

FUNDAÇÃO GETÚLIO VARGAS
ESCOLA DE ECONOMIA DE EMPRESAS DE SÃO PAULO

PHILIPP MICHAEL DAMBACH

**APPLYING PIOTROSKI'S F_SCORE TO THE GERMAN STOCK MARKET.
EVIDENCE FROM 2002-2016.**

**SÃO PAULO
2016**

FUNDAÇÃO GETÚLIO VARGAS
ESCOLA DE ECONOMIA DE EMPRESAS DE SÃO PAULO

PHILIPP MICHAEL DAMBACH

**APPLYING PIOTROSKI'S F_SCORE TO THE GERMAN STOCK MARKET.
EVIDENCE FROM 2002-2016.**

Dissertação apresentada à Escola de Economia de Empresas de São Paulo da Fundação Getúlio Vargas, como requisito para obtenção do título de Mestre Profissional em Economia.

Campo do Conhecimento:
International Master in Finance

Orientadores Prof. Dr. Ricardo R. Rochman e Pedro Lameira

**SÃO PAULO
2016**

Dambach, Philipp Michael.

Applying Piotroski's F_Score to the German stock market: evidence from 2002-2016 / Philipp Michael Dambach. - 2016.

47 f.

Orientadores: Ricardo Ratner Rochman, Pedro Lameira
Dissertação (MPFE) - Escola de Economia de São Paulo.

1. Mercado de capitais - Alemanha. 2. Ações (Finanças). 3. Investimento em valor.
4. Empresas - Avaliação. I. Rochman, Ricardo Ratner. II. Lameira, Pedro. III.
Dissertação (MPFE) - Escola de Economia de São Paulo. IV. Título.

CDU 336.763.2(43)

PHILIPP MICHAEL DAMBACH

**APPLYING PIOTROSKI'S F_SCORE TO THE GERMAN STOCK MARKET.
EVIDENCE FROM 2002-2016.**

Dissertação apresentada à Escola de Economia de Empresas de São Paulo da Fundação Getúlio Vargas, como requisito para obtenção do título de Mestre Profissional em Economia.

Campo do Conhecimento:
International Master in Finance

Data de Aprovação:

___/___/___.

Banca Examinadora:

Prof. Dr. Ricardo R. Rochman
FGV-EESP

Prof. Dr. Pedro Lameira
NOVA SBE

Prof. Dr. Maria João Major
NOVA SBE

ACKNOWLEDGEMENTS

I would like to thank Professor Dr. Ricardo Rochman for being one of my supervisors and having done an excellent work in his function. I also thank Pedro Lameira for his supportive and valuable comments on this project and for teaching a very insightful course of "Hedge Funds". Further thanks are dedicated to all those who in some form or another sparked my interest in the field of investment strategies. Finally, I want to express deep gratitude to my family for providing me with unfailing support and continuous encouragement throughout my years of study. This accomplishment would not have been possible without them. Thank you.

ABSTRACT

This work project applies Joseph Piotroski's F_SCORE to the German stock market between 2002 and 2016. Considering the smaller size of the German stock market, a F_SCORE_ADD was created to differentiate between companies with the same score. Portfolios that went long in expected winners and shorted expected losers generated strong results within the small cap sample. For large caps, the abnormality of returns was not significant after controlling for common risk factors and quality. This relates to the results of other researchers and questions the practicality of the investment strategy for institutional investors with a large capital base to employ.

KEY WORDS: Value Investing, Fundamentals, F_SCORE, CDAX

RESUMO

Esta dissertação aplica o *F_SCORE* de Joseph Piotroski ao mercado de ações alemão entre 2002 e 2016. Por causa do tamanho menor do mercado de ações alemão, um *F_SCORE_ADD* foi criado para diferenciar entre as empresas com a mesma pontuação. Carteiras que foram "long" em vencedores esperados e "short" em perdedores esperados renderam bons resultados dentro da amostra com empresas de baixo valor de mercado. Para as empresas de alta capitalização, a anormalidade de retornos não foi estatisticamente significativa após o controle de fatores de risco comuns e qualidade. Isto relaciona-se com os resultados de outros investigadores e questiona a praticidade desta estratégia de investimento para os investidores institucionais com uma grande base de capital para empregar.

PALAVRAS CHAVE: Investimento em valor, Fundamentos, *F_SCORE*, *CDAX*

TABLE OF CONTENTS

1. Introduction	p. 9
2. Literature Review	p. 11
3. Data and Methodology	p. 19
4. Results	p. 28
5. Summary and Conclusion	p. 38
6. Bibliography	p. 39
7. Appendices	p. 42

1. INTRODUCTION

The value anomaly is one of the best known persisting anomalies in the market. It generated significant abnormal returns for decades and built the foundation for many successful investors. Value investing is based on the idea of buying stocks for less than their intrinsic value. Stocks can trade below their intrinsic value if human judgement, when aggregated in the market, is errant in the short-term. The value investor hopes to exploit this by profiting from a mean-reversion process in the long-term. Different strategies exist when it comes to judge whether a stock is an appropriate investment for a value investor. With the emerging interest in the field of behavioral finance in the recent years, many researchers and practitioners looked for ways to limit the exposure of their investment strategies to the biases that impact human thinking when acting as an investor in the stock market. Not only during crises it becomes evident that investors tend to exaggerate in both directions – optimism and pessimism – and do not make investment decisions on a rational basis. This is why systematic investment strategies gained popularity. The idea behind these strategies is to filter companies based on a quantitative basis and form portfolios with the companies that the mechanism has chosen, regardless of any personal preference or disfavor of the investor towards these companies. These strategies do not aim at identifying the single future best performing stocks within a whole index but at buying a portfolio that was selected by a purely quantitative mechanism and on average delivers returns that outstrip the market. They thereby minimize the risk of falling victim to biases. The popularity of these strategies is due to the fact that they offer a simple set of behavioral rules that, when followed properly, lead to adequate returns. Because of the omission of a qualitative stock picking component, for example talking to the management of a given company in

order to gain further insights, quantitative strategies practice common diversification principles. Different strategies were presented by practitioners and academic research and tested for different markets.

Joseph Piotroski (2000) proposed such a systematic quantitative strategy that contains both a value measurement and a quality measurement. This work tries to contribute to the discussion of practicality of such strategies by applying Piotroski's method to the German stock market, analyzing the performance and discussing practical concerns when applying this method. It also extends the current state of research upon this method by adding a strength component named F_SCORE_ADD to the ranking system of the F_SCORE to make it applicable for smaller stock markets. Furthermore, apart from other research on this method, also quality factors are used when analyzing whether the method generates positive alpha after controlling for common risk factors.

2. LITERATURE REVIEW

Piotroski's strategy relies upon a value and a quality component. The subsequent literature review will present the academic foundation for these strategy determinants before presenting Piotroski's paper and the research related to it.

Systematic investing strategies try to profit from common market anomalies, of which one of the most prominent is the value anomaly. The first authors to postulate an investment strategy on a value basis are Graham/Dodd (1934). Since the publication of their book "Security Analysis", value investing evolved in many ways and nowadays subsumes a whole pool of different strategies and approaches.

Before the mid-1970s, some researchers suggested for the first time that, in contrast to the efficient market hypothesis, stocks with a low price-earnings ratio seem to have higher returns in the future than stocks with a high price-earnings ratio. Most of this early research contained inconsistencies such as the look-ahead bias or not adjusting the results for risk. Basu (1977) therefore tested this hypothesis himself and published the results in *The Journal of Finance*. His conclusion was that even after controlling for all biases, transaction costs and taxes, the effect persisted, providing evidence that stock prices do not fully reflect all available information. However, Basu (1983) found a significant size effect because the effect is stronger for stocks of smaller companies than for large corporations. Jaffe/Keim/Westerfield (1989) untangled the earnings yield effect from the size effect. Their results were that the earnings yield effect is present in every month of the year, while the size effect is negative only in January. Moreover, they found a positive effect on future returns for companies with negative earnings. Stattman (1980) as well as Rosenberg/Reid/Lanstein (1985) were the first to

demonstrate that low price-to-book firms have higher average returns in the future. Fama/French (1993) summarized that, different from prior academic theory, the average returns on stocks cannot only be explained by the market factor by Sharpe (1964) but also by size and book-to-market ratio which they considered in their three-factor model for asset pricing.

Many explanations for the persistence of the value anomaly were suggested in the literature. As a possible explanation De Bondt/Thaler (1985) presented in *The Journal of Finance* that market overreaction leads to exceptionally large future returns of former underperformers in terms of price-earnings ratios. They viewed this also as a proof for substantial inefficiencies in the market. Research for the Japanese stock market by Chan/Hamao/Lakonishkok (1991) proved that fundamental variables such as size, cash flow, book-to-market ratio and price-to-book ratio have a significant impact on a firm's future earnings.

Additional proof to the difference in returns between value and glamour stocks is brought by La Porta et al. (1997) who attributed these differences and their persistence to behavioral factors such as expectational errors. Unsophisticated investors may perceive glamour stocks as less risky and even for professionals such stocks may be easier to justify to clients and managers. According to the authors a risk premium explanation for the differences between glamour and value stock returns is not consistent due to the fact that earnings announcement returns are substantially higher for value stocks. Further support for this argumentation is brought by Stickel (1998) who revealed the tendency of analysts to prefer low over high book-to-market stocks, even though the evidence in the literature would lead to a contrary strategy. This affirms the hypothesis that picking such stocks seems easier explicable to a manager or client.

