FORECASTING FINANCIAL PERFORMANCE USING THE FSCORE

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ABSTRACT

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This study examines whether the industry effect variables can be used to detect investable high book-to-market firms that are neglected by the classic FSCORE method. Industry winners in the neglected firms cluster are called Underdogs. While the FSCORE method takes a financial picture of the high book-to-market firms, the industry effects variables identify the standing of the firm's performance relative to its peers. When industry effects are taken into consideration in combination with the FSCORE, a comprehensive fundamental analysis process is established. Using the Generalized Method of Moments framework, the direction and strength of the relationship between the industry effects variables and future returns are estimated. Results show that firms with an FSCORE above the industry average earn approximately 8% higher returns comparted to others. In addition, the industry winners method can separate future winners and losers in the neglected firms cluster, with the Underdog firms producing approximately 6% higher 12-month market-adjusted returns compared to others. The industry effects variables increase the number of investable firms by approximately 90%.

Keywords: FSCORE, Industry effects, Forecasting, Financial Performance

ÖZ

FSCORE YÖNTEMİ İLE FİNANSAL PERFORMANSIN TAHMİNİ

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Bu çalışma, endüstri etkisi değişkenlerinin, klasik FSCORE yöntemiyle ihmal edilen yüksek BM firmalarına yatırım yapılmasına izin verip vermeyeceğini incelemektedir. İhmal edilen firma kümesinin içindeki endüstri kazananları Underdog firmalar olarak adlandırılmaktadır. Endüstri etkisi değişkenleri endüstrinin firmalar üzerindeki etkilerini incelerken, FSCORE yöntemi defter değeri piyasa değeri oranı yüksek olan şirketlerin içsel durumunu gösterir. Böylece kapsamlı bir temel analiz süreci oluşturulur. Genelleştirilmiş Momentler Yöntemi endüstri etkisi değişkenleri ile gelecekteki getiriler arasındaki ilişkilerin yönünü ve gücünü açıklar. Sonuçlar, sektör kazananları ve on iki aylık piyasa ayarlı getirilerin sektör ortalamasının üzerindeki firmalar için yaklaşık %8'lik bir getiri artışı ile istatistiksel olarak anlamlı pozitif bir ilişkiye sahip olduğunu göstermektedir. Sektör kazananları yöntemi, ihmal edilen firmalar kümesindeki gelecekteki kazananları ve kaybedenleri ayırabilir; bu nedenle Underdog firmalar on iki aylık dönemde yaklaşık %6'lık piyasaya göre ayarlanmış getiri artışı üretir. Bu getiri artışının klasik FSCORE yöntemi ile ihmal edilen gruptan geldiğinin altını çizmek gereklidir. Sonuç olarak, sektör etkisi değişkenleri yatırım yapılabilir firma sayısını yaklaşık %90 oranında artırmıştır. Endüstri etkisi değişkenleri, defter değeri piyasa değeri oranı yüksek olan şirketlerin gelecekteki kazananlarını ve kaybedenlerini ayırabilir. Ayrıca endüstri etkileri yöntemi de FSCORE' un kapsamını ve gücünü artırmıştır.

Anahtar Kelimeler: FSCORE, Sektör Etkileri, Tahmin, Finansal Performans

To My Mother

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LIST OF ABBREVIATIONS

BM	Book-to-Market
CFO	Cash Flow from Operations
CLT	Central Limit Theorem
CP	Cash-Flow-to-Price
DM	Dividends to Market
EAFE	Europe, Australasia, and the Far East
EBIT	Earnings Before Income and Taxes
EBITDA	Earnings Before Interests, Taxes, Depreciation, and Amortization
EM	Earnings to Market
EP	Earnings-to-Price
EQ_OFFER	Equity Offers
EV	Enterprise Value
FIIs	Foreign International Investors
FSCORE	Aggregate Score
GICS	Global Industry Classification Standard
GMM	Generalized Method of Moments
GP	Gross Profitability
HBM	High Book-to-Market
HIFW	High FSCORE and Industry Winners
IL	Industry Losers
IW	Industry Winners
LFIL	Low FSCORE and Industry Losers
MA_RET	Market Adjusted Return
MCDM	Multiple Criteria Decision Making

MFs	Mutual Funds
MM	Method of Moment
MSCI	Morgan Stanley Capital International
MVE	Market Value of Equity
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PEG	Price/Earnings to Growth Ratio
ROA	Return on Assets
ROE	Return-on-Equity
SG	Sales Growth
SP500	Standard & Poor's 500
ST	Share Turnover
TSLS	Two Stage Least Squares
U.S.	United States
USA	United States of America
ΔLEVER	Change in the Leverage
ΔLIQUID	Change in the Liquidity
ΔMARGIN	Change in the Margin
ΔROA	Change in ROA
ΔTURN	Change in the Turnover

CHAPTER 1

INTRODUCTION

Company analysis is a crucial step in the fundamental analysis process. Company analysis takes a picture of the firm's financial health using financial statements from previous years. The FSCORE method is a simple accounting-based fundamental analysis methodology which has the objective of identifying future winners and losers among high book-to-market firms.

A company's stand-alone financial health is only one of the components in fundamental analysis. The company's industry position is another important dimension. The inherent profitability of the industry has effects on the profitability of the industry members. In addition, some firms may earn much higher returns comparted to others, regardless of the average profitability of their industry. Therefore, determining the position of a firm in the industry is an essential step for building competitive strategy (Porter [26]).

Porter and McGahan [25] show that industry effects constitute 19% of the aggregate variance in business-specific profitability while 32% are from firm-specific effects. Moreover, they show that industry effects are more persistent than firm-specific effects, consistent with the idea that the industry structure changes slowly. Based on these findings, this study includes an industry effects dimension in the FSCORE methodology. More specifically, this study examines whether the industry effect variables can help to identify investable firms among those that are "neglected" in

Pietroski's original FSCORE methodology where winners and losers are determined within high BM firms. The industry effect is incorporated into the analysis by comparing individual firms' FSCORES with the average FSCORE of their respective industries. Those firms whose FSCORE are below the industry average are labeled as "industry losers" and those with FSCORES above the industry average are labeled as"industry winners." If the industry winners are among those firms that the Pietroski method would have "neglected", then these firms are labeled as the "underdogs". The primary investment strategy is to buy the expected industry winners and sell the expected industry losers. The sample of this study is the non-financial high BM firms that are traded on the NYSE between the first quarter of 2000 and the fourth quarter of 2020.

In the literature, there are several studies that support the validity of the FSCORE method. Moreover, the FSCORE methodology was combined with other techniques in many studies (Shen & Yan and Chen [22]; Cho & Shin and Byun [34]; Dewandaru et al. [8]; Chen & Lee and Shih [11]. These studies show that combining the FSCORE method with other methods yields more robust results. Thus, the different techniques have increased the power of the FSCORE method. Since industry effects have not been addressed yet, this study aims to fill this gap in the literature.

The Generalized Method of Moments framework is used to estimatethe direction and strength of the relationship between the industry effects variables and future returns. Moreover, well-known factors that affect stock returns (MVE, BM, momentum, accruals, and equity offerings) have been added to the regression equations.

Results show that there is a significant and robust relationship between the industry effect variables and future returns. Furthermore, "Underdogs" earn approximately 6% higher market-adjusted returns over the next 12 months after controlling for other well-known return factors. It is essential to highlight that this return expectation is for firms that are originally "neglected" by the FSCORE methodology. It is also interesting to note that this group constitutes approximately 90% of the high BM sample.

Consequently, the study has several contributions to the current literature. First, the original FSCORE analysis is updated for a more recent period. Second, the industry effects dimension is added to the analysis. . Lastly, the study shows that it is possible to invest in firms that are neglected by the FSCORE method and earn abnormal market-adjusted returns. Hence, the study increases the total number of investable firms.

Chapter 2 reviews the prior literature on the FSCORE method. Chapter 3 presents the data and methodology, while Chapter 4 presents the empirical results. Lastly, Chapter 5 concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

Value investing is a widely used investing strategy in financial literature. Its main goal is to find a stock with a market value less than its intrinsic value. For this purpose, financial statement analysis has a crucial role in this strategy.

Many previous studies have documented returns of the high book-to-market (BM) firms (value stocks). The high BM firms' portfolio returns are due to the strong performance of a small number of firms. Piotroski [12] presented that less than 44% of all high BM firms provided positive market-adjusted returns in two years following portfolio formation. Therefore, discriminating the future winners and losers in the high BM firms cluster will shift the return distribution of investors to the right. The fundamental analysis method has been produced more successful results for high BM firms because value firms tend to be neglected by investors.

Moreover, financial statements represent the only available source since analysts do not generally follow these firms. And the high BM firms are financially distressed. Thus, it is necessary to focus on accounting base data such as leverage, liquidity, profitability, and cash flow for valuation purposes. FSCORE is one of the most practical ways of financial statement analysis. FSCORE is a score-based signal strategy that comprises nine financial signals. The signals have measured three main parts: profitability, financial leverage/liquidity, and operational efficiency. Every indication has been divided into good and bad signs. The indicator variable with a good signal equals one, while an indicator variable with a bad signal is zero. Hence, the sum of binary signals called FSCORE could attain a total score between zero and nine. FSCORE with zero or one is called losers, while eight and nine are the winners. The primary strategy is buying winners and shorting losers. Finally, the main goal of FSCORE is to measure the total financial condition of firms. The FSCORE method has been increased the mean return of the high BM firms by 7.5% in one year. The investment strategy that long position in expected winners and short position in expected losers has earned a 23% annual return between 1976 and 1996. Consequently, the FSCORE method is successful in discriminating future winners and losers. The FSCORE calculation method was thoroughly explained in the methodology section.

Extensive studies have been conducted on the FSCORE strategy. Among these studies, some articles have investigated the validity of FSCORE. Nguyen [31] has examined the relationship between financial information and stock returns. The author has used a score-based strategy to clarify the relationship. However, eight different signals have been selected to analyze firms' conditions. The data has been collected from firms listed on the Tokyo Stock Exchange. Fourteen thousand six hundred eight observations have been screened between 1992 and 2001. As a result of screening, a positive relationship between financial information and stock returns has been found. The results supported that a score-based portfolio strategy can outperform over essential value stocks portfolio. Some significant results have been highlighted again. Firstly, high score firms earn more monthly excess returns than low score firms. Additionally, small firms make an abnormal return, while large firms offer less. Finally, the score-based strategy's profitability comes from the return continuation, which means past winners are still winners for the next period.

Moreover, the validity studies have been examined in different markets. Hyde [5] has used the FSCORE strategy to discriminate between future winners and losers in global emerging markets. The author has conducted their research based on a dataset that took a period between January 2000 and December 2011 for all countries in the MSCI

Emerging Markets Index. The study has focused on all stocks rather than only deep value stocks because the emerging markets are slower to reflect new information to prices for all stocks, which is different than Piotroski [12]. The study has shown that FSCORE can distinguish high and low future returns in global emerging markets in line with earlier literature. However, some of the findings have differed from Piotroski [12]. First, there is no significant and statistically (0,06 pa premium difference) difference between small and large stocks. Second, the premium difference is more extensive for high momentum stocks than low momentum stocks. Hence, the analyst neglection is not the source of the premium to high F score stocks. As a result, despite differences between Piotroski [12] and Hyde [5], FSCORE is a substantial explanation of future winners and losers in global emerging markets and developed markets.

