Piotroski's F-Score in the Chinese A-Share Market

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Declaration

I declare that this is my own original work and that all sources have been accurately reported and acknowledged. It is submitted to the University of Cape Town for the degree of Master of Commerce. This dissertation has not been submitted for any degree or examination at this or any other university.

Abstract

This study examines whether Piotroski's (2000) F-Score strategy can successfully be applied to the Chinese A-Share market. The empirical evidence shows that in the Chinese A-Share market, the high F-Score portfolio significantly outperforms the low F-Score portfolio. Especially within a low BM firm sample, buying high F-Score firms and shorting low F-Score firms consistently, on average, generate 1.28% market adjusted profit per month. The results are robust for size partition. However, the benefits of Piotroski's F-Score strategy are concentrated in low liquidity and analyst following sample. Within the high BM firm sample, Piotroski's F-Score strategy cannot generate any significant return. The excess return of a low BM sample persists across time, as well as after controlling for size, book-to-market ratio, and market beta. In addition, if we measure risk in terms of beta and volatility, high F-Score firms are less risky than low F-Score firms. To conclude, the empirical evidence presented in this study suggests investors can use Piotroski's F-Score to identify mispriced stocks and earn abnormal returns in the Chinese A-share market, especially within a low BM firm sample.

Keywords: Fundamental Analysis, Abnormal Returns, Chinese A-Share Market, Piotroski's F-Score.

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1. Introduction

The efficient market hypothesis (EMH) developed by Eugene Fama (Fama 1970) has enjoyed wide academic support over the last few decades. According to the EMH, if the market is semi-strong form efficient, then no trading strategy based on historical and currently available information can earn excess risk-adjusted returns. In other words, all value-relevant accounting information is already fully incorporated into the stock when the financial statements are released. Therefore, analyzing financial statements should not offer any value. However, anomalies such as post-earnings-announcement drift (PEAD) challenge the EMH. PEAD is the tendency for a stock's cumulative abnormal returns to drift in the direction of an earnings surprise following an earnings announcement. This process may last for several days up to several months. The existence of the PEAD anomaly indicates that stocks might not always trade at their true fundamental value. Consequently, this provides an opportunity for investors to develop investment strategies that exploit inefficiencies of the market.

One well-studied strategy is fundamental investing. Fundamental investors rely on financial statement information to predict the intrinsic value of a stock, they buy(sell) stocks which are trading at prices substantially lower(higher) than their intrinsic value. Ou and Penman,1989 and Holthausen and Larcker, 1992 collectively show the ability of financial ratios derived from historical financial statements to predict future earnings changes and stock returns. Abarbanell and Bushee(1998) show that a fundamental strategy based on simple financial ratios can generate superior returns for investors.

Another well-known strategy is value investing. Value investors try to buy stocks that are undervalued. Valuation multiples such as the book-to-market (BM) value, is often used to determine whether a stock is a value stock or a growth stock. Stocks with high BM ratios are considered value stocks, while those with low ratios are classified as growth stocks. Evidence that value stocks outperform growth stocks (value/glamour effect) can be traced back to Basu (1977), who shows value stocks on average earn higher absolute and risk-adjusted rates of return than growth stocks. Basu's finding indicate that publicly available financial information is not fully reflected in stock price as fast as is stated in the EMH, and there seem to be lags and frictions in the adjustment process. However, Basu did not study what causes the value/glamour effect. Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994) are pioneer researchers who attempt to explain the value/glamour effect. Fama and French argue value stocks are riskier, therefore higher returns are appropriate compensation for increased risk. Lakonishok, Shleifer and Vishny, on the other hand, argue the value/glamour effect is a result of cognitive biases underlying investor behaviour.

Combining fundamental analysis with value investing, Piotroski (2000) developed a score based strategy (F-Score strategy) to identify high quality (high score) firms and low quality (low score) firms within a high (BM) sample. Piotroski shows that the average annualised market-adjusted returns to buying high score firms are 7.5% higher than simply buying the generic high BM portfolio. In addition, a long/short strategy based on his F_Score strategy yielded 23% annual return between 1976 and 1996. Furthermore, he shows that high scoring firms are fundamentally less risky than low scoring firms. Thus, he claims his strategy can improve returns without increasing risk.

Piotroski's impressive result sparked the interest of academics around the world. Many studies attempt to replicate Piotroski's strategy outside the U.S. but only a few could confirm his original findings (e.g. Rathjens and Schellhove, 2011, Tantipanichkul, 2011, Hyde, 2013). Studies such as those of Woodley, Jones and Reburn (2011), Attwood (2012), and Van der Merwe (2012), find that the F-Score strategy generates profit but that this is not statistically significant.

This study seeks to provide out-of-sample evidence on the effectiveness of the F-Score strategy. The Chinese A-Share market is interesting to study because it has a high percentage of retail investors and low foreign participation, compared to other countries. Retail investors account for 90% of the market's total trading volume (Cheung, Hoguet and Ng, 2014). Retail investors in general are less financially sophisticated then institutional investors. With little knowledge and limited experience in stock investments, most retail investors select stocks based on current rumors about companies. Thus, stock prices are often pushed too high, and then quickly corrected (Kang, Liu and Ni,2002). Therefore, it would be interesting to see whether Piotroski's F-Score strategy can identify mispriced stocks in China.

A major drawback of Piotroski's study is the choice of accumulation method. Piotroski (2000) selects a return accumulation period based on firm-specific financial year-ends, rather than establishing a common investment period for all firms. Piotroski's approach is common practice in accounting-based studies of anomalies. However, this is problematic in practice, because the weights of the hedged portfolio are unknown at the beginning of the accumulation period (Kim and Lee, 2014).

This paper attempts to address the limitations of the approach by Piotroski (2000). To build a tradable portfolio, all stocks need to have the same investment period. Therefore, it is necessary to make modifications to Piotroski's original strategy. In addition, we calculate returns as a monthly frequency instead of a yearly frequency, and use trailing 12-month data instead of year-end data to compute the F-Score.

We find that the F-Score strategy is effective at separating winners and losers in the Chinese A-Share market, especially within the low BM firm sample. On average, high F-Score firms outperform low F-Score firms by 1.28% per month. In addition, the excess return persists across time, as well as after controlling for known risk factors. Contrary to Piotroski's finding, the F-Score strategy does not work for the high BM firm sample. In addition, if we measure risk in terms of beta and volatility, high F-Score firms are less risky than low F-Score firms.

The remainder of this paper is organized as follows: The next section reviews the prior literature on the topic. Section 3 presents the data and research methodology. In sections 4 and 5 we present the results and discuss key findings. Section 6 examines the robustness of the F-score across time. In section 7 we test whether observed returns are abnormal. Section 8 discusses the risk characteristic of Piotroski's F-Score strategy. Finally, section 9 concludes the paper.

2 Literature Review

2.1 Book-to-Market Effect

The BM ratio is a financial ratio that is often used to determine whether a stock is undervalued or overvalued. It is calculated by taking the book value of a firm and dividing it by the firm's market value. The BM ratio is also commonly used in studies for categorizing whether a stock is a value stock or a growth stock. High BM stocks are often referred to as value stocks, which have generally displayed poor past performance. Low BM stocks are often referred to as growth stocks, and are those that have experience strong earnings growth in the past.

The structural outperformance of high BM stocks over low BM stocks is known as the Book-to-Market effect. A number of studies have shown that in the U.S, on average, high BM stocks outperform low BM stocks(Rosenberg, Reid, and Lanstein 1985, Fama and French 1992, Lakonishok, Shleifer and Vishny 1994). Similar results are also found in other countries, for example, China (Xiao and Xu ,2004), Japan (Chan, Hamao and Lakonishok, 1991), Hong Kong, Malaysia, Taiwan, Thailand (Chen and Zhang, 1998), France, Netherlands, Germany and U.K (Van der Put and Veld, 1996). Although the existence of the BM effect is widely accepted, there are two different explanations for its underlying cause., the risk-based view, and mispricing.

The risk-based view argues that the market is efficient. Different stocks are exposed to different amount of risk and, therefore, different expected returns. Fama and French (1992) find that size and BM ratio, not beta, explain most of the cross section of the expected stock returns. They rank stocks by their BM ratios, and classified the highest ranked portfolio as a "value" portfolio and the lowest ranked portfolio as a growth portfolio. They show that the value portfolio generated an average monthly return of 1.83%, while the return from the growth portfolio was only 0.30%. However, the betas of value and the growth portfolio are similar. Systematic risk is therefore not the explanation for the differences in returns. Fama and French (1992,1996) argue that the

BM ratio represents the financial distress risk, and that high BM firms are more prone to financial distress. Fama and French (1996) uses the multifactor, asset-pricing model of Merton (1973) to explain the relationship between financial distress factors and returns. Chen and Zhang (1998) examine the BM effect in several pacific rim countries. They find that value stocks (stocks with high BM ratios, low price-to-earnings ratios, or high dividend yield), in general, are riskier than growth stocks (stocks with low BM ratios, high Price-to-earnings, or low dividend yield). This is because value stocks are more likely to have poor past earnings, high future earnings volatility, high financial leverage, and a high probability of having a dividend cut. Vassalou and Xing (2004) find that BM ratio can be used as a proxy to assess a firm's default risk within a small firm sample. In a small firm sample, the BM effect is driven by default risk, i.e., small, high BM stocks earn excess return because they are more likely to default. Therefore, the corresponding higher returns for high BM stocks are compensation for increased risk

The alternative view, which led by studies by Lakonishok, Shleifer, and Vishny, (1994) argues that cognitive biases underlying investor behavior is the cause of the BM effect, not risk. If the high BM stocks are fundamentally risky, then they should underperform relative to low BM stocks during economic recessions, when the marginal utility of wealth is high. Using historical economic and market return data, Lakonishok, Shleifer, and Vishny divide their sample periods into "good" and "bad" states. They show that high BM stocks outperform low BM stocks in all states. They conclude that the superior returns on high BM stocks are because they are fundamentally risker than low BM stocks. In addition, Lakonishok, Shleifer, and Vishny postulate that the BM effect is caused by naïve investors' over-extrapolation of strong (weak) past earnings growth, which results in low (high) BM stocks to being temporally over (under) priced. As this optimism (pessimism) unravels over time, low (high) BM stocks will earn negative (positive) excess returns. La Porta (1997) shows that an investment strategy that seeks to exploit errors in analyst's forecasts is highly profitable. Low earning expectation stocks, on average, beat high earning expectation stocks by 20% p.a. La Porta's research suggests even sophisticated investors such as analysts make forecasts that are too extreme.