The other position is taken by Chen/Zhang (1998) who argued that value stocks are riskier as they tend to be under distress, highly leveraged and have high uncertainty concerning future earnings. The higher returns could be explained by these risk attributes. The authors moreover found evidence that value stocks had higher returns in many markets, but in high growth markets the spread tended to be smaller.

The second pillar for Piotroski's strategy is the quality component. The important theoretical discussion is hereby, whether fundamentals can provide meaningful insights about future stock returns and quality measurements can enhance the performance of the value anomaly.

Ou/Penman (1989) delivered evidence that financial statements contain valuable information about future earnings. They showed that with a contingent of financial ratios from historic financial statement data, future changes in earnings can be predicted. Engagement in stocks with a positive expected earnings change resulted in abnormal returns that cannot be explained by firm risk characteristics or size. Holthausen/Larcker (1992) also created a model based on fundamentals with which they managed to predict future excess returns.

Research mentioned in the value anomaly section stated that high book-to-market stocks tend to be neglected by analysts. Using fundamental analysis could therefore be especially profitable in an environment with a low analyst-following as Piotroski (2000) suggested.

Greenblatt (2006) presented a strategy that relies upon the earnings yield effect. He adds a quality measurement, which he defines as return on capital. During the sample period his strategy outperformed the market by a large extent. A proof for the efficacy of this

strategy for the Shanghai Stock Exchange was delivered by Yangxiu (2013). However, Wesley Gray and Tobias Carlisle (2013) argued that only the earnings yield is an important factor and the inclusion of the return on capital factor actually lowers the returns. This relates to similar arguments by Hsu and Kalesnik (2013) who concluded in their research that quality measurements like gross profitability, return on equity or gross margins are not robust and do not evidently carry a premium, whereas typical value measurements like book-to-price, earnings-to-price or cashflow-to-price persistently do.

On the other hand Asness et al. (2015) argued that controlling for quality helps for example increasing the significance and performance of the size effect. Earlier, Asness/Frazzini/Pedersen (2013) demonstrated that a quality factor that enables to discriminate between “quality” and “junk” companies yields a positive premium and can enhance the performance of value strategies. This revives the findings of Lev/Thiagarajan (1993) and Abarbanell/Bushee (1998) who built an investment strategy based on multiple fundamental signals that generated significant abnormal returns. Fama/French (2014) updated their earlier three-factor model with two new variables; they are considering profitability and investment patterns of companies as important new factors for asset pricing.

The main difference between the contrary findings and arguments seems to depend on whether single measurements or multiple aggregate fundamental signals are used. As will be discussed in the following section, Piotroski delivered evidence that using multiple fundamental signals provides better results than only a few.

Following up the mentioned research, Joseph Piotroski published his paper "Value Investing: The Use of Historical Financial Statements to Separate Winners from Losers" in 2000, introducing his fundamentally based quantitative strategy. Piotroski states that even though low price-to-book stocks outperform on average, this is due only to a few extremely well performing stocks while about 57% of these stocks in the sample actually underperformed. He therefore introduces a F_SCORE, a signaling score based on historical financial statement data that is meant to exclude those underperforming stocks in order to shift the returns distribution of the portfolio rightwards. Piotroski based himself on earlier research when selecting his screening variables. For example Sloan (1996) suggested that investors tend to focus on earnings while neglecting the information found in accruals and cash flow. This was incorporated in the ACCRUAL variable. Loughran/Ritter (1995) found that companies that issue new shares underperformed such ones that did not rely on this type of funding. This led to the EQ_OFFER variable. All determinants of the signals will be discussed further in the methodology section. The fact that historical financial information can be used to distinguish future winners and future losers is seen by Piotroski as a proof for stock prices not fully containing all historic signals.

Piotroski remarks that his signals should not be seen as the only ones that can be used when trying to determine financially strong companies from financial statement data. However, several researchers prove the robustness of the F_SCORE, for instance Scatizzi (2011) showed that using trailing twelve-month data instead of fiscal year data has no significant impact and Gray/Carlisle (2013) constructed an improved F_SCORE, with only slight performance enhancements. Piotroski himself tested, whether the Z-Score by Altman (1968) together with Δ ROA could discriminate successfully between

strong and weak firms. The answer was yes, but the F_SCORE offered further explanatory power. Other authors mentioned in the previous section provided similar approaches based on aggregate fundamental data. This examination will follow the original definitions of the F_SCORE in the further procedure.

Krüger/Beerstecher (2015) revisited Piotroski's F_SCORE strategy for the U.S market for the recent period of time. They confirmed the high abnormal returns and proved that those can only partially be explained by common risk factors. Nevertheless, they considered the strategy to be unprofitable from a practical point of view as liquidity constraints and trading costs inhibit investors from exploiting this anomaly. For individual investors with limited capital the strategy might be sufficient but for institutional investors it is not possible when one considers the amount of money they have to invest.

Kim/Lee (2014) stressed that the results of Piotroski are likely to be overstated because the accounting information of all firms would not be actually available for the given point of time used in the study.

For the Mexican stock market, Dosamantes (2013) researched whether fundamental strategies lead to positive excess market returns. He used signals based on accounting fundamentals and then built portfolios with stocks that yield high scores. The research specifically tested F_SCORE and the similar L_SCORE by Lev/Thiagarajan (1993). The market excess annual returns were positive and significant even after controlling for the FF3M factors, however, tended to decrease in the recent period of time.

Woodley/Jones/Reburn (2011) also replicated the original findings of Piotroski over the original sample period with the same U.S. stock market and then analyzed the

performance for the subsequent years. They confirmed Piotroski's results for the original sample period but stated that the following 12 years after the publication of the paper showed reverse results, meaning that firms with a low F_SCORE outperformed high F_SCORE stocks in the value stock segment and that stocks with a high F_SCORE effectively underperformed the value segment as a whole. The robustness of these results is still given after controlling for the size effect.

For the European stock market Amor-Tapia/Tascón (2016) tested different fundamentally based composite indicators, namely F_SCORE2, PEIS, F_SCORE and G_SCORE. Their findings are that only F_SCORE and G_SCORE, which is a fundamental score developed for growth stocks, deliver abnormal returns. Most of the returns are contributed by the short leg. However, they find evidence for limits of these strategies in idiosyncratic risk, transaction costs and noise trader momentum risk.

Hyde (2014) analyzed the deployment of the F_SCORE strategy in emerging markets. He demonstrated that high F_SCORE stocks indeed seem to offer a premium which cannot be explained by value, size or momentum. He argues that the common explanation that stocks with such a premium are neglected by analysts does not hold, as high F_SCORE stocks are usually heavily followed and analyzed.

Singh and Kaur (2015) tested the Piotroski F_SCORE in the Indian stock market. Their findings are that high F_SCORE stocks performed better than the sample of all value stocks and delivered abnormal returns even after controlling for size, momentum, value, recent equity offerings and accrual effects.

To sum up, the Piotroski method is based on a thoroughly researched theoretical framework, profiting from one of the most known persisting anomalies and extending

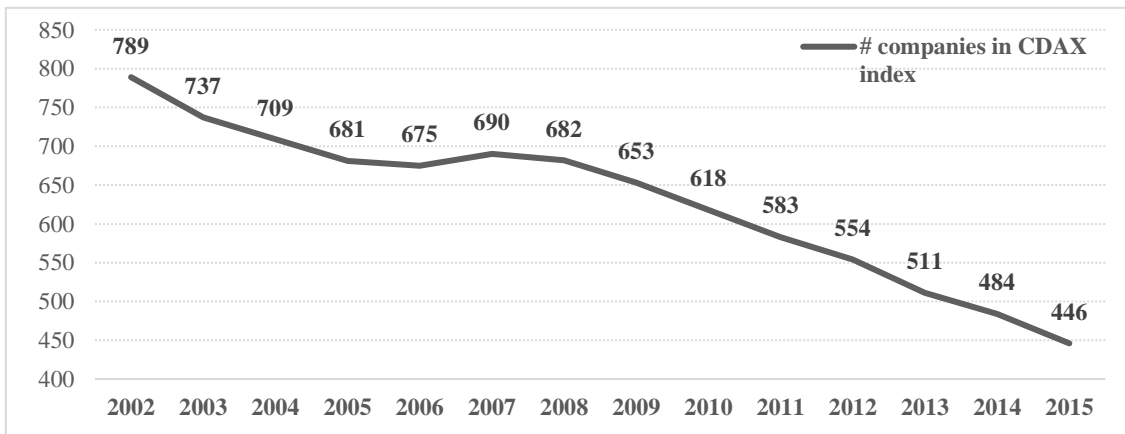
the efficacy using fundamental signals. Evidence about practicality and persistence shows, however, mixed results. This work project tries to add to the discussion by testing and developing the approach for the German stock market for the recent period of time whilst trying to create an additional sorting signal that makes the method applicable for smaller stock markets.

When testing whether any alpha attained by this method is significant after controlling for common risk factors, the author will also control for quality on the basis of Asness/Frazzini/Pedersen (2013) and Asness et al. (2015) and the new factors by Fama/French (2014) mentioned beforehand.