Singh & Kaur [15] have studied the added value of FSCORE on value stocks in the Indian stock market. The study has used the stock data in the Bombay Stock Exchange between 1996 and 2010. They have found that high FSCORE firms' portfolios can outperform both low and high book-to-market firms. The high FSCORE returns have been more extensive than the all high book-to-market portfolios by 18.402 percent per annum. The accrual effect has been positive, different from Piotroski [12]. Another difference with the original study is that the prior year equity offering has positively impacted subsequent returns. Consequently, the F SCORE strategy has the power of predicting future returns over the value stocks in the Indian stock market.

Ng& Shen [4] have used FSCORE to discriminate the future winners and losers between 2000- 2015 in seven Pacific-Basin markets: Hong Kong, Australia, Singapore, South Korea, Malaysia, Thailand, and Indonesia. They have put a different complexion on the strategy by using FSCORE with small-cap stocks. The results have shown that small-cap firms with high FSCORE can earn higher returns than value stocks with high FSCORE. The cause of this result is that small-cap firms are neglected more than value stocks. As a result, FSCORE is a solid strategy for discriminating winners and losers in seven Pacific-Basin markets.

Tapia& Tascon [2] have tested the performance of fundamental score strategies, which were Piotroski [12], Xue and Zhang [37], Mohanram [30], and Wahlen and Wieland [17]. The scores have been renamed FSCORE 1, FSCORE 2, FSCORE, and PEIS, respectively, for this study. They have selected a dataset that took a period between 1989 and 2011 for fourteen European markets (Austria, Belgium, Germany, Denmark, Finland, France, Greece, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom). They have calculated the scores along the same line as the original studies. However, they have implemented the techniques to the entire market rather than only BM firms. They have found that Piotroski's FSCORE1 and Mohanram's GSCORE can earn one year ahead buy-and-hold abnormal returns in the European markets. An abnormal return has been calculated as the firm-specific raw return minus market return in the same period. On the other hand, Xue and Zhang's FSCORE2 and Wahlen and Wieland's PEIS have not acquired the buy-and-hold abnormal returns. Overall, the results have shown the predictive power of Piotroski's FSCORE to discriminate between future winners and losers.

Banerjee& Deb [29] have examined the performance of FSCORE in the Indian equity market, the period between March 2003 and March 2013. They have found that firms with high FSCORE can generate higher returns than firms with low FSCORE, consistent with earlier literature. Moreover, they have shown that firms with positive ROA (ROA is a variable of FSCORE, F_ROA=1) have a significantly higher one-year buy-and-hold return over firms with negative ROA. Lastly, the FSCORE has produced favorable results in an emerging market like India with low financial transparency.

Turtle& Wang [10] have examined the relationship between basic accounting information and future portfolio performance using FSCORE. They have conducted their research based on a dataset that took a period between 1972 and 2014 for NYSE, AMEX, and NASDAQ Indexes. They have calculated the quarterly FSCORE for increasing the predictive power of strategy. They have found shreds of evidence that the premium of FSCORE is caused by information uncertainty. Consequently, high F

Score portfolios have performed best in the most excellent information uncertainty situations. Overall, the FSCORE has predictive power over future returns in the USA.

Yang et al. [19] have tested the FSCORE in Taiwan Stock Market from May 2008 to May 2018 by adding new stock selection methods. In the original study, Piotroski has filtered the stocks by book-to-market ratio. However, this study has used the Dividend–to–Price ratio, Earnings-to-Price ratio, and Book-to-Market ratio. The stocks have been separated into two groups: high FSCORE value portfolios and low FSCORE value portfolios. As a result, they have shown that value stock portfolios produce better monthly cumulative performance than growth stock portfolios. Moreover, the high FSCORE firms have superior monthly return performance than the low FSCORE firms. An impressive result is that high FSCORE stocks have lost less than low FSCORE stocks in the financial crisis such as 2008 and 2015. The constraint of FSCORE is that there is a time lag between prices and FSCORE because of the financial report publication time. Overall, the FSCORE has successfully selected winners and losers in Taiwan Stock Market from May 2008 to May 2018.

Walkshäusl [7] has examined the validity of FSCORE in a broad sample consisting of 20 developed non-US markets and 15 emerging markets from July 2000 to June 2018. The 20 developed non-US markets include the EAFE (Europe, Australasia, and the Far East) stock market, and emerging markets are selected from MSCI. The FSCORE has applied to all stocks rather than using only value stocks. The return premium of FSCORE has come from value stocks with high scores and growth stocks with low scores. The study has shown that FSCORE is a valuable strategy for predicting a return in non-US stock markets and emerging markets.

Some studies have criticized the FSCORE strategy. Kim & Lee [21] have examined the relationship between FSCORE premium and subsequent return accumulation periods. Piotroski [12] has used a firm-specific return accumulation period rather than a specific return accumulation period for all stocks. The critics have raised this point, claiming that the FSCORE premium comes from the preference for the return accumulation period. They have conducted two analyses which are called Analysis 1 and Analysis 2. Analysis 1 has replicated the study of Piotroski [12]. Analysis 2 has selected a standard starting date for all firms to explore the common return accumulation period's problem. The results showed that Analysis 1 gets a 30% higher hedge portfolio return for a year than Analysis 2. As a result, this result has supported that the FSCORE and subsequent stock returns have a relationship with the return accumulation period.

The weighted scoring stock selection models have some drawbacks. Firstly, they can't answer the relationship between the weights of stocks and portfolio performance. Secondly, they cannot detect the optimal weights of portfolios to optimize portfolio performance. Lastly, they are not capable of responding to the investors' preferences. Liu & Yeh [24] have aimed to construct a new weighted scoring stock selection model using neural networks and optimization techniques to cope with these disadvantages. They have shown that optimal weighted scoring techniques outperform the S&P 500 between 1990 - 1998 and 2000 - 2014 in an annual return. The new method's performance failed between 1998 - 2000. The reason behind this result has been dot com bubble occurred during this period. Thus, the market has been driven more by investor sentiment rather than fundamental analysis. Overall, the optimal weighted scoring stock selection technique has been helpful for investors' specific preferences.

As mentioned above, the premium of FSCORE has different motivations. The more acceptable argument of Piotroski [12] has been analyst neglection. The main idea behind this is small firms have less analyst coverage, and the market hasn't noticed the fundamental improvements. The FSCORE is a reliable tool to resolve this problem. However, Hyde [6] has shown that the analyst neglection does not explain the FSCORE premium. The study has examined the validity of FSCORE in Australia and the reasons for FSCORE premium. Hyde [6] has applied the FSCORE strategy to all stocks rather than value stocks. Results have shown that high FSCORE firms have higher analyst coverage than low FSCORE firms in Australia, contrasting with Piotroski [12].

Therefore, the analyst neglection is not a complete explanation for the premium of FSCORE.

Some studies have combined the FSCORE with other strategies. Shen & Yan and Chen [22] have integrated the Fuzzy-MCDM (Multiple Criteria Decision Making) methods into the FSCORE to separate winners and losers among the high BM banking stocks. They have changed Piotroski [12] accruals variable with the Return-on-Equity (ROE) variable. They have found that the ROE variable has a vital role in this new combined strategy for Taiwan's stock market. The study has focused on the banking sector, which previous studies have ignored. They have shown that the new method is suitable for Taiwan's stock market.

Value investment has been used in many ratios to find value stocks; the high BM ratio is one. Piotroski [12] filtered all stocks with a high BM ratio to attain the value stocks before using the FSCORE. Cho & Shin and Byun [34] have combined some value ratios with the FSCORE, called the two-dimensional value investment strategy. The ratios were book-to-market (BM), earnings-to-price (EP), cash-flow-to-price (CP), sales growth (SG), and equity share turnover (ST). The study has examined whether a two-dimensional value investment strategy could produce more returns than a one-dimensional strategy between 1981 and 2011 in the Korean stock market. They have used a strategy of buying value stocks with a higher FSCORE and selling glamor stocks with a lower FSCORE strategy. They have found that the two-dimensional strategy has beaten both value investment and FSCORE strategies. The two-dimensional strategy has produced a 27.9 percent buy-and-hold abnormal return, 8.97 percent more than the one-dimensional value investment strategy. Overall, Cho & Shin, and Byun [34] have shown that the two-dimensional value investment strategy has worked in the Korean stock market.

Dewandaru et al. [8] have studied active portfolio management using a multi-style strategy: value, quality, and Moment investing. The FSCORE has been used for the financial strength variable. These stock selection investing techniques have been used with the augmented Black Litterman factor model. The results have been significant for the multi-style strategy. However, they have found that FSCORE did not have the predictive ability for Dow jones's Islamic index in 1996 - 2012 because the FSCORE has been incorporated in the current price.

The FSCORE is a fundamental analysis technique to separate winners and losers in high BM stocks. In addition, the GSCORE is another stock selection technique to separate winners and losers in low BM stocks. Chen & Lee, and Shih [11] have examined the FSCORE and GSCORE and whether they can increase the performance of momentum strategy in USA stock markets (NYSE, AMEX, and NASDAQ) between 1973 and 2013. The study has shown that the combined investment strategy has produced more information than the momentum strategy. The market could not incorporate huge details into the price on time. Therefore, the integrated approach outperformed the momentum strategy by a 1.04 percent monthly return over the six-month holding period. Moreover, the integrated system has been suitable for high BM and low BM stocks. Overall, the combined strategy has produced more returns and information than the single momentum strategy.

The value investing strategy is taking a long position on value stocks. The value stocks have been distinguished by different ratios such as "High Earnings to Market (EM), Book-to-Market (BM), Dividends to Market (DM), Earnings Before Income and Taxes to Enterprise Value (EBIT/EV), and Earnings Before Interests, Taxes, Depreciation, and Amortization to Enterprise Value (EBITDA/EV) ratios." Piotroski [12] used the BM ratio to filter value stocks before using the FSCORE technique. Tikkanen & Aijo [16] have examined whether the FSCORE can increase the performance of different value investing strategies in European countries between 1992 - 2014. The lands consist of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. The strategy was to take a long position in high FSCORE stocks after filtered stocks by value investing strategy. The results have shown that the FSCORE has increased the performance of all value investing strategies. The best performance has been the EBITDA/EV strategy by 19.62%, followed by EBIT/EV with 19.28%. Overall, the FSCORE has improved the performance of all selected value investing strategies in all European countries between 1992 - 2014.

FSCORE from Piotroski [12] and GSCORE from Mohanram [30] have been mentioned as quality-driven investing strategies. Li & Mohanram [20] have combined quality-driven methods (FSCORE and GSCORE) with value-driven systems (value-to-price (V/P) and price/earnings to growth ratio (PEG)). The main goal has been whether the combined methods can produce higher excess returns than stand-alone methods. The integrated strategies have taken a long position in stocks with high FCORE or GSCORE with high V/P or NEGPEG, showing underpriced stocks. The short position has been taken in low FSCORE or GSCORE firms with low V/P or NEGPEG. The NEGPEG is the multiplication of the PEG ratio with -1 to positively correlate the PEG ratio with stock returns. The results have shown that the combined strategy has beaten the stand-alone system. The FSCORE with V/P has produced 15.06 percent hedge returns which are 6.71 percent more than FSCORE alone and 6.41 percent more than V/P alone. Similarly, FSCORE with NEGPEG has made 14.97 percent hedge returns. Moreover, the FSCORE and GSCORE are positively correlated with each other. They are negatively correlated with V/P and NEGPEG, which means quality is expensive. The combined strategy has generated more excess returns than stand-alone strategies in the US companies listed on NYSE/AMEX/NASDAQ between 1974 - 2015.

