Testing Piotroski's F_SCORE on the U.S. Stock Market

Xiangyu Mo and Yuzi Wang

Master Thesis in Finance

Stockholm School of Economics

Abstract

Piotroski (2000) documents a fundamental investing strategy based on F_SCORE to identify financially strong firms. In this paper, we investigate whether Piotroski's simple accounting-based fundamental method can still be applied to the U.S. market throughout 12 years from 2004 to 2015. Our results present that in general, the strategy of picking firms with high F_SCORE cannot significantly outperform the low F_SCORE. However, when analyzing low book-to-market stock quintile, we note that there are significant returns generated from strategies of high minus all and of high minus low. The raw returns of each approach are 3.6% and 12.1%, respectively. In the highest B/M quintile, we find that the high F_SCORE underperform the average firm by 5.5% in raw return and 4.1% in market-adjusted return. The strategy can identify winner stocks in small market capitalization. High F_SCORE portfolio outperforms average small firms (low F_SCORE small firms) by 3.8% (7%) regarding market-adjusted return at the 10% significance level. In conclusion, we find that the Piotroski's method only works in growth stocks and small market capitalization firms. It can differentiate winners' stocks from losers' under either condition.

Keywords: Piotroski, Abnormal Returns, Market Efficiency, U.S. Stock Market

Tutor: Michael Halling

Date: 2018-12-5

Table of Contents

Acronyms

BF Behavioral Finance

B/M Book-to-Market

CAPM Capital Asset Pricing Model

CFO Cash Flow from Operations

EMH Efficient Market Hypothesis

FV Fundamental Value

HML High Minus Low

MPT Morden Portfolio Theory

PEAD Post-Earnings-Announcement Drift

ROA Return on Asset

SMB Small Minus Big

1. Introduction

According to Efficient Market Hypothesis (EMH), as described by Fama (1970), the stock price of the listed companies should actively adjust to the announcement of new value-related information, such as financial statement or major events, and include all the information related to historical stock prices. Therefore, in an efficient market, it would be impossible for individuals to earn access return by applying fundamental analysis. In other words, investors cannot “beat the market”.

However, researchers have observed several market anomalies which contradict the market efficiency hypothesis, for example, the post-earnings announcement drift (Bernard & Thomas, 1989). The researches demonstrate that in the stock market, price could sometimes deviate from the fundamental value (FV) of certain stock. Therefore, investors and researchers have been attempting to find investment methods that would obtain excess returns without merely incurring higher risk.

One predominating strategy is known as fundamental investing which was based on Ball and Brown’s (1968) discovery that accounting information is value-relevant. The method intends to estimate a company’s future revenues or profits built upon known financial or accounting information to evaluate its FV. Consequently, fundamental researchers are pursuing to capture stocks which market prices are lower than firm’s FV, and purchase the stock to earn an excess return. Or they could distinguish stocks with prices higher than its FV, and take a short position on the stock.

Another universal approach is value investing which aims at identifying stocks that are temporarily undervalued. The assumptions of the strategy are that the FV of stocks is measurable and that the market price of stocks might temporally deviate from its FV. Usually, this type of investors attempts to identify an undervalued stock with the approach of analyzing the book-to-market ratio (B/M ratio). They would buy stock with high B/M ratio or sell stock with low B/M ratio. Researchers have discovered that a stock portfolio structured with higher B/M ratio have historically achieved surplus returns, compared with one with lower B/M ratio (Rosenberg, 1985). Others argue that value stocks are related to poor past performance and that the excess returns generated using value investing strategy are simply compensation for the additional risk. Therefore, investors would generate passive expectations towards the value stocks, causing a trend or possibilities of undervaluing or neglecting value stock.

The discovery of the market anomalies has encouraged the development of behavioral finance (BF). Contradicting to the EMH, which suggests that individual investors would take decisions rationally, researchers in the BH fields argue that investors are subjects to financial literacy, which can lead to irrational investment decisions and mispricing of assets. Furthermore, unlike EMH which suggests that there are no limitations of arbitrage, BF assumes that arbitrage limitations exist, which may harm the effectiveness of pricing.

In Piotroski (2000)'s paper, he incorporates both methods, fundamental analysis and value investing to generate a new strategy, F_SCORE. Piotroski indicates that investments in value stocks with promising financial performance could generate excess returns. And the method, F_SCORE, a binary system which contains 9 aspects, would help to distinguish those stocks. The 9 aspects aim at evaluating the company's operating ability, profiting performance, liquidity efficiency to generate the company's FV. A firm can be given a score between 0 to 9, 9 being the highest, and is expected to perform the best among others, meaning that it would carry the most promising financial status and lowest risk, while a score of 0 is assumed to perform the poorest. He claims that this strategy can increase returns without increasing the risk exposure, which suggests that the market is inefficient and investors can access abnormal return.

Piotroski chooses the US market of the years from 1976 to 1996. According to his documents, investors could gain a surplus return of approximately 7.5% a year applying the F_SCORE method. The surplus return can be even more encouraged if the investors purchase the winner value stock (high F_SCORE) and sell loser value stock (low F_SCORE). In this way, investors can obtain an excess return of 23% annually.

In this thesis, we plan on testing the fundamental investing method discussed in Piotroski's paper, to observe if applying the method to the U.S. stock market nowadays can still generate Piotroski's conclusion, and investigate if his approach is able to distinguish strong stocks from others. The time range would be chosen as between the year of 2004 to 2015. Because the investing environment and financial development for investors have developed enormously since Piotroski generated his F_SCORE approach. For example, transaction costs, accessibility of financial information. Taking these changes into consideration, it would be interesting to see if the results are still in line with Piotroski's (2000) analysis.

2. Theoretical Basis

In this part, we discuss the knowledge base of F_SCORE method and the theoretical foundation applied in order to test Piotroski's conclusion, including the efficient market hypothesis, anomalies, asset pricing models, and behavioral finance.

2.1 EMH (Efficient Market Hypothesis)

The first person who has brought up the concept of EMH is Fama (1970). His research was based on the study of Samuelson (1965) and Mandelbort (1966). In Fama's definition, a market that is efficient for securities would be including all the useful information and actual market prices would act in line with stocks' FV.

To dive into the concept of EMH, there are 3 basic assumptions.

Firstly, EMH suggests that individuals have the abilities to absorb the fundamental knowledge of trading in the market. In other words, investors on the market have all the knowledge and information they need to trade in the market, for example, the concept of earnings and risks.

Secondly, EMH assumes that individuals on the market are rational in making decisions. According to Fama's hypothesis, all investors in the market are assumed to be rational, able to understand the information correctly and able to use the information to guide their actions in a cohesive way. This assumption implies that the actors could boost their earnings to the most while keeping the risk relatively low. Meanwhile, it also suggests that once a new relevant information is announced, prices of related stocks would change quickly and accordingly based on the new information. Therefore, the price would always reflect all information that is available on the market.

Thirdly, EMH implies there is no limitation in terms of arbitrage. Prices can be distorted from its FV temporarily. Therefore, possibilities of arbitrage might exist due to certain irrational actions. When price distorted from FV, individuals would have the chance to earn riskless returns, known as arbitrage. Although this phenomenon might exist, it is only temporary according to Fama. Since once price changed from its fundamental value, rational investors on the market would take advantages of the situation by arbitraging, which in turns, pulling the price back towards its FV.

Fama (1970) restates the definition by distinguishing the efficient market into 3 different forms: weak efficiency, semi-strong efficiency, and strong efficiency market.

Weak market efficiency assumes that market prices have reflected all historical information related to stock price, including stock trading price, volume, etc. In this type of efficiency, it's impossible for individuals to gain surplus return using technical analysis, which uses past data and trading information to guide future investment strategy in order to beat the market. Since past trading data and information are open to everyone, every individual could take the chance to buy the stock instantly if there is an opportunity to gain extra return implied by past information. However, fundamental analysis could still be applied in this type of market efficiency.

Semi-strong market efficiency implies that prices have fully reflected all publicly available information about the company's operating prospects. This information includes transaction price, volume, profit data, profit forecast, company management status and other publicly disclosed financial information. If investors can get this information quickly, the stock price should respond quickly. In a semi-strong type of market, technical analysis strategy and fundamental investing method will all be unworkable, and only private information may help investors to generate surplus profits.

Strong market efficiency suggests that market prices have fully incorporated all the information regarding the firm's operation, including information that has been announced public or non-publicly. In other words, insider information is also included in the stock prices. In a strong market efficiency, there is no way for investors to beat the market, not even for insiders.

The general agreement of academics and investors is that the markets manifest in the semi-strong category (Bodie, et al., 2013). In semi-strong market efficiency, it would be impossible for individuals to gain surplus return using fundamental analysis. However, Piotroski (2000) contradicts the idea since his results show that it is possible to obtain excess returns using F_SCORE method.

2.2 Anomalies

Market anomalies, also known as market inefficiencies, are distortions of prices or returns in financial markets, and such distortions often conflict with the EMH. In the EMH, investors can only earn an average return. And the price and return distortions in the market are eliminated by the arbitrage behavior of traders. Market anomalies are the data characteristics of stocks that have been found to outperform the market. They usually happen temporarily. And when they happen, the investor could gain surplus returns. To spot anomalies, researchers need to capture those mispricing signals that appear in the markets. The characteristic of anomalies is that after adjusting the risk by asset pricing model, the return cannot be equal to zero (Bodie et al., 2013).

There are 3 steps to identify anomalies. Firstly, capture one or more market mispricing signals through academic research or data mining. Then test those signals using known and well-recognized factors. If the market anomalies still have significant excess returns after the tests and traditional finance and behavioral finance have relevant theoretical support, then these market anomalies might have the potential to become methods that could bring potential excess returns to investors (Zack, 2011).