3. DATA AND METHODOLOGY

This work tries to contribute to the discussion of practicality of Piotroski’s investing strategy by testing it on the German stock market. Therefore, the companies for the sample are drawn from the CDAX index which contains all stock corporations in Germany. The time horizon for the examination is 2002-2016, because reliable information about the historical index constituents is only available from the beginning of 2002 onwards. In addition, the focus is designed to lie on the recent years and financial crises. The strategy requires portfolio updates every year. Therefore the first step was to retrieve the Portfolio constituents at each year. This step is important in order to ensure that the data is as much “point in time” as possible. Using the current constitution of the index would lead to a survivorship bias, because it excludes all companies that got bankrupt or acquired throughout time.

Graph 1. Change in CDAX Index Constitution 2002-2015.



Graph 1 illustrates the extent to which the index constitution changed. In 2002 there were 789 companies included in the CDAX index, whereas in 2015 only 446 companies constitute the index. On average, the number of stocks in the index declined by 4.29%

annually. This proves the importance of using the actual index constitution of each respective year.

The next step was to retrieve the financial statement data needed to build portfolios based on Joseph Piotroski's method. All of the subsequent data was taken from Bloomberg, unless marked differently. First, the companies were ranked each year based on their price-to-book ratios. The F_SCORE was then calculated for the quintile with the lowest price-to-book ratios. It represents an aggregate score that assesses companies based on three key areas, namely profitability, financial performance and operating efficiency. Table 1 specifies the determinants of the F_SCORE within the three key areas.

Table 1. Determinants of the F_SCORE.

PROFITABILITY	
ROA	= Net income before extraordinary items divided by Total assets
CFO	= Cash flow from operations divided by Total assets
Δ ROA	= Current return on assets – ROA of previous year
ACCRUAL	= CFO – ROA
FINANCIAL PERFORMANCE	
Δ LEVER	= Long-term debt of this year – Long-term debt of previous year
Δ LIQUID	= Current ratio of this year – Current ratio of previous year
EQ_OFFER	= New shares issued
OPERATING EFFICIENCY	
Δ MARGIN	= Profit margin of this year – Profit margin of previous year
Δ TURN	= Asset turnover of this year – Asset turnover of previous year

The first area in which the companies are assessed is the area of profitability. Positive ROA and CFO can be seen as a positive sign when considering the poor earnings history of most value firms. Also any improvement in ROA is considered as a positive signal. The ACCRUAL variable reflects positive accrual adjustments, which Sloan (1996) showed to have a significant negative impact on future returns. Piotroski defines it as profits being greater than cash flow from operations. Whenever the opposite is the case it should be seen as a positive signal.

The next area is financial performance, which focuses on assessing changes in the capital structure. The first variable subsumes the change in long-term debt levels. Piotroski states that when distressed firms raise capital externally, this should be seen as a proof that they cannot generate enough funding internally. Moreover it makes the firms less financially flexible. The positive change in current ratio addresses the liquidity and should be seen as a positive signal when it is achieved. Following Loughran/Ritter (1995), who found that new-share-issuers tend to underperform, results in a disapproval for new shares in the EQ_OFFER variable. This also addresses the earlier point of external financing representing a lack of internal financing possibilities.

The last section deals with the operating efficiency of the respective companies. The two variables used are changes in gross margin and asset turnover. An improved gross margin ratio indicates cost reduction or a higher price for the products sold. A higher asset turnover is a sign for productivity improvements such as higher sales or an increase in the efficiency of a firm's operations.

Piotroski stresses that it is important to note that his variables are tailored for the distressed low price-to-book segment. He mentions that for other companies for

instance, additional leverage would not necessarily result in a negative signal. Table 2 explains all of the nine resulting binary signals that follow these determinants.

Table 2. Binary Signals from the Determinants of the F_SCORE.

$\text{If } ROA > 0, F_{ROA} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } CFO > 0, F_{CFO} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta ROA > 0, F_{\Delta ROA} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } ACCRUAL > 0, F_{ACCRUAL} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta LEVER < 0, F_{\Delta LEVER} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta LIQUID > 0, F_{ROA} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } EQ_{OFFER} \leq 0, EQ_{OFFER} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta MARGIN > 0, F_{\Delta MARGIN} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta TURN > 0, F_{\Delta TURN} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$

With the F_SCORE being the sum of the individual binary signals it can be described with the following equation. The highest possible score is accordingly 9 for a company with very strong prospects and 0 for a company of extremely low quality.

Equation 1. Composition of the F_SCORE.

$$F_SCORE = F_{ROA} + F_{CFO} + F_{\Delta ROA} + F_{ACCRUAL} + F_{\Delta LEVER} + F_{\Delta LIQUID} \\ + EQ_{OFFER} + F_{\Delta MARGIN} + F_{\Delta TURN}$$

Piotroski acknowledges that using simple binary signals could lead to an elimination of useful information. Furthermore, in some years many companies may have the same score, whereas other scores are relatively underrepresented. Because the German stock index is considerably smaller than the U.S. company horizon, this imposes restrictions on the original way Piotroski formed his portfolios. Instead of bundling companies with the same score into portfolios, this paper will work with deciles and quintiles. The reason is to ensure enough diversification as high and low F_SCORE ranks tend to be rarer than mediocre F_SCOREs.

In order to differentiate between companies with the same F_SCORE, as a second step a F_SCORE_ADD was created. Hence, for the portfolio construction, also the strength of the positive moves of the signal determinants scaled by total assets was considered. Table 3 shows the strength determinants for the F_SCORE_ADD which do not require additional information but use information that would otherwise be neglected when using only binary signals.

Table 3. Strength Determinants for F_SCORE_ADD.

$\text{If } ROA > 0, \text{Add}_{ROA} = \begin{cases} ROA, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } CFO > 0, \text{Add}_{CFO} = \begin{cases} CFO, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta ROA > 0, \text{Add}_{\Delta ROA} = \begin{cases} \Delta ROA, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } ACCRUAL > 0, \text{Add}_{ACCRUAL} = \begin{cases} CFO - ROA, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta LEVER < 0, \text{Add}_{\Delta LEVER} = \begin{cases} -\Delta LEVER, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta LIQUID > 0, \text{Add}_{\Delta LIQUID} = \begin{cases} \Delta LIQUID, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } EQ_{OFFER} \leq 0, \text{Add}_{EQ_{OFFER}} = \begin{cases} 1, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta MARGIN > 0, \text{Add}_{\Delta MARGIN} = \begin{cases} \Delta MARGIN, \\ 0 \text{ otherwise} \end{cases}$
$\text{If } \Delta TURN > 0, \text{Add}_{\Delta TURN} = \begin{cases} \Delta TURN, \\ 0 \text{ otherwise} \end{cases}$

Whenever a condition is fulfilled that would lead to a positive F_SCORE signal, the amount of positiveness is considered, for example how much the return on assets improved compared to the previous year.

Equation 2 illustrates, how the F_SCORE_ADD is calculated. All numbers from the F_SCORE_ADD determinants are added up and then divided by total assets. Within each F_SCORE, companies were then ranked based on their F_SCORE_ADD from highest to lowest values.

Equation 2. Composition of the F_SCORE_ADD.

F_SCORE_ADD

$$\begin{aligned} &= \left(\frac{1}{\text{Total Assets}} \right) * (\text{Add}_{ROA} + \text{Add}_{CFO} + \text{Add}_{\Delta ROA} + \text{Add}_{ACCRUAL} \\ &+ \text{Add}_{\Delta LEVER} + \text{Add}_{\Delta LIQUID} + \text{Add}_{EQOFFER}) + \text{Add}_{\Delta MARGIN} \\ &+ \text{Add}_{\Delta TURN} \end{aligned}$$

After ranking all companies in the low price-to-book ratio quintile based on first F_SCORE and then F_SCORE_ADD, portfolios were created based on deciles and quintiles. For instance, the highest ranked decile in each year would stand for a portfolio. Within each portfolio, all assets are assumed to be equally weighted.

In order to examine, whether the results are different for large and small corporations, the sample was also split between companies of less than 100 million € market capitalization and such that have a higher market capitalization. The same procedure mentioned above was then performed analogously for these two sample splits.

After determining the portfolios, the logged total return of each portfolio, which is defined in equation 3, was calculated on a monthly basis.

Equation 3. Calculation of Returns.

$$R_t = \ln \left(\frac{P_t + \text{dividend}}{P_{t-1}} \right)$$

Because it takes some time for companies to publish the results for their financial years and in order to avoid the look-ahead bias, the returns were calculated starting from the middle of the year. This 6 months lag has the purpose of diminishing biased errors due to the use of forward-looking information. The return of delisted companies was

calculated using the price to which they got delisted, the return of acquired companies was calculated using the price for which they got acquired.

