The Effectiveness of Fundamental Analysis on Value Stocks – an Analysis of Piotroski's F-score

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Abstract

In an efficient market, assets reflect all available information. Hence, investors cannot earn abnormal returns by conducting fundamental analysis since all financial data is impounded in the asset. The only way for an investor to earn higher returns is by incurring increased risk. However, a growing body of evidence appears to contradict market efficiency and common notion of risk compensation. Piotroski (2000) documents that a fundamental investing strategy based on F-score applied on value stocks can generate abnormal returns. F-score is a scoring system aiming at identifying financially strong firms. This paper replicates Piotroski's investment strategy on the US market for the period 2003-2015. My results show that a portfolio with high F-score earns a one-year market-adjusted return of 18.3 % annually. The corresponding return for a low F-score portfolio is 4 % annually. This significant mean return difference of 14.3 % indicates that fundamental analysis can be used to separate winner stocks from loser stock. The firms that document the highest returns are attributed with least financial distress, which contradicts the notion of risk compensation. The strongest benefit from the investment strategy is found in small and medium firms. The success of the investment strategy can be supported from a behavioral finance perspective. The findings suggest that limits to arbitrage may impede efficient pricing in small and medium firms. Moreover, value stocks are neglected by the investment community due to cognitive biases, and fundamental analysis can exploit this by finding financially strong performing firms in an unbiased fashion.

Keywords: F-score, Fundamental Analysis, Value Stocks, Abnormal Returns, Market Efficiency, Behavioral Finance

Contents

1. Introduction

According to the efficient market hypothesis, assets reflect all available information (Fama, 1965). In a semi-strong efficient market, assets reflect all public information such as financial data (Fama, 1970). Hence, in this efficiency form market actors cannot earn an excess return from conducting fundamental analysis since all public information is already impounded in the security. Asset pricing models, which assumes market efficiency, demonstrates that the only way for investors to earn a higher return is by incurring greater risk (e.g. Sharpe, 1964).

However, a growing body of evidence contradicts the efficient market hypothesis and the notion of risk compensation. Several academic studies have shown that fundamental analysis could generate abnormal returns and some appear to be anomalies. Fundamental analysis aims at finding mispricing signals by calculating the intrinsic value of a stock by primary using annual reports. Examples of fundamental investing strategies generating excess returns are post-earnings announcement drift (Bernard and Thomas, 1989) and accruals (Sloan, 1996).

In addition to fundamental investing, value stocks[1] have been generating returns that appear to be abnormal. Value stocks are securities attributed with a low valuation. In this paper, I will focus on the valuation metric book-to-market whereof a higher book-to-market implies a lower valuation. Fama and French (1992) among others shows that a portfolio constructed with high book-to-market stocks generate higher returns than a portfolio with low book-to-market stocks. Lakonishok et al., (1994) documents that value stocks are associated with poor prior performance, consequently investors tend to form overly pessimistic expectations on these stocks. As a consequence, value stocks have a tendency of being neglected which can lead to mispricing.

The discoveries of abnormal returns and anomalies have given rise for the field behavioral finance. This area opposes one of the key tenets in the efficient market hypothesis, that individuals process information rationally. Instead, individuals are assumed to be subjects to

[1] The term value stock and high book-to-market stock will be used synonymously. The terms refer to the same meaning.

cognitive biases and that this can lead to inefficiently priced assets. Moreover, contradictory to the efficient market hypothesis, behavioral finance assumes that limits to arbitrage exists and can impede an efficient pricing.

In this paper, I intend to investigate if a fundamental investing strategy when applied to value stocks based on Piotroski's F-score is effective in separating winner stocks from loser stocks. Furthermore, I intend to discuss whether this is consistent with risk compensation and market efficiency. In addition to Piotroski (2000), I discuss whether a behavioral finance perspective can support with explanations.

Piotroski (2000) find in his study that an investment strategy based on a simple accounting-based fundamental analysis applied on high book-to-market stocks can generate abnormal returns. The strategy builds on investing in value stocks with strong financial performance. To identify firms with strong financial performance Piotroski constructs a so-called F-score. The F-score is a binary scoring system with nine variables. The nine variables capture the factors profitability, leverage/liquidity and operating efficiency. Hence, a company can receive an F-score between 0 and 9 whereof 9 is the best score and is expected to have the strongest subsequent financial performance. Moreover, a score of 0 is expected to have the weakest financial performance.

Piotroski (2000) document for the US market between 1976 and 1996 that investors can increase the mean return with 7.5 % annually by investing in financially strong (high F-score) value stocks. Furthermore, he shows that an investment strategy that buys expected financially strong (high F-score) value stocks and short sell expected financially weak (low F-score) value stocks earn a return of 23 % annually.

This paper aims at replicating Piotroski's investment strategy on the US market for the period 2003-2015. The reason for choosing the US stock market is because the conditions for investors have dramatically changed since Piotroski performed his investment strategy. Among those changes are transaction costs, availability of financial information and screeners to identify F-score is easier and cheaper. Concerning these changes in conditions, the investment strategy should not generate excess returns in the same extension for the period I am investigating.

My results for the period 2003-2015 finds that a high F-score portfolio applied to value stocks generates an annual market-adjusted mean return of 18.3 %. In comparison with the entire value stock portfolio that earns a corresponding return of 12.3 %. A hedged portfolio that buys expected winners (high F-score) and short sells expected losers (low F-score) generates an annual market adjusted return of 14.3 %. This strong return suggests that fundamental analysis can be used to separate winner stocks from loser stocks among high book-to-market firms.

The strong returns generated by the investment strategy appear to contradict the notion of risk compensation since the firms with least financial distress have the best subsequent returns. In this paper, I document that value stocks have low analyst coverage. Prior research shows that the investment community neglects value stocks. This neglecting includes analysts and intuitional investors. This unwillingness towards value stocks may be an explanatory factor for the success of a fundamental analysis strategy as F-score. Since there only are few investors covering the investment universe of value stocks it may impede an efficient market pricing. The reason for investors ignoring value stocks can be due to cognitive biases such as anchoring, representativeness, expectational errors, optimism/pessimism and herding behavior among institutional investors.

The proceeding section provides an overview of theory and related academic studies on the efficient market hypothesis, asset pricing models, value stocks, fundamental investing, anomalies and behavioral finance. Section 3 explains Piotroski's F-score and the investment strategy in detail. Section 4 describes the methodology and tests employed in the paper. Section 5 and 6 presents the empirical results respectively analysis of the investment strategy. Finally, in section seven I give conclusions.

2. Theoretical Foundation

The strong returns from Piotroski's (2000) investment strategy appear to contradict the semi-strong efficiency form and risk compensation. Piotroski's investment strategy is based on fundamental signals and value stocks. Therefore, I will present the efficient market hypothesis, asset pricing models, value stocks, fundamental analysis, anomalies and behavioral finance.

2.1 The Efficient Market Hypothesis

The efficient market hypothesis is usually considered to have been established by Fama (1965, 1970) and furthermore also building on Samuelson (1965) and Mandelbrot (1966). Fama (1965) defines an efficient market as:

"…an "efficient" market for securities, that is, a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values."

Hence, in an efficient market, the efficient market hypothesis implies that security prices fully reflect all information and consequently assets react directly to new information and correctly impounds that information (Fama, 1965).

For a market to be efficient, the efficient market hypothesis is conditioned on primary three assumptions. First, the efficient market hypothesis assumes that basic knowledge is fulfilled, meaning that investors have complete information on underlying statistics regarding risk and return. Secondly, the efficient market hypothesis assumes that investors are rational. Hence, investors process information cognitively in an unbiased fashion. Consequently, investors impound information correctly without overreacting or underreacting. Finally, the efficient market hypothesis assumes no limits to arbitrage, meaning that if a mispricing occurs, investors will see the arbitrage opportunity and trade the asset until it reaches its correct price (intrinsic value). The effect of irrational investors creating mispriced assets will quickly disappear, due to rational investors exploiting the arbitrage opportunity. Factors that impede arbitrageurs acting on mispriced assets are transaction costs, shorting restrictions, the absence of alternative investments for the mispriced security and a limited amount of arbitrageurs (Zacks, 2011).

Fama (1970) extends the concept of efficient markets by defining three types of market efficiency: weak efficiency, semi-strong efficiency and strong efficiency. The first form, weak efficiency, states that security prices reflect all historical prices and other market data such as trading volume. This efficiency form implies that investors cannot earn an excess return by using data or strategies based on historical market trading data. In other words, technical analysis is fruitless since investors will exploit buying signals based on historical data in an instant manner.

A semi-strong efficient market incorporates the implications of weak efficiency. In addition, the semi-strong form asserts that asset prices reflect all publicly available information and impounds such information rapidly. This information consists of fundamental data such as income statements, balance statements, earnings estimates, etc. Hence, market actors cannot use fundamental analysis or technical analysis to earn excess returns (Bodie et al., 2013).

Finally, strong efficiency implies that private information (insider information) is reflected in security prices promptly. Strong efficiency incorporates the implications of the semi-strong and weak efficiency form. In this efficiency form, all information relevant to an asset is reflected in its price. In common with all three efficiency forms is that security prices should reflect all available information (Bodie et al., 2013).

The general academic consensus of market efficiency is that markets manifest in a semi-strong form. In this efficiency form, investors cannot earn abnormal returns by conducting fundamental analysis. Piotroski (2000) opposes the semi-strong efficiency form since his study shows that abnormal returns can be generated from a simple investment strategy.

