BI Norwegian Business School - campus Oslo

# GRA 19502

## Master Thesis

Component of continuous assessment: Thesis Master of Science

Enhancement of Value Strategies using the Profitability Premium

Navn: Lukas Brockmann

Start: 02.03.2017 09.00

Finish: 01.09.2017 12.00

# I. Abstract

The profitability premium can enhance value strategies. The anomaly is still significant after adding a profitability- (RMW) and investment (CMA) factor to the (Fama & French, 1993, 2015) three factor regression. A combination of the four anomalies-- Book-to-Market Equity, Operating Cashflow, Gross Profit and Operating Profit-- in a Mean Variance Portfolio achieves significant out of sample returns compared to the market and other anomaly portfolios. This simple strategy realizes an annualized Sharpe ratio of 1.30 between July 1966 to June 2016 and is even significant after transaction costs. In addition, after implementing mutual fund restrictions (no short selling, minimum market capitalization) it still earns a significant monthly Alpha of 0.22% and is therefore suitable for retail- and institutional investors.

# II. Table of Content

# 1 Introduction

In the last few decades many researchers found anomalies in average stock returns that cannot be captured by the CAPM Model (Lintner, 1965; Sharpe, 1964).

Early studies find that stocks with a high Earnings/Price (E/P) ratio generate higher risk adjusted returns than stocks with a low E/P ratio (Basu, 1977; Jaffe, Keim, & Westerfield, 1989). The most prominent factors, which generate anomaly returns are the size and Book Equity to Market Equity (BEME) effect. The size effect shows that companies with a low market capitalization (small) have a higher average return than high market cap companies (big) (Banz, 1981; K. C. Chan, Chen, & Hsieh, 1985; Cook & Rozeff, 1984). The BEME anomaly achieves significant outperformance when someone invests in high BEME stocks and sells low BEME stocks short (Fama & French, 1992; Lakonishok, Shleifer, & Vishny, 1994; Rosenberg, Reid, & Lanstein, 1985). (Fama & French, 1992) presents evidence that used in combination, size and BEME have explanatory power and subsume the E/P effect. Based on these results (Fama & French, 1993) develop a three factor model, which adds a size factor (SMB) and a BEME factor (HML) to the market risk premium (MKT) in CAPM.

Since Fama & French published their paper in 1993, much ink has flowed on the topic of finding factors that can explain the cross-sectional differences in average stock returns. Prominent factors are the accruals effect by (Sloan, 1996), where high accruals predict lower returns, the stock issuance effect (Daniel & Titman, 2006; Loughran & Ritter, 1995; Pontiff & Woodgate, 2008) and the momentum anomaly, which shows that buying winner stocks and selling loser stocks leads to abnormal returns (C. S. Asness, Moskowitz, & Pedersen, 2013; Fama & French, 2012; Jegadeesh & Titman, 1993). Beside these three anomalies that cannot be captured by the FF3 model the profitability factor and investment factor have gathered recent attention, because they seem to add additional power in explaining the cross section of returns. The investment anomaly shows that firms that invest more have a lower average stock return than firms that invest less (Anderson & Garcia-Feijóo, 2006; M. J. Cooper, Gulen, & Schill, 2008; Fama & French, 2008; Lyandres, Sun, & Zhang, 2008; Titman, Wei, & Xie, 2004), while the profitability anomaly can be described as a pattern where highly profitable firms earn higher average returns than less profitable firms (Ball, Gerakos, Linnainmaa, & Nikolaev, 2015; Fama & French, 2006; Haugen & Baker, 1996; Novy-Marx, 2013).

The vast number of new anomalies that have significant intercepts in the FF3 model led to a broad discussion about its power. (Lewellen, Nagel, & Shanken, 2010) criticize the FF3 model in a way that factors explain only up to 80% of the cross-sectional variation and that the hurdle to find significant explanatory factors that have a high cross sectional $R^2$ is low. (Harvey, Liu, & Zhu, 2015) argue that the threshold to find significant factors is too small and suggest that a t-stat of 3 should be necessary to avoid data mining biases. New factor models that are based on profitability and/or an investment factor lead to better predictions than the FF3 Model (Hou, Xue, & Zhang, 2015; Novy-Marx, 2013). Based on the dividend discount model approach by (Miller & Modigliani, 1961) and the evidence about profitability and investment anomalies, (Fama & French, 2015) add a profitability factor (RMW) and an investment factor (CMA) to their three factor model. Building up on these recent findings this thesis first evaluates if the profitability premium of (Novy-Marx, 2013) can overcome the mentioned hurdles and if it is still significant in the FF5 model.

The negative correlation of value and profitability has led to a change in the Asset Management industry, where investment managers like AQR Capital and Dimensional have incorporated the new factor in their anomaly related products (Trammel, 2014). Inspired by these developments this thesis seeks to find an anomaly portfolio that outperforms the simple anomalies and existing value/profitability anomaly strategies (Ball et al., 2015; Novy-Marx, 2013).

The first part of this thesis presents the current literature and evaluates eight value and profitability factors which could be considered for a factor portfolio. In the first part of section 4 we see that the factors vary over time and therefore a portfolio, that adjusts the weights according to the current market conditions is the most promising. I decided to use the simple Mean Variance Portfolio approach by (Markowitz, 1952) to define each assets' weight. In the second part of section 4 I analyse the best factors and test if the value and profitability factors are still significant in the FF5 model. I find that the Gross Profit factor (Novy-Marx, 2013) is only significant in small and big size portfolios, while Operating Profit (Ball et al., 2015) is high and significant in all but one size quintile. Afterwards I present the portfolio results and find that a Mean Variance Portfolio achieves an Alpha of 0.54 per month which is highly significant with a t-stat of (7.38). The portfolios Sharpe ratio exceeds the Equal Weighted Portfolio by 0.14 and is more than 3 times larger than the Sharpe ratio of the market. I also investigate the effect of transaction costs on this strategy. The results suggest that the strategy is highly profitable, even after implementing the typical annual transaction costs of close to 2% associated with value stocks (Frazzini, Israel, & Moskowitz, 2012). The last section implements mutual fund restrictions and shows that even a portfolio with short selling restrictions achieves a significant Alpha of 0.22 per month and that risk adjusted ratios like Information-, Treynor-and Sharpe ratio are consistently high. In addition, I analyse the size attributes of this strategy and find that it has a tilt towards mid- and large cap stocks, which makes it suitable for the majority of investors and easier to implement for fund managers.

# 2 Literature Review

## 2.1 Value factors

There are several accounting measures to evaluate if a company's stock is over- or undervalued. The following paragraphs will discuss value factors that have been proven to be significant over a period from 1972 to 2012 (Hou et al., 2015) and factors from more recent studies that have an even higher predictive power. The eight value and profitability factors presented here will be tested in section 4.

### 2.1.1 Earnings to price ratio

One of the earliest papers to test the value strategy of (Graham, 1949) was (Basu, 1977) who tests if the Earnings Price (E/P) ratio can predict future excess returns. He finds that high E/P stocks earn higher average and risk adjusted returns than low E/P stocks. (Ball, 1978) undertakes a meta study consisting of nearly 20 studies that consider the E/P anomaly effect. He assumes that the future excess returns documented are due to the fact that E/P is a proxy for omitted variables in the two parameter model and that those have a positive correlation with expected returns. (Reinganum, 1981) tests the firm size and E/P Ratio effect on the AMEX and finds results in favor of both anomalies as proxy for missing factors in the CAPM. Nevertheless, he shows that the E/P effect is subsumed by the firm size effect. Connecting this result with (Ball, 1978) it would suggest that firm size has a higher positive correlation with expected returns. (Basu, 1983) argues that this result is due to the fact that the results of (Reinganum, 1981) do not consider systematic and total risk. He finds that high E/P firms outperform low E/P firms independent of firm size. By adjusting for risk and E/P ratios the firm size effect gets insignificant. (Banz & Breen, 1986) argue that the anomaly effect of E/P ratio and the mixed previous results between the firm size and E/P relation is due to the way researchers use the available COMPUSTAT data. They find evidence that COMPUSTAT data has a look-ahead bias (researchers use empirical data for allocation in January that are only available to investors in several months) and an ex-post selection bias (non-existing firms are excluded) which seems to be the reason for the E/P effect. (Jaffe et al., 1989) use a longer observation period from 1951 to 1986 and evaluate the firm size and E/P ratio effect separately. They try to avoid the look-ahead bias by taking end of fiscal year earnings and the price at the end of march. They also include firms that disappeared during the fiscal year to reduce the ex-post selection bias. They find a positive individual size and E/P effect during the observation period from 1951 to 1986. Like (Cook & Rozeff, 1984) they also introduce the January effect and find evidence that E/P is significant in every months, while firm size is only significant during January. By using Moody’s Industrial Manual (Davis, 1994) avoids the previous mentioned biases and investigates the time period before COMPUSTAT (1940 to 1963). He also finds evidence for the predictive power of E/P ratio especially in January, but not for firm size, which could be due to the exclusion of very low market cap stocks from his sample.

### 2.1.2 Operating Cash flow to price ratio

Company valuations are typically based on the dividend discount model or the discounted cash flow model (Miller & Modigliani, 1961) to define the intrinsic value of a company based on expected future dividends/cash flows. Such expectations are made on the current accounting values and market conditions as well as market participants expectations of future growth. Therefore, a higher reported cashflow should lead to a higher company valuation. (Wilson, 1987) was one of the first researchers to evaluate if cashflow has an additional effect to earnings, since the earnings announcement is released prior to the annual report. Using an event study approach, he found that abnormal returns increased if cash flows were higher in the annual report. His results were significant, but only for a small sample of firms and the period from 1981 to 1982. Contrary (Bernard & Stober, 1989) find no significant effect due to high cash flows during their 35 quarter observation period. (L. K. C. Chan, Hamao, & Lakonishok, 1991) create the cash flow to price ratio (CF/P) to set the cashflow into relation to its current stock price. A high CF/P ratio is hereby associated with a value stock since it implies that the price compared to one dollar of cash flow generated is too low. In their test period from 1971 to 1988 they test the CF/P and E/P ratio in the Japanese market. They believe that the CF/P ratio yields better information than E/P since managers use the optimal type of depreciation to minimize tax liabilities and meet shareholders' expectation. The impact of CF/P on expected future returns is high and significant, while E/P is insignificant. This might be due to Japanese legislation that allows accelerated depreciation, since we have seen that other studies find a significant E/P effect in the US market that is consistent and significant over time (Cook & Rozeff, 1984; Davis, 1994). (Lakonishok et al., 1994) find that value stocks sorted on Sales Growth (SG) and CF/P outperform growth stocks for a holding period of 5 years and that the sort on CF/P is even more profitable than the sort on high E/P. They show that the real growth rate of value (growth) stocks are higher (lower) than anticipated by the market, based on past growth rates. Surprisingly the additional abnormal return generated by value stocks is not associated with higher fundamental risk.

(Sloan, 1996) investigates how the composition of accruals and cash flow in earnings effect future returns. He tests if high (low) cash flows (accruals) are a good indicator for current and future earnings persistence, and finds support for his hypothesis. In addition, he shows that high cash flows generate significant abnormal returns. He concludes that investors are not completely able to distinguish the quality of earnings and growth in the future. This hypothesis is supported by (Dechow & Sloan, 1997) who find that real growth rates are lower than analysts' forecasts, but the market initially prices stocks based on these forecasts. This effect explains up to 50% of the E/P abnormal return for value stocks. (Richardson, Sloan, Soliman, & Tuna, 2005) confirm (Sloan, 1996) earnings persistency hypothesis for the period 1962 to 2001. A recent study by (Hui, Nelson, & Yeung, 2016) compares industry wide and firm specific effects of earnings. They show that industry wide earnings persistency is less noisy than firm specific earnings and in addition that the accruals and cash flow effect reported in early firm specific studies is consistent for industry wide earnings persistency.

The cash flow component of CF/P in these studies is normally defined by the earnings plus depreciation (Sloan, 1996). (Desai, Rajgopal, & Venkatachalam, 2004) argue that this measure does not fully represent the operating cash flows of a firm and construct the new factor CFO/P, where CFO is operating income minus depreciation minus accruals. They show that in the presence of CFO/P the effect of E/P and Book Equity to market equity (BEME) is subsumed and highly significant and that CFO/P has a higher predictive power than CF/P. Most recently (Foerster, Tsagarelis, & Wang, 2016) show that the direct method of computing operating cash flows leads to superior predictive power compared to the indirect method used in most articles. Nevertheless, the direct method to compute the operating cashflow is more demanding since we need the cashflow statements of companies. These filings are only necessary since 1987 in the USA, which would lead to a loss of 24 years of data. This is the main reason why I use the indirectly computed CFOP factor.

### 2.1.3 Net payout yield

Dividends have been a variable for empirical asset pricing models. For example (Fama & French, 1988) use the dividend to price ratio (D/P) and find that it has a higher predictive power than E/P. In addition the significance increase with an increase in time horizon. (Hodrick, 1992) uses the D/P in a vector autoregression model (VAR) and finds that it is able to predict expected returns to some degree. For a one year holding period (Kothari & Shanken, 1997) show that BEME as well as D/P can predict expected returns. While BEME is better over the whole sample period from 1926 to 1991, D/P ratio is better in the subperiod from 1941-1991. In recent years researchers find that the predictive power of dividend yield decreases, for example (Valkanov, 2003) shows that the D/P ratio does not have predictive power after 1981, but is significant during 1946-1980. Several other papers question the predictive power of the P/D ex-post 1984 (Goyal & Welch, 2003; Lettau &

Ludvigson, 2005). The decline in predictability could be due to a decrease in dividend payout to shareholders. (Fama & French, 2001) document that "cash dividends falls from 66.5% of earnings in 1978 to 20.8% in 1999". On the other side more and more firms buy back shares in the market. During 1980 to 2000 share repurchases increased from 13% to 113 % of paid dividends (Grullon & Michaely, 2002). We can see that firms change their payout policy towards shareholder. (Boudoukh, Michaely, Richardson, & Roberts, 2007) therefore argue that the CF/P ratio does not represent the total cash payout to shareholder. They introduce the variable net payout yield (NO/P) which consists of dividends plus repurchases minus equity issuance and is supposed to be a better predictor for expected returns than D/P. They show that the NO/P subsumes the D/P ratio in the cross section of returns and generates higher abnormal returns. Also under the framework of (Goyal & Welch, 2003) NO/P is significant out of sample while D/P is not.

### 2.1.4 Book to market Equity

The most common value factor is BEME (the value of book equity compared to the value of current market equity), which has been proven to have a positive relation with the average stock returns in the US (Rosenberg et al., 1985). (L. K. C. Chan et al., 1991) also find that BEME has a high predictive power in the cross section of average returns in the Japanese market. (Fama & French, 1992) discover that the two variables B/M and size can explain most of the cross section of variations in average stock returns for the four factors E/P, size, BEME and leverage. (Fama & French, 1995) further investigate the reasons for the predictive power of BEME under the aspects of associated risk and relation to earnings. They find that BEME is associated with long term profitability and that high BEME firms (undervalued) typically have depressed earnings and are therefore riskier than low BEME firms (high stock price), which sustain profitable. This theory is supported by (N. f. Chen & Zhang, 1998) who show that high BEME firms have high leverage, higher earning uncertainty and cut dividends more often, which is associated with financial distress. This effect is proven in the US and in other developed markets like Japan or Hong Kong, but is nearly nonexistent in the "growth markets" Taiwan and Thailand during their observation period from 1970 to 1993. They assume that this is due to the different relative riskiness of these markets. The suggested relation between risk and high

BEME firms differ compared to a study of (Dichev, 1998) who uses the (Ohlson, 1980) O-score, which consists of 9 accounting variables that are related to default risk, to test if firms in financial distress also outperform the market like high BEME stocks. The result suggest that this is not the case, which contradicts (N. f. Chen & Zhang, 1998) and (Fama & French, 1995) conclusions. However, in his study there was no additional separation between high and low BEME firms. (Griffin & Lemmon, 2002) find that firms with a high BEME ratio and high O-score do not perform better than firms that are only sorted on high BEME ratio. This indicates that the BEME ratio already captures the high O-score and that it does not have additional power in predicting future returns. On the other side low BEME firms with a high O-score perform worse than other high BEME firms. (Griffin & Lemmon, 2002) also mention that those firms have exceptional high capex and that the reason for the high O-score is due to low or negative earnings. We know that investment factors (for example capex) have a negative slope to future expected returns and are associated with lower systematic risk, e.g. a lower equity risk premium (Berk, Green, & Naik, 1999; Titman et al., 2004). They conclude that the low average returns of (Dichev, 1998) are driven by the bad performance of those low BEME stocks. (Campbell, Hilscher, & Szilagyi, 2008) use a dynamic logit model to estimate long term default probabilities and find that independent of size and value effects firms with high default probabilities have a negative alpha. It can be concluded from these results, that the risk based explanation for the BEME premium is not the main reason for the abnormal returns.

## 2.2 Profitability factors

While the value strategy buys firms with high book equity to market equity, e.g. where the investor can buy a larger quantitiy of assets for a certain amount and short growth firms, the profitability strategy buys firms which have high profitability and sells firms with low profitability. Both strategies earn abnormal returns (Ball, 1978; Fama & French, 2006). This is interesting since profitability is associated with attributes of growth companies (low BEME), but generates similar returns as value stocks (Fama & French, 1993). (Fama & French, 1995) further investigate this result using a ratio that scales earnings on common book equity (EI/BE) and find the same pattern. In detail they show that portfolios sorted on high firm size, low BEME ratios and high EI/BE generate the highest returns. In the cross-section of returns EI/BE even has a higher predicitve power than size.

This results are interesting for researchers, since profitability factors which are associated with growth stocks should have a negative correlation to value stocks and therefore might be a good hedge for these investment strategies. The following part will discuss four common profitability factors that have been proven to be significant in the the cross section of returns. Surprisingly (C. S. Asness, Frazzini, & Pedersen, 2014) even find in their research about quality stocks, which are characterised as high growth, high payout, high safety and high profitability, that profitability is the most persistent factor in the long US and international sample.

### 2.2.1 Return on Equity

The research of profitability factors started quite late. One of the first papers who identify a significant factor in the cross-section of returns is from (Haugen & Baker, 1996) who test the relation between net income to book equity (ROE). They find that high profitability firms outperform low profitability firms. (Cohen, Gompers, & Vuolteenaho, 2002) also find a positive relation between ROE and average stock returns after controlling for BEME. (L. Chen, Novy-Marx, & Zhang, 2011) construct a high-minus-low (HML) portfolio based on ROE and are able to generate significant average returns of 0.71% per month. In a regression of current return, B/M and ROE (Campbell, Polk, & Vuolteenaho, 2010) find that B/M and ROE can predict the expected return and that the past returns do not have predictive power. In their weighted least square (WLS) test BEME has the highest predictive power, followed by ROE. Interestingly they choose a long observation period of five years before portfolio formation and a two to five year holding period. The ROE therefore is based on the 5 year trailing average. In a recent study of (Chattopadhyay, Lyle, & Wang, 2015) ROE and BM are modeld together as an expected return proxy (ERP) and has proven to be reliable predictor of future stock returns in-sample and out-of-sample.

### 2.2.2 Return on Assets

(Novy-Marx, 2013) argues that “firms with productive total assets should yield higher average returns than firms with unproductive assets”. Following this logic firms with higher productivity are more profitable and investors demand a higher rate of return.

Therefore it makes sense to not only test variables based on the book equity of a company, e.g. ROE, but also on the productivity of the overall assets, which also takes liabilities into account. The most general way to test this assumption is using the simple measure of earnings scaled by total assets (ROA).

For example (Balakrishnan, Bartov, & Faurel, 2010) find positive abnormal returns for their HML portfolios based on ROA. The holding period in their test is relatively short with one and two months. (Stambaugh, Yu, & Yuan, 2012) show that ROA generated monthly excess returns (over the risk free rate) of 0.64% for the long strategy and 0.98% for the HML portfolio, both statistically significant, for the period from 1972 to 2008. (Wang & Yu, 2013) find a significant profitability premium for ROE and ROA after testing for information uncertainties and limits of arbitrage. They show that investors underreact to profitability news and that this is more likely to happen in firms when there is high information uncertainty and arbitrage costs. (Piotroski & So, 2012) also find that growth firms with high ROA generate median annual returns of 6.8%, but after controlling for expectation errors in their sample the value and profitability anomalies can not generate excess returns. This risk based argumentation is in line with (Dechow & Sloan, 1997), that market participants overestimate growths rates and do not evaluate the fundamental financial situation of a company. Nevertheless, the risk based explanation for value and profitability stocks is not the main focus of this thesis and therefore negligible in the selection of tested anomalies.

### 2.2.3 Gross Profit to Assets

(Fama & French, 2006) take earnings as a proxy for profitability in their dividend discount model. They find that this profitability factor does not enhance the predictive power of BEME and firm size. (Novy-Marx, 2013) argues that earnings is not a good proxy for future profitability since there are other measures, like human capital development, marketing and reasearch & development (R&D), that are all expected to have a positive impact on future profitability, but are accounted for as an expense. His main argument for gross profit is that it is the cleanest accounting measure and therefore represents the true economic profitability of a company. The study shows that GP/A has predictive prower in the cross section of expected returns and subsumes other profitability measures based on EBITDA, asset turnover or profit margins, that are all independently significant (Novy-Marx, 2013). The strategy earns monthly excess returns over Fama and French three-factor model (FF3) of 0.43% for the long leg and 0.66% for the HML strategy with t-stats larger than 4 (Stambaugh et al., 2012). (Kogan & Papanikolaou, 2013) show that the relation between GPA and BEME is negative, which is in line with (Novy-Marx, 2013) results of a negative correlation of -18%. Overall they confirm his results in their replication.

#### 2.2.4 Operating profitability to Assets

(Ball et al., 2015) investigate the predictive power of GP/A and find that operating profitability (OP/A) has the same predictive power and leads to higher future return than GP/A. They suggest that selling, general, and administrative expenses (XSGA) can also be directly associated with the revenue firms generate. Beside this (Weil, Schipper, & Francis, 2013) explain that there is no precise accounting standard that specifies how firms should allocate these expenses between COGS and XSGA. Taking both expenses into consideration should therefore lead to a higher predictive power (Ball et al., 2015). They find that the t-stats increase from 5.46 for GP/A to 8.92 for operating profit and that risk adjusted returns increase to 0.74% per month.

### 2.3 Transaction costs

Seeing the variety of stock market anomalies, one might wonder if these strategies are even applicable in an environment with trading restrictions and most of all transaction costs. Especially high turnover strategies, like momentum, should see a strong effect in their excess returns and could even be eliminated.

The two main attributes of trading costs are the direct costs that occur with the trade (commission) and the impact of the price change in the underlying (bid-ask spread). (Stoll & Whaley, 1983) investigate if the firm size effect still earns significant excess returns after implementing transaction costs. They conclude that the returns differ over the investment horizon. A horizon of one month leads to negative excess returns, while a horizon of one to twelve months only yields positive, insignificant excess returns. The main reason for this is that transaction costs (commissions plus bid ask spread) are inversely related to the firm size of a company. (Schultz, 1983) confutes those results, by finding significant excess returns after transaction costs, if he includes AMEX stocks into the analysis. (Knez & Ready, 1996) analyze buy and hold strategies as well as weekly rebalancing strategies for small size portfolios. They show that the bid-ask spread for small stocks between 1988 to 1992 is 5 to 11% and find support for their hypothesis that a buy-and-hold strategy is superior to frequent rebalancing. A practice to avoid high bid-ask spread stocks leads to an overall decline in anomaly returns, which let them conclude that the size effect partly exists since transaction costs make it difficult to exploit. (L. K. C. Chan & Lakonishok, 1995) investigate large institutional trades and find that firm size, trading volume and the company behind the trade are important factors to measure the total cost of trades. The average roundtrip cost for their sample period from 1986 to 1988 is 1.32%. In addition, they find that investment managers that have high turnover strategies and need immediate trades occur higher costs. A similar study is done by (Keim & Madhavan, 1997) from 1991 to 1993. They have average trading cost of 0.49% and compare three different investment styles: Value, Index and Technical. They show that strategies which need immediate execution (technical) have the highest costs with 0.71%, while value orders, which typically are limit orders have transaction costs of only 0.3% for buying stocks and even negative for selling stocks. More relevant for the value strategies is that costs for the smallest companies are the highest and strongly dependent on the trading size. If the traded package is lower than 0.16% of the overall stocks market capitalization for the lowest size quintile the trading cost are 0.39%, but increase to 1.13% if the traded package is ≤0.89%. Importantly, they also show that NASDAQs broker structure leads to up to 4 times higher buy costs (market cap <98mn.), but that the sell costs for NASDAQ stocks can be even negative, while they tend to be higher for NYSE and AMEX stocks.

The momentum effect, which strategy it is to buy winner stocks and short sell loser stocks, is an anomaly that has achieved high excess returns (Jegadeesh & Titman, 1993). This anomaly is one with a high turnover, since it is adjusted each month and therefore a good example for the impact of transaction costs. (Lesmond, Schill, & Zhou, 2004) find that the stock positions in momentum strategies are tilted toward high trading cost stocks and that the strategy returns do not exceed transaction costs. (Korajczyk & Sadka, 2004) compare equal weighted, value weighted and liquidity weighted momentum strategies. Equal weighted strategies perform the best before transaction costs and the worst after transaction costs. They show that net of price impact (only commission) momentum strategies earn significant excess return over the Fama and French 3 factor model (FF3), but that the additional price impact limits the exploitation of this strategy to $2bn. (value weighted). (Novy-Marx & Velikov, 2016) evaluate the roundtrip cost of trading strategies and presents a decline from 4.2% in the 1960s to 1.6% in the 1990s and below 1% between 2000 and 2009. They estimate that the cost of equal weighted portfolios is four times larger than the cost of value weighted portfolios and that a simple buy-and-hold strategy for annual adjusted portfolios is sufficient. At last the research of (Frazzini et al., 2012) with data from 1998 to 2011 based on a large investment firm in the US show that the average trading cost for annual rebalanced factors, like SMB, is 1.46% and has an additional price impact of 24.2 basis points (BP). They find similar results to (Keim & Madhavan, 1997) that a short execution time and the size of the order increases transaction costs. As expected the high turnover strategy momentum leads to annual trading costs of 3.51% and a price impact of 23 BP.

We have seen that the broader efficient market hypothesis of (Fama, 1991), which states that "the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs" (Fama, 1991) holds for several anomalies, but not all. Further, efficient implementation strategies and a continuous decrease in transaction costs make it possible to exploit anomalies, even some high turnover strategies (Frazzini et al., 2012).

# 3 Methodology

Section 3 presents the anomaly related hypothesis that will be tested in the US stock market. The first part presents the data used for the thesis. The creation of each factor is described in detail in Appendix A. Afterwards the commonly used regression models will be presented and evaluated. The last section explains the portfolio creation method used in this thesis.

## 3.1 Research Question

Several papers show that there is a value- and profitability premium in the market. (Novy-Marx, 2013) presents evidence that these premia tend to be negatively correlated and that therefore profitability should be able to hedge value strategies. On the other side, new factor models are designed to better capture anomalies related to profitability and investments than the simple Fama and French 3 factor (FF3) model (Fama & French, 2015; Hou et al., 2015). Therefore, the main research question is:

Is the profitability premium still significant in the FF5 model and if so, can a combination of value and profitability factors outperform previous strategies?

In addition to this research question, I want to investigate the following mutual fund related hypotheses:

H1: Transaction costs eliminate anomaly returns.

H2: Short selling restrictions eliminate anomaly premia.

H3: A portfolio based on long only anomalies cannot beat the market.

H4: A long only anomaly portfolio is tilted towards small stocks.

By doing this the Thesis becomes more applicable to a broader range of investors. The self-financing anomaly portfolios can be difficult to implement and therefore are only feasible for hedge funds and large institutional investors which have the necessary resources. The mutual fund restrictions simplify the strategy and guarantee an easier implementation, which makes them suitable as an ETF product or mutual fund investment strategy.

## 3.2 Data

The thesis follows the structure of (Ball et al., 2015; Novy-Marx, 2013). The monthly stock returns are obtained from Center for Research in Security Prices (CRSP) and accounting data from COMPUSTAT. The sample consists of all ordinary common shares of firms that are traded on AMEX, NASDAQ and NYSE.

### 3.2.1 Delisting returns

(Beaver, McNichols, & Price, 2007) argue that delisting returns have a high effect on investment strategies and are often not considered in the evaluation of value strategies, especially BEME, CF/P and E/P. They find that the spread between the highest and lowest decile increases if delisting returns are included and that low deciles decrease more than high deciles. Most researchers after the year 2000 include the delisting returns that are now provided through CRSP, but there is no real consensus about delisted firms that are not reported by CRSP and are related to forced delisting, for example bankruptcy or insufficient assets. (Sloan, 1996) assumes a return of -100% while (Piotroski, 2000) assumes 0% and some even exclude delisted firms from the sample (Hribar & Collins, 2002). (Shumway & Warther, 1999) report a negative return for delisted and missing firms for the NASDAQ of -55%. Since this paper uses AMEX, NYSE and NASDAQ data the average delisting returns over all three stock exchanges of -30% found by (Shumway, 1997) is used. The CRSP delisting codes identify liquidations (delisting code: 400 to 490) and should therefore make it possible to avoid the ex-post selection bias (Banz & Breen, 1986).

