Proportion with positive returns					Number of observations		
	Glamour Low BM	Med BM	Value High BM	High-Low Difference	(t-stat)	Glamour Low BM	Med BM	Value High BM	High-Low Difference	(t-stat)	Glamour Low BM	Med BM	Value High BM
All firms:	-0.0405	0.0295	0.0924	0.1329	(21.66)	0.3793	0.4403	0.4647	0.0854	(21.99)	32,783	41,086	31,596
FSCORE:													
0	-0.1503	-0.2329	-0.1396	-	-	0.2838	0.2143	0.2817	-	-	74	70	71
1	-0.2633	-0.0747	-0.0210	-	-	0.2375	0.3259	0.3378	-	-	758	586	524
2	-0.1496	-0.0169	0.0179	-	-	0.2644	0.3423	0.3790	-	-	1,925	1,779	1,739
3	-0.1379	-0.0259	0.0418	-	-	0.2911	0.3700	0.4015	-	-	3,397	3,576	3,577
4	-0.0767	-0.0059	0.0689	-	-	0.3452	0.3978	0.4334	-	-	5,021	6,245	5,129
5	-0.0332	0.0250	0.0882	-	-	0.3802	0.4410	0.4623	-	-	6,817	8,336	6,214
6	0.0012	0.0482	0.1257	-	-	0.4160	0.4617	0.5047	-	-	7,127	9,260	5,984
7	0.0202	0.0709	0.1248	-	-	0.4433	0.4864	0.5051	-	-	5,328	7,261	4,961
8	0.0603	0.0584	0.1383	-	-	0.4665	0.4959	0.5159	-	-	2,013	3,384	2,700
9	0.0374	0.1104	0.1649	-	-	0.4520	0.5178	0.5380	-	-	323	589	697
Low Score	-0.1571	-0.0304	0.0270	0.1841	(10.83)	0.2761	0.3557	0.3878	0.1117	(13.10)	6,154	6,011	5,911
Med Score	-0.0318	0.0259	0.0955	0.1273	(15.78)	0.3844	0.4377	0.4684	0.0840	(16.21)	18,965	23,841	17,327
High Score	0.0314	0.0692	0.1325	0.1011	(9.62)	0.4498	0.4909	0.5114	0.0616	(7.81)	7,664	11,234	8,358
High-Low	0.1885	0.0996	0.1055	-	-	0.1737	0.1352	0.1236	-	-	-	-	-
(t-statistic)	(14.33)	(8.23)	(7.01)	-	-	(21.58)	(17.40)	(14.77)	-	-	-	-	-

Table 6
Returns to financial statement analysis-based investment strategy across traditional book-to-market and size portfolios

This table presents returns to a fundamental analysis based investment strategy over the fiscal years 1972 to 2001 conditional on firm size at the end of the fiscal year. Panel A presents raw returns; panel B presents market-adjusted returns. Book-to-market ratios are measured as the firm's book value of equity to market value of equity at the end of the fiscal year prior to portfolio formation. Firms are assigned to book-to-market portfolios on the basis of the preceding year's distribution of BM. Low, medium and high BM firms are classified as those firms below the 30th percentile, between the 40th and 70th percentiles and above the 70th percentile cutoffs from the preceding year's distribution. Firm size is measured as the firm's market value of equity at the end of the fiscal year prior to portfolio formation. Firms are assigned to size portfolios on the basis of the preceding year's distribution of MVE. Small, medium and large firms are classified as those firms below the 30th percentile, between the 40th and 70th percentiles and above the 70th percentile cutoffs from the preceding year's distribution. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. A firm-year is classified as being in the low (high) portfolio if the firm's FSCORE is less than or equal to three (greater than or equal to seven). T-statistics (in parentheses) for differences in the mean (median) returns between high and low FSCORE portfolios are from a t-test of means (sign ranked wilcoxon test). T-statistics on the difference in proportion of firms with positive returns is from a binomial test of proportions.