2.2 Asset Pricing Models - The Concept of Risk and Expected Returns

In efficient markets where investors are risk-averse and rational, the expected return of an asset is dependent on its inherent risk. In common for different asset pricings models are that they predict the relationship between risk and expected return. The expected return of an asset is estimated by the sum of risk-free rate and its risk premium. More specifically, the risk premium can be defined as the product of, the price of risk and the quantity of risk. The first component, the price of risk, is the required expected return per units of returns. The second element, the quantity of risk, is the number of units of risk. The price of risk is the same for all securities while the quantity of risk differs. Hence, it is essential to understand how risk is measured to estimate expected returns (Zacks, 2011).

When investing in an asset, the investor defers consumption today and consequently requires compensation for this. Investors have a preference for steady consumption levels and dislike volatile consumption levels. Hence, securities that are negatively correlated with consumption are considered as less risky than stocks that are positively correlated with consumption. Therefore, the risk is measured as covariance with consumption, which could be determined from utility maximization. This results in the following expression (Cochrane, 2001):

$$E\left(r - R_f\right) = -R_f \sigma(SDF, r) \quad (1)$$

SDF corresponds to the stochastic discount factor and is closely identical to consumption growth. The left-hand side of the equation corresponds to the risk premium of a security, and this is equal to a security's return covariance with the SDF variable. In, summary, equation (1) presents the theoretical intuition for the risk premium but is not practically applicable. It exists multiple models which are empirical applicable. In common for those models are that a number of risk factor are linearly related to the SDF and could in general terms be written as:

$$E\left(r - R_f\right) = \sum(B_j, \lambda_j) \qquad (2)$$

In this equation (2) the risk premium B_j is the quantity of risk and λ_j is the price of risk, whereas the sub-index j is the risk factor (Zacks, 2011).

2.2.1 Capital Asset Pricing Model

The capital asset pricing model referred to as the CAPM, is the most widely known asset pricing model and was introduced by Sharpe (1964) and Lintner (1965). The model predicts that investors cannot earn a higher expected return without incurring more risk. The CAPM defines two types of risk, unsystematic and systematic risk. The first type of risk, unsystematic, is the risk inherent in one company and can be avoided by investing in a diversified portfolio. Secondly, the systematic risk consists of the market risk and cannot be eliminated by diversifying. According to the CAPM, the expected return $E(R_i)$ of a security is equal to the risk-free rate (R_f) and the risk premium ($R_m - R_f$), which compensates for the systematic risk. The beta ($\mathrm{B_i}$) corresponds to the specific inherent risk for an asset in relation to the whole market risk. Hence, the equation for the expected return in CAPM is:

$$E(R_i) = R_f + B_i(E(R_m) - R_f) \quad (3)$$

Whereof $\mathrm{B_i}$ is:

$$B_i = \frac{\sigma(R_i, R_m)}{\sigma_m^2} \quad (4)$$

In comparison with equation (1), the CAPM finds the stochastic discount factor (SDF) as a linear function of the investors' total wealth. In equation (3) The price of risk is the risk premium and the quantity of risk equals to the beta coefficient. An implication of the CAPM is that the optimal portfolio for investors to hold is the market portfolio (Zacks, 2011).

2.2.2 Fama and French Three-Factor Model

One flaw in the CAPM is that the model only accounts for one risk factor, market risk. Several academic studies suggest that risk can be described as a multidimensional factor. Risk factors that have been left unexplained by the CAPM are the size premium and value premium.

Banz (1981) finds a size premium which is not explained by the market beta in CAPM. Small companies produce, on average, a higher return in relation to the market beta and in contrast larger companies generate, on average, a lower return relative its market beta. This size effect has been derived to higher risks in smaller companies. Among those risks are liquidity risk (Stoll and Walley, 1983) and exposure to more systematic risk factors (Chan and Chen, 1991).

Another risk factor that the market beta in CAPM does not capture is the value premium. Rosenberg, Reid and Leinstein (1985) shows that high book-to-market firms earn a higher return in comparison with companies that have a low book-to-market valuation. This value premium can be considered as compensation for risk. Fama and French (1992) document that value stocks are more financially distressed in comparison to other stocks. Hence, the high return from value stocks is a compensation for the additional risk of financial distress.

Fama and French (1992) observe that book-to-market and market capitalization explains asset returns more than just the market beta factor. Moreover, Fama and French (1993) extend the CAPM and introduce a three-factor model which includes size and book-to-market as a risk factor, in addition to the market risk. Hence, the expected return in this model is as follows:

$$E(R_i) = R_f + \beta_3(E\left(R_m - R_f\right) + b_s SMB + b_v HML \quad (5)$$

In this equation (5) expected return for a security is a function of the risk-free rate and three risk factors. First, the model accounts for the risk premium ($R_m - R_f$) multiplied by its sensitivity in relation to the market, measured as β_3. The SMB (Small Minus Big) variable accounts for the size premium and corresponds to the difference of returns on portfolios with small and large stocks. The HML (High Minus Low) factor considers the value premium and equals the return for a high book-to-market portfolio minus the return for a low book-to-market portfolio. The risk premium, SMB and HML corresponds to the price of risk and the coefficients $\beta_{3,}$ b_s, and b_v equals to the quantity of risk (Bodie et al., 2011).

2.3 Value Stocks and Value Investing

Value stocks are securities which have a low valuation regarding the intrinsic value or financial ratios related to earnings, cash flows and book value. In other words, value stocks are securities that are undervalued in absolute or relative terms in comparison to its market capitalization. Value investing is about identifying stocks with low valuation. In this section, I will focus on value stocks with a high book-to-market ratio, which is the ratio of a firm's book value scaled by its market capitalization (Ackert and Deaves, 2010).

Papers such as Rosenberg, Reid, and Lan- stein (1984), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994) finds that a portfolio constructed with high book-to-market stocks generate higher returns than a portfolio with low book-to-market stocks. This outperformance has been considered both as market efficiency and as inefficiency.

From a market efficiency standpoint, Fama and French (1992) argue that high book-to-market firms are financially distressed. As discussed in section 2.2.2, Fama and French three-factor model, a high-book-to market stock is considered with an additional risk attribute. Consequently, the strong return from the high book-to-market portfolio is a compensation for an increased risk inherent in value stocks. Fama and French (1992) and Chen and Zhang (1998) show that the superior returns from value stocks are not a mispricing signal. They document that value stocks are financially distressed concerning dividend reduction, leverage and earnings deviations. They reach the conclusion that the higher returns from high book-to-market stocks are a compensation for increased risk.

The strong performance from high book-to-market firms in comparison with low book-to-market (growth/glamour stocks) firms can also be attributed to market inefficiency. Lakonishok et al., (1994) documents that high book-to-market firms are associated with poor prior performance, consequently investors tend to form overly pessimistic expectations on these stocks. Consequently, these high book-to-market stocks are neglected and create market mispricing (undervaluation). Furthermore, they also show the opposite relations for growth stocks meaning that market actors form overly optimistically expectations and discount earnings to aggressive, which create market mispricing (overvaluation). Lakonishok et al., (1994) do not find any evidence for value stocks being riskier than growth stocks.

La Porta et Al. (1997) note that the pessimism that manifests for value stocks leads to earnings surprises in subsequent years. They document that stocks exposed to analyst coverage, with low estimated earnings growth outperform stocks with high estimated earnings growth. Moreover, value stocks tend to have a lack of analyst coverage, which results in fewer forecasts and recommendation for the investment community (Piotroski, 2000).

Piotroski (2000) observes that the strong return generated by a high book-to-market portfolio relies on a few stocks while a significant majority generates weak returns. This diversity of performance among value stocks gives an opportunity to distinguish between strong and weak companies. Therefore, Piotroski finds it interesting to apply a financial statement analysis using fundamental metrics on these high book-to-market firms.

2.4 Fundamental Investing - Fundamental Data Analysis

Fundamental investing is about earning excess returns by finding strong fundamental signals through analyzing a company's fundamental data. This information relates both to quantitative and qualitative data and is used to determine an intrinsic value of a company. The aim for fundamental investors is to find a mispricing signal based on a firm's intrinsic value. Fundamental investors recognize an investment opportunity if the intrinsic value exceeds market capitalization. Furthermore, this school of investing believe that markets are temporarily inefficient and that undervalued stocks will converge to its intrinsic value. The success of fundamental investing builds upon both market inefficiency and efficiency. As mentioned earlier, fundamental investors believe that investment opportunities can be found due to temporary inefficient mispricing signals. In contrast, fundamental investors expect the asset to revert to its intrinsic value, hence that the market is efficient (Bodie et al., 2013).

As discussed in section 2.1, the efficient market hypothesis, most academic studies assume that markets demonstrate in a semi-strong efficiency form. A key tenet of this efficiency form is that fundamental analysis cannot be used in the pursuit of earning excess returns since all financial data are impounded in security prices. However, a growing body of academic studies shows that assets behave in an inefficient manner in the short-term time perspective.

One of the first to provide an academic study on evaluating whether financial data is impounded in a timely manner or not, are Ball and Brown (1968). They examine if financial information in terms of accounting data are impounded to security prices. From this study, they find evidence for short-term inefficiencies. They find a so-called post-earnings announcement drift. During the period from 1957-1965, they investigated how a change in earnings would reflect in the stock price. They document that securities drift a period after earnings announcement which indicates that securities do not ultimately impound earnings on announcement days.