After calculating the decile returns, the CAPM, Fama-French three- and five-factor models (FF3M and FF5M), the Carhart four-factor model (C4FM), the FF3M plus the QMJ factor (Q4FM) and the C4FM plus the QMJ factor, which will be defined as Q5FM further in the text, were used in order to see if the strategy generates significant alpha after controlling for common risk factors and quality. The models were defined as follows, with r_{it} resembling the excess portfolio return after adjusting for the risk-free rate, which is proxied by the average one month money market rates (“Monatsgeld”) for the beginning of the sample period and the one-month EURIBOR after June 2012. CDAXRF is the excess return on the CDAX; SMB, HML, WML, RMW, CMA and QMJ are returns on zero-investment, factor-mimicking portfolios for size, book-to-market, momentum, profitability, investment patterns and quality.

CAPM: $r_{it} = \alpha_{iT} + b_{iT}CDAXRF_t + e_{it}$

FF3M: $r_{it} = \alpha_{iT} + b_{iT}CDAXRF_t + s_{iT}SMB_t + h_{iT}HML_t + e_{it}$

C4FM: $r_{it} = \alpha_{iT} + b_{iT}CDAXRF_t + s_{iT}SMB_t + h_{iT}HML_t + w_{iT}WML_t + e_{it}$

Q4FM: $r_{it} = \alpha_{iT} + b_{iT}CDAXRF_t + s_{iT}SMB_t + h_{iT}HML_t + q_{iT}QMJ_t + e_{it}$

Q5FM: $r_{it} = \alpha_{iT} + b_{iT}CDAXRF_t + s_{iT}SMB_t + h_{iT}HML_t + w_{iT}WML_t + q_{iT}QMJ_t + e_{it}$

FF5M: $r_{it} = \alpha_{iT} + b_{iT}CDAXRF_t + s_{iT}SMB_t + h_{iT}HML_t + r_{iT}RMW_t + c_{iT}CMA_t + e_{it}$

The factors for the German market used for the CAPM, FF3M and C4FM regressions are provided by Humboldt University Berlin. More information about the construction

of this multi-factor data set is delivered by Brückner et al. (2015).¹ Because the German factor data set only reaches until June 2015, the missing year's factors are proxied with the Fama/French European data set provided by Kenneth French.² This also applies for the two additional factors used for the Fama-French five-factor Model. The German QMJ factors were retrieved from the data set provided by AQR which is related to the paper by Asness/Frazzini/Pedersen (2013).³

¹ Source: <https://www.wiwi.hu-berlin.de/de/professuren/bwl/bb/data/fama-french-factors-germany/fama-french-factors-for-germany>

² Source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

³ Source: <https://www.aqr.com/library/data-sets/quality-minus-junk-factors-monthly>

4. RESULTS

The following section will present the results of the examination. First, tables with the raw returns will show the performance of each decile and quintile of the sample, both for the whole sample size as well as for large caps and small caps respectively. Thereafter, the results of benchmarking the excess returns over the risk free rate of the three samples with common risk factors and quality will be summarized and discussed.

Table 3. Descriptive Statistics of Returns – Whole Sample Size.

DECILES	Market	Deciles - Long only									
Risk & Return:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Arithmetic Return	6.77%	8.11%	3.67%	-2.76%	1.50%	-4.66%	-11.33%	-2.43%	-13.67%	-11.29%	-19.04%
Geometric Return	4.54%	6.13%	1.62%	-5.07%	-0.78%	-7.57%	-14.41%	-5.47%	-20.40%	-14.90%	-22.70%
Standard Dev.	21.13%	19.90%	20.23%	21.51%	21.37%	24.14%	24.80%	24.66%	36.67%	26.87%	27.07%
Info Sharpe	0.32	0.41	0.18	-0.13	0.07	-0.19	-0.46	-0.10	-0.37	-0.42	-0.70
Distribution:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Monthly Max	18.24%	16.90%	16.04%	17.17%	18.10%	20.11%	16.71%	17.74%	61.59%	14.86%	17.30%
Q3	4.07%	3.95%	3.70%	3.45%	3.89%	3.70%	3.06%	3.62%	3.69%	4.02%	2.96%
Med	1.38%	0.87%	0.70%	0.14%	0.28%	-0.20%	-0.26%	0.08%	-0.83%	0.09%	-1.23%
Q1	-2.54%	-2.60%	-2.51%	-2.73%	-2.85%	-3.83%	-4.47%	-3.95%	-5.03%	-4.55%	-6.18%
Monthly Min	-27.24%	-16.20%	-21.02%	-24.98%	-19.14%	-21.65%	-25.82%	-24.91%	-76.26%	-36.53%	-31.38%
Higher Moments:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Skewness	-1.04	-0.10	-0.51	-1.01	-0.39	-0.28	-0.63	-0.42	-1.20	-1.25	-0.65
Kurtosis	3.39	0.53	1.68	3.43	1.39	0.85	1.47	0.78	22.02	3.12	1.90
Positive Periods:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Positive Months	58.93%	55.95%	58.33%	51.79%	51.79%	47.02%	48.81%	50.00%	44.05%	50.60%	40.48%
Positive Years	64.29%	71.43%	64.29%	57.14%	57.14%	57.14%	42.86%	50.00%	35.71%	42.86%	21.43%

QUINTILES	Market	Quintiles - Long only					Quintiles - Long Short				
Risk & Return:	CDAX	1st	2nd	3rd	4th	5th	(1)-(10)	(1-2)-(9-10)	(1-3)-(8-10)	(1-4)-(7-10)	(1-5)-(6-10)
Arithmetic Return	6.77%	5.89%	-0.63%	-8.00%	-8.05%	-15.16%	27.14%	21.05%	17.67%	14.24%	12.73%
Geometric Return	4.54%	4.45%	-2.42%	-10.24%	-11.09%	-17.86%	24.17%	19.32%	16.19%	13.29%	11.97%
Standard Dev.	21.13%	16.98%	18.95%	21.17%	24.64%	23.21%	24.40%	18.64%	17.22%	13.79%	12.29%
Info Sharpe	0.32	0.35	-0.03	-0.38	-0.33	-0.65	1.11	1.13	1.03	1.03	1.04
Distribution:	CDAX	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Monthly Max	18.24%	15.59%	14.07%	15.01%	24.22%	16.08%	30.67%	17.36%	26.60%	21.10%	15.57%
Q3	4.07%	3.55%	3.29%	3.57%	3.16%	2.96%	6.37%	4.49%	3.92%	3.29%	3.17%
Med	1.38%	0.51%	0.24%	-0.07%	-0.19%	-0.36%	2.14%	1.84%	1.72%	1.43%	1.11%
Q1	-2.54%	-2.11%	-2.86%	-3.82%	-4.19%	-4.75%	-2.07%	-1.67%	-0.93%	-1.19%	-1.07%
Monthly Min	-27.24%	-16.70%	-20.79%	-18.34%	-41.52%	-27.87%	-16.92%	-14.09%	-23.06%	-15.02%	-11.66%
Higher Moments:	CDAX	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Skewness	-1.04	-0.31	-0.79	-0.46	-1.46	-0.73	0.33	0.19	-0.14	0.23	0.03
Kurtosis	3.39	1.15	2.24	0.38	8.01	1.41	1.36	1.03	6.88	4.46	2.15
Positive Periods:	CDAX	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Positive Months	58.93%	56.55%	53.57%	49.40%	48.81%	47.62%	65.48%	65.48%	68.45%	66.07%	63.69%
Positive Years	64.29%	57.14%	50.00%	57.14%	50.00%	42.86%	100.00%	85.71%	100.00%	85.71%	92.86%

Table 3 summarizes the results for the different deciles and quintiles of companies ranked according to F_SCORE and F_SCORE_ADD for the whole sample size. Long only returns are presented in the upper section and lower left hand side, whereas the

results for the long-short portfolios can be found in the lower right hand part of the table. When looking at the deciles it becomes clear, that from the highest to the lowest decile, the performance deteriorates almost gradually. The relationship is not perfect, but the arithmetic return correlates with the number of decile with a percentage of -90.95%. This means that the F_SCORE and F_SCORE_ADD ranking method performs quite well when discriminating between companies with different future prospects. The highest quintiles consist of companies with strong prospects and as observable, they performed well, whereas the bottom deciles consist of the companies with the worst prospects which noticeably perform very poorly. However, only the first decile manages to offer a better performance than the market and only three deciles yield positive returns on average. For the results in quintiles, the relationship between F_SCORE and F_SCORE_ADD rank and performance becomes even more stringent. The next step is to look at the long-short portfolios that go long in expected winners and short expected losers. Five long-short portfolios were formed, the first going long in the top decile and shorting the bottom decile, which is presented as (1)-(10), the second one longing the first two deciles while shorting the bottom two deciles and so on. The majority of returns is contributed by the short leg. Four of these portfolios offer a lower standard deviation than the market while at the same time offering a multiple of the market's returns. Accordingly, all of them offer attractive risk-return figures of above one. In the distribution of returns the median is always high and positive and in contrast to the market and the long only portfolios, the monthly maximum always exceeds the monthly minimum. Most of the long-short portfolios have a positive skewness, which means that the distribution is asymmetric with a bias towards more positive values. The number of positive months and years is largely increased.

The next paragraphs will discuss the difference of performance in large and small caps. For this examination the sample was split in half between companies that exceed a market capitalization of 100 million € and such that do not. Splitting the sample leads to a smaller sample base, because Piotroski's method works with the bottom quintile of price-to-book companies. Therefore the resulting portfolios contain less companies, which impacts diversification effects. This should be kept in mind when comparing the following results to the results for the whole sample size.