Agency factors may play a role in higher prices of low BM stocks. Stickel (1998) finds that, in the U.S, Wall Street tends to recommend investors buy glamour stocks with low BM ratios because glamour stocks have favorable characteristics, such as strong past earnings, strong price momentum, and positive earnings forecast, which makes these stocks easier to sell. Cai and Zheng (2004) argue that, because many institutional investors are required to follow the short-term benchmark, they chase glamour stocks, regardless of their future long-term returns, such irrational behavior tends to push up the stock price and reduce expected future returns.

2.2 Fundamental Analysis

Fundamental investing relies on using publicly available financial statement information to predict future returns. Ball and Brown (1968) show that stock prices reflect a firm's fundamentals. They build a forward-looking model to show that abnormal returns can be earned if one can perfectly forecast a company's future earnings. They also show that, by the time a company releases its annual report, 80% of the information is already incorporated in the stock price. Ball and Brown's work is the cornerstone of the fundamental investing strategy.

Ou and Penman (1989) test whether historical financial information has any predictive power concerning future earnings. They start with a pool of 68 financial ratios derived from publicly available information. Next, they select the most relevant ratios and combine them into a single measure called Pr. They show an investment strategy based on Pr yields 8.3% (14.5%) abnormal return for a 12 (24)-month buy-and-hold period. Holthausen and Larcker (1992) use a similar approach to predict stock returns directly, and find that their fundamental strategy yields 4.3%-9.5% abnormal return per year. One of the criticisms of the models of Ou and Penman (1989), and Holthausen and Larcker (1992) is the risk of overfitting the data, and the high cost associated with obtaining the data.

To address this limitation of the models of Ou and Penman (1989) and Holthausen and Larcker (1992), Lev and Thiagarajan (1993) utilize a simplified model and 12 financial ratios that are commonly used by financial analysts. Lev and Thiagarajan show all 12 financial ratios have the expected sign, and 7 out of the 12 financial ratios are statistically significant. Their research results suggest these financial ratios are value-relevant, and are positively correlated with future stock returns. Furthermore, they show that the result is strengthened after adjusting for macroeconomic and other variables. Using the same set of financial ratios, Abarbanell and Bushee (1997, 1998) confirm Lev and Thiagarajan (1993)'s finding. They show that investment strategies based on these financial ratios yield abnormal returns. Frenkel and Lee (1998) show a firm's intrinsic value can be estimated using consensus data with a residual income model. Their investment strategy generates significant positive returns. However, a limitation of their approach is that forward-looking data such as analyst's forecasts are not always available.

Other fundamental investment strategies focus on individual variables derived from financial statements. For example, Sloan (1996) observes that firms with high (low) accruals experience negative(positive) future returns. Novy-Marx (2012) shows gross profitability defined as gross profit over asset is effective at predicting a stock's cross-section of returns. These accounting-based investment strategies only require the calculation of one accounting ratio, and rely on a simple ranking method to form the stock portfolio.

2.3 Fundamental Analysis on Value and Growth Stocks

The characteristics of high BM stocks makes them suitable for fundamental analysis. The lack of analysts following the market makes it difficult for investors to access value-relevant information, other than historical financial statements. Financial statements therefore become a major source of information for investors who want to analyze high BM firms. Because of the lack of high quality forecasts from analysts as key input, intrinsic value models (e.g. Frank and Lee,1998) normally do not work well for high BM firms. Financial ratios derived from historical financial statements are therefore likely to be the most suitable tool for fundamental analysis.

In general, low BM stocks are associate with growth and positive outlooks. However, not every low BM stock is a true growth stock. A portfolio of low BM stocks can consist of small cap hyped stocks with very little earnings, as well as large, high quality firms, with a high proportion of unrecorded intangible assets. Mohanram (2005) argues that, although traditional fundamental analysis may have limited applicability for growth firms, other information from financial statements can be useful. Mohanram investigates whether a simple strategy based on financial analysis of low BM firms is effective at differentiating between winners and losers. He creates a G-Score based on a combination of traditional fundamental signals and industry benchmarks. He shows that an investment strategy based on buying high G-Score and shorting low G-Score firms consistently earns abnormal returns. The main contribution of Mohanram's work is that he shows fundamental analysis is not only useful for value stocks, but also useful for growth stocks. He finds that fundamental analysis is useful for low BM stocks because investors are overly optimistic about growth stocks' future performance, and as a result glamour stocks are temporarily overpriced. Piotroski (2005) applies his F-Score strategy to the growth stock sample and shows that the F-Score is also effective for separate winners and losers within a growth stock sample.

2.4 Piotroski's investment strategy

2.4.1 Piotroski's Investment idea

Piotroski (2000) examines whether a simple accounting-based fundamental analysis can improve investment returns within a high BM firm sample. Piotroski observed that the average return of a high BM portfolio often outperforms the market. However, within the high BM portfolio, most the firms underperform the market, and the success of the high BM portfolio relies on the strong performance of relatively few firms. Piotroski devised an accounting-based strategy (F-Score) for evaluating the financial strength of a firm. The F-Score is designed to differentiate fundamentally strong firms from fundamentally weak firms. Piotroski argues that high BM firms are most suitable for fundamental analysis because these firms are often neglected by analysts. As a group, high BM firms are thinly followed by analysts and receive low levels of interest from investors. Lack of dissemination channels means their stock price does not accurately reflect their true value. Financial statement analysis can therefore help investors identify under (over) priced stocks. Piotroski shows that his investment strategy can increase the return of a generic high BM portfolio by 7.5%, when selecting only the strong firms in the high BM firm sample. Furthermore, the strategy shifts the entire return distribution to the right. Even more impressive is that buying strong firms and shorting weak firms generated an average annual return of 23% over the study period, between 1976 and 1996.

2.4.2 Performed Tests and Results

To further examine whether the strategy really works, Piotroski (2000) evaluates a variety of issues. More specifically, he first tests whether the excess return earned is strictly a small size effect. He sorts the firms into three size categories and applies his F-Score strategy to each category. He finds the F-Score strategy is more effective with small and medium firms than with large firms. Particularly for small firms, the return difference between high F-score firms and the entire firm sample increased from 7.5% to 8.7%, and the return difference between high and low F-Score firms increased from 23% to 27%. By contrast, for large firms, the return difference between high and low F-score firms is much smaller, and statistically insignificant. Piotroski also examines the effectiveness of his F-Score after controlling for the share price, trading volume and analysts' following. He finds that the F-Score strategy is most effective for firms that have low share prices, low trading volumes, and ones that no analyst is following.

Second, Piotroski investigates whether the F-Score adds any value for explaining stock returns, beyond previously known anomalies. He estimates a regression model with the following variables: Market capitalization, BM ratio (Fama and French, 1992), momentum (Chan, Jegadeesh, and Lakonishok, 1996), accrual (Sloan, 1996), equity offering (Loughran and Ritter, 1995) and F-Score (Piotroski, 2000). The regression results were as follows, 1) the coefficient of the F-Score is positive and statistically significant, 2) after he includes the F-Score in the regression, previously known anomalies, such as market capitalization, BM ratio and momentum are still statistically significant. However, accruals and equity offering are not statistically significant.

Third, Piotroski partitions the high BM sample based on financial distress measured by Altman's Z-score (1968) and historical change in profitability, measured by ROA. He finds that firms with high returns have low distress risk and high ROA, and, furthermore, that the F-Score is robust in all partitions. This means the F-Score has explanatory power above and beyond commonly accepted financial health measures such as Altman's Z-score and ROA.

Fourth, Piotroski shows that the F-Score is positively correlated with a firm's subsequent performance, measured by ROA_{t+1}, and negatively correlated with the probability of delisting. His results suggest F-Score firms out-perform low F-Score firms because they have higher future earnings. This finding contradicts Fama and French (1995), who show that high BM firms have poor subsequent earnings.

2.4.3 Follow-Up Study

Mohr (2010) tested the effectiveness of the F-Score for a Eurozone low BM firm sample, between 1999 and 2010. Mohr finds the F-score can be an effective tool for separating winners and losers. High F-Score portfolios consistently outperform low F-Score portfolios over the entire sample period.

Rathjens and Schellhove (2011) investigate whether Piotroski's F-score can successfully be applied to the U.K market. They divide firms into five quantiles according to the BM ratio, and test the effectiveness of Piotroski's F-score in both the top (high BM firm portfolio) and bottom (low BM firm portfolio) quantiles. They find Piotroski's F-Score works well when applied to the U.K market, as well as in the low BM firm sample, but they find his F-Score does not generate significant returns in the high BM firm portfolio. In addition, Rathjens and Schellhove show there was no clear indication for a decrease in abnormal returns after the publishing of Piotroski's paper.

Hyde (2013) examines the F-Score in a global emerging market context. The universe is the constituents of the MSCI Emerging Market Index, which consist of 21 countries, including China. Hyde shows that Piotroski's F-score is highly effective for South Korea, India, South East Asia, China, and South Africa, and the result is robust, after controlling for firm size, momentum, holding period, and value. The return difference between high and low F-Score portfolios in China is 12.49%.

A study by Galdi and Broedel, Lopes (2009) finds that the F-score is effective when applied to the Brazilian stock market. However, the return is mainly driven by small, low liquidity firms. Attwood (2012) tests the F-Score using Piotroski's original methodology and finds that, in South Africa, high F-score firms earn higher returns than low F-Score firms, but the result is not statistically significant. Also in south Africa, Pullen (2013) uses a quarterly rebalancing strategy instead of an annual rebalancing strategy and shows that the F-Score strategy is both economically and statistically significant.

3. Data and Research Methodology

3.1 Sample Selection

All historical financial statement data, financial report release date, suspension lists, stock prices, and trading volumes are obtained from the Wind database . All delisted stocks are included, to avoid survivorship bias. We use data from April 2006 to October 2014. Although the Wind database has data before 2006, we exclude them, because these data are not suitable for this study. Prior to 2006, Chinese companies were required to prepare financial statement using the Chinese Accounting Standard (CAS) from the socialist period. Under these Chinese Accounting Standards, treatment of many financial statement items is vastly different than the way these are handled in International Financial Reporting Standards (IFRS) or the U.S Generally Accepted Accounting Principles (GAAP).

We start with all the firms in the CSI300 index. First, and then exclude banks and diversified financials, as gross profits are not available for these firms. This approach is consistent with prior studies on F-Score, such as those of Rathjens and Schellhove (2011), and Mohr (2010). Second, we remove all firms with 30-day average trading volume less than 10 million RMB. Using this liquidity filter, ensures that stocks in the sample are liquid enough for investors to trade. It also reduces the chance of picking limit-up or limit-down stocks. Third, using the suspension list provide by the Wind Database, we identify firms that are suspended, to ensure that the trading strategy does not generate buy/sell signals for stocks that cannot be traded. Fourth, we remove all negative BM ratio observations in the sample, because they cannot be classified as either value or growth stocks.