This discovered phenomenon has resulted in several research papers focusing on earnings changes and earnings surprises. Among those are Bernard and Thomas (1989; 1990), and Foster et al. (1984) which found a so-called post-earnings announcement drift and document that an investment strategy based on buying (selling) companies with extreme positive (negative) earnings surprises generates strong return performances.

Other examples of fundamental signals that suggest excess return can be earned from using fundamental data are dividend decreases (Michaely et al., 1995), seasoned equity offerings (Loughran and Ritter, 1995), share repurchases (Ikenberry et al., 1995) and accruals (Sloan 1996).

The previous examples of strong fundamental signals strategy have a rather one-dimensional approach. However, a number of research papers have tested advanced investment strategies that use an array of indicators. Ou and Pennman (1989) perform an investment strategy that earns a return of 12.5 %. They constructed a model which forecast firms' earnings for the upcoming year. If the probability exceeded 0.6, they bought the stock, and if the probability was below 0.4, they short sold the stock.

However, one problem with Ou and Pennman's (1989) methodology is data mining. Tortoriello (2009) describes the data mining issue as finding correlations in databases without considering the relationship that result in the correlations. In other words, there is a problem related to overfitting the data to a certain setting without testing it for another setting. Relating to the data mining issue, Holthaussen and Larcker (1992) tried Ou and Pennman's strategy for another period and could not find any evidence for the strategy anymore.

To avoid this problem with overfitting and data mining, subsequent studies have aimed at finding underlying factors before performing an investment strategy. To exemplify, Lev and Thiagarajan (1993) design a strategy based on a scoring system with 12 fundamental data indicators. The scoring system is based on what financial analysts in the industry find helpful and professional publications. They find that their scoring system is correlated to contemporaneous returns after controlling for earnings and size.

Piotroski (2000) aims at finding a contextual fundamental investment strategy for high book-to-market stocks. Hence, he designs a scoring system based on an array of fundamental signals that he expects are advantageous for investing in value stocks. These fundamental signals aim at capturing the underlying financial characteristics of value stocks. As mentioned in section 2.3 about value stocks we know that these stocks, in general, are financially distressed, have low analyst coverage, pessimistically held views on value stocks which can lead to earnings surprises, and that there is a spread distribution of their performance.

2.5 Anomalies

A discussed in section 2.3 Value stocks and value investing, and section 2.4 Fundamental investing, a number of academic studies show that abnormal returns can be generated from different characteristics in assets or fundamental signals and strategies. This growing body of evidence that seems to contradict the efficient market hypothesis has resulted in many anomalies. Anomalies are deviations that appear to not reconcile with the efficient market hypothesis. Testing if an anomaly deviates from the efficient market hypothesis, requires adjusting for risk by using a model such as capital asset pricing model or Fama and French three-factor model. To be considered as an anomaly the risk-adjusted return has to be greater or less than zero (Bodie et al., 2013).

The first step in identifying an anomaly is to find a mispricing signal. For example, as the one discussed earlier, earnings announcement drift, value premium effects etc. Secondly, the mispricing signal must be tested. Typically, this is approached by examining the economic significance measured as risk-adjusted return and the statistical reliability measured as t-statistics or other similar tests (Zacks, 2011).

2.5.1 Is The Anomaly Real?

One significant problem with defining an anomaly is the joint hypothesis problem. As stated earlier, an anomaly is suggested when a mispricing signal generates significant positive (negative) risk-adjusted returns. The joint hypothesis problem asserts that tests for anomalies are a joint test of risk-adjustment and efficient markets. The risk-adjustment procedure cannot with certainty claim that the asset pricing model reflects all risk. Hence, if the risk-adjustment rejects the efficient market, it can be due to misspecification of the asset pricing model, rather than the efficient market itself (Fama, 1970). This problem means that either can the asset pricing model be wrong or the market inefficient, which is impossible to conclude. In other words, what is presented as generating abnormal return does not have to be an anomaly since it can be a compensation for risk factors that is not captured by the asset pricing model (Ackert and Deaves, 2010).

2.6 Behavioral Finance

A growing body of evidence that appears to contradict the efficient market hypothesis and asset pricing models have given rise to a relatively new field in finance, behavioral finance.

This area uses knowledge from psychology to understand how human decision making, impact markets and individuals. Traditional finance assumes that individuals process information rationally. In behavioral finance, individuals are supposed to be subjects to cognitive biases, which can create mispricing and inefficiencies. Furthermore, the field accentuates that there is limit to arbitrages, which impedes markets to be efficient (Ackert and Deaves, 2010).

2.6.1 Limits To Arbitrage

As mentioned in section 2.1 about efficient market hypothesis, actions from irrational investors resulting in mispricing will quickly be arbitraged away by rational investors. However, behavioral finance highlights that there are limits to arbitrage, which impedes this from happening. One among those limits is transaction costs. Since arbitrageurs' accounts for net profit from a trade, transaction costs can limit an arbitrage opportunity. Another important limit is short sale constraints. A typical restriction for a short sale applies to smaller and illiquid stocks. Furthermore, the lender can recall the short sale if the stock appreciates too fast. Restriction to short selling applies for many institutional investors which limit the number of arbitrageurs. Another problem is arbitrageur presence, which means arbitrageurs are specialized in certain stocks and in combination with a limited number of arbitrageurs, not all assets are exposed to arbitrageurs. The arbitrageur may not be able to take a hedged position due to the absence of substitutes. Even though an arbitrageur finds a perfect substitute for an asset, there is a risk that the mispricing does not correct which is a risk for arbitrageurs (Ackert and Deaves, 2010).

2.6.2 Heuristics and Biases

Tversky and Kahneman (1974) have a series of articles where they present decisions under uncertainty. Humans are exposed to taking decisions with uncertain outcomes under a restricted time frame. Consequently, individuals cannot process all information and humans have developed shortcuts to make decisions. These shortcuts are referred to as heuristics. When decisions are made under uncertainty, individuals assess a subjective probability to an event or an outcome by using heuristics. When heuristics fail to make a rational judgement it renders in a cognitive bias.

A common heuristic that can lead to a bias is representativeness. Tversky and Kahneman (1972) defines representativeness as: "the degree to which [an event] (i) is similar in essential characteristics to its parent population, and (ii) reflects the salient features of the process by which it is generated". In other words, this heuristic is about misjudging probability based on how representative an event or characteristic is. Individuals tend to overestimate their capability of judging the probability, which can result in a bias.

Tversky and Kahneman (1974) documents that individuals tend to rely heavily on initial information to base decisions on future events. This cognitive bias is called anchoring. More specifically, it means that individuals anchor to irrelevant information as a reference (normally numbers) to determine the probability of an event or trait.

Individuals have a tendency to overestimate their knowledge and abilities. This psychological phenomenon formally refers to overconfidence and is well documented by researchers in behavioral finance (e.g. Hirshleifer, 2001). Overconfidence is a bias that portrays in different forms, and excessive optimism is one of those. Excessive optimism means that individuals assign probabilities to outcomes with a lack of realism (Armor and Taylor, 2002). Carleton et .al, (1998) document that analysts tend to have excess optimism over the companies they are following.

One criticism concerning biases used in behavioral finance is the research and discovery of those biases. To discover biases, researchers use experimental environments where the settings are defined for the participants. Consequently, this is not an exact replication of the actual decision making prevalent in the real world financial markets. Just the fact that participants know that they are in an experiment may cause them to divert from their normal behavior. Moreover, the participants typically have certain time limits and other restrictions which may not reconcile with the real world (Barberis and Thaler, 2005). However, the behavioral finance field is aware of this issue, but it remains a problem replicating decision making in financial markets (Hirshleifer, 2001).

3. Piotroski's Investment Strategy - Separating Winners From Losers

The purpose of Piotroski's (2000) paper is to examine if an investment strategy based on fundamental analysis can be used to produce abnormal returns when applied to a broad portfolio of high book-to-market stocks. Piotroski observes that value stocks, in general, tend to be financially distressed and this is associated with deteriorating profits, margins, leverage, liquidity etc. An improving change in these financial variables among value stocks should intuitively be advantageous in predicting returns. In this section, I present Piotroski's F-score, methodology, results and other evidence.

3.1 F-score

Piotroski (2000) constructs a binary scoring system, called F-score, derived from nine fundamental signals. The nine signals measure a stock's financial condition from three perspectives: profitability, financial leverage/liquidity and operating efficiency. A fundamental signal is classified as either good or bad whereof one is good and zero is bad.

Four variables relate to profitability, ROA (return on assets), CFO (cash flow from operations) ∆ROA (change in ROA) and accrual. ROA is defined as net income before extraordinary items divided by total assets at the beginning of the year. CFO equals cash flow from operations divided by total assets at the beginning of the year. IF ROA and CFO are positive Piotroski defines the indicator variable F_ROA and F_CFO equals one, else zero. The ∆ROA variable is the current year's ROA subtracted by the prior year's ROA. The corresponding indicator variable F_∆ROA equals to one if ∆ROA > 0, otherwise zero. The accrual signal is defined as ROA minus CFO and its indicator variable, F_Accrual equals to one if CFO > ROA, else zero.

Under financial leverage/liquidity, he defines three variables, ∆Lever (change in leverage), ∆Liquid (change in liquidity) and Eq_Offer (issuance of equity). The ∆Lever variable is the change in the ratio of total long-term debt to average total assets and an increase in financial leveraged is assumed to be bad. The indicator variable, F_∆Lever, equals one if financial leverage decreases, otherwise zero. ∆Liquid measures liquidity and equals the change in the current ratio (current assets divided by current liabilities) between current and prior year. An improvement in liquidity is assumed to be good, and the indicator variable equals one if F_∆Liquid > 0, else zero. The variable Eq_offer measures if a firm issue common equity. Assuming that issuing equity is bad for a high book-to-market firm the corresponding indicator variable F_EQ_Offer equals zero if the company issued equity, otherwise one.