Table 4. Descriptive Statistics of Returns – Large Caps.

DECILES	Market	Deciles - Long only									
	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Risk & Return:											
Arithmetic Return	6.77%	10.19%	9.82%	10.58%	-0.40%	2.17%	-3.75%	10.36%	-2.28%	-1.49%	-11.12%
Geometric Return	4.54%	8.33%	7.86%	7.97%	-3.40%	-1.26%	-7.79%	8.85%	-5.90%	-5.61%	-16.29%
Standard Dev.	21.13%	19.27%	19.82%	22.85%	24.51%	26.19%	28.39%	17.34%	26.89%	28.70%	32.14%
Info Sharpe	0.32	0.53	0.50	0.46	-0.02	0.08	-0.13	0.60	-0.08	-0.05	-0.35
Distribution:											
Monthly Max	18.24%	17.61%	13.21%	16.68%	24.38%	22.68%	25.35%	13.04%	29.77%	24.06%	34.08%
Q3	4.07%	4.73%	4.35%	5.13%	4.59%	4.00%	3.59%	3.95%	4.33%	4.85%	4.31%
Med	1.38%	1.10%	1.35%	1.36%	0.07%	1.00%	0.79%	1.26%	-0.10%	0.24%	-0.48%
Q1	-2.54%	-1.92%	-2.39%	-2.74%	-3.87%	-3.27%	-2.49%	-1.77%	-4.94%	-3.92%	-4.66%
Monthly Min	-27.24%	-21.66%	-24.19%	-21.72%	-24.80%	-30.90%	-46.43%	-19.92%	-19.89%	-40.98%	-36.86%
Higher Moments:											
Skewness	-1.04	-0.89	-0.89	-0.52	-0.52	-1.02	-1.73	-0.70	0.33	-1.01	-0.85
Kurtosis	3.39	2.44	2.20	1.12	1.53	3.93	8.35	1.84	1.41	4.05	3.42
Positive Periods:											
Positive Months	58.93%	60.12%	60.71%	58.33%	51.19%	55.36%	54.76%	60.12%	49.40%	51.79%	45.83%
Positive Years	64.29%	78.57%	71.43%	57.14%	57.14%	57.14%	50.00%	78.57%	42.86%	57.14%	50.00%

QUINTILES	Market	Quintiles - Long only					Quintiles - Long Short				
	CDAX	1st	2nd	3rd	4th	5th	(1)-(10)	(1-2)-(9-10)	(1-3)-(8-10)	(1-4)-(7-10)	(1-5)-(6-10)
Risk & Return:											
Arithmetic Return	6.77%	10.01%	5.09%	-0.79%	4.04%	-6.31%	21.31%	16.31%	15.16%	8.68%	8.13%
Geometric Return	4.54%	8.42%	2.89%	-3.46%	2.19%	-10.03%	17.19%	14.21%	13.74%	7.76%	7.39%
Standard Dev.	21.13%	17.81%	20.98%	23.11%	19.22%	27.31%	28.71%	20.48%	16.87%	13.58%	12.17%
Info Sharpe	0.32	0.56	0.24	-0.03	0.21	-0.23	0.74	0.80	0.90	0.64	0.67
Distribution:											
Monthly Max	18.24%	10.01%	18.55%	21.71%	16.15%	25.46%	38.01%	24.12%	15.93%	11.02%	10.21%
Q3	4.07%	4.68%	4.71%	3.87%	4.32%	4.06%	5.66%	4.80%	4.27%	3.24%	2.98%
Med	1.38%	1.67%	0.48%	0.50%	0.31%	-0.28%	1.31%	1.45%	0.88%	0.47%	0.68%
Q1	-2.54%	-1.92%	-2.75%	-2.64%	-3.00%	-4.08%	-2.53%	-1.81%	-1.57%	-1.38%	-1.37%
Monthly Min	-27.24%	-22.92%	-19.27%	-26.18%	-16.86%	-31.20%	-27.79%	-22.56%	-15.75%	-12.98%	-10.75%
Higher Moments:											
Skewness	-1.04	-1.17	-0.41	-0.89	-0.13	-0.78	0.97	0.20	-0.01	-0.05	-0.18
Kurtosis	3.39	2.80	0.76	3.13	0.60	2.86	4.50	3.06	1.60	0.83	0.87
Positive Periods:											
Positive Months	58.93%	59.52%	54.76%	55.36%	53.57%	47.62%	61.31%	58.93%	61.31%	55.95%	60.71%
Positive Years	64.29%	71.43%	50.00%	50.00%	50.00%	50.00%	78.57%	71.43%	78.57%	78.57%	85.71%

The first thing to notice when looking at the results for the large cap sample is that the top three deciles present better information Sharpe ratios compared to the market.

However, the relationship between number of decile and returns are less perfect, even when looking at quintiles. This is mainly due to the fact that the 7th decile is the best performing one, which proves that the Piotroski F_SCORE has a more limited application among large corporations with a probably high analyst following. As a result, the long-short portfolios have lower information Sharpe ratios compared to the whole sample size portfolios, the average being 0.75. Distribution of returns and higher moments do not show the same characteristics as in the whole sample size. More portfolios exhibit negative skewness and for some the monthly maximum does not outstrip the monthly minimum. Also, the percentage of positive years is lower.

Table 5. Descriptive Statistics of Returns – Small Caps.

DECILES	Market	Deciles - Long only									
Risk & Return:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Arithmetic Return	6.77%	9.79%	6.76%	0.77%	-9.05%	-9.25%	-9.85%	-15.39%	-32.68%	-15.31%	-22.60%
Geometric Return	4.54%	7.09%	3.75%	-3.20%	-14.01%	-13.22%	-13.73%	-20.64%	-48.58%	-19.79%	-30.10%
Standard Dev.	21.13%	23.25%	24.54%	28.18%	31.49%	28.18%	27.85%	32.41%	56.40%	29.94%	38.72%
Info Sharpe	0.32	0.42	0.28	0.03	-0.29	-0.33	-0.35	-0.47	-0.58	-0.51	-0.58
Distribution:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Monthly Max	18.24%	21.88%	23.65%	21.22%	35.95%	27.37%	19.71%	19.26%	95.13%	15.65%	26.09%
Q3	4.07%	4.78%	3.41%	4.50%	4.12%	3.68%	3.91%	4.53%	3.77%	3.70%	3.98%
Med	1.38%	0.79%	0.26%	-0.42%	0.29%	-0.17%	-0.64%	-0.43%	-1.04%	-0.37%	-1.22%
Q1	-2.54%	-2.95%	-3.25%	-4.34%	-4.16%	-4.78%	-4.78%	-6.64%	-7.62%	-5.67%	-6.62%
Monthly Min	-27.24%	-24.70%	-18.63%	-30.96%	-42.87%	-49.83%	-37.47%	-33.66%	-138.93%	-35.26%	-51.28%
Higher Moments:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Skewness	-1.04	-0.24	0.14	-0.19	-0.74	-1.04	-0.41	-0.59	-2.34	-0.95	-1.33
Kurtosis	3.39	1.54	1.01	1.03	4.51	7.80	2.21	1.20	35.92	2.08	4.84
Positive Periods:	CDAX	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Positive Months	58.93%	54.76%	52.98%	48.21%	51.79%	48.21%	45.24%	47.02%	41.67%	48.21%	45.24%
Positive Years	64.29%	57.14%	64.29%	42.86%	57.14%	42.86%	35.71%	42.86%	21.43%	35.71%	42.86%

QUINTILES	Market	Quintiles - Long only					Quintiles - Long Short				
Risk & Return:	CDAX	1st	2nd	3rd	4th	5th	(1)-(10)	(1-2)-(9-10)	(1-3)-(8-10)	(1-4)-(7-10)	(1-5)-(6-10)
Arithmetic Return	6.77%	8.28%	-4.14%	-9.55%	-24.04%	-18.95%	32.39%	27.23%	29.30%	23.56%	18.97%
Geometric Return	4.54%	6.35%	-7.19%	-12.13%	-30.13%	-22.63%	24.91%	23.99%	25.62%	21.00%	17.03%
Standard Dev.	21.13%	19.63%	24.69%	22.73%	34.92%	27.12%	38.69%	25.47%	27.13%	22.64%	19.67%
Info Sharpe	0.32	0.42	-0.17	-0.42	-0.69	-0.70	0.84	1.07	1.08	1.04	0.96
Distribution:	CDAX	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Monthly Max	18.24%	16.37%	24.19%	15.55%	43.37%	14.11%	55.91%	31.42%	47.43%	36.37%	28.96%
Q3	4.07%	4.05%	3.52%	3.41%	3.30%	3.48%	8.18%	6.18%	5.72%	4.81%	4.66%
Med	1.38%	0.74%	-0.62%	-0.33%	-1.31%	-0.96%	2.37%	2.72%	2.16%	2.17%	1.44%
Q1	-2.54%	-2.41%	-3.90%	-4.42%	-6.83%	-4.89%	-3.22%	-2.00%	-1.51%	-1.13%	-1.64%
Monthly Min	-27.24%	-18.50%	-25.35%	-30.13%	-72.24%	-35.55%	-39.50%	-18.92%	-29.04%	-22.06%	-19.45%
Higher Moments:	CDAX	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Skewness	-1.04	-0.30	-0.43	-0.58	-1.71	-1.16	0.53	0.43	1.14	0.57	0.32
Kurtosis	3.39	1.00	2.28	2.32	15.31	2.74	3.97	2.10	8.09	5.09	3.39
Positive Periods:	CDAX	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Positive Months	58.93%	55.95%	47.02%	45.24%	44.05%	45.83%	61.90%	63.69%	66.67%	67.86%	65.48%
Positive Years	64.29%	64.29%	64.29%	35.71%	35.71%	42.86%	78.57%	92.86%	92.86%	85.71%	78.57%