Unlike Piotroski (2000), who used only high BM stocks, our study considers both high and low BM stocks. The decision to extend the sample scope is mainly motivated by Mohr (2010) and Rathjens and Schellhove (2011). Both studies show that the success of Piotroski's F-Score is not confined to the high BM quantile. Including both high and low BM stocks allow us to test whether the F-Score strategy works, irrespective of firms' BM ratios.

The Wind Database does not provide the book-to-market ratio. The BM ratio is therefore obtained by inverting the Price-to-Book ratio. For each month, BM ratios are ranked. We classify low BM stocks as firms with BM ratios below the 33^{th} percentile, while firms with BM ratios above the 66^{th} percentile are classified as high BM stocks. After the data cleaning, we are left with 19,031 monthly observations.

3.2 Return Calculation

To calculate stock returns, we use forward adjusted price series from the Wind database. The forward adjusted price series has taken into account all cash and stock dividends, as well as other corporate actions. Hence it reflects the total return of a stock, under the assumption that cash dividends are reinvested immediately at zero cost. Returns are measured as one-month buy-and-hold returns. Measurement of these returns for month t commences on the first trading day of month t, until the first trading day of month t+1, i.e. all stocks are assumed bought and sold at the closing price on the first trading day of month t. If a firm is delisted during the holding period, we assume the return of that stock is zero, in line with Piotroski (2000). The market index used in this study is the CSI 300 total return index. The CSI 300 Index is a value-weighted index consisting of the 300 largest companies in China, based on free float market capitalization.

3.3 Piotroski's F-Score

Piotroski (2000) chose nine simple fundamental signals to measure the overall financial strength of a firm, related to three areas: profitability, financial leverage/liquidity, and operating efficiency. Each fundamental signal is a binary variable which may only take on a value of either zero or one. A variable is equal to one if the signal's realization is good, and zero otherwise. The F-Score is defined as the sum of nine binary variables. The highest possible financial strength corresponds to a score of nine, the lowest to a score of zero. All firms publish financial data in quarterly basis, for all the formulas below t represent financial quarter.

Category 1: Signals based on Earning and Cash Flow Profitability

Return on Asset (ROA)

F_ROA- return on assets: F_ROA is defined as a firm's 12-month trailing profit before extraordinary items, scaled by total asset at the beginning of the year. If F_ROA is positive, one point is awarded, and zero otherwise.

$$ROA(t) = \frac{\sum_{k=t-3}^{t} Net\ Income\ Before\ Extraordinary\ Item(k)}{Assets(t-4)}$$

Change in ROA (ΔROA)

F_ΔROA- Change in return on asset: F_ΔROA is defined as the current year's ROA minus last year's ROA. This variable gives an indication of the trend of a firm's profitability. If F_ΔROA is positive, one point is awarded, and zero otherwise.

$$\Delta ROA(t) = ROA(t) - ROA(t-4)$$

Cash flow from operations(CFO)

F_CFO- Cash flow from operations: F_CFO is defined as the 12-month trailing cash flow from operating activities, scaled by total asset at the beginning of the year. Firms which generate a positive cash flow are more likely to stay solvent and be less dependent on external debt. If F_CFO is positive, one point is awarded, and zero otherwise.

$$CFO(t) = \frac{\sum_{k=t-3}^{t} Cashflow\ from\ operations(k)}{Assets(t-4)}$$

Accrual

F_Accrual: F_Accrual is defined as ROA – CFO. Accruals measure the quality of earnings. Sloan (1996) provides evidence that positive accruals could be indicative of lower subsequent earnings and management of earnings. If F_Accrual is negative, one point is awarded, and zero otherwise.

$$Accrual(t) = ROA(t) - CFO(t)$$

Category 2: Signals based on Leverage, liquidity, and source of fund

Change in Leverage(ΔLeverage)

F_ΔLeverage- change in long-term leverage: The long-term debt asset ratio is defined as total long-term debt (including the portion of long-term debt classified as current), scaled by average total assets for the year. Highly levered balance sheets could be indicative of risk of insolvency, and an increase in leverage is regarded as a negative sign because it is indicative of a firm's inability to generate internal funding. If F_ΔLeverage is a negative, then one point is awarded, and zero otherwise.

$$\Delta Leverage(t) = \frac{Long{-}term\ \ Debt(t)}{\frac{1}{2}*Assets(t-4)+\frac{1}{2}*Assets(t)} - \frac{Long{-}term\ \ Debt(t-4)}{\frac{1}{2}*Assets(t-8)+\frac{1}{2}*Assets(t-4)}$$

Change in Liquidity(ΔLiquidity)

F_ΔLiquidity - Change in current ratio: Current ratio is defined as total current assets divide by total current liabilities. If F_ΔLiquidity is negative, then one point is awarded, and zero otherwise.

$$\Delta Liquidity(t) = \frac{Current\ Assets(t)}{Current\ liabilities(t)} - \frac{Current\ Assets(t-4)}{Current\ liabilities(t-4)}$$

Change in Equity

EQ - change in number of shares outstanding: If the current number of shares is less than the number of shares 12 months ago, then one point is awarded, and zero otherwise. Our calculation of the number of shares is adjusted for stock split.

Category 3: Signals based on operating efficiency

Change in Gross margin (ΔMargin)

ΔMargin - change in gross margin: Gross margin is defined as sales less cost of sales (12-month trailing). If ΔMargin is greater than one, then one point is awarded, and zero otherwise.

$$\Delta Margin(t) = \frac{\sum_{k=t-3}^{t}[Sales(k) - COS(k)]}{\sum_{k=t-3}^{t} Sales(k)} - \frac{\sum_{k=t-7}^{t-4}[Sales(k) - COS(k)]}{\sum_{k=t-7}^{t-4} Sales(k)}$$

Change in asset turnover (ΔTurnover)

ΔTurnover- change in asset turnover. Asset turnover is defined as 12-month trailing net sales scaled by total average. If ΔTurnover is greater than zero, then one point is awarded, and zero otherwise.

$$\Delta Turnover(t) = \frac{\sum_{k=t-3}^{t} Sales(k)}{\frac{1}{2} * Assets(t-4) + \frac{1}{2} * Assets(t)} - \frac{\sum_{k=t-3}^{t} Sales(k)}{\frac{1}{2} * Assets(t-8) + \frac{1}{2} * Assets(t-4)}$$

The aggregated F-Score is the sum of the individual binary signals. Mathematically, F-

Score is defined as follows:

$$F\_Score = F\_ROA + F\_\Delta ROA + F\_CFO + F\_Accrual + F\_Leverage \\ + F\_Liqudity + F\_EQ + F\_\Delta Margin + F\_\Delta Turnover$$

In this study, we ensure that the information needed for calculation of the F-Score and BM ratio is already available when the portfolio is formed (to avoid forward-looking bias). For example, if a firm's year-end report is released on 27th April, then for the March portfolio we only use 12-month trailing data up to the third quarter for that stock.

In this analysis, firms with F-Scores of seven or greater are classified as high score firms, and firms with F-scores of two or less are classified as low score firms. Since all buy and sell signals are generated on the last day of month t-1, we know precisely the weighting of each stock in the portfolio. The return of the portfolio is calculated based on the equally-weighted return of each stock in the portfolio.

4. Empirical Results

The empirical results are reported as the equally-weighted average one-month buy-and-hold returns. In this section, we first present the descriptive statistics of the high and low BM firm portfolio, then the returns of the F-Score strategy, conditioned on BM ratio, and, finally the returns of partition analysis, conditioned on size, liquidity and analyst coverage.

4.1 Descriptive statistics

Panel A of table 1 presents the descriptive statistics of firms in the sample, for all firm-year observations. The average high BM firm has a mean (median) market capitalization of 24,516 (3,917) million. The large difference between mean and median indicates the presence of some very large firms in the high BM sample. In contrast to

Piotroski (2000) the average firm's ROA is positive, with a mean and median of 0.036 (0.027), and 90% firms earn a positive profit. Furthermore, the average high BM firm saw an increase in CFO and a decrease in accrual.

Low BM firms are much smaller than the high BM firms in terms of capitalization and assets. This result is expected, because most of the low BM firms are small growth firms. Consistent with Fama and French (1995), the average low BM firm earns higher ROA than the average high BM firm. In addition, the average low BM firm also saw an increase in ROA. However, the average low BM firm has negative cash flows, and their leverage (liquidity) is higher (lower) than in the previous year.

Panel B of Table 1 presents the returns for both high and low BM portfolios. The mean market-adjusted return of high (low) BM firms is 0.38% (-0.49%). Consistent with Laknoshok, Shleifer, and Vishny (1994), high (low) BM firms earn positive (negative) market-adjusted returns, following portfolio formation. The median of the high (low) BM firm portfolio is -0.74% (-1.13%), indicating that the majority of the firms underperform the market. Comparing the return distribution of our low BM firm portfolio to the return distribution of Our high BM firm portfolio, we discover that the low BM firm portfolio has a wider return distribution. If the F-Score strategy can eliminate the firms in the left tail of the return distribution, then the F-Score should be more effectively applied to the low BM firms than to the high BM firms.

4.2 Return of Piotroski's Strategy

As the F-Score consists of nine signals, it can have ten values, from zero to nine. Due to too few observations in portfolio 0, we decide to merge portfolio 0 and portfolio 1, and, as a result, portfolio 1 consists of all firms with F-Scores of 0 and 1. Table 2 presents the returns to the F-Score strategy. Panel A of table 2 shows that most of the observations are clustered around the F-Score between 3 and 7, indicating that the vast majority of the firms have conflicting performance signals, which is consistent with Piotroski (2000). The high score portfolio, on average earns 0.48%, the low score portfolio on average earns -0.51%. The return difference is 0.98%, statistically significant at the 1% level, indicating that the long high F-Score portfolio and short low F-Score portfolio may be very effective.

Unlike Piotroski (2000), we find the F-Score does not work within the high BM firm sample. Although high score firms earn a return of 0.67%, and they outperform low score firms by 0.65%, the t-statistics show that the return difference is not statistically significant. Furthermore, the F-Score strategy does not shift the return distribution of the high BM firm portfolio to the right. The 10th percentile of high (all) F-Score firms is -10.81% (-9.87%) and the 90th percentile is 11.89 (12.24%). The high score portfolio underperforms the generic high BM portfolio in the 10th and 90th percentile, indicating that the F-score strategy cannot eliminate the worst performing firms, and cannot identify the outperforming firms in the high BM firm sample. Figure 1 shows the cumulative returns of long high score firms and short low score firms for high BM sample. As we can see the cumulative return is very flat for most the sample period, high score firms did not consistently outperform low score firms. Figure 1 may explain why our t-test is not statistically significant.

