Abstract

This study investigates whether a simple accounting-based fundamental analysis can outperform the market. In this study, I use a fundamental signal (F_SCORE) to discriminate between eventual winners and losers. F_SCORE is based on a combination of traditional fundamentals such as ROA, cash flow from operations, and operating margin. I demonstrate that the mean return can be increased by at least 7.8% through hedging strategy that buys high F_SCORE firms and that shorts low F_SCORE firms. In particular, an investment strategy that buys high book-to-market (BM) firms with high F_SCORE and shorts low BM firms with low F_SCORE earns a 17.6% annual return. In other words the results are robust across a variety of partitions including size, share price, and trading volume. This study reveals that F_SCORE can predict future earnings. Further, empirical results do not support a risk-based explanation for the investment strategy. Overall, the results of the present study suggest that life cycle hypothesis advocated by Lee and Swaminathan[2000] holds true.

Keywords: Value Investing. Financial Statement Analysis. Market Efficiency. Life Cycle Hypothesis.

I. Introduction

This study investigates whether a simple accounting-based fundamental analysis outperforms the market. In particular, this study documents that hedging strategy that buys high book-to-market (BM) firms with a high fundamental signal (F_SCORE) and that shorts low BM firms with a low F_SCORE is successful at generating significant positive returns. Piotroski [2000] demonstrates that a simple financial statement analysis, when applied to a broad value portfolio, can shift the distribution of returns earned by an investor. He advocates his results corroborate the intuition behind “the life cycle hypothesis” advanced in Lee and Swaminathan [2000]. However, Piotroski [2000] applies financial statement analysis to high

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1 Throughout this paper, the terms "high book-to-market firms” and “value firms” are used synonymously, and the terms “low book to-market firms” and “growth firms” are also used synonymously.
BM firms. To explore the “life cycle hypothesis” it is necessary to examine whether the investment strategy can shift the distribution of returns for not only high BM firms but also low BM firms.

This present study reveals that a simple accounting-based fundamental analysis outperforms the market for not only high BM firms but also low BM firms and all firms. Specifically an investment strategy that buys high BM firms with a high $F_{SCORE}$ and that shorts low BM firms with low $F_{SCORE}$ earns a 17.6% annual return.

The remainder of this paper is organized as follows. In section II, I review prior literature on value investing, and financial statement analysis. In Section III describes a sample formation. Empirical results are presented in section IV and concluding remarks follow in section V.

II. Literature Review

1. Financial Statement Analysis

Academic research that examined the investment strategy using financial statements is classified into two approaches2. The first approach separates ultimate winners from losers by identifying a firm’s intrinsic value. The investment strategy shown by Frankel and Lee [1998] purchases stocks whose prices are undervalued, and shorts stocks whose prices are overvalued. Whether a stock is undervalued or overvalued is identified using the earnings forecasts of the analysts in conjunction with an accounting-based valuation model (e.g., residual income model, Feltham and Ohlson [1995]), and the strategy is successful at generating significant positive returns.

The second approach is a more dynamic investment approach that involves the use of multiple pieces of information contained in a firm’s financial statement. Ou and Penman [1989], and Abarbanell and Bushee [1998] demonstrate that a set of financial variables created from financial statements can accurately predict future changes in earnings and returns. One limitation of these studies is that complex methodologies and a vast amount of historical information are used to make necessary predictions. To overcome this limitation, Lev and Thiagrajan [1993] use 12 financial signals that are claimed to be useful to security analysts. They observe that these fundamental signals are correlated with contemporaneous returns after controlling for current innovations, firms size, and macroeconomic conditions (e.g., GNP growth, etc).

Following Piotroski [2000] and Mohanram [2004], the present study extends prior research conducted, by using context-specific financial performance measures to differentiate between strong and weak firms3. Instead of examining the relationship between future returns and particular financial signals, this study aggregates the information contained in an array of performance measures and forms portfolios on the basis of a firm’s overall signals. Piotroski [2000] defines the aggregate signal measure as the sum of the nine binary signals for high BM

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2 Nissim and Penman [2001] comprehensively identify financial ratios that are useful for securities valuation.