To capture operating efficiency, he uses the two variables ∆Margin (change in gross margin) and ∆Turn (change in asset turnover). ∆Margin is the firm's current gross margin ratio (gross profit divided by sales) less the prior year's gross margin ratio and F_∆Margin equals one if the margin improves, otherwise zero. The ∆Turn is defined as the change in a firm's current asset turnover (current sales scaled by the beginning of the year assets). If the asset turnover improves the indicator variable F_∆Turn equals one, else zero.

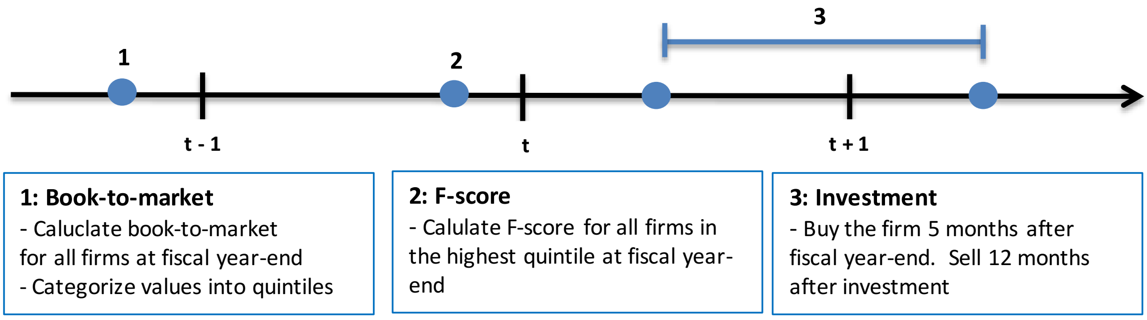
F-score is the sum of the binary fundamental signals (F_SCORE = F_ROA + F_ ∆ROA + F_CFO + F_ACCRUAL + F_∆MARGIN + F_∆TURN + F_∆LEVER + F_∆LIQUID + F_EQ_OFFER). Hence, the composite F-score can range from zero to nine and a firm with a higher F-score is expected to have a stronger financial performance. The investment strategy is based on selecting firms with high F-scores. A logical summary of all F-score variables is demonstrated in table 1 on page 23.

3.2 Piotroski's Methodology

Piotroski (2000) test the investment strategy between 1976 and 1996 on the US stock market. He selects companies with sufficient accounting data in Compustat. First, he calculates book-to-market at the time, t-1, for each firm at fiscal year-end and assigns the firm to a book-to-market quintile. Second, he calculates F-score for each firm in the highest book-to-market quintile at the time, t, fiscal year-end. Every firm receives an F-score for every year ranging from 0 to 9. He assigns low F-score firms (F-score 0-1) to one portfolio and high F-score firms (F-score 8-9) to another portfolio. He expects the high F-score firms to outperform the low F-score firms. Then he calculates firm-specific buy-and-hold returns over one year starting from the 5th month after fiscal year-end to make sure that financial information from year-end reports are available to investors. See figure 1 for an overview of the investment strategy at different steps over time. Piotroski also calculates market-adjusted returns by subtracting market returns from the firm-specific buy and hold returns for the same period.

Figure 1

Piotroski's investment strategy in three steps



The figure illustrates the three steps of Piotroski's investment strategy.

3.3 Piotroski's Results and Conclusions

Piotroski (2000) documents that a portfolio constructed by high F-score (8-9) firms within the highest-book-to market quintiles generate excess returns. Such a portfolio earns on average a one-year market-adjusted return of 7.5 % annually more than the entire high book-to-market portfolio. In the high book-to-market portfolio the entire distributions of returns are shifted to the right when investing in high F-score stocks. Furthermore, he observes that a hedged portfolio investment strategy, for high book-to-market firms, that shorts stocks with low F-score (0-1) and buys stocks with high F-scores earns on average 23 % market-adjusted returns annually. These outcomes are statistically significant and robust over time.

The greatest benefit from this strategy is found in small and medium sized companies, with low analyst coverage and low share turnover. Piotroski (2000) suggests that markets tend to underreact to changes in positive financial information for these value stocks due to they are neglected by investors

3.4 Supporting Evidence

Piotroski (2000) concentrated on the US capital market. Galdi and Lopez (2010) implemented Piotroski's investment strategy in the Brazilian markets from 1994-2004. Consistent with Piotroski, Galdi and Lopes found that a high F-score portfolio, when applied to value stocks, earn abnormal returns, such a portfolio generates a market-adjusted return of 26.7 % annually. In addition, a hedged portfolio (buys high F-score firms and short low F-score firms) applied to high book-to-market firms, earns a one-year market-adjusted returns of 41.8 % annually for the same period. Noma (2010) tested Piotroski's investment strategy in Japan for the period 1986 to 2001 and found that a hedged portfolio with high F-score on high book-to-market firms produces 17.6 % annual returns.

A similar strategy to Piotroski's F-score is Mohanram (2005) G-score strategy. Instead of focusing on value stocks (high book-to-market firms), Mohanram investigates if fundamental analysis of growth stocks (low book-to-market firms) could generate excess returns. Mohanram argues that growth stocks have different characteristics than value stocks, in terms of higher analyst coverage, better financial information availability and naïve discounting of earnings/accounting information. In the purpose of capturing the characteristics of growth stocks, the binary G-score uses eight signals and is applied on the low-book-to market portfolio. The metrics/signals focus on the categories profitability, earnings stability, growth stability, R&D expenditures and capital expenditures. One-year market-adjusted returns from a hedged G-score portfolio earns significant abnormal returns.

One important key message is that the effectiveness of fundamental investing is captured when fitting fundamental analysis to the right context. The F-score is designed for value stocks, and the G-score is purported for growth stocks.

4. Methodology

4.1 Sample Selection

I identify all firms with a USA ISO country code for the period 2003-2015 with sufficient price and book value data in the database, Compustat. The US stock market is chosen for three reasons. Piotroski (2000) performs his test on the US stock market during the period 1976-1996, and several conditions have changed for investors. First of all, the transactions costs are lower. Secondly, the availability of financial information and screeners to identify F-score is easier and cheaper. Finally, F-score has gotten a lot of attention among the investor community. Given that the F-score signal generates abnormal returns it should be arbitraged away. Regarding these conditions, the Piotroski's investment strategy should not generate excess returns in the same extension for the period I am investigating.

Another motivation for replicating Piotroski (2000) on the US market is to test for the problem, data-snooping. Lo and MacKinlay (1990) addresses data-snooping which refers to that the dataset might generate an accidental pattern and not a real pattern. By testing it for a new period, it is a test for if the success of the investment strategy is a real pattern or accidental pattern.

4.2 Calculations of Partitions; Book-to-Market and Size

For every year, I calculate the book-to-market ratios at fiscal year-end for all companies. Firms with negative book-to-market ratios are excluded. I assign all firms to a book-to-market quintile. I will only calculate F-score for companies in the highest book-to-market quintile.

In addition, I categorize the firms in the highest book-to-market quintile in size terciles based on its market capitalization. This size partition is based on previous year's fiscal year-end market capitalization. I assign the companies into either the small, medium or the large tercile.

4.3 Calculation of F-score

F-score is only calculated for firms in the highest book-to-market quintile. The variables in F-score are computed as described in section 3.1, F-score. For a summary of F-score definition, see table 1 below. Regarding the EQ_Offer variable, I assume that a firm issue new equity if common shares outstanding in year t are greater than common shares outstanding in year t-1.