	Glamour High BM Firms					Medium BM Firms					Value Low BM Firms				
	Small Firms	Medium Firms	Large Firms	Lg.-Sm Differ.	(t-stat)	Small Firms	Medium Firms	Large Firms	Lg.-Sm Differ.	(t-stat)	Small Firms	Medium Firms	Large Firms	Lg-Sm Differ.	(t-stat)
Panel A: Raw returns															
All firms:	0.0892	0.0616	0.1007	-	-	0.1862	0.1616	0.1370	-	-	0.2542	0.1929	0.1834	-	-
FSCORE:															
Low Score	0.0035	-0.0464	-0.0278	-0.0313	(-1.00)	0.1190	0.0925	0.0746	-0.0444	(-1.59)	0.1763	0.1265	0.1077	-0.0686	(-2.17)
Med Score	0.1051	0.0799	0.0983	-0.0068	(-0.37)	0.1900	0.1588	0.1298	-0.0602	(-4.16)	0.2596	0.1948	0.1841	-0.0755	(-5.23)
High Score	0.2080	0.1413	0.1409	-0.0671	(-2.16)	0.2378	0.2113	0.1682	-0.0696	(-3.95)	0.3060	0.2348	0.2128	-0.0932	(-5.06)
High-Low	0.2045	0.1877	0.1687	-	-	0.1188	0.1188	0.0936	-	-	0.1297	0.1083	0.1051	-	-
(t-statistic)	(5.33)	(9.28)	(7.40)	-	-	(4.16)	(6.43)	(5.63)	-	-	(5.48)	(4.89)	(3.75)	-	-

Table 6 (continue)
Returns to financial statement analysis-based investment strategy across traditional book-to-market and size portfolios

	Glamour High BM Firms					Medium BM Firms					Value Low BM Firms				
	Small Firms	Medium Firms	Large Firms			Small Firms	Medium Firms	Large Firms			Small Firms	Medium Firms	Large Firms		
Panel B: Market-adjusted returns															
All firms:	-0.0552	-0.0649	-0.0125	-	-	0.0608	0.0334	0.0059	-	-	0.1322	0.0612	0.0276	-	-
FSCORE:															
Low Score	-0.1523	-0.1718	-0.1272	0.0251	(0.82)	-0.0169	-0.0350	-0.0414	-0.0245	(-0.90)	0.0529	-0.0013	-0.0259	-0.0788	(-2.52)
Med Score	-0.0352	-0.0494	-0.0165	0.0187	(1.06)	0.0661	0.0289	0.0012	-0.0649	(-4.59)	0.1395	0.0632	0.0289	0.1106	(7.80)
High Score	0.0727	0.0212	0.0274	-0.0453	(-1.51)	0.1182	0.0867	0.0282	-0.0900	(-5.26)	0.1812	0.1001	0.0469	0.1343	(7.52)
High-Low	0.2250	0.1930	0.1546	-	-	0.1351	0.1217	0.0696	-	-	0.1283	0.1014	0.0728	-	-
(t-statistic)	(6.12)	(9.78)	(7.03)	-	-	(4.83)	(6.75)	(4.34)	-	-	(5.49)	(4.61)	(2.66)	-	-
Panel C: Number of observations															
All firms:	6,223	12,479	14,081	-	-	8,972	17,335	14,779	-	-	15,816	11,743	4,037	-	-
Low Fscore	2,003	3,007	1,144	-	-	1,987	2,765	1,259	-	-	3,304	2,131	476	-	-
Med Fscore	3,202	7,001	8,762	-	-	4,739	10,148	8,954	-	-	8,410	6,520	2,397	-	-
High Fscore	1,018	2,471	4,175	-	-	2,246	4,422	4,566	-	-	4,102	3,092	1,164	-	-

Table 7
Returns to financial statement analysis-based investment strategy across bankruptcy risk portfolios: Articulation of the level of bankruptcy risk and changes in financial condition

This table presents returns to a fundamental analysis based investment strategy over the fiscal years 1972 to 2001 conditional on firm size at the end of the fiscal year. Panel A presents raw returns; panel B presents market-adjusted returns. Bankruptcy risk (OH) is measured using the score from Ohlson (1980)'s bankruptcy prediction model at the end of the fiscal year prior to portfolio formation. Firms are assigned to bankruptcy risk quintiles on the basis of the preceding year's distribution of OH. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. A firm-year is classified as being in the low (high) portfolio if the firm's FSCORE is less than or equal to three (greater than or equal to seven). T-statistics (in parentheses) for differences in the mean (median) returns between high and low FSCORE portfolios are from a t-test of means (sign ranked wilcoxon test). T-statistics on the difference in proportion of firms with positive returns is from a binomial test of proportions.