3 Beneish, Lee, and Tarpley [2001] apply the concept of contextual fundamental analysis to predict extreme stock returns. Their results suggest that it is important to carry out contextual financial statement analysis.
firms or value firms. Mohanram [2004] uses eight fundamental signals to create an index for low BM firms or growth firms. In contrast, this study defines the aggregate signal measure as the sum of only three binary signals.

2. Value Investing

This study explores a refined investment strategy based on value investing. Several academic studies (e.g., Fama and French [1992], Lakonishok, Shleifer and Vishny [1994], and Chan, Hamao and Lakonishok [1991]) examine the stock returns of high BM firms (“value” stocks) relative to low BM firms (“growth” or “glamour” stocks). An empirical regularity of these data is that the returns of value stocks over the past 30 years have been significantly greater than those of growth stocks. Chan, Hamao, and Lakonishok [1991] test cross-sectional differences in returns on Japanese firms due to the underlying behavior of four variables: earnings yield, size, BM, and cash yield. They demonstrate that the BM ratio is statistically and economically the most important of the four variables examined.

Such a strong return performance has been attributed to both market efficiency and market inefficiency. First, Fama and French [1992] propose that the BM ratio captures a priced element of systematic risk, and that the observed difference in returns between value and growth stocks reflects a fair compensation for risk. In recent studies, Vassalou and Xing [2004] demonstrate that BM risk essentially proxies for default risk in high BM firms.

A second explanation for the observed return difference is market mispricing. Griffin and Lemmon [2002] explore the relationship between BM, distress risk, and stock return. They observe that firms with high distress risk have characteristics that make them more likely to be mispriced by investors, and conclude that these results are consistent with mispricing. Lakonishok, Shleifer, and Vishny [1994] claim that high BM firms’ stock prices are temporarily depressed because investors overreact to prior performance that is poor, and maintain expectations about future performance that is “too pessimistic.” Further, Laporta, Lakonishok, Shleifer, and Vishny [1997] demonstrate that this pessimism unravels in future periods, as evidenced by positive earnings surprises at subsequent quarterly earnings announcements. Ali, Hwang, and Trombley [2003] observe that the ability of the BM ratio to predict future returns is greater for firms with higher transaction costs, and with less ownership by sophisticated investors. Ali et al. [2003] conclude that these results are consistent with the view of market mispricing.

In the present study, I test whether an investment strategy based on financial statement analysis outperforms the market. In particular, this study examines whether an investment strategy that buys high BM firms with strong fundamental signals and that shorts low BM firms with weak fundamental signals enhances abnormal returns.

3. Financial Performance Signals

In this study, I utilize three fundamental signals to evaluate a firm’s performance and estimate future returns. The signals chosen are easy to interpret and implement compared with those used by Ou and Penman [1989]. I classify each firm’s signal realization as “good” or

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“bad” depending on the implication of the signal for future profitability and stock prices. If the signal’s realization is good (bad), an indicator variable for the signal is equal to one (zero). I define the aggregate signal measure, $F_{SCORE}$, as the sum of the three binary signals.

The first measure is $\Delta ROA$. I define ROA as net income before extraordinary items, scaled by beginning-of-the-year total assets. I define the first fundamental signal, $F_{\Delta ROA}$, as equal to one if $\Delta ROA$ is positive, and zero if otherwise.

The second measure is cash flow from operations. Following Sloan [1996], I define the variable CFO as the current year’s net income before extraordinary items minus ACCRUAL, scaled by beginning-of-the-year total assets. In this paper, ACCRUAL is computed using information from the balance sheet and income statement, as is common in the earnings management literature.

$$ACCRUAL = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta FI) - \Delta Allow - \Delta Dep$$

where

- $\Delta CA$ = change in current assets
- $\Delta Cash$ = change in cash and deposits
- $\Delta CL$ = change in current liabilities
- $\Delta FI$ = change in financing items (change in short-term borrowing, change in outstanding CP, change in long-term debt due within a year, and straight bonds and CB due within a year)
- $\Delta Allow$ = change in loss allowances for accounts receivable + change in reserve for bonus payable and salary payable + change in short-term reserve accounts + change in allowance for future retirement bonus + change in long-term reserve accounts
- $\Delta Dep$ = depreciation

I define a second fundamental signal, $F_{CFO}$, to equal one if CFO is positive, and zero if otherwise.