On the other hand, Panel C shows the F-Score is working for the low BM firm sample. Consistent with Mohanram (2005), we find that firms in the high score portfolio earn positive but small market-adjusted returns, while firms in the low score portfolio earn large negative market-adjusted returns. This indicates that the F-Score strategy is more effective at identifying potential underperforming stocks in the low BM firm portfolio. The mean return of the high (low) score portfolio is 0.23% (-1.05%), the return difference is 1.28%, and statistically significant. When analyzing the return distribution in table 2, one can see that the F-Score strategy shifts the return distribution of the low BM firm portfolio to the right. The 25th percentile, median, 75th, and 90th returns of the high F-Score portfolio are significantly higher than the returns of the low F-Score portfolio, and the generic low BM portfolio. However, the 10th percentile of the high F-Score portfolio return is 0.31% lower than the low F-Score portfolio, and 0.41% lower than the generic low BM portfolio. In contrast, the low F-Score portfolio underperforms the generic low BM portfolio in all the percentiles. This indicates that the F-Score can successfully identify poor performing firms in the low BM firm portfolio. Figure 2 shows the cumulative returns of long high score firms and short low score firms for low BM sample. The cumulative return has a fairly consist upward trend which shows high score firms consistently outperform low score firms.

Table 1

Financial and Return Characteristics of Sample Firms between 2006 and 2014

Table 1 shows the mean, median, and standard deviation of sample firms' value on F-Score variables. F-Score variables have been winsorized at 1% and 99%. Returns are calculated as the market adjusted one-month buy-and-hold returns. n/a means that the value is not available.

Variable	**Mean**	**Median**	**Std Dev**	**% Positive**
Panel A1 : Financial Characteristics of High BM Firms				
MVE	24,516	3,917	128,555	n/a
Asset	79,783	3,590	758,767	n/a
BM ratio	0.715	0.682	0.732	n/a
ROA	0.036	0.027	0.075	0.900
∆ROA	-0.004	-0.003	0.086	0.430
∆Margin	-0.004	-0.004	0.058	0.446
CFO	0.006	0.008	0.033	0.641
∆Liqudity	-0.072	-0.022	0.718	0.459
∆Leverage	0.004	0.000	0.059	0.338
∆Turnover	-0.004	-0.004	0.058	0.446
Accural	-0.005	-0.005	0.075	0.444
Panel A2 : Financial Characteristics of Low BM firms				
MVE	12,145	2,752	59,514	n/a
Asset	10,120	1,824	89,751	n/a
BM ratio	0.142	0.194	0.256	n/a
ROA	0.070	0.050	0.105	0.910
∆ROA	0.000	0.000	0.100	0.500
∆Margin	-0.001	-0.002	0.060	0.474
CFO	-0.054	-0.062	0.598	0.414
∆Liqudity	-0.109	-0.012	0.910	0.473
∆Leverage	0.004	0.000	0.054	0.267
∆Turnover	-0.001	-0.002	0.060	0.474
Accural	0.002	-0.002	0.090	0.476

Panel B : One-Month Market Adjusted Buy-and-Hold Returns	**Mean**	**25%**	**75%**	**% positive**
Low BM	-0.49%	-7.57%	5.88%	45.26%
High BM	0.38%	-5.02%	4.64%	45.88%

Table 2

Returns to an Investment Strategy Based on F-Score

Table 2 presents one-month buy-and-hold market adjusted returns, The F-Score is equal to the sum of nine individual variables. Or F-Score = F_ROA + F_ΔROA + F_CFO + F_Accrual + F_Leverage + F_Liqudity + F_EQ + F_ΔMargin + F_ΔTurnover. Where each binary signal equals one (zero) if the variable indicates improved (deteriorated) future performance. The high (low) score portfolio consists of firms with an aggregate score of 7,8, or 9 (0,1, or 2). The F-Score 1 group consists of firms with an aggregate score of 0 or 1. t-statistics for mean returns are from two-sample t-tests assuming unequal variance. Significance levels using two-tailed tests are represented by ***1% level; **5% level; *10% level.

Panel A :All Firms

F-Score	*N*	*Mean*	*0.1*	*0.25*	*Median*	*0.75*	*0.9*	*% Positive*
1	217	-0.96%	-13.54%	-7.43%	-1.91%	4.79%	15.96%	38.71%
2	1141	-0.42%	-11.25%	-6.68%	-1.47%	4.72%	12.38%	43.56%
3	3032	-0.23%	-11.59%	-6.36%	-0.95%	5.26%	12.65%	44.59%
4	5007	-0.21%	-11.50%	-6.16%	-1.08%	5.09%	12.68%	44.44%
5	5871	-0.07%	-11.76%	-6.28%	-1.02%	5.16%	13.10%	45.00%
6	4989	-0.15%	-12.42%	-6.30%	-0.94%	5.15%	13.21%	45.28%
7	3431	0.26%	-12.05%	-5.99%	-0.58%	5.65%	13.66%	46.93%
8	1890	0.20%	-11.93%	-6.19%	-0.75%	5.68%	14.03%	46.93%
9	419	0.28%	-12.14%	-5.76%	-0.45%	5.26%	12.81%	49.16%
Low		-0.51%	-11.45%	-6.79%	-1.62%	4.74%	12.49%	42.78%
High		0.48%	-12.14%	-5.90%	-0.52%	5.69%	13.83%	47.46%
High-Low		0.98%	-0.69%	0.89%	1.11%	0.95%	1.34%	
t-statistic		3.01***						
p-value		0.003						

Panel B :High BM Firms

F-Score	***N***	***Mean***	***0.1***	***0.25***	***Median***	***0.75***	***0.9***	***% Positive***
1	79	-0.21%	-9.47%	-6.02%	-2.23%	2.49%	12.50%	34.18%
2	386	0.06%	-9.73%	-5.40%	-1.17%	4.20%	12.06%	43.78%
3	988	0.34%	-9.84%	-5.22%	-0.61%	4.29%	12.27%	45.45%
4	1581	0.45%	-9.57%	-4.95%	-0.82%	4.85%	11.81%	45.98%
5	2045	0.40%	-9.69%	-5.03%	-0.93%	4.62%	12.68%	45.09%
6	1566	0.12%	-10.34%	-5.19%	-0.87%	4.53%	12.50%	44.83%
7	949	0.77%	-9.72%	-4.84%	-0.02%	5.17%	11.94%	49.84%
8	631	0.31%	-10.81%	-4.69%	-0.78%	4.55%	11.66%	45.96%
9	156	1.58%	-8.37%	-3.95%	0.72%	5.37%	12.47%	55.13%
All		0.38%	-9.87%	-5.02%	-0.74%	4.64%	12.24%	45.88%
Low		0.02%	-9.58%	-5.67%	-1.40%	3.81%	12.29%	42.15%
High		0.67%	-10.81%	-4.68%	-0.23%	4.97%	11.89%	48.91%
High-Low		0.66%	-1.24%	0.99%	1.17%	1.16%	-0.40%	
t-statistic		1.27						
p-value		0.20						

Panel C :Low BM Firms

F-Score	***N***	***Mean***	***0.1***	***0.25***	***Median***	***0.75***	***0.9***	***% Positive***
1	69	-3.3%	-21.0%	-10.6%	-1.7%	6.3%	11.2%	43.5%
2	349	-0.6%	-12.7%	-7.7%	-1.4%	5.4%	13.2%	45.3%
3	1048	-1.0%	-13.6%	-7.9%	-1.6%	5.6%	12.3%	43.0%
4	1645	-0.9%	-13.3%	-7.5%	-1.3%	5.6%	13.2%	44.1%
5	1883	-0.6%	-13.6%	-7.7%	-1.3%	5.7%	14.1%	44.8%
6	1818	-0.5%	-14.1%	-7.5%	-1.0%	5.8%	13.5%	45.8%
7	1356	0.2%	-14.0%	-7.3%	-0.8%	6.5%	14.7%	46.2%
8	657	0.5%	-12.0%	-6.9%	-0.3%	6.4%	15.2%	49.6%
9	113	-0.7%	-14.8%	-9.1%	-1.3%	7.0%	13.5%	45.1%
All		-0.5%	-13.6%	-7.6%	-1.1%	5.9%	13.7%	45.3%
Low		-1.1%	-13.7%	-8.1%	-1.6%	5.5%	12.7%	45.0%
High		0.2%	-14.0%	-7.3%	-0.7%	6.5%	14.8%	47.2%
High-Low		1.3%	-0.3%	0.8%	0.9%	1.0%	2.1%	
t-statistic		2.01**						
p-value		0.045						

Figure 1 Cumulative hedged returns to an investment strategy based on F-Score (high BM sample)

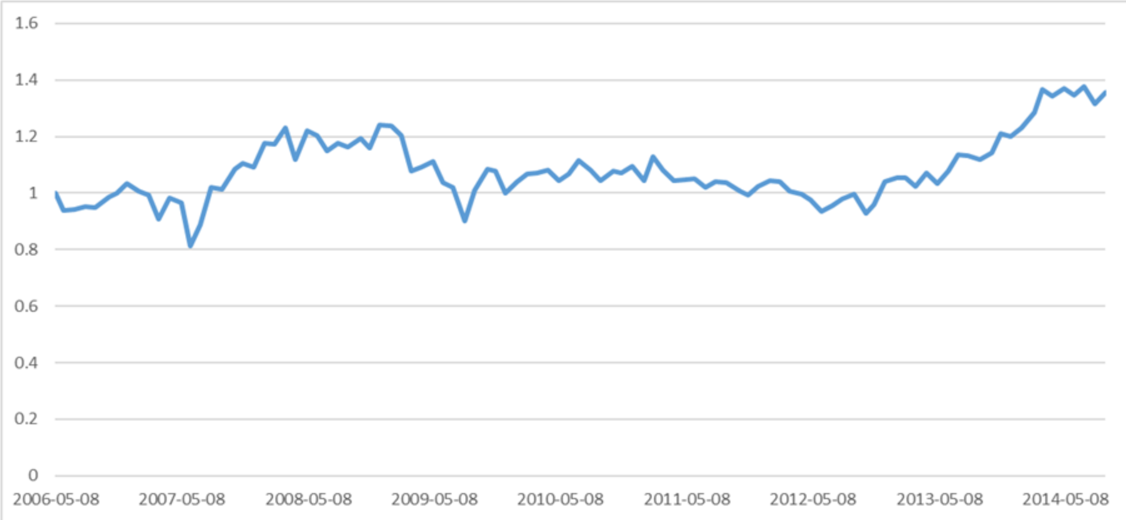
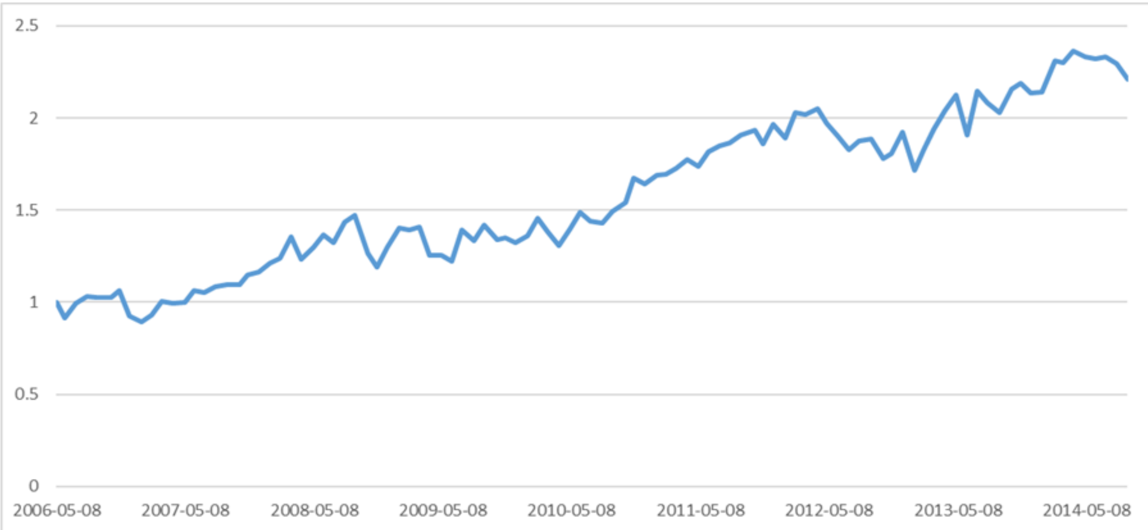