Table 5 summarizes the statistics for the small cap sample. Of all three samples, it offers the highest return for the top decile and quintile. The relationship between F_SCORE and F_SCORE_ADD rank and returns is more stringent than for the large cap sample. In the quintiles however, the relationship appears not perfect due to the large negative performance of the 8th decile. The distribution of returns seems more extreme in the small cap sample with some deciles having high monthly maxima and minima and extreme kurtosis figures. Also, the numbers of positive years and months are the lowest for this sample. The long-short portfolios offer higher information Sharpe ratios of around one compared to the large cap sample. Also the spread between high F_SCORE and low F_SCORE companies is the highest in this sample, resulting in an average return of 32.39% for the portfolio that goes long in the top decile and short in the bottom decile. The long-short portfolios exhibit monthly maxima that largely exceed the monthly minima. Also, the skewness for all portfolios is positive and almost all portfolios have a leptokurtic distribution. The number of positive months is high and the portfolios offered positive results in almost all years of the period studied.

To conclude, the F_SCORE and F_SCORE_ADD ranking system is able to discriminate between companies with strong prospects and such that will perform poorly in a fairly gradual manner. Portfolios that go long expected winners and short expected losers would have generated attractive risk-return figures for the period studied. Splitting the sample between large and small caps reveals differences in performance. For the large cap sample size the F_SCORE did not work as perfect as in the small cap sample. A reason may be that the companies with a large market capitalization have a higher analyst following, which may lead to a faster incorporation of fundamentals in prices. This would affect the practicality of the Piotroski F_SCORE

for this sample, especially when one considers the half-year lag between the end of a financial year and the actual investment period. Small caps showed a more stringent relationship between F_SCORE rank and performance. Therefore the risk-return metrics are more attractive. On the other hand, the small cap sample exhibits more extreme statistics, with high kurtosis figures and mostly negative deciles for the long only portfolios. Also, the majority of returns is yielded by the short leg. It seems that these companies are more distressed and in a worse state compared to the large cap companies. Also, these companies appear less investible due to the fact that they are of a low market capitalization. This may impose liquidity constraints and high transaction costs, which may make investing in these companies with the Piotroski method unfeasible. On the other hand, this may be also the reason for the profitability of investing in this segment with the F_SCORE method, as fundamental data does not get incorporated as fast.

The next step was to benchmark the returns with common factor models. Six different regressions were performed. The first one is the Capital Asset Pricing Model by Sharpe (1964), the second one is the Fama-French three-factor model by Fama/French (1996), the third one their extended five-factor model (2014), the fourth one is the four-factor model by Carhart (1997), the fifth one is the Q4FM, which resembles the FF3M extended with a quality-minus-junk factor (QMJ) introduced by Asness/Frazzini/Pedersen (2013), and the sixth one is the Q5FM, which will resemble the C4FM extended with the QMJ factor. Three summary tables for each sample will be presented and discussed, the regression output can be found in the the appendix.⁴

⁴ All regressions were performed using EViews. The appendix (pages 37 – 42) exhibits all outputs.

Table 6. Regression Summary for Long-Short Portfolios – Whole Sample Size.⁵

Model:	<i>Whole Sample Size</i>	(1)–(10)	(1-2)–(9-10)	(1-3)–(8-10)	(1-4)–(7-10)	(1-5)–(6-10)
<i>CAPM:</i>	α	*	*	*	*	*
	CDAX-Rf	X	*	*	*	*
<i>FF3M:</i>	α	*	*	*	*	*
	CDAX-Rf	X	*	*	*	**
	SMB	X	X	X	X	X
	HML	X	X	X	X	X
<i>C4FM:</i>	α	*	*	*	*	*
	CDAX-Rf	X	***	X	X	X
	SMB	X	X	X	X	X
	HML	X	X	X	X	X
	WML	X	***	**	**	**
<i>Q4FM:</i>	α	*	*	**	*	*
	CDAX-Rf	X	X	X	X	X
	SMB	X	X	X	X	X
	HML	X	X	X	X	X
	QMJ	X	X	***	X	X
<i>Q5FM:</i>	α	*	*	**	**	**
	CDAX-Rf	X	X	X	X	X
	SMB	X	X	X	X	X
	HML	X	X	X	X	X
	WML	X	***	***	***	***
	QMJ	X	X	X	X	X
<i>FF5M:</i>	α	*	*	**	**	**
	CDAX-Rf	X	X	X	X	X
	SMB	X	X	X	X	X
	HML	X	X	X	X	X
	RMW	X	**	*	*	**
	CMA	X	X	X	X	X

Table 6 summarizes the regression outputs for the portfolios drawn from the complete sample size. Controlling the excess returns of the five long-short portfolios over the risk-free rate for the risk-adjusted market return, size, value, momentum, quality, profitability and investment patterns results in a positive and significant alpha at the 5%

⁵ For all three regression summary tables the following symbols mark the significance of the variables.

* Significant at the 1% level ** Significant at the 5% level
 *** Significant at the 10% level X Not significant

level for all portfolios in all models. Adding quality factors or controlling for the profitability and the investment patterns of the companies does not manage to eliminate the alpha achieved by Piotroski's method. Interestingly, the RMW factor by Fama/French (2014) performed better as a variable than the QMJ factor by Asness/Frazzini/Pedersen (2013).

Table 7. Regression Summary for Long-Short Portfolios – Large Caps.

Model:	<i>Large Cap Sample</i>	(1)–(10)	(1-2)–(9-10)	(1-3)–(8-10)	(1-4)–(7-10)	(1-5)–(6-10)
<i>CAPM:</i>	α	*	*	*	**	**
	CDAX-Rf	*	*	*	**	***
<i>FF3M:</i>	α	*	*	*	**	**
	CDAX-Rf	*	*	*	*	***
	SMB	**	*	**	X	X
	HML	X	**	X	X	X
<i>C4FM:</i>	α	**	**	*	X	X
	CDAX-Rf	**	*	**	X	X
	SMB	**	**	X	X	X
	HML	X	**	***	X	X
	WML	X	*	*	*	**
<i>Q4FM:</i>	α	***	***	*	X	X
	CDAX-Rf	X	**	**	X	X
	SMB	**	**	*	X	X
	HML	X	***	*	X	X
	QMJ	***	*	***	X	X
<i>Q5FM:</i>	α	***	X	**	X	X
	CDAX-Rf	X	X	X	X	X
	SMB	***	***	X	X	X
	HML	X	***	***	X	X
	WML	X	*	*	**	***
QMJ	X	*	X	X	X	
<i>FF5M:</i>	α	**	*	*	***	***
	CDAX-Rf	*	*	*	***	X
	SMB	**	**	***	X	X
	HML	X	***	X	X	X
	RMW	X	***	X	X	X
	CMA	X	X	X	***	***

For the large cap sample controlling for common risk factors and quality diminishes the alpha obtained by Piotroski's F_SCORE strategy. In contrast to the whole sample size, the QMJ factor hereby explains the returns better than the RMW factor. A possible explanation could be that the QMJ factor by Asness/Frazzini/Pedersen (2013) is derived from the Gordon growth model, which may be more suitable for large corporations. The Q5FM model seems to capture the returns the best.

Table 8. Regression Summary for Long-Short Portfolios – Small Caps.

Model:	<i>Small Cap Sample</i>	(1)–(10)	(1-2)–(9-10)	(1-3)–(8-10)	(1-4)–(7-10)	(1-5)–(6-10)
<i>CAPM:</i>	α	*	*	*	*	*
	CDAX-Rf	**	*	*	**	**
<i>FF3M:</i>	α	*	*	*	*	*
	CDAX-Rf	**	*	*	*	*
	SMB	X	X	X	X	X
	HML	X	***	X	X	***
<i>C4FM:</i>	α	*	*	*	*	*
	CDAX-Rf	**	**	*	**	**
	SMB	X	X	X	X	X
	HML	X	***	X	X	***
	WML	X	X	X	X	X
<i>Q4FM:</i>	α	*	*	*	*	*
	CDAX-Rf	**	X	***	X	X
	SMB	X	X	X	X	X
	HML	X	***	X	X	X
	QMJ	X	X	X	X	X
<i>Q5FM:</i>	α	*	*	*	*	*
	CDAX-Rf	**	X	***	X	X
	SMB	X	X	X	X	X
	HML	X	***	X	X	X
	WML	X	X	X	X	X
	QMJ	X	X	X	X	X
<i>FF5M:</i>	α	*	*	*	*	*
	CDAX-Rf	**	***	X	X	X
	SMB	X	X	X	X	X
	HML	X	***	X	X	X
	RMW	X	X	X	***	***
	CMA	X	X	X	X	X

In the small cap sample the alpha for all portfolios is significant above the 1% level. The only significant variable above the 10% level is the excess return of the CDAX over the risk-free rate. Controlling for common risk factors, quality, profitability and investment patterns does not affect the abnormality of returns in this sample.