### 3.2.2 Data usage

I match the data between COMPUSTAT and CRSP with a 6 months' lag for COMPUSTAT data. This is necessary to avoid look-ahead bias. The look-ahead bias theory was first researched by (Banz & Breen, 1986) and is related to the way COMPUSTAT treats accounting data. For example, the annual report is not available at the end of the fiscal year but only several months afterwards, typically during the first 6 months. But COMPUSTAT adds the accounting data to the end of the company's fiscal year when it gets available.

The look-ahead bias is therefore present in the data if the researcher forms the portfolio in January based on the end of fiscal year data provided by COMPUSTAT. For example, when historical data from COMPUSTAT is used to sort portfolios on high E/P (firms that have a low market equity compared to earnings) at the end of the company's fiscal year, the high earnings from the future annual report are considered, but the current, lower share price. This generates a certain return and therefore leads to the look-ahead bias. Several papers use a lag of 4 months for annual data (Bradshaw, Richardson, & Sloan, 2006; Hirshleifer, Hou, Teoh, & Zhang, 2004; Hou et al., 2015; Jaffe et al., 1989; Piotroski & So, 2012) or 6 months (Ball, Gerakos, Linnainmaa, & Nikolaev, 2016; Fama & French, 1995; Gerakos & Linnainmaa, 2016; Novy-Marx, 2013). It seems that researchers are indifferent about the lag of four or six months, since there is no literature available that focuses exclusively on this topic. The (U.S. Securities and Exchange Commission, 2009) requires companies to file Annual reports (10-K) up to 90 days after their fiscal year. Taking the first April (fourth month) might be more reasonable. On the other side if companies report later because of good reasons we would exclude them from the sample. Beside this Fama and French use June to form the portfolios. Since researchers are indifferent and it would be a lot of work to reconstruct the regression models with reallocation in the end of April I will use the end of June for my factor creation.

### 3.2.3 Sample period

I set the sample period from January 1962 to December 2016. This is due to the inclusion of the American Stock Exchange (AMEX) to COMPUSTAT in 1962 (Jaffe et al., 1989). Another reason is that Book Equity data prior to 1962 is sometimes missing and also the possible selection bias towards large corporations described by (Fama & French, 1992). Using the six-month lag after the end of fiscal year the asset pricing tests start for a period from July 1963 through December 2016. The only exemptions are ROA and ROE, which need two years of existing data and start in July 1964. I will also exclude financial firms, because the high leverage of those firms do not have the same meaning than high leverage in normal companies (Fama & French, 1992). Even though this might be true (Novy-Marx, 2013) does not find a significant difference in his results excluding financial firms. Since he does not apply factors that are based on leverage but only on price or total assets this might be reasonable. If there would be a measure that focuses on financial distress, like the O-Score (Ohlson, 1980) the results could be different. Financial firms are identified as companies with a one digit standard industrial classification (SIC) code of six.

Companies are included, when they have the following data available on the day of portfolio formation. The past performance for the last one month r(1,0) and 12 to two months r(2,12), firm size log(ME), the value factors BEME, E/P, CFO/P, NO/P and profitability factors ROA, ROE, GP/A, OP/A. The detailed accounting data needed and the computation of those factors is described in Appendix A. The Appendix also gives insight into the formation of deciles and the creation of the 25 BEME portfolios.

## 3.3 Pearson and Spearman correlation

We first evaluate which factors might be a good hedge for one another. There are several ways to measure the relation between two variables. The Pearson correlation shows the linear relation between two variables (Pearson, 1895), where -1 indicates a negative relation, 0 no relation and 1 a total positive relation (Lee Rodgers & Nicewander, 1988). Equation 1 shows the function for two variables $X$ and $Y$, where $X_i$ and $Y_i$ are the individual values at each observation $i$ and $\bar{X}$ and $\bar{Y}$ are the respective means for the whole sample.

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{[\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2]^{\frac{1}{2}}} \quad (1)$$

The Spearman correlation measures the strength and direction of a monotonic relationship (can be linear or not) between two variables. This means that the behavior between the variables is analyzed rather than the linear relation (Pearson). The Spearman correlation measures the Covariance between the Pearson correlation for ranked variables. The main advantage of this is that a small quantity of outliers do not falsify the relation between the two variables (Spearman, 1904).

$$\rho = 1 - \frac{6 \sum {D_i}^2}{n(n^2 - 1)} \quad (2)$$

, where $D_i$ represents the difference between the ranked pairs at each observation $i$ and $n$ is the number of rank pairs (Corder & Foreman, 2014). An advantage of the Spearman correlation is that it can also be used for non-monotonic data. (Maslov & Rytchkov, 2010) show that all their nine tested anomalies have a non-monotonic relationship, which would support the use of the Spearman correlation over the Pearson correlation. Since I am not visualizing the data, I cannot distinguish between the monotonic and linear relationship of the factors. Therefore, I will use both measurements and evaluate the patterns.

## 3.4 Regression Models

The literature has proven that the eight presented anomalies explain the cross section of expected returns. Besides CFOP, which is the oldest measure from 2004, all factors have been tested in the last 3 years, which makes it unreasonable to compare the sample and post sample period. Therefore we are not looking at the Fama MacBeth cross sectional regression model (Fama & MacBeth, 1973), but instead analyze the recent Fama French 5 factor (FF5) model (Fama & French, 2016) more thoroughly. All results in this paper are based on the FF5 model. For explanations in factor loadings and impact of new factors the CAPM model (Sharpe, 1964) and the Fama French 3 factor (FF3) model (Fama & French, 1993) results are also presented.

### 3.4.1 CAPM

The capital asset pricing model (CAPM) was first introduced by (Sharpe, 1964) and is the first regression model to set the return of a security in relation to the market return based on its risk characteristics, e.g. the Beta to the market risk premium. He argues that individual stocks behave in a linear relation to the market index. The regression is presented in equation 3

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + \varepsilon_t \quad (3)$$

, where $R_t$ is the monthly portfolio return, $R_{Ft}$ is the 1 month T-Bill rate and $R_{Mt}$ is the value weighted return of all stocks listed on NYSE, AMEX and NASDAQ. As mentioned before, the anomalies cannot be explained by the market risk premium alone and more complex regression models are necessary to capture their return characteristics.

### 3.4.2 Fama French 3 Factor model

The paper of (Fama & French, 1993) is probably the most influential paper of the last 30 years and shifted the research in finance from pure hypothesis testing to actually analyzing the data and try to find ways to improve predictive models.

Their 3 Factor model (FF3) is based on the factors: Market risk premium (MKT), Small minus Big (SMB) and High minus low (HML). The regression is presented in equation 4.

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + \varepsilon_t \quad (4)$$

, where $R_t$ is the return of the portfolio, $R_{Ft}$ is the 1 month T-Bill and $R_{Mt}$ is the value weighted return of all stocks listed on NYSE, AMEX and NASDAQ. SMB is measured as the average return on the three small portfolios (value, neutral, growth) minus the average of the three big portfolios. HML is the average of small value and large value stocks minus the average of small growth and large growth stock returns. $\alpha$ is the intercept und $\varepsilon_t$ is the error term, which is assumed to be IID.

The reasoning behind the model is to capture the stock price variations that the CAPM (Lintner, 1965; Sharpe, 1964) cannot explain. This is achieved if the intercept $\alpha$ is zero. In their paper (Fama & French, 1996) show in table 1 that the intercepts are relatively small, between -0.45 and 0.2 and significant, which indicates that the model is not perfectly able to capture average returns, but seems to be able to capture most of them. The high $R^2$ and t-stats explain the variation of returns over time, e.g. if we have a high $R^2$ for one factor it would indicate that it explains well the covariance, but it does not explain the mean. The $\alpha$ instead shows the variation across portfolios in average returns, which is more relevant than $R^2$ and high t-stats in explaining the model. To test if all $\alpha$ are jointly zero Fama and French use the F-test (Gibbons, Ross, & Shanken, 1989) and have to reject their hypothesis on a 0.004 level (Fama & French, 1996).

### 3.4.3 Fama French 5 Factor model

Based on recent research form investment anomalies (Anderson & Garcia-Feijóo, 2006; M. J. Cooper et al., 2008; Titman et al., 2004), which typically have a negative slope to average returns and the profitability premium (Novy-Marx, 2013), (Fama & French, 2015) introduce an investment factor (CMA) and profitability factor (RMW).

Equation 5 shows the five factor regression model where the first three factors are computed as in (Fama & French, 1993).

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t \qquad (5)$$

The new variables are constructed as followed. They first get sorted on size and afterwards on operating profitability for $RMW$ (robust minus weak) and investments for $CMA$ (Conservative minus aggressive). The procedure is the same as for HML, for $CMA_t$ they take the average of small conservative and big conservative stocks and subtract the average of small aggressive and big aggressive stocks. $RMW_t$ is the average of small robust and big robust minus the average of small weak and big weak.

Beside the double sorted portfolio on size and momentum, the intercepts for all other portfolios decreases with the introduction of the FF5 model and vary in a range from 0.098 to 0.126 (Fama & French, 2016) (table 2). (Hou, Xue, & Zhang, 2014) compare the FF5 model with their four factor model, consisting of the factors MKT, size investment and ROE, which is based on a corporate finance approach (q-theory) rather than the asset pricing theory (APT) used for FF5 and find that their model can effectively capture all FF5 factors, without using HML. (Fama & French, 2016) also highlight that the HML factor is redundant in the presence of the profitability and investment factor. (Wahal, 2016) investigates the pre-1963 period and proves that HML is relevant in the FF5 model during this sample period. (C. Asness & Frazzini, 2013) argue that the redundancy of HML is due to its construction. They construct the HML factor based on current prices instead of prices with a 6 months' lag and in addition add the momentum anomaly as a sixth factor. As a result, HML is significant again, but CMA is not. Even so (Hou et al., 2015) might be a more reliable model than FF5, since it can also capture the momentum anomaly, there is no database available and to create the model based on a triple sort on size, investment and ROE I would need quarterly accounting data. This leads me to the decision to use the FF5 model. This can be justified by the fact that I am not implementing the momentum factor or a sort on momentum in my portfolios, which FF5 fails to capture.

In a recent discussion the profitability and investment factors were further analyzed in their ability to forecast future investment opportunities. (Fama & French, 2008) argue that their asset growth variable used in CMA is not robust in predicting future stock market returns. (I. Cooper & Maio, 2016) support this argument, but show that CMA is good at predicting the future economic activity. They find that both variables add additional information to the existing three factor framework. In addition (Barroso & Maio, 2017) present evidence that both factors have a positive in sample risk return tradeoff, while this effect is negative for the size and momentum factor. From this discussion, I conclude that it is useful to base my reasoning on regression results of the FF5 model rather than the CAPM or FF3 model.

## 3.5 Mean Variance Portfolio

The indication of this thesis is to see if the combination of anomalies improves the overall results of value strategies and possibly exceeds previously achieved risk adjusted factor portfolio results. (Novy-Marx, 2013) shows that a combination of value and profitability strategy improves the performance, due to a negative correlation. Section 4 tests eight anomalies and identifies four promising value and profitability strategies. Besides implementing an equal weighted (EW) portfolio, it might be interesting to test if an allocation based on a mean variance portfolio optimization can outperform the individual factors and the EW portfolio. The mean variance portfolio strategy is based on (Markowitz, 1952) and in my case I am going to use the 'efficient frontier of risky assets', which yields the perfect mean variance (MV) portfolio for a desired expected return, based on the assets risk/return characteristics. For this I need the following expected return equation.

$$E(r_p) = \sum_{i=1}^{n} w_i \times E(r_i) \tag{6}$$

, where n is the total number of assets, $w_i$ the weight of asset $i$ in the portfolio and $E(r_i)$ the expected return of each asset in sample. The portfolio variance is presented in equation 7.

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Cov(r_i, r_j) \tag{7}$$

, where $\sigma_p^2$ is computed based on the covariance matrix between all assets, $i \ to \ n$ and $j \ to \ n$. The Covariance of the same asset is the variance ($Cov(r_i, r_i) = \sigma_i^2$). Even so the portfolio is called Mean Variance portfolio, this is only due to the technique of (Markowitz, 1952) to optimize the portfolio, the MVP used in this thesis maximizes the risk adjusted return, e.g. Sharpe ratio, instead of minimizing the in sample variance. The purpose is to achieve a high out of sample risk adjusted return. Under the assumption that a high in sample risk adjusted return leads to a high out of sample risk adjusted return we should maximize the Sharpe ratio, which is computed as in equation 8 (Bodie, Kane, & Marcus, 2014).

$$Sharpe \ ratio_p = \frac{E(r_p) - r_f}{\sigma_p} \tag{8}$$

, where $\sigma_p$ is the portfolio standard deviation and $r_f$ the risk-free rate. In my computations, all returns are already deducted by the risk-free rate. Depending on computational results the mean variance portfolio will be based on a rolling window or extending window.

# 4 Results

The first part of section 4 discusses all value and profitability factors, based on their descriptive statistics, correlation and excess return over common regression models. After deciding on the most suitable two value and two profitability factors I will construct double sorted portfolios based on size and the individual factor. In addition, I analyze if a portfolio based on these factors leads to superior risk adjusted performance compared to the market and other scientific results. There is a broad discussion about the after-transaction cost performance of anomaly strategies. This makes it reasonable to see if the developed portfolio yields excess returns after the implementation of these costs. In a last step, there is a discussion about constructing anomaly portfolios with a short selling restriction to make it available to smaller institutional- and retail investors. Beside the risk return characteristics, the market capitalization of the strategy will be reviewed, since mutual funds tend to have minimum market capitalization requirements to consider a stock/fund/ETF for their portfolio and anomaly strategies tend to be tilted towards small stocks (Fama & French, 1993).

## 4.1 Selecting Factors

### 4.1.1 Descriptive statistics and regression intercepts

In most factors, the returns increase with the rank of the decile, where the lowest decile generates the smallest return and the highest decile the best return. This case is especially present in the case of ROE, where the lowest decile generates an average insignificant excess return of 0.08, while the second decile already earns 0.38. In general, the profitability factors do not increase as steadily as the value factors over the deciles, for example the 6$^{th}$ decile of ROA earns a return of 0.58, while the highest decile only earns 0.48. This suggests that firms that are medium to highly profitable yield similar future returns, while firms who reported bad earnings will underperform in the next year. This effect increases in the sales dependent variables gross profit (GPA) and operating profit (OP). It indicates that low sales or high sales related expense, e.g. a low gross profit margin leads to underperformance, or even negative performance in the case of the lowest OP decile. The HML portfolios for value are lower than most profitability factors, this is based on the significantly lower returns in the lowest profitability decile, rather than the long only portfolios. As observed before, the top 50% of the profitability portfolios only vary a bit, while the value portfolios steadily increase, which makes long only portfolios more profitable.

In the last column, I present the average number of observations for each factor. This number increased from 670 observations in 1963 for the NOP factor to a maximum of 6110 observations for EP in 1998 and declined in the 2000s to an average of 3300 for all factors. The number of observations for NOP are quite low, since not all companies pay dividends or buy back shares, especially small market capitalization companies. The average number is still 1691, which is enough to create a HML portfolio with 338 stocks. Table 1 also presents the significance level of the means. The t-stats are computed as in equation 10 (Brooks, 2014).

$$t - stat = \frac{\hat{\propto} - \propto}{SE(\hat{\propto})} \tag{9}$$

, where $\hat{\propto}$ is the estimated intercept and $SE(\hat{\propto})$ is the sample standard error. The hypothesis for this test is that the mean of the decile returns is equal to zero. As we can see most of the returns are significantly different from zero above the 5$^{th}$ decile. Surprisingly only the High Minus Low (HML) portfolios of GPA and OP are significant at the 1% level which indicates that the other HML portfolios either achieve a to low return, due to a relatively high return in the lowest decile portfolio, for example CFOP (0.57) and BEME (0.42) or that the standard deviation is not as small as expected for a self-financing portfolio.

**Table 1 Return Distribution**

All High Minus Low (HML) factors are combinations of long 10th decile and short 1st decile. Two exceptions are BEME and EP, which are based on the lowest and highest quintiles (Fama & French, 1993; Hou et al., 2015). All decile returns are excess returns, deducted by the 1 month risk free rate. The returns are presented in percentage. For an easier implementation, I only use value weighted excess returns to compute the decile returns. The average number of observations per factor is presented in the last column. The t-stat with the hypothesis that the mean is zero is presented in the row below each factor decile return.

| | | Percentiles | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Factor | HML | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | N |
| BEME | 0.34 | 0.42 | 0.39 | 0.55 | 0.49 | 0.56 | 0.59 | 0.72 | 0.72 | 0.76 | 0.73 | 3597 |
| | *1.87* | *1.98* | *1.97* | *2.98* | *2.62* | *3.12* | *3.15* | *3.92* | *3.90* | *3.65* | *3.59* | |
| EP | 0.47 | 0.37 | 0.25 | 0.33 | 0.19 | 0.49 | 0.56 | 0.59 | 0.73 | 0.81 | 0.74 | 3677 |
| | *1.71* | *1.18* | *0.91* | *1.32* | *0.82* | *2.38* | *3.18* | *3.36* | *4.21* | *4.45* | *3.72* | |
| CFOP | 0.20 | 0.57 | 0.44 | 0.34 | 0.26 | 0.24 | 0.46 | 0.65 | 0.68 | 0.80 | 0.77 | 3670 |
| | *1.33* | *2.02* | *1.66* | *1.41* | *1.13* | *1.06* | *2.49* | *3.96* | *4.27* | *4.51* | *3.71* | |
| NOP | 0.23 | 0.36 | 0.50 | 0.43 | 0.43 | 0.54 | 0.61 | 0.62 | 0.69 | 0.72 | 0.58 | 1691 |
| | *1.6* | *1.67* | *2.37* | *2.12* | *2.35* | *3.10* | *3.56* | *3.71* | *4.16* | *4.04* | *3.06* | |
| ROE | 0.43 | 0.09 | 0.39 | 0.57 | 0.49 | 0.54 | 0.52 | 0.47 | 0.51 | 0.52 | 0.52 | 3341 |
| | *1.82* | *0.25* | *1.4* | *2.4* | *2.3* | *2.87* | *2.93* | *2.59* | *2.74* | *2.83* | *2.54* | |
| ROA | 0.25 | 0.24 | 0.40 | 0.40 | 0.54 | 0.53 | 0.59 | 0.51 | 0.51 | 0.48 | 0.49 | 3415 |
| | *0.99* | *0.69* | *1.36* | *1.7* | *2.54* | *2.86* | *3.29* | *2.83* | *2.84* | *2.58* | *2.48* | |
| GPA | 0.55 | 0.14 | 0.44 | 0.44 | 0.44 | 0.61 | 0.51 | 0.50 | 0.52 | 0.65 | 0.69 | 3630 |
| | *3.07* | *0.56* | *2.53* | *2.24* | *2.27* | *3.28* | *2.57* | *2.42* | *2.57* | *3.47* | *3.62* | |
| OP | 0.60 | -0.04 | 0.17 | 0.31 | 0.39 | 0.49 | 0.52 | 0.48 | 0.56 | 0.59 | 0.55 | 3161 |
| | *2.42* | *-0.13* | *0.6* | *1.3* | *1.75* | *2.41* | *2.67* | *2.67* | *2.85* | *3.25* | *2.84* | |

I further investigate how volatile the HML portfolios are and if they are able to achieve Alpha in the simple CAPM (Lintner, 1965; Sharpe, 1964), the Fama French 3 factor model (FF3) (Fama & French, 1993) and the more recent Fama French 5 factor model (FF5) (Fama & French, 2015).

In table 2 we can see that the volatility of profitability strategies is higher compared to value, so that the good HML results mentioned in table 1 are nearly offset due to a lower annualized Sharpe ratio. The highest Sharpe ratios are given by BEME and EP which both achieve 0.34 for the value factors and 0.42 for the profitability factor GPA. The OP Sharpe ratio is nearly as good as the best value factors with a ratio of 0.33.

The CAPM measures the factor market exposure, by regressing the factor on the market risk premium ($mkt - rf$). In a perfect market the CAPM should be able to generate an intercept of zero. Table 2 shows that all intercepts diverge largely from zero in the CAPM, which indicates that it does not have power in the cross-section of average returns. (Fama & French, 1993) justify this assumption by presenting intercepts that diverge from zero on 25 size and BEME sorted portfolios. They create two additional factors to capture the size effect (SMB) and the book equity effect (HML). To test if the new variables help to explain the cross section of returns they use the F-Test from (Gibbons et al., 1989), which tests with a certain confidence level if the joint intercepts of all regressions are zero. Even so most of the intercepts of 25 portfolios are in fact zero the F-test is still rejected at the 95% level. The rejection is only due to large BEME stocks (growth stocks). The model overestimates large growth stocks (-0.34%) and underestimates small growth stocks (0.21%) (Fama & French, 1993).

The $R^2$ shows how much of the variance of the dependent variable, in Fama and French's case each of the 25 portfolios, can be explained by the independent variable. If $R^2$ is one it means that the linear regression model perfectly estimates the portfolio returns, if it is zero the independent variables do not have any impact and only the intercept explains the returns (Brooks, 2014).

$R^2$ is computed as in equation 9.

$$R^2 = 1 - \frac{\sum_i {\varepsilon_i}^2}{\sum_i (y_i - \hat{y})^2} \tag{10}$$

, where $\sum_i {\varepsilon_i}^2$ is the sum of squared residuals and $\sum_i (y_i - \hat{y})^2$ the total sum of each data point minus the mean squared.

The high average $R^2$ of 93% for all regressions, where the lowest is a big, high BEME portfolio with $R^2$ of 81% show that in fact big stocks are problematic for the model (Fama & French, 1996). In table 2 the presented intercepts give us the exact same picture. The intercepts of value stocks are reduced and even slightly negative for BEME and the intercepts of profitability stocks increase due to the construction of the model to capture undervalued stocks. I assume that operating cashflow (CFOP) cannot be captured by the additional SMB and HML variables since it is based on working capital, e.g. the reversed accrual effect of (Sloan, 1996). In table 4 we can also see that the Pearson correlation with BEME is -0.04, which indicates that a BEME independent variable should not be able to capture CFOP.

(Fama & French, 2015) develop a 5 factor model which adds two variables, one to capture profitable stocks, RMW and one to capture investment anomalies, which typically have a negative slope to expected returns (M. J. Cooper et al., 2008; Titman et al., 2004), CMA. We can see that it is able to bring BEMEs intercept to zero and reduce all profitability related variables significantly. Even so it corrects the flaws of FF3 to capture growth stocks it still is not able to predict perfectly the average returns of my factors. OP still has an alpha of 0.66 per month and surprisingly the simple ROE factor also earns a premium of 0.37. The regression is able to reduce the GPA premium to a mere 0.20. The value factor CFOP is only slightly effected and decreases to 0.33, which is in line with (Fama & French, 2016) result that they are not able to capture the accrual premium. NOP stays constant at 0.17.

**Table 2 Regression intercepts and factor volatility**
Column two presents the excess return after deducting the 1 month risk free rate. STD is the volatility in percentage per month. Column three presents the annualized monthly Sharpe ratio and in the last columns the regression intercepts. The regressions are estimated monthly using data from July 1963 through June 2016. The t-stats are presented below the corresponding row for each factor.

| Variable | Excess Return | STD | Sharpe Ratio | α CAPM | FF3 | FF5 |
|---|---|---|---|---|---|---|
| BEME | 0.34 | 3.50 | 0.34 | 0.38 | -0.08 | 0.004 |
| | (1.87) | | | (2.76) | (-0.92) | (0.04) |
| EP | 0.47 | 4.85 | 0.34 | 0.66 | 0.43 | 0.22 |
| | (1.71) | | | (3.61) | (2.57) | (1.40) |
| CFOP | 0.20 | 3.78 | 0.18 | 0.33 | 0.36 | 0.33 |
| | (1.33) | | | (2.31) | (2.67) | (2.36) |
| NOP | 0.23 | 3.56 | 0.22 | 0.31 | 0.17 | 0.17 |
| | (1.60) | | | (2.26) | (1.23) | (1.26) |
| ROE | 0.43 | 5.92 | 0.25 | 0.65 | 0.86 | 0.37 |
| | (1.82) | | | (2.87) | (4.33) | (2.33) |
| ROA | 0.25 | 6.36 | 0.14 | 0.49 | 0.73 | 0.29 |
| | (0.99) | | | (2.01) | (3.49) | (1.59) |
| GPA | 0.55 | 4.53 | 0.42 | 0.64 | 0.72 | 0.21 |
| | (3.07) | | | (3.56) | (4.04) | (1.48) |
| OP | 0.60 | 6.21 | 0.33 | 0.84 | 1.12 | 0.66 |
| | (2.42) | | | (3.62) | (5.83) | (3.86) |

### 4.1.2 Regression analysis

In table 3 we see that the intercept of BEME is insignificant and therefore equal to zero. Interestingly when SMB and HML are present, the MKT factor does not have any explanatory power, which implies that CAPM cannot capture the BEME effect and supports the market inefficiency hypothesis. Looking at the other value factors only EP and CFOP have t-stats larger than 2 and their intercepts are therefore significant at the 5% level. It is worth to notice that those factors have a low, but significant negative loading on SMB, which means that they cannot be explained by the size anomaly and are rather medium to large market capitalization companies. In all factors besides BEME the table presents significant negative loadings on the market risk premium (MKT), which is understandable since all presented factors have proven to be anomalies to the CAPM. Besides this MKT is the only long only variable in this regression. By using HML portfolios the MKT variable will have difficulties to measure the returns of combined long and short positions. As expected all profitability factors have high negative loadings on SMB and HML, which indicates that they are growth companies (low BEME and big size). The negative loadings on all factors for the profitability variables also indicates that this model is not perfect to capture those returns which makes it reasonable that all intercepts are high and significant at the 1% level. The $R^2$ for the factors are low, only the BEME factor has a $R^2$ larger than 0.6. (Fama & French, 1993) have shown that on average $R^2$ is higher than 0.9 in their 25 double sorted size and BEME portfolios, but they also find that the extreme deciles have the lowest $R^2$. By using a hedged portfolio based on those deciles the predictability of the factor model decreases further. This leads me to the conclusion that $R^2$ is not a good statistical measure in this test, but rather an indicator of model improvement from FF3 to FF5. In FF3 all profitability factors have a $R^2$ lower than 0.42 and GPA even has an $R^2$ of only 0.05.

**Table 3 Fama French three factor loadings**

This table shows monthly value-weighted average excess returns to portfolios sorted on the eight anomaly variables. Variables are created as in Appendix A. Panel A presents regression results of FF3 with the individual factor loadings and t-stats to test which factors are significant in each model.

FF3 regression: $R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t$

The last column, presents the $R^2$ of each regression.

| | Alphas and three-factor loadings | | | | |
|---|---|---|---|---|---|
| Variable | Intercept | MKT | SMB | HML | $R^2$ |
| BEME | -0.08 | 0.01 | 0.35 | 0.94 | 0.62 |
| | (-0.92) | (0.32) | (11.95) | (29.72) | |
| EP | 0.43 | -0.22 | -0.28 | 0.62 | 0.27 |
| | (2.57) | (-5.47) | (-4.89) | (10.10) | |
| CFOP | 0.36 | -0.17 | -0.44 | 0.09 | 0.22 |
| | (2.67) | (-5.21) | (-9.65) | (1.81) | |
| NOP | 0.17 | -0.14 | 0.07 | 0.31 | 0.11 |
| | (1.23) | (-4.26) | (1.58) | (6.26) | |
| ROE | 0.86 | -0.29 | -0.93 | -0.12 | 0.33 |
| | (4.33) | (-6.11) | (-14.15) | (-1.67) | |
| ROA | 0.73 | -0.30 | -1.07 | -0.13 | 0.36 |
| | (3.49) | (-6.10) | (-15.47) | (-1.72) | |
| GPA | 0.72 | -0.15 | -0.20 | -0.13 | 0.05 |
| | (4.04) | (-3.60) | (-3.40) | (-1.99) | |
| OP | 1.11 | -0.31 | -1.15 | -0.21 | 0.42 |
| | (5.83) | (-6.85) | (-17.99) | (-2.98) | |

In table 4, I analyze if the two new factors in FF5, RMW and CMA, improve the FF3 model and more importantly if they can capture some of the profitability factors cross sectional returns, which FF3 is not able to do. The first thing to notice is that for all eight factors SMB decreases, which indicates that RMW and CMA can capture the size effect to some extent. For the value factors, it is a mixed picture, the factor loadings of BEME for HML and SMB do not change much and are still significant. CMA does not enhance the predictability, but the profitability factor has a significant negative effect on BEME. Now the intercept is effectively zero and insignificant. I conclude that this model perfectly models the BEME effect. The value factors CFOP and EP have high loadings on RMW, which makes sense since they are both constructed based on earnings, which is related to operating profitability. Their intercepts decrease and only CFOP is still significant for the four value factors. In my opinion NOP is the most interesting value factor in the FF5 regression.