The last measure is $\Delta MARGIN$. I define MARGIN as the firm’s current gross margin ratio (gross margin scaled by total sales). I define $\Delta MARGIN$ as the current year’s MARGIN minus the prior year’s MARGIN. I define the third fundamental signal, $F_{\Delta MARGIN}$, as equal to one if $\Delta MARGIN$ is positive, and zero if otherwise.

III. Data and Sample Description

Empirical tests were conducted using firms listed on the first or second section of the Tokyo Stock Exchange, where all required data are available. The sample period covered in this study was from March 1986 to March 2001. In the present study, I used a consolidated financial statement$. The sample was limited to nonfinancial firms, and I excluded firms with a fiscal year end on March 31st. I also excluded a firm’s data if it had a negative book equity value.

I measured firm-specific returns as one-year buy-and-hold returns. The measurement of

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$Ito$ [1991] demonstrates that consolidated financial statements are more informative relative to parent financial statements in Japan.
future stock returns began from July 1st. In this study, I define market-adjusted returns as the buy-and-hold return minus the TOPIX (Tokyo Stock Price Index) return over the corresponding period. I winsorized observations whose market-adjusted return were in the most extreme 1% of my observations.

Annual financial statement information was obtained from the ASTRA database supplied by Quick. Monthly returns were obtained from Kabuka Toshi Shuekiritu 2002, provided by the Japan Securities Research Institute. Stock prices and trading volumes were obtained from a Kabuka CD-ROM provided by the Toyo Keizai Simpousha Publisher. This selection process yielded 10,385 firm-year observations.

The primary methodology in this study was to form portfolios based on the firm’s aggregate score (\(F\_SCORE\)). I classified firms whose \(F\_SCORE\) equaled 0 as low \(F\_SCORE\) firms. I expected these firms to have the worst subsequent returns. Alternatively, firms with the strongest fundamental signals, or an \(F\_SCORE\) equal to 3, were classified as high \(F\_SCORE\) firms. I expected these firms to have the best subsequent stock performance.

This study mainly examined whether the high \(F\_SCORE\) portfolio outperformed the low \(F\_SCORE\) portfolio. Piotroski [2000] demonstrates a simple financial statement analysis strategy that, when applied to high BM firms, generated positive abnormal returns. As pointed out by Guay [2000], it is questionable why high BM firms are appropriate samples for testing the investment strategy. In contrast, Mohanram [2004] demonstrates that financial statement analysis, appropriately tailored for growth firms, can be suitably modified to be very successful for low BM firms.

To explore the dynamics of financial statement analysis, this study examines whether the strong \(F\_SCORE\) portfolio outperformed the weak \(F\_SCORE\) portfolio for not only high BM firms but also low BM firms, and all firms. The present study defined high BM firms as firms with a BM ranked above 66.6 percentile. Low BM firms were defined as firms with BM ranked below 33.3 percentile.

Panel A of Table 1 reports descriptive statistics for all pooled data. The average (median) firm had a mean (median) 0.0105 (-0.0248) market-adjusted return.

In Panel B of Table 2, I present 12-month market-adjusted returns for firms with sufficient data to identify BM quartiles. From Panel B, high BM firms outperform low BM firms with a 5.4% difference per year. This result is consistent with prior research that showed that value firms outperformed growth firms.