The biggest challenge in terms of identifying anomalies is the joint-hypothesis problem. As mentioned before, mispricing signals are used to capture anomalies. Then the asset pricing models are used to test the risk adjustments and market efficiency to see if they can reject the EMH. The EMH assumes that stock prices fully reflect all public information. Therefore, investment strategies cannot systematically achieve excess returns. Since the models are not perfect, the process of adjusting risk may not be able to include all risk factors. Therefore, there are two possibilities when the models reject the EMH. One is that excess returns exist, which would reject EMH. The other is that the models are not perfect and cannot reflect all risk factors (Fama, 1970). Therefore, just because risk-adjusted excess returns exist does not mean that anomalies exist at the same time. The excess returns could be prices or compensations of the risk factors that are not covered in the asset pricing models that were applied (Ackert and Deaves, 2010).

Hou et al. (2014), using data in U.S. stock market from 1967 to 2014, record 447 market anomalies that are generally believed to be able to bring excess returns and make tests on those excess returns. They conclude that the markets are very effective most of the time. It is very difficult to find reliable excess returns. However, they do not completely deny the existence of the market's abnormality. They confirm that after the tests there are some excess returns existing. Due to the arbitrage restrictions in the market, these relatively reliable market anomalies could not be completely erased.

2.3 Asset Pricing Models

As mentioned in 2.1, the EMH assumes that market practitioners are risk-averse and rational. Therefore, stock prices are only determined by their original risk. What all different types of asset-pricing models have in common is that they are tempting to capture the relationship between stock expected returns and risk.

2.3.1 CAPM (Capital Asset Pricing Model)

The CAPM interprets the connection between market risks and expected returns of assets, especially stocks. And it studies how the equilibrium price is formed. It is the pillar of the modern financial theory and is widely used in investment decision-making and corporate finance. In the CAPM model, the expected return of a stock is represented as the sum of the risk-free rate and the risk premium of the market. Furthermore, risk premium could denote the price and the volume of risk. Introduced independently by Sharpe (1964), Treynor (1962), Lintner (1965) and Mossin (1966), the CAPM is built upon the morden portfolio theory (MPT) by Markowitz (1952). Markowitz's study, also known as mean-variance analysis, assumes that investors are risk averse and will always choose assets that are less risky if the returns are the same.

According to Sharpe's (1964) research, market risk can be broken down into two categories: Systematic risk and idiosyncratic risk. Systematic risk has an impact on the whole market, while idiosyncratic risk is more related to the single company and its relevant events. Systematic risk would be impossible to diversify away since it's a risk that the entire market is facing. However, it is possible to lower idiosyncratic risk by using different portfolios or investing strategies.

The CPAM formula can be concluded as follows:

$$\mathrm{E(R_x)} = \mathrm{R_f} + \beta_\mathrm{x}(\mathrm{E(R_m)} - \mathrm{R_f}) \tag{1}$$

$$\beta_x = \frac{\sigma(R_x, R_m)}{\sigma_m^2} \tag{2}$$

In equation (1), $E(R_x)$ stands for the expected return of stock X while $E(R_m)$ represents the expected return of the market. R_f represents the market risk-free rate, which tells the time value of money since it is the opportunity value of risk-free assets. Beta X, representing the unsystematic risk of stock X, captures the sensitivity of stock X's expected return to changes in the market returns. $(R_m - R_f)$ denotes the market risk premium and represents the systematic risk of the market.

In formula (2), β_x describes the ratio of covariance of asset X's return with the market return and the variance of market return. The β coefficient of the whole market itself is 1. If the β coefficient is equal to 1, the price of asset X moves in line with the entire market. If the β coefficient is greater (less) than 1, it shows that the return of stock X fluctuates more (less) than the market returns. If β_x is negative, it shows that the moving direction of stock X is opposite to the moving direction of the market. When the market returns increase (decrease), the return of stock X falls (increase).

According to the CAPM model, the market portfolio, an entirely diversified portfolio in terms of risk and leverage, is the most ideal portfolio for individuals to hold. The model also indicates the risk price and risk volume, which are risk premium and β_x (Zack, 2011).

2.3.2 Fama and French's Three Factor Model

Since the CAPM is a one-factor model, which only contains the risk factor. It is not sufficient enough to explain other factors that can also affect the price of stocks. Fama and French (1992) study the factors that determine the differences in returns between stocks, using data of all stocks listed on NYSE, AMEX, and NASDAQ from 1963 to 1990. They find that the β of the stock market cannot explain the difference in return on stocks. While the market capitalization and book-to-market ratio of listed companies can explain stocks more.

Therefore, Fama and French extend the CAPM by introducing two additional factors, market capitalization (size), and B/M ratio, to form a new three-factor model. In the three-factor model, they describe the expected return of asset as following:

$$E(R_x) = R_f + \beta_i(E(R_m - R_f)) + s_i SMB + h_i HML \tag{3}$$

According to formula (3), the three-factor model considers the expected return of asset X to be an equation of risk-free rate and 3 factors, the risk factor β_i, the size factor s_i, and the B/M factor h_i. Same as CAPM, the three-factor model accounts for the risk part as the multiple of expected risk premium and risk factor. Additionally, they include the size part by adding in the formula the multiple of size premium SMB (Small Minus Big) and size factor. Moreover, the influence of B/M ratio is described as the multiple of value premium HML (High Minus Low) and B/M factor.

2.3.3 Fundamental Investing Method

Fundamental analysis helps investors find stocks which have the potential to gain extra return by evaluating a company's FV. The method mainly uses quantitative and qualitative information, such as a firm's operating abilities and profitability, to calculate the firm's FV. If a company's stock price is not in line with the company's FV, or a mispricing signal appears, then an arbitrage opportunity might exist. More specifically, individuals would purchase a stock if its FV exceeds its current market price. The assumption of this method is that the price of a security is determined by its intrinsic value. The price is subject to frequent changes due to political, economic, psychological and other factors. It is difficult for the price to be completely in line with the value. But price will always fluctuate around the value. Rational investors should make investment decisions based on the relationship between security prices and values. In other words, fundamental analysis believes that in the short-term, the market can be inefficient temporarily, and the underperforming stock price would slowly move back to its FV. However, in long-term, fundamental analysis considers the markets to be efficient. Since no matter how the stock price fluctuates, it will always be in line with the FV (Bodie et al., 2013). As mentioned in EMH, most academic studies believe that the current market is in a semi-strong efficiency market. Based on the characteristics of semi-strong efficiency, fundamental analysis cannot be applied to obtain extra returns, since prices have fully reflected all publicly available information. However, more and more researches show that the stock market might not be efficient in short-term.

Ball and Brown (1968) used empirical research method to explore whether accounting earnings are related to stock prices and whether accounting earnings have other potential use. It is the first time scientific evidencs has shown that the price of the securities will respond to the information of the financial report. Through examination, they find that the stock prices would not change accordingly right after the announcement of the changes in the revenues. For companies that have achieved quarterly higher profits, their returns on excess assets tend to continue "drift" in the upwards direction for at least sixty days after the release of the earnings. Similarly, companies with poor reporting tend to "drift" downwards for the same length of time.

However, according to EMH, after the company's financial status is announced, the information should be quickly digested by investors and reflected in the market price. Therefore, Ball and Brown (1968) conclude that markets are not efficient in short-term. And they named this phenomenon post-earnings-announcement drift (PEAD). Based on Ball and Brown's research, Bernard and Thomas (1990) break down the concept of PEAD into two parts and imply that investors could earn excess returns if they purchase firm's stocks with very positive earnings or selling those with negative revenues.

Ou and Penman (1989) share the same opinion that company's financial data, which indicates the FV of the firm, could have a huge impact on stock price. And stock prices can deviate from FV in short-term. However, the stock prices would still move towards the FV gradually. Therefore, abnormal returns can be generated when individuals spot those firms that deviate temporarily from the company's FV and invest accordingly. Greig (1992) argues that the returns should be recognized as normal returns since it can be explained by considering the company's size and beta factor. Later on, researchers point out another controversy regarding Ou and Penman's work, which is data mining and over-fitting. In statistics, over-fitting is "the production of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore, fail to fit additional data or predict future observations reliably". Among those researches, Holthaussen and Larcker (1992) test Ou and Penman's method in a different time range and do not manage to get the same result. The strategy appears to be invalid if the time range is changed, which prove the point that over-fitting problem might exist in Ou and penman's method.

In order to solve the problem in Ou and Penman's strategy, researchers start to capture elemental factors firstly and then form their strategy model accordingly. For example, Lev and Thiagarajan (1993) expand the relationship between financial earnings and stock returns. They include 12 basic analytical variables that were considered to be value-related into the regression equation and illustrate the economic significance of these 12 variables. The empirical results show that these twelve variables have a significant correlation with market returns. Therefore, they confirm the correlation between those variables and company value. It proves that in addition to the earnings variables, there are some basic analytical variables that are also related to company value. The basic analytical work done by financial analysts is useful and necessary for valuation.

Similarly, Poitroski (2000) also develops a 9-factor scoring system, which he believes are helpful to outperform the market. The signals should have the potential to capture value stocks' essential financial features and the abilities to help investors earn extra returns in value stocks. The definition and characteristics of value stocks will be included in 2.3.4 and more information about Poitroski's model is discussed in Part 2.5.

