Sector Betting in the Gross Profitability Anomaly

A performance analysis and sector betting effects in the U.S equity market

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Abstract

This thesis presents an analysis of quality investing; more specifically how gross profitability scaled by book assets can generate abnormal returns in the U.S market, as previously illustrated by Novy-Marx (2012). Our contribution is to explain these abnormal returns through a sector betting effect, which occurs while constructing portfolios on the gross profitability metric.

In the first part of the analysis, we replicate Novy-Marx (2012). We utilize return- and accounting data from 1963 to 2016 and firstly investigate whether gross profitability predicts the cross section of returns. Our Fama-Macbeth regression show that gross profitability scaled by assets has roughly the same prediction power as book-to-market in terms of t-values. Furthermore, we construct a univariate portfolio sort using the same accounting metric. Our results yield a significant monthly alpha of 0.48% in the Fama French three-factor model. These results are very similar to what Novy-Marx (2012) finds.

Next, we analyse the effect of sector betting within this portfolio sort. We complete three individual strategies to achieve this. Firstly, we demean gross profitability scaled by assets by the yearly sector average. This nearly eliminates under- or overweighting the respective sectors. Demeaning also leads to a reduction in portfolio performance in all our different performance measures. Secondly, we continue to complete the same portfolio sort within the sectors. Our results show that gross profitability to assets, does not generate abnormal returns in seven out of nine sectors. Thirdly, we complete a strategy where we are long low profitability stocks in high profitability sectors, and short high profitability stocks in low profitability sectors. This strategy yields a significant alpha of 0.48. Our results provide strong evidence that sector components of stock returns account for much of the individual gross profitability anomaly.

Lastly, we combine gross profitability and book-to-market in two different strategies and test for performance. Our results suggests that controlling for profitability in a book-to-market sorted portfolio increases performance. Additionally, a combination portfolio of straight profitability and straight book-to-market displays less sector betting and reduced volatility.

Preface

This master thesis is written as a concluding part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH). The thesis is written within the field of our major in Finance. First and foremost, we would like to thank our supervisor Francisco Santos, for great guidance and support throughout our thesis. He has provided us with great insight in to the field of quantitative finance and investments. His courses on the mentioned fields have provided us with a great foundation, and they are deeply recommended for other students at NHH. Furthermore, we would like to thank the R-community and our professor in the field of applied programming, Ivan Belik. Respectively, they have given us the necessary knowledge and support to write the numerous lines of code, which is the bedrock of our thesis.

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1 Introduction

This thesis aims to take a closer look at how quality factors can explain returns of exchange traded companies in the U.S market. As is, it is also a test of market efficiency. Inspired by Novy-Marx (2012), we focus on the profitability, as measured by the ratio of a firm's gross profits scaled by its book assets.[1] Moreover, we try to account for the profitability anomaly since explaining the abnormal returns of profitability is financially and rationally hard (Frazzini and Pedersen, 2013). Our suggested explanation for the anomaly is based upon a sector betting effect, which occurs when sorting on gross profitability. Similar effects have been found for the momentum anomaly, (Moskowitz and Grinblatt, 1999) and for the book-to-market anomaly (Asness, Porter and Stevens, 2000).

As Novy-Marx (2012) and Asness, Frazzini and Pedersen (2013) have found, profitability predicts stock returns on a significant level. In addition, Piotroski (2000) finds that using quality accounting measures adds a large significant alpha when combined with value as in book-to-market. Our first null hypothesis is therefore that gross profitability can generate abnormal returns in the U.S stock market. To test this hypothesis we complete a Fama-MacBeth (1973) cross sectional regression on all individual stocks in the U.S stock market from 1963 until 2015. Our results suggest that gross profitability has a significant power of predicting returns. It yields roughly the same prediction power as book to market in terms of t-values, which is widely recognized by academics. Furthermore, we complete portfolio sorts based upon the gross profitability of firms. The results shows a similar relationship, where high profitability firms outperform low profitability firms on average. Our zero-cost, high- -minus-low profitability portfolio generates a significant monthly alpha of 0.48 percent using the Fama and French three factor model (1993), not adjusted for transaction costs. Our findings are in line with what Novy-Marx have previously found

Consistent with Novy-Marx (2012) our high minus low profitability portfolio has a negative market beta as well as negative factor loadings in the Fama French 3 factor model(FF3). Additionally, it also performs well during financial recessions, making a risk-based explanation hard to present.

[1] $(Revenue - COGS)/(Total \quad Assets)$

As traditional explanations of abnormal risk adjusted returns are hard to present for quality factors, we have researched an alternative explanation. Our findings are related to a sector betting effect, which occurs when picking portfolios based on gross profitability scaled on book assets.[2] Initially our hypothesis is that sorting the U.S stock universe on profitability will cause the portfolios to be tilted towards certain sectors, which in turn can cause abnormal returns through reduced diversification and sector outperformance.

We test this hypothesis through investigating the sector positions in our portfolios. The results are very clear, presenting a picture where certain sectors are heavily over- or underweighted. In practice, this causes our high minus low profitability portfolio to be sector betting through a large part of the long positions being centred around sectors with naturally large gross profitability – i.e. consumers and technology. While short positions are centred around energy, utilities, real estate and telecom. Financials are excluded in our study, but, if included, financial stocks are heavily shorted.

To further investigate our hypothesis of sector betting as an explanation for abnormal risk adjusted returns, we run several different tests: Firstly, we demean gross profitability by the yearly sector average, and proceed to construct portfolios following the same methodology.[3] As expected when one demeans, the sector betting effect is in large part eliminated due to long and short positions being balanced for the individual sectors. Furthermore, we observe a decrease in our alpha employing FF3 from 0.48 to 0.39. While the decreased alpha in the FF3 model not being striking, we would like to highlight that our average excess returns and sharpe ratio decreases significantly after demeaning. The alpha stays relatively high in the FF3 due to large negative loadings in the risk factors.

Moreover, we run the same portfolio sorts within the individual sectors. The alphas are only significant in three of our nine sectors, and they are also smaller. In certain sectors the alphas are negative, where we can observe the lowest quintile sorted on profitability outperforms the high quintile causing negative returns for our long-short portfolios. Observing the results in the individual sectors, the relationship of profitability and returns appear much weaker, making an argument for our hypothesis of sector betting being a contributor to abnormal risk adjusted returns of gross profitability strategies.

Additionally, we employ a test where we buy the low profitability quintiles of the two sectors

[2]Large under- and overweighting in individual industrial sectors

[3]Demeaning refers to subtracting the sample sector average from the individual stock gross profitability

with the highest average gross profitability, while selling the two top profitability quintiles within the sectors with the lowest average gross profitability.[4] As a prerequisite, we test for the average gross profit within these quintile portfolios. Both the top quintile portfolios we sell in the individual tests, does on average have a higher profitability than the two low quintile portfolios we buy. This zero-cost portfolio should generate negative returns if individual stock gross profitability is the primary source of the gross profitability strategy. On the other hand, it should generate positive profits if sector betting is driving the gross profitability effect. Our results give us a positive and significant alpha of 0.48. In short, selling high profitable firms and buying lower profitable firms achieves a significant alpha due to them being in different sectors. This once again makes for an argument of sector betting effects contributing to the abnormal risk adjusted returns achieved by profitability sorting.

In the last section, we combine gross profitability and book-to-market in two different strategies to test for performance and sector betting. Firstly replicating Novy-Marx creating a bivariate sort that controls for profitability within a book-to-market sort. Secondly, we hold 50 percent of the univariate gross profitability portfolio, and 50 percent of the univariate book-to-market portfolio. We find that controlling for profitability increases the performance of a book-to-market sort, yet it still displays significant sector betting. Our 50-50 combination portfolio exhibit less sector betting, and as a possible consequence the volatility is greatly reduced.

In short, this thesis contributes to the quantitative field of finance within factor investing. More specified, we extend the research provided by Novy Marx on quality factor investing through gross profitability. Explanations for abnormal returns of quality investing has been a puzzle in asset pricing theory. We find evidence that persistence in sector return components generates significant profits that may account for much of the abnormal returns of the gross profitability strategy.