All long-short portfolios show a small and negative beta towards the market excess return. This means that the returns of these portfolios are not very and negatively correlated with market movements, which could provide attractive characteristics, when added to a portfolio that has considerable market risk. Splitting the sample revealed that the long cap sample with corporations of a market capitalization above 100 million € did not perform as well and stringent as would be desirable. Furthermore, the returns achieved in this sample can be mimicked by portfolios that load upon common risk factors and quality. The small cap on the other hand presented attractive, stable alpha that persists after controlling for common risk factors, quality, profitability and investment patterns. Other authors however suggested, that this alpha is not harvestable in practice due to liquidity and size constraints associated with small companies. This may be an explanation for the persistence of this anomaly.

5. SUMMARY AND CONCLUSION

The systematic quantitative investment method based on Piotroski's F_SCORE yielded positive and stable results in the German stock market for the sample period of 2002-2016. Using a F_SCORE_ADD appeared a viable way to expand the application of the Piotroski F_SCORE to smaller stock markets. Further research can contribute to the discussion of this extension of the F_SCORE.

A portfolio that goes long in expected winners and shorts expected losers based on fundamental signals for stocks within the highest book-to-market quintile of the CDAX index generated high abnormal returns even after controlling for common risk factors and quality. In fact, the portfolio returns had very little and negative correlation with the market and the strategy appeared stable throughout the sample period.

However, when splitting the sample between small and large corporations it becomes clear that the strategy delivers abnormal returns only for the small cap sample consisting of companies with a market capitalization lower than 100 million €. This may make the strategy unfeasible for institutional investors due to liquidity and trading constraints, considering the amount of capital that usually needs to be employed by such players. These results relate to the findings of other authors and may be one reason for the persistence of the anomaly.

6. BIBLIOGRAPHY

Abarbanell, Jeffrey, and Brian Bushee. 1997. "Fundamental Analysis, Future Earnings, and Stock Prices." *Journal of Accounting Research*, 35: 1-24.

Abarbanell, Jeffrey, and Brian Bushee. 1998. "Abnormal Returns to a Fundamental Analysis Strategy". *Accounting Review*, 73: 19-45.

Altman, Edward. 1968. "Financial Ratios, Discriminant analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance*, 23(4): 589-609.

Amor-Tapia, Borja, and María Tascón. 2016. "Separating Winners from Losers: Composite Indicators Based on Fundamentals in the European Context." *Journal of Economics and Finance*, 66(1): 70-94.

Asness, Clifford, Andrea Frazzini, and Lasse Pedersen. 2013. "Quality Minus Junk." *Working Paper*.

Asness, Clifford, Andrea Frazzini, Ronen Israel, Tobias Moskowitz, and Lasse Pedersen. 2015. "Size Matters, If You Control Your Junk." *Working Paper*.

Basu, Sanjoy. 1977. "Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis." *The Journal of Finance*, 32(3): 663-682.

Basu, Sanjoy. 1983. "The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence." *Journal of Financial Economics*, 12(1): 129-156.

Brückner, Roman, Patrick Lehmann, Martin Schmidt, and Richard Stehle. 2015. "Another German Fama/French Factor Data Set." <http://ssrn.com/abstract=2682617>.

Campbell, John, and Robert Shiller. 1988. "Stock Prices, Earnings, and Expected Dividends." *The Journal of Finance*, 43(3): 661-676.

Carhart, Mark. 1997. "On Persistence in Mutual Fund Performance." *The Journal of Finance*, 52(1): 57-82.

Chan, Louis, Yasushi Hamao, and Josef Lakonishok. 1991. "Fundamentals and Stock Returns in Japan." *The Journal of Finance* 46(5): 1739-1789.

Chen, Nai-fu, and Feng Zhang. 1998. "Risk and Return of Value Stocks." *Journal of Business*, 71(4): 501-535.

De Bondt, Werner, and Richard Thaler. 1985. "Does the Stock Market Overreact?" *The Journal of Finance*, 40(3): 793-805.

Dosamantes, Carlos. 2013. "The Relevance of Using Accounting Fundamentals in the Mexican Stock Market." *Journal of Economics, Finance and Administrative Science*, 18: 2-10.

- Fama, Eugene, and Kenneth French.** 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance*, 47(2): 427-465.
- Fama, Eugene, and Kenneth French.** 1996. "Multifactor Explanations of Asset Pricing Anomalies." *The Journal of Finance*, 51(1): 55-84.
- French, Eugene, and Kenneth French.** 2014. "A Five-Factor Asset Pricing Model." *Fama-Miller Working Paper*.
- Fama, Eugene, and Marshall Blume.** 1966. "Filter Rules and Stock-Market Trading." *The Journal of Business*, 39(1): 226-241.
- Graham, Benjamin, and David Dodd.** 1934. *Security Analysis*. New York: McGraw-Hill.
- Gray, Wesley, and Tobias Carlisle.** 2013. *Quantitative Value: A Practitioner's Guide to Automating Intelligent Investment and Eliminating Behavioral Errors*. Hoboken, New Jersey: John Wiley & Sons.
- Greenblatt, Joel.** 2006. *The Little Book That Beats the Market*. Hoboken, New Jersey: John Wiley & Sons.
- Haugen, Robert, and Nardin Baker.** 1996. "Commonality in the Determinants of Expected Stock Returns." *Journal of Financial Economics*, 41: 401.
- Holthausen, Robert, and David Larcker.** 1996. "The Prediction of Stock Returns Using Financial Statement Information." *Journal of Accounting and Economics* 15(3): 373-411.
- Hsu, Jason, and Vitali Kalesnik.** 2014. *Finding Smart Beta in the Factor Zoo*. Newport Beach, California: Research Affiliates.
- Hyde, Charles.** 2014. "An Emerging Markets Analysis of the Piotroski F-score." *The Finsia Journal of Applied Finance*, 2: 23-28.
- Jaffe, Jeffrey, Donald Keim, and Randolph Westerfield.** 1989. "Earnings Yields, Market Values, and Stock Returns." *The Journal of Finance*, 44(1): 135-148.
- Kim, Sohyung, and Cheol Lee.** 2014. "Implementability of Trading Strategies Based on Accounting Information: Piotroski (2000) Revisited." *European Accounting Review*, 23(4): 553-558.
- Kothari, Suthawan.** 2001. "Capital markets research in accounting." *Journal of Accounting and Economics*, 31(1-3): 105-231.
- Krauss, Christopher, Tom Krüger, and Daniel Beerstecher.** 2015. "The Piotroski F-Score: A fundamental value strategy revisited from an investor's perspective." *IWQW Discussion Paper Series*, 13: 1-27.
- La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert Vishny.** 1997. "Good News for Value Stocks: Further Evidence on Market Efficiency." *The Journal of Finance*, 52(2): 859-874.

- Lev, Baruch, and S. Ramu Thiagarajan.** 1993. "Fundamental Information Analysis." *Journal of Accounting Research*, 31(2): 190-215.
- Loughran, Tim, Jay Ritter.** 1995. "The New Issues Puzzle." *The Journal of Finance*, 50(1): 23-51.
- Ou, Jane, and Stephen H. Penman.** 1989. "Accounting Measurement, Price-Earnings Ratio, and the Information Content of Security Prices." *Journal of Accounting Research*, 27: 111-144.
- Ou, Jane, and Stephen H. Penman.** 1989. "Financial Statement Analysis and the Prediction of Stock Returns." *Journal of Accounting and Economics*, 11: 295-329.
- Piotroski, Joseph.** 2000. "Value Investing: The Use of Historical Financial Statements to Separate Winners from Losers." *Journal of Accounting Research*, 38.
- Piotroski, Joseph, and Eric So.** 2011. "Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach." *Review of Financial Studies*, 25(9): 2841-2875.
- Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein.** 1985. "Persuasive Evidence of Market Inefficiency." *Journal of Portfolio Management*, 11: 9-17.
- Scatizzi, Cara.** 2010. "Adjusting for the real world: Testing variations of Piotroski's Screen." *AII Journal*, 32(4): 21-26.
- Sharpe, William.** 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *The Journal of Finance*, 19(3): 425-442.
- Singh, Jaspal, and Kiranpreet Kaur.** 2015. "Adding value to value stocks in Indian stock market: an empirical analysis." *International Journal of Law and Management*, 57(6): 621-636.
- Sloan, Richard.** 1996. "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?" *The Accounting Review*, 71(3): 289-315.
- Stattman, Dennis.** 1980. "Book Values and Stock Returns." *The Chicago MBA: A Journal of Selected Papers*, 4: 25-45.
- Stickel, Scott.** 1998. "Analyst Incentives and the Financial Characteristics of Wall Street Darlings and Dogs." *The Journal of Investing*, 16(3): 23-32.
- Woodley, Melissa, Steven Jones, and James Reburn.** 2011. "Value Stocks and Accounting Screens: Has a Good Rule Gone Bad?" *Journal of Accounting and Finance*, 11(4): 87-104.
- Yangxiu, Ye.** 2013. "Application of the Stock Selection Criteria of Three Value Investors, Benjamin Graham, Peter Lynch, and Joel Greenblatt: A Case of Shanghai Stock Exchange from 2006 to 2011." *International Journal of Scientific and Research Publications*, 3(8): 1-7.