2.3.4 Value Investing Method

Value investing can be summarized as buying undervalued stocks (value stocks). Value stocks mainly refer to securities whose prices are lower relative to the company's FV or accounting data such as profits, earnings or cash flows. So value investing aims at looking for stocks with low valuation based on known information. One of the measurements in terms of finding value stocks is B/M ratio, which implies the ratio between the book value to the market price per share of stock. As some studies shown, companies with higher B/M ratio have higher average monthly yields than companies with lower B/M ratio. This phenomenon is known as BM effect.

Many researchers discover the BM effect in their studies. As mentioned in 2.3.2, Fama and French (1992) study stocks in the US market, and find that the combination with the highest B/M ratio has a monthly average yield that exceeds the one with lowest B/M value by 1.53%. Xiao and Xu (2004) calculate the stock yield data for one, two, and three years separately using the A-share stock data of the Shanghai and Shenzhen stock markets from June 1993 to June 2001, and believe that the BM effect exists.

Researchers have different point of view in terms of how to interpret BM effect. Fama and French (1992) argue that BM effect represents a risk factor – financial distress risk. Distressed companies are more sensitive to changes in business cycle factors such as credit conditions. While high BM firms are usually underperforming companies with bad fundamental figures such as operations and leverage. They are financially vulnerable and therefore riskier than low BM companies. It can be seen that the high income obtained by the high BM company is a compensation for its own high risk.

Black (1993), MacKinlay (1995) argue that the BM effect is only the result of a particular sample that exists during a particular test period. It is the result of data mining. Kothari et al. (1995) also believe that the selection bias that occurs during the construction of BM combination causes the existence of the BM effect. However, Chan et al. (1991), Davis (1994), Fama and French (1998) and others find that the BM effect is significant after testing the stock market outside the United States or lengthening the test period, thus negating the interpretation of Black et al.

DeBont and Thaler (1987), Lakonishok et al. (1994) argue that the evolution of the BM effect is built upon individual's overreaction to the company's fundamental information. Firms with high BM usually perform poorly on fundamental aspects, so investors irrationally underestimate the stock value of high BM companies. Low BM companies perform better fundamentally, so investors overestimate the value of low BM companies. This irrational expectation of stocks would cause the mispricing of value stocks (underpricing) and growth stocks (overpricing). It can be seen that investors are often over-pessimistic about companies with poor fundamentals and over-optimistic about companies with good fundamentals. When the overreaction is corrected, the high BM company will have higher returns than the low BM company.

Daniel and Titman (1997) believe that BM and size are not risk factors and that the stock revenues are not determined by risk. In fact, BM and size represent the characteristics of the company, referred to as "characteristic factors". They also represent investor preferences and determine the level of stock earnings. High BM companies are called “value stock” because their values are underestimated since they perform badly in fundamental data. On the contrary, low BM companies are called “growth stock”, since they are overvalued. Since investors prefer to hold growth stocks with good fundamentals and hate to hold value stocks with poor fundamentals, high BM companies have higher returns.

2.4 Behavioral Finance (BF)

A large number of empirical studies of financial markets have found many phenomena that are contradicting to EMH. To explain these anomalies, some financial scientists analyze investors behavior based on the research results of cognitive psychology. A large number of high-quality theoretical and empirical literature emerged in the field, forming the academic field we now know as behavioral finance. BF theory believes that the market price of securities is not only determined by the FV of securities but also largely influenced by the behavior of investors. Therefore, investor psychology and behavior have a significant impact on the pricing and changes in the securities market. It is contradicting to the EMH since BF confirm that limitations of arbitraging exist (Ackert and Deaves, 2010). Moreover, the EMH believes that investors are rational in terms of making decisions using available knowledge on the market. While BF implies otherwise. Individuals would make decision basing on their knowledge. Whether the decision is rational or not depends on one’s knowledge and financial literacy.

2.4.1 Limits to arbitrage

The EMH considers that market participants are rational, that there is no friction in the market, and that investors can handle all information correctly. Participants in the market can quickly eliminate pricing errors in the market through arbitrage. In short, “prices reflect all information correctly” and “there is no free lunch in the world”. It means that there is no strategy that can be used to earn risk-adjusted excess returns. BF argues that the EMH hypothesis is not entirely correct. Market participants cannot quickly or correctly eliminate pricing errors that exist in the market. The process of elimination might be longer. Or the method of elimination would bring additional risks. These problems lead to pricing errors that cannot be completely eliminated, which make it possible for investors to earn excess returns or cause excess losses. "Price is correct" can deduce that "there is no free lunch in the world"; but "there is no free lunch in the world", cannot conclude that "price is correct." Market objective constraints and human congenital defects have led to frequent pricing errors in the stock market.

2.4.2 Heuristic Biases

Heuristic cognitive bias, or heuristic bias, means that investors often make investment decisions based on “Rules of Thumb”. Investment decisions they are made based on “heuristics” are inaccurate since individuals may not have all the relevant knowledge and information they need. If the missing knowledge is important, then there will be serious deviations between estimation and reality.

There are three main types of heuristic cognitive bias:

(1) Representative Deviation

Investors often have a tendency of making a typical event or feature as a representation of future success or failure. For example, investors often think that a good listed company is equivalent to a good stock. They think that the listed company has a long-term profit and that the stock quality should be good. However, they have neglected that the past stock prices of profitable listed companies already contain their past profit information. The future price may or may not under-perform the market depending on the company's current or expected profitability. Because the stock price reflect the future expectation, rather than realized history.

(2) Availability deviation

Individuals tend to rely on the first thoughts and information when making decisions. And they believe that these easily perceived or recalled events appear more often. They use this mentality as a basis for judgment. This method of judgment is called availability heuristics.

Usually, the things or memories that individuals can easily recall are most likely the events that happened frequently in the past or the unusual events that have occurred recently. But these memories or information may also be unimportant or insufficient for judgment. And they may lead to deviations in judgment. Therefore, when making investment decisions, individuals should distinguish the characteristics of the information available and determine whether it’s useful information or not.

(3) Anchoring effect

Irrational investors tend to find a reference point when making decisions. They are not evaluating the investment return itself, but the comparison between investment return and the reference point. The investment decisions made based on this mentality are not objective. Because when the reference point changes, the decision will change as well. For example, if an investor uses the bid price as a reference point, he will decide whether to keep holding or sell the stock based on the difference between the stock price and the reference point rather than the future expectation of the stock.

2.5 Piotroski's F_SCORE method

The general idea of Piotroski's F-score method is to evaluate whether an investment strategy builds upon fundamental analysis could be applied to generate surplus return when adopted to a portfolio with high B/M ratio. However, since companies with high B/M ratio are usually financially distressed (such as revenues, margins, profitability) if only use B/M ratio as an indicator, most of the selected companies would not perform well, which would drag down the overall performance of the strategy. Therefore, if a company's financial data is moving toward a good direction, then we will be able to distinguish between good companies and bad companies and invest accordingly.

Accordingly, Piotroski comes up with a scoring system. He proposes nine important financial indicators and uses these indicators to score the company in order to distinguish the good and bad company. Each outcome of the nine indicators is binary, meaning that for each indicator, a company can score 1 (if it performed well) or 0 (if it performed poorly). Poitroski's F_SCORE approach examines the company's financial situation through the nine criteria in table 1. Then uses formula 4 to generate total signal value.

F_SCORE judges the company by the above 9 factors. For each indicator, one score is obtained. The company with relatively higher investment value can be obtained by comparing the scores of different companies.

Analyzing the F_SCORE method, we can see that the first, second, and fourth factors evaluate the company's cash flow, which is a risk-control condition. Because cash flow is a guarantee for the company's healthy operations. And the company's bankruptcy is largely due to insufficient cash.

Table 1

Definition of F_SCORE

	Aspects	**Indicators**	**Criteria/ Definition**
1	Profitability	ROA	Positive net income Net income before extraordinary items
2		CFO	Positive operating cash flows Cash flow from operations
3		ΔROA	Higher return on assets than the previous year Current year's ROA less the prior year's ROA
4		Accrual	Operating cash flows greater than net income Current year's ROA less CFO
5	Leverage Liquidity	ΔLever	Lower debt than the previous year Change in ratio of total long-term debt to average total asset
6		ΔLiquid	Higher current ratio than previous year Change in ratio of current assets to current liabilities
7		EQ_OFFER	Less stock dilution than the previous year Change in common equity
8	Operating Efficiency	ΔMargin	Higher gross margin than the previous year Current gross margin ratio less the one of previous year's
9		ΔTurn	Higher asset turnover than the previous year Current asset turnover ratio less the one of previous year's

The table introduces the definitions and characteristics of F_SCORE designed by Piotroski (2000).

The third factor judges whether the company is expanding or shrinking. It is generally believed that the larger the company is, the better the company's condition is and the greater the future returns are.

$$F_{Score} = F_{ROA} + F_{CFO} + F_{\Delta ROA} + F_{Accrual} + F_{\Delta Lever} + F_{\Delta Liquid} + F_{EQ_{OFFER}} + F_{\Delta Margin} + F_{\Delta Turn} \quad (4)$$

The fifth factor implies that the company's leverage should be reduced year by year. The assumption is that the priority of the money earned is to repay the loan. If the company is losing money, the leverage will increase in order to maintain the company's operation.

As for factor 6, the current ratio is the ratio of between current assets and current liabilities. It is used to measure the ability of a company's current assets turning into cash to pay for liabilities before the short-term debt expires. Generally speaking, the higher the ratio is, the stronger the liquidity of the company’s assets is and the stronger the short-term solvency is. The current ratio is required to increase each year, which implies that the company's solvency is getting stronger.