The outline for this thesis is as follows. Section two summarizes the relevant literature on the field. We proceed to describe our data and methodology in section three. Section four includes the analysis of our hypotheses, strategies and findings. At last we conclude our thesis in section five.

[4] A quintile is a statistical value of a data set that represents 20% of a given population.

2 Literature Review

Markets not being fully efficient in accordance with traditional pricing models have been documented in numerous papers. Using various strategies, academics and practitioners have achieved abnormal risk adjusted returns. Abarbanell and Bushee (1998) examine whether investment strategies based upon a number of accounting measures from the financial statements, can generate abnormal returns. Using changes in inventory, accounts receivable and gross margins among others, they achieve a 12-month cumulative size-adjusted abnormal return of 13,2 percent. Incorporating information from financial statements have proven to reject traditional market efficiency, as also proven by Fama and French (1993) , which is essential for the topic of quality investing.

Quality investing as a term is not a new term in the financial literature, even though popularized as of late in the factor literature. It goes as far back as Graham and Dodd (1934), who stated that "investors must always consider the price as well as the quality of the security." Even though the price aspect have gotten more attention in literature through various value approaches, the quality aspect is also well documented.

In contrast to value, quality does not however have a clear definition. Traditionally one have separated between value strategies and growth strategies. However, quality investing falls in neither of the categories. Growth measures have been included in the quality measure by Asness, Frazzini and Pedersen (2013), and can possibly be seen as a part of the quality term. However, there is also a strong relationship between quality and value. *"Both are designed to acquire productive capacity cheaply. Value strategies do this by financing the purchase of inexpensive assets through the sale of expensive assets, while profitability strategies achieve the same end by financing the purchase of productive assets through the sale of unproductive assets"* (Novy-Marx, 2013). Yet, they are highly dissimilar as high quality stocks tend to require a higher price, while low quality stocks tends to get a price discount. Thus also leading a value strategy to be quite the opposite of a quality strategy from one point of view. The two strategies have proven to work best when combined, achieving higher risk adjusted returns (Novy-Marx, 2012; Assness, Frazzini Pedersen, 2013; Piotroski and So, 2012). Historically, this has not been a secret for practicioners. Warren Buffet famous words: "It is far better to buy a wonderful business at a fair price than to buy a fair business at a wonderful price"

(Buffet, 1989) illustrates this strategy, which later have been researched by academics. Even though quality has been documented to generate abnormal returns when combined with value, it has also been found to do so on its own.

One of the more influential people advocating quality investing over the past decades is Jeremy Grantham, whose management firm GMO describes quality as "low financial leverage, high profitability and low earnings volatility" (Grantham, 2004). Similar strategies have been used by other practitioners such as Joel Greenblatt, which outlines the importance of quality defined as return on invested capital in his book "The Little Book that Beats the Market" (2006).

Academics have also documented similar effects. Sloan (1996) finds that earnings quality is not fully priced in financial markets by looking at accrual and cash flow information. Piotroski (2000) presents an "F-score" which is based upon nine different measures of quality using financial statements, inspired by Graham and Sloan. Investment strategies based on this F-score combined with value have dramatically outperformed traditional value strategies (Piotroski, So, 2012). Asness, Frazzini and Pedersen (2013) have a similar approach where they construct a quality minus junk factor using several different financial measures of profitability, growth, safety and payout. However, they also run these tests without combining it with a value aspect. This strategy achieves a significant FF3 monthly alpha of 0,97 percent in the U.S market.

The profitability aspect of quality investing has been researched extensively by Novy-Marx (2012), and to some degree by Fama and French (2008). Fama and French employs earnings as a simple proxy for profitability, while Novy-Marx claims that gross profitability is a better proxy as his results are much stronger. He argues that gross profitability is the cleanest accounting measure of true economic profitability. *"The farther down the income statement one goes, the more polluted profitability measure become, and the less related they are to true economic profitability"* (Novy-Marx, 2012). Additionally, he scales gross profitability on book assets to illustrate the productiveness of the firm. Productive assets should lead investors to demand higher average returns. As this is true, higher profitability should lead investors to demand higher average returns, when productivity is defined as gross profits over book assets. Variation in profitability should thus identify variation in investors required return. This argument is consistent with, but not predicted on, rational pricing (Novy-Marx, 2012).

Employing gross profitability scaled on book assets, Fama-Macbeth regressions finds that gross profitability has roughly the same prediction power as book to market for the cross section of returns. Furthermore, Novy-Marx completes portfolio sorts where his zero-cost high minus low portfolio generates a monthly alpha of 0,52 percent employing the FF3. Much of the alpha is generated through profitability sorted portfolios load negatively in both SMB and HML. Intuitively this makes sense, since empirically quality firms are often large and priced more expensively (Novy-Marx, 2012).

The results have presented a puzzle for asset pricing theory. Asness, Frazzini and Pedersen (2013) notes that a risk-based explanation is hard to present. Quality stocks tend to perform well during downturns, they are low beta and load negatively in the respective risk factors of SMB and HML. They further explain the abnormal returns as either an anomaly, data mining or a yet-not-identified risk factor. Novy-Marx (2012), excludes the liquidity premium explanation as his tests also works in the largest and most liquid stocks through double sorting on size and profitability.

As shown by Moskowitz and Grinblatt's (1999) factor returns can be driven by industry betting effects. This effect has to a degree not been researched extensively, within the quality investment field. Novy-Marx (2012) has performed a simple analysis on his gross profitability sort, where he demeans gross profitability by the Fama French 49 industries average and finds that the alpha is reduced slightly. He also performs a strategy where he hedges every position for industry exposure, through shorting selling the industry portfolio, achieving similar results. Moreover, he finds that returns are reduced significantly employing the different industry adjustments. Yet, he also finds that industry adjusting leads to higher sharpe ratios, due to lower volatility in the portfolio. Additionally, he finds that industry adjusted gross profitability has more power predicting the cross section of returns compared to book-to-market and straight gross profitability.

In our thesis we would like to expand on the work of Novy-Marx on gross profitability (2012). Moskowitz and Grinblatt (1999) find significant evidence that the momentum anomaly's abnormal returns are in large part explained by industry betting. A different analysis has been presented by Asness, Porter and Stevens (2000) on the book-to-market effect, documenting a comparable effect. This thesis will present a similar analysis for the gross profitability anomaly.

3 Data and Methodology

3.1 Data

The data and analysis of this thesis covers the entire period from July 1963 to July 2016. Monthly equity data is retrieved from the Centre of Research in Security Prices (CRSP). Annual financial statements is respectively retrieved from Compustat. The monthly risk free rate, market premium, and the Fama French factors including momentum is retrieved from the website of Kenneth R. French. These monthly data points are merged against their respective data frames after the portfolio formation process.

The sample starts out with firms traded on NYSE, Amex, and NASDAQ. All other than ordinary common shares is excluded from the data set. In cases where the price of a share is set to the negative bid/ask spread, the absolute value of the share price is used. Additionally, share prices are also adjusted for dividends and stock splits.

The equity data also includes specification of the Standard Industrial Classification (SIC) and Global Industry Classification Standard (GIC). We utilize both classifications for the purpose of the research. Whereas SIC is deployed for the Fama MacBeth regression to seek consistency with regards to Novy-Marx (2012). However, for the majority of the research GIC is deployed as it has clearer syntax with regards to classification.

To reduce survivorship bias we include returns on shares of companies that are active, inactive and delisting returns. Moreover, this creates a more inclusive data frame. With regards to delisting returns, we have cases where we can observe both delisting returns and standard returns, in these cases the standard return is chosen.

Annual financial statement data is retrieved for the period July 1962 till December 2015. Accounting data from December year t, is matched with return data starting in July year t+1. This is done to ensure that accounting data is aligned with the market, such we assume that accounting data is available in the market space at all times. Implying a minimum of a six month lag, which can be considered conservative (Fama-MacBeth, 1973).