Panel A: One-year ahead raw returns to FSA strategy across bankruptcy risk portfolios

	Mean portfolio returns					Proportion of positive returns					Number of observations				
	Low O-score	O-score	O-score	O-score	High O-score	Low O-score	O-score	O-score	O-score	High O-score	Low O-score	O-score	O-score	O-score	High O-score
All firms:	0.1623	0.1644	0.1648	0.1654	0.1152	0.5873	0.5923	0.5776	0.5449	0.4400	21,336	20,950	20,821	20,837	21,521
FSCORE:															
0	n/a	0.1473	0.1125	0.0377	-0.0717	n/a	0.5000	0.3846	0.3514	0.3307	0	4	13	74	124
1	-0.1689	-0.0780	0.1402	0.0704	-0.0432	0.5000	0.3273	0.4913	0.4226	0.3314	5	55	173	407	1,231
2	-0.0023	0.1085	0.1640	0.0973	0.0388	0.4717	0.4563	0.4885	0.4597	0.3607	53	355	653	1,316	3,066
3	0.0970	0.1106	0.1129	0.1019	0.0656	0.5009	0.4976	0.4992	0.4748	0.3953	537	1,244	1,781	2,563	4,425
4	0.1335	0.1223	0.1304	0.1244	0.1090	0.5503	0.5320	0.5379	0.5139	0.4337	2,057	2,799	3,274	3,748	4,517
5	0.1489	0.1488	0.1417	0.1622	0.1631	0.5815	0.5741	0.5642	0.5413	0.4806	4,399	4,557	4,449	4,327	3,635
6	0.1747	0.1727	0.1723	0.1945	0.2174	0.5895	0.6137	0.6031	0.5858	0.5176	6,120	5,201	4,752	3,935	2,363
7	0.1748	0.1957	0.2084	0.2323	0.2250	0.5969	0.6353	0.6248	0.6080	0.5634	5,319	4,283	3,670	2,890	1,388
8	0.1604	0.2049	0.2231	0.2628	0.2675	0.6143	0.6428	0.6367	0.6348	0.5779	2,419	2,041	1,734	1,287	616
9	0.2201	0.2367	0.2177	0.2889	0.3632	0.6442	0.6764	0.6056	0.6483	0.6346	430	411	322	290	156
Low Score	0.0872	0.1039	0.1274	0.0965	0.0392	0.4983	0.4831	0.4954	0.4633	0.3735	592	1,658	2,620	4,360	8,846
Med Score	0.1589	0.1528	0.1504	0.1610	0.1521	0.5803	0.5811	0.5721	0.5473	0.4688	12,576	12,557	12,475	12,010	10,515
High Score	0.1729	0.2010	0.2134	0.2447	0.2471	0.6046	0.6401	0.6273	0.6183	0.5727	8,168	6,735	5,726	4,467	2,160
High-Low	0.0857	0.0971	0.0860	0.1482	0.2079	0.1063	0.1570	0.1319	0.1550	0.1992	-	-	-	-	-
(t-statistic)	(2.65)	(4.93)	(4.75)	(8.86)	(10.08)	(5.00)	(11.54)	(11.30)	(14.79)	(16.85)	-	-	-	-	-

Table 7 (continued)
Returns to financial statement analysis-based investment strategy across bankruptcy risk portfolios: Articulation of the level of bankruptcy risk and changes in financial condition

Panel B: One-year ahead market-adjusted returns to FSA strategy across bankruptcy risk portfolios