Table 1

Defintion of F-score

Variable	Definition	Score
Profitability		
Return on assets (ROA)	$ROA_t = \frac{Net\ income\ before\ extraordinary\ items_t}{Assets_{t-1}}$	$F\_ROA_t = 1\ if\ ROA_t > 0$ $F\_ROA_t = 0\ if\ ROA_t < 0$
Operational Cash Flow (CFO)	$CFO_t = \frac{Cash\ flow\ from\ operations_t}{Assets_{t-1}}$	$F\_CFO_t = 1\ if\ CFO_t > 0$ $F\_CFO_t = 0\ if\ CFO_t < 0$
Change in return on assets (ΔROA)	$\Delta ROA_t = ROA_t - ROA_{t-1}$	$F\_\Delta ROA_t = 1\ if\ \Delta ROA_t > 0$ $F\_\Delta ROA_t = 0\ if\ \Delta ROA_t < 0$
Accruals	$Accrual_t = CFO_t - ROA_t$	$F\_Accrual_t = 1\ if\ Accrual_t > 0$ $F\_Accrual_t = 0\ if\ Accrual_t < 0$
Leverage/Liquidity		
Change in Leverage (ΔLever)	$\Delta Lever_t = \frac{Long\ term\ debt_t}{(\frac{1}{2}Assets_t + \frac{1}{2}Assets_{t-1})} - \frac{Long\ term\ debt_{t-1}}{(\frac{1}{2}Assets_{t-1} + \frac{1}{2}Assets_{t-2})}$	$F\_\Delta Lever_t = 1\ if\ \Delta Lever_t < 0$ $F\_\Delta Lever_t = 0\ if\ \Delta Lever_t > 0$
Change in Liquidity (ΔLiquidity)	$\Delta Liquid_t = \frac{Current\ assets_t}{Current\ liabilites_t} - \frac{Current\ assets_{t-1}}{Current\ liabilites_{t-1}}$	$F\_\Delta Liquid_t = 1\ if\ \Delta Liquid_t > 0$ $F\_\Delta Liquid_t = 0\ if\ \Delta Liquid_t < 0$
Equity offer (Eq_Offer), Issuance of new equity	$Eq\_Offer_t = Common\ shares\ outstanding_t - Common\ shares\ outstanding_{t-1}$	$F\_Eq\_Offer_t = 1\ if\ Eq\_Offer_t = 0$ $F\_Eq\_Offer_t = 0\ if\ Eq\_Offer_t > 0$
Operating efficiency		
Change of Margin (ΔMargin)	$\Delta Margin_t = \frac{(Sales_t - COGS_t)}{Sales_t} - \frac{(Sales_{t-1} - COGS_{t-1})}{Sales_{t-1}}$	$F\_\Delta Margin_t = 1\ if\ \Delta Margin_t > 0$ $F\_\Delta Margin_t = 0\ if\ \Delta Margin_t < 0$
Change in turnover (ΔTurn)	$\Delta Turn_t = \frac{Sales_t}{Assets_{t-1}} - \frac{Sales_{t-1}}{Assets_{t-2}}$	$F\_\Delta Turn_t = 1\ if\ \Delta Turn_t > 0$ $F\_\Delta Turn_t = 0\ if\ \Delta Turn_t < 0$
Composite Score		
F-score	*F-score = F_ROA + F_CFO + F_ΔROA + F_Accrual + F_ΔLever + F_ΔLiquid + F_EQ_Offer + F_ΔMargin + F_turnover*	$F-score = x$ $0 \leq x \leq 9$

The table shows how all nine F-score variables are calculated and how the score is set.

Financial data to compute F-score is retrieved from the period 2001-2014, whereof every year corresponds to fiscal year-ends (financial report year). Every firm in the highest book-to-market quintile at the year t-1 is used to calculate F-score in year t. To calculate F-score in year t, I need financial data from year, t, t-1 and t-2. All firms with insufficient data to compute F-score are excluded. From the highest book-to-market quintile with sufficient data, I obtain a sample of 5654 firm-year observations across the period.

4.4 Calculations of Returns

I compute firm-specific raw returns and market-adjusted returns as one-year buy-and-hold returns. To compute returns I need to retrieve data from 2003-2015. The data is retrieved from the Compustat database. I calculate raw returns (R_i), market returns, (MR_i), and market adjusted returns (MAR_i) as in the equations below:

$$R_i = \frac{(P_t - P_{t-1})}{P_t} \quad (7)$$

$$MR_i = \frac{(P_t - P_{t-1})}{P_t} \quad (8)$$

$$MAR_i = R_i - MR_i \quad (9)$$

The market-adjusted return (equation 9) is the raw return (equation 7) subtracted by the value weighted market index return (equation 8). The market return is based on the Standard & Poors 500 index (S&P500). The reason for choosing this benchmark is because the S&P500 is generally considered as a leading indicator for the US stock market. If a security delists during the investment period, the return is assumed to be zero. When constructing portfolios, I calculate the equally-weighted average return.

The investment is made at the beginning of the 5th month after fiscal year-end, and the exit is made 12 months after that. The reason for choosing the 5th month is to ensure that financial information from the fiscal year is available.

As additional test, it would be interesting to risk-adjust the returns with the CAPM and the three-factor model but due to time restriction that is excluded in this study. The aim of this study is to replicate and Piotroski (2000) and he does not perform risk-adjustments. Instead, I analyze risk compensation from a theoretical standpoint. However, even if I performed risk-adjustments it would still be difficult to reach conclusions if the returns are abnormal or not because of the joint hypothesis problem.

4.5 Performed Tests

One of the major objectives of this study is to test if a high F-score portfolio (7-9) outperforms a low F-score portfolio (0-2) in terms of returns. In addition, the portfolios are compared to the entire high book-to-market portfolio.

To assess the relationship between the different F-score variables and the composite F-score I perform a Spearman correlation test.

The return data will be presented as percentiles (10^{th}, 25^{th}, median, 75^{th}, 90^{th}) and means. The reason for this is because I expect the return data to have a wide distribution.

To test if the return differences are statistically significant, I will perform a one-tailed two-sample t-test with assumed unequal variances. A t-test implies a hypothesis test, which consists of a null hypothesis and an alternative hypothesis.

$$H_o: \beta_1 = 0 \text{ (10)}$$

$$H_1: \beta_1 \neq 0 \text{ (11)}$$

The null hypothesis (10) determines that there is no relation between the variables. If there is a statistical significance, I will reject the null hypothesis. If the p-values is lower than 0.01, 0.05 and 0.10 corresponding to a significance level of 99 %, 95 % and 90 %.

I will divide the firms in the highest book-to-market quintile into three terciles, small medium and large. For every year, I assign the firms into a size tercile. The size partition is based on the previous year's market capitalization at fiscal year-end. The reason for doing this partition is because I want to document whether a size effect exists or not.

Finally, I will investigate how many firms in the highest book-to-market quintile that have analyst coverage by using Thomson-Reuters I/B/E/S. The reason for investigating analyst coverage is that I want to know if the value stocks tend to be neglected by the investor community, as shown in previous research.

5. Empirical Results

5.1 Descriptive Statistics

Table 2 presents descriptive statistics from the highest book-to-market quintile consisting of 5 654 firm-year observations between 2003 and 2015. The table document all financial characteristics for all F-score variables (except Eq_offer, equity issuance), book-to-market and market capitalization. The firms have a mean (median) book-to-market ratio of 1.892 (1.186) and a year-end market capitalization of 1116.883 (89.619). As shown in table 2, the firms in the high book-to-market quintile have features attributed to financial distress and poor performance. For example, the firms on average documents a negative mean on the profitability variables ROA (-0.060) and ΔROA (-0.030). Furthermore, the operating efficiency variables show a negative mean in ΔTurn (-0.165) and ΔMargin (-0.362). The leverage/liquidity variables indicate financial distress since the mean value is negative of ΔLever and ΔLiquid. As a consequence, of the poor performance regarding mean and median, a majority of the firms do not have a positive signal. For example, the ΔROA only exhibits a proportion of 0.486 with a positive signal.

As mentioned earlier, the result in table 2 indicates that value stocks are financially distressed. This result is consistent with previous research. Fama and French (1995) show that high book-to-market firms are on average attributed with financial distress.

Table 2

Financial characteristics of high book-to-market firms

Financial charachteristics

Variable	**Mean**	**Median**	**Standard Deviation**	**Proportion with positive signal**
Market capitalization	1116.883	89.610	5774.302	NA
Book-to-market	1.892	1.186	10.456	NA
ASSETS	2540.028	202.351	9785.511	NA
ROA	-0.060	0.006	0.773	0.532
ΔROA	-0.030	-0.001	0.999	0.486
ΔMargin	-0.362	0.000	21.395	0.491
CFO	0.020	0.051	0.480	0.745
ΔLiquid	-0.216	-0.010	397.793	0.485
ΔLever	0.012	0.000	0.198	0.441
ΔTurn	-0.165	0.009	13.263	0.530
Accrual	0.080	0.053	0.853	0.801

The table documents the financial characteristics of the high book-to-market portfolio in terms of market capitalization, book-to-market and F-score variables for all sample firms. Market capitalization is calculated as the number of shares outstanding multiplied by closing price at fiscal year-end. Book-to-market is computed as book value at fiscal year-end scaled by market capitalization. All the other variables are calculated as in table 1. The table displays the variables as mean, median, standard deviation and proportion with a positive signal. The sample consists of 5 654 firm-year observations between 2003 and 2015. NA corresponds to not available.

5.2 Returns Conditioned on Book-to-Market

Table 3 provides one-year buy-and-hold returns for all firms in the highest book-to-market quintile and the percentage in the portfolio with positive returns. The one-year mean (median) raw return is 0.203 (0.037) and the corresponding market-adjusted return is 0.123 (-0.039). Although the high-book-to market portfolio earns a strong return, a majority of the companies earn a negative return. The proportion of firms with a negative market-adjusted return is close to 54 % in comparison to the entire portfolio. Hence, the strong mean return is dependent on the right-tail of the distribution. An investment strategy that shifts the returns from the left-tail of the distribution to the right-tail would consequently improve the mean returns.

The results documented in table 3 are coherent with preceding academic research. For example, Fama and French (1992) and Lakonishok et al. (1994) show that a high book-to-market portfolio earns positive one-year market adjusted returns.

Table 3

Return characteristics of high book-to-market firms

Buy-and-hold returns from a High book-to-market portfolio

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Percentage Postive
One year returns							
Raw	0.203	-0.500	-0.239	0.037	0.414	1.026	0.529
Market-adjusted	0.123	-0.501	-0.278	-0.039	0.290	0.874	0.461

The table shows one-year buy-and-hold returns as raw returns and market-adjusted returns. The return of a company is computed as one-year buy-and-hold returns starting at the 5th month after fiscal year-end. If a firm is delisted, the return is assumed to be zero. The market-adjusted return is the raw return subtracted by the value-weighted market index return. The sample consists of 5 654 firm-year observations between 2003 and 2015.