Figure 2 Cumulative hedged returns to an investment strategy based on F-Score (low BM sample)



4.3 Portion Analysis

A concern of any investment strategy is whether the strategy picks a set of firms that are small, or thinly traded. If this is the case, such an investment strategy will be very difficult to implement in real life. Piotroski (2000) proposes four firm assessment characteristics: size, trading volume, analyst following, and share price. In this analysis, we follow a similar approach except we do not use share price as an indicator of stock liquidity, because in China low share price stocks are often the most liquid.

4.3.1 Size Partition

The median value of market capitalization is calculated at the last day of month t-1, based on the entire sample. Any firm with market capitalization above (below) the median is classified as a large (small) firm. Within the large (small) firm sample, we further separate firms into high BM firms and low BM firms.

Panel A1 of table 3 presents the return by size of the high BM firm sample. For the large (small) firm sample the return of the high score portfolio is 0.06% (1.35%), the return of the low score portfolio is -0.36% (0.22%), the return difference is therefore 0.34% (0.68%). t-statistics indicate that the return difference is not statistically significant for both the small and large firm samples. The return difference of the small firm sample is larger than the return difference of the large firm sample, consistent with Piotroski (2000), who finds that his F-Score works better in small firms.

Panel A1 of table 3 presents the return by size partition of the low BM firm sample. For large(small) firms the return of the high score portfolio is -0.05% (0.69%), the return of the low score portfolio is -1.44% (-0.81%), and therefore the return difference is 1.39% (1.50%). t-statistics indicate the return difference is statistically significant at the 10% level for both the large and small firm samples. It is worth noting that the success of the F-Score strategy in the large firm sample relies heavily on the ability to short low F-Score firms. When analyzing the returns of the small and large firm samples, it is clear that the small firms outperform the large firms. this result is consistent with Cheung, Hoguet and Ng (2015). If an investor wants to capture the small-cap and BM premium, they could buy small high BM firms with high F-Scores and short large low BM firms with low F-Scores. This investment strategy yields a market-adjusted return of 2.79% per month, which is equivalent to 39.13% per annum (if compounded). Overall, our research result is consistent with the findings of Piotroski (2000) and Mohanram (2005), both papers show fundamental analysis works better in small firm samples than in large firm samples. However, Piotroski (2000) finds his F-Score strategy is not statistically significant in the large firm sample. In contrast, we find the F-Score strategy is equally effective for the small and large firm samples.

4.3.2 Liquidity partition

The median value of the daily trading volume is calculated on the last day of month t-1 and based on the full sample. Any firms with trading volumes above (below) the median is classified as high (low) liquidity firms. Within the high (low) liquidity firm sample we separate the high BM firms and low BM firms.

Panel B1 of table 3 presents the return by liquidity partition of the high BM firm sample. For high (low) liquidity firms the return of the high score portfolio is 0.28% (0.93%), the return of the low score portfolio is -0.10% (0.08%), and the return difference is 0.38% (0.85%). t-statistics indicate the return difference is not statistically significant for either the large or small firm sample.

Panel B2 of Table 3 shows that, in the low BM firm sample, the benefit of the F-Score strategy is concentrated in the low liquidity firm sample. For low liquidity firms the return of the high (low) score portfolio is 0.79% (-0.70%), the return difference is 1.49% and it is statistically significant. In contrast, the return difference is not statistically significant in the high liquidity sample. The return difference for the high liquidity sample is quite high (1.30%). However, due to the high return volatility, the F-Score strategy failed the significance test in our high liquidity sample. The evidence from the low BM firm sample suggests that the usefulness of the F-Score strategy is concentrated in the low liquidity firms in the low BM firm sample.

Table 3
Returns to an Investment Strategy Based on F-Score by Size, liquidity, and Analyst Following

High BM

Panel A1 : One-Month MAR by Size Partition

	Small Firms		*Large Firms*	
	N	***Mean***	***N***	***Mean***
All	4520	0.91%	3809	0.17%
Low Score	299	0.22%	166	-0.36%
High Score	826	1.35%	910	0.06%
High-Low		1.12%		0.42%
t-statistics		1.565		0.587
p-value		0.118		0.558

Panel B1 : One-Month MAR by Liquidty Partition

	Low Liquidity Firms		*High Liquidity Firms*	
	N	***Mean***	***N***	***Mean***
All	5124	0.74%	3199	0.31%
Low Score	301	0.08%	164	-0.10%
High Score	1052	0.93%	684	0.28%
High-Low		0.85%		0.38%
t-statistics		1.39		0.40
p-value		0.164		0.687

Panel C1 : One-Month MAR by Analyst Following Partition

	No Analyst		*With Analyst*	
	N	***Mean***	***N***	***Mean***
All	370	1.00%	7953	0.55%
Low Score	34	0.22%	431	-0.13%
High Score	50	1.93%	1686	0.63%
High-Low		1.72%		0.76%
t-statistics		1.96*		1.42
p-value		0.054		0.156

Low BM

Panel A2 : One-Month MAR by Size Partition

	Small Firms		*Large Firms*	
	N	***Mean***	***N***	***Mean***
All	3647	0.22%	5208	-0.44%
Low Score	257	-0.81%	161	-1.44%
High Score	789	0.69%	1337	-0.05%
High-Low		1.50%		1.39%
t-statistics		1.783*		1.702*
p-value		0.075		0.089

Panel B2 : One-Month MAR by Liquidity Partition

	Low Liquidity Firms		*High Liquidity Firms*	
	N	***Mean***	***N***	***Mean***
All	3395	0.32%	5460	-0.48%
Low Score	208	-0.70%	210	-1.41%
High Score	789	0.79%	1337	-0.11%
High-Low		1.49%		1.30%
t-statistics		1.65*		1.42
p-value		0.099		0.157

Panel C2 : One-Month MAR by Analyst Following Pa

	No Analyst		*With Analyst*	
	N	***Mean***	***N***	***Mean***
All	325	-1.01%	8530	-0.14%
Low Score	20	-1.27%	398	-1.04%
High Score	77	-0.17%	2049	0.24%
High-Low		1.09%		1.28%
t-statistics		0.358		1.97**
p-value		0.723		0.049

4.3.3 Analyst Following

The sample is divided into two groups: Firms that are not followed by analysts (neglected firms) and firms with an analyst following. Analyst following is calculated as the number of analysts who followed the firm in the past 180 days. The number of firms in each group differs significantly: Fewer firms are not being followed by analysts. The number of firms being followed by analysts in the high (low) BM portfolio is 7953 (8539). It seems there is no significant difference between the high and low BM firm samples in terms of number of analysts who follow these firms. This finding is not consistent with the findings of Stickel (1998), who finds that high BM firms are less likely to be covered by analysts.

Panel C1 of Table 3 shows that, in the high BM firm sample, the F-Score strategy can successfully differentiate winners and losers within the sample of firms not being followed by analysts. The return of the high (low) score portfolio in the sample with no analyst following is 1.93% (0.22%), the return difference is 1.72% and it is statistically significant at the 10% level. This result is consistent with Piotroski (2000), who finds stocks are more likely to be mispriced if their coverage by analysts is low. Fundamental analysis is therefore most useful for such stocks. Within the high BM firm sample, the average firm with no analyst following sample earns 1.00%, while the average firm in the sample with an analyst following earns 0.55%. Again, this finding is consisting with Piotroski (2000). The high score portfolio in the sample with no analyst following earns 1.93%, indicating that the market underprices the high quality ‘neglected’ firms.

In contrast, Panel C2 of Table 3 shows that in the low BM firm sample, the F-Score strategy is significant in the sample with analyst following. The return of the high (low) score portfolio of firms with an analyst following is 0.24% (-1.04%). The return difference is 1.28%, statistically significant at the 5% level. The result contradicts the findings of Mohanram (2005), which was that fundamental analysis is more effective with firms which have no analyst coverage in the low BM firm sample. However, analysing the returns of the samples in the high and low score portfolios with analyst coverage, we discover that most of the profit from the F-Score strategy comes from shorting low score firms. This indicates that the market overprices the poor fundamental glamour stocks, or that the market is slow to realise deterioration in a firm’s fundamental.

5. Analysis of Empirical Results

5.1 High BM firm Sample

Evidence from the previous section shows the F-score does not work for the high BM firm sample as a whole. A possible explanation is that the market has already incorporated all the fundamental information in the stock price at the time when the portfolio is formed, and the market is efficient for the high BM firm sample.

Tables 4 and 5 present the evidence that could provide us with more insight as to why the F-Score does not work for the high BM firm sample. Panel A of Table 4 presents the correlations for each of the F-Score signals, as well as the one-month buy-and-hold market-adjusted return. Not all F-Score signals are positively correlated with Market-adjusted-returns (MAR). The correlation of F_Accrual and F_ΔLiqudity with MAR is negative, indicating that obtaining a score of 1 for F_Accrual and F_ΔLiqudity could negatively impact the returns of the F-Score strategy. In general, the correlation between the F-Score signal and the market adjusted return is fairly weak, indicating that the market has already priced in much of the information in the F-Score signal. Table 5 shows the contribution of each F-Score signal to the F-Score strategy. The return differential is defined as the average return of firms with a score of 1, minus the average return of firms with a score of 0. A one-tailed t-test is performed to test whether the average return of firms with a score of 1 is significantly higher than the average return of firms with a score of 0, and t-statistics are presented in the last column. Panel A of table 5 shows only the ROA demonstrating a statistically significant ability to separate firms. Seven signals are positively related to future returns, but these are not statistically significant. F_ΔLiqudity shows a negative sign, and it is statistically significant. Conflicting signals within the F-Score is not expected, and, therefore, it is necessary to investigate the impact of not including F_ΔLiqudity in the F-Score. The result of the analysis is presented in the next section.