Finally, FSCORE has been used to measure the financial strength of firms. Choi & Sias [28] have used FSCORE as an economic strength tool to estimate future demand by institutional investors. Financial stability has predicted the future institutional direction because the price has driven institutional demand related to firms' future returns. After FSCORE's information are publicly available, the institutional breadth has increased by 11.15 institutions in high FSCORE firms while decreasing by 0.05 institutions in low FSCORE firms. Therefore, the FSCORE has the power to forecast future returns and future institutional demand.

For investing decisions, assessing firms' financial health is a necessary process. Therefore, many studies have focused on finding healthy firms or distressed firms. Agrawal [18] has pointed out that Altman (1968) focused on the financial distress risk of firms, and Ohlson (1980) focused on the bankruptcy prediction of firms. However, they have ignored some crucial parts of financial distress firms, such as the earnings quality and equity dilution. Agrawal [18] has used the FSCORE to find the default risk of Indian stocks between 2000 - 2012. The study has examined the aggregate score (FSCORE) and individual components of FSCORE to estimate the default risk. The results have shown that FSCORE and individual components have the power to find defaulting firms. High FSCORE firms have less probability of defaulting. The leverage has a positive relationship with defaulting firms. Defaulting firms have faced an increase in leverage compared to the previous year, which means ΔLeverage is 0 for the period. Defaulting firms have a lower ROA ratio as compared to non-defaulting firms. Moreover, the individual components have better prediction power than the aggregate score. Overall, the aggregate score (FSCORE) and individual components can find defaulting firms in India between 2000 - 2012.

Gopikumar et al. [36] have examined the relationship between financial strength (FSCORE) and ownership of foreign international investors (FIIs) and mutual funds (MFs) in India between 2001 - 2017. Moreover, the relationship between the right of FIIs and MFs with FSCORE components which are profitability (F-profitability), efficiency (F-efficiency), and leverage (F-risk), have been investigated. The result shows that MFs and FIIs positively correlate with firms' financial strength. FIIs have preferred riskier firms related to leverage components, while MFs have preferred higher profitability firms associated with profitability components of FSCORE. Therefore, profitability and leverage components played a crucial role in estimating future ownership of FIIs and MFs in Indian firms. Overall, the aggregate score

(FSCORE) hasn't had discriminative power in demand for FIIs and MFS. However, the profitability (F-profitability) and leverage (F-risk) have strong discrimination power in identifying the high and low ownership of both FIIs and MFs in India between 2001 - 2017.

Piotroski [12] and some later studies on FSCORE have supported that information uncertainty is a possible reason for FSCORE premium. Kumsta & Vivian [32] have examined whether the financial strength (FSCORE) premium comes from information uncertainty or liquidity in the UK between 1992 - 2010. The results have shown that financial strength has produced more returns in illiquid UK stocks. The illiquid stocks have generated 20% zero-cost arbitrage returns, while 12% in liquid stocks. The results show that the lower uncertainty firms generate higher returns than those with UK investors who prefer a lower information uncertainty portfolio. In sum, the financial strength (FSCORE) has produced more return when applying to illiquid firms which are financially weak. Therefore, the FSCORE premium has depended on liquidity rather than information uncertainty.

The financial strength (FSCORE) has been used to assess the quality of firms in some studies. Ng & Shen [3] have examined the gross profitability (GP) and FSCORE as a quality investing strategy in five Asian stock markets (Hong Kong, Japan, Korea, Singapore, and Taiwan) between 2000 - 2016. In addition, the study has examined the relationship between stock quality and subsequent institutional demand as part of the following stock return. The results have shown that high FSCORE stocks generate positive returns in all five Asian markets. However, high FSCORE stock returns are positive in the Taiwan market, but it is not significant. The lowest return is from Japan with 0.61 percent, and the highest return is 1.37 percent in Hong Kong. The high-quality stocks earn more than low-quality stocks for both GP and FSCORE. However, the GP hasn't generated significant returns except in Hong Kong and Korea.

Further, the institutional investor prefers high-quality stocks rather than low-quality stocks. As an exciting result, the study has shown that "If the value of FSCORE is increased by 1, the monthly stock return is increased by 0.20 percent (Hong Kong), 0.03 percent (Japan), 0.06 percent (Korea), 0.17 percent (Singapore), and 0.11 percent (Taiwan), respectively.". In sum, the quality investing strategy has the power to produce positive returns in five Asian stock markets between 2000 - 2016. The FSCORE has produced more returns than GP. Moreover, the quality investing strategy has the power to estimate future institutional demand.

CHAPTER 3

DATA AND METHODOLOGY

3.1. Data Collection and Sample Selection

The data consists of fundamental accounting data to calculate the FSCORE. Firms listed on the New York Stock Exchange (NYSE) are selected from the Thomson Reuters database. Financial firms are excluded from the sample since their financial statements have unique characteristics. Delisted firms are kept in the sample in order to avoid survivorship bias. The sample period is between March 2000 and December 2020. While downloading the data by using the Thomson Reuters Excel interface, some firms had missing observations. For each firm, the individual page dedicated to the company in Thomson Reuters was visited to determine whether these missing observations occur because data are not available in the TR system or because the Excel interface failed to retrieve the data. If data were available, then the missing observations were obtained and filled by individually extracting the data from the company page. After data editing, each firm's market values and BM ratios were calculated in Excel. Afterwards, firms were ranked by using their BM ratios in order to choose the highest quintile at the beginning of each year. Consequently, the final sample is the non-financial high BM NYSE firms between the first quarter of 2000 and the last quarter of 2020.

3.2. Variable Construction

3.2.1. FSCORE

Piotroski [12] has developed the FSCORE technique to separate future winners and losers within the high-book-to-market (HBM) firms. FSCORE consists of nine fundamental signals to measure a firm's performance in three areas:

- **Profitability:** ROA, ΔROA, CFO, and ACCRUAL
- **Financial leverage/Liquidity:** ΔLEVER, ΔLIQUID, and EQ_OFFER
- **Operating efficiency:** ΔMARGIN, and ΔTURN

Each signal is categorized as "good" or "bad" depending on the impact of the signal on future prices and profitability. The signal variable equals one if the signal's realization is good, zero otherwise. The aggregate signal measure (FSCORE) equals the sum of the nine binary signals. Therefore, the FSCORE ranges between zero and nine. Based on each quarter's financial statement data, the FSCORE is calculated for the sample firms.

3.2.2. Industry Effect

The firm-specific effects are essential for the fundamental analysis process. Piotroski [12] proposed the FSCORE to capture company-specific effects; however, as argued above, firms are affected by their industry as well. The industry effect is integrated into the analysis by measuring the mean performance signal of the industry (the average FSCORE of the sector) and it is used as a cut-off point. Namely, firms with FSCORES that are below their industry average are designated as "industry losers" while firms with FSCORES above the industry average are designated as "industry winner" Based on this classification, a portfolio strategy devised where industry winners are bought and industry losers are sold.

3.2.3. Control Variables

In addition to the FSCORE and the dummy variables that identify industry winners and losers, the models also include several control variables that are shown to affect the future expected returns.

3.2.3.1. Market Value of Equity (MVE)

MVE is calculated as the number of shares outstanding at fiscal quarter-end times the closing share price and measuresn the effect of company size on returns. In order to smooth out the differences in size among firms, natural logarithm of MVE is used in estimations.

3.2.3.2. Book to Market (BM) Ratio

The book to Market (BM) ratio is used to distinguish value stocks (high Book to Market (HBM) firms) from growth stocks (Low Book to Market firms). The BM is calculated as the book value of equity at the end of the fiscal quarter and it is scaled by the MVE. Once again, the logarithm of BM is included in the estimations.[1]

3.2.3.3. Momentum

Momentum, where past winners (losers) are expected to be future winners (losers) is a highly documented effect in stock markets [9]. In order to account for the momentum effect, the momentum variable is computed as the six-month market-adjusted buy-and-hold return directly preceding the portfolio formation date.

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[1] The raw BM ratio was added to the regression analysis instead of the log (BM), and GMM estimation was repeated. The results are qualitatively the same.

3.2.3.4. Accruals

Accruals are created when revenues or expenses are recorded at the time of their relevant transactions and not at the time of the actual related cash flows. Piotroski argues that the relationship between earnings and cash flows is essential for high book-to-market firms because if profits are greater than the cash flow from operations, this would be a bad signal regarding the future profitability of the firm since accruals would be accumulating on the liability side [12]. Previous literature (Sloan [33]) shows that the historical level of accruals has a strong relationship with the future stock returns. The accruals variable is calculated as net income before extraordinary items minus cash flow from operations, scaled by beginning-of-the-year total assets.

3.2.3.5. Equity Offer

Recent equity offerings have a negative relationship with future firm earnings (Myers & Majluf [35], Miller & Rock [27]). The main reason behind this idea is that generally financially distressed firms raise external capital to service future obligations. The indicator variable would equal one if the firm raised external capital during the prior fiscal quarter, and zero otherwise.

3.2.4. Calculation of Returns

The final sample includes the non-financial high BM firms whose shares are traded on the NYSE between the first quarter of 2000 and the fourth quarter of 2020. First, the one-year and two-year buy-and-hold future raw returns are calculated for the firms. After that, the Standard and Poor's (S&P) 500 index is selected as the market proxy and the one-year and two-year buy-and-hold future raw returns are calculated for the market index as well. Lastly, the market-adjusted buy-and-hold future returns are calculated for the firms as the buy-and-hold return of the firm minus the market index return for the relevant time horizon.

3.2.5. Calculation of the FSCORE

Piotroski's FSCORE consists of nine fundamental signals to measure three areas of the firm's financial condition. Each signal realization is categorized as "good" or "bad" depending on the impact of the signal on future prices and profitability. The signal variables equal one if the signal's realization is good, zero otherwise. Ultimately, the composite score (FSCORE) equals the sum of the nine binary signals.

3.2.5.1. Profitability

The profitability category provides information about the firm's ability to generate funds internally. Four variables (RAO, ΔROA, CFO, and ACCRUAL) are calculated to assess the firm's performance in this category.

Return on Assets (ROA) is calculated as the net income before extraordinary items scaled by the beginning of the quarter's total assets. If the firm's ROA is greater than zero, then the indicator variable (F_ROA) equals one, zero otherwise.

Change in ROA (ΔROA) is calculated as the current quarter's ROA minus the previous quarter's ROA. If the firm ΔROA is greater than zero, then the indicator variable (F_ΔROA) equals one, zero otherwise.

Cash Flow from Operations (CFO) is calculated as CFO scaled by the beginning of the quarter's total assets. If the firm's CFO is greater than zero, then the indicator variable (F_CFO) equals one, zero otherwise.

ACCRUAL is calculated as the current quarter's net income before extraordinary items minus cash flow from operations, scaled by the beginning of the quarter's total assets. If the firm's CFO is greater than ROA, then the indicator variable (F_ ACCRUAL) equals one, zero otherwise.