Table 2 shows Spearman correlations between individual fundamental signal indicator variables, the aggregate fundamental signal score \(F\_SCORE\), and the one-year buy-and-hold market-adjusted returns. \(F\_SCORE\) is highly correlated with ΔROA and ΔMARGIN (0.778 and 0.770, respectively), whereas CFO has a weaker correlation with the \(F\_SCORE\) than ΔROA and ΔMARGIN (0.429). As expected, \(F\_SCORE\) has a positive correlation with one-year market-adjusted returns (0.093). Individual fundamental signals have a positive correlation with future returns; however, these variables have a weaker correlation than the \(F\_SCORE\). Overall, the aggregate \(F\_SCORE\) is expected to outperform a simple investment strategy that is based on ΔROA or CFO, or ΔMARGIN alone.
### Table 1. Descriptive Statistics

**Sample consists of 10,385 firm-years between 1986 and 2001**

#### Panel A: Firm Characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAR</td>
<td>0.0105</td>
<td>-0.0248</td>
<td>0.2772</td>
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<tr>
<td>MVE</td>
<td>220084</td>
<td>59181</td>
<td>588816</td>
</tr>
<tr>
<td>ΔROA</td>
<td>0.0006</td>
<td>-0.0001</td>
<td>0.0222</td>
</tr>
<tr>
<td>CFO</td>
<td>0.0487</td>
<td>0.0481</td>
<td>0.0610</td>
</tr>
<tr>
<td>ΔMARGIN</td>
<td>0.0006</td>
<td>0.0006</td>
<td>0.0238</td>
</tr>
<tr>
<td>MOMENTUM</td>
<td>0.1044</td>
<td>0.0511</td>
<td>0.3098</td>
</tr>
<tr>
<td>ACCRUAL</td>
<td>0.0306</td>
<td>-0.0309</td>
<td>0.0549</td>
</tr>
<tr>
<td>PRICE</td>
<td>3180</td>
<td>672</td>
<td>76263</td>
</tr>
<tr>
<td>TRADING VOLUME</td>
<td>0.4597</td>
<td>0.3154</td>
<td>0.5169</td>
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</tbody>
</table>

#### Panel B: Buy and Hold Returns from a BM Investment Strategy

<table>
<thead>
<tr>
<th></th>
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<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>4-1 Difference</th>
<th>t-Statistic/p-Value</th>
</tr>
</thead>
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<td>0.025</td>
<td>0.030</td>
<td>0.054</td>
<td>6.90</td>
</tr>
<tr>
<td>n</td>
<td>2608</td>
<td>2596</td>
<td>2596</td>
<td>2590</td>
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<td>0.000</td>
</tr>
</tbody>
</table>

* The firm characteristics are computed as follows.

MAR = 12-month buy-and-hold return of the firm minus buy-and-hold return for TOPIX over the same investment horizon. The return cumulation period begins four months after the fiscal year end of the year when the financial variables were measured.

MVE = market value of common equity measured as of the fiscal year end. Market value is computed as the number of shares outstanding at fiscal year end times the closing share price.

ΔROA = change in annual ROA for the year preceding portfolio formation. ROA is calculated as net income before extraordinary items divided by beginning-of-the-year total assets.

CFO = difference between net income before extraordinary items minus accrual divided by beginning-of-the-year total assets.

ΔMARGIN = change in annual MARGIN for the year preceding portfolio formation. MARGIN is calculated as gross margin divided by total sales.

MOMENTUM = six-month market adjusted buy-and-hold return. The return calculation period begins six months before the preceding portfolio formation.

ACCRUAL = change in non-cash current assets minus change in current liabilities minus change in allowance, less depreciation expense, all divided by beginning-of-the-year total assets.

PRICE = the firm's price per share at the end of the fiscal year preceding portfolio formation.

TRADING VOLUME = total number of shares traded during the prior fiscal year divided by the average number of shares outstanding during the year.

### Table 2. Spearman Correlation Analysis between Market-Adjusted Return, the Three Fundamental Signals, and the Composite Signal (F_SCORE)

<table>
<thead>
<tr>
<th></th>
<th>ΔROA</th>
<th>CFO</th>
<th>ΔMARGIN</th>
<th>F_SCORE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAR</td>
<td>0.084</td>
<td>0.054</td>
<td>0.051</td>
<td>0.093</td>
</tr>
<tr>
<td>ΔROA</td>
<td>1.000</td>
<td>0.086</td>
<td>0.367</td>
<td>0.778</td>
</tr>
<tr>
<td>CFO</td>
<td>1.000</td>
<td>0.070</td>
<td>0.429</td>
<td></td>
</tr>
<tr>
<td>ΔMARGIN</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F_SCORE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* The three individual factors in this table represent indicator variables as equal to one (zero) if the underlying performance measure was a good (bad) signal about future firm performance.
IV. Empirical Results

1. Returns to a Financial Statement Analysis Strategy

Table 3 reports the returns to a fundamental investment strategy. Panel A presents the returns for all firms, Panel B presents the returns for high BM firms, and Panel C presents the returns for low BM firms.

