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VALUE INVESTING AND FINANCIAL STATEMENT ANALYSIS*

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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[1].

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 approaches[2]. 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] demontrate 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 firms[3]. 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

[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[4]. 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

[4] Chan, Hamao, and Lakonishok [1991] relate fundamentals and stock returns between 1971 and 1988.

"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 ΔROA. I define ROA as net income before extraordinary items, scaled by beginning-of-the-year total assets. I define the first fundamental signal, F_ΔROA, as equal to one if ΔROA 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.

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

where ΔCA = change in current assets
ΔCash = change in cash and deposits
ΔCL = change in current liabilities
ΔFI = 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)
ΔAllow = 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
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 ΔMARGIN. I define MARGIN as the firm's current gross margin ratio (gross margin scaled by total sales). I define ΔMARGIN as the current year's MARGIN minus the prior year's MARGIN. I define the third fundamental signal, F_ΔMARGIN, as equal to one if ΔMARGIN 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[5]. 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

[5] 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[a]

Panel A: Firm Characteristics

Variable	Mean	Median	Standard Deviation
MAR	0.0105	−0.0248	0.2772
MVE	220084	59181	588816
ΔROA	0.0006	−0.0001	0.0222
CFO	0.0487	0.0481	0.0610
ΔMARGIN	0.0006	0.0006	0.0238
MOMENTUM	0.1044	0.0511	0.3098
ACCRUAL	−0.0306	−0.0309	0.0549
PRICE	3180	672	76263
TRADING VOLUME	0.4597	0.3154	0.5169

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

	1st	2nd	3rd	4th	4-1 Difference	t-Statistic/p-Value
MAR	−0.024	0.011	0.025	0.030	0.054	6.90
n	2608	2596	2596	2590		0.000

[a] 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*)[a]

	ΔROA	CFO	ΔMARGIN	F_SCORE
MAR	0.084	0.054	0.051	0.093
ΔROA	1.000	0.086	0.367	0.778
CFO		1.000	0.070	0.429
ΔMARGIN			1.000	0.770
F_SCORE				1.000

[a] 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.

Table 3. One-Year Market-Adjusted Buy-and-Hold Returns to Investment Strategy Based on Fundamental Signals

Panel A : All Firms

	Mean	10%	25%	Median	75%	90%	n
All Firms	0.011	−0.302	−0.169	−0.025	0.152	0.364	10385
F_SCORE							
0	−0.036	−0.359	−0.225	−0.066	0.098	0.324	682
1	−0.006	−0.324	−0.184	−0.041	0.134	0.362	3304
2	0.006	−0.298	−0.166	−0.029	0.144	0.344	3191
3	0.042	−0.272	−0.141	0.009	0.186	0.404	3208
3-0 Difference	0.078						
t-Statistic/p-Value	6.700	0.000					

Panel B: High BM Firms

	Mean	10%	25%	Median	75%	90%	n
All Firms	0.029	−0.298	−0.154	0.006	0.179	0.381	3474
F_SCORE							
0	−0.003	−0.336	−0.178	−0.027	0.120	0.356	291
1	−0.001	−0.328	−0.184	−0.023	0.150	0.346	1283
2	0.023	−0.290	−0.152	0.007	0.176	0.345	1004
3	0.088	−0.239	−0.102	0.072	0.235	0.459	896
3-0 Difference	0.091						
t-Statistic/p-Value	4.752	0.000					

Panel C: Low BM Firms

	Mean	10%	25%	Median	75%	90%	n
All Firms	−0.020	−0.328	−0.203	−0.064	0.113	0.353	3474
F_SCORE							
0	−0.087	−0.407	−0.257	−0.136	0.057	0.269	209
1	−0.029	−0.352	−0.224	−0.074	0.091	0.381	949
2	−0.017	−0.319	−0.194	−0.065	0.112	0.346	1102
3	−0.005	−0.305	−0.187	−0.040	0.137	0.346	1214
3-0 Difference	0.083						
t-Statistic/p-Value	4.084	0.000					

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_*

SCORE of 3 is the largest.

The most striking result in Table 3 is the monotonic positive relationship between *F_SCORE* and one-year market-adjusted returns. As documented in panel A, high *F_SCORE* (score 0) firms significantly outperformed low *F_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_SCORE* firms and high *F_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_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_SCORE* to the small firm portfolio resulted in a mean difference between high and low *F_SCORE* firms of 0.107, significant at the 1% level. Similarly, applying the *F_SCORE* to the medium firm portfolio resulted in a mean difference between high and low *F_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_SCORE* to a medium firm portfolio resulted in a mean difference between high and low *F_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.