3.2.5.2. Leverage, Liquidity, and Source of Funds

The three variables in this category (ΔLEVER, ΔLIQUID, and EQ_OFFER) provide information about the changes in the firm's capital structure and its ability to meet future debt service obligations.

Change in the Leverage (ΔLEVER) is equal to the current debt-to-assets ratio minus the previous quarter's debt-to-assets ratio. The debt-to-assets ratio is equal to the firm's total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets. If the firm's ΔLEVER is negative, then the indicator variable (F_ΔLEVER) equals one, zero otherwise.

Change in Liquidity (ΔLIQUID) is equal to the firm's current-quarter current ratio minus the previous quarter's current ratio. The current ratio is computed as total current assets divided by total current liabilities. If the firm's ΔLIQUID is positive, then the indicator variable (F_ ΔLIQUID) equals one, zero otherwise.

The equity offer (EQ_OFFER) variable indicates whether the firm is issuing additional commong stock to finance its operations. If the firm did not issue common equity in the previous quarter, then the indicator variable (F_ EQ_OFFER) equals one, zero otherwise.

3.2.5.3. Operating Efficiency

The two variables (ΔMARGIN and ΔTURN) provide information about the changes in the efficiency of the firm's operations.

Change in theMargin (ΔMARGIN) is calculated as the firm's current gross margin ratio minus the previous quarter's gross margin ratio. The gross margin ratio is calculated as gross margin scaled by total sales. If a firm's ΔMARGIN is positive, then the indicator variable (F_ ΔMARGIN) equals one, zero otherwise.

Change in the Turnover (ΔTURN) is calculated as the current quarter's asset turnover ratio minus the previous quarter's asset turnover ratio. The asset turnover ratio is calculated as total sales scaled by the beginning of the quarter's total assets. If a firm's ΔTURN is positive, then the indicator variable (F_ ΔTURN) equals one, zero otherwise.

3.2.5.4. The Aggregate Score (FSCORE)

The aggregate score is the sum of the individual binary signals as shown below:

FSCORE = F_ROA+ F_CFO+ F_ΔROA+ F_ACCRUAL+ F_ ΔLEVER+ F_ ΔLIQUID+ F_ EQ_OFFER+ F_ ΔMARGIN+ F_ ΔTURN)

3.2.5.5. Low versus High FSCOREs and Industry Effects

Following Piotroski [12], if a firm's aggregate score (FSCORE) equals zero or one, then it is labeled as a low FSCORE firm. Similarly, if a firm's aggregate score (FSCORE) equals eight or nine, then it is labeled as a high FSCORE firm.

Furthermore, the industry effects are incorporated into the FSCORE analysis by categorizing a firm as an "industry loser" if its FSCORE is below its industry average, and as an "industry winner" if its FSCORE is above its industry average.

3.3. Model Building

The Generalized Method of Moment (GMM) framework is used to analyze the data. This section will explain the variables included in the GMM and regression models.

The dependent variable in the models is the company return, which is calculated as either a 12-month or a 24-month buy-and-hold return, as described above.

The independent variables are the FSCORE, high FSCORE dummy (future winner), low FSCORE dummy (Future Loser), industry winner dummy, industry loser dummy, the market value of equity (MVE), book to market (BM) ratio, momentum (MOMENT), historical accruals (ACCRUAL), and equity offer (EQ_OFFER) dummy.

3.3.1. Equations

The first model analyzes the explanatory power of the FSCORE regarding the future company return:

$$MA\_RET_{i(t+1)} = \alpha + \beta_1 \, log(MVE_{it}) + \beta_2 \, log(BM_{it}) + \beta_3 \, Moment_{it} + \beta_4 \, Accrual_{it} + \beta_5 \, EQ\_Offer_{it} + \beta_6 \, FSCORE_{it} + \varepsilon_{it} \quad (1)$$

The *i* and *t* represent the firm and the time (quarter), respectively. MA_RET represents either the 12-month or 24-month market-adjusted buy and hold return while α is the constantand β1 and β6 as the coefficients of the independent variables, and ε is the error term. The coefficient of interest in the first model is β_6 and a company is expected to have a higher return if it has a higher FSCORE.

The second model analyzes the explanatory power of the industry winners (IW) dummy regarding the company's future return potential. This variable conveys more information compared to the raw FSCORE since it is based on the compan's industry position as well. The coefficient of interest is β_6 and a positive relationship is expected since a company is expected to generate higher future returns if it is an "industry winner" in the current period:

$$MA\_RET_{i(t+1)} = \alpha + \beta_1 \, log(MVE_{it}) + \beta_2 \, log(BM_{it}) + \beta_3 \, Moment_{it} + \beta_4 \, Accrual_{it} + \beta_5 \, EQ\_Offer_{it} + \beta_6 \, IW_{it} + \varepsilon_{it} \quad (2)$$

The third model uses the industry losers (IL) dummy as the variable of interest, along with the other control variables:

$$MA\_RET_{i(t+1)} = \alpha + \beta_1 \log(MVE_{it}) + \beta_2 \log(BM_{it}) + \beta_3 Moment_{it} + \beta_4 Accrual_{it} + \beta_5 EQ\_Offer_{it} + \beta_6 IL_{it} + \varepsilon_{it} \quad (3)$$

Once again, the coefficient of interest is β_6 and a negative relationship is expected since a company is expected to generate lower future returns if it is an "industry loser" in the current period.

The fourth model introduces a new dummy. This new variable is an interaction between the High FSCORE and the Industry Winner dummies. In other words, the new dummy (HIFW) modifies Piotroski's High FSCORE dummy by also determining whether the firm with an FSCORE of 8 or 9 is also above its industry average. For example, the case where the industry average is 8 and the firm's FSCORE is also 8 would be very different from the case where the industry average is 5 and the firm's FSCORE is 8, since in the second scenario, the company would be a much better performer in comparison to its peers.

$$MA\_RET_{i(t+1)} = \alpha + \beta_1 \log(MVE_{it}) + \beta_2 \log(BM_{it}) + \beta_3 Moment_{it} + \beta_4 Accrual_{it} + \beta_5 EQ\_Offer_{it} + \beta_6 HFIW_{it} + \varepsilon_{it} \quad (4)$$

The coefficient of interest, β_6, is expected to be positive since companies with a high FSCORE who are also industry winners in the current period are expected to generate higher future returns.

The fifth model includes a similar interaction dummy. This time, the LFIL dummy is equal to 1 if the firm's FSCORE is equal to 0 or 1 and it is also below the industry average. Similar to the HFIW interpretation, the case where the industry average is 1 and the firm's FSCORE is also 1 would be very different from the case where the industry average is 5 and the firm's FSCORE is 1, since in the second scenario, the company would be a much worse performer in comparison to its peers.

$$MA\_RET_{i(t+1)} = \alpha + \beta_1 \log(MVE_{it}) + \beta_2 \log(BM_{it}) + \beta_3 Moment_{it} + \beta_4 Accrual_{it} + \beta_5 EQ\_Offer_{it} + \beta_6 LFIL_{it} + \varepsilon_{it} \quad (5)$$

The coefficient of interest, β_6, is expected to be negative since companies with a low FSCORE who are also industry losers in the current period are expected to generate lower future returns.

The sixth and final model includes another dummy variable that modifies the original Piotroski approach of using the FSCORE for forecasting company returns. In his study, Piotroski focuses his attention only on the "high FSCORE (8 or 9)" and "low FSCORE (0 or 1)" firms. All other firms with an FSCORE in the 2 to 7 range are kept out of the analysis. Since one of the main objectives of this thesis is to incorporate the industry effect into the FSCORE analysis, a new dummy variable (UNDERDOG) is defined that equals 1 if a company has an FSCORE between 2 and 7 which is also above the relevant industry average. Such firms are "ignored" by the Piotroski analysis but may have a potential to be successful since they are performing better than their peers. Consequently, the coefficient of interest, β_6, is expected to be positive.

$$MA\_RET_{i(t+1)} = \alpha + \beta_1 \, log(MVE_{it}) + \beta_2 \, log(BM_{it}) + \beta_3 \, Moment_{it} + \beta_4 \, Accrual_{it} + \beta_5 \, EQ\_Offer_{it} + \beta_6 \, Underdog_{it} + \varepsilon_{it} \tag{6}$$

Table 3.1.1. Variable Definitions

Variable	**Definition**	**Calculation**
Market Value of Equity (MVE)	The total dollar value of a company's equity	Number of shares outstanding at fiscal quarter-end multiplied by the closing share price
Book to Market (BM) Ratio	The company's book value to its market value	MVE scaled by the book value of equity at the end of the fiscal quarter
Momentum (Moment)	Continuance of an existing market trend	Six-month market-adjusted buy-and-hold return directly preceding the portfolio formation date
Accruals (Accrual)	The relationship between earnings and cash flow levels	Net income before extraordinary items minus cash flow from operations, scaled by the beginning-of-the-year total assets
Equity Offer (EQ_Offer)	İssuing common equity	The indicator variable (EQ_Offer) equals one if the firm raised equity capital in the previous quarter, and zero otherwise
FSCORE	The aggregate score	The sum of the individual binary signals (F_ROA+ F_CFO+ F_ΔROA+ F_ACCRUAL+ F_ ΔLEVER+ F_ ΔLIQUID+ F_ EQ_OFFER+ F_ ΔMARGIN+ F_ ΔTURN)
Industry Winners (IW)	Above the average FSCORE of the industry	The indicator variable (IW) equals one if the firm's FSCORE is above the industry average, and zero otherwise
Industry Losers (IL)	Below the average FSCORE of the industry	The indicator variable (IL) equals one if the firm's FSCORE is below the industry average, and zero otherwise
Industry Winners and High FSCORE (HFIW)	The industry winners in high FSCORE firms cluster	The indicator variable (HFIW) equals one if the firm's FSCORE is equal to 8 or 9 and also above the industry average, and zero otherwise
Industry Losers and Low FSCORE (LFIL)	The industry losers in low FSCORE firms cluster	The indicator variable (LFIL) equals one if the firm's FSCORE is equal to 0 or 1 and also below the industry average, and zero otherwise
Underdog	The industry winners in conflicting signal firms cluster (FSCORE between 2 and 7)	The indicator variable (Underdog) equals one if the firm's FSCORE is in the 2 to 7 range and also above the industry average, and zero otherwise

3.4. Estimation Methodology

3.4.1. Panel Data Analysis

Panel data is the collection of cross-sectional observations in a certain period. Cross-sections consist of units such as individuals, countries, households, and firms. In other words, the panel data consists of a combination of cross-section and time-series data.

General equation:

$Y_{it} = \alpha_{it} + \beta X_{it} + \varepsilon_{it} \quad i = 1,\ldots,N \; ; \; t = 1,\ldots,T$

$Y: Dependent\ variable, X: Independent\ variable$

$\alpha: Constant, \beta$: Coefficient of the independent variable, ε: Error term

$i: Cross - section\ units, t: Time$

3.4.1.1. Properties of Panel Data

3.4.1.1.1. Balanced and Unbalanced Panel Data

The balanced panel data have the same number of observations for all cross-sections. The unbalanced panel data have missing values at some time observations for some of the units.