For all firms, most observations are clustered around an F_SCORE between 1 and 3. However, 682 observations are classified with an F_SCORE of 1. For high BM firms, the number of observations classified with an F_SCORE of 1 is the smallest, and the number of observations classified with an F_SCORE of 3 is smaller than those classified with an F_SCORE of 1 or 2. On the other hand, for low BM firms, the number of observations classified with an F_SCORE of 0 is the smallest, and the number of observations classified with an F_
The most striking result in Table 3 is the monotonic positive relationship between \( F_{\text{SCORE}} \) and one-year market-adjusted returns. As documented in panel A, high \( F_{\text{SCORE}} \) (score 0) firms significantly outperformed low \( F_{\text{SCORE}} \) firms in the year following portfolio formation (mean market-adjusted returns of 0.042 versus -0.036, respectively). The mean return difference of 0.078 is significant at the 1% level using a \( t \)-statistic.

As shown in panels B and C, for high BM firms (low BM firms) the return difference between low \( F_{\text{SCORE}} \) firms and high \( F_{\text{SCORE}} \) firms is 0.091 (0.083). The mean difference is also statistically significant at the 1% level for both high BM firms and low BM firms. On the whole, it is clear that the \( F_{\text{SCORE}} \) discriminates between eventual winners and losers. Moreover, the investment approach is useful for not only all firms but also high BM firms and low BM firms. This means that the investment approach can shift the entire distribution of returns earned. For example, a high BM investor can shift the entire distribution to the right and a short seller who shorts a low BM investor can shift the entire distribution to the left.

2. Returns Conditional on Firm Size

One concern is whether the excess returns generated, employing a fundamental analysis strategy are a small firm effect, namely a size effect. If the size effect is reflected on excess returns, it is impossible to apply the fundamental strategy across all firm size categories. For this analysis, I ranked all firms annually into three size portfolios independent of their BM ratios. In this study, I defined size as a firm’s market capitalization at the most recent fiscal year end. Given the financial characteristics of the high BM firms, a majority of the firms (1,657) were in the bottom third of market capitalization (47.7%), while 1,197 (34.5%) and 620 (17.8%) were classified in the middle and top size portfolios, respectively. On the other hand, for low BM firms, a preponderance of the firms (1,583, 45.6%) were assigned to the top size, while 886 (25.5%) and 1,005 (28.9%) were classified in the bottom and middle size portfolios, respectively.

Panel A of Table 4 demonstrates that excess returns earned were concentrated in small or middle firms. Panel B shows that for high BM firms, excess returns earned were concentrated in small and middle firms. Applying the \( F_{\text{SCORE}} \) to the small firm portfolio resulted in a mean difference between high and low \( F_{\text{SCORE}} \) firms of 0.107, significant at the 1% level. Similarly, applying the \( F_{\text{SCORE}} \) to the medium firm portfolio resulted in a mean difference between high and low \( F_{\text{SCORE}} \) firms of 0.111, significant at the 1% level. However, for large size firms, the mean difference was statistically insignificant at the 10% level.

In contrast, panel C shows that above-market returns generated by a low BM portfolio were concentrated in medium firms. Applying the \( F_{\text{SCORE}} \) to a medium firm portfolio resulted in a mean difference between high and low \( F_{\text{SCORE}} \) firms of 0.156, significant at the 1% level. But the differentiation was weak among the smallest firms, where the mean return difference was 0.060. Specifically, for the largest firms, the mean difference was statistically insignificant at the 10% level.