There are certain criteria for the merged data set, for the Fama MacBeth regressions firms must have non-missing value of equity, book-to-market, gross profit, and current month return. However, for the portfolio sorts on gross profit to assets we do not need to ascertain values for book-to-market. Consequently, sample size varies on how many accounting variables are employed. However, equally for all tests we exclude financial firms, this is done through either by SIC- or GIC codes. SIC defines this as the first digit of six, and GIC classifies this as all firms with code 40. With the GIC classification we have 11 pre determined sectors, due to the bivariate sorts within sectors we cannot expand this to further accompany more sectors due to a lack of data points. Since we employ NYSE break points throughout the thesis, bivariate sorting becomes an issue for more granulare definitions of sectors. Bivariate sorting based on two independent variables poses no problem, however, sorting for the same variable twice is at higher granularities.

3.2 Gross profits to assets and the book-to-market ratio

Gross profits is argued to be the cleanest accounting measure of true economic profitability, this much due to pollution of the true economic profitability further down the income statement (Novy-Marx, 2012). Gross profits can be defined as total revenues minus cost of goods sold.

$$GrossProfits = Revenues - COGS$$

Whereas COGS assembles all expenses directly related to production, as well as cost of materials, direct labour, amortization of life of less than two years, license fees, lease payments, maintenance and repairs, taxes other than income taxes, and expenses related to distribution and warehousing, and heat, lights and power (Novy-Marx, 2012). Both total revenue and COGS is found under REVT and COGS respectively in Compustat.

Book-to-market is defined as book equity scaled by market equity. We defined market equity as total number of shares outstanding times the annual fiscal year ending price. This also helps avoid unintentional positions in momentum. Book equity is constructed as shareholder equity, plus deferred taxes, minus preffered stock. To ascertain these values we follow Novy-Marx (2012). [1]

$$B/M = \frac{SE+DFT-PS}{ME_{t12}}$$

Additionally, we do not allow for negative book value of equities in the Fama MacBeth regressions, this is due to taking the natural logarithm of the book-to-market ratio. However, for the portfolio sorts we include negative book values. We want to create a data set which is as representative as possible of the population. Fama and French (1992) find that returns to investing in companies with a negative book value of equity is high.

3.3 Fama MacBeth: Cross-sectional regression

The two stage Fama MacBeth regression makes it possible to examine if some factors can explain asset returns. Firstly one would estimate betas for some factors using normal OLS regression, this is done to obtain an estimate of the factor exposure of some asset. Fama MacBeth uses a five year rolling window for the estimation. One regression is done per asset on the respective factors. The beta retrieved is known as the empirical beta, and is thus not necessarily the true beta. A general case is shown below:

$$R_{n,t} = \alpha_n + \beta_n(R_m) + \epsilon_{n,t}$$

The next step in the procedure is to perform a n cross-sectional regressions of the returns on the m estimates of the betas. In this case the betas used is the betas from step one.

$$R_{i,T} = \lambda_{T,0} + \lambda_{n,1}\hat{\beta}_{i,f_i} + \epsilon_{i,T}$$

[1] "Stockholders equity ... Compustat (SEQ) if available, or else common equity plus the carrying value of preferred stock (CEQ + PSTX) if available, or else total assets minus total liabilities (AT - LT). Deferred taxes is deferred taxes and investment tax credits (TXDITC) if available, or else deferred taxes and/or investment tax credit (TXDB and/or ITCB). Prefered stock is redemption value (PSTKR) if available, or else liquidating value (PSTKRL) if available, or else carrying value (PSTK)."

From this we use the n estimates to calculate the Fama MacBeth t-statistic and standard error. However, for our purpose we do not need to estimate factor exposure through beta estimation since we utilize accounting measures. This enables us to estimate the regression following step two, this is practically done through the R-software, using the "plm package". Where (Millo, 2008) argues that the Fama MacBeth procedure is nothing more than the mean group estimator, this enables us to tweak the index variables of the regression software to perform the t cross-sectional regressions according to Fama MacBeth.

Furthermore, we follow Novy-Marx (2012), and windsorize all independent variables at the one percent level. Moreover, we also take the log of the book-to-market ratio as well as the market equity. Continuing, a large variety of fiscal year ends is reported by Compustat, this gives rise as to how one should lag the accounting data. However, as illustrated by Novy-Marx (2012) if you isolate fiscal year endings December and run the Fama MacBeth regression it yields very similar results as to adjusting this further. The majority of data points does indeed have fiscal year ends December. We assume that companies do indeed have fiscal year end December with exception of January which is matched with return data starting July same year.

3.4 Portfolio analysis: Pricing models

Fama French three factor model

The Fama French 3 factor model (1993), adds two additional risk factors to the traditional CAPM-model, which are HML and SMB respectively. The two factors are constructed to reflect a portfolio's exposure to the two different risk classes. In short, SMB is constructed as a portfolio that is long stocks with small market capitalizations, while being short stocks with large market capitalizations. HML is formed as a portfolio being long stocks with high book-to-market ratios, while being short stocks with low book-to-market ratios. The two factors are explained as risk factors in the original paper, as Fama and French (1993) argue that exposure to these stocks increases risk. The FF3 abnormal returns are estimated running the following regression:

$$r_t - r_{f,t} = \alpha + \beta_1(r_{m,t} - r_{r,t}) + \beta_2 HML_t + \beta_3 SMB_t + \epsilon_t$$

Carhart four factor model

The Carhart four factor model (1997), is an extension of the FF3 model adding an additional risk factor, momentum (MOM). Momentum in a stock is described as the tendency for the stock price to continue rising if it is going up and to continue declining if it is going down. The MOM can be calculated by subtracting the equal weighted average of the lowest performing firms from the equal weighed average of the highest performing firms, lagged one month (Carhart, 1997). Following the same procedure as Fama and French (1993), a short-long portfolio is formed on this basis. The C4FM abnormal returns are estimated running the following regression:

$$r_t - r_{f,t} = \alpha + \beta_1(r_m - r_{f,t}) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \epsilon_t$$

Fama French five factor model

As an extension to their original tree factor model, Fama and French developed the five factor model (2015). They argue that the tree factor model was an inadequate model for expected returns because the three factors overlook a variation in average returns related to profitability and investment (Fama, French, 2015). Consequently they add the RMW and CMA factors to the three factor model. The RMW factor is long high operating profitability, and short low operating profitability. While CMA is short high investment, and long low investment as measured by total assets growth. The FF5 abnormal returns are estimated running the following regression:

$$r_t - r_{f,t} = \alpha + \beta_1(r_m - r_{f,t})\beta_2 HML_t + \beta_3 SMB_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t$$

The excess returns of our constructed portfolios are in each month t regressed against the individual pricing models. The individual betas represent the exposure to the market premium and the respective risk factors. As Fama French points out, portfolio evaluation is easy if you believe in their models. If results are taken at face value, evaluating performance of a managed portfolio is straightforward. The intercept in the time-series regression of the managed portfolio's excess return on our five explanatory returns is the average abnormal return needed to judge whether a manager can beat the market, that is, whether he can use special information to generate average returns greater than those on passive combinations of the mimicking returns for the five risk factors (Fama, French, 1993).

3.5 Portfolio sorts

Firstly we sort gross profits to assets into quintiles for the entire sample data employing NYSE breakpoints. This is done every twelth month, i.e end of June each year. Extracting each quintile results in five independent data frames. From each quintile we make five different portfolios consisting of monthly returns. Value weighted returns are calculated by taking firm n's market equity and dividing this by the total monthly market equity times the return of firm n. Taking the monthly sum of all firms yields the value weighted return series.

$$VWR_m = \sum \left(\frac{ME_{t_n}}{ME_{t_m}} * r_n \right)$$

Furthermore, we merge the risk free rate and the respective risk factors to each portfolio. This being the Fama French three factor model, Carhart four factor model, and the Fama French five factor model. Moreover, we subtract the risk free rate from all portfolios, and divide the risk factors by one hundred to set the same scale. From this we create the high minus low gross profit to asset portfolio by taking the highest quintile portfolio subtracting the lowest. The resulting portfolio and all quintiles is then regressed against FF3, C4FM, and FF5.

It must also be mentioned that the same procedure is applied to the book-to-market ratio. This provides a basis of comparison, but more importantly it serves as a robustness check of the R-scripts against Novy-Marx results (2012).

For the demeaned portfolio sorts on gross profits to assets, we calculate the average gross profit by industry per year. The resulting matrix is then merged against the firms sector and date in order to subtract the average gross profit from all firms. This procedure is also employed to re-calculate the NYSE break points.