**Table 4 Fama French 5 factor loadings**
This table shows monthly value-weighted average excess returns to portfolios sorted on the eight anomaly variables. Variables are created as in Appendix A. The table presents regression results of FF5 with the individual factor loadings and t-stats to test which factors are significant in each model.
The last column, presents the $R^2$ of each regression.
FF5 regression:

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t$$

| | Alphas and five-factor loadings | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Intercept | MKT | SMB | HML | RMW | CMA | $R^2$ |
| BEME | 0.004 | -0.01 | 0.29 | 0.93 | -0.26 | 0.02 | 0.65 |
| | (0.04) | (-0.49) | (9.69) | (22.50) | (-6.44) | (0.36) | |
| EP | 0.22 | -0.19 | -0.10 | 0.72 | 0.76 | -0.23 | 0.39 |
| | (1.40) | (-4.76) | (-1.82) | (9.47) | (10.23) | (-2.08) | |
| CFOP | 0.33 | -0.17 | -0.40 | 0.14 | 0.18 | -0.12 | 0.33 |
| | (2.36) | (-4.90) | (-8.35) | (2.17) | (2.71) | (-1.25) | |
| NOP | 0.17 | -0.11 | 0.00 | 0.08 | -0.30 | 0.50 | 0.17 |
| | (1.26) | (-3.32) | (0.01) | (1.29) | (-4.73) | (5.34) | |
| ROE | 0.36 | -0.18 | -0.59 | -0.09 | 1.49 | -0.09 | 0.61 |
| | (2.33) | (-4.83) | (-11.12) | (-1.26) | (20.37) | (-0.79) | |
| ROA | 0.29 | -0.21 | -0.77 | -0.11 | 1.32 | -0.07 | 0.55 |
| | (1.59) | (-4.74) | (-12.53) | (-1.30) | (15.70) | (-0.53) | |
| GPA | 0.21 | -0.03 | 0.11 | -0.26 | 1.37 | 0.26 | 0.43 |
| | (1.48) | (-0.73) | (2.22) | (-3.80) | (20.32) | (2.62) | |
| OP | 0.66 | -0.19 | -0.88 | -0.36 | 1.18 | 0.32 | 0.57 |
| | (3.86) | (-4.59) | (-15.18) | (-4.44) | (14.77) | (2.65) | |

Both SMB and HML are close to zero and insignificant. It has a negative loading on RMW and a positive loading on CMA, both with t-stats of -4.73 and 5.34. The high loading on CMA could be due to the low NOP decile, companies that invest a lot cannot pay out high dividends or any dividends at all and vice versa companies that pay out a lot, most likely already financed all outstanding investments. The loading on RMW indicates that companies with high net payouts are less profitable. The quintessence is that those two factors perfectly eliminate the NOP effect of (Boudoukh et al., 2007) with a low and insignificant intercept of 0.17. I conclude that the FF5 regression is able to enhance the return predictability of value factors. The more interesting aspect lies on the profitability factors.

The main question after analyzing the FF3 model and profitability factors is if the profitability premium only exists, because the used model is not appropriate. I think that this is the case to some extent, since the high and significant loadings on RMW of more than 1.18 for all profitability factors indicate that a simple profitability factor in the Fama and French regressions can capture most of the high intercepts seen before. The results from CMA loadings are not as clear. Factors based on earnings (ROE and ROA) have negative loadings, most likely since all investment expenses are already accounted for and the factors based on sales (GPA and OP) have significant positive loadings. The argument for the latter is that investments, marketing, R&D and other sales increasing expenses will increase future profitability. This might make sense at first glance but the literature proves that investment has a negative slope to expected returns (Titman et al., 2004). The positive loading therefore indicates that high gross margin companies do not invest much or that the other sales related expenses neutralize the investment effect. The intercepts are significant at the 1% level for OP and at the 5% level for ROE. Unexpectedly GPA, which previously generated an alpha of 0.72 with a t-stat of 4.04 now only achieves 0.21 with a t-stat of 1.48. Even so I previously said $R^2$ is not very useful in explaining the factors, the change in $R^2$ might tell us something about the new factors impact. In FF3 the $R^2$ for the profitability factors was low, for GPA close to zero, now the $R^2$ increased on average by 0.29 (0.08 for the value factors). In my opinion, this is largely due to the RMW factor and not the CMA factor. This argumentation is in line with (Hou et al., 2015) who show that a model based on a profitability factor, in their case ROE, is better than the FF3 and Carhart model in predicting the cross section of returns.

#### 4.1.3 Correlations

For the portfolio creation, it is not only relevant to know if factors are able to achieve excess returns but also, how they behave to each other. In table 5 the relation between the factors is tested with the Pearson correlation in panel A (Equation 1) and the Spearman correlation in panel B (Equation 2).

On a first view, it is to notice that the value factors are not strongly correlated, only the correlation between EP and CFOP is 0.59 and the others are below 0.36. There is also a slightly negative correlation between BEME and CFOP, which combined in a portfolio should enhance the overall performance. This indicates that CFOP is a decent hedge for BEME. The BEME factor is strongly negatively correlated to all profitability factors, while the factors EP and CFOP are semi strongly correlated with ROE and ROA around 0.5. This makes sense, since earnings is the basis to construct those four factors. EP has a relatively high correlation with OP of 0.43 and a lower correlation of 0.29 with GPA. The NOP factor has a slightly negative correlation with all profitability factors. The profitability factors are highly correlated with each other. All correlations are between 0.48 and 0.90.

If we assume that the relation between factor returns in non-monotonic the Spearman correlation should present more reliable results. The correlation results are shown in panel B. The changes between the value factors are ±0.03, beside the BEME/CFOP correlation, which is now slightly positive at 0.04 instead of -0.03. Between the profitability factors only GPAs correlation to all the other profitability factors decreases on average by -0.10, the others decrease less. The correlation between value and profitability factors are generally lower. The correlation between BEME and GPA is now -0.42 followed by -0.34 for OP. This correlation is higher than the -0.53 correlation reported by (Novy-Marx, 2013) for the sample period July 1963 to December 2010. This difference is most likely due to the way I use the data, since I do not trim the independent variables at the 1% level and add six more years of data.

Looking at the results from the Sharpe ratios in table 2, the regressions in table 3/4 and the correlations in table 5 panel B, we can narrow down the factors to BEME, CFOP, GPA and OP. The BEME factor can be perfectly explained by the FF3 and FF5 model, nevertheless the economic effect is more important for this thesis, which is high due to a strong negative correlation to the profitability factor and a relatively high Sharpe ratio of 0.34. The CFOP factor is the only value factor that is still significant in the FF5 test, due to the models incapability to capture the accruals effect (Fama & French, 2016). The excess return of 0.20 and its Sharpe ratio of 0.18 are low, but the neutral correlation to profitability stocks and low correlation to BEME of 0.33 might still enhance a portfolio. OP is strongly significant in the FF5 model and should therefore be included in the test. The inclusion of GPA might not be clear, since both GPA and OP have sales as their input variable, but it has the highest Sharpe ratio of 0.42, the highest negative exposure to value stocks and the lowest correlation between profitability factors to OP with 0.41.

**Table 5 Correlations**
This table presents Pearson (Panel A) and Spearman rank (Panel B) correlations between the eight factors. The correlations are for the sample period from July 1964 to June 2016, since ROE and ROA have a two-year lag. The correlations are based on the excess factor returns after deducting the 1 month risk free rate.

| | Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| Panel A Pearson Correlations | | | | | | | | | |
| (1) | BEME | 1.00 | | | | | | | |
| (2) | EP | 0.25 | 1.00 | | | | | | |
| (3) | CFOP | -0.03 | 0.59 | 1.00 | | | | | |
| (4) | NOP | 0.36 | 0.21 | 0.15 | 1.00 | | | | |
| (5) | ROE | -0.27 | 0.50 | 0.48 | -0.09 | 1.00 | | | |
| (6) | ROA | -0.24 | 0.44 | 0.47 | -0.06 | 0.90 | 1.00 | | |
| (7) | GPA | -0.32 | 0.29 | 0.17 | -0.07 | 0.55 | 0.48 | 1.00 | |
| (8) | OP | -0.31 | 0.43 | 0.42 | -0.06 | 0.76 | 0.76 | 0.50 | 1.00 |
| Panel B Spearman Correlations | | | | | | | | | |
| (1) | BEME | 1.00 | | | | | | | |
| (2) | EP | 0.24 | 1.00 | | | | | | |
| (3) | CFOP | 0.04 | 0.60 | 1.00 | | | | | |
| (4) | NOP | 0.33 | 0.23 | 0.17 | 1.00 | | | | |
| (5) | ROE | -0.29 | 0.44 | 0.45 | -0.05 | 1.00 | | | |
| (6) | ROA | -0.24 | 0.41 | 0.44 | -0.01 | 0.88 | 1.00 | | |
| (7) | GPA | -0.42 | 0.13 | 0.11 | -0.12 | 0.43 | 0.38 | 1.00 | |
| (8) | OP | -0.34 | 0.36 | 0.38 | 0.00 | 0.73 | 0.73 | 0.41 | 1.00 |

### 4.1.4 Risk adjusted returns of selected factors

In the following figures, I will present the five-year trailing Sharpe ratios of BEME, CFOP, GPA and OP for the sample period July 1968 to June 2016. The annualized Sharpe ratios are computed by multiplying the monthly Sharpe ratio with $\sqrt{12}$. Figure 2 shows an equal weighted portfolio of all four factors compared to the market Sharpe ratio. Figure 3 presents four portfolios based on the value factors BEME and CFOP, in combination with one of the other profitability factors. In Appendix C, the figures with more than two factors are presented in a better quality.

In figure 1 we can see that the selected factors have a negative relation. In 1968, the BEME and GPA factors have a high trailing Sharpe ratio, while OP and CFOP are both highly negative. The effects reverse over time. During 1975 to 1982 the value strategies have a positive Sharpe ratio, while both profitability strategies are negative.

During periods where BEME is low (1990 to 2002) CFOP is still positive and the profitability factors generate high Sharpe ratios of more than 0.5, with OP realizing a Sharpe ratio of over 1.5 in several years. OP and GPA are still high after the financial crisis in 2008, while the BEME factor has a negative ratio of -0.5 in 2016. CFOP is strongly negatively correlated to BEME in recent years and yields a positive SR since 2015. From this figure, we can conclude that the power of each factor differs over time and that especially the selected four factors show their negative correlation.

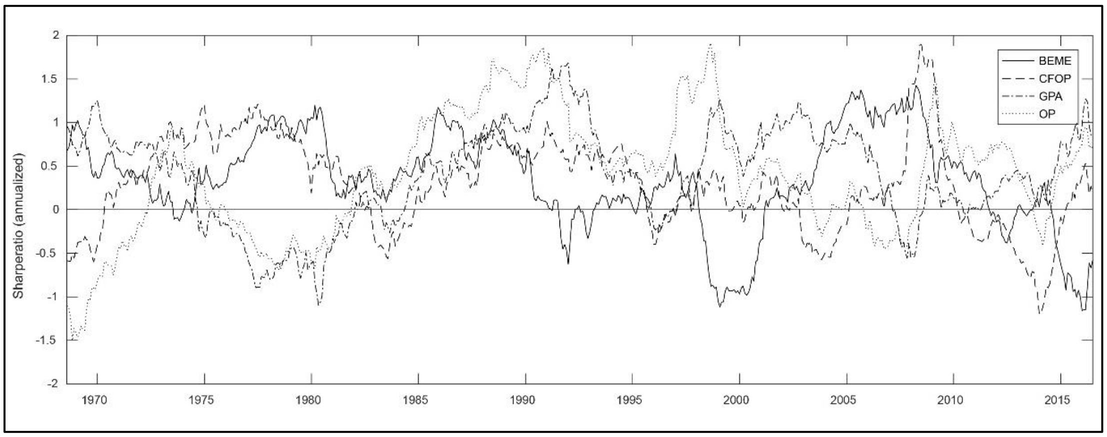


Figure 1 5-year trailing Sharpe ratio for HML portfolios

Figure 2 presents the Sharpe ratio of an equal weighted portfolio between the four factors, compared to the market Sharpe ratio. The result is that we can achieve a significant higher Sharpe ratio of 0.62, which shows that the negative correlation leads to superior returns. Nevertheless, this equal weighted portfolio, even so it achieves superior returns over the market, which has an average SR of 0.42, is four times the size of the market portfolio and self-financing[1]. Short selling and other restrictions as well as counterparty risk might have an effect on the strategy.

[1] The procedure is the same as in (Novy-Marx, 2013) where he computes the sums of Sharpe ratios.

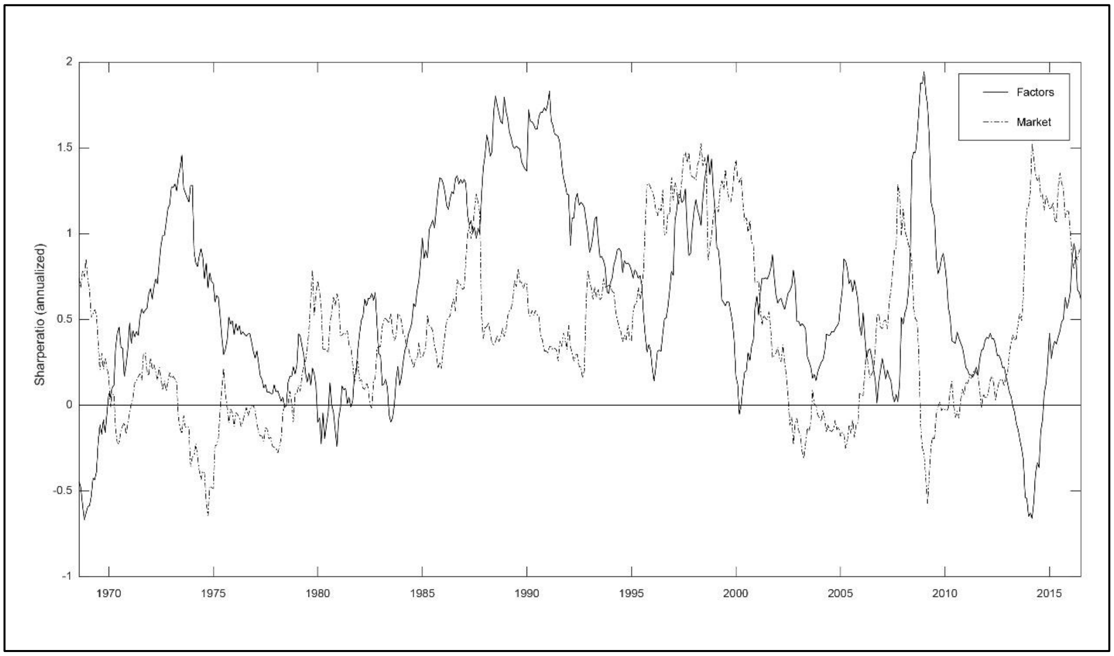


Figure 2 Combined portfolio

In figure 3 we observe how portfolios based on two of the four factors perform over the sample period. Only the negatively correlated factors are tested, which leads to four portfolios, twice the size of the market portfolio. The most astonishing result is that BEME/GPA only a negative trailing SR of -0.17 in 2000 and otherwise is always positive, which no other factor portfolio achieves. It also has the highest average SR of 0.7 (table 6) and is therefore higher than the equal weighted factor portfolio with 0.62. The portfolios based on CFOP do not satisfy the expectations, where the CFOP/OP portfolio achieves the same SR as OP of 0.4 and the CFOP/GPA portfolio is 0.46 compared to the GPA factor of 0.4.

**Table 6 trailing sharpe ratios factor portfolios**

The 5 year trailing Sharpe ratios are presented based on the single anomaly factors, the mixed factor portfolio, which is an equal weighted portfolio based on the single anomaly factors and four portfolios which were constructed based on their negative correlation. In the last column the market sharpe ratio is presented for comparison.

| | Single factor | | | | | Factor portfolios | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | BEME | CFOP | GPA | OP | MKT | BEME/ OP | BEME/ GPA | CFOP/ OP | CFOP/ GPA | Mixed |
| Sharpe ratio | 0.35 | 0.29 | 0.41 | 0.40 | 0.41 | 0.59 | 0.70 | 0.47 | 0.58 | 0.62 |

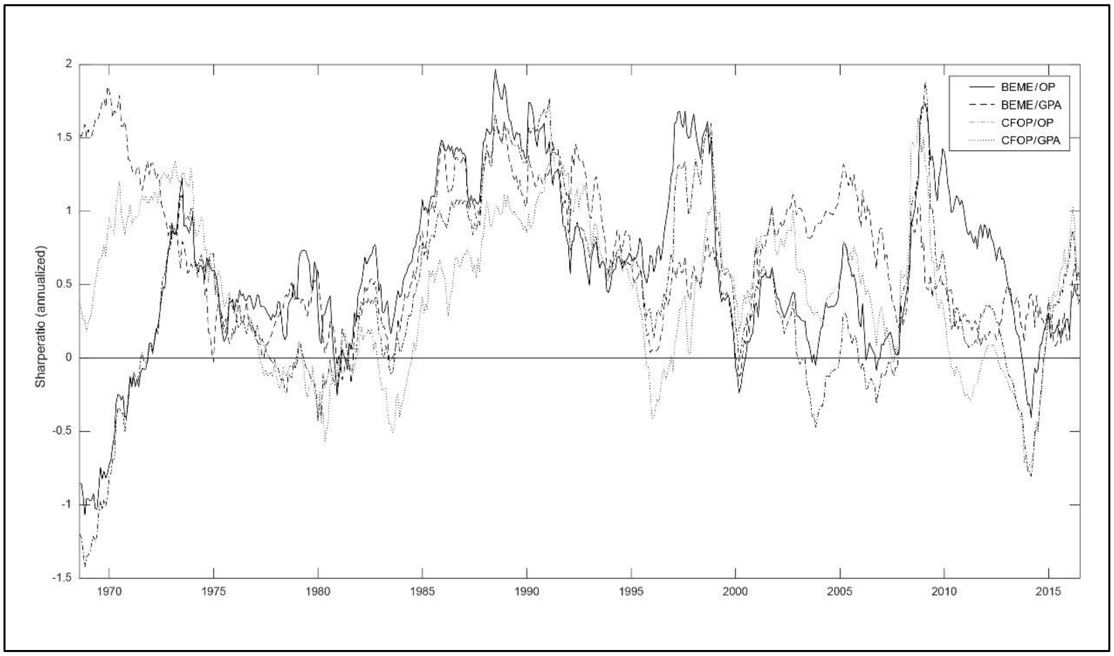


Figure 3 portfolio combinations Value and Profitability

## 4.2 Portfolio results

After displaying factor results for single sorted portfolios, based on the individual factors, I will use double sorted portfolios on size and the anomaly factor for BEME, CFOP, GPA and OP to further analyze their probabilities in terms of size. With the double sort, we can further analyze the profitability and value premium return characteristics and identify is the size of companies affect the self-financing portfolios.

### 4.2.1 Double sorted portfolios

By creating 25 portfolios, based on the NYSE size breakpoints and the quintile factor breakpoints, I reduce the stocks in each portfolio, which should make it easier for investment companies to allocate the funds.

Table 7 panel A presents the sorts on market equity and BEME. The table shows us that small firms with high BEME ratios have the highest average excess returns of 1.00 per month. This effect declines with an increase in firm size. On the other side size portfolios with low BEME ratios behave in the opposite way. Low size portfolios with the lowest BEME ratio generate a return of only 0.15, while the returns increase to 0.56 in the 4th size quintile. The difference between the Low and 2nd BEME quintile is on average 0.41, until the 3rd size quintile, which indicates that small growth stocks perform the worst. The smallest HML portfolio has a return of 0.85 and an annualized Sharpe ratio of 0.67, which is 0.33 higher than the simple sorted HML portfolio based on BEME in table 2. The indication of this strategy is that small undervalued firms are desirable investments for portfolio manager. The implementation of this strategy might be problematic since small firms are less traded and might have larger bid ask spreads. In addition, this portfolio holds more stocks (842) than the simple BEME portfolio (720).

Panel B shows the CFOP quintiles. The size effect also has an impact on this strategy, but the returns between the lowest and highest quintile are not as extreme as they are for BEME. In the small size and low CFOP quintile, companies earn on average 0.62 per month and in the small size and high CFOP quintile it is 0.97, which yields a factor return of only 0.35. On the other side the standard deviation of this strategy is quite low with 3.37%. The returns in the larger HML portfolios increase slightly since the returns in the lowest CFOP portfolio decline more (-0.07) than the highest portfolio (-0.06). The highest Sharpe ratio is 0.46 in the 3rd size quintile. The optimal strategy for the CFOP factor would be to construct portfolios based on its corners. This means that we would go long the small size high CFOP portfolio and short the big size low CFOP portfolio. Such a strategy yields a HML return of 0.67 with a Sharpe ratio of 0.56. The table shows us that growth companies with low operating cashflow underperform the market, while small companies with high operating cashflows outperform their peers.

In Panel C I present the profitability factor GPA. As the value factors, the highest returns are achieved in the small size, high GPA portfolio with 0.98. The return in the highest GPA decile decreases gradually until it achieves only 0.62 in the big size, high GPA portfolio. It seems that the size of a company does not significantly affect the lowest GPA companies, since the small and the big size low GPA portfolios have a return of 0.34 and 0.33 respectively. In (Novy-Marx, 2013) the difference is 0.10 higher, which leads him to the decision to use the corner portfolios to create a HML portfolio. In his case this yields a return of 0.77, while in my sample it is slightly lower at 0.65, but still more profitable than the small HML portfolio with 0.64. In general, his portfolio might be easier to implement, because large stocks are easier to sell short and the number of short sells decreases from 438 stocks in the small portfolio to 57 in the big portfolio, unfortunately the monthly volatility is higher in the corner HML (5%) than the small HML portfolio (3.03%), which would lead to a Sharpe ratio of only 0.45 instead of 0.78. Panel C indicates that companies with low gross profit underperform independent from their size.

The 25 OP portfolios in panel D yield similar results than panel C. The high OP quintile achieves returns close to GPA, but it seems that a low OP ratio is better at predicting which stocks will underperform in the next year. The small size low OP portfolio is by far the least profitable of all 100 portfolios with 0.08, which is close to the -0.04 return in table 1 and leads to the highest Sharpe ratio for the HML portfolio with 0.78. The average excess return in the low OP deciles is 0.30 compared to 0.35 for BEME, 0.43 for CFOP and 0.39 for GPA.

**Table 7 Double sorts on market equity and factor**

The table presents the 25 double sorted portfolios based on size and the four factors: BEME, CFOP, GPA and OP. The returns presented are monthly average excess returns over the risk-free rate between July 1963 to June 2016. In the first sort, I use the Market capitalization breakpoints, provided by the Kenneth French website to form 5 portfolios in June. In addition, I form factor quintiles for each size portfolio, which yields 25 portfolios in total. HML is the high factor quintile minus the low factor quintile. SR is the annualized monthly Sharpe ratio of the HML portfolio. N represents the average number of stocks in each factor quintile rounded to the nearest integer. Panel A represents BEME, Panel B CFOP, Panel C GPA and Panel D OP.

Panel A BEME portfolio average excess returns

| | BEME quintiles | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Size quintiles | Low | 2 | 3 | 4 | High | HML | SR | N |
| Small | 0.15 | 0.61 | 0.87 | 0.90 | 1.00 | 0.85 | 0.67 | 421 |
| 2 | 0.27 | 0.67 | 0.77 | 0.87 | 0.82 | 0.55 | 0.44 | 106 |
| 3 | 0.35 | 0.73 | 0.74 | 0.77 | 0.85 | 0.50 | 0.37 | 75 |
| 4 | 0.56 | 0.52 | 0.64 | 0.67 | 0.78 | 0.22 | 0.17 | 63 |
| Big | 0.42 | 0.47 | 0.49 | 0.51 | 0.58 | 0.16 | 0.15 | 57 |

Panel B CFOP portfolio average excess returns

| | CFOP quintiles | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Size quintiles | Low | 2 | 3 | 4 | High | HML | SR | N |
| Small | 0.62 | 0.39 | 0.48 | 0.88 | 0.97 | 0.35 | 0.36 | 438 |
| 2 | 0.43 | 0.43 | 0.71 | 0.95 | 0.86 | 0.43 | 0.44 | 110 |
| 3 | 0.42 | 0.61 | 0.68 | 0.86 | 0.87 | 0.45 | 0.46 | 77 |
| 4 | 0.40 | 0.54 | 0.72 | 0.70 | 0.78 | 0.38 | 0.42 | 64 |
| Big | 0.29 | 0.32 | 0.53 | 0.52 | 0.69 | 0.40 | 0.40 | 57 |

Panel C GPA portfolio average excess returns

| | GPA quintiles | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Size quintiles | Low | 2 | 3 | 4 | High | HML | SR | N |
| Small | 0.34 | 0.48 | 0.72 | 0.89 | 0.98 | 0.64 | 0.74 | 438 |
| 2 | 0.42 | 0.61 | 0.74 | 0.73 | 0.88 | 0.46 | 0.49 | 110 |
| 3 | 0.45 | 0.71 | 0.79 | 0.74 | 0.80 | 0.35 | 0.36 | 77 |
| 4 | 0.42 | 0.59 | 0.62 | 0.67 | 0.84 | 0.42 | 0.42 | 64 |
| Big | 0.33 | 0.40 | 0.51 | 0.47 | 0.62 | 0.29 | 0.30 | 57 |

Panel D OP portfolio average excess returns

| | OP quintiles | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Size quintiles | Low | 2 | 3 | 4 | High | HML | SR | N |
| Small | 0.08 | 0.46 | 0.72 | 0.79 | 0.98 | 0.90 | 0.78 | 389 |
| 2 | 0.28 | 0.66 | 0.74 | 0.80 | 0.88 | 0.60 | 0.58 | 96 |
| 3 | 0.49 | 0.68 | 0.72 | 0.80 | 0.78 | 0.29 | 0.26 | 65 |
| 4 | 0.34 | 0.61 | 0.71 | 0.68 | 0.76 | 0.42 | 0.46 | 52 |
| Big | 0.33 | 0.53 | 0.47 | 0.50 | 0.57 | 0.24 | 0.25 | 45 |

To further analyze the difference in profitability and value anomalies table 8 panel A shows the firm size in each portfolio and the average BEME ratio in panel B for both profitability strategies. In the Appendix B table 8A I also display the two value strategies. In the GPA small size portfolios, the average firm size does not vary significantly with a higher GPA loading, which means that GPA is not associated with large companies. The only difference can be seen in the big high GPA portfolio compared to the big low GPA, which is $68.4mn. smaller on average. The return of the big HML portfolio is also the smallest in table 7 panel C, so that this effect seems irrelevant. Panel B offers more information. It presents high BEME loadings on the low size low GPA portfolio of 9.97. Those stocks are associated as high value stocks and the small size high GPA portfolio only has a BEME ratio of 1.19. As we know from (Fama & French, 1993) small stocks tend to be value stocks, e.g. their book equity is more likely to be higher than the market equity, and this seems to be the case here, since the BEME ratio is never below one in the low size portfolios. In the larger portfolios, the 4$^{th}$ and high quintile of GPA the BEME ratio is always equal or smaller to one, while the lowest quintile is above one. Based on panel B we can conclude that GPA is more associated with growth stocks than it is with value stocks.

In panel A the OP quintiles show that high OP companies tend to be larger companies. In all size portfolios, the high OP quintile has a larger average firm size than the low quintile. Stocks in the small size low OP portfolio are on average only half the size of the small size high quintile, with $0.41 million compared to $0.86 million. Contradicting to this the BEME ratio is quite large with 1.92 in the high OP quintile and 1.47 in the low quintile. This could be one of the reasons why the negative spearman correlation between BEME and OP is only -0.34 compared with -0.42 between BEME and GPA (table 5). Table 8A shows that the firm size of high BEME firms is on average 0.48 million and that the high BEME quintiles are always larger than the low BEME quintiles. On the other side, low BEME quintiles only have an average BEME ratio of 0.21 through all size portfolios. This shows that profitability strategies tend to invest in different stocks than value strategies, but that the stocks valuation is less relevant to yield positive or negative results. The CFOP strategy in table 8A proves that it is in fact a value strategy, with BEME ratios of over

1 in the highest quintile. On the other side the overall BEME ratios are low, which explains the neutral correlation of 0.04.