The gross profit margin in indicator 8 reflects the value growth of a commodity after it has been produced. In other words, the more value is added, the more gross margins are. For example, the gross profit and the marginal price of a product would increase, if some functions of a product are added through the differential design of research and development compared with the competitors. Therefore, factor 8 reflects whether the company's competitiveness is continually increasing.

The asset turnover rate in factor 9 is a very important indicator to examine the efficiency of enterprise asset operations. It reflects the turnover rate of all assets from input to output during the operation period, as well as the management quality and utilization efficiency of all assets of the enterprise. The investigation here is to see whether the company's asset utilization efficiency is increasing year by year.

In order to carry out the research, Piotroski uses the financial database in the U.S. stock market. He first identifies companies with sufficient data to calculate the book/market ratio each year from 1976 to 1996, and then divides the companies into five groups based on their book/market ratios, and finds that the first group of companies have average B/M ratio of 2.444 and the market cap is 188.5 million. These companies have very poor business performance. And, accordingly, their net profit and gross profit have fallen. While the leverage ratio has risen.

In the final sampling, Professor Piotroski retains only the first of the five groups of companies. Because the financial statements of these companies are more complete. A total of 14,043 companies with high book/market ratios are selected. Piotroski then calculates the total F_SCORE signal value of each company. As a result, a total of 396 companies has a total signal value of 0 or 1, indicating that the expected stock performance of these companies was the worst. While the total signal value of 1,448 companies is 8 or 9, indicating that these companies have the best-performing stocks.

Although all companies with high B/M ratios have an overall absolute return of 5.9% within one year of the creation of the portfolio, more than half of the stocks have negative absolute returns. After grouping these companies with the basic signals described above, Piotroski found that the absolute yield of the stock with the lowest overall signals was -9.6% a year. In contrast, the absolute yield of the stock with the highest overall signals was 13.4% a year. The overall high B/M stock is 7.5% higher than the stock portfolio and 23% higher than the stock with the lowest signal.

He also finds that most of the high-yield winners have very low turnover rates and no analysts tracking them. Further analysis shows that Piotroski's investment strategy is best suited for small and medium-sized companies with low transaction volumes and lack of analyst tracking. In addition, the success of this strategy does not seem to rely on purchasing stocks with low prices.

Another noteworthy finding is that low-yield companies are more than five times more likely to be delisted than high-yield companies. Piotroski points out that this result is surprising. Because the observed stock returns and related financial performance characteristics are not in line with people's general understanding of risk. People generally think that companies with higher risks should have higher returns. However, the available evidence seems to indicate that the market is slow to respond to good news in the financial statements of high B/M company.

Finally, Piotroski also finds other evidence that the market's response to previous financial statement information was not strong enough. What’s worthy of attention is that there is a positive link between these signal values and the market's response to the next quarterly reports. Companies with high signal values rise an average of 5% during the next quarter's report period, while companies with low signal values rise less than 1% during the same period.

3. Methodology

In this section, we introduce our methodology that is similar to Piotroski's (2000) method to test whether the investing approach still works on the U.S. stock market from 2004 to 2015. Furthermore, we make our modifications to the investment strategy. In contrast to Piotroski's (2000), the dataset includes all firms instead of firms with a high book-to-market ratio. We present our methodology below.

3.1 Sample Selection

In Mohanram's (2005) research, he concludes that the B/M ratio is not a must condition for this value investment strategy to work. In fact, he finds out that the approach can be applied to other B/M range. Inspired by his findings, we decide to broaden the sample range to the entire U.S. stock market.

Since our sample contains the whole stock market from 2004 to 2015, we obtain annual fundamentals and price information from Compustat from the fiscal year 2002 to year 2016. In practice, we exclude firms that do not have sufficient accounting information to calculate F_SCORE. Moreover, we exclude firms with negative B/M values in our study. In total, from 2002 to 2016, we obtain a dataset of 30315 firm-year observations.

3.2 Book-to-Market and Size Calculation

The dataset selected was then subjected to 3 steps of basic analysis: First, we calculate a B/M ratio for each firm and each year. For the calculation of the market value of equity, we use the stock price multiplied by the number of common shares outstanding at the end of each fiscal year. Book value is calculated by subtracting total liabilities, preferred shares and intangible assets from total assets. Second, the firms are classified into quintiles based on the book-to-market ratio and into three market capitalization size: small, medium and large. We do not limit our sample to high B/M firms only but to all firms. The aim of this is to test how well F_SCORE works on a broader scope across different size terciles and B/M quintiles. Third, we calculate the F_SCORE, based on the fiscal year-end fundamentals. The detailed process is presented below in section 3.3.

3.3 F_SCORE Calculation

For each firm that has a positive B/M ratio at the end of fiscal year t – 1, we replicate Piotroski's (2000) definition of F_SCORE to calculate the nine indicator variables at the end of fiscal year t. The calculation is presented in table 2.

Table 2

Calculation of 9 F_SCORE Factors

Name	Description
ROA	$\text{Net income Before Extraordinary Items}_t/\text{Assets}_{t-1}$ $\text{F\_ROA}_t = 1 \text{ if } \text{ROA}_t > 0$, else 0
CFO	$\text{Cash Flow From Operation}_t/\text{Assets}_{t-1}$ $\text{F\_CFO}_t = 1 \text{ if } \text{CFO}_t > 0$, else 0
Δ ROA	$\text{ROA}_t - \text{ROA}_{t-1}$ $\text{F\_}\Delta\text{ROA}_t = 1 \text{ if } \Delta\text{ROA}_t > 0$, else 0
ACCRUAL	$\text{ACCRUAL}_t = \text{CFO}_t - \text{ROA}_t$ F_ACCRUAL $_t$= 1 if ACCRUAL > 0 , else 0
Δ LEVER	$\text{Long Term debt}_t/(\frac{1}{2}\text{Assets}_t + \frac{1}{2}\text{Assets}_{t-1})$ $-\text{Long Term debt}_{t-1}/(\frac{1}{2}\text{Assets}_{t-1} + \frac{1}{2}\text{Assets}_{t-2})$ $\text{F\_}\Delta\text{LEVER}_t$ =1 if $\Delta\text{LEVER}_t < 0$, else 0
Δ LIQUID	$\text{Current Ratio}_t - \text{Current Ratio}_{t-1}$ $\text{F\_}\Delta\text{LIQUID}_t$ =1 if $\Delta\text{LIQUID}_t > 0$, else 0
EQ_{OFFER}	$\text{Common Shares Outstanding}_t - \text{Common Shares Outstanding}_{t-1}$ F_EQ_OFFER_t=1 if $\text{EQ}_{\text{OFFER},t} = 0$, else 0
Δ MARGIN	$\text{Growth Profit Margin}_t - \text{Growth Profit Margin}_{t-1}$ $\text{F\_}\Delta\text{MARGIN}_t$=1 if $\Delta\text{MARGIN} > 0$, else 0
Δ TURN	$\text{Sales}_t/\text{Assets}_{t-1} - \text{Sales}_{t-1}/\text{Assets}_{t-2}$ $\text{F\_}\Delta\text{TURN}_t$=1 if $\Delta\text{TURN}_t > 0$, else 0

The table provides a specific definition of nine F_SCORE indicator variables according to Piotroski (2000). Each F_SCORE indicator variable displays financial strength of a firm with "1" being good and "0" being bad. Current Ratio is defined by using current assets divided by current liabilities. Growth Profit Margin is calculated by using sales less cost of goods sold, scaled by sales. The investment strategy is based on the sum of the variables above.

3.4 Computation of Returns

For a 12-month buy-and-hold return, we measure it by starting to buy the firm's stock from the beginning of the fifth month after fiscal year-end, and selling it at the beginning of the seventeenth month. The rationale for buying the stock after 5 months is to make sure that the annual fundamental information is public for investors. For example, if a company fiscal year ends on 2006/10/31, we calculate the B/M ratio on 2005/10/31, buy the stock on 2007/3/1 and sell it on 2008/3/1. We use equally-weighted method to construct our portfolio.

One-year raw return formula is:

$$RAW_{i,t} = \frac{P_{i,t_{exit}}}{P_{i,t_{invest}}} - 1$$

One-year market return formula is:

$$MKT_{i,t} = \frac{P_{S\&P500,t_{exit,i}}}{P_{S\&P500,t_{invest,i}}} - 1$$

One-year market-adjusted return formula is:

$$MAR_{i,t} = RAW_{i,t} - MKT_{i,t}$$

We assume that the return of a delisted firm is zero. Delisting could be voluntary or involuntary. Companies that fail to meet the minimum requirements set by stock exchange, will be delisted. Minimum requirements may require the company to meet certain financial ratio or a minimum price. This situation indicates the company's poor governance. In that case, some companies would choose to be acquired by private equity firms and have new shareholders. Therefore, the company can apply for delisting, thus the financial situation can be beneficial.

Each year, the portfolio is constructed by holding all stocks that are considered to be purchased equally. The portfolio changes each year, since company's financial position, which can be represented by the change of F_SCORE, is not constant. We assume that the investor builds the portfolio by adding or deleting the stocks once the fiscal report is out.

3.5 Performing Tests

Similar to Piotroski's (2000) research, we perform a Spearman correlation test to measure correlations among raw returns, market-adjusted returns and the F_SCORE variables so that we are able to see if the F_SCORE variables are a good indicator of future performance.

Our study goals sought to measure the reliability of return difference between firms with a high F_SCORE (8-9) and firms with a low F_SCORE (0-1). Statistical analysis needs to be performed to test if the differences are significant or not. We apply one-tailed two-sample t-test. The sample is analysed through R to calculate t-test statistics. This test consists of two hypothesis scenarios: a null hypothesis and an alternative hypothesis.