We also deploy a bivariate sort which aims to sort gross profits to assets within each sector. We start out by defining a sorting algorithm which aims to sort NYSE data into break points for each sector. Moreover, when NYSE data is sorted respectively, we define a sorting algorithm that matches NYSE break point data to each respective sector from the main data frame. This results in ten separate data frames. Furthermore, we define a sorting function that sorts within each data frame into quintiles by NYSE break points. The next step aims to extract each quintile in each data frame. In this step we observe that the real estate sector does not inherent enough data points for a proficient measure, and is thus dropped from the frame.

This results in 45 data frames ordered by sectors. Moreover, we define an algorithm that assign each sector quantile to one final data frame. This algorithm also scales all variables, and subtracts the risk free rate. Consquently, we arrive at nine unique data frames, one for each sector, which is sorted into quintiles based on gross profit to assets. From this we regress nine high minus low portfolios, and 45 quintiles against their respective risk factors.

Additionally, we also employ a bivariate sort for book-to-market and gross profitability. We start with a univariate sort of the book-to-market ratio. Following this we extract gross profitability breakpoints for each book-to-market quintile. Sorting on the breakpoints yield quintiles of gross profitability within each respective book-to-market quintile, resulting in 25 portfolios, see figure 3.1:

Table 3.1: Bivariate sort: Illustration table 1

		GP/A				
		L	2	3	4	H
B/M	L	1.1	1.2	1.3	1.4	1.5
	2	2.1	...	...	...	...
	3	3.1	...	...	...	...
	4	4.1	...	...	...	...
	H	5.1	...	...	...	...

In table 4.1, 1.1 indicates low book-to-market and gross profitability. Horizontally we hold book-to-market constant and only vary the gross profitability quintiles. Vertically gross profitability is hold constant and book-to-market is varied. For all 25 portfolios we have one combination of all possible portfolio combinations between book-to-market and gross profitability. This results in five horizontal and vertical high minus low portfolios which is regressed against their respective risk factors.

Furthermore, a combination portfolio is made where we take the highest book-to-market and gross profitabilty portfolios and subtract the lowest book-to-marrket and gross profitability portfolios. This is found in the four lowest- and highest portfolios, see table 3.2:

Table 3.2: Bivariate sort: Illustration table 2

		GP/A				
		L	2	3	4	H
B/M	L	1.1	1.2	...	...	...
	2	2.1	2.2	...	...	...
	3	...	...	...	...	...
	4	...	...	...	4.4	4.5
	H	...	...	...	5.4	5.5

Lastly, we also want to test book-to-market and gross profitability sorts independent of each other, and how a combination of both affects the excess returns and sector specific positions. This is done by doing two independent univariate sorts on both gross profitabilty and book-to-market. We continue to weight each return series by 50 percent, and then combine the two, constructing one portfolio.

3.6 Econometric techniques and statistics

An important note before we go into more specific tests is that with this thesis we are given certain models which we test against. These models are indeed well known and recognised, however this limits some of the adjustments we can to the models we test for. We do not seek to form the best model, however we seek to test against well known models.

As a result of the portfolio formation and sorting we retrieve a large amount unique time series of returns. It is therefore important to gain understanding of some of the processes inherent within each time series. Where we first deploy tests for non-linearity, heteroscedasticity, serial correlation, and multicollinearity. Additionally, we want to gain som insight with regards to the distributions of the series, hence the importance of normality for the interpretation of the t statistics.

In the tests nonlinearity in the series we follow Baum (2006) and Chen, et al. (2003), where we plot the standardized residuals against each independent variable in the regression. Where one wants to observe a random scatter plot of points, which indicates that there is no problem with nonlinearity.

For heteroskedasticity we utilize the Breusch-Pagan and Cook-Weisberg test. If there is indication of heteroskedasticity in the series we use white errors to control for this (Baum, 2006).

An important test for time series analysis is serial correlation in the residuals. Following Baum (2006) we deploy the Breusch and Godfrey test to test for serial correlation at a five percent significance level. Additionally we deploy the Durban Wattson test for serial correlation, however with this test we only look at first order auto correlation. Moreover, deploying both tests will give more accurate readings. If there is strong indication of serial correlation we can use the Prais-Winsten and Cochrane-orcutt regression with Cochrane-Orcutt transformation.

Variance inflation factor (VIF) is used to test for multicollinearity. This test measures how much the variance of the estimated regression coefficients are inflated, as compared to when the predictor variable is not linearly related (Kutner, Nachtsheim, Neter, 2004). There is evidence of collinearity if the mean VIF is greater than one, or if the largest VIF is in excess of ten.

Importantly for the interpretation of the t-statistic is the assumption of normality in the series. We compute summary statistics for all value weighted return series, including quantiles one to five, high minus low portoflios, to observe if the returns are indeed normally distributed. This test can tell us how confident we can be in the interpretation of the t-statistics.

4 Empirical Results and Analysis

4.1 Gross profitability and the cross section of expected returns

To investigate how well gross profitability scaled by book assets can predict returns, we employ a Fama MacBeth cross sectional regression (Fama, MacBeth, 1972), following the methodology of Novy-Marx (2012). The regression includes controls for book to market (log(B/M)) and size (log(ME)). As mentioned previously, the regression include data from 1962 until 2016. The data sample excludes financial stocks. However, including financials does not impact the results greatly.

Table 4.1: Results of Fama MacBeth regression of returns on gross profitability (REV minus COGS) scaled by assets (AT). The regression includes controls for the logarithm of book-to-market and market equity. Independent variables are windsorized at the one and 99% levels. Slope coefficients are multiplied by 10^2, and the sample covers the period July 1963 till July 2016.

	α	GP	log(B/M)	log(M/E)
Estimate	0.0166	0.66	0.34	-0.11
t-value	4.56	4.76	5.32	-2.82

As we can read from table 4.1, gross profitability predicts returns with nearly the same power as book to market, and stronger than what size does. This implies that more profitable stocks generates higher returns than less profitable stocks on average. Gross profitability obtains a t-stat of 4.76, while book to market and size obtains t-stats of 5.32 and -2.82 respectively. According to Ball, Gerakos and Linnainmaa (2015), the average coefficient estimates can be interpreted as monthly returns on long-short trading strategies for the individual variables. Consequently, they note that t-values can be interpreted as annualised sharpe ratios times $\sqrt{t}$. This methodology would yield an annual sharpe ratio of 0.64 for our gross profits to assets variable. Our results for gross profitability are slightly weaker than what Novy-Marx (2012) finds. This can possibly be explained by our sample having six additional years included. Yet, our results are in line with what Novy-Marx finds, and the same conclusions are drawn. Mainly, that gross profitability is a strong predictor of the cross section of returns, and is significantly stronger than what have been found earlier for net earnings (Fama, French, 1992).

4.2 Portfolio sorts on gross profitability

As noted, the Fama Macbeth regression implies that gross profitability predicts average returns. However, these regressions weight each observation equally, and therefor put formidable weigh on micro- and nano-cap stocks which make up for a small portion of the total market capitalization. Additionally, Fama Macbeth regressions are also sensitive to outliers, and this makes for a possibly misspecified parametric relation between the variables (Novy-Marx, 2012). Our portfolio sort on gross profitability scaled by assets should adjust for these issues by value-weighting our positions and non-parametrically testing gross profitability's ability to predict returns. We create a univariate portfolio sort, employing NYSE breakpoints on gross profitability scaled by book assets.

Table 4.2: Results of portfolio sorts on gross profitability to assets regressed against the Fama French three factor model. The six portfolios displayed in the table is a result of univariate quintile sorting on gross profitability to asset on the entire sample data, covering the period July 1963 till 2016 employing NYSE breakpoints. The H-L portfolio is a result of the highest- minus lowest quintile of the sort. Additionally, r^e is the monthly average excess returns of the portfolios.