Another possible explanation for why the F-Score does not work within the high

BM firm sample could be the treatment of the returns of delisted firms. Like Piotroski (2000), we assume all delisted firms have zero returns. Such a simplified assumption is not realistic in practice. There are two types of delisting: The first is when firms that delist due to bad performance. The second is when firms delist due to mergers and acquisitions. Assuming that both types of delisting have zero returns is not realistic, because delistings due to bad performance are likely to result in large negative returns, whereas the latter type of delisting could result in large positive returns. Ma (2003) shows that, in China, firms earn significant market-adjusted returns after mergers and acquisitions. Although we identify the potential problem with our return calculation method, we cannot distinguish between type 1 and type 2 delistings, because of the lack of data. The impact of using simplified delisted returns on the return of the F-Score strategy is therefore not examined in this study.

5.2 Low BM firms

On the other hand, the F-Score works well for the low-BM firms. Panel B of Table 4 shows that the correlation between F-Score and returns are all positive. Furthermore, the correlation between F-Score and MAR is significantly higher for low BM firms than for high BM firms. indicating that the F-Score is more effective when applied to a low BM firms than to high BM firms. It is worth noting that, in low BM firms F_Accrual (0.6%) and F_ΔLiqudity (0.04%) are two of the weakest signals, and this shows that F_Accrual and F_ΔLiqudity are not very effective for predicting future returns. Panel B of table 5 shows that five out of the nine signals in the F-Score show statistically significant ability to separate firms in terms of future returns. F_ΔLiqudity and F_ΔLeverage show negative signs. Again, evidence shows that F_ΔLiqudity is not a useful signal for predicting future returns. Nevertheless, that F-Score works within low BM firm sample should not be a surprise, because prior studies such as those of Piotroski (2004), Rathjens and Schellhove (2011), and Mohr (2010) show that the F-Score is effective in differentiating winners and losers within low BM firm samples. As

Table 4

Spearman Correlation amongst F-Score Fundamental Signals and returns

Panel A : High BM Firms

	F1	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*	*F-Score*
MAR	0.032	0.004	0.020	-0.003	0.013	-0.024	0.009	0.003	0.004	0.016
F1: F_ROA	1.000	0.085	0.181	-0.158	0.027	0.106	0.093	0.078	-0.088	0.316
F2: F_CFO		1.000	0.061	0.620	0.143	-0.068	0.065	0.100	0.010	0.497
F3: F_∆ROA			1.000	-0.018	0.010	0.106	0.258	0.468	-0.011	0.599
F4: F_Accural				1.000	0.147	-0.094	0.014	0.048	0.092	0.419
F5: F_∆Leverage					1.000	-0.178	-0.011	-0.023	-0.018	0.243
F6: F_∆Liqudity						1.000	0.066	0.085	-0.007	0.261
F7: F_∆Margin							1.000	0.100	0.038	0.430
F8: F_∆Turnover								1.000	0.049	0.513
F9: F_EQ									1.000	0.256

Panel B : Low BM Firms

	F1	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*	*F-Score*
MAR	0.012	0.016	0.022	0.006	0.010	0.000	0.035	0.013	0.023	0.034
F1: F_ROA	1.000	0.112	0.261	-0.218	0.002	0.128	0.136	0.111	-0.173	0.310
F2: F_CFO		1.000	0.023	0.488	0.092	-0.013	0.083	0.035	0.050	0.455
F3: F_∆ROA			1.000	-0.089	-0.028	0.170	0.295	0.438	-0.009	0.584
F4: F_Accural				1.000	0.113	-0.110	-0.002	0.019	0.179	0.368
F5: F_∆Leverage					1.000	-0.141	0.014	-0.002	0.068	0.275
F6: F_∆Liqudity						1.000	0.081	0.097	-0.064	0.304
F7: F_∆Margin							1.000	0.057	-0.013	0.441
F8: F_∆Turnover								1.000	0.093	0.491
F9: F_EQ									1.000	0.314

Rathejens and Schellhove (2011) point out, most of the F-Score signals can be regarded as a positive for both high and low BM firms. e.g F_ROA, F_∆ROA, F_∆Margin, F_∆Turnover, F_Accruals and F_CFO.

5.3 Modified F-Score

This section investigates the impact on returns, by removing F_ΔLiqudity as a signal from the F-Score calculation. The key question we try to answer is if removing F_ΔLiqudity from the original F-Score formula improves the returns of the F-Score strategy. We define a new F-Score model (Modified F-Score). The modified F-Score only has only 8 binaries, as F_ΔLiqudity is removed from the original model. Everything else remains unchanged.

Panel A of Table 6 presents the returns of the modified F-Score strategy for the high BM firm sample. The return difference of the F-Score strategy for the high BM sample improves, from 0.66% to 0.90%, and the return difference is statistically significant. The 10th (90th) percentile return difference of the high-low portfolio improves from -1.24% (-0.40%) to -0.38% (-0.02%). In the low BM firm sample, the return difference of the F-Score strategy marginally increases from 1.28% to 1.29%. However, the modified F-Score improves 10th percentile returns of the high-low portfolio by 0.31%, and the return distribution of the modified F-Score is positive for all percentiles. The above evidence indicates that F_ΔLiqudity may not be a useful signal.

Table 5

Relation between Individual F-Score Signals and future returns

Table 5 shows the one-month buy-and-hold market adjusted return of individual F-Score signals and their significance. t-statistics for the mean difference are from two sample t-tests. Significance levels using one-tailed tests are represented by *** 1%; ** 5%; * 10%. Prefix "F_" is omitted for succinctness.

Panel A: High BM Firms

Signal	*1*	*0*		
	Mean	*Mean*	*(1)-(0)*	*t-statistics*
ROA	0.76%	0.17%	0.59%	1.84*
CFO	0.74%	0.37%	0.37%	1.42
ΔROA	0.90%	0.62%	0.29%	1.37
Accural	0.67%	0.58%	0.09%	0.40
ΔLeverage	0.71%	0.70%	0.01%	0.06
ΔLiqudity	0.44%	0.90%	-0.46%	2.20**
ΔMargin	0.81%	0.68%	0.13%	0.63
ΔTurnover	0.68%	0.70%	-0.02%	0.12
EQ	0.70%	0.66%	0.04%	0.23

Panel B: Low BM Firms

Signal	*1*	*0*		
	Mean	*Mean*	*(1)-(0)*	*t-statistics*
ROA	-0.16%	-0.56%	0.40%	0.99
CFO	-0.09%	-0.74%	0.65%	2.16**
ΔROA	0.14%	-0.35%	0.49%	1.86*
Accural	-0.09%	-0.39%	0.31%	1.17
ΔLeverage	-0.26%	-0.16%	-0.10%	0.48
ΔLiqudity	-0.24%	-0.13%	-0.11%	0.47
ΔMargin	0.27%	-0.57%	0.83%	3.54***
ΔTurnover	0.06%	-0.43%	0.49%	1.86*
EQ	0.04%	-0.52%	0.57%	2.39**

Table 6

Return to an Investment Strategy Based on Modified F-Score

Table 6 presents one-month buy-and-hold market adjusted returns, Mod_F-Score is equal to sum of **eight** individual variables. Or Mod_F-Score = F_ROA + F_ΔROA + F_CFO + F_Accrual + F_Leverage + F_EQ + F_ΔMargin + F_ΔTurnover. Where each binary signal equals to one(zero) if the variable indicates improved (deteriorated) future performance. The high (low) score portfolio consists of firms with an aggregate score of 7 or 8 (0,1, or 2). The F-Score 1 group consists of firms with an aggregate score of 0 or 1. t-statistics for mean returns are from two-sample t-tests assuming unequal variance. Significance levels using 2 tailed tests are represented by ***1% level; **5% level; *10% level.

Panel A :High BM Firms

Mod_F_Score	***N***	***Mean***	***0.1***	***0.25***	***Median***	***0.75***	***0.9***	***% Positive***
1	168	-0.68%	-9.78%	-6.13%	-2.24%	2.85%	12.44%	36.90%
2	612	0.07%	-9.57%	-4.86%	-1.22%	4.22%	11.89%	43.79%
3	1163	0.53%	-9.65%	-5.22%	-0.61%	4.49%	13.13%	45.83%
4	1959	0.50%	-9.27%	-4.94%	-0.86%	4.83%	12.04%	45.74%
5	1872	0.28%	-10.31%	-5.16%	-0.82%	4.57%	12.66%	45.41%
6	1403	0.02%	-10.47%	-5.27%	-0.85%	4.31%	12.22%	45.69%
7	859	0.80%	-10.39%	-4.69%	-0.25%	5.36%	12.72%	48.54%
8	351	0.83%	-8.98%	-4.11%	0.09%	5.00%	9.99%	50.71%
All		0.37%	-9.89%	-5.04%	-0.77%	4.61%	12.34%	45.84%
Low		-0.09%	-9.61%	-5.38%	-1.48%	3.66%	12.17%	42.31%
High		0.81%	-9.98%	-4.57%	-0.15%	5.24%	12.16%	49.17%
High-Low		0.90%	-0.38%	0.81%	1.32%	1.58%	-0.02%	
t-statistic		2.02**						
p-value		0.044						

Panel B :Low BM Firms

Mod_F_Score	***N***	***Mean***	***0.1***	***0.25***	***Median***	***0.75***	***0.9***	***% Positive***
1	130	-2.25%	-20.96%	-9.92%	-0.81%	6.50%	11.83%	47.69%
2	574	-0.69%	-12.67%	-7.72%	-1.93%	5.56%	12.83%	42.16%
3	1340	-1.22%	-14.25%	-7.88%	-1.29%	5.15%	12.40%	43.66%
4	2021	-0.66%	-12.87%	-7.55%	-1.36%	5.45%	13.28%	44.19%
5	1919	-0.15%	-13.60%	-7.15%	-0.69%	6.40%	14.13%	47.11%
6	1714	-0.55%	-14.33%	-8.01%	-1.33%	6.05%	14.53%	43.99%
7	978	0.44%	-12.67%	-7.07%	-0.28%	6.62%	14.81%	49.08%
8	275	-0.14%	-14.21%	-7.69%	-0.91%	6.29%	13.67%	47.64%
All		-0.50%	-13.64%	-7.60%	-1.10%	5.90%	13.70%	45.26%
Low		-0.98%	-13.36%	-8.12%	-1.88%	5.59%	12.51%	43.18%
High		0.31%	-13.35%	-7.23%	-0.50%	6.48%	14.73%	48.76%
High-Low		1.29%	0.01%	0.89%	1.39%	0.89%	2.23%	
t-statistic		2.31**						
p-value		0.021						

6. Performance of Piotroski's F-Score Across Time

6.1 Calendar year

In this section, we examine the robustness of the F-Score strategy across time. First, we present the results of the performance of the F-Score for each calendar year between 2006 and 2014. Second, we present the performance of the F-Score during reporting and non-reporting months.