Overall, it is clear that the improvement in return predictability was isolated to firms in the bottom two-thirds of market capitalization.
3. Partition Analysis: Share Price and Share Turnover

The analysis of returns conditional on firm size shows that return predictability is concentrated in smaller and medium firms; therefore, investigating whether these returns are realizable is necessary. To the extent that the abnormal returns of the investment strategy are concentrated in firms with a lower stock price or lower level of liquidity, observed returns may not reflect an investor’s ultimate experience. Therefore, this study explores two other partitions of the sample: share price and trading volume.

Similar to results based on market capitalization partitions, Table 5 shows that excess
returns earned were concentrated in small or middle price portfolios. Panel B shows that for high BM firms, excess returns earned were concentrated in small or middle price portfolios. Applying the $F_{\text{SCORE}}$ to the small price portfolio resulted in a mean difference between high and low $F_{\text{SCORE}}$ firms of 0.124, significant at the 1% level. Similarly, applying the $F_{\text{SCORE}}$ to a medium price portfolio resulted in a mean difference between high and low $F_{\text{SCORE}}$ firms of 0.138, significant at the 1% level. However, for large price portfolios, the mean difference was negative and statistically insignificant at the 10% level.

Panel C shows that above-market returns generated by a low BM portfolio were concentrated in smaller price portfolios. Applying the $F_{\text{SCORE}}$ to a small price portfolio resulted in a mean difference between high and low $F_{\text{SCORE}}$ firms of 0.009, significant at the 1% level. Similarly, applying the $F_{\text{SCORE}}$ to a medium price portfolio resulted in a mean difference between high and low $F_{\text{SCORE}}$ firms of 0.138, significant at the 1% level. But differentiation is weak among the large price portfolio, where the mean return difference was 0.041 and statistically insignificant at the 10% level.

Contrary to the results based on market capitalization and stock price partitions, the portfolio results across all trading volume partitions are statistically and economically
Panel A: All Firms

<table>
<thead>
<tr>
<th></th>
<th>Low Volume</th>
<th></th>
<th>Medium Volume</th>
<th></th>
<th>High Volume</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>n</td>
<td></td>
<td>Mean</td>
<td>n</td>
<td></td>
</tr>
<tr>
<td>F_SCORE</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>−0.007</td>
<td>254</td>
<td>−0.047</td>
<td>224</td>
<td>−0.045</td>
<td>67</td>
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<tr>
<td>3</td>
<td>0.063</td>
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<td>0.054</td>
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<td>185</td>
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<td>0.113</td>
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<tr>
<td>t-Statistic/p-Value</td>
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<td>5.111</td>
<td>0.000</td>
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Panel B: High BM Firms

<table>
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<tr>
<th></th>
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<th>Medium Volume</th>
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<td></td>
<td>Mean</td>
<td>n</td>
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<tr>
<td>F_SCORE</td>
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<tr>
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<td>3.189</td>
<td>0.002</td>
<td>2.846</td>
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Panel C: Low BM Firms

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<tr>
<th></th>
<th>Low Volume</th>
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<th>High Volume</th>
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<td></td>
<td>Mean</td>
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<td>0</td>
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<td>65</td>
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<td>−0.044</td>
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</tbody>
</table>

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

* Firms are classified into trading volume portfolios in a manner similar to firm size (see Table 4).

significant. Panel A of Table 6 shows that the low, medium, and high trading volume portfolios yielded a significant positive mean return difference of 0.071, 0.101, and 0.113, respectively. As demonstrated in panel B, for high BM firms, similar significant positive return differences existed in low, medium, and high trading volumes as well. However, panel C shows that for low BM firms, the low and medium trading volume portfolios yielded a significant positive mean difference at the 10% level and 1% level, respectively, while high trading volume portfolios yielded an insignificant positive mean difference at the 10% level.

Overall, the evidence suggests that the benefits to financial statement analysis were concentrated in small or middle size portfolios and small or middle stock price portfolios. However, the benefits are unlikely to disappear after accounting for trading volume.