	Mean portfolio returns					Proportion of positive returns					Number of observations				
	Low O-score	O-score	O-score	O-score	High O-score	Low O-score	O-score	O-score	O-score	High O-score	Low O-score	O-score	O-score	O-score	High O-score
All firms:	0.0335	0.0370	0.0382	0.0374	-0.0121	0.4503	0.4551	0.4475	0.4295	0.3623	21,336	20,950	20,821	20,837	21,521
FSCORE:															
0	n/a	0.0195	0.0000	-0.1192	-0.2306	n/a	0.5000	0.3846	0.2568	0.2419	0	4	13	74	124
1	-0.3316	-0.1614	0.0251	-0.0650	-0.1809	0.0000	0.2909	0.3757	0.3366	0.2681	5	55	173	407	1,231
2	-0.1146	-0.0339	0.0393	-0.0263	-0.0847	0.3774	0.3409	0.3859	0.3807	0.2880	53	355	653	1,316	3,066
3	-0.0234	-0.0003	-0.0109	-0.0281	-0.0693	0.3724	0.3915	0.3942	0.3656	0.3214	537	1,244	1,781	2,563	4,425
4	0.0070	-0.0015	0.0047	-0.0043	-0.0172	0.4176	0.4051	0.4081	0.3984	0.3582	2,057	2,799	3,274	3,748	4,517
5	0.0196	0.0189	0.0165	0.0362	0.0351	0.4437	0.4371	0.4374	0.4211	0.3931	4,399	4,557	4,449	4,327	3,635
6	0.0438	0.0427	0.0437	0.0694	0.1001	0.4556	0.4661	0.4623	0.4618	0.4376	6,120	5,201	4,752	3,935	2,363
7	0.0460	0.0677	0.0784	0.0978	0.0981	0.4617	0.4903	0.4872	0.4855	0.4705	5,319	4,283	3,670	2,890	1,388
8	0.0363	0.0777	0.1010	0.1380	0.1510	0.4638	0.5091	0.5063	0.5198	0.4903	2,419	2,041	1,734	1,287	616
9	0.0765	0.1049	0.0832	0.1648	0.2656	0.4907	0.5329	0.4627	0.5241	0.6090	430	411	322	290	156
Low Score	-0.0326	-0.0128	0.0040	-0.0325	-0.0925	0.3716	0.3776	0.3908	0.3656	0.3013	592	1,658	2,620	4,360	8,846
Med Score	0.0293	0.0242	0.0237	0.0344	0.0272	0.4452	0.4420	0.4392	0.4273	0.3881	12,576	12,557	12,475	12,010	10,515
High Score	0.0448	0.0730	0.0855	0.1137	0.1253	0.4639	0.4986	0.4916	0.4979	0.4861	8,168	6,735	5,726	4,467	2,160
High-Low	0.0774	0.0858	0.0815	0.1462	0.2178	0.0923	0.1210	0.1008	0.1323	0.1848	-	-	-	-	-
(t-statistic)	(2.46)	(4.45)	(4.62)	(8.90)	(10.87)	(4.47)	(9.05)	(8.69)	(12.66)	(15.89)	-	-	-	-	-

Table 8
Returns to financial statement analysis-based investment strategy across traditional book-to-market and bankruptcy risk portfolios

This table presents returns to a fundamental analysis based investment strategy over the fiscal years 1972 to 2001 conditional on firm size at the end of the fiscal year. Panel A presents raw returns; panel B presents market-adjusted returns. Book-to-market ratios are measured as the firm's book value of equity to market value of equity at the end of the fiscal year prior to portfolio formation. Firms are assigned to book-to-market portfolios on the basis of the preceding year's distribution of BM. Low, medium and high BM firms are classified as those firms below the 30th percentile, between the 40th and 70th percentiles and above the 70th percentile cutoffs from the preceding year's distribution. Bankruptcy risk (OH) is measured using the score from Ohlson (1980)'s bankruptcy prediction model at the end of the fiscal year prior to portfolio formation. Firms are assigned to bankruptcy risk quintiles on the basis of the preceding year's distribution of OH. Raw returns are defined as the twelve-month buy-and-hold return for each firm; market-adjusted returns are measured as raw returns minus the corresponding twelve-month return of the CRSP value-weighted market index. Return compounding starts at the beginning of the fifth month after fiscal year end. If the firm delists prior to the end of the twelve-month compounding period, the delisting return is assumed to be zero. A firm-year is classified as being in the low (high) portfolio if the firm's FSCORE is less than or equal to three (greater than or equal to seven). T-statistics (in parentheses) for differences in the mean (median) returns between high and low FSCORE portfolios are from a t-test of means (sign ranked wilcoxon test). T-statistics on the difference in proportion of firms with positive returns is from a binomial test of proportions.