	Portfolios					
	H-L	Low	Q2	Q3	Q4	High
α	0.481	−0.204	−0.114	−0.090	0.045	0.275
	[4.31]	[−2.33]	[−1.59]	[−1.21]	[0.66]	[4.97]
MKT	−0.029	0.976	0.991	1.017	1.016	0.946
	[−1.11]	[47.26]	[44.48]	[46.98]	[62.98]	[52.54]
SMB	−0.099	0.039	−0.065	0.033	−0.004	−0.053
	[−2.64]	[1.35]	[−2.20]	[0.87]	[−0.19]	[−1.75]
HML	−0.406	0.155	0.159	0.094	−0.182	−0.299
	[−9.94]	[4.85]	[4.79]	[2.58]	[−7.31]	[−7.99]
r^e	0.30%	0.35%	0.44%	0.49%	0.50%	0.65%
Observations	637	637	637	637	637	637
Adjusted R^2	0.13	0.79	0.86	0.86	0.88	0.91

The table shows our zero-cost high minus low portfolio, and the five individual quintiles of the gross profitability sort as the dependant variables, with FF3 regressions on all the individual portfolios. Additionally, we have included the average monthly excess return for the respective portfolios. We can observe a positive relationship of excess returns and rising gross profitability. The bottom quintile achieves excess returns of 0.35%, while the top quintile has excess returns of 0.65%. The high minus low portfolio necessarily generates the spread between these two, 0.30%. This portfolio has a monthly standard deviation of 2.96%, resulting in an annualized sharpe ratio of 0.35. This is higher than the 0.33 the market achieved over the same time period. Moreover, the high minus low portfolio generate an alpha of 0.48% monthly, with a t-statistic of 4.31. Implying once again that gross profitability generates abnormal returns. We can also observe a positive relationship of increasing alphas from low gross profitability quintiles, to high profitability quintiles. However, only the bottom and top quintiles has significant alphas of -0.20% and 0.275% respectively.

Consistent with our Spearman correlation tests (Appendix A), we can observe that our high minus low portfolio loads negatively in the HML factor, with a coefficient of -0.406 and a t-statistic of -9.94. Additionally, the quintile portfolios exhibit large variation in their HML loadings. The least profitable quintiles have positive loadings in HML, while the most profitable stocks have negative loadings in HML. The low quintile having a significant HML loading of 0.15, while the top quintile having a significant HML loading of -0.29. In other words, profitable firms are growth firms in the sense of having low book-to-markets, and low profitable firms are value firms having high book-to-markets. This is consistent with Asness, Frazzini and Pedersen (2013) findings, implying there is a “price of quality”. As is, the gross profitability strategy is a great hedge for value strategies, and the two have proven to work extraordinary well when combined (Assness, Frazzini, Pedersen, 2013; Novy-Marx, 2012).

Our results are very similar to what Novy-Marx (2012) finds. Where we find an alpha of 0.48% and an average excess return of 0.30% for the high minus low portfolio, he finds an alpha of 0.52% and an excess return of 0.31%. The slight differences might possibly be explained by our six additional sample years.

4.2.1 Carhart Four Factor Model

Additionally, we use the same return series from our portfolio sort as the dependant variable, and apply Carhart's four factor model (Carhart, 1997) as the independent variables.

Table 4.3: Results of portfolio sorts on gross profitability to assets regressed against the Carhart four factor model. The six portfolios displayed in the table is a result of univariate quintile sorting on gross profitability to asset on the entire sample data, covering the period July 1963 till 2016 employing NYSE breakpoints. The H-L portfolio is a result of the highest- minus lowest quintile of the sort.

	Dependent variable:					
	H-L	Low	Q2	Q3	Q4	High
α	0.362	0.001	0.021	0.061	0.204	0.363
	[3.22]	[0.01]	[0.30]	[0.80]	[3.25]	[5.86]
Mkt.RF	−0.007	0.937	0.994	1.005	0.984	0.930
	[−0.27]	[49.11]	[61.22]	[56.51]	[66.24]	[63.62]
SMB	−0.086	0.028	−0.053	0.031	−0.003	−0.058
	[−2.35]	[1.06]	[−2.37]	[1.24]	[−0.16]	[−2.87]
HML	−0.347	0.070	0.123	0.057	−0.245	−0.277
	[−8.49]	[2.38]	[4.93]	[2.09]	[−10.69]	[−12.29]
MOM	0.129	−0.225	−0.154	−0.136	−0.178	−0.096
	[4.90]	[−11.90]	[−9.55]	[−7.74]	[−12.07]	[−6.66]
Observations	637	637	637	637	637	637
Adjusted R^2	0.16	0.83	0.87	0.86	0.90	0.89

The high minus low portfolio generates an alpha of 0.36% monthly, 0,12% lower than in the FF3 model. This is due to the positive loading the momentum factor. Momentum is built upon share prices which have recently increased continues to increase, and share prices that have decreased continues to decrease. This is consistent with Novy-Marx (2012), where he finds that gross profitability strategies is persistent for roughly 24 months. This differs from B/M strategies, which are typical contrarian and loads negatively in momentum. As a note, we can observe that our top quintile achieves a similar alpha to that of the high minus low portfolio. Even the 4th quintile has a significant monthly alpha of 0.2%.

4.2.2 Fama French Five Factor Model

Lastly, we once again use the same return series as the dependant variable, and apply the FF5 model as the independent variables.

Table 4.4: Results of portfolio sorts on gross profitability to assets regressed against the Fama French five factor model. The six portfolios displayed in the table is a result of univariate quintile sorting on gross profitability to asset on the entire sample data, covering the period July 1963 till 2016 employing NYSE breakpoints. The H-L portfolio is a result of the highest- minus lowest quintile of the sort.

	Dependent variable:					
	H-L	Low	Q2	Q3	Q4	High
α	0.247	−0.006	−0.077	−0.065	0.055	0.241
	[2.47]	[−0.07]	[−1.06]	[−0.82]	[0.78]	[3.93]
Mkt.RF	0.019	0.927	1.018	1.035	1.008	0.947
	[0.79]	[46.81]	[57.16]	[53.16]	[58.76]	[62.92]
SMB	0.068	−0.083	−0.093	0.022	0.003	−0.015
	[1.99]	[−3.02]	[−3.74]	[0.82]	[0.12]	[−0.72]
HML	−0.407	0.230	0.145	0.076	−0.131	−0.176
	[−8.55]	[5.98]	[4.19]	[2.03]	[−3.93]	[−6.05]
RMW	0.665	−0.474	−0.158	−0.024	0.038	0.191
	[14.19]	[−12.51]	[−4.64]	[−0.64]	[1.16]	[6.65]
CMA	0.020	−0.169	0.074	0.063	−0.113	−0.148
	[0.29]	[−2.99]	[1.45]	[1.13]	[−2.30]	[−3.45]
Observations	637	637	637	637	637	637
Adjusted R^2	0.34	0.83	0.86	0.84	0.88	0.89

The high minus low portfolio exhibits an alpha of 0.25% monthly, significantly lower than in the other models. This is explained by the large positive loading in the RMW factor. This is not surprising, given that RMW is built upon a tertile sort on operating profitability, which should be closely related to our quintile sort of gross profitability. The lower quintile portfolios, have negative loading in RMW, while the higher quintiles have positive loadings in RMW. Furthermore, gross profitability is not related to the CMA factor of Fama French, which is constructed on aggressive and conservative investment. Our high minus low portfolio has an insignificant coefficient for CMA, and so does quintile two and three.

Summarized, our gross profitability to assets sort has significant alphas in all the three models applied. The results from the FF5 model is especially strong, since another profitability factor is used as an independent variable. It also displays a higher average return and sharpe ratio than the market.

4.3 Sector betting test

In this section, we are looking to test our hypothesis of sector betting occurring when performing univariate portfolio sorts on gross profitability to assets. By sector betting, we are referring to sectors being under- or overweighted in our portfolios. The fact that factor investing might lead to sector betting is not a new phenomenon, and has been proven in numerous other factors (Moskowitz and Grinblatt, 1999; Cohen, Polk, 1998). As mentioned, we use the Global Industry Classification Standard (GIC) to split the individual stocks into a total of 11 sectors, where we have 10 remaining sectors after excluding financials.