### 4. Other Source of Cross-Sectional Variations in Returns

Another concern is whether a correlation between the $F\_SCORE$ and another known return pattern, such as momentum or accrual reversal, could drive the observed return patterns. This section addresses these issues.
In terms of the $F_{\text{SCORE}}$ being correlated with another systematic pattern in realized returns, several known effects could have a strong relationship with the $F_{\text{SCORE}}$. In the present study, I ran the following cross-sectional regression to explicitly control for some variables.

$$\text{MAR}_i = \alpha + \beta_1 \log(\text{MVE}_i) + \beta_2 \log(\text{BM}_i) + \beta_3 \text{MOMENT}_i + \beta_4 \text{ACCRUAL}_i + \beta_5 F_{\text{SCORE}}_i.$$
MOMENT equals the firm’s six-moth market-adjusted return prior to portfolio formation. Underreaction to historical information and financial events, which should be the ultimate mechanism underlying the success of F_SCORE, is also the primary mechanism underlying momentum strategy (Chan, Jegadeesh and Lakonishok [1996]). Sloan [1996] and others have shown that accruals predict future stock returns. Panel A of Table 7 shows that after controlling for size and BM, the coefficient on the F_SCORE is significant, at around 0.023. The economic implication of these results is that a one-point improvement in F_SCORE is associated with an approximate 2.3% increase in one-year market-adjusted returns generated, subsequent to portfolio formation. Moreover, the addition of control variables designed to control momentum and accrual reversal had no impact on the robustness of the F_SCORE to predict future returns.

Panels B and C of Table 7 present results from pooled regressions for high BM firms and low BM firms. Of greater interest is that the coefficient on the F_SCORE is larger than that of low BM firms. The coefficient on the F_SCORE of high BM firms is highly significant, at 0.036. On the other hand, the coefficient on the F_SCORE of low BM firms is significant, at 0.017. These empirical results suggest that an investment strategy that uses F_SCORE is more useful for value firms.

5. Future Firm Performance Conditional on the Fundamental Signals

In this section, I provide evidence on the mechanics underlying the success of the investment strategy. In particular, I show that F_SCORE successfully predicts the future earnings of a firm.

Table 8 presents evidence on the relationship between F_SCORE and the level of future earnings. For all firms, a significant positive relation exists between F_SCORE and future profitability. The mean spread in one-year-ahead ROA realizations is about 3% (the difference is significant at the 1% level). For high (low) BM firms, the mean spread is 2.3% (4.3%)—both differences are significant at the 1% level. These empirical results indicate that F_SCORE can predict future earnings.
6. Value Investing and Financial Statement Analysis

The combined evidence suggests that an aggregate fundamental signal can discriminate...
between eventual winners and losers. Piotroski [2000] demonstrates that his fundamental signal can shift the distribution of returns to the right when applied to a broad portfolio of high BM firms. Mohanram [2004] demonstrates that financial statement analysis is effective even for growth firms.

In contrast, this study reveals that $F_{SCORE}$ can shift the distribution of the returns of both high BM firms and low BM firms. In other words, $F_{SCORE}$ can shift the distribution of returns to value stocks to the right and the distribution of returns to growth stocks to the left. In this section, I examine whether a zero investment portfolio buys high BM firms with a high $F_{SCORE}$ and shorts low BM firms with a low $F_{SCORE}$.

Table 9 shows the empirical results. Panel A shows that a hedging strategy that longs high BM firms with a high $F_{SCORE}$ and shorts low BM firms with a low $F_{SCORE}$ earns a statically significant 17.6% annual return. Panels B, C, and D show that zero investment portfolios generate excess returns independent of size, stock price, and trading volume. These results suggest that an investment strategy that applies both fundamental analysis and value investing earns significant abnormal returns.

### 7. Risk or Mispricing

The empirical results so far support the view that markets fail to impound fully the information in fundamental signals. To check robustness, this study examined $F_{SCORE}$ and
risk, and examined two risk measures: $\beta$ and total return volatility.