Table 7 shows the mean MAR for high and low score groups for each of the calendar years (2006-2014). For the high BM firm sample, the strategy is not very robust across time. In only five out of the nine years is the mean return difference positive, and in only two out of the nine years is the mean return difference statistically significant. In 2010 the negative mean return difference is statistically significant. On the other hand, for the low BM firm sample, the strategy is remarkably robust across time. The return difference is positive in nine out of the nine years, and in four out of the nine years the return difference is statistically significant.

6.2 Reporting vs Non-Reporting Month

In China, about 95% of the firms report year-end numbers between March and April, and 100% of the firms report first quarter numbers in April. 91% of the firms report mid-year numbers during August, and 100% of the firms report third quarter numbers during October. Based on this observation, we define March, April, August and October as reporting months, and the other months as non-reporting months.

Table 8 presents the returns of our long-short strategy (long high score firms, short low score firms) for reporting and non-reporting months. In the high BM firm sample, the long-short strategy earns 1.24% during reporting months, and the return is statistically significant at the 10% level. This result is consistent with Piotroski (2000) who finds that, for neglected firms (high BM firms), the F-Score strategy is most effective during the period.

Table 7

Performance of F-Score Strategy Across Time

Table 7 shows the mean one-month buy-and-hold market adjusted returns (MAR), as well as the difference between high and low score F-Score portfolios, and its significance from May 2006 to October 2014. Returns are grouped by calendar year i.e, starting from January to December. t-statistics for mean returns are from two-sample t-tests assuming unequal variance. Significance levels using one-tailed tests are represented by ***1% level; **5% level; *10% level.

Panel A : High BM Firms

	High Score	***Low Score***		
Year	***Mean MAR***	***Mean MAR***	***Difference***	***t-Statisitcs***
2006	-2.32%	-1.60%	-0.72%	1.01
2007	1.36%	2.48%	-1.12%	0.94
2008	1.92%	3.16%	-1.24%	0.78
2009	2.44%	1.44%	1.00%	0.73
2010	-1.08%	0.31%	-1.38%	1.39*
2011	0.86%	-0.47%	1.33%	1.72*
2012	-0.05%	-0.78%	0.72%	0.89
2013	0.60%	-0.73%	1.33%	1.35*
2014	-2.31%	-3.28%	0.98%	0.71

Panel B : Low BM Firms

	High Score	***Low Score***		
Year	***Mean MAR***	***Mean MAR***	***Difference***	***t-Statisitcs***
2006	-1.45%	-2.43%	0.98%	1.45*
2007	-0.15%	-3.37%	3.21%	1.62*
2008	-0.30%	-3.14%	2.84%	1.52*
2009	0.67%	-0.59%	1.27%	1.12
2010	1.83%	1.56%	0.27%	0.78
2011	-0.51%	-1.07%	0.56%	0.96
2012	0.11%	-0.78%	0.88%	0.76
2013	1.14%	-0.17%	1.30%	0.91
2014	-1.89%	-4.53%	2.63%	1.43*

Table 8

Performance of F-Score Strategy for Reporting and Non-Reporting Months

Table 8 shows the long-short profit of the F-Score strategy for reporting and non-reporting months. Reporting months are March, April, August, and October. The rest are classified as non-reporting months. t-statistics for mean returns are from two-sample t-tests assuming unequal variance. Significance levels using two-tailed tests are represented by ***1% level; **5% level; *10% level.

	Reporting Month		*Non-Reporting Month*			
	N	*Mean Long-Short Return*	*N*	*Mean Long-Short Return*	*Difference*	*t-Statisitcs*
High BM	33	1.24%*	68	-0.08%	-1.32%	-1.012
Low BM	33	-1.31%**	68	2.38%***	3.70%	2.45**

when new fundamental information is released. My results also show that markets react to new information very quickly. As we can see, the excess return disappears in the month after the release of the financial report.

In the low BM firm sample, long-short strategy earns -1.31% during reporting months, and 2.38% during non-reporting months. Both returns are statistically significant. This means market participants tend to misprice low BM firms when the flow of new information is at its peak. It is beyond the scope of this study to investigate the cause of such irrational behavior. The results in this study suggest that high F-Score stocks are temporarily underpriced, and low F-Score stocks are temporarily overpriced during reporting months. However, in the month after the release of a financial report, the market slowly corrects the mispricing. As a result, large excess returns are earned during non-reporting months.

To sum up, in the high BM sample the evidence supports the “neglect hypothesis”, which states that the lack of a dissemination channel causes stock prices not to accurately reflect their true fundamental. The market corrects the mispricing when new financial information is released. In the low BM sample, the evidence shows that the profitability of the F-Score strategy is driven by irrational pricing.

7. Regression Analysis

The results in the previous sections show that the F-Score is effective at differentiating winners and losers in the all-share sample, as well as in the low BM firm sample. However, at this point, it is still unclear whether the observed returns are correlated with other well-documented risk factors. We therefore evaluate whether the observed returns are correlated with known risk factors, by regressing the stock returns on the following control variables: BM measured as the log of book-to-market ratio, and Size, measured as the log of market capitalization. Prior studies, such as those of Piotroski (2000), Mohanram (2005), and Mohr (2010) include accrual, momentum, and equity offering as known risk factors in their regression analyses, when assessing whether the F-Score is effective after controlling for known risk factors. Other studies use accrual (Sloan, 1996), and recent equity offerings (Loughran ad Ritter, 1995), both of which have been shown to predict future stock returns in the U.S market. However, no studies show that these two factors have the same effect in China, and we therefore do not include accruals and equity offerings in our regression model. Xiao and Xu (2004) show that the momentum effect is not significant in China, and therefore momentum is also not included in our model as a known risk factor. We estimate the following regressions, each with and without the F-score as an independent variable.

$$R_i = \alpha + \beta_1 \log (SIZE_i) + \beta_2 \log (BM_i) + \beta_3 \text{ F-Score} \quad (1)$$

$$MAR_i = \alpha + \beta_1 \log (SIZE_i) + \beta_2 \log (BM_i) + \beta_3 \text{ F-Score} \quad (2)$$

R_i is the raw return of stock i and MAR_i is the market-adjusted return of stock i. If the market is efficient and Size and BM already incorporate all risks, adding the F-Score as an additional risk factor should not significantly increase the explanatory power (R^2) of the regression model. In addition, the coefficient of the F-Score (β_3) should not be significant.

The result of the regression analysis is presented in table 9. Panel A1 shows all coefficients of the base regression model have the expected sign. The coefficient of Size is negative, which shows the presence of the small-size effect. The coefficient of BM is positive, which shows the presence of the BM effect. t-statistics show both variables are statistically significant at the 1% level. Adding the F-Score to the base regression model increases R^2 from 1.83% to 1.91%. Low R^2 is expected when regressing returns on risk factors instead of on risk premiums. The coefficient of the F-Score is positive and statistically significant at the 1% level. After adding the F-Score to the model we find that Size and BM are still statistically significant, indicating that the F-Score is independent of the other three risk factors. Hence the F-Score adds value even after controlling for known risk factors.

Panel A2 shows that, in the high BM firm sample, the size effect is still present. However, the coefficient of BM becomes negative, and the t-statistics show it is not statistically significant. This result is reasonable, since we already control for the BM effect in the high BM firm sample. The coefficient is positive, but not statistically significant. Adding the F-Score only increases R^2 by 0.002%, and the increase is negligent if we round R^2 to two decimal places. The F-Score therefore does not add value in the high BM firm sample. The regression result is consistent with our prior results.

Panel A3 shows that, in the low BM firm sample, the coefficient of Size is positive and statistically significant, but the coefficient of BM is not significant. The coefficient of the F-Score is positive and statistically significant. Furthermore, adding the F-Score to the base regression increases R^2 from 1.66% to 1.76%. Hence the F-Score adds value in the low BM portfolio even after controlling for known risk factors.

Panel B1, B2, and B3 show the results of regressing MAR against risk factors and the F-Score. The result is almost identical to the result shown in Panel A. The results shown in Panel B indicate that the F-Score still adds value in all share portfolios and the low BM portfolio after adjusting for market return, as well as known risk factors. In Panel B3 we see that the coefficient of the F-Score is 0.16%, which means every point improvement in the F-Score will result in a 0.16% increase in MAR.

8.Characteristic of the F-Score Portfolio

So far we have shown that the high F-Score portfolio outperforms the low F-Score portfolio. However, it is not clear whether the outperformance is a result of pure market mispricing, or whether the high F-Score portfolio exhibits higher risk than the low F-Score portfolio. Tantipanichkul (2011) shows that high F-Score portfolios have significantly higher beta than low F-Score portfolios. However, other studies, such as those of Mohr (2010) and Noma (2010) show that there is no significant difference between high F-Score and low F-Score portfolios in terms of risk. The first part of this section presents evidence concerning whether a high score portfolio is riskier than a low score portfolio, using two common risk measures: Beta and standard deviation. The second part of this section presents the fundamental characteristics of high F-Score portfolios and low F-Score portfolios. A high F-Score indicates that a firm's fundamental is improving. However, a high F-Score does not necessarily indicate that a firm is a high-quality firm. In the second part of this section, we examine whether the F-Score differentiates high-quality firms from low-quality firms.

Table 9

Regression analysis: Controlling for Risk Factors

Table 9 presents the results of regressing the one-month raw and market adjusted (MAR) return on BM, SIZE and F-Score. SIZE (BM) is proxied by the logarithm of market capitalization (Book-to-market ratio).

Regression model:

$$\text{Return} = \alpha + \beta_1 \log(\text{SIZE}_i) + \beta_2 \log(\text{BM}_i) + \beta_3 \text{ F-Score}$$

Significance level represented by ***1% level; **5% level; *10% level.