5.3 Correlation Between F-score Variables

Table 4 documents the relationship in terms of Spearman correlation between the nine F-score variables, composite F-score and one-year buy-and-hold returns. The most interesting results documented in table 4 are the relationship between the composite F-score and returns. The correlation between raw returns and composite F-score is 0.062, and the corresponding figure for market-adjusted return and composite F-score is 0.075, both are significant at the 5 % level. The strongest explanatory variables for returns appears to be the CFO, Accrual and Eq_offer. These variables exhibit a low positive correlation close to zero.

Table 4

Spearman correlation analysis between one-year returns, the F-score variables and the composite F-score for high book to market firms

	ROA	Δ ROA	Δ Margin	CFO	Δ Liquid	Δ Lever	Δ Turn	Accrual	Eq_offer	F_score
R_Return	-0.022	-0.023	-0.016	0.057	0.016	-0.023	0.041	0.062	0.061	0.062
Ma_Return	0.020	-0.009	-0.007	0.060	0.017	-0.030	0.015	0.028	0.056	0.075
ROA	1	0.436	0.201	0.507	0.197	-0.157	-0.203	-0.475	0.078	0.539
Δ ROA	-	1	0.348	0.150	0.147	-0.034	0.193	-0.303	-0.006	0.503
Δ Margin	-	-	1	0.117	0.107	-0.018	0.053	-0.091	0.015	0.440
CFO	-	-	-	1	0.127	-0.183	-0.059	0.363	0.028	0.556
Δ Liquid	-	-	-	-	1	0.065	-0.071	-0.086	0.015	0.328
Δ Lever	-	-	-	-	-	1	0.085	-0.030	0.007	-0.303
Δ Turn	-	-	-	-	-	-	1	0.146	0.059	0.199
Accrual	-	-	-	-	-	-	-	1	-0.080	0.006
Eq_offer	-	-	-	-	-	-	-	-	1	0.288

The table documents Spearman correlation for one-year returns, the F-score variables and the composite F-score. R_Return and Ma_Return correspond to raw return and market-adjusted return. Returns are calculated as described in table 3 and the F-score variables are calculated as described in table 1. The sample consists of 5 654 firm-year observations between 2003 and 2015.

5.4 Returns Conditioned on F-score

Table 5 provides one-year raw returns for the fundamental investment strategy applied on the highest book-to-market quintile. The table presents return for all firms, separate aggregate F-score and portfolios with high and low aggregate F-score. Furthermore, the table documents the proportion of firms with positive returns and the number of observations.

As shown in table 5, most firms are clustered around a mediocre F-score between three and seven while a smaller proportion is located in the weak fundamental signal portfolio with an F-score between zero and two, and the strong signal portfolio with an F-score between seven and nine.

One of the most interesting results in table 5 is the relationship between F-score and mean raw returns. A higher F-score clearly indicates a higher mean raw return (except for F-score 4 and 5). Furthermore, the high F-score portfolio with a mean raw return of 0.260 outperforms a low F-score portfolio with a mean raw return of 0.131. The mean return difference of 0.129 (between the high and low F-score portfolio) is significant at the 1 % level using t-statistics. The low F-score portfolio consists of a proportion of 0.430 with positive returns while the corresponding figure for the high F-score portfolio is 0.574.

The table also shows that the high F-score portfolio earns a higher raw return with a mean of 0.260 compared than all firms (i.e. the highest book-to-market quintile) with a mean of 0.203. This mean return difference of 0.058 is significant at the 5 % level using t-statistics.

The result from table 5 clearly indicates that F-score can separate winner stocks from loser stocks in terms of returns since the high F-score portfolio outperforms the low F-score portfolio. In summary, the results are consistent with Piotroski's (2000) findings.

Table 5

Buy-and-hold raw return for the investment strategy based on F-score

One-year raw returns	Mean	10%	25%	Median	75%	90%	% Positive	n
All firms	0.203	-0.500	-0.239	0.037	0.414	1.026	0.529	5654
F-score								
0	0.129	-0.384	-0.200	0.000	0.433	0.685	0.444	9
1	0.135	-0.683	-0.392	-0.076	0.327	1.173	0.419	117
2	0.130	-0.651	-0.354	-0.036	0.375	1.177	0.434	334
3	0.175	-0.622	-0.299	0.014	0.430	1.141	0.508	693
4	0.216	-0.528	-0.279	0.017	0.483	1.163	0.508	1038
5	0.173	-0.507	-0.225	0.041	0.396	0.965	0.536	1177
6	0.209	-0.444	-0.205	0.055	0.390	0.883	0.549	1071
7	0.236	-0.427	-0.183	0.064	0.404	0.850	0.570	746
8	0.286	-0.408	-0.159	0.071	0.412	0.935	0.578	367
9	0.344	-0.454	-0.245	0.117	0.544	1.637	0.588	102
Low F-score	0.131	-0.668	-0.357	-0.047	0.371	1.184	0.430	460
High F-score	0.260	-0.424	-0.179	0.071	0.418	0.911	0.574	1215
High - All	0.057	0.076	0.060	0.034	0.004	-0.115	0.044	-
P(T<=t one tail)	0,042**	-	-	(0,000)	-	-	-	-
T-critical	1.646	-	-	-	-	-	-	-
High - Low	0.129	0.245	0.178	0.118	0.047	-0.273	0.143	-
P(T<=t one tail)	0,004***	-	-	(0,000)	-	-	-	-
T-critical	2.330	-	-	-	-	-	-	-

The table represents one-year buy-and-hold raw returns for the investment strategy. All firms consist of the companies in the highest book-to-market quintile. F-score is computed as described in table 1 and raw returns as described in table 3. An F-score of 9 represents the strongest signal and 0 the weakest signal. The low F-score portfolio consists of firms with an aggregate score between 0 and 2, and the high F-score portfolio consists of firms with an aggregate F-score between 7 and 9. T-statistics are computed for mean returns. T-statistics are from a one-tailed two-sample test (assume unequal variance) whereof *, ** and *** signals that the mean returns are higher on the significant level 10 %, 5 % and 1 %. The number of firms equals to n in the table. The sample consists of 5 654 firm-year observations between 2003 and 2015.

Table 6 presents one-year market-adjusted returns for the fundamental investment strategy applied on the highest book-to-market quintile. The market-adjusted return equals to raw returns subtracted by the value-weighted market returns (S&P500). Table 6 indicates the same result as in table 5. A high F-score portfolio earns a mean market-adjusted return of 0.183, and a low F-score portfolio earns a corresponding return of 0.040. The mean return difference of 0.142 is statistically significant at the 1 % level using t-statistics. A comparison with the high F-score portfolio and all firms (i.e. firms in the highest book-to-market quintile) documents a mean return difference of 0.060 with a statistical significance at the 5 % level using t-statistics. Just as concluded from table 5, the results in table 6 clearly indicate that an investment strategy based on F-score can separate winner stocks from loser stocks in terms of returns.

Table 6

Buy-and-hold market adjusted return for the investment strategy based on F-score

One year market adjusted returns	Mean	10%	25%	Median	75%	90%	% Positive	n
All firms	0.123	-0.501	-0.278	-0.039	0.290	0.874	0.461	5654
F-score								
0	0.015	-0.451	-0.196	-0.179	0.291	0.707	0.444	9
1	0.056	-0.741	-0.402	-0.107	0.246	0.973	0.393	117
2	0.036	-0.624	-0.382	-0.152	0.248	1.070	0.371	334
3	0.091	-0.597	-0.354	-0.075	0.290	0.933	0.440	693
4	0.133	-0.527	-0.295	-0.045	0.334	1.014	0.452	1038
5	0.094	-0.493	-0.266	-0.032	0.271	0.841	0.460	1177
6	0.131	-0.439	-0.247	-0.025	0.283	0.750	0.479	1071
7	0.159	-0.413	-0.239	-0.003	0.272	0.706	0.499	746
8	0.207	-0.415	-0.228	-0.014	0.330	0.788	0.493	367
9	0.264	-0.413	-0.218	0.012	0.413	1.333	0.500	102
Low F-score	0.040	-0.637	-0.384	-0.146	0.257	1.069	0.378	460
High F-score	0.183	-0.414	-0.233	-0.002	0.295	0.773	0.497	1215
High - All	0.060	0.087	0.045	0.037	0.005	-0.101	0.036	-
P(T<=t one tail)	0,029**	-	-	(0,000)	-	-	-	-
T-critical	1.646	-	-	-	-	-	-	-
High - Low	0.142	0.223	0.151	0.145	0.038	-0.296	0.119	-
P(T<=t one tail)	0,0009***	-	-	(0,000)	-	-	-	-
T-critical	2.330	-	-	-	-	-	-	-

The table represents one-year buy-and-hold market-adjusted returns for the investment strategy. Market-adjusted return equals to a stock's raw return subtracted by the value-weighted market return (index S&P500). All other variables equal to the description in table 5. The sample consists of 5 654 firm-year observations between 2003 and 2015.

5.5 Returns Conditioned on Size

Table 7 provides one-year market-adjusted buy-and-hold returns for the investment strategy by size partition. The size separation is based on the previous year's market capitalization at fiscal year-end. The partitions result in three terciles: small, medium and large. The reason for investigating this is to find out if the investment strategy holds for all sizes or if there is a particular size effect.