Null hypothesis: $H_0: \beta_1 = 0$

Alternative Hypothesis: $H_1: \beta_1 \neq 0$

A null hypothesis will be rejected if the P-value is lower than 10%, 5% or 1% at the corresponding significance level of 90%, 95%, 99%. If the null hypothesis is rejected, we can conclude that there is no difference between the means and that the alternative is favoured.

4. Empirical Result

4.1 Descriptive Statistics

Table 3 provides descriptive statistics about the financial characteristics of the portfolio. The portfolio includes all sizes of market capitalization and all B/M quintiles. Market capitalization and B/M ratio's calculation is introduced in section 3.2. The sample contains 30315 firm-year observations from 2004 to 2015. "NA" means that the result is unavailable.

Table 3

Financial Characteristics

Variable	Mean	Median	Std. Dev.	Proportion With Positive Signal
ROA	-0.004	0.045	1.129	72.56%
CFO	0.072	0.092	0.466	82.43%
Δ ROA	0.120	0.000	15.254	50.05%
Δ ACCRUAL	0.076	0.054	0.988	81.91%
Δ LEVER	-0.002	0.000	0.146	30.48%
Δ LIQUID	-0.019	0.005	5.988	50.54%
EQ_Offer	3.635	0.203	79.684	68.57%
Δ MARGIN	-2.173	0.000	211.887	50.46%
Δ TURN	-0.263	-0.002	22.232	49.05%
Market Cap	5501.6	550.5	20895.4	NA
Total Assets	5262.9	483.2	19705.9	NA
B/M Ratio	0.526	0.351	0.723	NA

The table contains financial statistics of the portfolio for all sample stocks. The variables are basic financial measurements (including market capitalization, total assets and Book-to-Market ratio measured at the end of the fiscal year) and nine values related to F_SCORE created by Piotroski(2000). The values are presented and used later to calculate the nine accounting-based signals of F_SCORE, which displays financial strength of a firm with "1" (good) and "0" (bad). The detailed computation of F_SCORE is presented in table 2. The dataset includes 30315 firm-year observations from year the 2004 to 2015. NA corresponds to Not Available.

As shown in Table 1, the average (median) ROA realization is -0.004 (0.045), however, the average growth of ROA shows there is an increase of 0.120 each year. To the contrary, Piotroski (2000) only researches on high B/M firms and has a -0.01 mean return of growth ROA, which tells us that high B/M firms generally perform poorly. From table 3, the average(median) B/M ratio is 0.526 (0.351), in comparison with Piotroski's (2000) 2.444(1.721). The table also shows that on average there are declines in leverage and liquidity than previous year. On the whole market, we find out that there is a significant difference between our average market capitalization 5501.6 and Piotroski's 188.5; this finding is also able to explain the difference between the mean of our total assets 5652.9 and his 1043.9.

4.2 Return Overview

In this section, we study a 12-month buy-and-hold investment strategy with raw and market-adjusted return distributions respectively on all firm portfolio, high B/M portfolio and low B/M portfolio. The result is presented in table 4.

Table 4

Buy-And-Hold Return Distributions

One-Year Returns For All Firms

	Mean	10th %tile	25th %tile	Median	75th %tile	90th %tile	Percentage Positive
Returns							
Raw	0.066	-0.483	-0.251	0.012	0.274	0.624	0.512
Mkt-Adj.	-0.006	-0.486	-0.280	-0.065	0.171	0.493	0.418

One-Year Returns For High B/M Firms

	Mean	10th %tile	25th %tile	Median	75th %tile	90th %tile	Percentage Positive
Returns							
Raw	0.142	-0.475	-0.235	0.033	0.369	0.845	0.532
Mkt-Adj.	0.032	-0.513	-0.308	-0.072	0.224	0.671	0.423

One-Year Returns For Low B/M Firms

	Mean	10th %tile	25th %tile	Median	75th %tile	90th %tile	Percentage Positive
Returns							
Raw	0.028	-0.512	-0.266	0.003	0.241	0.529	0.504
Mkt-Adj.	-0.029	-0.502	-0.277	-0.059	0.148	0.416	0.421

The table provides 12-month buy-and-hold raw return and market-adjusted return distributions. The distributions are presented in three panels, from top to bottom: distribution all sample firms, distribution of high B/M quintile and distribution of low B/M quintile. High B/M is defined as the highest B/M ratio quintile from all firms. Low B/M is defined as the lowest quintile from all firms. The distribution contains the mean, the 10^{th} /25^{th} /50^{th} /75^{th} /90^{th} percentile as well as proportion of positive numbers in each category. We define marked-adjusted return by using the raw return less the market return over the same investment horizon. The dataset includes 30315 firm-year observations from year 2004 to 2015.

The reason that the mean market-adjusted return on the top panel of table 4 is not 0 is because we use value-weighted market index return (S&P 500) as our market return rather than the average return of all firms.

Among these scenarios, the sample size of high (low) portfolio is both 6062. We notice that the average raw return in all sample firm portfolio is 6.6%, in comparison with high B/M portfolio's 14.2%, and with 2.8% in low B/M portfolio. The table indicates that the portfolio of value stocks has higher returns in general. Moreover, the high B/M portfolio exhibits that the distribution is shifted to the right further than the other two. For the high B/M portfolio, the difference between raw and market-adjusted return is far larger than the other two portfolios.

In contrast to Piotroski(2000), we do not include the calculation of two-year returns on the portfolios. Also, He displays that the one-year raw (market-adjusted) returns are 0.239 (0.059), which is even much higher than our high B/M scenario's 0.142 (0.032). The 10^{th} and the 90^{th} percentile of one-year raw returns of his are -0.391 and 0.902. Our results are -0.475 and 0.845. Thus, the benchmarks in our research are quite different when comparing the returns of high B/M firms.

4.3 Correlation Between Returns and F_SCORE

Table 5 displays the correlation between 12-month buy-and-hold returns and nine F_SCORE variables of all sample firms. There is a positive correlation relationship of 0.04 (0.056) between F-SCORE and raw return (market-adjusted return). The returns can also be strongly positively explained by ROA, LEVER, ACCRUAL, CFO, and Equity Offer. Meanwhile, the returns are negatively related to Δ ROA, MARGIN and TURNOVER. When we compare our result to Piotroski's (2000) study, the one-year returns from his Spearman correlation test are all positively related to the nine factors. I assume the reason could be because our sample size is the whole stock market and Piotroski only exhibits firms with high B/M ratio.

Table 5

Spearman Correlation Test Between Returns, Nine Fundamental Signals and F_SCORE For All Firm Portfolio.

	ROA	Δ ROA	ACCRUAL	LEVER	MARGIN	CFO	LIQUID	TURN	EQ	FSCORE
Raw	0.049	-0.037	0.038	0.032	-0.018	0.088	0.010	-0.030	0.056	0.040
Mkt-Adj	0.070	-0.021	0.032	0.036	-0.014	0.097	0.005	-0.015	0.054	0.056
ROA	1.000	0.197	-0.107	0.109	0.109	0.531	0.092	0.038	0.134	0.544
Δ ROA	-	1.000	-0.114	0.041	0.301	0.059	0.058	0.392	-0.053	0.567
ACCRUAL	-	-	1.000	0.049	-0.005	0.252	-0.076	-0.038	0.032	0.201
LEVER	-	-	-	1.000	0.041	0.129	-0.042	-0.063	-0.041	0.336
MARGIN	-	-	-	-	1.000	0.059	0.055	0.103	-0.031	0.476
CFO	-	-	-	-	-	1.000	0.046	-0.018	0.128	0.506
LIQUID	-	-	-	-	-	-	1.000	-0.039	-0.046	0.300
TURN	-	-	-	-	-	-	-	1.000	-0.051	0.393
EQ	-	-	-	-	-	-	-	-	1.000	0.270
FSCORE	-	-	-	-	-	-	-	-	-	1.000

The table summarizes Spearman correlation test result on one-year buy-and-hold raw/market-adjusted returns and nine F_SCORE indicator variables. The indicator variables equal to 1(0) if the underlying performance is good(bad). This test shows the correlation among these factors. Raw corresponds to raw return. Mkt-Adj corresponds to market-adjusted returns. The rest variables represent nine F_SCORE signals. The F_SCORE signals are described in table 1. The dataset represents 30315 firm-year observations between 2004 and 2015.

4.4 Returns

4.4.1 Returns on F_SCORE for All Firms

Table 4 presents 12-month buy-and-hold raw returns across F_SCORE. Since our study focuses on all firms, we want to examine the efficiency of Piotroski's (2000) investment strategy regardless of B/M ratio and market capitalization. We replicate the method that classifies firms with high F_SCORE (8 to 9) and firms with low F_SCORE (0 to 1). The total number of firm-year observations is recorded in each category.

We test whether or not we can separate the high F_SCORE return from the average return of all firms as well as from the low F_SCORE portfolio's average return.