When employing accounting data, there could be large variations in accounting measures in various sectors or industries. Firstly, we test for the average gross profits across our 10 sectors (Appendix D). As expected, the sectors exhibit large variation in their average gross profits to assets. The utility sector has a yearly average of 0.12 gross profits to assets, while consumer staples average 0.55. These large variations should in turn lead to sector betting in our portfolio sort. We apply a simple test where we count the average number of long- and short positions in the individual sectors for our portfolio sorted on gross profitability to assets.

Table 4.5: Results of long and short positions in each sector pre-demeaning. Based on univariate quintile sorting, where positions are retrieved from the highest and lowest quintile. Sector positions are retrieved from the entire sample data covering July 1963 till 2016.

	10	15	20	25	30	35	45	50	55	60
Sector	Energy	Materials	Industrials	Consm.disc	Consm.stpl	Health C.	IT	Telecom	Utilities	Real Estate
Long	11%	25%	51%	60%	70%	37%	65%	33%	2%	5%
Short	89%	75%	49%	40%	30%	63%	35%	67%	98%	95%

The table illustrates that the majority of the sectors are heavily over- or underweighted. Sectors energy, utilities and real estate are shorted with 89%, 98% and 95% respectively in our portfolio after sorting on gross profitability. Other sectors are also over- or underweighted except for industrials, which is fairly balanced. This confirms our hypothesis of sorting on gross profitability leading to sector betting. The tremendous underweighting in energy, utilities and real estate makes sense financially. These sectors traditionally demand large investments to generate profits. Since we are scaling gross profits on book assets, this ratio will naturally be lower in these sectors. The opposite can be argued for the consumer sectors and information technology, which our portfolio sort strategy on average overweights.

As a note, we would emphasize that these are not value weighted positions, only the average number of positions in the portfolio. This is not perfectly consistent with our value weighted portfolio formation. There is reason to believe that the long positions should be tilted slightly upwards, due to our negative loadings in SMB factor. Negative loadings in SMB should lead to the long portfolio having larger firms than the short portfolio, and therefore value weighted positions should be larger in our long portfolio. However, it is consistent with our measures of average gross profits to assets across the sectors, and it is financially sound following the arguments of what sectors naturally have small or large gross profits to assets. It is also consistent with Novy-Marx (2012), who points out that industry betting occurs.

4.3.1 Portfolio sort employing sector demeaning

Having established that sector betting occurs under a gross profits to assets portfolio sort, we are further looking to analyse how this affects the portfolio performance. In this section, we employ the same portfolio sort as in section 4.2. The only difference being that the gross profits to assets of all the individual stocks, is demeaned by the yearly sector average.

For our purposes, the point of demeaning is to reduce sector betting. To test if demeaning has achieved this, we apply the same test as completed in section 4.3.

Table 4.6: Results of long and short positions in each sector post-demean. Based on univariate quintile sorting, where positions are retrieved from the highest and lowest quintile. Sector positions are retrieved from the entire sample data covering July 1963 till 2016.

	10	15	20	25	30	35	45	50	55	60
Sector	Energy	Materials	Industrials	Consm.disc	Consm.stpl	Health C.	IT	Telecom	Utilities	Real Estate
Short	49%	51%	53%	56%	59%	49%	51%	52%	37%	32%
Long	51%	49%	47%	44%	41%	51%	49%	48%	63%	68%

As we can observe in the table, the long and short positions in the individual sectors are now centred around 50%. The exception being utilities and real estate, which are now overweighted, yet less extreme than before demeaning. We conclude that demeaning has eliminated sector betting to a large degree. To analyse how eliminating sector betting as affected the portfolio performance, we complete the same FF3 regressions as in section 4.2

Table 4.7: Results of portfolio sorts on gross profitability to assets regressed against the Fama French three factor model after demeaning. The six portfolios displayed in the table is a result of univariate quintile sorting on gross profitability to asset on the entire sample data, covering the period July 1963 till 2016 employing NYSE breakpoints. The H-L portfolio is a result of the highest- minus lowest quintile of the sort. Additionally, r^e is the monthly average excess returns of the portfolios.

	Dependent variable:					
	H-L	Low	Q2	Q3	Q4	High
α	0.389	−0.177	−0.125	−0.059	0.027	0.212
	[4.10]	[−2.25]	[−1.69]	[−1.03]	[0.43]	[3.77]
MKT	−0.181	1.128	1.042	0.937	0.999	0.946
	[−8.06]	[60.55]	[59.39]	[47.43]	[57.57]	[71.04]
SMB	−0.252	0.166	0.124	−0.073	−0.114	−0.085
	[−7.91]	[6.31]	[4.98]	[−3.20]	[−4.90]	[−4.51]
HML	−0.34	0.107	0.111	0.096	−0.020	−0.240
	[−10.02]	[3.74]	[4.09]	[3.47]	[−0.66]	[−11.65]
r^e	0.12%	0.47%	0.47%	0.46%	0.50%	0.58%
Observations	637	637	637	637	637	637
Adjusted R^2	0.24	0.87	0.86	0.88	0.89	0.90

The table shows the results of FF3 regressions on the high minus low portfolio, and all the five individual quintiles. The high minus low portfolio generates a monthly alpha of 0.389%, a reduction from 0.481% pre-demeaning. These results are not striking in themselves, yet we would like to emphasize that portfolios sorted on gross profitability to assets tend to always yield alphas in the FF3 model due to negative loadings in all the risk factors. The FF3 does in fact not capture much of variation or risk in quality sorted portfolios. (Asness, Frazzini, Pedersen, 2013) As noted in the table, the R2 of the high minus low regression is

0.13. Therefore, we will analyse the two portfolios with other performance measures as well.

The average returns of the portfolios has changed significantly. We no longer see the clear monotonic relationship, where higher gross profits in the quintiles, leads to higher returns. After demeaning, the average returns of the three lowest quintiles are roughly equal at 0.47% monthly, while the two top quintiles rises to 0.5% and 0.58% respectively. While pre-demean, the average returns steadily rise from 0.35% in quintile one, to 0.66% in quintile five. Moreover, this leads to a reduction in the average return of the high minus low portfolio from 0.30% pre-demean to 0.12% after demeaning. This is a tremendous decrease in average returns of 60%, which is illustrated in Appendix C, where we can observe that the spread between the high and low quintile in the two different portfolios is substantial. This implies that sorting on demeaned gross profitability to assets does not work nearly as well as non-demeaned return wise.

Table 4.8: Summary results from the demeaned and non-demeaned regression alphas of FF3-, C4FM-, and FF5-model. Additionally, r^e is the average monthly excess return, and Sharpe refers to the annualized Sharpe Ratio r^e/σ.

	$\alpha FF3$	$\alpha C4FM$	$\alpha FF5$	r^e	Sharpe
Non Demean	0.48%	0.36%	0.25%	0.30%	0.35
	[4.31]	[3.20]	[2.47]		
Demean	0.39%	0.24%	0.17%	0.12%	0.16
	[4.10]	[2.56]	[1.94]		

As the returns decrease significantly, we can observe an opposite effect in the volatility of the demeaned portfolio. The monthly standard devation decreases from 0.0296 to 0.0269. This is to be expected, as our demeaned portfolio has increased diversification, through eliminating sector betting to a large degree. Novy-Marx (2012), finds similar results. The demeaned portfolio generates a sharpe ratio of 0.16, while the pre-demean portfolio has a sharpe ratio of 0.35, as noted earlier.

Furthermore, we also utilize the Carhart Four Factor Model (C4FM) and the FF5 as performance measures of the two different portfolios. Employing the C4FM, we can observe a reduction in alpha from 0.36% pre-demean to 0.24% post-demean, yet still significant. As mentioned previously, momentum appears to explain some variation in portfolios sorted on gross profitability to assets. The FF5 reduces the alphas in both portfolios, compared to both FF3 and C4FM. This is explained by the RMW factor, this is sound given that it is built upon robust operating profitability, which in turn should be closely related to gross profitability. The demeaned portfolio generates an alpha of 0.17%. However, it is not significant. The pre-demean portfolio achieves a significant alpha of 0.25%.