Table 7 indicates that there is a size effect to the investment strategy. The small firms earn a higher return on all aspects including aggregate F-scores, the high F-score portfolio, in comparison with the medium and large firms. For the small firms, the high F-score portfolio earns a market-adjusted return of 0.343, and the corresponding low F-score portfolio earns 0.085. The mean return difference between the high and low F-score portfolio (in small firms) equals to 0.259 and is significant at the 1 % level using t-statistics. The medium firms' exhibit a mean return difference between the high and low F-score portfolio of 0.206 and is significant at the 1 % level using t-statistics. However, for the large firms, there is no statistical significance for the mean return differences. The large firms have a poor performance with lower mean returns than the other size categories.

From the results in table 7, it appears that the strongest benefit from the investment strategy is found in small firms and medium firms while there appears to be no benefit among the large firms. Since there is such a big return difference between small and large firms, it indicates that the F-score strategy is not just a size effect.

Table 7

One-year market-adjusted buy-and-hold returns based on the investment strategy by size partition

One-year market-adjusted returns

	Small Firms			Medium Firms			Large Firms		
	Mean	Median	n	Mean	Median	n	Mean	Median	n
All firms	0.229	-0.045	1885	0.119	-0.032	1884	0.02	-0.03	1885
F-score									
0	0.017	-0.190	7	-0.179	-0.179	1	0.196	0.196	1
1	0.147	-0.051	62	-0.028	-0.222	36	-0.084	-0.236	19
2	0.064	-0.143	166	-0.024	-0.179	122	0.092	-0.009	46
3	0.197	-0.090	262	0.045	-0.118	234	0.005	-0.019	197
4	0.195	-0.083	351	0.159	-0.018	335	0.047	-0.037	352
5	0.211	-0.004	354	0.114	-0.027	376	-0.014	-0.055	447
6	0.285	0.044	306	0.129	-0.051	364	0.014	-0.032	401
7	0.290	-0.051	217	0.147	0.035	258	0.066	-0.009	271
8	0.420	-0.025	127	0.211	0.086	118	-0.017	-0.093	122
9	0.401	0.155	33	0.300	-0.014	40	0.059	-0.009	29
Low Score	0.085	-0.131	235	-0.026	-0.179	159	0.043	-0.075	66
High score	0.343	-0.030	377	0.180	0.041	416	0.041	-0.033	422
High - All	0.115	0.015	-	0.061	0.072	-	0.022	-0.001	-
P(T<=t one tail)	0,091*	(0,000)	-	0,046**	(0,000)	-	0.256	(0,000)	-
T-critical	1.283	-	-	1.647	-	-	1.283	-	-
High - Low	0.259	0.101	-	0.206	0.220	-	-0.001	0.042	-
P(T<=t one tail)	0,004***	(0,000)	-	0,0007***	(0,000)	-	0.494	(0,000)	-
T-critical	2.333	-	-	2.340	-	-	1.291	-	-

The table shows the one-year market-adjusted buy-and-hold returns based on the investment strategy on the high book-to-market quintile, across size terciles. The size partition is based on previous year's fiscal year-end market capitalization, which is divided into the three terciles small, medium and large. All other variables equal to the description in table 5 and 6. The sample consists of 5 654 firm-year observations between 2003 and 2015.

5.6 Analyst Coverage

Table 8 shows the number of firms and the percentage of the total sample with and without analyst coverage. The table shows that the proportion with analyst coverage among value stocks is 0.359 and the corresponding figure without analyst coverage is 0.641. These results indicate that the analyst community generally neglects value stocks.

The findings in table 8 are consistent with prior academic research. For example, La Porta et al. (1994) document that value stocks are neglected by the investor community.

Table 8

Analyst coverage on high book-to-market firms

Analyst coverage	With analyst coverage		Without analyst coverage	
	n	Percentage	n	Percentage
All firms	2032	0.359	3622	0.641

Table 2: The table presents the number of firms and the percentage with and without analyst coverage in the highest book-to-market quintile. The sample consists of 5 654 firm-year observations between 2003 and 2015.

6. Analysis of Empirical Results

6.1 Fundamental Analysis on Value Stocks

The investment strategy based on a simple fundamental analysis strategy applied on value stocks appear to be successful in separating winner stocks from loser stocks. A high F-score portfolio outperforms a low F-score portfolio and the entire value stock portfolio, measured as both raw returns and market-adjusted returns. The mean return differences are statistically significant. Moreover, a stock with higher F-score, on average, generates a higher return than a stock with lower F-score.

According to my results, the investment strategy appears to work best in small firms followed by medium sized firms. Moreover, for large companies, the strategy does not show any benefit or statistical significance. The benefit of fundamental analysis appears to be the greatest for small firms followed by medium firms. These results are consistent with Piotroski (2000) that documents benefit in small and medium firms while large firms show no effect.

In table 9, I present a comparison between Piotroski's and my results. The table shows the mean returns measured as one-year market-adjusted returns. Similar to Piotroski's findings, I document that the strategy still generates abnormal returns. For example, the high F-score portfolio earns a one-year market-adjusted return of 13.4 % (Piotroski) and 18.3 % (my results).

Table 9

Comparison with Piotroski's results

One-year market adjusted returns		
	Piotroski's Result	Results
Time frame	1976-1996	2003-2016
All firms	5.9%	12.3%
High score	13.4%	18.3%
Low score	-9.6%	4.0%
High - Low	23.0%	14.2%
High - All	7.5%	6.0%

The table compares the main results in terms of one-year market-adjusted return found in Piotroski's (2000) paper and found in this paper. All firms refer to all stocks in the highest book-to-market quintile. Piotrioski's results are based on 14 043 firm-year observation and my results are based on 5 654 firm-year observations.

Why is it that this simple accounting-based binary scoring system works on value stocks? One important factor for the success of F-score is that the strategy captures the underlying characteristics of value stocks. Fama and French (1995) and Chen and Zhang (1998) among others, show that high book-to-market companies on average are financially distressed. This financial distress implies declining profit, margin, cash flow, liquidity etc. Consistent with my results in table 2, I observe that value stocks are attributed with financial distress. Since the firms on average, document a declining profitability, deteriorating operating efficiency and declining solvency. Logically, a positive change in these variables would imply a change in the firm's subsequent performance. Below I will discuss how the nine F-score variables (ROA, ΔROA, CFO, Accruals, ΔLever, ΔLiquid, Eq_Offer, ΔMargin and ΔTurn) captures the underlying characteristics of value stocks.

As mentioned earlier, value firms demonstrate weak profitability and a company able to generate a positive profit and cash flow shows an ability to generate funds internally. This characteristic is captured by the F-score variables ROA, ΔROA and CFO. Sloan (1996) shows that earnings generated by positive accruals, meaning that profits are greater than cash flows, are a bad indicator of future profitability and consequently returns. Since, value firms on average are financially distressed the firms may have an incentive to manage earnings by using positive accruals (Sweeney, 1994). This problem is captured by the F-score variable Accruals.

Furthermore, the financial distress entails that the firm is struggling to meet future debt obligations. Hence, a decrease in leverage is seen as a good financial signal for value firms although an increased leverage can be attributed with both a positive (Harris and Raviv, 1990) and a negative signal (Miller and Rock, 1985). However, a financially distressed company raising capital regarding long-term debt is a signal of failing to generate enough internal funds. The problem to meet debt obligations entails that an increase in liquidity is a positive signal. As discussed above, a financially distressed firm raising capital is a negative signal (Miller and Rock, 1985). Therefore, issuance of new equity is considered as a negative signal. All these characteristics are captured by the F-score variables, ΔLever, ΔLiquid and Eq_Offer.

An improvement in operating efficiency signals yields more internal funds, which is a problem for value firms (Piotroski, 2000). Hence, an improvement in operating efficiency is considered as a positive signal which is captured by the F-score variables ΔMargin and ΔTurn.

In summary, one potential explanatory factor for the success of the investment strategy is because it adapts a context-specific strategy for value stocks. Value firms have special financial conditions attributed with financial distress. By using a selection of financial signals that captures positive underlying economic changes, that indicate a diminishing financial distress it appears to be possible to separate the best performing firms and consequently stocks that earn most returns.

6.2 Anomaly – Risk or Mispricing?

To assess whether the abnormal returns from the investment strategy can be attributed as an anomaly or not I will discuss the results from a risk compensation standpoint.

6.2.1 Risk Compensation

As discussed above, the F-score captures how financially distressed a firm is. Hence, a higher F-score means that the firm is attributed with less financial distress. The results in table 4 and 5 documents that a higher F-score on average earns a higher return than lower F-score firms. Moreover, these mean return differences are statistically significant. In other words, firms with less financial distress earn a higher return than firms with higher financial distress. This excess return is not consistent with the theory behind risk compensation since increased risk should be compensated with higher expected returns.

The capital asset pricing model only depends on the risk factor market risk, and consequently, does not incorporate the risk factors in value stocks. However, Fama and French (1992) show that value stocks are attributed with financial distress. In Fama and French (1993) three-factor model they expand the CAPM with the risk factors book-to-market and size. Consistent with my results in table 2 and 3, I document that the high-book-to market portfolio earns above market-adjusted return and that the firms are financially distressed. However, my results from table 5 and 6 appear to contradict the three-factor model since the firms with the best financial condition, and least financial distress earns the strongest return.

However, the greatest benefit from the strategy is found among small firms. The size effect can be a compensation for risk according to the three-factor model. Fama and French (1993) have size as a risk factor in the three-factor model because smaller companies are associated with higher risk and should be compensated with higher returns. A typical risk factor for smaller companies, documented by Stoll and Walley (1983), is that they are attributed with illiquidity. Since my results document that there is such a big return difference between small and large firms, it indicates that the F-score strategy is not just a size effect. Moreover, the omitted effect of large firms supports that there are limits to arbitrage and that behavioral biases exist.