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

Panel A: All Firms

	Small Firms		Medium Firms		Large Firms	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.040	344	−0.068	207	0.023	131
1	−0.017	1136	−0.015	1095	0.015	1073
2	0.002	999	−0.004	1082	0.020	1110
3	0.048	995	0.047	1053	0.032	1160
3-0 Difference	0.088		0.115		0.009	
t-Statistic/p-Value	4.578	0.000	5.522	0.000	0.392	0.695

Panel B: High BM Firms

	Small Firms		Medium Firms		Large Firms	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.025	164	−0.008	82	0.088	45
1	−0.021	617	0.004	422	0.042	244
2	0.019	446	0.019	371	0.039	187
3	0.082	430	0.103	322	0.074	144
3-0 Difference	0.107		0.111		−0.014	
t-Statistic/p-Value	3.875	0.000	3.230	0.001	−0.345	0.731

Panel C: Low BM Firms

	Small Firms		Medium Firms		Large Firms	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.068	101	−0.158	67	−0.020	41
1	−0.041	255	−0.049	281	−0.008	413
2	−0.014	266	−0.035	316	−0.008	520
3	−0.008	264	−0.003	341	−0.004	609
3-0 Difference	0.060		0.156		0.016	
t-Statistic/p-Value	1.645	0.101	4.354	0.000	0.390	0.696

[a] Each year, all firms are ranked on the basis of the most recent fiscal year-end market capitalization. The 33.3 and 66.6 percentile cutoffs from the prior year's distribution of firm size (MVE) are used to classify firms into small, medium, and large firms each year. MVE = market value of equity at the end of the fiscal year *t*. Market value is computed as the number of shares outstanding at fiscal year end times closing share price.

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

TABLE 5. ONE-YEAR MARKET-ADJUSTED BUY-AND-HOLD RETURNS TO INVESTMENT STRATEGY BASED ON FUNDAMENTAL SIGNALS BY SHARE PRICE[a, b]

Panel A: All Firms

	Small Price		Medium Price		Large Price	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.050	291	−0.054	234	0.016	157
3	0.066	1017	0.042	1058	0.020	1133
3-0 Difference	0.116		0.097		0.003	
t-Statistic/p-Value	5.672	0.000	5.270	0.000	0.144	0.885

Panel B: High BM Firms

	Small Price		Medium Price		Large Price	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.009	115	−0.059	112	0.106	64
3	0.115	376	0.079	342	0.050	178
3-0 Difference	0.124		0.138		−0.057	
t-Statistic/p-Value	3.742	0.000	4.913	0.000	−1.473	0.142

Panel C: Low BM Firms

	Small Price		Medium Price		Large Price	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.009	115	−0.059	112	0.106	64
3	0.115	376	0.079	342	0.050	178
3-0 Difference	0.124		0.138		−0.057	
t-Statistic/p-Value	3.742	0.000	4.913	0.000	−1.473	0.142

[a] Share price equals firm's price per share at the end of the fiscal year preceding portfolio formation.
[b] Firms are classified into share price portfolios in a manner similar to firm size (see Table4).

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_SCORE* to the small price portfolio resulted in a mean difference between high and low *F_SCORE* firms of 0.124, significant at the 1% level. Similarly, applying the *F_SCORE* to a medium price portfolio resulted in a mean difference between high and low *F_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_SCORE* to a small price portfolio resulted in a mean difference between high and low *F_SCORE* firms of 0.109, significant at the 1% level. Similarly, applying the *F_SCORE* to a small price portfolio resulted in a mean difference between high and low *F_SCORE* firms of 0.099, 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

Table 6. One-Year Market-Adjusted Buy-and-Hold Returns to Investment Strategy Based on Fundamental Signals by Trading Volume[a, b]

Panel A: All Firms

	Low Volume		Medium Volume		High Volume	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.007	254	−0.047	224	−0.045	67
3	0.063	955	0.054	1017	0.068	185
3-0 Difference	0.071		0.101		0.113	
t-Statistic/p-Value	3.381	0.001	5.111	0.000	2.846	0.005

Panel B: High BM Firms

	Low Volume		Medium Volume		High Volume	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	0.024	127	−0.009	97	−0.045	67
3	0.093	414	0.095	297	0.068	185
3-0 Difference	0.069		0.104		0.113	
t-Statistic/p-Value	2.329	0.020	3.189	0.002	2.846	0.005

Panel C: Low BM Firms

	Low Volume		Medium Volume		High Volume	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.077	65	−0.159	60	−0.044	84
3	0.010	213	0.006	311	−0.014	690
3-0 Difference	0.087		0.165		0.031	
t-Statistic/p-Value	1.952	0.052	4.792	0.000	0.996	0.320

[a] 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.
[b] Firms are classified into trading volume portfolios in a manner similar to firm size (see Table4).