**Table 8 Average Size and BEME loadings**

Panel A presents the firm size (millions of dollar) for the 25 portfolios based on size and the profitability factors GPA and OP. Panel B shows the average BEME ratio per portfolio over the sample period from July 1963 to June 2016.

| | Panel A Portfolio average firm size ($mn.) | | | | | Panel B portfolio average BEME ratio | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | GPA quintiles | | | | | GPA quintiles | | | | |
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | 0.63 | 0.73 | 0.72 | 0.71 | 0.64 | 9.97 | 9.84 | 5.18 | 2.78 | 1.19 |
| 2 | 4.12 | 4.14 | 4.12 | 4.11 | 4.14 | 1.62 | 1.96 | 1.65 | 1.00 | 0.61 |
| 3 | 9.25 | 9.28 | 9.23 | 9.20 | 9.16 | 1.24 | 1.38 | 1.23 | 0.78 | 0.48 |
| 4 | 22.60 | 23.00 | 22.40 | 23.06 | 22.84 | 1.13 | 1.06 | 0.92 | 0.68 | 0.41 |
| Big | 110.4 | 125.1 | 154.3 | 192.7 | 178 | 1.03 | 0.85 | 0.86 | 0.45 | 0.31 |
| | OP quintiles | | | | | OP quintiles | | | | |
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | 0.41 | 0.58 | 0.73 | 0.81 | 0.86 | 1.47 | 5.10 | 6.17 | 4.05 | 1.92 |
| 2 | 4.03 | 4.06 | 4.17 | 4.17 | 4.19 | 1.42 | 1.51 | 1.49 | 1.17 | 0.65 |
| 3 | 9.45 | 9.51 | 9.50 | 9.58 | 9.52 | 1.07 | 1.17 | 1.12 | 0.75 | 0.49 |
| 4 | 23.28 | 23.86 | 24.01 | 24.32 | 24.51 | 1.08 | 0.89 | 0.73 | 0.58 | 0.44 |
| Big | 114.2 | 143.6 | 165.4 | 184 | 227 | 0.92 | 0.71 | 0.54 | 0.73 | 0.30 |

### 4.2.2 Regression analysis

The analysis of the average excess returns in table 7 and the BEME loadings give a first indication about the portfolio properties. To evaluate if a portfolio should be included we test if it holds in the FF5 regression model and can generate significant alpha. Table 9 runs the FF5 regression on all value portfolios (50 in total) and presents their intercepts in panel A and the corresponding t-stats in panel B. (Fama & French, 2016) have already proven that BEME is well captured by the five factor model and in table 4 I come to the same conclusion, since the BEME intercept is only 0.004 and insignificant with a t-stat of 0.04. Similar patterns are found in table 9 panel A. In 20 out of 25 portfolios the intercepts are ±0.10 and insignificant. The values at the 1% significance level are in the low BEME, small, 4$^{th}$ and big size quintiles. This indicates that FF5 has problems to capture the low BEME factor. These results are nearly the same as for the FF3 regression in table 9A, which shows that the two additional factors do not help to capture the value outlier.

The situation is different for the CFOP value factor. In table 5 we have seen that it has a neutral correlation to BEME, but at the same time seems to be a value factor since it has large BEME loadings in the highest CFOP quintile and similar firm size patterns (table 8A). The FF5 model does well in capturing the outliers of CFOP, since small/big size low CFOP and small/big size high CFOP portfolios are insignificant. The results are similar to BEME and FF5 does a good job in capturing the portfolios, even so there are some significant outliers in the 2nd CFOP quintile at the 5% level. The strongest outlier is the 2nd size low CFOP portfolio with an intercept of -0.20 and t-stat of -3.11. The FF5 improves the results from the FF3 model (table 9A), which only captured 14 out of 25 portfolios compared to now 20 out of 25. In the next part, I will analyze how the RMW and CMA variables effect CFOPs HML portfolios, but from table 9 and 9A it indicates that they do have an impact.

**Table 9 FF5 Alpha Value factors**

Panel A presents the Fama and French 5 factor (FF5) regression intercepts for each of the 25 size and BEME/CFOP factors. Panel B reports the corresponding t-stats.
FF5 regression: $R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t$

Panel A intercepts

| | BEME quintiles | | | | | CFOP quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | -0.34 | -0.10 | 0.08 | 0.03 | 0.05 | -0.20 | -0.24 | -0.13 | 0.12 | 0.09 |
| 2 | -0.18 | 0.02 | -0.02 | 0.00 | -0.08 | -0.30 | -0.11 | 0.04 | 0.10 | -0.01 |
| 3 | 0.06 | 0.20 | -0.01 | -0.03 | 0.01 | -0.17 | 0.21 | 0.05 | 0.10 | 0.05 |
| 4 | 0.31 | -0.02 | -0.09 | -0.09 | 0.05 | -0.17 | 0.19 | 0.07 | -0.01 | 0.04 |
| Big | 0.25 | 0.03 | -0.04 | -0.01 | -0.01 | -0.02 | 0.09 | 0.10 | 0.03 | 0.11 |

Panel B t-stats

| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Small | -2.83 | -1.25 | 1.18 | 0.41 | 0.48 | -1.41 | -2.20 | -1.51 | 1.94 | 1.14 |
| 2 | -1.97 | 0.32 | -0.33 | 0.05 | -1.03 | -3.11 | -1.29 | 0.57 | 1.71 | -0.11 |
| 3 | 0.59 | 2.43 | -0.18 | -0.47 | 0.18 | -1.80 | 2.34 | 0.73 | 1.60 | 0.72 |
| 4 | 3.58 | -0.29 | -1.21 | -1.18 | 0.63 | -1.84 | 2.21 | 0.97 | -0.16 | 0.60 |
| Big | 3.22 | 0.54 | -0.65 | -0.13 | -0.08 | -0.22 | 1.26 | 1.68 | 0.47 | 1.45 |

Table 10 provides more information about the profitability factors, regarding their intercepts in the FF5 regression. The picture is contrary to the value factors, since it seems that the high factor decile cannot be captured by the FF5 variables. For GPA the small, 4th and big size portfolio yield an intercept larger than 0.22 which are significant at the 1% level. For OP, these results are even more pregnant, with intercepts of 0.28 and 0.31 in the 4th and big size portfolio with corresponding t-stats of 3.29 and 4.59. For GPA, the low intercept quintiles are never significant, while the small and 2nd size quintile of OP yield highly negative intercepts of -0.46 and -0.27, which are both significant at the 1% and 5% level respectively. The FF5 model can capture 19 GPA portfolios and 17 OP portfolios. Other papers in this area (Ball et al., 2015; Novy-Marx, 2013) only use the FF3 model explain the intercepts. Table 10A also presents the results for the FF3 regression on all 50 profitability portfolios, which shows us that the FF3 model can only cover 15 GPA portfolios and 13 OP portfolios, where the low and high OP factor quintiles cannot be captured. In this way, the FF5 model improves the FF3 regression with its profitability and investment factor. It is especially good at explaining the lower factor quintiles, since they are mostly insignificant.

**Table 10 FF5 Alpha Profitability factors**

Panel A presents the Fama and French 5 factor (FF5) regression intercepts for each of the 25 size and GPA/OP factors. Panel B reports the corresponding t-stats.
FF5 regression: $R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t$

Panel A intercepts

| | GPA quintiles | | | | | OP quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | -0.20 | -0.34 | -0.11 | 0.11 | 0.22 | -0.46 | -0.31 | -0.12 | -0.08 | 0.20 |
| 2 | -0.06 | -0.21 | -0.06 | -0.08 | 0.13 | -0.27 | -0.23 | -0.05 | -0.06 | 0.14 |
| 3 | 0.09 | -0.04 | 0.04 | 0.03 | 0.14 | 0.08 | -0.15 | -0.08 | 0.05 | 0.17 |
| 4 | 0.03 | -0.13 | -0.09 | 0.07 | 0.24 | -0.18 | -0.10 | -0.04 | 0.03 | 0.28 |
| Big | -0.05 | -0.12 | 0.03 | 0.16 | 0.26 | -0.06 | 0.04 | -0.02 | 0.08 | 0.31 |

Panel B t-stats

| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Small | -1.65 | -3.72 | -1.38 | 1.37 | 2.65 | -2.83 | -2.94 | -1.48 | -1.11 | 2.73 |
| 2 | -0.58 | -2.55 | -0.92 | -1.20 | 1.75 | -2.30 | -2.89 | -0.77 | -0.84 | 1.87 |
| 3 | 0.97 | -0.50 | 0.59 | 0.38 | 1.76 | 0.61 | -1.78 | -1.04 | 0.65 | 2.08 |
| 4 | 0.29 | -1.47 | -1.13 | 0.94 | 3.15 | -1.70 | -1.10 | -0.47 | 0.46 | 3.29 |
| Big | -0.67 | -1.50 | 0.39 | 2.18 | 3.57 | -0.69 | 0.55 | -0.34 | 1.21 | 4.59 |

In table 11 and 12 we see the regression results for the HML portfolios, in terms of average excess return and FF5 with the corresponding loadings on each variable. In addition to the five size quintiles we introduce two HML strategies based on the corners of the 25 portfolios, namely SHMBL (small size high factor minus big size low factor) and BHMSL (big size high factor minus small size low factor). This introduction is due to observations made in table 7 that HML portfolios based on the corners can lead to superior performance, for example in the case of CFOP and that it therefore might be interesting to see the loadings of such a quintile combination for all factors.

Table 11 presents the results for the value factors, while table 12 covers the profitability factors. For BEME the highest average excess return is realized in the smallest quintile with 0.85 and is highly significant with a t-stat of 4.87. Until the 3rd size quintile the returns are significant at the 1% level and in addition the SHMBL portfolio generates the second largest return with 0.57 and a t-stat of 2.63. The MKT variable is still negative and close to zero for all portfolios, besides SHMBL. The loading on SMB are negative and significant for nearly all portfolios, only the big size and SHMBL portfolio have positive loadings. The positive loading in the big size portfolio indicates that between the largest stocks the small stocks outperform the big stocks. The SMB factor for the SHMBL factor has the highest explanatory power in its regression, which shows that the size variable captures the returns. Since BEME is actually the HML factor, but created based on different deciles it is reasonable that these loadings are typically close to 0.9. In the discussion about table 9 and 9A I concluded that the RMW and CMA variables do not increase the predictive power of the regression model in a significant way. The positive and significant loadings in table 11 panel A contradict my assumption and show that in fact it has an impact on BEME. Nevertheless, the reasoning is not of the limit since the FF3 model is already able to capture most of the returns, since the average intercept is low at -0.08 (table 3). A look on the lowest BEME factor quintile in table 9 and 9A indicates that RMW and CMA is useful to reduce the average intercepts from -0.17 (FF3) to 0.02 (FF5). The average intercepts in the higher BEME quintiles only vary by ± 0.06.

**Table 11 FF5 regression value HML portfolios**

Panel A presents the mean and regression results of the BEME and CFOP High Minus Low (HML) portfolios. In addition to the five size HML portfolios it also shows the corner portfolios SMB (small size high factor minus big size low factor) and BMS (big size high factor minus small size low factor). The returns are excess returns for the sample period July 1963 to June 2016. The regression used is FF5:

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t$$

Panel A FF5 loadings

| | BEME | | | | | | | CFOP | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | ret | α | MKT | SMB | HML | RMW | CMA | ret | α | MKT | SMB | HML | RMW | CMA |
| Small | 0.85 | 0.39 | -0.04 | -0.14 | 0.85 | 0.53 | 0.29 | 0.35 | 0.29 | -0.14 | -0.27 | 0.08 | 0.61 | 0.09 |
| 2 | 0.55 | 0.10 | -0.05 | -0.20 | 0.96 | 0.27 | 0.38 | 0.43 | 0.29 | -0.21 | -0.20 | 0.40 | 0.53 | 0.08 |
| 3 | 0.50 | -0.04 | -0.05 | -0.17 | 0.90 | 0.35 | 0.69 | 0.45 | 0.23 | -0.18 | -0.17 | 0.31 | 0.47 | 0.44 |
| 4 | 0.22 | -0.26 | -0.06 | -0.08 | 1.00 | 0.26 | 0.38 | 0.38 | 0.22 | -0.19 | -0.10 | 0.37 | 0.33 | 0.24 |
| Big | 0.16 | -0.26 | -0.01 | 0.15 | 0.84 | -0.10 | 0.37 | 0.39 | 0.12 | -0.11 | 0.02 | 0.46 | 0.26 | 0.32 |
| SHMBL | 0.57 | -0.20 | 0.06 | 1.28 | 0.91 | -0.07 | 0.40 | 0.67 | 0.10 | -0.10 | 1.09 | 0.52 | 0.28 | 0.30 |
| BHMSL | 0.44 | 0.33 | -0.10 | -1.27 | 0.79 | 0.50 | 0.25 | 0.07 | 0.31 | -0.16 | -1.34 | 0.02 | 0.59 | 0.11 |

Panel B t-stats

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Small | 4.87 | 3.23 | -1.34 | -3.46 | 14.87 | 9.45 | 3.39 | 2.62 | 2.68 | -5.52 | -7.41 | 1.56 | 12.17 | 1.25 |
| 2 | 3.19 | 1.00 | -1.83 | -5.67 | 19.76 | 5.61 | 5.32 | 3.19 | 3.11 | -8.97 | -6.28 | 8.89 | 11.95 | 1.15 |
| 3 | 2.66 | -0.40 | -2.02 | -4.62 | 17.54 | 6.83 | 9.07 | 3.36 | 2.45 | -7.72 | -5.26 | 6.98 | 10.73 | 6.71 |
| 4 | 1.25 | -2.58 | -2.36 | -2.41 | 20.63 | 5.36 | 5.25 | 3.03 | 2.27 | -8.03 | -3.06 | 8.10 | 7.38 | 3.58 |
| Big | 1.06 | -2.45 | -0.20 | 4.22 | 16.73 | -1.96 | 4.96 | 2.93 | 1.12 | -4.11 | 0.48 | 8.75 | 4.97 | 4.05 |
| SHMBL | 2.63 | -1.83 | 2.03 | 33.73 | 17.12 | -1.27 | 5.14 | 4.05 | 1.11 | -4.29 | 33.91 | 11.62 | 6.37 | 4.52 |
| BHMSL | 1.74 | 2.59 | -3.17 | -28.96 | 12.85 | 8.34 | 2.80 | 0.30 | 2.07 | -4.34 | -26.53 | 0.30 | 8.47 | 1.07 |

As mentioned for table 7 the corner self-financing portfolio for CFOP (SHMBL) generates the highest average excess return with a t-stat of 4.05. This high average return is also due to a high significant loading on SMB of 1.09 and HML of 0.52. On the other side its intercept is only 0.10 and insignificant with a t-stat of 1.11. For all but the big size portfolio the intercepts are over 0.22 and significant at the 5% level and in the small and 2nd size portfolio at the 1% significance level. For these two portfolios, the CMA loading is low and insignificant, while RMW is high and strongly significant for all CFOP portfolios. It seems that CMA cannot capture the low size portfolio returns but handles the bigger portfolios better, where loadings increase to 0.33 on average and are significant at the 1% level. The conclusion here is the same as for the simple HML portfolio in table 3, that accruals are a weak point of the FF5 model (Fama & French, 2016) and since operating cashflow is the other part of earnings it should be difficult for the regression model to observe the effect.

The small GPA portfolio and the SHMBL portfolio yield high average excess returns with 0.65 and 0.66 respectively to the 0.55 return of the normal GPA factor in table 2. In addition, the intercepts are nearly double as high for the small GPA portfolio and the big size portfolio is also higher with 0.31 and a t-stat of 2.68. The MKT and SMB factor do not have a strong effect on the regression of the small and big size portfolio. The HML factor intercept for the small size portfolio is -0.01 and insignificant, while it is -0.47 and significant at the 1% level for the big portfolio. In most cases the CMA variable does not explain the return, while the RMW variable is always above 0.59 for the 5 size quintiles and significant with t-stats larger than 10.88. The negative loadings on HML identify GPA as a growth strategy.

OP yields the highest average return of 0.90 for all HML portfolios and has a corresponding significant intercept of 0.66 in the small size quintile. The loadings on SMB are negative and significant, so that we can support the previous observation in table 8 that the average firm size increases and the factor increases with the higher factor quintiles. The three lowest size quintiles have the highest loading on RMW, with 0.94 (small), 0.80 (2nd) and 0.85 (3rd). The effect decreases to 0.46 in the SHMBL portfolio. Interestingly the corner portfolios generate good average returns around 0.5 and the intercept for the BHMSL portfolio is 0.78 with a t-stat of 4.88. All the other BHSML portfolios yield insignificant returns. This means that OP might also be a profitable strategy for larger stocks. The impact of CMA on the profitability strategies is typically low and insignificant.

With these results, we can now discuss the first part of the main research question, if the profitability premium is still significant after the FF5 regression. (Novy-Marx, 2013) (table 4) presents average intercepts of 0.5 and t-stats of more than 2.71 and up to 4.27 for all GPA HML portfolios in the FF3 regression. In table 12 the average intercept for GPA is 0.24 and it is only significant in the small and big size HML portfolio. On the other side OP is relatively robust in the FF5 regression beside the 3rd size quintile. (Ball et al., 2015) present average FF3 intercepts of 0.57 in table 8 panel B, which decrease to an average of 0.40 after the FF5 regression in my sample. Their t-stats are always above 4 in all size quintiles. In table 12 we see that the 3rd size quintile is insignificant, but otherwise the intercepts have t-stats above 3.26. I conclude that the profitability premium can partly be captured by the FF5 regression and that the premium declines rather strongly by about 0.20 for both factors. On the other side the premium does not vanish and therefore can be exploited by the market even after the implementation of a profitability variable in the FF3 regression model.

**Table 12 FF5 regression profitability HML portfolios**

Panel A presents the mean and regression results of the GPA and OP High Minus Low (HML) portfolios. In addition to the five size HML portfolios it also shows the corner portfolios SMB (small size high factor minus big size low factor) and BMS (big size high factor minus small size low factor). The returns are excess returns for the sample period July 1963 to June 2016. The regression used is FF5:

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t$$

Panel A FF5 loadings

| | GPA | | | | | | | OP | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | ret | α | MKT | SMB | HML | RMW | CMA | ret | α | MKT | SMB | HML | RMW | CMA |
| Small | 0.65 | 0.42 | 0.02 | 0.08 | -0.01 | 0.71 | 0.08 | 0.90 | 0.66 | -0.03 | -0.17 | -0.03 | 0.94 | 0.25 |
| 2 | 0.46 | 0.19 | 0.03 | 0.32 | -0.21 | 0.77 | 0.20 | 0.60 | 0.41 | -0.10 | 0.14 | -0.34 | 0.80 | 0.41 |
| 3 | 0.35 | 0.05 | 0.11 | 0.43 | -0.25 | 0.81 | 0.08 | 0.28 | 0.09 | -0.09 | 0.19 | -0.46 | 0.85 | 0.47 |
| 4 | 0.41 | 0.22 | 0.14 | 0.35 | -0.43 | 0.62 | 0.11 | 0.43 | 0.47 | -0.11 | 0.10 | -0.42 | 0.50 | 0.05 |
| Big | 0.29 | 0.31 | -0.01 | 0.09 | -0.47 | 0.59 | -0.07 | 0.24 | 0.37 | -0.16 | -0.01 | -0.43 | 0.52 | -0.11 |
| SHMBL | 0.66 | 0.27 | 0.08 | 1.37 | -0.20 | 0.25 | 0.01 | 0.65 | 0.26 | -0.07 | 1.26 | -0.09 | 0.46 | 0.08 |
| BHMSL | 0.02 | 0.07 | 0.00 | 0.79 | 0.00 | -0.53 | -0.37 | 0.49 | 0.78 | -0.12 | -1.44 | -0.36 | 1.00 | 0.06 |

Panel B t-stats

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Small | 5.37 | 3.79 | 0.89 | 2.16 | -0.21 | 13.61 | 1.09 | 5.69 | 5.00 | -0.98 | -3.74 | -0.44 | 15.08 | 2.67 |
| 2 | 3.56 | 1.60 | 1.09 | 7.83 | -3.68 | 13.78 | 2.42 | 4.25 | 3.26 | -3.31 | 3.16 | -5.65 | 13.49 | 4.68 |
| 3 | 2.63 | 0.41 | 4.04 | 11.20 | -4.56 | 15.22 | 1.03 | 1.90 | 0.68 | -2.92 | 4.24 | -7.36 | 13.65 | 5.08 |
| 4 | 3.08 | 1.87 | 5.08 | 8.77 | -7.77 | 11.52 | 1.31 | 3.32 | 3.93 | -3.87 | 2.44 | -7.47 | 8.89 | 0.64 |
| Big | 2.21 | 2.68 | -0.25 | 2.31 | -8.46 | 10.88 | -0.81 | 1.81 | 3.29 | -5.54 | -0.33 | -7.89 | 9.63 | -1.41 |
| SHMBL | 3.30 | 2.39 | 2.93 | 34.81 | -3.64 | 4.63 | 0.13 | 3.76 | 2.50 | -2.73 | 35.02 | -1.87 | 9.26 | 1.06 |
| BHMSL | 0.15 | 0.67 | 0.03 | 23.41 | 0.06 | -11.37 | -5.35 | 1.79 | 4.88 | -2.99 | -26.44 | -4.79 | 13.37 | 0.52 |

### 4.2.3 Mean Variance Portfolio

Since I have proven that the profitability premium still exists after the FF5 regression model I have to evaluate the second part of the main research question. Can we combine value and profitability factors in a way that exceed previously documented simple combination strategies? For this I will evaluate which HML factor yields the most promising results in the Pearson- and Spearman correlation.

For each factor the corner portfolios were the first or second best option, which is why they are included. For BEME, GPA and OP the small size strategies yield the highest return, while for CFOP the second highest strategy is the 3rd size quintile. In addition, I add the BHMSL factor of OP since it earns high risk adjusted returns and is mostly allocated in large cap stocks, while the other strategies do not earn significant returns with this strategy. The factors that earn the highest average excess return over time are the small BEME HML portfolio with 0.83 (t-stat 4.87) and the small OP portfolio with 0.9 (t-stat 5.69) (table 9 and 10). To improve those strategies a negative correlation to the other factors is needed. For the evaluation, I will only consider the Spearman correlations in panel B, since it is possible that the data has a non-linear relation. When we look at CFOP the 3rd size HML portfolio has a positive correlation to BEME (0.49) and to OP (0.26), but the SHMBL portfolio reduces the correlation with BEME to 0.17 and is negative to OP with -0.19. In addition, the SHMBL portfolio yields the highest return with 0.65 and is significant at the 1% level (table 11).

**Table 13 Correlations**
This table presents Pearson (Panel A) and Spearman rank (Panel B) correlations between the nine HML portfolios. The correlations are for the sample period from July 1963 to June 2016. The correlations are based on the excess factor returns after deducting the 1 month risk free rate.

| | Var. | Size | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A Pearson Correlations | | | | | | | | | | | |
| (1) | BEME | Small | 1.00 | | | | | | | | |
| (2) | BEME | SHMBL | 0.29 | 1.00 | | | | | | | |
| (3) | CFOP | 3rd | 0.59 | 0.00 | 1.00 | | | | | | |
| (4) | CFOP | SHMBL | 0.19 | 0.84 | 0.09 | 1.00 | | | | | |
| (5) | GPA | Small | 0.17 | -0.20 | 0.22 | -0.04 | 1.00 | | | | |
| (6) | GPA | SHMBL | -0.36 | 0.51 | -0.44 | 0.54 | 0.09 | 1.00 | | | |
| (7) | OP | Small | 0.36 | -0.32 | 0.46 | -0.18 | 0.64 | -0.34 | 1.00 | | |
| (8) | OP | SHMBL | -0.25 | 0.56 | -0.21 | 0.67 | 0.07 | 0.80 | -0.16 | 1.00 | |
| (9) | OP | BHMSL | 0.32 | -0.72 | 0.43 | -0.60 | 0.42 | -0.68 | 0.77 | -0.58 | 1.00 |
| Panel B Spearman Correlations | | | | | | | | | | | |
| (1) | BEME | Small | 1.00 | | | | | | | | |
| (2) | BEME | SHMBL | 0.27 | 1.00 | | | | | | | |
| (3) | CFOP | 3rd | 0.49 | -0.06 | 1.00 | | | | | | |
| (4) | CFOP | SHMBL | 0.17 | 0.81 | 0.03 | 1.00 | | | | | |
| (5) | GPA | Small | 0.06 | -0.19 | 0.09 | -0.05 | 1.00 | | | | |
| (6) | GPA | SHMBL | -0.30 | 0.46 | -0.44 | 0.49 | 0.18 | 1.00 | | | |
| (7) | OP | Small | 0.16 | -0.34 | 0.26 | -0.19 | 0.63 | -0.22 | 1.00 | | |
| (8) | OP | SHMBL | -0.27 | 0.49 | -0.28 | 0.61 | 0.09 | 0.76 | -0.11 | 1.00 | |
| (9) | OP | BHMSL | 0.21 | -0.73 | 0.35 | -0.60 | 0.34 | -0.59 | 0.70 | -0.55 | 1.00 |

Figure 4 compares the small GPA and OP portfolios with their 5-year trailing Sharpe ratios. After 1980, the OP portfolio typically outperforms the GPA portfolio, even so it varies more over time. This and the results from the previous part lead me to the decision to choose the small OP portfolio as the main profitability factor. Unfortunately, the correlation between OP and BEME is slightly positive at 0.16 so that we cannot earn a risk premium. The more volatile SHMBL GPA portfolio is chosen over the small HML GPA portfolio. The reasoning behind this is that Panel B shows a strong negative correlation with BEME (-0.30) for this factor, a negative correlation with OP (-0.22) and a highly negative correlation with CFOP (-0.44), which will enhance the mean variance strategy. In the following I will name the chosen strategies only by their factor, e.g. SHMBL CFOP will be CFOP.

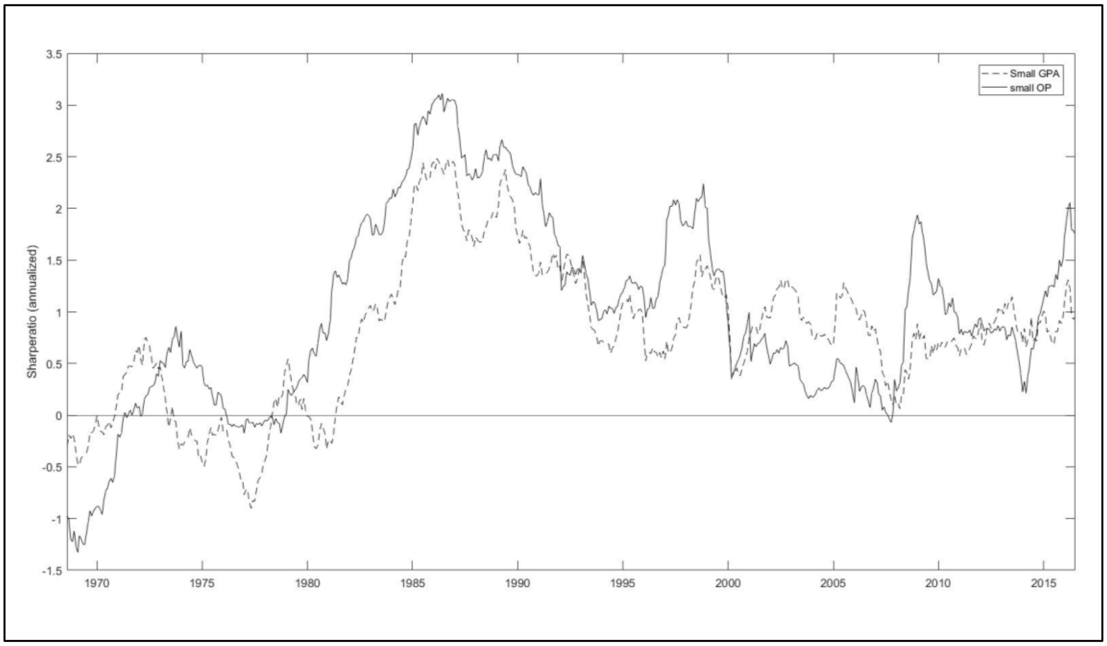


Figure 4 5-year trailing Sharpe ratios small GPA and OP portfolios

In general, the idea is that we can hedge some of the risk that exists due to the positively correlated OP and BEME portfolios with a smaller allocation to CFOP and GPA. I present the Sharpe ratios for the strategies in figure 5. We can see that in some phases CFOP and GPA outperform OP and BEME, for example around 1980 and 2005. A Larger version is presented in Appendix C.