Summarized, all the performance measures are reduced by demeaning by the sector average. Additionally, the average returns are reduced by 60%. Hence, there is no doubt that performance is reduced through eliminating sector betting. However, it does not prove to be conclusive evidence that sector betting is the driving effect behind abnormal returns of sorting on gross profitability to assets. There is still significant alphas in two out of three models post-demeaning. Additionally, the reduced performance might be caused by some effect unknown to us, aside from eliminating sector betting.

4.3.2 Portfolio sorts within the individual GIC sectors

We continue to test for sector betting effects, through completing the same quintile gross profitability to assets sort within the individual sectors. We are not able to complete the test in the real estate sector, due to a low number of observations. Thus, we are left with nine sectors. If our hypothesis of sector betting leading to abnormal returns in the portfolio sort of the entire U.S stock universe is correct, our portfolio sorts within the sectors should not yield abnormal returns.

Table 4.9: Summary results of regression alphas from FF3-, C4FM-, and FF5-model in all sectors. All results covers the period July 1963 till July 2016.

	10	15	20	25	30	35	45	50	55
Sector	Energy	Materials	Industrials	Consm.disc	Consm.stpl	Health C.	IT	Telecom	Utilities
αFF3	0.68%	0.29%	0.25%	0.49%	0.01%	0.62%	0.45%	− 0.26%	0.25%
	[3.68]	[1.38]	[1.77]	[3.13]	[0.37]	[3.10]	[1.86]	[−1.00]	[1.35]
αC4FM	0.56%	0.18%	0.25%	0.37%	0.10%	0.40%	0.10%	−0.16%	0.18%
	[3.00]	[0.88]	[1.77]	[2.30]	[0.60]	[1.95]	[0.43]	[−0.63]	[0.95]
αFF5	0.65%	0.09%	0.07%	0.32%	0.01%	0.29%	0.25%	−0.37%	0.26%
	[3.43]	[0.42]	[0.47]	[2.00]	[0.05]	[1.48]	[1.04]	[−1.40]	[0.13]

The table reports alphas using the high minus low portfolios of the individual sectors as the dependant variable, with respect to, respectively, the FF3-, C4FM- and the FF5 model. The results show that alphas to a large degree are diminished within the individual sectors.

Employing the FF3 model only three out of nine sectors generate significant alphas, while using the same gross profitability to assets sort. The three sectors being energy, consumer discretionary and telecom. Moreover, using the C4FM and FF5 as independent variables only two out of nine sectors achieve alphas (Energy and Consumer Discretionary). These are rather striking results, given that our original portfolio sort achieves solid significant alphas in all the three models. The cumulative returns of the individual sector sorts are also shown in appendix B. They illustrate a similar picture, where the top quintile of gross profitability stocks barely outperforms the bottom quintile in most sectors. In some cases, the bottom quintile outperforms the top quintile. We can also observe that excess returns no longer monotonically increase with the gross profitability to assets of the individual stocks in the individual quintiles. It is hard to reason why the portfolio sort work well within two of the sectors. A possible explanation is that gross profitability scaled by assets, is a much more powerful predictor of returns in certain sectors. Different accounting measures are known to be more valuable in certain sectors. As an example gross profitability does not inhibit the same importance if a large part of the firms cost are categorized under R&D or SG&A. This coincides with the energy- and consumer discretionary sectors, which generates significant alphas in all three models. Where a large part of the costs are categorized under COGS and reflected in gross profitability. However, it is more of a puzzle regarding the health care sector, where the opposite is true. One must note that the health care sector only has a significant alpha in the FF3 model.

One can argue that sorting on gross profitability does not generate abnormal returns within the sectors, as only two out of nine sectors achieves significant alphas in all three models. Since there by construction is no sector betting involved with portfolio sorts within the respective sectors, our hypothesis of sector betting leading to abnormal returns in the original sort, definitely seem to have some grounds. However, the alphas are positive in eight out of nine sectors, but only significant in two. There is still some positive relationship of sorting on gross profitability, yet it is much weaker than when sorting the entire universe. Another point is that the coefficients in the regressions shows large variations across the sectors. We do not observe the same initially negative loadings in SMB and HML for quality sorts, which are apparent when sorting the entire universe. This is explained by the sectors having characteristics of size and book-to-market in their own right. Certain sectors do on average have smaller companies and higher book-to-market ratios on average, and we can observe positive loadings in certain sectors, which in turn leads to diminished alphas. To isolate the gross profitability effect and sector outperformance, it would be possible to construct sector specific factors for the individual sectors. However, we did not find this valuable enough given the scope of such an exercise, and our available time frame for this thesis.

4.3.3 Isolating the sector effect: Long sectors - short gross profitability

In this section we complete a strategy that should isolate the sector effects in our gross profitability sorts. It is inspired by Moskowitz and Grinblatt's paper (1999), where they complete a similar strategy for the momentum anomaly. After having sorted on gross profitability to assets within the sectors, we buy the lowest quintiles of the two sectors with the highest gross profitability, while selling the top quintiles within the two sectors with the lowest gross profitability. Moskowitz and Grinblatt (1999), use the top and bottom three sectors, yet they have split the universe in to 20 different industries in contrast to our 10 sectors.

As a prerequisite, we test for the average gross profitability to assets within these portfolios. The portfolio we are buying is on average less profitable than the portfolio we are selling. Thus, we are in practice short profitability but we are buying and selling different sectors. If profitability is the driving force behind the abnormal returns, this strategy should yield a negative alpha.

Table 4.10: Regression result from long sectors minus short profitability against the Fama French three factor model. We buy the lowest quintiles of the two sectors with the highest gross profitability, while selling the top quintiles within the two sectors with the lowest gross profitability.

	α	Mkt.RF	SMB	HML
Estimate	0.48	−0.12	0.05	0.13
t value	1.98	−2.06	0.62	1.50

The table reports the regression of described portfolio's returns as the dependant variable employing the FF3 model as independent variables. We can observe that the portfolio generates a significant monthly alpha of 0.48%. These are noteworthy results, given that we are buying less profitable stocks than we are selling. This gives grounds for our hypothesis of sector betting driving the abnormal returns in our original portfolio. However, one must point out that we are not directly short gross profitability. We buy less profitable stocks, but we are not buying the least profitable stocks in the universe and vice versa. It should also be mentioned that this strategy does not yield a significant alpha in the C4FM- nor the FF5 model. One must, however, keep in mind that the 0 hypothesis here is that this strategy should yield a negative alpha and not an alpha of 0, which is the basis for the t-statistic calculation.

The explanation for the abnormal returns, is that the sectors with a high average gross profitability to assets displays higher returns for the sector as a whole on average. Now, what is puzzling is that gross profitability is not necessarily the driver behind these returns, as portfolio sorts within these industries does not work well as displayed in the previous section. Yet, in the original portfolio one ends up tilting the portfolio towards these sectors due to their naturally high gross profits and thus gains higher returns due to sector outperformance, which is not necessarily driven by higher gross profits. In practice, this is the effect we are referring to as sector betting. Gross profitability to assets portfolio sorts therefore looks like a bet on sector outperformance, which in turn drives the abnormal returns.

4.4 Combining gross profitability and book-to-market

As both Asness, Frazzini and Pedersen (2013) and Novy-Marx (2012) points out, quality or gross profitability portfolios exhibit better performance when combined with book-to-market. In this section we will combine gross profitability and book-to-market in two different strategies and once again test for sector betting effects. Initially we test for the average book-to-market in the individual sectors to illustrate that book-to-market and profitability over- and underweight different sectors (Appendix D). As this is true, one would think that combining the two should reduce sector betting, and possibly volatility due to better diversification.

4.4.1 Controlling for gross profitability within book-to-market

As we have previously illustrated there is negative correlation between gross profitability and book-to-market. A univariate sort on book-to-market yields a portfolio with unprofitable stocks, and a univariate sort for gross profitability yields a portfolio with expensive stocks. Controlling for gross profitability should improve the performance by avoiding to buy stocks that are "more unprofitable than cheap" and avoid selling stocks that are "more profitable than expensive". To test for this we complete a bivariate portfolio sort, following the procedure of Novy-Marx (2012).

Table 4.11: Bivariate sorts on B/M and GP/A - Including high minus low regressions. The GP/A and B/M quadrant displays the average excess returns of 25 portfolio combinations. The GP/A strategies quadrant displays the vertical high- minus low portfolio regressions against Fama French three factor model. For the B/M strategies quadrant this displays the horisontal regressions of high- minus low portfolios.