In summary, it is not possible to conclude whether the abnormal returns from the investment strategy is inconsistent with risk compensation and if this is an anomaly. First of all the theoretical arguments diverts. Second, I have not performed a risk-adjustment for the returns. Even if I would perform a risk-adjustment in accordance with the three-factor model, I would still not be able to conclude if the investment strategy is anomalous or not. The reason for this is the joint hypothesis problem, as discussed earlier in the theory section.

6.3 Behavioral Finance Analysis

In this section, I discuss the results from a behavioral finance perspective in regard to limits to arbitrage, heuristics and biases.

6.3.1 Limits to Arbitrage

According to the efficient market hypothesis, in the semi-strong efficiency form, it is not possible to conduct fundamental analysis to earn an excess return. However, the results documented in table 4 and 5 shows that a fundamental analysis based on F-score appear to discriminate between the winner and loser stocks. Moreover, the high F-score portfolio outperforms the low F-score portfolio with statistical significance. Hence, this opposes the semi-strong efficiency form.

The efficiency form can however vary across size. Since the investment, strategy showed no benefit to large companies, but in small and medium firms, it is more probable to assume that large firms are exposed to a semi-strong efficiency form and, small and medium firms to a weak efficiency form.

Since Piotroski (2000) presented the results of the F-score strategy, it has spread across the investor community. The investment strategy has been recognized in articles from Forbes and Bloomberg, among others. Moreover, a numerous of investment screeners have been established, aimed at identifying F-score firms in the investment universe (Zacks, 2000).

In this paper, I have shown that the investment strategy still generates, what appear to be, excess returns. According to the efficient market hypothesis, inefficiencies that generate abnormal returns will quickly be arbitraged away by rational investors. Given the widespread attention the investment strategy has been exposed to, it is probable to assume that the excess returns should have been arbitraged away. One reason for arbitrageurs not exploiting this situation can be because that the abnormal returns are not abnormal and are just compensation for risk. From another point of view, it can be because the abnormal returns are a subject of limits to arbitrage.

The results documented in this paper find that the investment strategy produces the greatest returns in small firms followed by medium firms while the large firms show no effect. The reason for this can be limits to arbitrage in medium firms and especially small firms. It is common knowledge that small firms are restricted and more commonly restricted to short selling. The restriction of short selling hinders mispricing signals to be detected in some cases. Moreover, the number of arbitrageurs are limited due to a lot of institutional investors are restricted to invest in large firms.

In summary, limits to arbitrage may impede an efficient pricing in medium firms and especially small firms, which can be an explanatory factor for that the investment strategy produces the strong returns.

6.3.2 Heuristics and Biases

Heuristics and biases can provide explanations for the success of the investment strategy. As discussed earlier, value stocks are typically neglected by the investment community. In this paper, I show that value stocks have low analyst coverage (see table 8). This unwillingness to value stocks can be argued generating mispricing signals which a fundamental strategy as F-score can exploit.

The main characteristic of value stocks is the low valuation. A low valuation implies low expectations on future earnings. Because of anchoring, investors and analysts anchor on recent earnings. Consequently, investors will anchor on these recent low earnings from value stocks and expect them to have subsequently low earnings. Thereby value stocks are neglected by the investment community.

As shown in table 8 value stocks have low analyst coverage. A stock without analyst coverage can lead to lower valuation than a stock with analyst coverage. The reason for this is that analysts tend to be overoptimistic (Carleton et .al, 1998). Hence, value stocks are not exposed to this overoptimistic analyst forecast which may cause irrational overpriced stocks.

Another reason for value stocks high returns is judgement errors leading to expectational error hypothesis. Investors tend to put excessive weight on recent performance and discount recent sales growth too far into the future. Reversely investor tends to become overly pessimistic of poor performance. This is supported by Lakonishok et al. (1994) that document how market participants consistently overestimate the future performance of growth stocks in comparison to value stocks. This leads to overreaction to good news and the stock appreciates to fast in value which leads to overvaluation in growth stocks and undervaluation in value stocks. As a consequence, value stocks can be exposed to earnings surprises.

Companies that have had good prior performance are labeled by investors as good companies. Due to representativeness bias, investors may incorrectly conclude that good companies are good investments. This bias may lead investors to favor growth stocks rather than value stocks. MacGregor et al. (1992) provide evidence for this bias.

Institutional investors are exposed to agency problems. Since investor, as argued earlier, have a preference for growth stocks, due to anchoring, expectational error hypothesis and representativeness, institutional investors may suboptimally allocate money to growth stocks rather than value stocks. Lakonishok et al. (1992) document that intuitional investors avoid value stocks due to the agency problem. A more recent study by Jiang (2010) shows that institutional investors follow a herding behavior. Portfolio managers tend to choose consensus stocks because of their own reputational risk. By going along with other portfolio managers actions, the risk of standing out as a bad portfolio manager decreases. A consensus stock is typically not a value stock. This leads to overpriced securities become more overpriced and reversely underpriced securities becomes more underpriced.

In summary, anchoring, expectational errors, representativeness, overconfidence, low analyst coverage and agency problems among institutional investors lead to that the investment community is overly pessimistic and neglects value stocks. Consequently, this might lead to mispricing among value stocks. Hence, a fundamental investing strategy based on F-score can exploit this by identifying financially strong firms, which is being ignored by the investment community.

7. Conclusions

In this paper, I have tested an investment strategy by using fundamental analysis applied on high book-to-market firms in the US market between 2003 and 2015. The investment strategy aims at replicating Piotroski's (2000) F-score. The so-called F-score is a binary scoring systems with nine variables capturing profitability, leverage/liquidity and operating efficiency. The aim of the F-score is to identify financially strong firms respectively financially weak firms. A firm with high F-score is expected to have a strong subsequent financial performance and consequently a strong subsequent return. I show that an investment strategy that buys high F-score (7-9) in the highest book-to-market quintile earns on average a one-year market-adjusted return of 18.3 % annually over the period from 2003-2015. In comparison with the entire high book-to-market quintile that earns a corresponding return of 12.3 %, the high F-score portfolio, outperforms this by 6 %. A portfolio constructed with low F-sore (0-2) firms earns on average a one-year market-adjusted return of 4 % annually. In contrast, the high F-score portfolio earns 14.3 % more. This mean differences in returns are mostly statistical significant on the 1 % level while some are significant at the 5 % level using t-statistics.

The results from the investment strategy indicate that fundamental analysis can be used to separate winner stocks from loser stocks. The usefulness of fundamental analysis opposes an efficient market in the semi-strong efficiency form. The strongest benefit for the investment strategy is found in small followed by medium sized companies. The strategy does not show any benefit among large companies. One feasible explanation for this is limits to arbitrage, which may impede an efficient pricing in medium firms and especially small firms. Moreover, the results appear to contradict risk compensation. Fama and French (1992) propose that the outperformance of high book-to-market stocks is a compensation for financial distress. However, the results show that the stocks with the strongest return are attributed with least financial distress and reversely the firms with most financial distress have the weakest return performance. Fama and French (1992) also documents that smaller firms are riskier than larger firms and the strong return from small firms is a compensation for risk. My results show that a high F-score portfolio with small firms generates a performance of 34.3 % annually (one-year market-adjusted returns) and this strong performance indicates that F-score is not only a size effect.

The strong performance of the investment strategy can be explained from a behavioral finance perspective. These explanations relate to three factors. First, investors have a tendency of focusing too much on past performance. Value stocks have in general a history of low growth and poor performance, which leads to overly pessimistic low expectations on the future. The combination of value stocks poor historic performance and investors focusing too much on history leads to unfairly low valuation. Second, investors have a tendency of favoring good companies regardless of valuation. Given the poor history of value stocks, investors do not classify value stocks as good companies, which leads to neglecting of value stocks. Third, value stocks are less exposed to analyst coverage and institutional investors due to agency problems. In summary, these three factors relate to the biases anchoring, expectational errors, representativeness and overconfidence generating overoptimistic and overpessimistic views. All these biases, lead to value stocks are being neglected by the investment community leading to unfairly low valuation and this can be exploited by a fundamental strategy as F-score which finds financially strong performing firms in an unbiased fashion.

As a further research, to find an answer whether the strong return from the F-score strategy can be attributed to risk or mispricing, would be to risk-adjust the returns with the Fama and French three-factor model. However, Fama (1970) states that a test of anomaly is a joint test of market efficiency and the asset pricing models risk factors. When observing abnormal returns, it is impossible to conclude whether market actors have behaved irrational or if the asset pricing model captures all risk. Even though if the three-factor model would find abnormal risk-adjusted returns it would remain inconclusive. Furthermore, it would be interesting to investigate if it exists limits to arbitrage in small and medium sized firms by checking for liquidity.

One limitation that this study may be exposed to is statistical reliability. Barber and Lyon (1997) and Fama (1998) among others emphasize the problem with statistical reliability when discovering abnormal returns. The problem refers to that only using one statistical method may not be sufficient for statistical reliability. In this study, I only perform t-statistics, which is a limitation.

Although further research is still needed and this papers modest ambition to contribute to the literature, this paper is in line with Piotroski's results that fundamental analysis can separate winner stocks from loser stocks. First, this paper contributes to existing literature by using a more recent data set. Moreover, this study adds to existing research by introducing a behavioral finance perspective that to the best of my knowledge, previous writers have not shed light on.

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