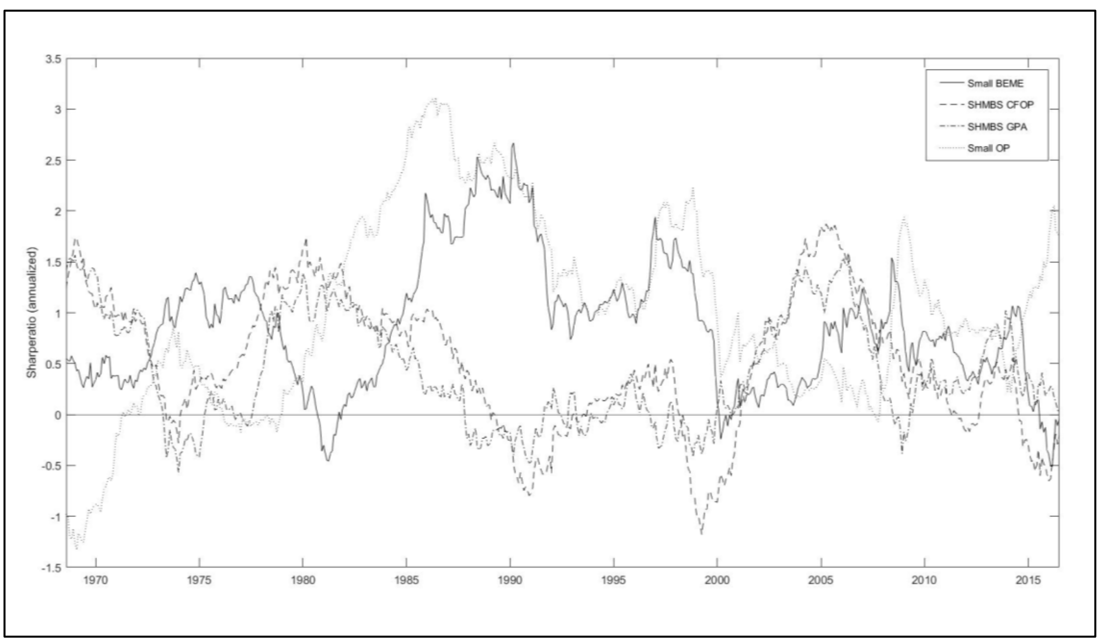


Figure 5 5-year trailing Sharpe ratios for BEME, CFOP, GPA, OP

For the mean variance portfolio (MVP), the minimum allocation of 10% in each factor is necessary, since we need a certain amount of money to be able to execute the self-financing portfolios. The number of stocks per small decile is around 430 and the big deciles around 50 (table 7), which makes this decision reasonable. For the two main factors, BEME and OP, I require a minimum allocation of 20%. This indicates that 40% of the allocation is based on the sample periods mean variance optimization between the factors. I use three years of observations, because it exceeds the sample size of 30 months and in the previous tables we have seen that the factors are changing over time, sometimes very rapidly, so that an observation period of five years might be too slow to adjust to new market conditions. After three years of observations the first allocation of funds begins in July 1966. The weights are computed based on the Mean Variance portfolio optimization as explained in the methodology section for each year.

Figure 6 shows the allocation after each portfolio optimization. The weights are determined based on the maximization of the Sharpe ratio in the three-year observation period. As expected OP typically has the highest allocation. In figure 1 we have seen that OP had a negative five year trailing Sharpe ratio before 1970, while GPA was around 0.5. In this situation, the GPA factor seems to subsidize the OP factor. This can be seen again in the period from 2000 to 2006, where OP was negative and GPA has the highest Sharpe ratio of all four factors (figure 5). The CFOP factor is nearly always close to its minimum allocation of 10%, especially in the last eight years. The change of weights over time, shows that factors perform different over time, but also that the effect gets stronger after a certain time again, for example BEME had a high allocation in the beginning of 1970 and then again in the beginning of 1990. This is also the reason why we do not want to exclude CFOP from the analysis, since we believe that factors are based on cyclical patterns. In some economic environment, it will be more useful to have more operating cash flow, for example high interest rate environments, compared to high sales. It would be interesting to know which macro-economic factors drive the different factor returns, but this is a question for further research.

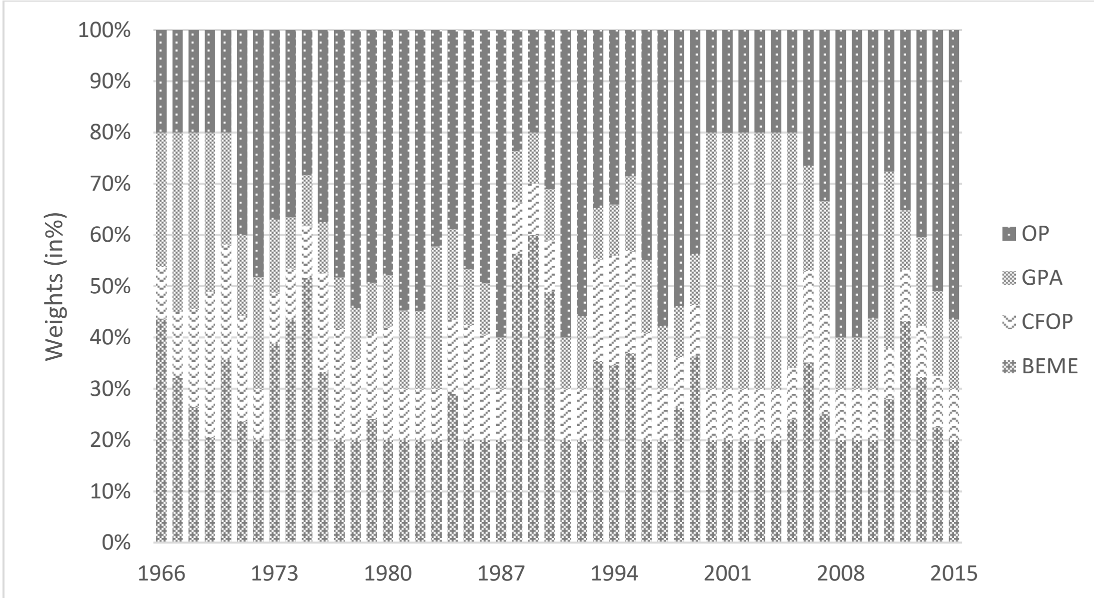


Figure 6 Weights of MVP over time

Figure 7 shows the annual Sharpe ratio (SR), based on the one year performance and the annualized monthly standard deviation. It presents the mean variance (MV) portfolio based on the weights in figure 6, an equal weighted (EW) portfolio and the market portfolio (MKT). I will not focus on the astonishing high SR for MVP and EWP, but rather on the negative outliers of the strategies. We can see that before 2000 the market had four Sharpe ratios lower than -1, while the factor portfolios were slightly positive in 1968 and 1970 and highly positive during 1982 and 1984. Only in 1973 both strategies were worse than the market, where MVP had a SR of -1.51 and EWP of -2.07. Over time we see that the strategies typically outperform MKT by a lot, where MKTs highest SR is 3.08 (1996) it is 5 for MVP (1989) and 5.24 for EWP (1994). The strategies typically reverse to a high SR after having negative returns (see 2000 to 2002, 2003 to 2007, 2008 to 2013 and most recently 2014 to 2016). From figure 7 it is not quite clear if the MVP leads to a superior performance over the EWP portfolio.

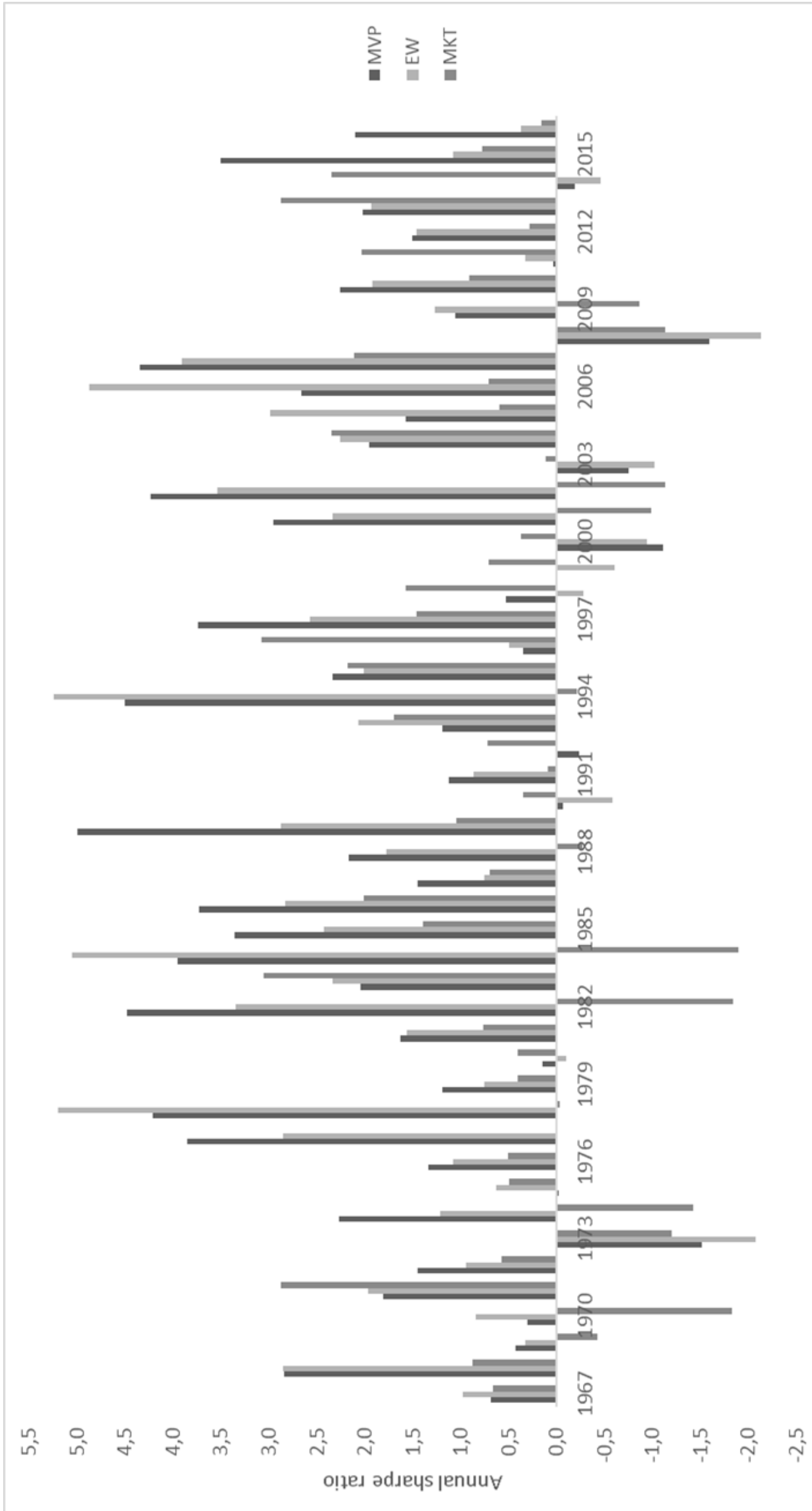


Figure 7 Annual Sharpe ratio MVP, EWP, MKT

Table 14 shows us that the simple Mean Variance portfolio (MVP) achieves a higher annualized Sharpe ratio of 1.30 compared to the equal weighted portfolio (EWP) of 1.16. MKT has a SR of 0.38 as expected. This leads me to the conclusion that a simple mean variance portfolio can increase a factor portfolio, even so it is only by 0.14. The MVP is simple to implement and should therefore be used by portfolio managers who want to invest in this strategy. It is also important to mention that I did not optimize the MVP in sample, for example by testing, which optimization (max. expected return, min. standard deviation or maximize Sharpe ratio) during the three-year observation period yields the highest Sharpe ratio or which observation period maximizes the results.

As a last step, I will confirm if the new factor portfolios can be captured by the prominent regression models. Since we have a combination of value and profitability factors, which are negatively correlated (table 13) and have different size loadings on each of the factors (table 11 and table 12) it is unlikely that the regression models can capture the returns. This seems to be the case. The intercepts for FF3 and FF5 are both high and significant at the 1% level. The difference between the average return of 0.85 and its FF5 intercept of 0.54 show that the regression model cannot capture the portfolio returns. The market intercept is captured by its own factor (market risk premium) and is therefore zero, but I include it to show the Sharpe ratio of 0.38. Another important aspect is that the returns of MVP and EWP are both positively skewed. If we have a positive skewness it indicates that the standard deviation overestimates risk, which is good for a portfolio, even so it also means that it diverges from the normal distribution (Bodie et al., 2014). On the other side MKT has a negative skewness of -0.51, which is typical for stock markets, as (Estrada, 2008) has shown for daily data in global stock markets. The skewness for the EW portfolio of 0.85 is higher than MVPs 0.14, which indicates that MVP is closer to the normal distribution. It depends on the investor to decide if a higher positive skewness is worth the 0.07% average return difference between the two strategies. The excess kurtosis for MVP is the same as for the market. This indicates that it has outliers, as discussed in figure 7. To sum it up, we have seen that the Mean Variance portfolio helps to increase the risk adjusted returns of combined factor portfolios based on two value and two profitability strategies. The increasingly high outperformance over the market shows the impact of combining significant factor strategies with negative correlations.

**Table 14 Regression results combined factor portfolios**

Column 2 to 4 show the excess average return, standard deviation, skewness, excess kurtosis and annualized Sharpe ratio for the sample period from July 1966 to June 2016. We also present the FF3 regression intercepts for each factor portfolio:

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + \varepsilon_t$$

and the FF5 regression intercepts:

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t$$

, with their corresponding t-stats.

| | | | | | | FF3 | | FF5 | |
|---|---|---|---|---|---|---|---|---|---|
| Portf. | Mean | $\sigma$ | Skew. | Kurt. | SR | α | t-stat | α | t-stat |
| MVP | 0.85 | 2.27 | 0.14 | 1.78 | 1.30 | 0.74 | 8.95 | 0.54 | 7.38 |
| EWP | 0.78 | 2.34 | 0.85 | 1.00 | 1.16 | 0.59 | 8.58 | 0.37 | 6.71 |
| MKT | 0.50 | 4.53 | -0.51 | 1.79 | 0.38 | 0 | -0.32 | -0.01 | -0.37 |

Looking at other papers who combined profitability and value factors, we can see that this strategy outperforms the equal weighted BEME/GPA portfolio of (Novy-Marx, 2013) with a Sharpe ratio of 0.85. (Ball et al., 2015) find a in sample Sharpe ratio of 1.40 for their portfolio combination based on operating profitability, MKT, SMB, HML and UMD (Momentum factor). This might indicate that our strategy is tilted to much towards profitability, but on the other side they combine five different factors (size, value, MKT, Momentum and OP), which should reduce volatility. Overall the out of sample result for the MV portfolio is strong and highly significant and can dramatically improve investor portfolios. A further allocation between other styles might improve the results. In addition, the use of more complicated to construct factors should enhance the strategy. For example, the directly computed cash based profitability measure should lead to better results in terms of the profitability factor (Ball et al., 2016). This also holds for the CFOP factor, who does not get a high allocation over the sample period. (Foerster et al., 2016) have shown that the direct way to compute operating cashflows has a higher predictive than the indirect way used in this thesis. Due to the complexity, we could not implement the enhanced CFOP and OP factor, but believe that it should benefit the MVP Sharpe ratio. In general, my results support the assumption of the main research question.

### 4.2.4 Transaction costs

After showing that a mean variance portfolio based on profitability and value factors yields high risk adjusted returns we will take a look at the implementation aspects of the strategy. As discussed in the literature review, transaction costs can eliminate anomalies and high turnover anomalies suffer the most. On the other side with the right allocation technique transaction costs can be reduced significantly (Novy-Marx & Velikov, 2016).

Value strategies are traded only twice a year, I sell stocks at the 30th of June and invest in the new strategy at the 1st of July. This means that I pay transaction costs twice, for selling the strategy and buying the new strategy. I will assume that I pay the same for buying and selling stocks. In addition, I ignore short selling restrictions, assume that I can sell every stock short and that it does not require a margin. The transaction cost is a percentage of the market value of the portfolio at the time of the transaction. Since the portfolio is restructured in 2 days, this also indicates that the cost of buying are lower than the cost of selling.[2] In reality buying stocks seems to be more expansive than selling stocks, and in some cases selling stocks is even associated with negative costs (Keim & Madhavan, 1997), which should balance each other out. We will test what common level of transaction costs for both trades lead to an alpha of zero in the FF5 regression and what the break-even transaction cost is to still earn significant alpha. Out of simplicity I assume that the transaction costs cover the total cost, e.g. commission plus price changes due to trading. (Frazzini et al., 2012) have shown that the average price impact of value strategies is 24.2 basis points (BP).

Table 15 presents the MVP results after transaction costs. In the first column, we can see the initial performance without transaction costs. The transaction costs are presented as basis points (BP). In the literature review it became clear that costs for small stocks increase for AMEX and NYSE to 1.13% and can be four times higher for NASDAQ stocks (Keim & Madhavan, 1997). Nevertheless, the strategy still has a high SR of 0.75 at 2% trading costs and generates alpha over the FF5 model by 0.20 at the 1% significance level. The last three rows show, at which costs, the intercept

[2] Example: Market value portfolio 30.06. $100, transaction costs 1%. Cost at 30.06. $1. MV portfolio 01.07. 99, transaction costs $0.99.

gets insignificant at the 1% level, at the 5% level and when it becomes zero. The strategy still earns significant returns at costs below 225BP, only earns 0.03 less than the market but is less risky, with a Sharpe ratio that is 0.28 higher than the market. This means that up to annual transaction costs of 4.5% the strategy is still profitable. (Frazzini et al., 2012) have shown that roundtrip costs for value strategies are lower than 2%, based on real transaction data between 1998 and 2011. At 2% (100 BP trading costs) the MV strategy only earns 0.17% less per month than a strategy without transaction costs.

**Table 15 Transaction costs**

Each row shows the average excess return over the 1 month risk free rate, the Sharpe ratio, FF5 intercept and t-stat for the strategy after transaction costs for the Mean Variance (MV) portfolio). The transaction costs are measured in basis points (BP). The data is computed based on the mean variance portfolio returns in table 14.

| Transaction costs | Average ret | Sharpe ratio | Intercept | t-stat |
|---|---|---|---|---|
| 0 | 0.85 | 1.30 | 0.54 | 7.38 |
| 25 | 0.81 | 1.24 | 0.50 | 6.80 |
| 50 | 0.77 | 1.17 | 0.46 | 6.20 |
| 75 | 0.73 | 1.10 | 0.42 | 5.59 |
| 100 | 0.68 | 1.04 | 0.37 | 4.97 |
| 150 | 0.60 | 0.90 | 0.29 | 3.73 |
| 200 | 0.51 | 0.75 | 0.20 | 2.53 |
| 209 | 0.50 | 0.73 | 0.19 | 2.32 |
| 225 | 0.47 | 0.68 | 0.16 | 1.95 |
| 318 | 0.32 | 0.43 | 0.00 | 0.00 |

I therefore can say that the first hypothesis related to the mutual fund restrictions, that transaction costs eliminate the portfolio anomaly returns, can be rejected. The MVP we use is based on simply combining the individual value and profitability strategies. (Israel & Villalon, 2013) have shown in a portfolio example with the three anomalies Value, Profitability and Momentum that these negatively correlated strategies sometimes take offsetting positions, which increases transaction costs and reduces returns. A portfolio that evaluates stocks in terms of all anomaly loadings

Simultaneously increases the portfolio Sharpe ratio by 19.35%. This would be a strong argument for investors to choose a self-financing portfolio, that uses this approach rather than buying each strategy by itself and could also further improve the results of this thesis.

## 4.3 Smart Beta ETF

Smart Beta ETFs break the relation between the price and weight of a stock in an index. The main reason for smart Beta stocks is that value weighted indices overweight high valuation stocks and undervalue low valuation stocks. The Value strategy indicates that overvalued stocks reverse at some point in the future and vice versa small stocks outperform (Banz, 1981), so that changing the weights based on a factor, for example size, leads to better performance. (ResearchAffiliates, 2017) published findings which shows that Smart Beta ETFs added value over the market index by at least 1.3% annually. In this way, it seems that Smart Beta is desirable for investors. While initially Smart Beta Strategies just overweight certain stocks in an index, (TowerWatson, 2013) sees it as a way to capture widespread risk premia that were initially only available through expensive active strategies. This would also indicate that an implementation of the self-financing portfolios is possible. Nevertheless, the following part only includes long portfolios, to be available to a wide range of investors.

### 4.3.1 Short selling restriction

In a first step, I analyze the portfolios for the four factors that could be selected for the mean variance portfolio with short selling restriction, e.g. a long only strategy. The selection of profitability strategies is based on the significant and positive intercepts in the FF5 regression in table 8. We have seen that FF5 captures BEME and in most cases CFOP (table 7). To make a reasonable selection I present the average excess returns for all 25 double sorted value portfolios, corresponding t-stats and their Sharpe ratios in table 16. From this we can see that the top two BEME and CFOP quintiles are significant at the 1 percent level for all size quintiles. To evaluate the risk adjusted performance panel C presents the Sharpe ratio of the portfolios. It seems that CFOP is better in terms of risk adjusted performance compared to BEME, but also that the highest Sharpe ratios are not associated with the highest CFOP quintile but the second highest.

**Table 16 Factor returns BEME and CFOP**
The table presents the 25 double sorted portfolios based on size and the two factors: BEME, and CFOP. The returns presented are monthly average excess returns over the risk-free rate between July 1963 to June 2016. The first sort uses the Market capitalization breakpoints, provided by the Kenneth French website to form 5 portfolios in June. In addition, we form factor quintiles for each size portfolio, which yields 25 portfolios in total. Panel B shows the corresponding t-stats and panel C the Sharpe ratio for each portfolio.

Panel A Portfolio average excess returns

| | BEME quintiles | | | | | CFOP quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Size quintiles | | | | | | | | | | |
| Small | 0.15 | 0.61 | 0.87 | 0.90 | 1.00 | 0.62 | 0.39 | 0.48 | 0.88 | 0.97 |
| 2 | 0.27 | 0.67 | 0.77 | 0.87 | 0.82 | 0.43 | 0.43 | 0.71 | 0.95 | 0.86 |
| 3 | 0.35 | 0.73 | 0.74 | 0.77 | 0.85 | 0.42 | 0.61 | 0.68 | 0.86 | 0.87 |
| 4 | 0.56 | 0.52 | 0.64 | 0.67 | 0.78 | 0.40 | 0.54 | 0.72 | 0.70 | 0.78 |
| Big | 0.42 | 0.47 | 0.49 | 0.51 | 0.58 | 0.29 | 0.32 | 0.53 | 0.52 | 0.69 |

Panel B t-stats

| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Size quintiles | | | | | | | | | | |
| Small | 0.45 | 2.30 | 3.53 | 3.76 | 3.87 | 1.92 | 1.27 | 1.76 | 3.86 | 4.15 |
| 2 | 0.89 | 2.53 | 3.21 | 4.00 | 3.53 | 1.44 | 1.54 | 2.98 | 4.42 | 3.91 |
| 3 | 1.20 | 2.98 | 3.36 | 3.75 | 4.05 | 1.48 | 2.35 | 3.10 | 4.59 | 4.23 |
| 4 | 2.17 | 2.34 | 3.14 | 3.37 | 3.95 | 1.53 | 2.27 | 3.71 | 3.76 | 3.99 |
| Big | 2.04 | 2.51 | 2.76 | 3.03 | 3.38 | 1.35 | 1.59 | 3.09 | 3.27 | 4.02 |

Panel C Sharpe ratio

| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Size quintiles | | | | | | | | | | |
| Small | 0.06 | 0.32 | 0.48 | 0.52 | 0.53 | 0.26 | 0.17 | 0.24 | 0.53 | 0.57 |
| 2 | 0.12 | 0.35 | 0.44 | 0.55 | 0.49 | 0.20 | 0.21 | 0.41 | 0.61 | 0.54 |
| 3 | 0.17 | 0.41 | 0.46 | 0.51 | 0.56 | 0.20 | 0.32 | 0.43 | 0.63 | 0.58 |
| 4 | 0.30 | 0.32 | 0.43 | 0.46 | 0.54 | 0.21 | 0.31 | 0.51 | 0.52 | 0.55 |
| Big | 0.28 | 0.35 | 0.38 | 0.42 | 0.46 | 0.19 | 0.22 | 0.42 | 0.45 | 0.55 |

The risk adjusted performance tends to be higher in the small size quintiles but still has higher ratios than the market in the big size quintile, with a monthly excess return of 0.46 (BEME) and 0.55 (CFOP) compared to MKT with 0.38 (table 14). In table 16A we present the ratios for the profitability factors. The profitability strategies have worse Sharpe ratios than the value strategies. While BEME has an average SR of 0.52 and CFOP 0.56 in its highest quintiles, GPA only achieves 0.49 and OP 0.46. This is due to the high volatility of profitability strategies. We have noticed in the discussion about table 5 that profitability is especially good at finding stocks that will underperform in the future, that OP even has negative returns in its lowest decile (table 1) and that the high decile returns are similar to the returns of value strategies. Nevertheless, the FF5 results in table 8 present highly significant intercepts in the smallest, 4th and big size high profitability factor portfolio.

For the Spearman correlation, I consider the two profitability portfolios that are significant at the 1 percent level in the FF5 regression (table 10), as well as the two value portfolios based on the highest t-stat of their average excess return. In table 17 the eight factors are presented. Unfortunately, the correlations are not as promising as they were for the self-financing portfolios in table 13.

**Table 17 Correlations Long only portfolio**

This table presents Pearson (Panel A) and Spearman rank (Panel B) correlations between the nine long only portfolios. The correlations are for the sample period from July 1963 to June 2016. The correlations are based on the excess factor returns after deducting the 1 month risk free rate.

| | Var. | Size | Factor | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A Pearson Correlations | | | | | | | | | | | |
| (1) | BEME | 2nd | 4th | 1.00 | | | | | | | |
| (2) | BEME | 3rd | High | 0.92 | 1.00 | | | | | | |
| (3) | CFOP | 2nd | 4th | 0.97 | 0.91 | 1.00 | | | | | |
| (4) | CFOP | 3rd | 4th | 0.94 | 0.93 | 0.94 | 1.00 | | | | |
| (5) | GPA | 4th | High | 0.86 | 0.83 | 0.88 | 0.89 | 1.00 | | | |
| (6) | GPA | Big | High | 0.67 | 0.67 | 0.69 | 0.72 | 0.83 | 1.00 | | |
| (7) | OP | 4th | High | 0.84 | 0.81 | 0.86 | 0.86 | 0.95 | 0.79 | 1.00 | |
| (8) | OP | Big | High | 0.68 | 0.67 | 0.70 | 0.72 | 0.83 | 0.93 | 0.83 | 1.00 |
| Panel B Spearman Correlations | | | | | | | | | | | |
| (1) | BEME | 2nd | 4th | 1.00 | | | | | | | |
| (2) | BEME | 3rd | High | 0.90 | 1.00 | | | | | | |
| (3) | CFOP | 2nd | 4th | 0.96 | 0.88 | 1.00 | | | | | |
| (4) | CFOP | 3rd | 4th | 0.92 | 0.92 | 0.92 | 1.00 | | | | |
| (5) | GPA | 4th | High | 0.86 | 0.82 | 0.88 | 0.89 | 1.00 | | | |
| (6) | GPA | Big | High | 0.66 | 0.67 | 0.68 | 0.71 | 0.81 | 1.00 | | |
| (7) | OP | 4th | High | 0.85 | 0.81 | 0.86 | 0.87 | 0.95 | 0.78 | 1.00 | |
| (8) | OP | Big | High | 0.67 | 0.68 | 0.70 | 0.71 | 0.81 | 0.92 | 0.82 | 1.00 |

The lowest Spearman correlation is 0.66 between the BEME (2nd/4th) portfolio and the GPA (Big/High) portfolio. Beside these two factors we take the OP (Big/High) portfolio, since it has a correlation of 0.67 with BEME ($2^{nd}/4^{th}$). Both CFOP returns are highly correlated with BEME with 0.96 and 0.92. They are less correlated with the chosen profitability factors. The portfolios are so similar that we will take the one with the highest t-stat (4.59) in table 16, which is CFOP ($3^{rd}/4^{th}$).

### 4.3.2 Mean Variance Portfolio

Table 18 presents the long only portfolio results. It shows the out of sample results for the Mean Variance Portfolio (MVP) with a three-year rolling window from July 1966 to June 2016. Since I do not have short selling restrictions a minimum allocation of 10 percent to each of the four factors should be sufficient for an implementation, which means that 60% are allocated based on the mean variance optimization. As in the previous section I compute the weight based on the maximized in sample Sharpe ratio. Beside the MVP, table 16 also presents the equal weighted portfolio, the four-individual factor returns and the market return.