3.4.1.1.2. Cross-section Effects and Time Effects

The panel data consist of many units, and each unit has its unique features which affect the result of panel data analysis. It is defined as the cross-section effect. At the same time, each period has special features called the time effects.

3.4.1.1.3. Homogeneous and Heterogeneous Panel Data

Homogeneous panel data assume that the model parameters are common across cross-sections.

Homogeneous model: $Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it}$ $\quad i=1, ..., N; t=1, ..., T$

The constant α and the coefficient β are the same across units and time. Any differences across units affect the model only through the error term.

Heterogeneous panel data allow any model parameters to vary across cross-sections.

Heterogeneous model: $Y_{it} = \alpha_i + \beta_i X_{it} + \varepsilon_{it}$ $\quad i=1, ..., N; t=1, ..., T$

The constant α and the coefficient β are group-specific.

3.4.1.2. Advantages and Disadvantages of Panel Data

3.4.1.2.1. Advantages of Panel Data

The panel data provides additional advantages and benefits of cross-section and time-series data. The main advantage of using panel data has been increased the number of observations for the analysis because of combining cross-section and time-series data. Moreover, the panel data also allows the study of economic problems that can't be solved with cross-section or time-series data. The units used in the analysis are generally heterogeneous. However, time series and cross-section data analysis can't control heterogeneity, while panel data analysis has a unique control system for this problem. The cross-sectional analysis only examines the relationships at a single point in time, whereas panel data has the power to explore the dynamic variations of the relationships. Another crucial advantage of panel data analysis is to reduce the omitted variable bias [14].

3.4.1.2.2. Disadvantages of Panel Data

The error term is of great importance in panel data models because it carries the time series specific bias, the cross-sections specific bias, and the panel data specific bias. Therefore, the error term in panel data models is often biased. The most crucial problem in panel data studies is accessing and organizing the data.

3.4.2. Ordinary Least Squares (OLS)

The regression equations were defined in the previous section.

The simple linear regression equation: $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad i = 1, 2, \ldots, n$

The regression coefficients are β_0 and β_1. β_0 is the constant. β_1 is the coefficient of the independent variable X. ε is the error term.

The critical problem is the estimation of coefficients of the regression equation. Ordinary least squares (OLS) is a well-known technique to solve this problem under certain assumptions. The Gauss-Markov theorem showed that the OLS is the best linear unbiased estimate (BLUE) when the error terms are independent and equal variance [13]. The purpose of OLS is to optimize the model by minimizing the sum of the squares of the error terms. Therefore, the OLS tries to estimate the coefficient that minimizes the function($\sum_{i=1}^{n} \varepsilon i^2$).

The classical assumptions for OLS to be the BLUE are

Linearity: The relationship between X and Y is linear.

Strict exogeneity: The error terms should be independent of the value of the independent variables, X. Mathematically; $E(\varepsilon i|Xi) = 0$ and $E(\varepsilon i) = 0$

No perfect multicollinearity: Independent variables (X_i) should not be correlated. Mathematically;$X_i \; i \neq j$

ε is the random variable.

The expected value of ε is zero. Mathematically; $E(\varepsilon i) = 0$

Homoscedasticity: The variance of the ε is constant. Mathematically; $Var(\varepsilon i|Xi) = \sigma^2$ (When this requirement is violated, this is called heteroscedasticity.)

The error terms (ε_i) have zero correlation with each other. Mathematically; $i \neq j$ $Cov(\varepsilon i, \varepsilon j) = 0$

Nonautocorrelation: the error terms are uncorrelated between observations (X_i). Mathematically; $Cov(\varepsilon i, Xi) = 0$

ε is the normal distribution. Mathematically; $\varepsilon i \sim N(0, \sigma^2)$

Under these assumptions, OLS tries to estimate coefficients(β_0 and β_1) that minimizes the sum of the squares of the error terms.

The mathematical expression of OLS:

$$\varepsilon = Y - \breve{Y} = Y - \beta_0 - \beta_1 X$$

To minimize the following equation:

$$\sum_i^n \varepsilon_i{}^2 = \sum_i^n (Y - \breve{Y})^2 = \sum_i^n (Y - \beta_0 - \beta_1 X)^2$$

The first derivatives of the equation must be equal to zero to get a minimum value. Therefore, the derivatives of the above expression with respect to β_0 and β_1 separately and set them equal to zero.

$$\sum Y = n\beta_0 + \beta_1 X$$

$$\sum YX = \beta_0 \sum X + \beta_1 \sum X^2$$

$$\beta_0 = \frac{\sum X^2 \sum Y - \sum X \sum XY}{n \sum X^2 - (\sum X)^2}$$

$$\beta_0 = \frac{n \sum XY - \sum X \sum Y}{n \sum X^2 - (\sum X)^2}$$

3.4.3. Generalized Method of Moments (GMM)

The Generalized Method of Moment (GMM) was formalized by Hansen [23] and has become one of the most widely used estimation methods for models in economics and finance. GMM is a highly used technique to analyze panel data models. However, GMM can also apply to other datasets other than panel data. GMM is a widespread technique because it isn't required exact assumptions like other well-known techniques such as OLS. Especially, GMM doesn't require complete knowledge of the data distribution.

Understanding the Method of Moment (MM) is the first step to covering the GMM method. MM starts with the understanding of moment phenomena. The Moment means distance in the MM method. The first Moment is "Mean," which means the average distance from zero. The population mean (or population average) is usually denoted with μ. If y is a random variable describing the population of interest, we also write the population mean as $E(y)$, the expected value or mean of y.

The second Moment is "Variance," which means the average squared distance from the mean. The population variance is usually denoted with σ^2 or $Var(y)$ = $E[(y - \mu)^2]$. After understanding the moments, the following equation should be examined to understand MM.

$E[Z'_i(y_i - X_i\beta)]$

Z'_i = *Instrumental Variables*

$(y_i - X_i\beta)$ = *Error Terms*

This entire expectation equation is roughly covariance. The covariance is a measure of the joint variability of two random variables. The estimation criteria for the MM is that the betas should be found so that the covariances between the instruments and all residuals are zero. Therefore, every residual is uncorrelated with every instrumental variable.

$\hat{\beta} = (Z'X)^{-1}Z'Y$ is a closed-form solution that gives the betas to satisfy constraints.

GMM estimation assumes that the data and model parameters satisfy a specific moment condition.

Moment condition: $g(\theta_0) = \mathbb{E}[f(W_t, Z_t; \theta_0] = 0$

θ : Kx1, model parameters

θ_0: True value of θ

$f(.)$: Rx1 vector of function

W_t: Model Variables

Z_t: Instruments

The crucial assumption is that the model parameters are identified. The function zero takes value zero if and only if the function is evaluated in the actual parameter vector.

Identification: $g(\theta_0) = 0 \Leftrightarrow \theta = \theta_0$

It ensures that there is a unique vector θ_0 that solves the equation system.

In practice, $g(\theta_0)$ is unknown.

Sample moments : $g_T(\theta_0) = 1/T \sum_{t=1}^{T} f(W_t, Z_t; \theta_0)$; $g_T(\theta_0)$: Rx1, θ_0 : Kx1

Firstly, R equals K means exact identification. Mathematically, it means $g_T(\theta_0) = 0$, so it has unique solution under $\hat{\theta}_{MM}$.

Secondly, R greater than K means over-identification, so it derives GMM estimator under $\hat{\theta}_{GMM}$. In other words, the R is greater than K, meaning that there are more moments than parameters. It denotes this case over-identification. In this case, there is no solution to the equation system. But it turns out that there is still an estimator which indicates the GMM estimator.

In this case, instead of setting $g_T(\theta_0) = 0$, it tries to minimize the distance between $g_T(\theta_0)$ and 0. In order to measure the distance, the quadratic form is considered. A more general class of estimators is obtained by using a weighting matrix in the quadratic form of MM.

$g_T(\theta_0) = \grave{g}_T(\theta_0)\, W_t\, g_T(\theta_0)$

W_t is a positive definite matrix.

It has three implications;

- $g_T(\theta_0) \geq 0$
- All moments have positive weights.
- Some moments may be more important than others. Hence, they have more weight.

Given the choices of W_t which is a positive matrix; it defines the GMM estimator of θ as the argument that minimizes the quadratic form. It means the argument that minimizes the distance between the moments $g_T(\theta_0)$ and 0.

So, GMM estimator, $\hat{\theta}_{GMM}$

$\hat{\theta}_{GMM} = argmin_\theta\, g_T(\theta_0)$

3.4.3.1. Properties of GMM Estimator

3.4.3.1.1. Consistency

$g(\theta_0) = 0 \Leftrightarrow \theta = \theta_0$

Apply Law of Large Numbers: $1/T\ \sum_{t=1}^{T} f(W_t, Z_t; \theta_0) = \mathbb{E}[f(W_t, Z_t; \theta_0]$

Assume that data are stationary. Hence, any choice of weight matrix W_t, GMM estimator is consistent.

3.4.3.1.2. Asymptotic Normality

Assume that some condition supplies as for the consistency case, so identification and LLN are applied.

And Central Limit Theorem (CLT) applies: $\sqrt{T} 1/T \ \sum_{t=1}^{T} f(W_t, Z_t; \theta_0) \ \rightarrow \ N(0, S)$

S : Asymptotic covariance matrix of $f(W_t, Z_t; \theta_0)$

The CLT applies if the data is stationary and quickly dependent under these conditions, so the GMM estimator is asymptotically normally distributed.

Then, $\sqrt{T} \ (\ \hat{\theta}_{GMM} \ - \ \theta_0) \ \rightarrow \ N(0, V)$

V is an asymptotic covariance matrix with a specific structure that depends on the first derivative of function f and asymptotic variance of the f. It also depends on weight matrix W.

Mathematically,

$V \ = \ (\grave{D}WD)^{-1}\grave{D}WSWD(\grave{D}WD)^{-1}$

$D \ = \ \mathbb{E}[\partial f(W_t, Z_t; \theta_0 / \partial \grave{\theta}]$

$W \ = \ plim \ _{T \rightarrow \infty} W_T$, depends on the choice of W_T

3.4.3.2. The Optimal Weighting Matrix

In general, the GMM estimator depends on the choice of weight matrix W. There is an optimal choice for the W. It makes the optimal GMM which produces the GMM estimator with the smallest asymptotic variance. The smallest possible variance that the GMM estimator takes depends on selecting weight matrix W. And then, it makes GMM asymptotically efficient.

The weight matrix W should be the inverse of the S matrix, then the GMM estimator can get the smallest possible variance, so the GMM estimator is efficient.

The smallest possible variance is obtained when $W = S^{-1} : \; V \left(\grave{D} S^{-1} D\right)^{-1}$

$$S = 1/T \; Var \, (\sum_{t=1}^{T} f(W_t, Z_t; \theta_0)) \; _{T\to\infty}$$

W_t optimal, when $plim_{T\to\infty} \, W_T^{opt} = W = S^{-1}$

Consequently, the GMM estimator has investigated the data to get robust results. Moreover, the "Spearman Correlation" has been used to analyze the correlation between variables. In addition, the "Two-Sample T-Test" was used to examine whether there was a significant difference between mean returns. And "Wilcoxon Signed Ranked Test" was used to understand whether there is a difference between the median returns. The data editing and FSCORE calculation were using Excel. The Eviews program has been used for the GMM analysis.