Table 6

All Firms One-Year Raw Return by F_SCORE

F_SCORE	Mean	10th	25th	Median	75th	90th	N
0	5.86%	-77.1%	-22.8%	8.7%	40.2%	51.8%	49
1	5.61%	-63.9%	-43.1%	-7.7%	34.9%	96.3%	525
2	4.75%	-59.4%	-38.2%	-7.5%	27.6%	83.0%	1512
3	5.09%	-56.7%	-34.7%	-4.7%	27.6%	75.9%	3221
4	8.65%	-50.0%	-26.9%	1.0%	30.8%	71.6%	5141
5	7.33%	-46.6%	-21.9%	2.7%	27.9%	60.9%	6577
6	6.42%	-44.1%	-21.7%	2.6%	26.4%	56.1%	6477
7	5.29%	-42.2%	-22.1%	1.6%	24.3%	53.7%	4578
8	6.30%	-41.7%	-19.7%	2.0%	25.9%	56.4%	1964
9	8.61%	-45.1%	-17.2%	6.7%	31.1%	55.1%	272
All	6.60%	-48.3%	-25.1%	1.2%	27.4%	62.4%	30315
Low Score(0,1)	5.63%	-64.1%	-42.0%	-5.6%	36.7%	90.1%	2086
High Score(8,9)	6.58%	-42.1%	-19.3%	2.6%	26.5%	55.8%	2236
High - All	-0.02%	-48.7%	-25.9%	-4.0%	19.9%	49.2%	
P(T<=t) one-tail	0.51						
t-stat	-0.02						
High-Low	0.95%	21.9%	22.7%	8.2%	-10.3%	-34.4%	
P(T<=t) one-tail	0.37						
t-stat	0.33						

The table summarizes 12-month buy-and-hold raw return distributions across different F_SCORE groups for all firms. F_SCORE is an accounting-based scoring system presented in Piotroski's (2000) investment strategy. The table shows the return distributions of high(low) F_SCORE group. The high portfolio consists of firms with a score of 8 and 9. The low portfolio consists of firms with a score of 0 and 1. F_SCORE of 9(0) indicates that the company is in the strongest(weakest) financial position. The detailed computation of F_SCORE is presented in table 2. The distribution contains the mean, the 10^{th} /25^{th} /50^{th} /75^{th} /90^{th} percentile as well as the number in each F_SCORE category. The table also presents the strategies of High-All (High-Low) by taking the mean value of high F_SCORE portfolio less the mean value of all firms (the mean value of low F_SCORE portfolio). T-statistics of mean return is from a one-tailed two sample test (assuming unequal variances). The significance level of 10%, 5%, and 1% can be represented by *, ** and***, respectively. The dataset represents 30315 firm-year observations between 2004 and 2015.

As Table 6 presents, the raw return from F_SCORE 9 outperforms the low ones. The return of F_SCORE 4 also stands out to us , especially with the sample size 5141. In the median group, the firms perform monotonically better as F-SCORE increases except for F_SCORE 0.

The strategy of picking high F_SCORE does not outperform others at a statistical significance level of 90%. This method cannot separate the winners from the losers in all sample firms.

To make a comparison with previous findings, we calculate the market-adjusted return by subtracting value-weighted market returns (S&P500) from the raw return during the same holding period. The result is presented in table 7.

Table 7

All Firm One-Year Market-Adjusted Return by F_SCORE

F_SCORE	Mean	10th	25th	Median	75th	90th	N
0	-2.14%	-50.9%	-37.0%	-4.5%	23.1%	42.1%	49
1	-2.96%	-67.2%	-46.0%	-15.9%	23.1%	78.4%	525
2	-2.85%	-59.7%	-40.9%	-15.6%	19.4%	66.9%	1512
3	-2.23%	-57.9%	-37.1%	-11.9%	16.7%	62.8%	3221
4	0.79%	-51.4%	-30.0%	-6.8%	19.9%	56.8%	5141
5	-0.16%	-45.5%	-25.8%	-5.2%	17.2%	47.0%	6577
6	-0.61%	-44.1%	-24.8%	-5.2%	16.2%	43.4%	6477
7	-1.10%	-43.2%	-24.4%	-5.7%	16.1%	42.0%	4578
8	-0.39%	-42.3%	-23.6%	-4.6%	16.1%	43.8%	1964
9	2.22%	-34.9%	-18.3%	-0.5%	18.9%	41.5%	272
All	-0.64%	-48.6%	-28.0%	-6.5%	17.1%	49.3%	30315
Low Score(0,1)	-2.89%	-66.7%	-45.4%	-14.3%	23.1%	74.5%	2086
High Score(8,9)	-0.07%	-41.8%	-22.8%	-4.1%	16.5%	43.6%	2236
High - All	0.56%	-41.1%	-22.2%	-3.5%	17.1%	44.3%	
P(T<=t) one-tail	0.26						
t-stat	0.65						
High-Low	2.82%	-66.0%	-44.8%	-13.7%	23.7%	75.2%	
P(T<=t) one-tail	0.15						
t-stat	1.03						

The table summarizes 12-month buy-and-hold market-adjusted return distributions across different F_SCORE groups for all firms. We measure F_SCORE, distributions, high (low) groups and the rest in a manner that is similar to table 6. We define marked-adjusted return by using the raw return less the market return over the same investment horizon. In this study the market return is S&P500. The dataset represents 30315 firm-year observations between 2004 and 2015.

The result mostly is in accordance with what we have in table 6. Both tables do not present a value investment strategy to pick the winner stocks since P-values are larger than 10%. The reasons could be because the strategy only works on portfolios with certain B/M ratios.

4.4.2 Returns Conditioned on B/M Ratio

Table 6 and 7 show the one-year raw and market-adjusted returns across different B/M ratios. We have already presented that the performance of F_SCORE for all samples, we believe it is useful to dig into what makes the returns high or low. The portfolio is categorized into 5 quintiles, with 5 being the highest B/M ratio and 1 being the lowest.

Table 8

One-Year Raw Return by B/M ratio All Firms

	Low		**B/M Quintiles**		High	
F-SCORE	1	2	3	4	5	All
0	-8.4%	11.0%	-7.9%	-2.0%	21.0%	5.9%
1	-5.6%	4.1%	9.2%	8.9%	9.4%	5.6%
2	-9.7%	2.0%	-1.8%	5.3%	19.4%	4.8%
3	-4.3%	-1.4%	5.9%	4.3%	14.8%	5.1%
4	3.4%	2.1%	7.2%	10.0%	18.5%	8.7%
5	4.3%	4.9%	7.0%	6.6%	14.1%	7.3%
6	4.7%	5.1%	5.7%	5.3%	12.3%	6.4%
7	4.6%	3.8%	4.1%	6.3%	9.3%	5.3%
8	5.9%	4.0%	5.0%	9.3%	8.5%	6.3%
9	12.2%	17.7%	-1.3%	6.3%	9.3%	8.6%
All	**2.8%**	**3.7%**	**5.6%**	**6.7%**	**14.2%**	**6.6%**
Low	-5.7%	5.0%	7.9%	7.9%	10.4%	
High	6.4%	5.5%	4.3%	8.9%	8.7%	
High - All	3.6%	1.9%	-1.3%	2.2%	-5.5%	
t-stat	2.11**	-0.94	0.65	-1.00	1.90**	
High - Low	12.1%	0.6%	-3.6%	1.0%	-1.8%	
t-stat	1.86**	-0.08	0.49	-0.18	0.27	

The table displays 12-month buy-and-hold raw return distributions across different F_SCORE as well as different book-to-market quintiles for all firms. F_SCORE is an accounting-based scoring system presented in Piotroski's (2000) investment strategy. The high portfolio consists of firms with a score of 8 and 9. The low portfolio consists of firms with a score of 0 and 1. F_SCORE of 9(0) means that the company is in the strongest(weakest) financial position according to Piotroski(2000). The detailed computation of F_SCORE is presented in table 2. The book-to-market ratio is defined by using the book value of equity of a firm divided by its market capitalization at the fiscal year-end. The table also presents the strategies of High-All (High-Low) by taking the mean value of high F_SCORE portfolio less the mean value of all firms (the mean value of low F_SCORE portfolio). T-statistics of return is from a one-tailed two sample test (assuming unequal variances). The significance level of 10%,5%, and 1% can be represented by *, ** and***, respectively. The dataset represents 30315 firm-year observations between 2004 and 2015.

Table 9

One-Year Market-Adjusted Return by B/M ratio For All Firms

	Low		**B/M Quintiles**		High	
F-SCORE	1	2	3	4	5	All
0	-23.3%	2.4%	-13.4%	-5.9%	10.4%	-2.1%
1	-12.5%	-4.4%	-1.4%	0.1%	1.2%	-3.0%
2	-14.6%	-4.5%	-9.0%	-0.5%	8.1%	-2.9%
3	-9.1%	-6.9%	-0.3%	-1.2%	2.9%	-2.2%
4	-2.3%	-3.4%	0.3%	1.9%	6.3%	0.8%
5	-2.2%	-1.4%	0.5%	-0.9%	3.4%	-0.2%
6	-1.4%	-0.3%	-0.7%	-2.2%	1.9%	-0.6%
7	-0.2%	-1.2%	-2.7%	-0.5%	-0.9%	-1.1%
8	0.1%	-2.1%	-1.3%	2.7%	-0.9%	-0.4%
9	6.7%	12.0%	-4.2%	-0.8%	-1.1%	2.2%
All	**-2.9%**	**-2.0%**	**-1.0%**	**-0.4%**	**3.2%**	
Low F-SCORE	-12.9%	-3.6%	-2.4%	-0.4%	2.0%	
High F-SCORE	0.7%	-0.6%	-1.6%	2.2%	-0.9%	
High- All	3.6%	1.4%	-0.6%	2.7%	-4.1%	
t-stat	2.344***	-0.79	0.34	1.3437*	1.54*	
High-Low	13.6%	3.0%	0.8%	2.6%	-3.0%	
t-stat	2.19**	-0.44	-0.11	-0.52	0.50	

The table displays 12-month buy-and-hold market-adjusted return distributions across different F_SCORE as well as different book-to-market quintiles for all firms. Market-adjusted return is defined by using the raw return less the market return over the same investment horizon. The rest variables are described in table 8. The dataset represents 30315 firm-year observations between 2004 and 2015.