The first six columns show descriptive statistics of the portfolio. After this we compute the outperformance compared to the market and the corresponding t-stat using the FF5 regression (Equation 5) and get the Beta to the MKT factor. Based on the descriptive statistics I compute the Sharpe ratio to measure the total risk exposure of the portfolios. The unsystematic risk of the portfolio is based on the MKT loadings ($\sigma_{\varepsilon}$) and the Information ratio is used to set the regression alpha in relation to the residual volatility. The Treynor ratio measures the systematic risk exposure of the portfolio. The reason why we added these two risk measurements is that we want to see if the portfolio might be a good fit for retail investors. If investors want to invest all their money in the portfolio alone the Sharpe ratio will be a good indicator, but most likely the investors already hold a well-diversified portfolio, in that case the Treynor ratio would show the investor the risk adjusted return based on the taken systematic risk. Like (C. S. Asness et al., 2014) we also include the Information ratio to give an indication about the level of risk the outperformance of the strategy holds. If the investors want to optimize a mean variance portfolio, only ETFs that have a positive and significant intercept over the regression model will improve the SR of their portfolio (Ball et al., 2015). With the information ratio those investors can see how reliable the achieved alpha is. The Risk characteristics unsystematic risk, Information ratio and Treynor ratio are computed as followed (Bodie et al., 2014).

$$\sigma_{\varepsilon} = \sqrt{\left(\sigma_p^2 - \beta_M^2 \times \sigma_M^2\right)} \tag{11}$$

, where p is the individual portfolio, $\beta$ is the loading of the portfolio on the market risk premium in the regression and $\sigma_M^2$ is the Variance of the market returns.

$$Information\,ratio_p = \frac{\alpha_p}{\sigma_{\varepsilon}} \tag{12}$$

, where $\alpha_p$ is the outperformance over the regression and $\sigma_{\varepsilon}$ is the unsystematic risk of the portfolio.

$$Treynor\ Ratio_p = \frac{\bar{r}_p - \bar{r}_f}{\sigma_{\varepsilon}} \tag{13}$$

, where $\bar{r}_p - \bar{r}_f$ is the average monthly excess return over the one-month risk free rate. Sharpe ratio, Information ratio and Treynor ratio are annualized.

The first thing that becomes clear is that the long only portfolios do not show the extraordinary results like the self-financing portfolios did (table 14). The high positive correlations in table 15 already indicate that the factors will not lead to superior results in a mean variance portfolio. The MVP yields an average monthly excess return of 0.73 over the risk-free rate with a standard deviation of 4.78. This is lower than the 5.61 and 4.82 of the value factors and OP with 4.92, but higher than the 4.64 of GPA. The maximum outlier is -23.5%, which is similar to the other factor returns, beside BEME with a maximum loss of 28.2%. On the other side the maximum positive outlier is lower than those of the individual factors. The skewness is negative at -0.58 compared to a positive skewness of 0.14 in the self-financing MVP. Both skewness and kurtosis are close to MKTs value. For EWP, the negative skewness is lower at -0.46, but the excess kurtosis is 2.31 compared to 1.98 for MVP. Both strategies achieve a significant outperformance over the market by 0.22 and 0.16 percent with t-stats of 3.64 and 3.92 for MVP and EWP respectively.

**Table 16 Long only portfolio results**
The table presents the four input factor returns, as well as the Mean Variance- and Equal Weighted portfolio returns and the MKT return. Columns two to seven present the descriptive statistics mean, volatility, minimum, maximum, skewness and excess kurtosis. Columns eight to ten show the FF5 regression results. Columns eleven to fourteen present the risk characteristics, e.g. Sharpe ratio, unsystematic risk, Information ratio and Treynor ratio of the portfolio. The Sharpe-, Information- and Treynor ratio are annualized. Beta is the loading on the MKT factor.

| | | | | | | | FF5 | | | Risk Characteristics | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portf. | Mean | Std | Min | Max | Skew | Kur | $\alpha$ | $t(\alpha)$ | $\beta$ | SR | $\sigma_{\varepsilon}$ | IR | TR |
| MVP | 0.73 | 4.78 | -23.5 | 15.2 | -0.58 | 1.98 | 0.22 | 3.64 | 0.96 | 0.53 | 1.53 | 0.38 | 2.63 |
| EW | 0.71 | 4.56 | -24 | 18.6 | -0.46 | 2.31 | 0.16 | 3.92 | 0.95 | 0.54 | 1.12 | 0.37 | 2.58 |
| BEME | 0.84 | 5.61 | -28.2 | 29.9 | -0.30 | 3.36 | 0.01 | 0.18 | 1.01 | 0.52 | 2.82 | 0.01 | 2.88 |
| CFOP | 0.84 | 4.82 | -23.1 | 22.1 | -0.40 | 2.85 | 0.09 | 1.39 | 0.95 | 0.60 | 2.15 | 0.14 | 3.06 |
| GPA | 0.60 | 4.64 | -21.6 | 22.5 | -0.22 | 2.09 | 0.24 | 3.22 | 0.91 | 0.45 | 2.17 | 0.39 | 2.30 |
| OP | 0.55 | 4.92 | -23.1 | 16.1 | -0.34 | 1.36 | 0.30 | 4.28 | 0.93 | 0.39 | 2.15 | 0.41 | 2.05 |
| MKT | 0.50 | 4.54 | -23.2 | 16.1 | -0.51 | 1.79 | 0 | 0 | 1 | 0.38 | 0 | 0.00 | 1.72 |

By combining the four factors, the returns of MVP get significant at the 1% level and the strategy achieves an annualized Sharpe ratio of 0.53 that is larger than both profitability factors and the BEME factor. For an investor who only holds this portfolio the Sharpe ratio would be the measure to choose. If the investor has a well-diversified portfolio, e.g. without unsystematic risk, the return to systematic risk would be crucial. This risk adjusted return is measured by the Treynor ratio, which is 2.63 for the MVP and 2.58 for the EWP portfolio, while it is 2.88 for BEME and 3.06 for CFOP. An investor who only cares about the excess returns should use the Information ratio, which sets the regression alpha in relation to the portfolios unsystematic risk. We can see that for this kind of investor the MVP portfolio yields a high ratio of 0.38 and 0.37 for EWP. The profitability strategies have the highest ratios with 0.39 (GPA) and 0.41 (OP). In total the MVP achieves 0.05 higher alpha than the EWP portfolio, while having similar risk characteristics which shows that the OOS mean variance optimization is desirable.

We can say that the profitability anomalies are still existent after implementing short selling restrictions, but that value anomalies are captured well under the FF5 regression and are insignificant. Therefore, we cannot reject the second hypothesis.

Even so this is the case a portfolio based on value and profitability anomalies achieves a high and significant alpha over 0.15 in the FF5 regression with low unsystematic risk while having a market beta close to 1. All risk adjusted ratios are high, but never the largest of the four factors, which indicates that the positive effect of the self-financing strategies cannot be realized in a long only portfolio. For retail and smaller institutional investors an allocation to this ETF is still a good idea since all risk based ratios are high. Institutional investors might want to pick the individual anomalies to meet their portfolios goals. By achieving these results, I can reject the third hypothesis that a portfolio based on long only anomalies cannot beat the market.

### 4.3.3 Minimum Market Capitalization

We have seen in prior sections that value weighted indices are easier to implement and yield higher after transaction cost returns than equal weighted strategies (Korajczyk & Sadka, 2004; Novy-Marx & Velikov, 2016). The argument for this is that the bid-ask spread for small stocks is to large so that anomaly returns before transaction costs cannot be exploited. This reasoning is also used by asset management companies to evaluate if a stock is suitable for a certain portfolio or not. A low bid-ask spread and high liquidity are often more valuable than a high expected return in an illiquid asset. This is especially the case for mutual funds, which might need to quickly liquidate assets in order to payout shareholders. For this reason, the allocation to small stocks is rare and the focus lies on mid cap and large cap stocks.

To measure the market capitalization of the anomalies, compared to the market I compute the average market capitalization per stock in each strategy and sort it to its corresponding ME breakpoint (5% steps) from the Kenneth French Website, between June 1966 to June 2015. The results are presented in figure 8. I chose to use this measure as an alternative to a simple average since the market capitalization in the stock market increased dramatically over the last decades and a simple average would falsify the true allocation of assets and would present them to be more tilted towards small size companies than they really are. The X-Axis shows every 5% percentile for market equity and the Y-Axis the number of years in which the portfolio fell in this percentile. Since I chose the big size quintile for both profitability strategies it is not surprising that the GPA factor occurs six times in the 19$^{th}$ 5% percentile and 44 times in the highest percentile, while OP is always in the highest percentile. The value factors are allocated more towards lower market cap stocks, where CFOP is 12 times in the $10^{th}$ 5% percentile and 38 times in the $11^{th}$. The BEME factor is allocated to small stocks in the $6^{th}$ and $7^{th}$ 5% percentile. As a result, the MV portfolio varies between the $16^{th}$ and the $20^{th}$ 5%percentile depending on which factor is overweight in the in sample mean variance computations.

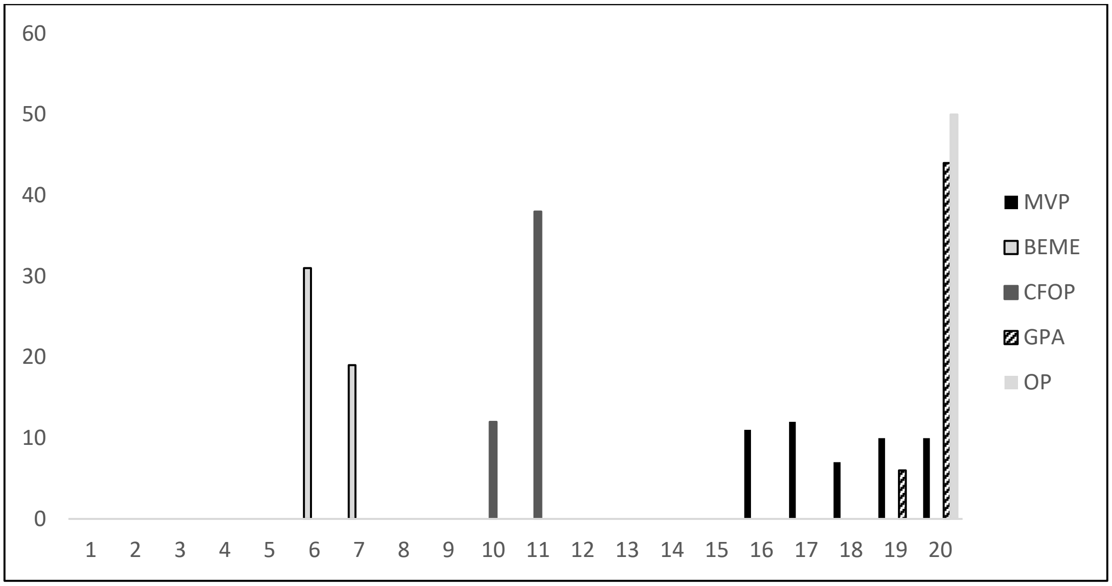


Figure 8 Market capitalization of factors and MVP

Even so OP always lies in the highest market capitalization percentile it does not necessarily mean that it is only allocated to the largest stocks. Figure 9 shows the relative relation between the highest percentile market cap and the average stock market capitalization in the OP factor. As we can see OPs average market capitalization varies in a Range of 5% to 15% of the average market capitalization in the highest 5% percentile.

Therefore, the MVP portfolio is not a growth portfolio but more tilted towards mid cap stocks. This also indicates that the transaction costs are lower than they would be for value anomalies and we can reject the fourth hypothesis that a portfolio based on value and profitability anomalies is mainly allocated in small stocks.

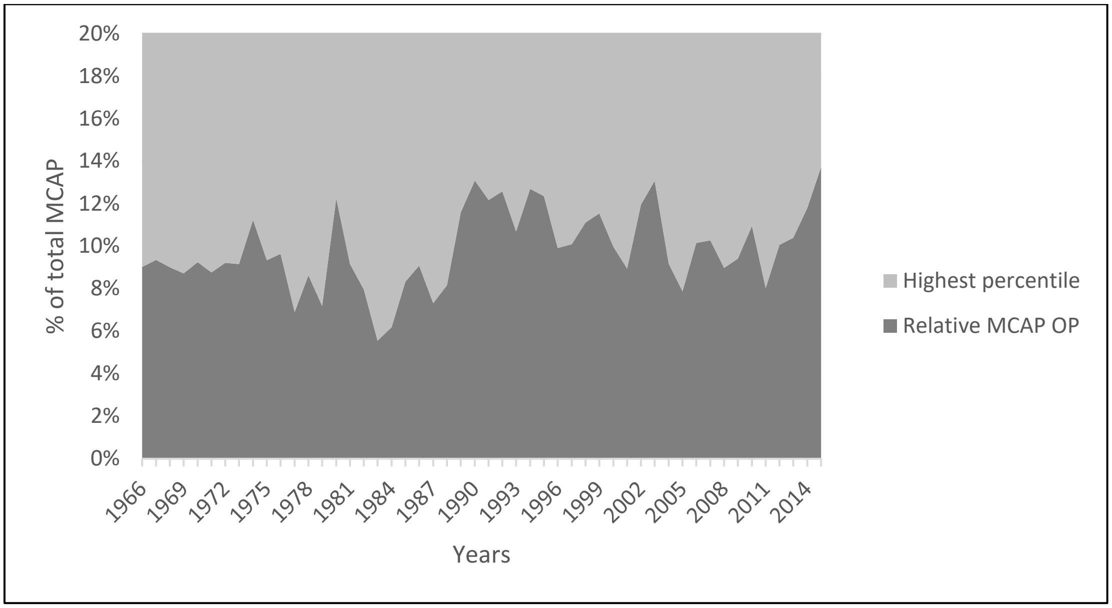


Figure 9 relation between OP market cap and total market cap in the highest percentile

# 5 Conclusion

As presented by (Ball et al., 2015) the Operating Profitability factor has a higher predictive power in the cross section of returns than the Gross Profit factor of (Novy-Marx, 2013). In the Fama and French five factor model (Fama & French, 2015) only the small and big self-financing portfolios are significant for Gross Profit, while they are for Operating Profit in all beside the 3rd size quintile. The FF5 model reduces the profitability premium on average by 0.20%, but the anomaly can still be exploited. Therefore, this thesis has shown that the profitability premium still exists in the market and can be used to enhance anomaly portfolios due to its negative correlation to value strategies. A combination of four anomaly factors in a Mean Variance Portfolio earns a significant monthly anomaly premium of 0.54% and has an annualized Sharpe ratio of 1.30. Even the implementation of transaction costs cannot vanish the high returns. The strategy earns a significant return up to annual transaction costs of 4.18%, which is higher than the typical 1.70% associated with value strategies (Frazzini et al., 2012). While this strategy is typically only available to hedge funds, it might be replicable through ETFs and made available to smaller institutional- and retail investors. The thesis therefore tests characteristics that are typical restrictions for these investors, mainly the short-selling restriction and the minimum market capitalization of stocks. The results show that the value premium vanishes in the light of the FF5 model, but that high profitability deciles earn large, significant monthly premia of up to 0.30%. A combination of those factors in a Mean Variance Portfolio earns a premium of 0.22% while reducing the unsystematic risk by 45.74% compared to value strategies and 29.49% to profitability strategies. The Sharpe ratio of such a portfolio is 0.15 higher than the market and is simple to implement due to its tilt towards mid and large cap stocks.

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# Appendix A Factors

To construct the deciles of the individual factors, at the end of June in each year t, I use NYSE breakpoints to sort stocks into deciles based on those factors for the fiscal year ending in calendar year t−1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

## A.1 Value factors

**A.1.1. E/P** To construct (Basu, 1983) earnings price (E/P) deciles I use NYSE breakpoints to split stocks into deciles based on E/P at the date of portfolio formation in the end of June of each year t. E/P is income before extraordinary items (COMPUSTAT annual item IB) for the fiscal year ending in calendar year t−1 divided by the Market Equity (ME from CRSP) at the end of December of t−1.

$$E/P = \frac{IB_{t-1}}{ME_{t-1}}$$

**A.1.2. CFO/P** Operating cash flow to price is based on (Desai et al., 2004). CFO/P is IB plus depreciation (COMPUSTAT annual item DP) for the fiscal year ending in calendar year t-1 minus non-cash working capital (Sloan, 1996) divided by the ME at the end of December of t-1.

$$CFO/P = \frac{IB_{t-1} + DP_{t-1} - WC\ Acc.}{ME_{t-1}}$$

A.1.2.1 WC Acc. I use (Sloan, 1996) Balance Sheet approach to compute non-cash working capital. All values measure the changes (Δ) between December of year t-2 and December of t-1. It is computed by using change in current assets (COMPUSTAT annual item ACT) minus change in cash and short-term investments (COMPUSTAT annual item CHE) minus the sum of changes in current liabilities (COMPUSTAT annual item LCT) minus changes of debt in current liabilities (COMPUSTAT annual item LCT) minus Income tax payable (COMPUSTAT annual item TXP).

$$WC\ Acc. = \Delta ACT - \Delta CHE - (\Delta LCT - \Delta DLC - \Delta TXP)$$

**A.1.3. NO/P** Net payout is computed by Dividends on common stocks (COMPUSTAT annual item DVC) plus repurchases minus stock issuance. Repurchases are the sum of purchase of common and preferred stocks (COMPUSTAT annual item PRSTKC) plus all negative changes in the number of preferred stock (COMPUSTAT annual item PSTKRV) between t-2 and t-1. Stock issuance is sale of common and preferred stock (COMPUSTAT annual item SSTK) minus all positive changes in the value of preferred stock (Boudoukh et al., 2007).

If $\Delta PSTKRV < 0, then$

$$NO/P = \frac{DVC_{t-1} + (PRSTKC_{t-1} - \Delta PSTKRV) - SSTK_{t-1}}{ME_{t-1}}$$

If $\Delta PSTKRV \geq 0, then$

$$NO/P = \frac{DVC_{t-1} + PRSTKC_{t-1} - (SSTK_{t-1} - \Delta PSTKRV)}{ME_{t-1}}$$

**A.1.4. BEME** The ratio is computed as in (Fama & French, 1992). Book equity (BE) is total shareholder equity (COMPUSTAT annual item SEQ), plus balance sheet deferred taxes and investment tax credit (COMPUSTAT annual item TXDITC) minus preferred stock (COMPUSTAT annual item PSTK). Because of changes in FASB109 TXDITC is not added to FF Factors for all variables after 1993. In my opinion this could result in look ahead bias, since the investors back in 1993 would still add TXDITC to SEQ, but out of consistency I follow FFs procedure to compute Book Equity.

If date ≤ 1993

$$BE/ME = \frac{SEQ_{t-1} + TXDITC_{t-1} - PSTK_{t-1}}{ME_{t-1}}$$

If date > 1993

$$BE/ME = \frac{SEQ_{t-1} - PSTK_{t-1}}{ME_{t-1}}$$

A.1.4.1. BE annual If total shareholder equity (SEQ) is not available, I construct it like (Davis, Fama, & French, 2000) in the following priority. Book value of common equity (COMPUSTAT annual item CEQ) plus value of preferred stock (PSTK) or book value of assets (COMPUSTAT annual item AT) minus book value of liabilities (COMPUSTAT annual item LT). If value of preferred stock is not available, I use preferred stock redemption value (COMPUSTAT annual item PSTKR) or liquidating value (COMPUSTAT annual item PSTKL).

## A.2 Profitability factors

**A.2.1. ROE** is income before extraordinary items (COMPUSTAT annual item IB) divided by one year lagged BE (see A.1.4.2.).

Monthly value weighted returns are computed for each month t. The deciles are rebalanced annually at the beginning of t+1. I follow (Hou et al., 2015) procedure and only include companies that have their end of fiscal year data in the 6 months prior to portfolio formation.

$$ROE = \frac{IB_t}{BE_{t-1}}$$

where t is equal to the last earnings announcement defined by IB and t-1 stands for the 1-year lag.

**A.2.2. ROA** is income before extraordinary items (COMPUSTAT annual item IB) divided by one year lagged Assets (COMPUSTAT annual item AT). The procedure regarding computation, deciles, returns and rebalancing is the same as for ROE (A.2.1.)

$$ROA = \frac{IBQ_t}{ATQ_{t-1}}$$

**A.2.3. GPA** I follow (Novy-Marx, 2013) procedure to create his gross-profit-to-asset factor. I use Revenue (COMPUSTAT annual item REVT) minus cost of goods sold (COMPUSTAT annual item COGS) to create Gross Profits (GP) scaled by current Assets (COMPUSTAT annual item AT). He does not use lagged assets like the ROA factor to create GPA.

$$GPA = \frac{REVT_{t-1} - COGS_{t-1}}{AT_{t-1}}$$

**A.2.4. OP** OP is constructed following (Ball et al., 2015). It is Gross Profits (GP) as defined in A.2.3. minus the sum of Selling, General and Administrative Expense (COMPUSTAT annual item XSGA) minus Research and Development Expense (COMPUSTAT annual item XRD).

$$OP_{t-1} = REVT_{t-1} - COGS_{t-1} - (XSGA_{t-1} - XRD_{t-1})$$

# Appendix B Tables

**Table 8A Average Size and BEME loadings**

Panel A presents the firm size (millions of dollar) for the 25 portfolios based on size and the value factors BEME and CFOP. Panel B shows the average BEME ratio per portfolio over the sample period from July 1963 to June 2016.

| Panel A Portfolio average firm size | | | | | | Panel B portfolio average BEME | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | BEME quintiles | | | | | BEME quintiles | | | | |
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | 0.76 | 0.80 | 0.75 | 0.65 | 0.48 | 0.24 | 0.55 | 0.86 | 1.25 | 2.55 |
| 2 | 4.14 | 4.13 | 4.13 | 4.08 | 4.01 | 0.22 | 0.45 | 0.66 | 0.91 | 1.75 |
| 3 | 9.23 | 9.21 | 9.13 | 9.10 | 9.12 | 0.21 | 0.42 | 0.62 | 0.87 | 1.62 |
| 4 | 23.35 | 23.41 | 22.45 | 22.86 | 22.53 | 0.20 | 0.40 | 0.59 | 0.84 | 1.54 |
| Big | 190.2 | 185.4 | 158.6 | 132.5 | 99.5 | 0.18 | 0.35 | 0.53 | 0.75 | 1.28 |
| | CFOP quintiles | | | | | CFOP quintiles | | | | |
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | 0.40 | 0.63 | 0.83 | 0.90 | 0.69 | 7.51 | 0.93 | 0.80 | 0.95 | 3.41 |
| 2 | 3.96 | 4.10 | 4.21 | 4.21 | 4.11 | 1.43 | 0.58 | 0.59 | 0.77 | 2.27 |
| 3 | 9.05 | 9.22 | 9.39 | 9.38 | 9.23 | 0.93 | 0.50 | 0.60 | 0.76 | 1.76 |
| 4 | 22.17 | 22.76 | 23.03 | 23.36 | 22.92 | 0.76 | 0.46 | 0.58 | 0.73 | 1.44 |
| Big | 118 | 150.7 | 178.4 | 173.3 | 139 | 0.57 | 0.41 | 0.52 | 0.70 | 1.02 |

**Table 9A FF3 Alpha Value factors**

Panel A presents the Fama and French 3 factor (FF3) regression intercepts for each of the 25 size and BEME/CFOP factors. Panel B reports the corresponding t-stats.

FF3 regression: $R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + \varepsilon_t$

| Panel A intercepts | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | BEME quintiles | | | | | CFOP Quintiles | | | | |
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | -0,60 | -0,19 | 0,05 | 0,02 | 0,03 | -0,39 | -0,46 | -0,29 | 0,12 | 0,12 |
| 2 | -0,36 | -0,05 | -0,02 | 0,06 | -0,09 | -0,45 | -0,29 | 0,03 | 0,18 | 0,03 |
| 3 | -0,19 | 0,08 | 0,03 | 0,01 | 0,02 | -0,37 | 0,01 | 0,03 | 0,20 | 0,10 |
| 4 | 0,12 | -0,05 | -0,02 | -0,04 | 0,02 | -0,31 | 0,03 | 0,13 | 0,06 | 0,07 |
| Big | 0,17 | 0,08 | 0,03 | 0,00 | -0,04 | -0,14 | 0,00 | 0,14 | 0,10 | 0,13 |
| Panel B t-stats | | | | | | | | | | |
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | -4,72 | -2,25 | 0,66 | 0,33 | 0,29 | -2,71 | -3,95 | -3,20 | 2,00 | 1,61 |
| 2 | -3,85 | -0,61 | -0,26 | 1,02 | -1,26 | -4,58 | -3,27 | 0,51 | 2,89 | 0,49 |
| 3 | -1,80 | 0,97 | 0,35 | 0,17 | 0,33 | -3,73 | 0,13 | 0,43 | 2,99 | 1,39 |
| 4 | 1,33 | -0,68 | -0,35 | -0,50 | 0,25 | -3,27 | 0,35 | 1,91 | 0,88 | 0,95 |
| Big | 2,19 | 1,30 | 0,44 | 0,00 | -0,65 | -1,69 | 0,02 | 2,36 | 1,51 | 1,89 |

**Table 10A FF3 Alpha Profitability factors**

Panel A presents the Fama and French 3 factor (FF3) regression intercepts for each of the 25 size and GPA/OP factors. Panel B reports the corresponding t-stats.
FF3 regression: $R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + \varepsilon_t$

Panel A intercepts

| | GPA quintiles | | | | | OP quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Small | -0,49 | -0,41 | -0,14 | 0,08 | 0,19 | -0,83 | -0,45 | -0,14 | -0,04 | 0,20 |
| 2 | -0,32 | -0,23 | -0,06 | -0,02 | 0,16 | -0,59 | -0,21 | -0,02 | 0,03 | 0,17 |
| 3 | -0,17 | -0,08 | 0,05 | 0,04 | 0,16 | -0,31 | -0,11 | -0,02 | 0,10 | 0,16 |
| 4 | -0,16 | -0,12 | -0,09 | 0,07 | 0,29 | -0,40 | -0,11 | 0,02 | 0,07 | 0,24 |
| Big | -0,17 | -0,14 | 0,04 | 0,12 | 0,32 | -0,23 | 0,05 | 0,00 | 0,12 | 0,29 |

Panel B t-stats

| Size | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Small | -3,69 | -4,57 | -1,81 | 1,01 | 2,30 | -4,72 | -4,23 | -1,85 | -0,55 | 2,79 |
| 2 | -3,02 | -2,87 | -0,88 | -0,37 | 2,19 | -4,57 | -2,70 | -0,25 | 0,43 | 2,40 |
| 3 | -1,58 | -0,92 | 0,65 | 0,58 | 2,05 | -2,17 | -1,27 | -0,26 | 1,33 | 2,07 |
| 4 | -1,63 | -1,36 | -1,17 | 0,93 | 3,81 | -3,59 | -1,25 | 0,27 | 1,00 | 2,87 |
| Big | -2,19 | -1,72 | 0,59 | 1,64 | 4,29 | -2,44 | 0,75 | 0,02 | 1,79 | 4,31 |

**Table 16A Factor returns GPA and OP**

The table presents the 25 double sorted portfolios based on size and the two factors: GPA, and OP. The returns presented are monthly average excess returns over the risk-free rate between July 1963 to June 2016. In the first sort, I use the Market capitalization breakpoints, provided by the Kenneth French website to form 5 portfolios in June. In addition, I form factor quintiles for each size portfolio, which yields 25 portfolios in total. Panel B shows the corresponding t-stats and panel C the Sharpe ratio for each portfolio.