	Glamour High BM Firms					Med BM Firms					Value Low BM Firms				
	Low O-score	Quin2	Quin3	Quin4	High O-score	Low O-score	Quin2 O-score	Quin3 O-score	Quin4 O-score	High O-score	Low O-score	Quin2 O-score	Quin3 O-score	Quin4 O-score	High O-score
Panel A: Raw returns															
All firms:	0.1163	0.1030	0.1041	0.1091	0.0204	0.1861	0.1540	0.1519	0.1454	0.1505	0.2067	0.2358	0.2185	0.2193	0.2283
FSCORE:															
Low Score	0.0085	-0.0023	0.0310	0.0425	-0.0516	0.1208	0.0707	0.1122	0.0787	0.1092	0.1634	0.2148	0.1858	0.1362	0.1354
Med Score	0.1137	0.0943	0.0929	0.1032	0.0597	0.1810	0.1468	0.1424	0.1406	0.1645	0.2130	0.2241	0.2007	0.2195	0.2734
High Score	0.1282	0.1451	0.1625	0.1809	0.1848	0.1991	0.1885	0.1896	0.2175	0.2333	0.2011	0.2600	0.2706	0.3146	0.3292
High-Low	0.1197	0.1474	0.1315	0.1384	0.2364	0.0783	0.1178	0.0774	0.1388	0.1241	0.0377	0.0452	0.0848	0.1784	0.1938
(t-statistic)	(3.02)	(4.52)	(3.30)	(3.93)	(7.53)	(1.34)	(5.05)	(3.17)	(5.74)	(3.46)	(0.61)	(1.02)	(2.61)	(5.98)	(4.66)

Table 8 (continued)
Returns to financial statement analysis-based investment strategy across traditional book-to-market and bankruptcy risk portfolios

	Glamour High BM Firms					Med BM Firms					Value Low BM Firms				
	Low O-score	Quin2	Quin3	Quin4	High O-score	Low O-score	Quin2 O-score	Quin3 O-score	Quin4 O-score	High O-score	Low O-score	Quin2 O-score	Quin3 O-score	Quin4 O-score	High O-score
Panel B: Market-adjusted returns															
All firms:	-0.0016	-0.0147	-0.0161	-0.0183	-0.1135	0.0498	0.0258	0.0253	0.0184	0.0270	0.0710	0.1008	0.0881	0.0899	0.1073
FSCORE:															
Low Score	-0.0902	-0.0925	-0.0856	-0.0827	-0.1897	-0.0094	-0.0466	-0.0114	-0.0504	-0.0229	0.0268	0.0820	0.0596	0.0055	0.0161
Med Score	-0.0089	-0.0247	-0.0305	-0.0230	-0.0708	0.0463	0.0156	0.0173	0.0141	0.0448	0.0786	0.0895	0.0699	0.0927	0.1519
High Score	0.0169	0.0245	0.0486	0.0481	0.0551	0.0602	0.0628	0.0586	0.0913	0.1238	0.0640	0.1235	0.1389	0.1796	0.2044
High-Low	0.1071	0.1170	0.1342	0.1308	0.2448	0.0696	0.1094	0.0700	0.1417	0.1467	0.0372	0.0415	0.0793	0.1741	0.1883
(t-statistic)	(2.81)	(3.77)	(3.51)	(3.84)	(7.95)	(1.21)	(4.93)	(2.98)	(5.98)	(4.23)	(0.62)	(0.93)	(2.46)	(5.91)	(7.91)
Panel C: Number of observations															
All firms:	8,492	5,560	4,406	4,862	9,463	8,684	9,260	9,217	7,935	5,990	4,160	6,130	7,198	8,040	6,068
Low Fscore	217	354	480	884	4,219	270	742	1,068	1,572	2,359	105	562	1,072	1,904	2,268
Med Fscore	5,208	3,588	2,788	2,918	4,463	5,101	5,554	5,620	4,608	2,958	2,267	3,415	4,067	4,484	3,094
High Fscore	3,067	1,618	1,138	1,060	781	3,313	2,964	2,529	1,755	673	1,788	2,153	2,059	1,652	706