In alignment with Rathjens and Schellhove's (2011) study on the U.K. market, our results show that the strategy works better in the lowest B/M quintile. Despite having the lowest raw and market-adjusted returns in general compared to other quintiles, the Piotroski's method works in growth stocks. For raw returns, the strategy of buying high F_SCORE portfolio can generate 3.6% more than the average firms in the same quintile; same strategy applied to the marketed-adjusted area also results in the same return of 3.6%. The results are significant at the 1% level and 5% level respectively for raw and market-adjusted returns. The other strategy of buying high F_SCORE stocks and shorting low F_SCORE stocks can generate 12.1% and 13.6% on raw and market-adjusted return respectively, with P-values both lower than 0.05.

As B/M ratio moves up to 5, the effectiveness of picking winner stock strategy gradually disappear. In fact, In the highest B/M quintile, buying high F_SCORE strategy not only does not give the investors a positive marked-adjusted return but also is outperformed by the average return. The results are significant at the 10% (5%) level on the raw return table (market-adjusted return table). Another discovery is that for high F_SCORE group (7 to 9), as B/M ratio increases, the market-adjusted returns decrease. This situation also happens in the raw return except only for the F_SCORE 9 portfolio.

This observation is contradicted by the theory of Piotroski's(2000) as he records that the high F_SCORE firms perform better than the average and low F_SCORE firms in the same quintile. We find that in the highest B/M quintile, high F_SCORE portfolios are outperformed by the average portfolio at a 10% statistical significance level. Moreover, we note that only in the lowest quintile can we find a monotonically increasing return pattern ranging from 0 to 9.

Exploring the distribution patterns behind this dataset, we look back at table 6 and 7. Regardless what the B/M ratio is, F_SCORE indeed improves the return from the 10^{th} percentile to the median range. If we go beyond median, especially on the 90^{th} quantile, the high F_SCORE portfolio tends to be outperformed by the lower one, on average by at least 30% in market-adjusted returns and 35% in raw returns.

In conclusion, F_SCORE strategy, as analyzed above, is efficient in picking winner firms out of loser firms in the growth stock portfolio. For the value stocks, the high F_SCORE group gets outperformed by the average value stock.

4.4.3 Returns Conditioned On Size

After observing the difference across B/M ratios, the next step is to test if there is a size effect across different market capitalization sizes. We equally divide the whole portfolio into three divisions (ex. small, medium and large) based on its market value and evaluate one-year raw and market-adjusted returns. The results are presented in Table 10 and Table 11.

Table 10

One-Year Raw Return by Size

	Small Firms			Medium Firms			Large Firms		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
F-SCORE									
0	-0.2%	-5.5%	35	22.3%	22.0%	12	14.5%	14.5%	2
1	5.3%	-8.4%	351	7.0%	-7.6%	141	3.3%	-2.9%	33
2	3.3%	-10.7%	962	7.1%	-6.7%	417	7.8%	6.3%	133
3	6.8%	-8.2%	1625	3.8%	-3.6%	1103	2.5%	0.6%	493
4	10.2%	-1.9%	1953	9.2%	2.2%	1820	5.7%	2.7%	1366
5	8.9%	-1.7%	1936	7.1%	2.2%	2289	6.3%	5.2%	2351
6	8.5%	-0.3%	1667	6.9%	1.6%	2183	4.7%	4.4%	2627
7	8.5%	-1.3%	987	5.6%	2.0%	1446	3.6%	2.5%	2145
8	12.5%	0.5%	415	4.9%	-0.2%	537	4.5%	3.8%	1012
9	7.6%	-3.7%	72	6.9%	5.5%	56	9.8%	9.3%	144
All	8.2%	-2.8%	10003	6.7%	1.0%	10004	5.0%	3.8%	10306
Low	4.8%	-7.8%		8.2%	-3.7%		3.9%	-1.7%	
High	11.8%	-0.1%		5.1%	0.7%		5.2%	4.7%	
High-All	3.6%	2.7%		-1.7%	-0.3%		0.2%	0.9%	
t-stat	1.38*			0.92			-0.18		
High-Low	7.0%	7.8%		-3.1%	4.4%		1.2%	6.5%	
t-stat	1.67**			0.5247			-0.13		

The table displays 12-month buy-and-hold raw return distributions across different F_SCORE as well as different market capitalizations for all firms. F_SCORE is an accounting-based scoring system presented in Piotroski's (2000) investment strategy. The detailed computation of F_SCORE is presented in table 2. The high(low) portfolio consists of firms with a score of 8 or 9(0 or 1). F_SCORE of 9(0) means that the company is in the strongest(weakest) financial position according to Piotroski (2000). Market capitalization is defined by using the share closing price multiplied by the number of shares outstanding at the fiscal year-end. The table also presents the strategies of High-All (High-Low) by taking the mean value of high F_SCORE portfolio less the mean value of all firms (the mean value of low F_SCORE portfolio). T-statistics of return is from a one-tailed two sample test (assuming unequal variances). The significance level of 10%,5%, and 1% can be represented by *, ** and***, respectively. The dataset represents 30315 firm-year observations between 2004 and 2015.

Table 11

One-Year Market-Adjusted Returns by Size

	Small Firms			Medium Firms			Large Firms		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
F_SCORE									
0	-5.5%	-11.8%	35	8.9%	11.8%	12	-10.1%	-10.1%	2
1	-2.5%	-16.5%	351	-3.3%	-16.0%	141	-7.2%	-7.4%	33
2	-4.1%	-17.5%	962	-0.6%	-13.7%	417	-0.9%	-6.7%	133
3	-1.1%	-15.4%	1625	-2.6%	-9.8%	1103	-5.1%	-8.7%	493
4	2.0%	-9.6%	1953	2.2%	-5.4%	1820	-2.8%	-5.4%	1366
5	1.3%	-9.2%	1936	-0.4%	-5.9%	2289	-1.2%	-2.8%	2351
6	1.7%	-7.7%	1667	-0.2%	-5.3%	2183	-2.4%	-4.3%	2627
7	1.1%	-9.0%	987	-1.2%	-6.1%	1446	-2.0%	-4.5%	2145
8	5.2%	-7.1%	415	-1.8%	-5.1%	537	-1.9%	-3.8%	1012
9	-0.7%	-11.7%	72	-2.1%	-0.5%	56	5.3%	2.0%	144
All	0.6%	-10.5%	10003	-0.4%	-6.4%	10004	-2.1%	-4.2%	10306
Low	-2.7%	-16.2%		-2.3%	-14.0%		-7.4%	-7.4%	
High	4.3%	-7.5%		-1.9%	-4.6%		-1.0%	-3.1%	
High-All	3.8%	3.0%		-1.5%	1.8%		1.1%	1.1%	
t-stat	1.5245*			0.92			1.08		
High-Low	7.0%	8.7%		0.4%	9.4%		6.4%	4.3%	
t-stat	1.79**			-0.08			-0.70		

The table displays 12-month buy-and-hold market-adjusted return distributions across different F_SCORE as well as different market capitalizations for all firms. F_SCORE is an accounting-based scoring system presented in Piotroski's (2000) investment strategy. The detailed computation of F_SCORE is presented in table 2. Market-adjusted return is defined by using the raw return less the market return over the same investment horizon. The rest variables are as described in table 10. The dataset represents 30315 firm-year observations between 2004 and 2015.

Table 10 and Table 11 show that in the small firm portfolio, we can use the strategy to pick out the winner stocks. Table 10 and Table 11 are mostly the same regarding return patterns. Here we take Table 11 as an example to analyse: The high F_SCORE portfolio return is 3.8% outperforming the average small firms, 7.0% better than the low F_SCORE portfolio, at a significance level of 10% and 5% respectively. This result is partly in line with Piotroski's (2000), as he discovers that the medium market size portfolio is also statistically significant on high minus all and high minus low strategies.

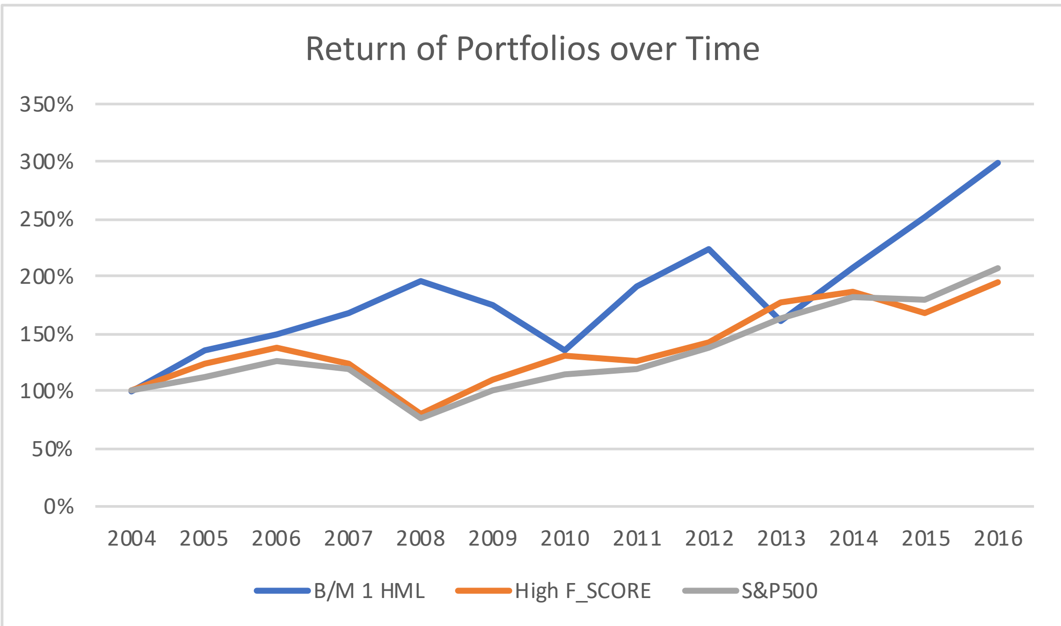
The monotonically increasing return pattern discovered before can be found in the small firm portfolio, arguably in the large firm portfolio as well. This observation indicates that for small firm portfolios, the investment strategy works better in the sense of picking higher return stocks simply with higher F_SCORE.