Panel A Portfolio average excess returns

| | GPA quintiles | | | | | OP quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Size quintiles | | | | | | | | | | |
| Small | 0.34 | 0.48 | 0.72 | 0.89 | 0.98 | 0.08 | 0.46 | 0.72 | 0.79 | 0.98 |
| 2 | 0.42 | 0.61 | 0.74 | 0.73 | 0.88 | 0.28 | 0.66 | 0.74 | 0.80 | 0.88 |
| 3 | 0.45 | 0.71 | 0.79 | 0.74 | 0.80 | 0.49 | 0.68 | 0.72 | 0.80 | 0.78 |
| 4 | 0.42 | 0.59 | 0.62 | 0.67 | 0.84 | 0.34 | 0.61 | 0.71 | 0.68 | 0.76 |
| Big | 0.33 | 0.40 | 0.51 | 0.47 | 0.62 | 0.33 | 0.53 | 0.47 | 0.50 | 0.57 |

Panel B t-stats

| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Size quintiles | | | | | | | | | | |
| Small | 1.15 | 1.83 | 2.78 | 3.44 | 3.75 | 0.23 | 1.66 | 2.89 | 3.26 | 3.83 |
| 2 | 1.67 | 2.49 | 2.98 | 2.97 | 3.56 | 0.91 | 2.63 | 3.20 | 3.33 | 3.43 |
| 3 | 2.05 | 3.02 | 3.35 | 3.18 | 3.41 | 1.68 | 2.88 | 3.19 | 3.53 | 3.14 |
| 4 | 2.19 | 2.73 | 2.75 | 3.02 | 3.85 | 1.32 | 2.68 | 3.23 | 3.20 | 3.25 |
| Big | 1.86 | 2.14 | 2.79 | 2.41 | 3.43 | 1.54 | 2.96 | 2.56 | 2.77 | 2.96 |

Panel C Sharpe ratio

| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| Size quintiles | | | | | | | | | | |
| Small | 0.16 | 0.25 | 0.38 | 0.47 | 0.51 | 0.03 | 0.23 | 0.40 | 0.45 | 0.53 |
| 2 | 0.23 | 0.34 | 0.41 | 0.41 | 0.49 | 0.13 | 0.36 | 0.44 | 0.46 | 0.47 |
| 3 | 0.28 | 0.41 | 0.46 | 0.44 | 0.47 | 0.23 | 0.40 | 0.44 | 0.48 | 0.43 |
| 4 | 0.30 | 0.38 | 0.38 | 0.41 | 0.53 | 0.18 | 0.37 | 0.44 | 0.44 | 0.45 |
| Big | 0.26 | 0.29 | 0.38 | 0.33 | 0.47 | 0.21 | 0.41 | 0.35 | 0.38 | 0.41 |

# Appendix C Figures

**Figure 1A**

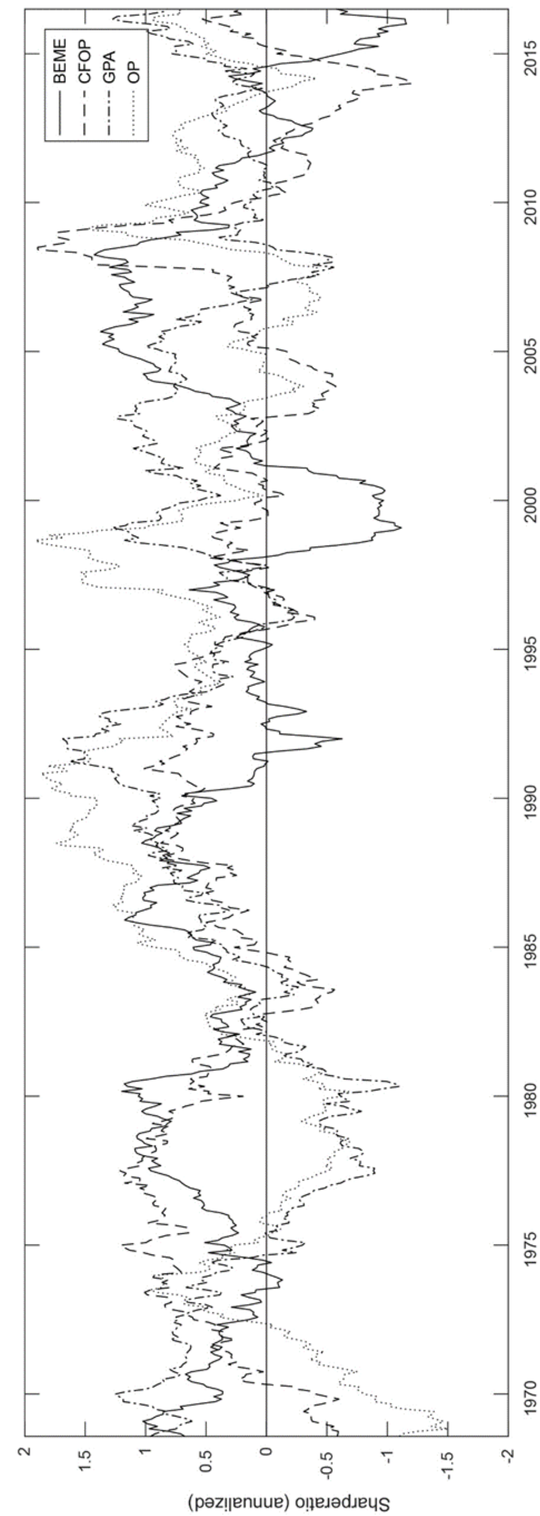


**Figure 2A**

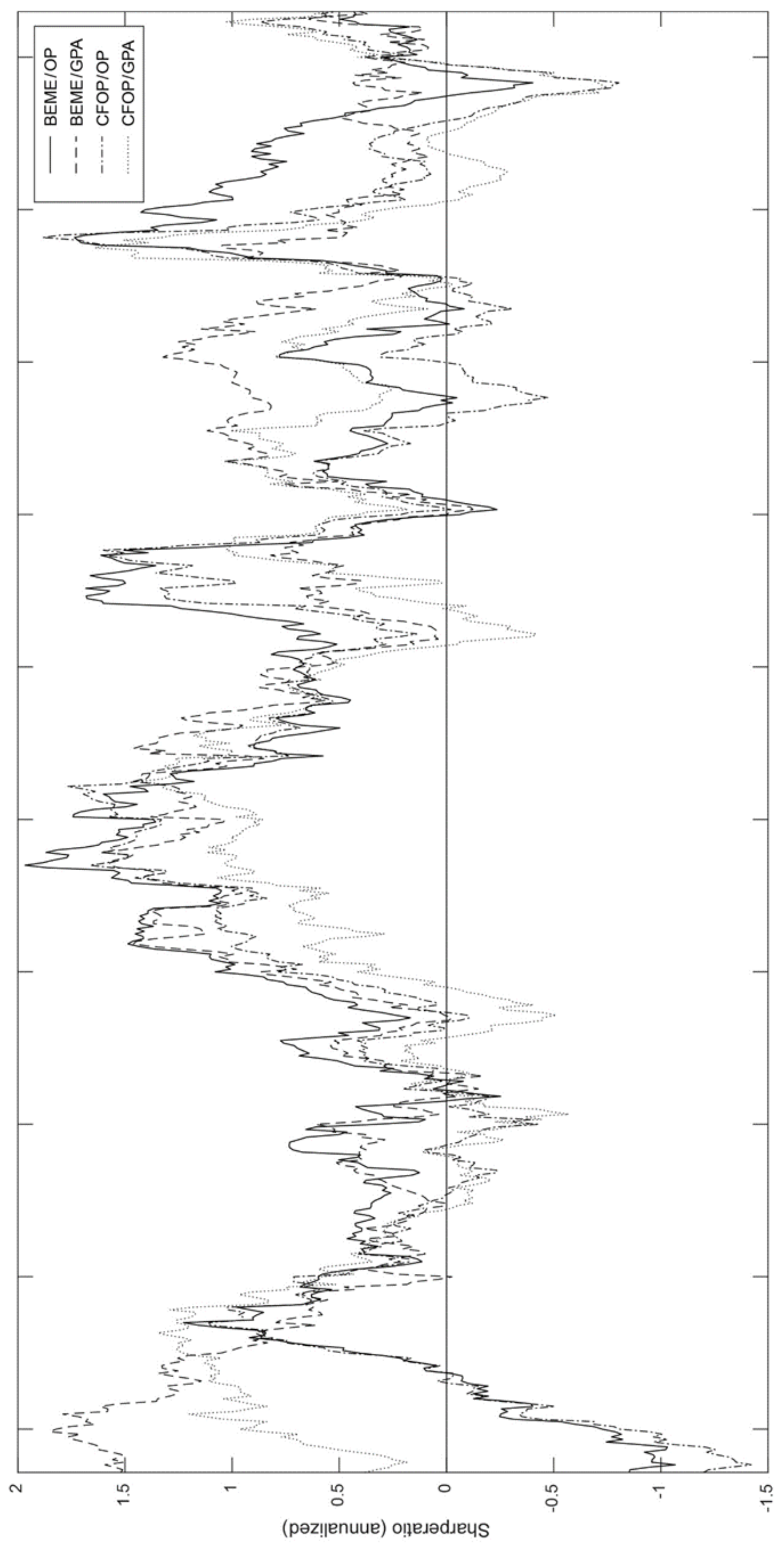
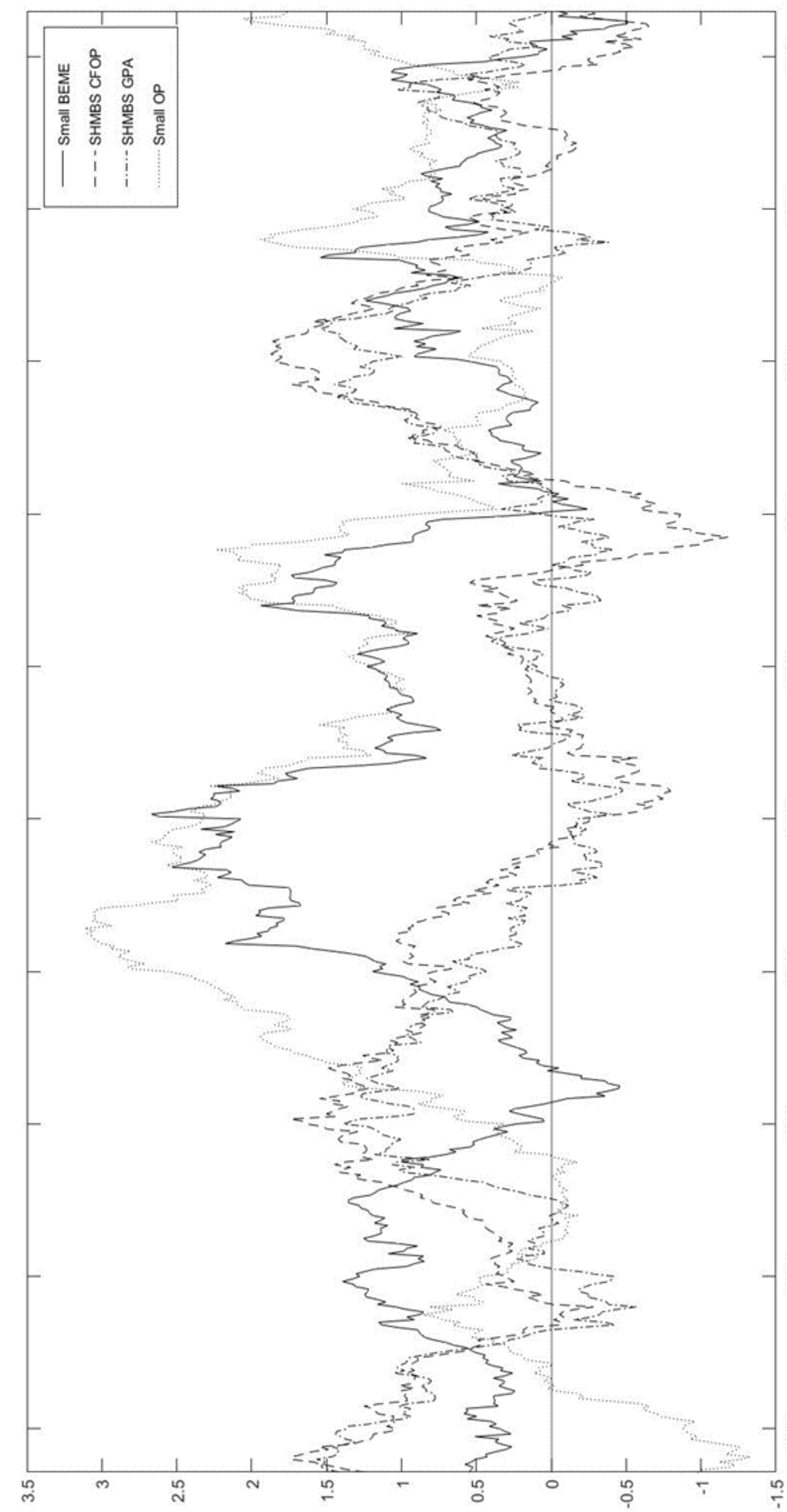

BEME/OP
BEME/GPA
CFOP/OP
CFOP/GPA
Sharperatio (annualized)
2
1.5
1
0.5
0
-0.5
-1
-1.5
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015

**Figure 5A**


Small BEME
SHMBS CFOP
SHMBS GPA
Small OP
Sharperatio (annualized)
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015

# Appendix D Preliminary Master Thesis

Lukas Brockmann: **1002941**

Preliminary Master Thesis report

## Enhancement of value strategies using profitability factors

Hand-in-date:

15.01.2017

Campus:

BI Oslo

**GRA 19502** Preliminary Master Thesis Report

Supervisor:

Ilan Cooper

Program:

Master of Science Finance

## Section 1: Introduction

In the last few decades many researchers found anomalies in average stock returns that cannot be captured by the CAPM Model (Lintner, 1965) or (Sharpe, 1964). For example (Basu, 1977) finds that stocks with a high Earnings/Price (E/P) ratio generate higher risk adjusted returns than stocks with a low E/P ratio. (Banz, 1981) finds that companies with a low market capitalization (small) have a higher average return than high market cap companies (large). (Fama & French, 1992; Lakonishok, Shleifer, & Vishny, 1994; Rosenberg, Reid, & Lanstein, 1985) show that a high book to market (BE/ME) value yields larger average returns. These results prove to some extent that the value investment strategy of (Graham, 1949) and (Dreman, 1982), which proposes to buy stocks that are undervalued and short stocks that are overvalued, generates superior returns.

Even though researchers find higher average returns for these strategies there is no consensus why this is the case. (Lakonishok et al., 1994) argue that the high average return is due to the fact that these "… strategies exploit the suboptimal behaviour of the typical investors", which is in line with (Bondt & Thaler, 1985) who find evidence in favour of their overaction hypothesis that market participants overreact to unforeseen events. Like (Basu, 1977) they try to prove that the efficient market hypothesis, which states that stock prices reflect all information available in the market (Malkiel & Fama, 1970), is biased by investor expectations and that it is therefore possible to exploit this inefficiency. (Dreman, 1982) thinks that the reaction to several continuous negative E/P events led the investors to be too pessimistic about the stock value and indicates that the stock is trading below its normal price. (Bondt & Thaler, 1985) show that those "loser" stocks reverse to their "true" value at some point in the future and yield an abnormal return.

(Fama & French, 1992) do not fully agree with this view and suggest that value strategies generate a higher return because undervalued stocks bear higher fundamental risk and must compensate the investor for the additional risk. (K. C. Chan & Chen, 1991) find that small firms are typically less efficient (performed poorly in the last periods) and have higher leverage compared to large firms. They find evidence that these differences require a higher equity premium for small stocks and conclude that this is the reason for a higher average return. This supports (Huberman, Kandel, & Karolyi, 1987) finding that firms of the same size are similar in risk and that their returns behave in the same way. Nevertheless, (Fama & French, 1992) cannot prove their hypothesis since the higher average returns are not associated with a higher risk level (higher beta).

The most commonly used regression model to evaluate, if value factors are able to generate excess returns is the Fama and French 3 Factor model (FF3) (Fama & French, 1993). It uses the factors marketriskpremium ($r_m - r_f$), small minus big market capitalization stocks (SMB) and high-minus-low book equity to market equity (BE/ME) stocks (HML) to capture expected average returns. The model captures most of the anomalies that are not explained by the CAPM but also has short comings with other anomalies, for example, net share issues (Loughran & Ritter, 1995), accruals (Sloan, 1996), volatility (Ang, Hodrick, Xing, & Zhang, 2006) and momentum (Jegadeesh & Titman, 1993). The factor E/P is the most common one, because it yields the superior return of value stocks but is associated with growth stocks, which should normally underperform. (Basu, 1983) for example shows that if we control for E/P ratios the value effect of firm size gets insignificant.

(Fama & French, 2006) find that profitable firms earn higher average returns then unprofitable firms. (Novy-Marx, 2013) uses the gross profit to assets (GP/A) ratio as a profitability measure and discovers that a high ratio generates significant higher average returns. Beside this he shows that profitability and value stocks have a negative correlation. Therefore he proposes to use the profitability strategy as a hedge for value strategies to increase risk adjusted returns, which it achieves. (Kogan & Papanikolaou, 2013) replicate his research for their sample to find a relation between growth opportunities and their sensitivity to Investment specific technology shocks and find consistent patterns. Beside this there are other factors that are associated with profitability, have a low BE/ME ratio and generate significant average returns. Examples would be return on net operating assets (RONA), Profit Margin (PM) or Return on Equity (ROE) (Haugen & Baker, 1996; Soliman, 2008). These finding further support the assumption for a profitability premium in the market, but also that there is not only one profitability accounting ratio that leads to superior results in prediction of future returns.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive literature overview of value and profitability factors and their effect on average stock returns. Section 3 provides information regarding the data and discusses the methodology to capture the effect of the strategies. In section 4 the different value and profitability factors will be evaluated individually and together for the US stock market from July 1963 to December 2016. Section 5 uses (Novy-Marx, 2013) approach to implement a combined portfolio of the best individually tested value and profitability factors. Section 6 will test if the effects are still significant if regressed by Fama and French 5 factor model (FF5), Carhart and Q-Factor model. Section 7 provides the conclusion of the research.

## Section 2: Literature Review

### 2.1 Value factors

There are several accounting measures to evaluate if a company's stock is over- or undervalued. The following paragraphs will discuss value factors that have been proven to be significant over a period from 1972 to 2012 (Hou, Xue, & Zhang, 2015) and factors from more recent studies that have an even higher predictive power. The four value and profitability factors presented here will be tested in section 4.

2.1.1. Earnings to price ratio (E/P)

One of the earliest papers to test the value strategy of (Graham, 1949) was (Basu, 1977) who tests if the Earnings Price (E/P) Ratio can predict future excess returns. He finds that high E/P stocks earn higher average and risk adjusted returns than low E/P stocks. (Ball, 1978) undertakes a meta study consisting of nearly 20 studies that consider the E/P anomaly effect. He assumes that the future excess returns documented are due to the fact that E/P is a proxy for omitted variables in the two parameter model and that those have a positive correlation with expected returns. (Reinganum, 1981) tests the firm size and E/P Ratio effect on the AMEX and finds results in favor of both anomalies as proxy for missing factors in the CAPM.

Nevertheless, he shows that the E/P effect is subsumed by the firm size effect. Connecting this result with (Ball, 1978) it would suggest that firm size has a higher positive correlation with expected returns. (Basu, 1983) argues that this result is due to the fact that the results of (Reinganum, 1981) do not consider systematic and total risk. He finds that high E/P firms outperform low E/P firms independent of firm size. By adjusting for risk and E/P ratios the firm size effect gets insignificant. (Banz & Breen, 1986) argue that the anomaly effect of E/P ratio and the mixed previous results between the firm size and E/P relation is due to the way researchers use the available COMPUSTAT data. They find evidence that COMPUSTAT data has a look-ahead bias (researchers use empirical data for allocation in January that are only available to investors in several months) and an ex-post selection bias (non-existing firms are excluded) which seems to be the reason for the E/P effect. (Jaffe, Keim, & Westerfield, 1989) use a longer observation period from 1951 to 1986 and evaluate the firm size and E/P ratio effect separately. They try to avoid the look-ahead bias by taking end of fiscal year earnings and the price at the end of march. They also include firms that disappeared during the fiscal year to reduce the ex-post selection bias. They find a positive individual size and E/P effect during the observation period from 1951 to 1986. Like (Cook & Rozeff, 1984) they also introduce the January effect and find evidence that E/P is significant in every months, while firm size is only significant during January. By using Moody's Industrial Manual (Davis, 1994) avoids the previous mentioned biases and investigates the time period before COMPUSTAT (1940 to 1963). He also finds evidence for the predictive power of E/P ratio especially in January, but not for firm size, which could be due to the exclusion of very low market cap stocks from his sample.

### 2.1.2 Operating Cash flow to price ratio (CFO/P)

Company valuations are typically based on the dividend discount model or the discounted cash flow model (Gordon & Shapiro, 1956) to define the intrinsic value of a company based on expected future dividends/cash flows. Such expectations are made on the current accounting values and market conditions as well as market participants expectations of future growth. Therefore, a higher reported cashflow should lead to a higher company valuation. (Wilson, 1987) was one of the first researchers to evaluate if cashflow has an additional effect to earnings, since the earnings announcement is released prior to the annual report. Using an event study approach, he found that abnormal returns increased if cash flows were higher in the annual report. His results were significant, but only for a small sample of firms and the period from 1981 to 1982. Contrary (Bernard & Stober, 1989) find no significant effect due to high cash flows during their 35 quarter observation period. (L. K. C. Chan, Hamao, & Lakonishok, 1991) create the cash flow to price ratio (CF/P) to set the cashflow into relation to its current stock price. A high CF/P ratio is hereby associated with a value stock since it implies that the price compared to one dollar of cash flow generated is too low. In their test period from 1971 to 1988 they test the CF/P and E/P ratio in the Japanese market. They believe that the CF/P ratio yields better information than E/P since managers use the optimal type of depreciation to minimize tax liabilities and meet shareholders' expectation. The impact of CF/P on expected future returns is high and significant, while E/P is insignificant. This might be due to Japanese legislation that allows accelerated depreciation, since we have seen that other studies find a significant E/P effect in the US market that is consistent and significant over time (Cook & Rozeff, 1984; Davis, 1994). (Lakonishok et al., 1994) find that value stocks sorted on Sales Growth (SG) and CF/P outperform growth stocks for a holding period of 5 years and that the sort on CF/P is even more profitable than the sort on high E/P. They show that the real growth rate of value (growth) stocks are higher (lower) than anticipated by the market, based on past growth rates. Surprisingly the additional abnormal return generated by value stocks is not associated with higher fundamental risk.

(Sloan, 1996) investigates how the composition of accruals and cash flow in earnings effect future returns. He tests if high (low) cash flows (accruals) are a good indicator for current and future earnings persistence, and finds support for his hypothesis. In addition, he shows that high cash flows generate significant abnormal returns. He concludes that investors are not completely able to distinguish the quality of earnings and growth in the future. This hypothesis is supported by (Dechow & Sloan, 1997) who find that real growth rates are lower than analysts' forecasts, but the market initially prices stocks based on these forecasts. This effect explains up to 50% of the E/P abnormal return for value stocks. (Richardson, Sloan, Soliman, & Tuna, 2005) confirm (Sloan, 1996) earnings persistency hypothesis for the period 1962 to 2001. A recent study by (Hui, Nelson, & Yeung, 2016) compares industry wide and firm specific effects of earnings. They show that industry wide earnings persistency is less noisy than firm specific earnings and in addition that the accruals and cash flow effect reported in early firm specific studies is consistent for industry wide earnings persistency.

The cash flow component of CF/P in these studies is normally defined by the earnings plus depreciation (Sloan, 1996). (Desai, Rajgopal, & Venkatachalam, 2004) argue that this measure does not fully represent the operating cash flows of a firm and construct the new factor CFO/P, where CFO is operating income minus depreciation minus accruals. They show that in the presence of CFO/P the effect of E/P and Book Equity to market equity (BE/ME) is subsumed and highly significant and that CFO/P has a higher predictive power than CF/P. Most recently (Foerster, Tsagarelis, & Wang, 2016) show that the direct method of computing operating cash flows leads to superior predictive power compared to the indirect method used in most articles.

### 2.1.3 Net payout yield (NO/P)

Dividends have been a variable for empirical asset pricing models. For example (Fama & French, 1988) use the dividend to price ratio (D/P) and find that it has a higher predictive power than E/P. In addition the significance increase with an increase in time horizon. (Hodrick, 1992) uses the D/P in a vector autoregression model (VAR) and finds that it is able to predict expected returns to some degree. For a one year holding period (Kothari & Shanken, 1997) show that BE/ME as well as D/P can predict expected returns. While BE/ME is better over the whole sample period from 1926 to 1991, D/P ratio is better in the recent subperiod from 1941-1991. In recent years researchers find that the predictive power of dividend yield decreases, for example (Valkanov, 2003) shows that the D/P ratio does not have predictive power after 1981, but is significant during 1946-1980. Several other papers question the predictive power of the P/D ex-post 1984 (Goyal & Welch, 2003; Lettau & Ludvigson, 2005). The decline in predictability could be due to a decrease in dividend payout to shareholders. (Fama & French, 2001) document that “cash dividends falls from 66.5% of earnings in 1978 to 20.8% in 1999”. On the other side more and more firms buy back shares in the market. During 1980 to 2000 share repurchases increased from 13% to 113 % of paid dividends (Grullon & Michaely, 2002). We can see that firms change their payout policy towards shareholder. (Boudoukh, Michaely, Richardson, & Roberts, 2007) therefore argue that the CF/P ratio does not represent the total cash payout to shareholder. They introduce the variable net payout yield (NO/P) which consists of dividends plus repurchases minus equity issuance and is supposed to be a better predictor for expected returns than D/P. They show that the NO/P subsumes the D/P ratio in the cross section of returns and generates higher abnormal returns. Also under the framework of (Goyal & Welch, 2003) NO/P is significant out of sample (OOS) while D/P is not.

#### 2.1.4 Book to market Equity (BE/ME)

The most common value factor is BE/ME (the value of book equity compared to the value of current market equity), which has been proven to have a positive relation with the average stock returns in the US (Rosenberg et al., 1985). (L. K. C. Chan et al., 1991) also find that BE/ME has a high predictive power in the cross section of average returns in the Japanese market. (Fama & French, 1992) discover that the two variables B/M and size can explain most of the cross section of variations in average stock returns for the four factors E/P, size, BE/ME and leverage. (Fama & French, 1995) further investigate the reasons for the predictive power of BE/ME under the aspects of associated risk and relation to earnings. They find that BE/ME is associated with long term profitability and that high BE/ME firms (undervalued) typically have depressed earnings and are therefore riskier than low BE/ME firms (high stock price), which sustain profitable. This theory is supported by (N. f. Chen & Zhang, 1998) who show that high BE/ME firms have high leverage, higher earning uncertainty and cut dividends more often, which is associated with financial distress. This effect is proven in the US and in other developed markets like Japan or Hong Kong, but is nearly nonexistent in the “growth markets” Taiwan and Thailand during their observation period from 1970 to 1993. They assume that this is due to the different relative riskiness of these markets. The suggested relation between risk and high BE/ME firms differ compared to a study of (Dichev, 1998) who uses the (Ohlson, 1980) O-score, which consists of 9 accounting variables that are related to default risk, to test if firms in financial distress also outperform the market like high BE/ME stocks. The result suggest that this is not the case, which contradicts (N. f. Chen & Zhang, 1998) and (Fama & French, 1995) conclusions. However, in his study there was no additional separation between high and low BE/ME firms. (Griffin & Lemmon, 2002) find that firms with a high BE/ME ratio and high O-score do not perform better than firms that are only sorted on high BE/ME ratio. This indicates that the BE/ME ratio already captures the high O-score and that it does not have additional power in predicting future returns. On the other side low BE/ME firms with a high O-score perform worse than other high BE/ME firms. (Griffin & Lemmon, 2002) also mention that those firms have exceptional high capex and that the reason for the high O-score is due to low or negative earnings. We know that investment factors (for example capex) have a negative slope to future expected returns and are associated with lower systematic risk, e.g. a lower equity risk premium (Berk, Green, & Naik, 1999; Titman, Wei, & Xie, 2004). They conclude that the low average returns of (Dichev, 1998) are driven by the bad performance of those low BE/ME stocks. (Campbell, Hilscher, & Szilagyi, 2008) use a dynamic logit model to estimate long term default probabilities and find that independent of size and value effects firms with high default probabilities have a negative alpha. It can be concluded from these results, that the risk based explanation for the BE/ME premium is not the main reason for the abnormal returns.

### 2.2 Profitability

While the value strategy buys firms with high book equity to market equity, e.g. where the investor can buy a larger quantitiy of assets for a certain amount and short growth firms, the profitability strategy buys firms which have high profitability and sells firms with low profitability. Both strategies earn abnormal returns (Ball, 1978; Fama & French, 2006). This is interesting since profitability is associated with attributes of growth companies (low BE/ME), but generates similar returns as value stocks (Fama & French, 1993). (Fama & French, 1995) further investigate this result using a ratio that scales earnings on common book equity (EI/BE) and find the same pattern. In detail they show that portfolios sorted on high firm size, low BE/ME ratios and high EI/BE generate the highest returns. In the cross-section of returns EI/BE even has a higher predicitve power than size.

This results are interesting for researchers, since profitability factors which are associated with growth stocks should have a negative correlation to value stocks and therefore might be a good hedge for these investment strategies. The following part will discuss four common profitability factors that have been proven to be significant in the the cross section of returns. Surprisingly (Asness, Frazzini, & Pedersen, 2014) even find in their research about quality stocks, which are characterised as high growth, high payout, high safety and high profitability, that profitability is the most persistent factor in the long US and international sample.

### 2.2.1 Return on Equity (ROE)

The research of profitability factors started quite late. One of the first papers who identify a significant factor in the cross-section of returns is from (Haugen & Baker, 1996) who test the relation between net income to book equity (ROE). They find that high profitability firms outperform low profitability firms. (Cohen, Gompers, & Vuolteenaho, 2002) also find a positive relation between ROE and average stock returns after controlling for BE/ME. (L. Chen, Novy-Marx, & Zhang, 2011) construct a high-minus-low (HML) portfolio based on ROE and are able to generate significant average returns of 0.71% per month. In a regression of current return, B/M and ROE (Campbell, Polk, & Vuolteenaho, 2010) find that B/M and ROE can predict the expected return and that the past returns do not have predictive power. In their weighted least square (WLS) test BE/ME has the highest predictive power, followed by ROE. Interestingly they choose a long observation period of five years before portfolio formation and a two to five year holding period. The ROE therefore is based on the 5 year trailing average. In a recent study of (Chattopadhyay, Lyle, & Wang, 2015) ROE and BM are modeld together as an expected return proxy (ERP) and has proven to be reliable predictor of future stock returns in-sample and out-of-sample.