Dependent Variable: 1_2_9_10 Method: Least Squares Date: 08/01/16 Time: 23:01 Sample: 2002M07 2016M06 Included observations: 168					Dependent Variable: 1_3_8_10 Method: Least Squares Date: 08/01/16 Time: 23:02 Sample: 2002M07 2016M06 Included observations: 168					Dependent Variable: 1_4_7_10 Method: Least Squares Date: 08/01/16 Time: 23:03 Sample: 2002M07 2016M06 Included observations: 168				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020745	0.006216	3.337455	0.0010	C	0.024318	0.006674	3.643570	0.0004	C	0.018276	0.005579	3.275737	0.0013
CDAX_RF	-0.185999	0.142814	-1.302385	0.1946	CDAX_RF	-0.296369	0.153351	-1.932623	0.0550	CDAX_RF	-0.193340	0.128192	-1.508199	0.1335
SMB	-0.213414	0.200121	-1.066422	0.2878	SMB	-0.315264	0.214885	-1.467127	0.1443	SMB	-0.222073	0.179632	-1.236267	0.2181
HML	-0.382971	0.214074	-1.789970	0.0755	HML	-0.314779	0.229867	-1.369390	0.1728	HML	-0.250652	0.192156	-1.304417	0.1939
WML	0.040219	0.127657	0.315352	0.7531	WML	-0.047486	0.137075	-0.346425	0.7295	WML	-0.012279	0.114587	-0.107155	0.9148
QMJ	0.299938	0.288634	1.039162	0.3003	QMJ	0.161818	0.309928	0.522114	0.6023	QMJ	0.211510	0.259083	0.816382	0.4155
R-squared	0.079403	Mean dependent var	0.021368	R-squared	0.064852	Mean dependent var	0.023094	R-squared	0.060975	Mean dependent var	0.018311			
Adjusted R-squared	0.050993	S.D. dependent var	0.073443	Adjusted R-squared	0.035989	S.D. dependent var	0.078245	Adjusted R-squared	0.031993	S.D. dependent var	0.065273			
S.E. of regression	0.071546	Akaike info criterion	-2.401900	S.E. of regression	0.076824	Akaike info criterion	-2.259536	S.E. of regression	0.064221	Akaike info criterion	-2.617925			
Sum squared resid	0.829244	Schwarz criterion	-2.290330	Sum squared resid	0.956114	Schwarz criterion	-2.147966	Sum squared resid	0.668134	Schwarz criterion	-2.566355			
Log likelihood	207.7596	Hannan-Quinn criter.	-2.356619	Log likelihood	195.8010	Hannan-Quinn criter.	-2.214256	Log likelihood	225.9657	Hannan-Quinn criter.	-2.572644			
F-statistic	2.794546	Durbin-Watson stat	2.021118	F-statistic	2.248925	Durbin-Watson stat	2.294970	F-statistic	2.103687	Durbin-Watson stat	2.168292			
Prob(F-statistic)	0.018922			Prob(F-statistic)	0.052142			Prob(F-statistic)	0.067537					

Dependent Variable: 1_5_6_10 Method: Least Squares Date: 08/01/16 Time: 23:04 Sample: 2002M07 2016M06 Included observations: 168					Dependent Variable: 1_10_10 Method: Least Squares Date: 08/01/16 Time: 23:07 Sample: 2002M07 2016M06 Included observations: 168					Dependent Variable: 1_2_9_10 Method: Least Squares Date: 08/01/16 Time: 23:08 Sample: 2002M07 2016M06 Included observations: 168				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.013810	0.004840	2.853626	0.0049	C	0.029254	0.009257	3.160326	0.0019	C	0.021389	0.005948	3.595783	0.0004
CDAX_RF	-0.115666	0.111196	-1.040203	0.2998	CDAX_RF	-0.415322	0.193985	-2.141003	0.0338	CDAX_RF	-0.210797	0.124656	-1.691033	0.0928
SMB	-0.160162	0.155815	-1.027899	0.3055	SMB	-0.312435	0.309498	-1.009490	0.3142	SMB	-0.209306	0.198886	-1.052394	0.2942
HML	-0.269807	0.166679	-1.614402	0.1084	HML	-0.129209	0.340128	-0.644490	0.5202	HML	-0.397561	0.218568	-1.818934	0.0708
WML	-0.001852	0.099394	-0.018636	0.9852	RMW	-0.535704	0.706919	-0.757801	0.4497	RMW	0.575211	0.454271	1.266230	0.2072
QMJ	0.271258	0.224732	1.207027	0.2292	CMA	0.117999	0.724163	0.162340	0.8708	CMA	0.338010	0.465364	0.726335	0.4687
R-squared	0.064091	Mean dependent var	0.014484	R-squared	0.035874	Mean dependent var	0.025669	R-squared	0.080742	Mean dependent var	0.021368			
Adjusted R-squared	0.035205	S.D. dependent var	0.056713	Adjusted R-squared	0.006117	S.D. dependent var	0.111598	Adjusted R-squared	0.052370	S.D. dependent var	0.073443			
S.E. of regression	0.065706	Akaike info criterion	-2.902402	S.E. of regression	0.111236	Akaike info criterion	-1.519899	S.E. of regression	0.071494	Akaike info criterion	-2.403355			
Sum squared resid	0.602709	Schwarz criterion	-2.790632	Sum squared resid	2.005211	Schwarz criterion	-1.407338	Sum squared resid	0.828337	Schwarz criterion	-2.291783			
Log likelihood	249.8018	Hannan-Quinn criter.	-2.857121	Log likelihood	133.5884	Hannan-Quinn criter.	-1.473628	Log likelihood	207.8819	Hannan-Quinn criter.	-2.358075			
F-statistic	2.218738	Durbin-Watson stat	2.323825	F-statistic	1.205580	Durbin-Watson stat	2.102203	F-statistic	2.845817	Durbin-Watson stat	2.047473			
Prob(F-statistic)	0.054882			Prob(F-statistic)	0.308865			Prob(F-statistic)	0.017184					

Dependent Variable: 1_3_8_10 Method: Least Squares Date: 08/01/16 Time: 23:10 Sample: 2002M07 2016M06 Included observations: 168					Dependent Variable: 1_4_7_10 Method: Least Squares Date: 08/01/16 Time: 23:12 Sample: 2002M07 2016M06 Included observations: 168					Dependent Variable: 1_5_6_10 Method: Least Squares Date: 08/01/16 Time: 23:13 Sample: 2002M07 2016M06 Included observations: 168				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022369	0.006351	3.474866	0.0007	C	0.017338	0.005307	3.287267	0.0013	C	0.013664	0.004612	2.962496	0.0035
CDAX_RF	-0.203773	0.133096	-1.576110	0.1170	CDAX_RF	-0.163375	0.111210	-1.442095	0.1512	CDAX_RF	-0.111410	0.096655	-1.158259	0.2507
SMB	-0.233070	0.212351	-1.097567	0.2740	SMB	-0.172452	0.177433	-0.971929	0.3325	SMB	-0.130756	0.154211	-0.847901	0.3977
HML	-0.297372	0.233366	-1.274273	0.2044	HML	-0.226234	0.194992	-1.160218	0.2477	HML	-0.259506	0.169472	-1.531261	0.1277
RMW	0.752448	0.485027	1.551353	0.1228	RMW	0.671118	0.405271	1.655978	0.0997	RMW	0.620531	0.352230	1.761721	0.0800
CMA	0.260356	0.496872	0.523990	0.6010	CMA	0.101400	0.415168	0.244238	0.8074	CMA	0.173407	0.360832	0.480576	0.6315
R-squared	0.076742	Mean dependent var	0.023094	R-squared	0.073758	Mean dependent var	0.018311	R-squared	0.073190	Mean dependent var	0.014484			
Adjusted R-squared	0.048246	S.D. dependent var	0.078245	Adjusted R-squared	0.045171	S.D. dependent var	0.065273	Adjusted R-squared	0.044585	S.D. dependent var	0.056713			
S.E. of regression	0.076334	Akaike info criterion	-2.272332	S.E. of regression	0.063782	Akaike info criterion	-2.651631	S.E. of regression	0.055434	Akaike info criterion	-2.912172			
Sum squared resid	0.943958	Schwarz criterion	-2.160762	Sum squared resid	0.659039	Schwarz criterion	-2.520061	Sum squared resid	0.497822	Schwarz criterion	-2.806602			
Log likelihood	196.8759	Hannan-Quinn criter.	-2.227052	Log likelihood	227.0570	Hannan-Quinn criter.	-2.586351	Log likelihood	250.8224	Hannan-Quinn criter.	-2.866891			
F-statistic	2.693119	Durbin-Watson stat	2.308203	F-statistic	2.580069	Durbin-Watson stat	2.171308	F-statistic	2.558614	Durbin-Watson stat	2.322057			
Prob(F-statistic)	0.022881			Prob(F-statistic)	0.028247			Prob(F-statistic)	0.029395					