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.

TABLE 7. COEFFICIENTS FROM POOLED REGRESSION

Panel A: All Firms

	Intercept	Log(MVE)	Log(BM)	Moment	Accrual	F_SCORE	Adj.R^2
(1)	−0.086	0.023	0.066	−	−	−	0.006
	−4.10	5.24	7.46	−	−	−	
(2)	−0.122	0.022	0.067	−	−	0.024	0.012
	−5.74	4.85	7.65	−	−	8.38	
(3)	−0.084	0.022	0.065	−0.019	−0.215	−	0.008
	−3.95	4.89	7.31	−2.19	−4.36	−	
(4)	−0.114	0.020	0.067	−0.026	−0.111	0.023	0.013
	−5.29	4.46	7.60	−2.93	−2.16	7.77	

Panel B: High BM Firms

	Intercept	Log(MVE)	Log(BM)	Moment	Accrual	F_SCORE	Adj.R^2
(1)	−0.115	0.031	0.045	−	−	−	0.002
	−2.55	3.20	1.93	−	−	−	
(2)	−0.177	0.032	0.040	−	−	0.036	0.017
	−3.87	3.23	1.73	−	−	7.17	
(3)	−0.117	0.031	0.046	−0.018	−0.184	−	0.003
	−2.56	3.15	1.96	−1.03	−2.02	−	
(4)	−0.171	0.030	0.045	−0.032	0.006	0.037	0.017
	−3.72	3.11	1.93	−1.80	0.06	7.05	

Panel C: Low BM Firms

	Intercept	Log(MVE)	Log(BM)	Moment	Accrual	F_SCORE	Adj.R^2
(1)	−0.087	0.016	0.030	−	−	−	0.002
	−2.34	2.33	1.78	−	−	−	
(2)	−0.107	0.014	0.029	−	−	0.017	0.005
	−2.86	1.94	1.71	−	−	3.29	
(3)	−0.077	0.014	0.030	−0.026	−0.161	−	0.004
	−2.04	1.96	1.75	−1.96	−2.05	−	
(4)	−0.094	0.011	0.029	−0.029	−0.106	0.016	0.006
	−2.48	1.60	1.71	−2.15	−1.31	3.05	

Note: This table represents coefficients from the following cross-sectional regression: [a]$MAR_i = \alpha + \beta_1 \log(MVE_i) + \beta_2 \log(BM_i) + \beta_3 MOMENT_i + \beta_4 ACCRUARL_i + \beta_5 F\_SCORE_i$.

[a]MAR = one-year market-adjusted return. The one-year market-adjusted return equals the firm's 12-month buy-and-hold return minus the buy-and-hold return of the TOPIX over the same investment horizon. MVE = market value of equity at the end of fiscal year *t*. Market value is computed as the number of shares outstanding at fiscal year-end times the closing share price. BM = book value of equity of fiscal year *t*, scaled by MVE. MOMENT = six-month market-adjusted buy-and-hold return over the six months directly preceding the date of portfolio formation. ACCRUAL = ΔCA − ΔCash − (ΔCL − ΔFI) − ΔAllow − Dep. All variables are scaled by beginning-of-the-year total assets. F_SCORE = sum of three individual binary signals.

In terms of the *F_SCORE* being correlated with another systematic pattern in realized returns, several known effects could have a strong relationship with the *F_SCORE*. In the present study, I ran the following cross-sectional regression to explicitly control for some variables.

$$MAR_i = \alpha + \beta_1 \log(MVE_i) + \beta_2 \log(BM_i) + \beta_3 MOMENT_i + \beta_4 ACCRUARL_i + \beta_5 F\_SCORE_i$$

Table 8. Future Earnings Performance Based on Fundamental Signals

	All Firms		High BM Firms		Low BM Firms	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	−0.004	682	−0.002	291	−0.013	209
1	0.012	3304	0.010	1283	0.012	949
2	0.019	3191	0.016	1004	0.020	1102
3	0.026	3208	0.021	896	0.030	1214
3-0 Difference	0.030		0.023		0.043	
t-Statistic/p-Value	24.501	0.000	14.546	0.000	15.917	0.000

Note: This table presents the one-year-ahead mean realizations of return on assets. ROA equals income before extraordinary items scaled by beginning-of-the-year total assets.