### 2.2.2 Return on Assets (ROA)

(Novy-Marx, 2013) argues that “firms with productive total assets should yield higher average returns than firms with unproductive assets”. Following this logic firms with higher productivity are more profitable and investors demand a higher rate of return. Therefore it makes sense to not only test variables based on the book equity of a company, e.g. ROE, but also on the productivity of the overall assets, which also takes liabilities into account. The most general way to test this assumption is using the simple measure of earnings scaled by total assets (ROA).

For example (Balakrishnan, Bartov, & Faurel, 2010) find positive abnormal returns for their HML portfolios based on ROA. The holding period in their test is relatively short with one and two months. (Stambaugh, Yu, & Yuan, 2012) show that ROA generated monthly excess returns (over the risk free rate) of 0.64% for the long strategy and 0.98% for the HML portfolio, both statistically significant, for the period from 1972 to 2008. (Wang & Yu, 2013) find a significant profitability premium for ROE and ROA after testing for information uncertainties and limits of arbitrage. They show that investors underreact to profitability news and that this is more likely to happen in firms when there is high information uncertainty and arbitrage costs. (Piotroski & So, 2012) also find that growth firms with high ROA generate median annual returns of 6.8%, but after controlling for expectation errors in their sample the value and profitability anomalies can not generate excess returns. This risk based argumentation is in line with (Dechow & Sloan, 1997), that market participants overestimate growths rates and do not evaluate the fundamental financial situation of a company. Nevertheless, the risk based explanation for value and profitability stocks is not the main focus of this thesis and therefore negligible in the selection of tested anomalies.

### 2.2.3 Gross Profit to Assets (GP/A)

(Fama & French, 2006) take earnings as a proxy for profitability in their dividend discount model. They find that this profitability factor does not enhance the predictive power of BE/ME and firm size. (Novy-Marx, 2013) argues that earnings is not a good proxy for future profitability since there are other measures, like human capital development, marketing and reasearch & development (R&D), that are all expected to have a positive impact on future profitability, but are accounted for as an expense. His main argument for gross profit is that it is the cleanest accounting measure and therefore represents the true economic profitability of a company. The study shows that GP/A has predictive prower in the cross section of expected returns and subsumes other profitability measures based on EBITDA, asset turnover or profit margins, that are all independently significant (Novy-Marx, 2013). The strategy earns monthly excess returns over Fama and French three-factor model (FF3) of 0.43% for the long leg and 0.66% for the HML strategy with t-stats larger than 4 (Stambaugh et al., 2012). (Kogan & Papanikolaou, 2013) show that the relation between GPA and

BE/ME is negative, which is in line with (Novy-Marx, 2013) results of a negative correlation of -18%. Overall they confirm his results in their replication.

### 2.2.4 Cash based Operating profitability to Assets (CbOP/A)

(Ball, Gerakos, Linnainmaa, & Nikolaev, 2015) investigate the predictive power of GP/A and find that operating profitability (OP/A) has the same predictive power and leads to higher future return than GP/A. They suggest that selling, general, and administrative expenses (XSGA) can also be directly associated with the revenue firms generate. Beside this (Weil, Schipper, & Francis, 2013) explain that there is no precise accounting standard that specifies how firms should allocate these expenses between COGS and XSGA. Taking both expenses into consideration should therefore lead to a higher predictive power (Ball et al., 2015). They find that the t-stats increase from 5.46 for GP/A to 8.92 for operating profit and that risk adjusted returns increase to 0.74% per month. By deducting accruals from operating profit (Ball, Gerakos, Linnainmaa, & Nikolaev, 2016) create a cash based operating profit (CbOP/A) measure that has even higher power than operating profit itself. This makes sense in the way that accruals have a negative slope to future expected returns and should therefore reduce predictability (Desai et al., 2004; Fairfield, Whisenant, & Yohn, 2003; Sloan, 1996). This adjustment improves the operating profit factor even further in terms of predictive power and monthly return.

## 2.3 Momentum

Under Momentum we understand the drift subsequent to announcements of firms. (Rendleman, Jones, & Latane, 1982) study the impact of unexpected earnings announcements and find that only half of the impact affects the stock price immediately and that the other half occurs gradually over the 90 days after the event. The gradually adjustment process is defined as momentum. The momentum trading strategy can be defined as followed: Invest in winning stocks and go short on losing stocks. (Foster, Olsen, & Shevlin, 1984) find results in favour of the momentum hypothesis using the Standardized Unexpected Earnings (SUE) factor for a holding period of 1 month (SUE-1) and 6 months (SUE-6). They find that the positive returns increase with firms that have a smaller size. Another possibility to capture the momentum of a stock is based on the previous stock price. (Jegadeesh & Titman,

1993) use this “price momentum” to profit from previously seen stock prices in the market. They take the realized past return over the last 6 months and a holding period between 1 and 31 months. They find evidence of the momentum hypothesis for a time lag of 1 months (R6-1) and 6 months (R6-6). They also show that this effect reversals after a holding period longer than 12 months and that the realized abnormal returns are not due to the systematic risk of the stock, which is consistent with the delayed pricing theory. (Fama & French, 1996) use the three-factor model to evaluate stock returns and find that it cannot explain the positive abnormal return for most frequencies of the momentum strategy. (L. K. C. Chan, Jegadeesh, & Lakonishok, 1996) find support for the price and the earnings surprise momentum strategy, but stronger results for the price momentum effect. A different approach is proposed by (Moskowitz & Grinblatt, 1999) who use the average return of industries to capture momentum. They find that their strategy can explain individual stock momentum strategies in all cases beside a holding period of 12 months. (Pan, Liano, & Huang, 2004) find positive autocorrelations in industry portfolios and therefore explain the industry momentum to some extent. Anyway, they only find positive results for a short holding period of up to 1 month. This paragraph showed us that momentum is existent in the market, but that it only generates positive returns in a relatively short holding period. For my thesis, it might make be reasonable to also sort on momentum and see if it can improve the value-profitability portfolio.

## Section 3: Methodology

In this section I present the hypothesis that will be tested in the American stock market as well as the data and regression models used for the analysis in the following sections.

Several papers show that there is a value- and profitability premium in the market. (Novy-Marx, 2013) proves that these premiums tend to be negatively correlated and that therefore profitability should be able to hedge value strategies. On the other side, new factor models tend to capture anomalies better than the simple FF3 model. Therefore, my two main research questions are:

1. Are there value and profitability factors in the market that can enhance (Novy-Marx, 2013) investment strategy?
2. Are these factors still significant in FF5, Carhart and Q-Factor model?

In addition to these research questions, I want to investigate the following hypotheses:

1. A sort on Momentum improves the risk adjusted performance of my strategy.
2. Transaction costs eliminate the anomaly.

**3.1 Data**

This paper follows the structure of (Ball et al., 2016; Ball et al., 2015; Novy-Marx, 2013). The monthly stock returns are obtained from Center for Research in Security Prices (CRSP) and accounting data from COMPUSTAT. The sample consists of all ordinary common shares of firms that are traded on AMEX, NASDAQ and NYSE.

(Beaver, McNichols, & Price, 2007) argue that delisting returns have a high effect on investment strategies and are often not considered in the evaluation of value strategies, especially BE/ME, CF/P and E/P. They find that the spread between the highest and lowest decile increases if delisting returns are included and that low deciles decrease more than high deciles. Most researchers after the year 2000 include the delisting returns that are now provided through CRSP, but there is no real consensus about delisted firms that are not reported by CRSP and are related to forced delisting, for example bankruptcy or insufficient assets. (Sloan, 1996) assumes a return of -100% while (Piotroski, 2000) assumes 0% and some even exclude delisted firms from the sample (Hribar & Collins, 2002). (Shumway & Warther, 1999) report a negative return for delisted and missing firms for the NASDAQ of -55%. Since this paper uses AMEX and NYSE beside NASDAQ data the average delisting returns over all three stock exchanges of -30% found by (Shumway, 1997) is used. I'm using the CRSP delisting codes to identify liquidations (delisting code: 400 to 490) and should therefore be able to avoid the ex-post selection bias (Banz & Breen, 1986).

I match the data between COMPUSTAT and CRSP with a 6 months' lag for COMPUSTAT data. This is necessary to avoid look-ahead bias. The Look-ahead bias theory was first researched by (Banz & Breen, 1986) and is related to the way COMPUSTAT treats accounting data. For example, the Annual report is not available at the end of the fiscal year but only several months afterwards, typically during the first 6 months. But COMPUSTAT adds the accounting data to the end of the company's fiscal year when it gets available.

The look-ahead bias is therefore present in the data if the researcher forms his portfolio in January based on the end of fiscal year data provided by COMPUSTAT. For example, when historical data from COMPUSTAT is used to sort portfolios on high E/P (firms that have a low market equity compared to earnings) at the end of the company's fiscal year, the high earnings from the future AR are considered, but the current, lower share price. This generates a certain return and therefore leads to the look-ahead bias. Several papers use a lag of 4 months for annual data (Bradshaw, Richardson, & Sloan, 2006; Hirshleifer, Hou, Teoh, & Zhang, 2004; Hou et al., 2015; Jaffe et al., 1989; Piotroski & So, 2012) or 6 months (Ball et al., 2016; Fama & French, 1995; Gerakos & Linnainmaa, 2016; Novy-Marx, 2013). It seems that researchers are indifferent about the lag of four and six months, since there is no literature available that focus on this topic. The (U.S. Securities and Exchange Commission, 2009) requires companies to file Annual reports (10-K) up to 90 days after their fiscal year. So, taking the first April (fourth month) might be more reasonable. On the other side if companies report later because of good reasons we would exclude them from the sample. This is the main reason why I use the six month lag in my computations.

I set the sample period for January 1962 to December 2016. This is due to the inclusion of the American Stock Exchange (AMEX) to COMPUSTAT in 1962 (Jaffe et al., 1989). Another reason is that Book Equity data prior to 1962 is sometimes missing and also the possible selection bias towards large corporations described by (Fama & French, 1992). Using the six-month lag after the end of fiscal year the asset pricing tests start for a period from July 1963 through December 2016. I will also exclude financial firms, because the high leverage of those firms normally does not have the same meaning than high leverage in normal companies (Fama & French, 1992). Even though this might be true (Novy-Marx, 2013) does not find a significant difference in his results excluding financial firms. Since he does not apply factors that are based on leverage but only on price or total Assets this might be reasonable. If there would be a measure that focuses on financial distress, like the O-Score (Ohlson, 1980) the results might differ. Financial firms are identified as companies with a one digit standard industrial classification (SIC) code of six.

Companies are included, when they have the following data available on the day of portfolio formation. The past performance for the last one month r(1,0) and 12 to two months r(2,12), firm size log(ME), the value factors BE/ME, E/P, CFO/P, NO/P and profitability factors ROA, ROE, GP/A, CbOP/A. The detailed accounting data needed and the computation of those factors is described in Appendix A. The Appendix also gives insight into the formation of deciles and the creation of the 25 BE/ME portfolios.

### 3.2 Pearson and Spearman correlation

I first evaluate which factors might be a good hedge for one another. There are several ways to measure the relation between two variables. I will shortly discuss the Pearson and Spearman correlation and their interpretation. The Pearson correlation shows the linear relation between two variables (Pearson, 1895), where -1 indicates a negative relation, 0 no relation and 1 a total positive relation (Lee Rodgers & Nicewander, 1988). Equation 1 shows the function for two variables $X$ and $Y$, where $X_i$ and $Y_i$ are the individual values at each observation $i$ and $\bar{X}$ and $\bar{Y}$ are the respective means for the whole sample.

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{[\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2]^{\frac{1}{2}}} \tag{1}$$

The Spearman correlation on the other hand measures the strength and direction of a monotonic relationship (can be linear or not) of two variables. This means that the behavior between the variables is analyzed rather than the linear relation (Pearson). The Spearman correlation measures the Covariance between the Pearson correlation for ranked variables. The main advantage of this is that a small quantity of outliers do not falsify the relation between the two variables (Spearman, 1904). For example (Jondeau & Rockinger, 2003) show that skewness and kurtosis are large and significant in most of their samples.

$$\rho = 1 - \frac{6 \sum {D_i}^2}{n(n^2-1)} \tag{2}$$

, where $D_i$ represents the difference between the ranked pairs at each observation $i$ and $n$ is the number of rank pairs (Corder & Foreman, 2014). An advantage of the Spearman correlation is that it can also be used for non-monotonic data. (Maslov & Rytchkov, 2010) show that all their nine tested anomalies have a non-monotonic relationship, which would support the use of the Spearman correlation. Since I am not visualizing the data, I cannot distinguish between the monotonic and linear relationship of the factors. Therefore, I will use both measurements and evaluate the patterns.

### 3.3 Fama MacBeth Regression

The (Fama & MacBeth, 1973) two-step regression is a practical and simple way to test in what way our factors describe portfolio or asset returns. In the first step, I test the factor exposure, which means that I regress the portfolio return with one or more factors time series to see how exposed the portfolio is to these factors (e.g. Betas). Equation 3 shows the regression to obtain the factor betas.

$$R_{i,t} = \alpha_1 + \beta_{i,F_1} F_{j,t} + \beta_{i,F_2} F_{2,t} + \cdots + \beta_{i,F_m} F_{m,t} + \varepsilon_{i,t}$$

$$R_{2,t} = \alpha_2 + \beta_{2,F_1} F_{j,t} + \beta_{2,F_2} F_{2,t} + \cdots + \beta_{2,F_m} F_{m,t} + \varepsilon_{2,t}$$

$$\vdots$$

$$R_{n,t} = \alpha_n + \beta_{n,F_1} F_{j,t} + \beta_{n,F_2} F_{2,t} + \cdots + \beta_{n,F_m} F_{m,t} + \varepsilon_{n,t} \tag{3}$$

, where $R_{i,t}$ is the return of portfolio $i$ to $n$ ($n$ equals total number of portfolios) at time $t$. $F_{j,t}$ is the factor $j$ to $m$ ($m$ equals total number of factors). $\beta_{i,F_j}$ is the factor exposure of each portfolios return to a given factor $F_j$. $t$ goes from 1 through $T$.

After obtaining the estimates for $m$ Betas (in the following declared as $\hat{\beta}$) from equation 3 i can go forward with the second step. Hereby I run $T$ cross sectional regressions on the estimated $\hat{\beta}_j$s. $\hat{\beta}_j$ stays constant over time since I now want to evaluate if a higher factor exposure leads to higher returns. The effect will be captured by the regression coefficients $\gamma$. Equation 4 shows the regression.

$$R_{i,t} = \gamma_{i,0} + \gamma_{i,1}\hat{\beta}_{i,F_1} + \gamma_{i,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{i,m}\hat{\beta}_{i,F_m} + \varepsilon_{i,1}$$

$$R_{i,2} = \gamma_{2,0} + \gamma_{2,1}\hat{\beta}_{i,F_1} + \gamma_{2,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{2,m}\hat{\beta}_{i,F_m} + \varepsilon_{i,2}$$

$$\vdots$$

$$R_{i,T} = \gamma_{T,0} + \gamma_{n,1}\hat{\beta}_{i,F_1} + \gamma_{n,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{n,m}\hat{\beta}_{i,F_m} + \varepsilon_{i,T} \quad (4)$$

, where $R$ is the same as in equation 3. In each regression $i$ goes through 1 to $n$. To compute the risk premium, I will assume that the error terms $\varepsilon_{i,t}$ are independent and identically distributed (IID) and therefore do not omit my $y_m$ results. As an output, I get $m + 1$ (taking the constant $\gamma_{i,0}$ into account) cross section coefficients $\gamma$ for each factor exposure $\hat{\beta}_{i,F_m}$ each with length $T$. I can now compute the risk premium $\gamma_m$ for Factor $F_m$ by averaging the coefficient for each regression, see equation 5.

$$\gamma_m = \frac{\sum_{i=1}^{n} \gamma_{i,m}}{T} \quad (5)$$

And get the standard errors of $\gamma_m$ using equation 6.

$$SE(y_m) = \frac{\gamma_m}{\sigma_{\gamma_m}/\sqrt{T}} \quad (6)$$

**3.4 Fama and French 3 Factor Model**

The (Fama & French, 1993) 3 Factor model (FF3) is probably the most influential paper of the last 30 years and shifted the research in finance from pure hypothesis testing to actually analyzing the data and try to find ways to improve predictive models.

FF3 is based on three factors: The market risk premium (MRP), Small minus Big (SMB) and High minus low (HML). The regression is presented in equation 7.

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + \varepsilon_t \quad (7)$$

, where $R_t$ is the return of the portfolio, $R_{Ft}$ is the 1 month T-Bill and $R_{Mt}$ is the value weighted return of all stocks listed on NYSE, AMEX and NASDAQ. $SMB$ is measured as the average return on the three small portfolios (value, neutral, growth) minus the average of the three big portfolios. HML is the average of small value and large value stocks minus the average of small growth and large growth stock returns. $\alpha$ is the intercept und $\varepsilon_t$ is the error term, which is assumed to be IID.

The reasoning behind the model is to capture the stock price variations that the CAPM (Lintner, 1965; Sharpe, 1964) cannot explain. This is achieved if the intercept $\alpha$ is 0. In their paper (Fama & French, 1996) show in table 1 that the intercepts are relatively small, between -0.45 and 0.2 and significant, which indicates that the model is not perfectly able to capture average returns, but seems to be able to capture most them. The high $R^2$ and t-stats explain the variation of returns over time, e.g. if we have a high $R^2$ for one factor it would indicate that it explains well the covariance, but it doesn't explain the mean. The $\alpha$ instead shows the variation across portfolios in average returns, which is more relevant than $R^2$ and high t-stats in explaining the model. To test if all $\alpha$ are jointly zero Fama and French use the F-test (Gibbons, Ross, & Shanken, 1989) and have to reject their hypothesis on a 0.004 level (Fama & French, 1996).

(Lewellen, Nagel, & Shanken, 2010) criticize the FF 3 model in a way that factors explain up to 80% of the cross-sectional variation in the 25 Size-BE/ME sample portfolios and that the hurdle to find significant explanatory factors that have a high cross sectional $R^2$ is quite low.

### 3.5 Fama and French 5 Factor model

Based on recent research form investment anomalies, which typically have a negative slope to average returns (Anderson & Garcia-Feijóo, 2006; Cooper, Gulen, & Schill, 2008; Titman et al., 2004) and the profitability premium (Novy-Marx, 2013), (Fama & French, 2016) introduce an profitability factor (CMA) and investment factor (RMW).

Equation 8 shows the 5 factor regression where the first three factors are computed as in (Fama & French, 1993).

$$R_t - R_{Ft} = \alpha + b[R_{Mt} - R_{Ft}] + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_t \qquad (8)$$

The new variables are constructed as followed. They first get sorted on size and afterwards on investment for $RMW$ (robust minus weak) and operating profitability for $CMA$ (Conservative minus aggressive). The procedure is the same as for HML, for $CMA_t$ they take the average of small conservative and big conservative and subtract the average of small aggressive and big aggressive. $RMW_t$ is the average of small robust and big robust minus the average of small weak and big weak.

Beside the size-$r_{2,12}$ (MOM) sorted portfolio the intercept for all other portfolios decreases with the introduction of the FF5 model and varies in a range from 0.098 to 0.126 (Fama & French, 2016) table 2.

### 3.6 Carhart model

(Carhart, 1997) investigates mutual fund performance and cannot explain the superior returns of last year fund winners to future returns using CAPM. He proposes a four-factor model, consistent of FF3 factors and a factor related to last year return (Momentum). The linear relation between the highest and lowest quintile in this factor explains the future performance to a high extent. Nevertheless, it must be noticed that all intercepts are consistently negative. I present the Carhart model in equation 9.

$$r_{it} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + p_{iT}PR1YR_t + \varepsilon_{it} \quad (9)$$

Where t = 1 to T, $r_{it}$ is the return of a portfolio in excess of the 1 month T-Bill, RMRF, SMB and HML are the FF3 factors (Fama & French, 1993) and PR1YR is the average 30% highest $r_{2,12}$ minus the average lowest $r_{2,12}$. The momentum factor is based on (Jegadeesh & Titman, 1993) approach. Following PR1YR will be related to as UMD (Up minus down).

### 3.7 Q-Factor model

(Hou et al., 2015) use their q-factor model and find that it has the least rejections from F-Tests (which indicates that the intercepts are on average 0), which makes it reasonable to test the value-profitability portfolio on it to test how robust the returns are. They argue that their two new factors subsume the HML predictive power. Equation 10 shows the Q-Factor model.

$$r_{it} - r_{ft} = \alpha_{iq} + \beta_{iMKT}MKT_t + \beta_{iME}SMB_t + \beta_{iI/A}I/A_t + \beta_{iROE}ROE_t + \varepsilon_i$$

(10)

Where $r_{it}$ is the portfolio return, $MKT$ and $SMB$ are the (Fama & French, 1993) factors for market return and firm size, Investment to Asset ratio $(I/A)$ is from (Cooper et al., 2008) and Return on Equity $(ROE)$ is from (Haugen & Baker, 1996). It is especially interesting to test this model since it is the only one that does not consider the HML factor.

# Appendix A

To construct the deciles of the individual factors, at the end of June in each year t, I use NYSE breakpoints to sort stocks into deciles based on those factors for the fiscal year ending in calendar year t−1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

### A.1. Value factors

**A.1.1. E/P** I construct (Basu, 1983) earnings price (E/P) deciles I use NYSE breakpoints to split stocks into deciles based on E/P at the date of portfolio formation in the end of June of each year t. E/P is income before extraordinary items (COMPUSTAT annual item IB) for the fiscal year ending in calendar year t−1 divided by the Market Equity (ME from CRSP) at the end of December of t−1.

$$E/P = \frac{IB_{t-1}}{ME_{t-1}}$$

**A.1.2. CFO/P** Operating cash flow to price is based on (Desai et al., 2004). CFO/P is IB plus depreciation (COMPUSTAT annual item DP) for the fiscal year ending in calendar year t-1 minus non-cash working capital (Sloan, 1996) divided by the ME at the end of December of t-1.

$$CFO/P = \frac{IB_{t-1} + DP_{t-1} - WC\ Acc.}{ME_{t-1}}$$

**A.1.2.1 WC Acc.** I use (Sloan, 1996) Balance Sheet approach to compute non-cash working capital. All values measure the changes (Δ) between December of year t-2 and December of t-1. It is computed by using change in current assets (COMPUSTAT annual item ACT) minus change in cash and short-term investments (COMPUSTAT annual item CHE) minus the sum of changes in current liabilities (COMPUSTAT annual item LCT) minus changes of debt in current liabilities (COMPUSTAT annual item LCT) minus Income tax payable (COMPUSTAT annual item TXP).

$$WC\ Acc. = \Delta ACT - \Delta CHE - (\Delta LCT - \Delta DLC - \Delta TXP)$$

**A.1.3. NO/P** Net payout is computed by Dividends on common stocks (COMPUSTAT annual item DVC) plus repurchases minus stock issuance. Repurchases are the sum of purchase of common and preferred stocks

(COMPUSTAT annual item PRSTKC) plus all negative changes in the number of preferred stock (COMPUSTAT annual item PSTKRV) between t-2 and t-1. Stock issuance is sale of common and preferred stock (COMPUSTAT annual item SSTK) minus all positive changes in the value of preferred stock (Boudoukh et al., 2007).

If $\Delta PSTKRV < 0, then$

$$NO/P = \frac{DVC_{t-1} + (PRSTKC_{t-1} - \Delta PSTKRV) - SSTK_{t-1}}{ME_{t-1}}$$

If $\Delta PSTKRV \geq 0, then$

$$NO/P = \frac{DVC_{t-1} + PRSTKC_{t-1} - (SSTK_{t-1} - \Delta PSTKRV)}{ME_{t-1}}$$

The data for total expenditure of stocks and the sale of stocks start in 1971, I report returns of NO/P deciles starting in June 1972.

**A.1.4. BE/ME** The ratio is computed as in (Fama & French, 1992). Book equity (BE) is total shareholder equity (COMPUSTAT annual item SEQ), plus balance sheet deferred taxes and investment tax credit (COMPUSTAT annual item TXDITC) minus preferred stock (COMPUSTAT annual item PSTK). Because of changes in FASB109 TXDITC is not added to FF Factors for all variables after 1993. In my opinion this is could result in look ahead bias, since the investors back in 1993 would still add TXDITC to SEQ, but out of consistency I follow FFs procedure to compute Book Equity.

If date ≤ 1993

$$BE/ME = \frac{SEQ_{t-1} + TXDITC_{t-1} - PSTK_{t-1}}{ME_{t-1}}$$

If date > 1993

$$BE/ME = \frac{SEQ_{t-1} - PSTK_{t-1}}{ME_{t-1}}$$

**A.1.4.1. BE annual** If total shareholder equity (SEQ) is not available, I construct it like (Davis, Fama, & French, 2000) in the following priority. Book value of common equity (COMPUSTAT annual item CEQ) plus value of preferred stock (PSTK) or book value of assets (COMPUSTAT annual item AT) minus book value of liabilities (COMPUSTAT annual item LT). If value of preferred stock is not available, I use preferred stock redemption value (COMPUSTAT annual item PSTKR) or liquidating value (COMPUSTAT annual item PSTKL).

**A.1.4.2. BE quarterly** is quarterly total shareholder equity (COMPUSTAT quarterly item SEQQ) plus quarterly balance sheet deferred taxes and investment tax credit (COMPUSTAT quarterly item TXDITCQ), minus preferred stock (COMPUSTAT quarterly item PSTKQ). If total shareholder equity (COMPUSTAT quarterly item SEQQ) is not available, I construct it as described in A.1.4.1, but with quarterly data.

### A.2. Profitability factors

**A.2.1. ROE** is quarterly income before extraordinary items (COMPUSTAT quarterly item IBQ) divided by 1-quarter lagged BE (see A.1.4.2.).

In the beginning of each month t I create the ROE deciles based on NYSE breakpoints and the most recently released quarterly earnings (COMPUSTAT quarterly item RDQ). Monthly value weighted returns are computed for each month t. The deciles are rebalanced monthly at the beginning of t+1. I follow (Hou et al., 2015) procedure and only include companies that have their end of fiscal quarter that corresponds that is related to the RDQ in the 6 months prior to portfolio formation. They include this restriction to avoid stale earnings information.

$$ROE = \frac{IBQ_t}{BE_{t-1}}$$

where t is equal to the last quarterly earnings announcement defined by RDQ and t-1 stands for the 3-month lag to the previous quarter.

**A.2.2. ROA** is quarterly income before extraordinary items (COMPUSTAT quarterly item IBQ) divided by 1-quarter lagged Assets (COMPUSTAT quarterly item ATQ). The procedure regarding computation, deciles, returns and rebalancing is the same as for ROE (A.2.1.)

$$ROA = \frac{IBQ_t}{ATQ_{t-1}}$$

**A.2.3. GPA** I follow (Novy-Marx, 2013) procedure to create his gross-profit-to-asset factor. I use Revenue (COMPUSTAT annual item REVT) minus cost of goods sold (COMPUSTAT annual item COGS) to create Gross Profits (GP) scaled by current Assets (COMPUSTAT annual item AT). He does not use lagged assets like the ROA factor to create GPA.

$$GPA = \frac{REVT_{t-1} - COGS_{t-1}}{AT_{t-1}}$$

**A.2.4. CbOPA** The cash based operating profitability factor is constructed following (Ball et al., 2016). It is Operating profitability (OP) as defined in (Ball et al., 2015) plus changes in non-cash based Assets (CBA) scaled by end of last year assets (COMPUSTAT annual item AT).Where change means the difference between the assets book value at t-2 compared to t-1.

$$CbOPA = \frac{OP_{t-1} + \Delta CBA}{AT_{t-1}}$$

**A.2.4.1. OP** OP is constructed following (Ball et al., 2015). It is Gross Profits (GP) as defined in A.2.3. minus the sum of Selling, General and Administrative Expense (COMPUSTAT annual item XSGA) minus Research and Development Expense (COMPUSTAT annual item XRD).

$$OP_{t-1} = REVT_{t-1} - COGS_{t-1} - (XSGA_{t-1} - XRD_{t-1})$$

**A.2.4.2. CBA** The change in non-cash based assets is based on (Ball et al., 2016). Change is defined as difference between value of an asset at t-2 to t-1. It is computed using change in accrued expense (COMPUSTAT annual item XACC) plus change in trade accounts payable (COMPUSTAT annual item AP) minus change in accounts receivable (COMPUSTAT annual item RECT) minus change in inventory (COMPUSTAT annual item INVT) minus prepaid expense (COMPUSTAT annual item XPP) plus the sum of deferred revenue current (COMPUSTAT annual item DRC) minus deferred revenue long-term (COMPUSTAT annual item DRLT).

$$\Delta CBA = \Delta XACC + \Delta AP - \Delta RECT - \Delta INVT - \Delta XPP + (\Delta DRC - \Delta DRLT)$$

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