Another interesting finding is that companies in the lowest size category have more firms with 0 and 1 F_SCORE than the other two categories. This fact can be explained by Fama and French (1992) documenting that stocks with a high B/M ratio, in general, are more likely to experience financial distress compared to lower B/M sections.

4.4.4 Portfolio Raw Returns over Time

From table 8 we know that the average return of high F_SCORE can outperform low F_SCORE significantly in the same lowest B/M quintile, we want to know what the compound return of this strategy is over time. We also want to compare it to the strategy of buying high F_SCORE and the market index S&P500. Figure 1 provides these three performances throughout the calendar year 2004 to 2015.

Figure 1



This figure shows one-year buy-and-hold raw compound returns on different portfolios over time. The portfolios consist of: a portfolio of high minus low in lowest B/M quintile, a portfolio of high F_SCORE, the value-weighted market return index S&P500. High minus low means that we buy stocks with a high F_SCORE and short ones with a low F_SCORE. Piotroski(2000) uses a binary system F_SCORE to measure a firm's financial position. The F_SCORE is computed in table 2. We define portfolio with high(low) F_SCORE with an F_SCORE of 8-9 (0-1). The portfolio is equally-weighted between all stocks. The dataset represents 30315 firm-year observations between 2004 and 2015.

From Figure 1 we notice that the high F_SCORE portfolio's return is almost in line with the S&P500. The strategy of high minus low significantly outperforms the other two, especially during the financial crisis of 2008. However, the portfolio value drops from 2008 to 2010 and 2012 to 2013 while the other two portfolios gradually increased. Despite declining in value, the HML portfolio still beat the market in 2010. In the end, the HML portfolio value becomes 300%, while the other two are only around 200%. This graph shows that, with F_SCORE method, we can pick the winner stocks from the lowest B/M quintile to beat the market.

5. Conclusion

In this paper, we partly replicate Piotroski's (2000) accounting-related investment strategy, F_SCORE and test if we can still apply the approach in the same market from 2004 through 2015. Besides, we extend our sample scope to have a better overview of the performance of the investment strategy. The F_SCORE system consists of nine signals in a binary system, which can reflect the financial position and profitability of a company. We can follow this simple method to invest better by identifying winner stocks that generate higher returns from loser stocks. In general, we buy(sell) stocks with high(low) F_SCORE. In this case, we set the high F_SCORE with value 8-9 and the low with 0-1.

Our empirical results show that the strategy of picking high F_SCORE portfolio cannot significantly outperform the low F_SCORE for all sample firms. However, when analyzing into low book-to-market ratio quintile, we note that there are significant returns from strategies of high minus all and of high minus low, whose raw returns are 3.6% and 12.1%, respectively. This finding indicates that the strategy works, but only in the lowest B/M ratio portfolio. In the highest B/M quintile, we find that the average firm outperforms the high F_SCORE by 5.5% in raw return and 4.1% in market-adjusted return; our conclusion contradicts Piotroski's (2000).

On the other hand, the strategy can pick winner stocks in the small market capitalization category. High F_SCORE portfolio outperforms average small firms (low F_SCORE firms) by a market-adjusted return of 3.8% (7%) at the 10% significance level. This finding is in line with Piotroski's (2000).

We also show in our graph that the HML portfolio in the lowest B/M quintile can significantly outperform the market in the long run.

In conclusion, we find that the Piotroski's method only works in growth stocks and small market capitalization firms. It can differentiate winners stocks from loser stocks under either condition.

References

Ackert L.F., and Deaves R., 2010, Behavioral finance: psychology, decision-making and markets, Cengage Learning 28–30, 60–73, 83–102, 106–117, 219–234.

Ball R, 1992, The earnings-price anomaly, Journal of Accounting and Economics 15(2–3), 319–345.

Ball R., and Brown P, 1968, An empirical evaluation of accounting income numbers, Journal of Accounting Research 6(2), 159–178.

Bernard V. L., and Thomas J. K, 1989, Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27, 1–36.

Black F., 1993, Estimating expected return, Financial Analysts Journal 49(5), 36–38.

Bodie Z., Kane A., and Marcus A. J., 2013, Essentials of Investments (Boston, Mass, Irwin/McGraw Hill Global edition)

Chan L., K. C., and Chen N.-F., 1991, Structural and return characteristics of small and large firms, The Journal of Finance 46(4), 1467–1484.

Chan L., K. C., Jegadeesh N., and Lakonishok J, 1996, Momentum strategies, The Journal of Finance 51(5), 1681–1713.

Chen, N.-F., and Zhang F, 1998, Risk and return of value stocks, The Journal of Business 71(4), 501–535.

Daniel K., and Titman S, 1997, Evidence on the characteristics of cross sectional variation in stock returns, The Journal of Finance 52(1), 1–33.

Davis J. L., Fama, E. F., and French K. R., 1999, Characteristics, covariances, and average returns: 1929–1997, working paper, SSRN eLibrary.

DeBondt W., and Thaler R., 1985, Does the stock market overreact? The Journal of Finance 40(3), 793–805.

Fama E. F., 1965, The behavior of stock-market prices, The Journal of Business 38(1), 34–105.

Fama E. F., 1970, Efficient capital markets: A review of theory and empirical work, Journal of Finance 25(2), 383–417.

Fama E. F., Fisher L., Jensen M. C., and Roll R, 1969, The adjustment of stock prices to new information, International Economic Review 10(1), 1.

Fama E. F., and French K. R., 1992, The cross-section of expected stock returns, The Journal of Finance 47(2), 427–465.

Fama E. F., and French K. R, 1993, Common risk factors in the returns on stock and bonds, Journal of Financial Economics 33(1), 3–56.

Fama E. F., and French K. R, 1995, Size and book-to-market factors in earnings and returns, The Journal of Finance 50(1), 131–155.

Greig A. C., 1992, Fundamental analysis and subsequent stock returns, Journal of Accounting and Economics 15(2–3), 413–442.

Hirshleifer D., Hou K., Teoh S. H., and Zhang Y, 2004, Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

Holthausen R, and Larcker D, 1992, The Prediction of Stock Returns Using Financial Statement Information, Journal of Accounting and Economics 15, 373–411.

Hou K., Xue C., and Zhang L., 2017, Replicating anomalies, No. w23394, National Bureau of Economic Research.

Jegadeesh N., and Titman S, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, The Journal of Finance 48(1), 65–91.

Kothari S., and Warner J. B., 1997, Measuring long-horizon security price performance, Journal of Financial Economics 43(3), 301–339.

Lakonishok J., Shleifer A., and Vishny R. W., 1994, Contrarian investment, extrapolation, and risk, The Journal of Finance 49(5), 1541–1578.

Lev B., and Thiagarajan S. R., 1993, Fundamental information analysis, Journal of Accounting Research 31(2), 190–215.

Lintner J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, The Review of Economics and Statistics 47(1), 13–37.

MacKinlay, A. C., 1995, Multifactor models do not explain deviations from the CAPM, Journal of Financial Economics 38(1), 3–28.

Mandelbrot B, 1966, Forecasts of future prices, unbiased markets, and" martingale" models, The Journal of Business 39(1), 242–255.

Markowitz H., 1952, Portfolio selection, The Journal of Finance 7(1), 77–91.

Mossin J, 1966, Equilibrium in a capital asset market, Econometrica: Journal of the econometric society, 768–783.

Ou J. A., and Penman S. H., 1989, Financial statement analysis and the prediction of stock returns, Journal of Accounting and Economics 11(4), 295–329.

Penman S. H., 1991, An evaluation of accounting rate-of-return, Journal of Accounting, Auditing and Finance 6(2), 233–255.

Piotroski J. D., 2000, Value investing: The use of historical financial statement information to seperate winners from losers, Journal of Accounting Research 38, 1–41.

Piotroski J. D., 2005, Discussion of ’Separating winners from losers among low book- to-market stocks using financial statement analysis’, Review of Accounting Studies 10(2–3), 171–184.

Rosenberg B., Reid K., and Lanstein R., 1985, Persuasive evidence of market inefficiency, Journal of Portfolio Management 11(3), 9–16.

Rathjens, and Schellhove, 2011, Simple Financial Analysis and Abnormal Stock Returns.

Samuelson P. A, 1965, Proof That Properly Anticipated Prices Fluctuate Randomly, Industrial Management Review 6 (2), 41–49.

Sharpe W. F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, The Journal of Finance 19(3), 425–442.

Treynor J. L.,1962, Market value, time and risk, working paper.

Weetman P., and Gray S. J., 1990, International financial analysis and comparative corporate performance: The impact of UK versus US accounting principles on earnings, Journal of International Financial Management and Accounting 2(2–3), 111–130.

Xiao J., and Xu X., 2004, Empirical study on the effectiveness of China's stock market value reversal investment strategy, Economic Research 3, 55–64, in Chinese.

Zacks L., 2011, The Handbook of Equity Market Anomalies: Translating Market Inefficiencies into Effective Investment Strategies, 1st edition (Hoboken, N.J., Wiley)