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* of high BM firms 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.

TABLE 9. ONE-YEAR MARKET-ADJUSTED BUY-AND-HOLD RETURNS TO HEDGING STRATEGY BASED ON VALUE INVESTING AND FINANCIAL STATEMENT ANALYSIS

Panel A: One-Year Market-Adjusted Buy-and-Hold Returns and Future Earnings Performance Based on Value Investing and Fundamental Signals

	MAR		ROA $t+1$	
	Mean	n	Mean	n
Low BM with F_SCORE=0	−0.087	209	−0.013	209
High BM with F_SCORE=3	0.088	896	0.021	896
Difference	0.176		0.033	
t-Statistic/p-Value	8.063	0.000	15.277	0.000

Panel B: One-Year Market-Adjusted Buy-and-Hold Returns and Based on Value Investing and Fundamental Signals by Size Partition[a, d]

	Small Firms		Medium Firms		Large Firms	
	Mean	n	Mean	n	Mean	n
Low BM with F_SCORE=0	−0.068	101	−0.158	67	−0.020	41
High BM with F_SCORE=3	0.082	430	0.103	322	0.074	144
Difference	0.150		0.262		0.094	
t-Statistic/p-Value	4.558	0.000	7.026	0.000	2.103	0.037

Panel C: One-Year Market-Adjusted Buy-and-Hold Returns and Based on Value Investing and Fundamental Signals by Share Price Partition[b, d]

	Small Price		Medium Price		Large Price	
	Mean	n	Mean	n	Mean	n
Low BM with F_SCORE=0	−0.089	102	−0.116	56	−0.053	51
High BM with F_SCORE=3	0.115	376	0.079	342	0.050	178
Difference	0.204		0.195		0.103	
t-Statistic/p-Value	5.966	0.000	5.295	0.000	2.320	0.021

Panel D: One-Year Market-Adjusted Buy-and-Hold Returns and Based on Value Investing and Fundamental Signals by Trading Volume Partition[c, d]

	Low Volume		Medium Volume		High Volume	
	Mean	n	Mean	n	Mean	n
Low BM with F_SCORE=0	−0.077	65	−0.159	60	−0.044	84
High BM with F_SCORE=3	0.093	414	0.095	297	0.068	185
Difference	0.170		0.254		0.112	
t-Statistic/p-Value	4.394	0.000	6.718	0.000	2.908	0.004

[a] Firm size means MVE. MVE=market value of equity at the end of fiscal year t. Market value is computed as the number of shares outstanding at fiscal year end times the closing share price.
[b] Share price equals a firm's price per share at the end of the fiscal year preceding portfolio formation.
[c] 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.
[d] Firms are classified into firm size, share price, and trading volume portfolios in a manner similar to firm size (see Table 4).

6. Value Investing and Financial Statement Analysis

The combined evidence suggests that an aggregate fundamental signal can discriminate

TABLE 10. RELATION BETWEEN *F_SCORE* AND RISK MEASURES

Panel A: β[a]

	All Firms		High BM Firms		Low BM Firms	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	1.021	618	1.016	252	1.096	197
1	0.956	3046	0.933	1156	1.017	884
2	0.944	2967	0.907	938	0.997	1002
3	0.920	3041	0.886	842	0.960	1144
3-0 Difference	−0.102		−0.131		−0.137	
t-Statistic/p-Value	−4.76	0.000	−3.97	0.000	−3.40	0.001

Panel B: Total Return Volatility[b]

	All Firms		High BM Firms		Low BM Firms	
	Mean	n	Mean	n	Mean	n
F_SCORE						
0	0.122	676	0.118	288	0.131	207
1	0.115	3261	0.111	1266	0.126	934
2	0.109	3161	0.102	999	0.121	1087
3	0.110	3170	0.103	887	0.119	1193
3-0 Difference	−0.012		−0.015		−0.011	
t-Statistic/p-Value	−5.14	0.000	−2.39	0.017	−4.84	0.000

[a] I measure β using monthly returns for 60 months before preceding portfolio formation. This decreases the sample number to 9672.

[b] Total Return Volatility = standard deviation of 12-month returns before the preceding portfolio formation. This decreases the sample number to 10268.

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: β and total return volatility.

I calculate β 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 β for all firms, high BM firms, and low BM firms. For all firms, an *F_SCORE* 0 portfolio has a mean β of 1.021, while an *F_SCORE* 3 portfolio has a mean β of 0.920. In addition, the difference between mean β 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.

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