Moreover, Spearman correlation was applied in Eviews. Lastly, the "Two-Sample T-Test" and "Wilcoxon Signed Ranked Test" were applied in the SPSS. Significant results have been obtained from the analyses. First and foremost, it is possible to invest in the neglected firms in previous studies (firms with conflicting signals) with this new perspective.

CHAPTER 4

RESULTS and ANALYSIS

4.1. Primary motivation of the study

As an initial step in the analysis, FSCORES are calculated on a quarterly basis for all sample firms between the first quarter of 2000 and the fourth quarter of 2020. Table 4.1.a presents the frequency distribution of FSCORES over the range between the minimum (0) and maximum (9) scores. As can be seen in the table, majority of the observations are distributed between 2 and 7 (10,008 out of 11,136), indicating that, according to Piotroski's original classification, majority of the firms have "conflicting performance signals" since these scores are neither "high" nor "low". Piotroski [12] presents similar results and does not designate an investment strategy for firms whose scores fall in the 2 to 7 range.

Table 4.1.a.: The Distribution of FSCORE between 2000 Q1 and 2020 Q4

FSCORE	0	1	2	3	4	5	6	7	8	9	Total
Firms	86	193	618	1,325	1,998	2,330	2,137	1,600	735	114	11,136

Based on Piotroski's classification, majority of the firms are "neglected" by the classical FSCORE approach. This thesis argues that by taking into account the industry position of the company, it may be possible to identify future winners from among the "neglected" group of companies whose FSCORES are between 2 and 7.

According to Table 4.1.b, all low FSCORE firms are also industry losers whereas 96% of high FSCORE firms are industry winners. As such, the industry winner and industry loser designations may not add a lot of new information to Piotroski's original "high" versus "low" FSCORE classifications. However, when the "neglected" group of firms is analyzed, it is seen that 57% of these firms are industry winners. If a company's performance relative to its peers (the industry effect) is a significant determinant of future returns, then identifying the industry winners among the neglected firms may lead to a successful investment strategy. This group of firms is named as the "underdogs" since they would be ignored by the original Piotroski classification but they may still turn out to be investable firms that generate positive future returns

Table 4.1.b.: The Industry Winners and Losers in Low/High FSCORE and Conflicting Signal Clusters between 2000 Q1 and 2020 Q4

	Low FSCORE Firms	High FSCORE Firms	Conflicting Signal Firms*
Industry Winners	0 (0%)	812 (96%)	4,322 (43%)
Industry Losers	279 (100%)	37 (4%)	5,686 (57%)
Total Observations	279	849	10,008

*Firms with an FSCORE between 2 and 7

4.2. Description of Empirical Tests

In order to test the forecasting ability of the FSCORE in combination with industry effects, porfolios are formed to pursue the investment strategy of buying winners and selling losers. Ultimately, the objective of the analyses is to determine whether the portfolios that are long in "industry winners" or the "underdogs" and short in "industry losers" generate significant and positive market-adjusted returns. Please note that all stocks are chosen from among the high BM stocks.[2]

[2] When the analyses are repeated for all firms and not just high BM firms, the results stay qualitatively the same. In order to conserve space and to provide results that are comparable to the Piotroski study, only the high BM results are reported.

4.3. Descriptive Evidence about High Book-to-Market Firms

Table 4.3.a. presents descriptive statistics about the financial characteristics of the high book-to-market firms and evidence of long-term returns from portfolios that are long in these stocks. Panel A shows that the mean BM ratio is 1.613 in high BM firms, and the mean market capitalization is 2,959 million dollars. The average ROA is 0.0017, and the mean Gross Margin is 2.2162. Piotroski [12] presented a negative mean for ROA and Gross Margin, contrary to this study. This result may be due to the difference in sample periods. Based on the evidence presented in Table 4.3.a, it is not possible to argue that the portfolio of high BM firms consists of poor-performing firms.

Panel B presents the twelve-month and twenty-four-month buy-and-hold returns for the portfolio of all HBM firms. Consistent with previous literature, the HBM firms earn positive market-adjusted returns in the twelve-month and twenty-four-month periods following portfolio formation. Similar to the Piotroski findings [12], 46% of firms earn negative market-adjusted returns over the twelve-month return period. Piotroski [12] showed that approximately 57% of firms made negative market-adjusted returns.

Table 4.3.a.: Financial and Return Characteristics of High Book-to-Market Firms (11,136 Firm-Quarter Observations between 2000 Q1 and 2020 Q4)

Panel A: Financial Characteristics					
Variable	Mean	Median	Standard Deviation	Maximum	Minimum
MVE (in millions of $)	2,959	635	9,469	215,389	0.0001
BM	1.613	1.142	2.160	102.679	0.813
ROA	0.0017	0.0044	0.3966	40.0033	-11.2725
ΔROA	0.0034	-	0.4084	40.6229	-6.2679
ΔMARGIN	2.2162	-	234.4723	24740.6667	-226.1425
CFO	0.0381	0.0275	0.5450	56.8632	-6.5131
ΔLIQUID	-0.0064	-	6.7394	489.6190	-490.0494
ΔLEVER	-0.0023	-0.0001	0.0670	1.1023	-0.8538
ΔTURN	-0.0063	-	0.0730	2.9373	-1.3698
ACCRUAL	-0.0364	-0.0271	0.1805	2.0930	-16.8598

Panel B: Buy and Hold Returns from HBM firms						
Returns	Mean	10^{th} Percentile	25^{th} Percentile	Median	75^{th} Percentile	90^{th} Percentile
12-Month Returns						
Raw	0.271	-0.456	-0.175	0.122	0.461	0.971
Market-Adjusted	0.191	-0.462	-0.219	0.044	0.355	0.837
24-Month Returns						
Raw	0.557	-0.491	-0.159	0.236	0.783	1.607
Market-Adjusted	0.384	-0.605	-0.294	0.081	0.584	1.387

Table 4.3.b. presents descriptive statistics about the industry-winner firms and evidence of the long-term returns of from portfolios that are long in these stocks. Panel A shows that the mean BM ratio is 1.552 in industry-winner firms, and the mean market capitalization is 3,465 million dollars. The mean BM Ratio has decreased in industry winner firms against the high BM firms. The mean market value of equity of industry winners is bigger than the whole HBM firms sample. The mean ROA is 0.0145, which is higher than the average ROA for the whole HBM firms sample. These figures indicate that when high book-to-market firms are industry winners, they havebetter mean performance.

Panel B presents the twelve-month and twenty-four-month buy-and-hold returns for the portfolio of all industry-winner firms. The industry winner firms produce positive mean market-adjusted returns during the twelve-month and twenty-four-month periods immediately following portfolio formation. Moreover, both the twelve- and twenty four-month returns for this sample are larger than those for the portfolio of all high BM firms.

Table 4.3.b.: Financial and Return Characteristics of Industry Winner Firms (5,135 Firm-Quarter Observations between 2000 Q1 and 2020 Q4)

Panel A: Financial Characteristics of Industry Winner Firms					
Variable	Mean	Median	Standard Deviation	Maximum	Minimum
MVE	3,465	755	10,123	215,389	0.1275
BM	1.552	1.119	1.968	56.972	0.813
ROA	0.0145	0.0077	0.5592	40.0033	-0.7233
ΔROA	0.0153	0.0027	0.5686	40.6229	-0.7431
ΔMARGIN	4.9087	0.0072	345.2710	24740.6667	-7.2598
CFO	0.0550	0.0349	0.7947	56.8632	-0.2888
ΔLIQUID	0.0419	0.0184	0.7405	19.6602	-15.7855
ΔLEVER	-0.0089	-0.0024	0.0600	0.7258	-0.7366
ΔTURN	0.0022	0.0036	0.0792	2.9373	-0.8103
ACCRUAL	-0.0405	-0.0290	0.2432	1.2652	-16.8598

Panel B: Buy and Hold Returnsfrom Industry Winner Firms						
Returns	Mean	10^{th} Percentile	25th Percentile	Median	75th Percentile	90^{th} Percentile
12-Month Returns						
Raw	0.299	-0.421	-0.142	0.152	0.473	0.978
Market-Adjusted	0.219	-0.424	-0.183	0.069	0.365	0.850
24-Month Returns						
Raw	0.590	-0.468	-0.135	0.258	0.790	1.564
Market-Adjusted	0.416	-0.590	-0.271	0.102	0.594	1.355

Table 4.3.c. presents the Spearman correlations between the twelve-month and twenty-four-month buy-and-hold market-adjusted returns, the individual fundamental signal indicator variables, FSCORE, industry losers dummy, and the industry-winners dummy. The industry-winners and FSCORE have a significant positive correlation

with twelve-month and twenty-four-month future returns (0.051, 0.026 for industry winners and 0.058, 0.014 for FSCORE). The industry losers have a significant negative correlation with twelve-month and twenty-four-month future returns (-0.063 and -0.043, respectively). This is additional evidence thatthe industry effect variables can separate winners from losers. As expected, the industry-winners have a high positive correlation with FSCORE (0.687).

Table 4.3.c.: Spearman Correlation Analysis between Twelve-mounth and Twenty-Four-mounth Market Adjusted Returns, the Nine Fundamental Signals, FSCORE, Industry Losers and Industry Winners for High-Book-to-Market Firms

	ROA	ΔROA	ΔMARGIN	CFO	ΔLIQUID	ΔLEVER	ΔTURN	ACCRUAL	EQ_OFFER	FSCORE	IL	IW
12MA-RET	0.037	0.056	0.060	0.009	0.011	-0.048	0.026	-0.003	0.020	0.058	-0.063	0.051
24MA-RET	0.034	0.028	0.027	-0.024	0.004	-0.043	-0.009	0.024	0.024	0.014	-0.043	0.026
ROA	1.000	0.401	0.206	0.190	0.088	-0.198	0.113	0.144	0.098	0.479	-0.318	0.318
ΔROA	-	1.000	0.428	-0.047	0.054	-0.058	0.357	0.220	-0.023	0.519	-0.371	0.364
ΔMARGIN	-	-	1.000	-0.032	0.038	-0.037	0.209	0.108	-0.010	0.470	-0.330	0.329
CFO	-	-	-	1.000	-0.025	-0.105	0.019	-0.897	0.057	0.382	-0.214	0.211
ΔLIQUID	-	-	-	-	1.000	0.261	-0.043	0.058	-0.014	0.193	-0.138	0.146
ΔLEVER	-	-	-	-	-	1.000	-0.001	0.022	0.061	-0.259	0.185	-0.184
ΔTURN	-	-	-	-	-	-	1.000	0.004	-0.019	0.403	-0.223	0.225
ACCRUAL	-	-	-	-	-	-	-	1.000	-0.020	-0.198	0.091	-0.089
EQ_OFFER	-	-	-	-	-	-	-	-	1.000	0.267	-0.209	0.203
FSCORE	-	-	-	-	-	-	-	-	-	1.000	-0.693	0.687
IL	-	-	-	-	-	-	-	-	-	-	1.000	-0.870
IW	-	-	-	-	-	-	-	-	-	-	-	1.000

*12MA-RET: Twelve-month and buy-and-hold market adjusted returns, 24MA-RET: twenty-four-month buy-and-hold market adjusted returns, IL: Industry Losers, IW: Industry Winners

Table 4.3.d. presents the returns to the FSCORE and industry effect strategies. Panel B gives twelve-month buy-and-hold market-adjusted returns. Moreoever, the twelve-month buy-and-hold raw returns are shown in Panel A, and the twenty-four-month buy-and-hold market-adjusted returns are in Panel C. This thesis focuses on the twelve-month buy-and-hold market-adjusted returns in order to present comparable results to the Piotroski study [12]. As documented in panel B, high FSCORE firms significantly underperform against low FSCORE firms in the year following portfolio formation (mean market-adjusted returns of 0.174 versus 0.280, respectively). The mean return difference of -0.106 is significant at the 1% level using a traditional parametric t-statistic. Moreover, the mean return difference between the high FSCORE firms and the high BM firms is -0.018 (0.174 versus 0.191). The difference is statistically significant at the 1% level using the traditional parametric t-statistic. These results are not consistent with Piotroski [12]. During the same return period, industry winner firms significantly outperform industry loser firms in the year following portfolio formation (mean market-adjusted returns of 0.219 versus 0.156, respectively). The mean return difference of 0.63 is significant at the 1% level using a traditional parametric t-statistic. Moreover, the mean return difference between industry winners and HBM firms is 0.027, statistically significant at the 1% level using the traditional parametric t-statistic.