I calculate $\beta$ using monthly returns for 60 months before preceding portfolio formation. Using 60 months of return data decreases the sample number from 10,385 to 9672. We see from Panel A of Table 10 that $F\_SCORE$ is negatively related to $\beta$ for all firms, high BM firms, and low BM firms. For all firms, an $F\_SCORE$ 0 portfolio has a mean $\beta$ of 1.021, while an $F\_SCORE$ 3 portfolio has a mean $\beta$ of 0.920. In addition, the difference between mean $\beta$ for $F\_SCORE$ 0 and $F\_SCORE$ 3 is significant.

I measure total return volatility as the standard deviation of monthly returns for 12 months preceding portfolio formation. This reduces the sample number to 10,268. The results are demonstrated in Panel B of Table 10. For all firms, high BM firms, and low BM firms, the $F\_SCORE$ is inversely related to total return volatility.

It seems reasonable to conclude that markets fail to impound fully the information in fundamental signals because the relation between $F\_SCORE$ and risk is not positive\(^6\). In other words, it is not a risk view, but a mispricing view that explains the abnormal returns gained by the investment strategy using $F\_SCORE$.

V. Conclusions

This study reveals that a simple accounting-based fundamental analysis outperformed the market. I used a fundamental signal ($F\_SCORE$) to discriminate between eventual winners and losers. I showed that mean returns can be increased by at least 7.8% through a hedging strategy that buys high $F\_SCORE$ firms and that shorts low BM firms. In particular, an investment strategy that buys high BM firms with a high $F\_SCORE$ and that shorts low BM firms with a low $F\_SCORE$ earned a 17.6% annual return. Further analysis shows that the $F\_SCORE$ can predict future earnings, and that these results do not support a risk-based explanation.

The results of this study support the “life cycle hypothesis” advanced in Lee and Swaminathan [2000]. These authors classify firms into four groups, i.e., early-stage momentum loser, late-stage momentum winner, early-stage momentum winner, and late-stage momentum winner. They claim that early-stage momentum losers that continue to support poor performance can become subject to extreme pessimism and experience low volume and investor negligence (i.e., a late-stage momentum loser). Eventually, the average late-stage momentum loser does “recover” and becomes an early-stage momentum winner. Similarly, early-stage momentum winners that continue to support good performance can become subject to extreme optimism and experience high volume and investor favoritism (i.e., a late-stage momentum winner). Finally, the average late-stage momentum winner does become an early-stage momentum loser.

Lee and Swaminathan [2000] distinguish momentum loser and momentum winner by stock price. Further, they use trading volume in addition to stock price to classify firms into four categories. In contrast, this study suggests that $F\_SCORE$ and BM are appropriate for identifying each firm’s location in the life cycle. Some differences exist between Lee and Swaminathan [2000] and this study; however, the value firms with high $F\_SCORE$ in this study have the same financial and market characteristics as those of late-stage momentum losers in

\[^6\] The reason why $F\_SCORE$ is inversely related to risk proxy calls for further consideration.
Lee and Swaminathan [2000]. Similarly, the growth firms with a low $F\_SCORE$ in this study have the same financial and market characteristics as those of late-stage momentum winners. In addition, the value firms with low $F\_SCORE$ (similar to early stage-momentum losers and the growth firms with high $F\_SCORE$) have the same characteristics as those of early-stage momentum winners.

It is not easy to accurately identify an individual firm's location in the life cycle. For example, it is difficult to identify firms with high BM and low $F\_SCORE$, and firms with low BM and high $F\_SCORE$ in the life cycle. However, this study suggests that contextual financial statement analysis could be a useful technique to identify separate late-stage momentum losers (winners) from early-stage momentum losers (winners), and that $F\_SCORE$ and BM are useful in identifying each firm's location in the life cycle.

As mentioned above, it is difficult to correspond with the empirical results and the life cycle hypothesis advocated by Lee and Swaminathan [2000]. However, this study emphasizes that contextual financial statement analysis can predict future returns and future earnings. Moreover, Piotroski [2000] and Mohanram [2004], and Beneish et al. [2001] reveal that contextual financial statement analysis, which applies for firms about to experience an extreme price movement in the next quarter, is useful. I believe that these studies open a number of possibilities for future research.

REFERENCES

Lakonishok, J., A. Shleifer R. Vishny [1994], “Contrarian Investment, Extrapolation, and Risk,”