Model	*Intercept*	*BM*	*Size*	*F-Score*	*R2*
Panel A1: All Firms(Raw Return)					
1	0.494	0.018	-0.046		1.83%
	(21.09)**	(5.81)**	(-19.9)***		
2	0.488	0.019	-0.046	0.002	1.91%
	(20.84)**	(6.16)**	(-20.15)**	(4.41)***	
Panel A2: High BM Firms(Raw Return)					
1	0.073	-0.005	-0.009		
	(3.17)***	(-0.91)	(-4.00)***		0.20%
2	0.073	-0.004	-0.009	0.001	0.20%
	(3.15)***	(-0.85)	(-4.02)	(0.34)	
Panel A3: Low BM Firms(Raw Return)					
1	0.563	0.018	-0.052		1.66%
	(11.66)**	1.43	(-10.87)***		
2	0.554	0.019	-0.052	0.003	1.74%
	(11.46)**	(1.66)	(-10.95)	(2.66)**	

Model	*Intercept*	*BM*	*Size*	*F-Score*	*R2*
Panel B1: All Firms(MAR)					
1	0.089	0.007	-0.008		0.17%
	(5.43)**	(3.26)**	(-5.06)		
2	0.086	0.008	-0.008	0.001	0.20%
	(5.26)**	(3.51)**	(-5.26)	(3.07)**	
Panel B2: High BM Firms(MAR)					
1	0.099	-0.003	-0.009		0.04%
	(4.28)**	(-0.55)	(-4.04)***		
2	0.099	-0.002	-0.009	0.000	0.10%
	(4.26)**	(-0.47)	(-4.07)**	(0.50)	
Panel B3: Low BM Firms(MAR)					
1	0.062	0.003	-0.006		0.17%
	(1.71)*	(0.55)	(-1.66)*		
2	0.056	0.004	-0.006	0.002	0.20%
	(1.56)	(0.73)	(-1.73)*	(2.19)**	

8.1 Portfolio Risks

Beta and volatility are calculated using weekly return, ensuring that there are at least 100 weeks of data available. In the high BM firm sample, the risk of the high F-Score portfolio is much smaller than that of the low F-Score portfolio. The mean betas of the high and low F-Score portfolios are 1.02 and 1.25, respectively, and the difference is statistically significant at the 1% level. Similarly, the mean volatility for the high score portfolio is lower than the mean volatility of the low score portfolio, and again the difference is statistically significant at the 1% level. Similarly, in the low BM firm sample, the high score portfolio is significantly less risky than the low score portfolio in terms of market beta and volatility. Furthermore, we find that the mean beta of the high BM portfolio and mean beta of the low BM portfolio are virtually identical: The high BM portfolio has a mean beta of 1.09 and the low BM portfolio has a mean beta of 1.05.

To sum up, the evidence suggests that the fact that the high score portfolio outperforms the low score portfolio is not a result of the high score portfolio's high risk. In fact, we show that the high score portfolio has less risk than the low-score portfolio for both high and low BM firms.

Table 10
Relationship between the F-Score portfolio and Risk Measures

Beta is calculated using weekly returns, after ensuring that at least 100 weeks of data is available. Volatility (Vol) is calculated using daily return, and the number represented in this table is mean one-year volatility. t-statistics for mean returns are from two-sample t-tests assuming unequal variance. Significance levels using two-tailed tests are represented by ***1% level; **5% level; *10% level.

Panel A: High BM Firms					*Panel B: Low BM Firms*				
	β	*Bull* β	*Bear* β	*Std*		β	*Bull* β	*Bear* β	*Std*
1	1.02	0.96	1.08	1.35%	***1***	0.86	0.91	0.78	1.27%
2	1.01	1.02	0.84	1.26%	***2***	0.95	0.96	1.07	1.26%
3	1.05	1.16	0.93	1.26%	***3***	1.02	1.10	0.97	1.24%
4	1.04	1.07	0.99	1.21%	***4***	0.96	0.95	0.88	1.14%
5	1.01	1.10	0.98	1.16%	***5***	0.98	1.11	0.87	1.15%
6	0.99	1.12	1.01	1.15%	***6***	0.91	1.02	0.76	1.08%
7	0.97	1.08	0.92	1.14%	***7***	0.93	1.05	0.82	1.10%
8	0.99	1.11	1.00	1.15%	***8***	0.93	1.02	0.85	1.12%
All	1.01	1.11	0.97	1.16%	***All***	0.95	0.86	1.03	1.09%
High	0.98	1.09	0.95	1.14%	***High***	0.93	1.04	0.83	1.08%
Low	1.02	1.04	0.88	1.27%	***Low***	0.90	0.90	0.99	1.21%
High-Low	-0.04	0.05	0.06	-0.14%	***High-Low***	0.03	0.14	-0.15	-0.13%

8.2 Portfolio Fundamentals

An investor would like to know the quality of the portfolio they are holding, and for this study we select six common variables that are used to measure the quality of a firm. We choose Return on Equity (ROE), and Return on Asset (ROA), as measures of the level of profitability, Gross Margin (GM) and Net Profit Margin (NPM) as measures of earning quality, and Revenue Growth and Earnings per Share (EPS) growth as measures of growth ability. Both EPS growth and revenue are based on analysts' one-year forecasts.

Panel A presents statistics of the six quality variables. For both high and low BM firms, the high score portfolio has higher earnings, better earning quality, and faster growth than the low score portfolios. It is very clear that the F-Score can successfully differentiate the fundamentally strong firms from the fundamentally weak firms. Panel B shows that high score firms are cheaper than low score firms in terms of P/E ratio and P/B ratio. This indicates that the F-Score strategy is biased towards picking value stocks. Panel C shows that high and low F-score portfolios are similar in terms of liquidity (measured by average daily trading volume). It is worth mentioning that liquidity is extremely high for both high and low F-Score firms, as the average daily trading volume is over 150 million per stock, so liquidity is not an issue when implementing the F-Score strategy in China. Analyzing the average number of stocks in both the and high and low F-Score portfolios, we discover that the average number of stocks in the low F-Score portfolio for high and low BM firms is only 4 and 2 per month, and this might be a problem for investors who wish to implement our long-short F-Score strategy.

Table 11

Characteristic of the Piotroski's F-Score Portfolio

The table shows the mean of the sample of firms on the selected quality variable, valuation ratios, and the liquidity measures. Earnings per share growth and revenue growth is defined as one-year historical growth rate. All variables in Panel A have been winsorized at 1% and 99%. The mean price-to-earnings ratio is calculated as the inverse of mean earnings-yield (i.e 12 month-trailing net income before extraordinary item/total market capitalization). The mean price-to-book ratio is calculated as the inverse of mean book-yield (i.e 12 month-trailing net income before extra-ordinary item/owner's equity). Negative earnings-yield and book-yield are excluded.

		Market	***High BM***		***Low BM***	
			High Score	***Low Score***	***High Score***	***Low Score***
Panel A :Quality Variable						
Return on Equity		10.3%	11.6%	0.5%	16.3%	9.8%
Return on Asset		5.5%	4.5%	0.5%	11.0%	7.0%
Gross Margin		28.5%	26.4%	14.6%	36.5%	30.5%
Net Profit Margin		9.0%	18.3%	2.6%	16.0%	11.8%
Earning per Share Growth		11.6%	13.1%	-28.8%	39.4%	-4.4%
Revenue Growth		16.6%	20.4%	10.5%	26.1%	19.7%
Panel B: Valuation Ratios						
Price to Earning Ratio		14.8	14.2	428.6	31.6	51.2
Price to Book Ratio		1.9	1.3	1.7	6.7	7.3
Panel C: Liquidity						
Average Daily Trading volume	***(in millions)***		192.3	149.9	217.3	208.6
Average Market Capitalization	***(in millions)***		8,310.5	2,497.8	3,870.1	2,374.3
Avg No. of stocks per month			31	4	15	2
High No. of stocks per month			55	11	28	8
Low No. of stocks per month			14	0	3	0

9. Conclusion

In this study, we replicate Piotroski's (2000) F-Score strategy, and investigate whether it is possible to identify mispriced stocks in the Chinese A-Share market between 2006 and 2014. We show that, within a high BM sample of firms, high-Score firms on average outperform low-Score firms. However, the t-test shows the return difference is not statistically significant. This means the F-Score cannot successfully differentiate between winners and losers in assessing firms. Unlike Piotroski (2000) we find no evidence of the F-Score strategy's ability to shift the entire return distribution of high BM firms to the right. In fact, the 10th and 90th percentile high score firms underperform low score firms.

Within our low BM firm sample, high score firms outperform low score firms by 1.28% per month, and the result is statistically significant. However, a substantial portion of the return is driven by the poor performance of low F-Score firms. Admittedly, the strength of the strategy does not lie in picking which firms to buy, but rather which firms to short. The partition analysis shows the benefit of the F-Score strategy is robust across size, but concentrated in low liquidity firms and with firm which are reported on by market analysts.

We test if the observed return is abnormal. We find that, after controlling for known risk factors, i.e., book-to-market, size, and market beta, the F-Score is still effective at explaining future returns. The F-Score strategy is also robust across time. In a low BM firm sample, our long-short F-Score strategy shows nine out of nine positive years. In addition, the high score portfolio is less risky than the low score portfolio, in terms of the common risk measures beta and volatility. On average, a high score portfolio has higher profitability, better quality of earnings, faster growth, and lower valuation.

In this study, trading cost is not included in the back-testing of the F-Score strategy because the trading costs for both institutional and retail investors are extremely low. In 2014, the brokerage cost for retail investors was only 3 basis points(bps) for each leg of buy and sell, plus 10 bps of stamp duty. Institutional investors can even get brokerage costs down to 1.8 bps. In addition, the turnover of the F-Score strategy is 23% per month for the high BM sample and 32% per month for the low BM sample. Not accounting for trading costs is therefore unlikely to be a major issue for the purpose of this study. However, the ability to short low score firms is crucial for profitability of the F-Score strategy in the low BM firm sample. China's Security Regulatory Committee (CSRC) has very strict rules on short-selling. Usually short-selling is only allowed for large and liquid firms. We therefore suspect that in real world situations the profitability of the F-Score strategy in low BM firm samples is likely to be smaller then what we document in this study. More detailed analysis of the impact of short selling restrictions on the profitability of the F-Score strategy could provide further insight on its usefulness in low BM firm samples. However, such analysis is beyond the scope of this paper.

Previous studies on the F-Score have examined its effectiveness in different countries, including many emerging markets. However, to our knowledge, no research has been undertaken on the F-Score in the Chinese A-share market. Our empirical results provide some useful insights into the use of the F-Score in the Chinese A-share market. First, we show that the F-score strategy can successfully separate winners and losers in the low BM firm sample, but not in the high BM firm sample. These findings are contrary to the commonly-held belief that the F-Score strategy works well in high BM firm samples. Our finding is, however, consistent with those of Rathens and Schelhove (2011). The F-Score works in low BM firm samples because low BM firms tend to underreact to bad news when this news is released. Over time, the market slowly incorporates the bad news into the share price, and thus a high score portfolio significantly outperforms a low score portfolio during non-reporting months. Evidence shown in this study suggests investors can use the F-Score to identify low quality growth firms in China. The true profitability of shorting low quality growth firms is not clear. However, for long-only growth fund managers, an F-Score strategy can be a useful tool as a filter when selecting growth stock in China. Using the F-Score to avoid picking stocks which will be losers could certainly improve portfolio returns.

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