The industry winner firms significantly outperform high FSCORE firms in the year following portfolio formation (mean market-adjusted returns of 0.219 versus 0.174, respectively). The mean return difference of 0.045 is significant at the 1% level using a traditional parametric t-statistic. Moreover, the left tail of the return distribution (10^{th} percentile, 25^{th} percentile, and median) has shifted to the right (positive) after applying the industry-winners method. Overall, the High FSCORE has lost the ability to separate the future winners and losers. However, the industry effect strategies have the potential power to determine future winners and losers.

Table 4.3.d.: Buy and Hold Returns between 2000 Q1 and 2020 Q4

Panel A: Twelve-month Buy and Hold Raw Return							
	Mean	10%	25%	Median	75%	90%	n
All Firms	0.271	-0.456	-0.175	0.122	0.461	0.971	10,187
FSCORE							
0	0.496	-0.312	-0.136	0.161	0.465	1.086	83
1	0.208	-0.669	-0.329	0.006	0.498	0.997	159
2	0.215	-0.582	-0.289	0.035	0.405	1.062	538
3	0.271	-0.537	-0.237	0.070	0.511	1.080	1,188
4	0.270	-0.517	-0.214	0.070	0.443	1.005	1,827
5	0.258	-0.433	-0.160	0.135	0.457	0.938	2,146
6	0.277	-0.400	-0.129	0.151	0.466	0.959	1,974
7	0.308	-0.383	-0.117	0.167	0.462	0.912	1,490
8	0.250	-0.411	-0.142	0.136	0.439	0.823	674
9	0.240	-0.338	-0.151	0.092	0.345	0.714	108
Low FSCORE	0.307	-0.571	-0.266	0.116	0.493	1.068	242
High FSCORE	0.248	-0.387	-0.146	0.126	0.428	0.816	782
Industry Losers	0.235	-0.510	-0.215	0.084	0.448	0.940	4,792
Industry Winners	0.299	-0.421	-0.142	0.152	0.473	0.978	4,713
High FSCORE - All Firms	-0.023	0.069	0.029	0.004	-0.033	-0.155	-
t-Statistic / (p -Value)	2.021	-	-	0.498	-	-	-
High FSCORE – Low FSCORE	-0.059	0.184	0.120	0.011	-0.065	-0.252	-
t-Statistic / (p -Value)	2.035	-	-	0.566	-	-	-
Industry Winners – All Firms	0.028	0.035	0.032	0.030	0.012	0.006	-
t-Statistic / (p -Value)	2.021	-	-	0.001	-	-	-
Industry Winners – Industry Loser	0.064	0.089	0.073	0.068	0.025	0.038	-
t-Statistic / (p -Value)	2.021	-	-	0.003	-	-	-
Industry Winners – High FSCORE	0.051	-0.034	0.003	0.026	0.045	0.162	-
t-Statistic / (p -Value)	2.021	-	-	0.079	-	-	-

Table 4.3.e.: Buy and Hold Returns between 2000 Q1 and 2020 Q4

Panel B: Twelve-month Buy and Hold Excess Return

	Mean	10%	25%	Median	75%	90%	n
All Firms	0.191	-0.462	-0.219	0.044	0.355	0.837	10,158
FSCORE							
0	0.574	-0.270	-0.013	0.275	0.533	1.174	83
1	0.125	-0.567	-0.378	0.045	0.336	0.876	158
2	0.126	-0.523	-0.316	-0.069	0.300	0.965	537
3	0.178	-0.543	-0.273	-0.015	0.367	0.988	1,185
4	0.194	-0.516	-0.263	-0.006	0.333	0.876	1,821
5	0.178	-0.456	-0.210	0.062	0.363	0.815	2,140
6	0.198	-0.403	-0.174	0.065	0.374	0.827	1,965
7	0.308	-0.383	-0.117	0.167	0.462	0.912	1,490
8	0.175	-0.412	-0.189	0.055	0.346	0.724	671
9	0.166	-0.393	-0.218	0.023	0.262	0.563	108
Low FSCORE	0.280	-0.520	-0.284	0.096	0.392	1.134	241
High FSCORE	0.174	-0.410	-0.196	0.053	0.334	0.698	779
Industry Losers	0.156	-0.511	-0.259	0.001	0.335	0.805	4,774
Industry Winners	0.219	-0.424	-0.183	0.069	0.365	0.850	4,698
High FSCORE – All Firms	-0.018	0.052	0.023	0.009	-0.021	-0.139	-
t-Statistic / (p -Value)	2.021	-	-	0.614	-	-	-
High FSCORE – Low FSCORE	-0.106	0.109	0.088	-0.043	-0.057	-0.437	-
t-Statistic / (p -Value)	2.028	-	-	0.741	-	-	-
Industry Winners – All Firms	0.027	0.039	0.036	0.025	0.010	0.013	-
t-Statistic / (p -Value)	2.021	-	-	0.001	-	-	-
Industry Winners – Industry Losers	0.063	0.088	0.076	0.068	0.030	0.045	-
t-Statistic / (p -Value)	2.021	-	-	0.006	-	-	-
Industry Winners – High FSCORE	0.045	-0.013	0.013	0.016	0.031	0.152	-
t-Statistic / (p -Value)	2.021	-	-	0.543	-	-	-

Table 4.3.f.: Buy and Hold Returns between 2000 Q1 and 2020 Q4

Panel C: Twenty-four-month Buy and Hold Excess Return	Mean	10%	25%	Median	75%	90%	n
All Firms	0.384	-0.605	-0.294	0.081	0.584	1.387	9,287
FSCORE							
0	1.040	-0.294	0.109	0.552	1.268	2.215	79
1	0.089	-0.740	-0.490	-0.113	0.423	0.891	132
2	0.336	-0.676	-0.383	-0.005	0.591	1.580	480
3	0.346	-0.657	-0.357	0.058	0.582	1.468	1,051
4	0.424	-0.657	-0.305	0.069	0.611	1.433	1,659
5	0.365	-0.581	-0.287	0.088	0.555	1.364	1,954
6	0.366	-0.568	-0.271	0.108	0.613	1.371	1,817
7	0.452	-0.566	-0.261	0.119	0.571	1.368	1,390
8	0.339	-0.647	-0.296	0.037	0.453	1.084	625
9	0.292	-0.599	-0.326	0.082	0.440	1.030	100
Low FSCORE	0.445	-0.617	-0.330	0.124	0.712	1.541	211
High FSCORE	0.333	-0.632	-0.297	0.041	0.452	1.049	725
Industry Losers	0.337	-0.648	-0.333	0.050	0.550	1.372	4,305
Industry Winners	0.416	-0.590	-0.271	0.102	0.594	1.355	4,338
High FSCORE – All Firms	-0.052	-0.027	-0.002	-0.041	-0.132	-0.338	-
t-Statistic / (p -Value)	2.035	-	-	0.079	-	-	-
High FSCORE – Low FSCORE	-0.112	-0.015	0.033	-0.083	-0.260	-0.491	-
t-Statistic / (p -Value)	2.024	-	-	0.391	-	-	-
Industry Winners – All Firms	0.032	0.014	0.024	0.021	0.010	-0.032	-
t-Statistic / (p -Value)	2.024	-	-	0.019	-	-	-
Industry Winners – Industry Losers	0.080	0.058	0.062	0.053	0.044	-0.018	-
t-Statistic / (p -Value)	2.024	-	-	0.006	-	-	-
Industry Winners – High FSCORE	0.084	0.041	0.026	0.062	0.142	0.305	-
t-Statistic / (p -Value)	2.030	-	-	0.004	-	-	-

4.4. Regression Analysis

The literature is rich with studies that show that future stock returns are explained by company-specific information such as the market value of equity, book-to-market ratio, momentum, historical accruals, and equity offerings. Piotroski's FSCORE method primarily takes advantage of the underreaction in markets to publicly available historical financial informationTherefore, the Piotroski framework includes the FSCORE in the models as an "additional" variable along with the known return determinants so that it can be examined whether the FSCORE has explanatory power over and above those factors that are tested in the previous literature. This thesis adopts a similar approach and, as explained in Chapter 3, adds the FSCORE and industry effect variables to the models along with the control variables.

Regression analysis aims to show the direction and strength of the relationship between the FSCORE, industry effect variables, other known return factors, and the twelve-month market-adjusted buy and hold return. The models are estimated by using the GMM framework. The primary motivation for using GMM is that the distribution of the dependent variable is unknown. The choice of the weighting matrix is a primary step for GMM estimation to get an asymptotically efficient or optimal GMM estimator, as shown by Hansen [23]. This study uses the white weighting matrix. The White matrix is a consistent heteroskedasticity estimator of the long-run covariance. Second, the method of coefficient covariance calculation is an essential part of the GMM estimation. The White method is chosen for the coefficient covariance calculation in this study. There are different methods in Eviews, such as two-stage least squares (TSLS) and White. These weighting approaches can be combined to compute robust standard errors. The equations can use two-stage least squares for the estimation weighting matrix, while the White for the covariance calculation method. Estimations are repeated with different weighting approaches and the results are qualitatively the same. Cross-sectional and periodic fixed effects are included in the estimations as well.

Table 4.4.a. presents the GMM coefficients and p-values of the variables. As expected, the MVE and twelve-month market-adjusted buy-and-hold return have a significant and negative relationship. Thus, small-cap firms earn more returns in the twelve-month return period following portfolio formation. Moreover, the BM and twelve-month market-adjusted buy-and-hold return have a significant and positive relationship, implying that high BM firms produce higher returns in the twelve-month return period following portfolio formation.

As seen in the second column of Table 4.4.a., the FSCORE and twelve-month market-adjusted buy-and-hold return have a significant and positive relationship. A one-point improvement in the aggregate FSCORE is associated with a 3% increase in the twelve-month market-adjusted return earned after portfolio formation. This result is robust when FSCORE is included in the model along with different combinations of the control variables (Columns 2 and 6 in Table 4.4.a).

As seen in the third column of Table 4.4.a., the industry losers and twelve-month market-adjusted buy-and-hold return have a significant and negative relationship. The coefficient of the industry-losers variable is -0.074, implying that these firms earn returns that are 7.4% lower on average, compared to the rest of the firms in the sample. This result is robust when the industry losers dummy is included in the model along with different combinations of the control variables (Columns 3 and 7 in Table 4.4.a).

As seen in the fourth column of Table 4.4.a., as expected, the industry winners and twelve-month market-adjusted buy-and-hold return have a significant and positive relationship . The coefficient of the industry-winners dummy is 0.082, implying that these firms earn returns that are 8.2% higher on average, compared to the rest of the firms in the sample. Once again, this result is robust when the industry winners dummy is included in the model along with different combinations of the control variables (Columns 4 and 8 in Table 4.4.a).

As seen in Table 4.4.a., the momentum and equity offer variables do not seem to have a significant effect on portfolio returns. This finding is in contradiction to the Piotroski results [12]. This divergence may be due to the different sample period covered in this thesis.

Lastly, Table 4.4.a. presents the results of the Durbin-Watson test, a measure of autocorrelation. The Durbin-Watson test ranges between zero and four. A value of two indicates no autocorrelation. Moreover, a rule of thumb is that test statistic values of 1.5 to 2.5 are relatively normal. Values outside of the range imply autocorrelation problems. Also, Field [1] suggests that values under one or more than three are related to the autocorrelation problem. Hence, the estimation results presented in Table 4.4.a do not seem to suffer from an autocorrelation problem.

Table 4.4.a.: Coefficient Estimations from GMM Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**8.228^{c}** **(0.000)**	**8.135^{c}** **(0.000)**	**8.276^{c}** **(0.000)**	**8.196^{c}** **(0.000)**	**9.476^{c}** **(0.000)**	**9.368^{c}** **(0.000)**	**9.510^{c}** **(0.000)**	**9.433^{c}** **(0.000)**
Log(MVE)	**-0.919^{c}** **(0.000)**	**-0.927^{c}** **(0.000)**	**-0.921^{c}** **(0.000)**	**-0.920^{c}** **(0.000)**	**-1.057^{c}** **(0.000)**	**-1.064^{c}** **(0.000)**	**-1.057^{c}** **(0.000)**	**-1.056^{c}** **(0.000)**
Log(BM)	**0.815^{c}** **(0.000)**	**0.828^{c}** **(0.000)**	**0.821^{c}** **(0.000)**	**0.821^{c}** **(0.000)**	**0.718^{c}** **(0.000)**	**0.731^{c}** **(0.000)**	**0.725^{c}** **(0.000)**	**0.725^{c}** **(0.000)**
Momentum					-0.049 (0.219)	-0.059 (0.138)	-0.053 0.1860	-0.053 (0.186)
Accruals					**0.422^{b}** **(0.051)**	**0.428^{b}** **(0.050)**	**0.425^{b}** **0.050**	**0.426^{b}** **(0.050)**
EQ_Offer					0.002 (0.931)	-0.029 (0.314)	-0.012 0.650	-0.013 (0.638)
FSCORE		**0.031^{c}** **(0.000)**				**0.034^{c}** **(0.000)**		
Industry Losers			**-0.074^{c}** **(0.000)**				**-0.074^{c}** **(0.000)**	
Industry Winners				**0.082^{c}** **(0.000)**				**0.079^{c}** **(0.000)**
Adj. R-squared	0.279	0.281	0.280	0.280	0.286	0.288	0.287	0.287
Durbin-Watson	1.301	1.304	1.304	1.305	1.317	1.319	1.319	1.320
Observations	10,153	10,153	10,153	10,153	9,727	9,727	9,727	9,727

*a,b,c are significance levels (a= %10, b= %5, c= %1).

Table 4.4.b. presents the results of the new variables obtained by combining the FSCORE and the industry effect variables. The HFIW dummy represents industry-

winner firms in the high FSCORE cluster, the LFIL dummy represents industry-loser firms in the low FSCORE cluster, and the Underdog dummy represents the industry-winner firms in the conflicting signal firms cluster neglected by the FSCORE method (firms with an FSCORE between 2 and 7).

The HFIW and twelve-month market-adjusted buy-and-hold returns have a significant and positive relationship. After controlling for well-known return factors, firms who have FSCORES in the 8 to 9 range which is also higher than their industry average earn an approximately 8% higher return compared to the rest of the firms in the sample. Interestingly, the LFIL dummy does not have a significant coefficient, although the a priori expectation would be to find a negative estimate. Apparently, having an FSCORE of 0 or 1 is already an unfavorable signal and it does not seem to make a difference in the eyes of the investors if the firm is also an industry loser. Finally, the Underdog dummyand twelve-month market-adjusted buy-and-hold return have a significant and positive relationship. After controlling for well-known return factors, an Underdog firm earns approximately 6% higher on average compared to the rest of the firms in the sample. This an interesting result since in the original Piotroski study, these firms are ignored completely since they are characterized as “mixed signal” firms with FSCORES in the 2 to 7 range. When the industry position of such mixed signal firms is taken into account, it is possible to identify future winners, implied by the statistically significant 6% coefficient estimate[3].

[3] The outliers have been checked and winsorized. After that, the models have been re-estimated. There is no statistical difference between the results.

Table 4.4.b.: Coefficients from GMM Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**8.228^{c} (0.000)**	**9.476^{c} (0.000)**	**8.234^{c} (0.000)**	**8.231^{c} (0.000)**	**8.200^{c} (0.000)**	**9.483^{c} (0.000)**	**9.480^{c} (0.000)**	**9.440^{c} (0.000)**
Log(MVE)	**-0.919^{c} (0.000)**	**-1.057^{c} (0.000)**	**-0.921^{c} (0.000)**	**-0.920^{c} (0.000)**	**-0.919^{c} (0.000)**	**-1.059^{c} (0.000)**	**-1.058^{c} (0.000)**	**-1.056^{c} (0.000)**
Log(BM)	**0.815^{c} (0.000)**	**0.718^{c} (0.000)**	**0.817^{c} (0.000)**	**0.815^{c} (0.000)**	**0.818 (0.000)**	**0.720 (0.000)**	**0.718^{c} (0.000)**	**0.722^{c} (0.000)**
Moment		-0.049 (0.220)				-0.050 (0.207)	-0.049 (0.215)	-0.051 (0.204)
Accrual		**0.422^{b} (0.051)**				**0.418^{b} (0.052)**	**0.424^{b} (0.524)**	**0.427^{b} (0.049)**
EQ_Offer		0.002 (0.931)				-0.006 (0.832)	0.002 (0.955)	-0.002 (0.930)
HFIW			**0.079^{c} (0.002)**			**0.078^{c} (0.004)**		
LFIL				-0.026 (0.685)			-0.045 (0.579)	
Underdog					**0.060^{c} (0.000)**			**0.056^{c} (0.001)**
Adj. R-squared	0.279	0.286	0.279	0.279	0.280	0.286	0.286	0.286
Durbin-Watson	1.301	1.317	1.302	1.301	1.303	1.317	1.317	1.319
Observations	10,153	9,727	10,153	10,153	10,153	9,727	9,727	9,727

*a,b,c are significance levels (a= %10, b= %5, c= %1).

CHAPTER 5

CONCLUSION

This study demonstrates that the industry effect variables can allow investing in high BM firms that are ignored by the classic FSCORE methodology. As it is well known, fundamental analysis does not only examine the firm-specific effects, but also considers an industry effect on firms. In this thesis, the industry effect is measured by using the industry's average FSCORE. Firms with an FSCORE below their industry average are identified as "industry losers," firms with an FSCORE above their industry average are identified as "industry winners." While the FSCORE is an indication of the firm’s financial strength, the industry effect variables are used to determine the firm’s position with respect to its peers in the same industry.

Many studies have tested the validity of the FSCORE in different regions, markets, and countries. Moreover, some studies use the FSCORE as a measure of financial health. Lastly, some studies have combined the FSCORE with other well-known techniques in the literature. However, industry effects had not been included as part of the previous studies. Therefore, this new perspective is vital to fill the gap in the literature. Moreover, it allows for making a more comprehensive fundamental analysis process.

As stated previously, the initial point of this study is to show whether it is possible to invest in firms that are ignored by the classical FSCORE method. Thus, the industry winner firms in the neglected group (which have FSCOREs between 2 and 7) are called

"Underdogs." The central part of this analysis is to find industry winners among the neglected firms. The industry winners variable has a significant and positive correlation with the twelve-month and twenty-four-month market-adjusted returns. As expected, the industry losers variable has a significant and negative relationship with future returns. The left tail of the return distribution (10th percentile, 25th percentile, and median) has shifted to the right (positive) after applying the industry-winners method for high BM firms from a twelve-month market-adjusted returns perspective. The industry losers method has moved the return distribution to the left tail. The GMM estimation is used to explain the direction and strength of the relationship between the industry effects variables and future returns. The models also account for those variables that are shown to have a significant impact on future returns, suchthe MVE, the BM, momentum, accruals, and equity offering. The industry winners dummy and twelve-month market-adjusted buy-and-hold return have a significant and positive relationship and these firms earn returns that are 8.2% higher on average, compared to the rest of the firms in the sample. On the other hand, the industry losers dummy and twelve-month market-adjusted buy-and-hold return have a significant and negative relationship and these firms earn returns that are 7.4% lower on average, compared to the rest of the firms in the sample.

When the industry effects are combined with Piotroski's original classification of high, low and neglected firms, findings are even more interesting. If firms with an FSCORE in the 8 to 9 range are also above their industry averages, then they seem to earn approximately 7.9% more compared to the rest of the firms in the sample. It should be remembered that based on results in Table 4.4.a, a 1 unit increase in the FSCORE itself leads to an average 3% increase in future returns. The 7.9% increase demonstrated for the industry winners with an FSCORE of 8 or 9 implies an additional 5% return earned by industry winners.

Lastly, even though 90% of the entire sample of firms have FSCOREs that are in the 2 to 7 range, these firms were never part of the analysis in the Piotroski study. When industry winners among these “neglected” firms are identified (the “Underdogs”), it is seen that these firms generate 6% higher future returns compared to the rest of the firms in the sample. In other words, by taking into account the industry position of a firm, it is possible to identify investable firms among those that were deemed not investable as a result of the “mixed signals” they sent in the original Piotroski study.

Consequently, this study has contributes to the current literature in several ways. First, the FSCORE analysis is applied to a more recent sample period. Second, the industry effects are incorporated into the analysis and robust and significant results were presented. Lastly and most importantly, the study has shown that it is possible to invest in firms ignored by the FSCORE method. In light of these results, the industry-effects method will probably increase investors' investment success rates.

One limitation of this study is the initial contention regarding the accuracy of the FSCORE as a predictor of future returns. The fact that an updated sample still produced results that show a significant relationship between the FSCORE and future returns implies that the validity of Piotroski’s methodology still stands.

The validity of the industry effects approach should be investigated in different markets, regions, and countries. It is a crucial future study for the current literature. Moreover, there are many valuation techniques in the literature, such as GSCORE, so combining them with the industry effects method should be necessary for future works. Lastly, this study uses the mean (average) FSCORE to determine the industry effects. For those samples where the frequency distribution of the FSCORE over the 0 to 9 range is more skewed, the median FSCORE may be a better measurement of the industry’s overall standing.

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