		GP/A					*GP/A Strategies*				
		L	2	3	4	H	r^e	α	β_{mkt}	β_{smb}	β_{hml}
B/M	L	-0.07	0.26	0.27	0.46	0.61	0.68	0.84	-0.19	-0.25	0.01
								[3.83]	[-3.82]	[-3.40]	[0.12]
	2	0.25	0.49	0.63	0.69	0.79	0.54	0.45	-0.02	0.26	0.14
								[2.84]	[-0.61]	[4.98]	[2.38]
	3	0.38	0.56	0.79	0.84	0.95	0.57	0.46	0.02	0.35	0.05
								[3.21]	[0.65]	[7.29]	[0.88]
	4	0.56	0.68	0.89	0.86	0.87	0.31	0.11	0.144	0.57	-0.04
								[0.79]	[3.97]	[11.1]	[-0.78]
	H	0.65	0.86	1.11	1.12	1.11	0.46	0.30	0.04	0.65	-0.03
								[1.67]	[0.98]	[10.7]	[-0.51]
B/M Strategies	r^e	0.72	0.60	0.84	0.66	0.50					
	α	0.49	0.25	0.32	0.15	-0.04					
		[2.39]	[2.01]	[2.32]	[1.01]	[-0.26]					
	β_{mkt}	-0.14	-0.01	0.09	0.12	0.09					
		[-0.14]	[-0.16]	[2.98]	[3.37]	[2.53]					
	β_{smb}	0.03	0.41	0.65	0.79	0.93					
		[0.03]	[9.92]	[14.10]	[16.04]	[17.29]					
	β_{hml}	0.87	0.75	1.00	1.02	0.82					
		[0.87]	[16.68]	[19.64]	[18.87]	[14.04]					

The table shows the value-weighted excess returns to portfolios double sorted on book-to-market and gross profitability, and results of FF3 regressions on the ten different high minus low portfolios. Our results confirm that controlling for gross profitability within book-to-market improves performance. The excess returns increase almost monotonically with increasing profitability within the book-to-market sort. Our regressions does not show the same pattern with increasing alphas with increasing profitability. However, this is due to the return spread between the high and low portfolio is not necessarily increasing with profitability. In other words, both the high and low portfolio has increasing returns when controlling for profitability.

To adjust for this we construct an “optimal strategy”, which is no longer formed on a simple high minus low portfolio as illustrated in table 4.12. We continue to buy the four portfolios with both high book-to-market and high gross profitability , while shorting the four portfolios with low book-to-market and low gross profitability.

Table 4.12: Bivariate optimal portfolio regressed against Fama French three factor. Where the high portfolio consists of 4-4, 4-H, H-4, H-H, and the low portfolio consists of L-L, L-2, 2-L, 2-2, see table 4.11.

	α	Mkt.RF	SMB	HML
Estimate	0.45	−0.01	0.63	0.53
t value	[3.87]	[−0.28]	[16.02]	[12.31]

We can observe that this strategy yields a monthly alpha of 0.46, similar to that of the original gross profitability sort. Yet, this portfolio has very different characteristics from that of the straight profitability sort. As expected, this portfolio is loading heavily into the HML factor as we are firstly sorting for book-to-market. More surprisingly, is the significant coefficient of 0.636 in the SMB factor. Our "optimal strategy" is buying small stocks and selling large stocks. This point towards cheap and profitable stocks being small, while expensive and unprofitable stocks being large stocks. We have previously found that profitable stocks often are large, yet this combination finds the opposite due to first sorting for book-to-market.

Moreover, this portfolio realizes a monthly average excess return of 0.78%, considerably outperforming the straight profitability portfolio with a monthly return of 0.3%. The standard deviation is a monthly 3.65%, resulting in an annualized sharpe ratio of 0.74. Employing these simple performance measures, this strategy significantly outperforms straight profitability and book-to-market portfolios.

Within this portfolio, we have also performed sector betting tests. Surprisingly, this portfolio is also sector betting heavily. One would expect that a bivariate sort would decrease sector betting, as book-to-market and gross profitability over- and underweights different sectors. Looking at the volatility of the portfolio, we can also observe an increase from the univariate profitability sort. A possible explanation may be that diversification across sectors have actually decreased slightly in our bivariate sort.

4.4.2 A portfolio combination: Gross profitability and book-to-market

In this section, we combine gross profitability and book-to-market in a different manner. Instead of completing a bivariate sort, we hold 50% of the univariate gross profitability portfolio and 50% of the univariate book-to-market portfolio. As a consequence, we are no longer buying stocks that are both profitable and cheap. Yet, now we buy stocks that are individually cheap or profitable, while selling stocks that are individually expensive or unprofitable.

Table 4.13: Fama French three factor regression on combination portfolio. Formed from two unique univariate sorts on both book-to-market and gross profitability to assets, weighting each series 50% respectively.

	α	Mkt.RF	SMB	HML
Estimate	0.26	0.01	0.18	0.25
t value	[4.34]	[0.60]	[8.99]	[11.30]

The table reports a FF3 regression on this combined high minus low portfolio. This portfolio combination generates a monthly alpha of 0.26. Similar to the bivariate portfolio, it loads positively in both SMB and HML, yet with significantly smaller coefficients. Furthermore, the portfolio exhibits monthly average excess returns of 0.4%, roughly half of the bivariate portfolio. What is interesting, is a large reduction in the volatility of the portfolio. The monthly standard deviation of this portfolio is 1.7%, notably lower than in the bivariate or univariate profitability portfolio. It is no secret that book-to-market and gross profitability correlates negatively, and therefore reduce the risk of a combined portfolio. However, our hypothesis is that book-to-market and gross profitability over- and underweights different sectors, and this can be viewed as a partial explanation for this negative correlation. As such, we continue to test for sector betting in this portfolio.

Table 4.14: Results of long and short positions in each sector following combination portfolio. Based on two univariate quintile sorts, where positions are retrieved from the highest and lowest quintile. Sector positions are retrieved from the entire sample data covering July 1963 till 2016.

	10	15	20	25	30	35	45	50	55	60
Sector	Energy	Materials	Industrials	Consm.disc	Consm.stpl	Health C.	IT	Telecom	Utilities	Real Estate
Short	63%	58%	50%	56%	42%	63%	49%	64%	58%	68%
Long	37%	42%	50%	54%	58%	37%	51%	36%	42%	32%

The table reports that sector betting is reduced greatly compared to the bivariate sort and the univariate profitability sort. Most sectors are balanced towards 50 percent long and short positions. The exception being energy, telecom and real estate, which is less extreme than previous portfolios. As a consequence, the portfolio is more diversified across sectors. As book-to-market and gross profitability over- and underweights different sectors, this may serve as a partial explanation for their negative correlation. As such, it may also be an explanation for the volatility of the portfolio being significantly lower than in our other portfolios. There are obviously other reasons for the negative correlation, as book-to-market- and gross profitability sorts buy and sell stocks with very different characteristics. Yet, our sector betting tests illustrates that diversification is clearly increased when combining the two.

It must be noted that one no longer is buying stocks that are both profitable and cheap, and as a possible consequence the average returns are only half of what they are in the bivariate sort. Yet, the lower volatility leads to a sharpe ratio of 0.81, which is higher than in any other portfolio included in this thesis.

5 Concluding remarks

We find that gross profitability to assets has significant power predicting the cross section of returns, roughly the same as book-to-market. Additionally, we find that portfolio sorts on gross profitability scaled by assets generates significant alphas in all models employed, including the FF3, C4FM and FF5. This is consistent with similar findings of Novy-Marx (2012). Hence, we can conclude that gross profitability scaled by assets yields abnormal returns in the U.S market in the period of 1963-2016.

These findings present problems for earlier financial literature. Fama and French (1993) notes that high book-to-market stocks, consistently are less profitable than low book-to-market stocks. They therefore present this as a risk factor, where less profitable firms are more risky, and consequently investors require higher returns. If that was true, highly profitable firms should be less risky and therefore have lower required returns. Yet, our findings present a different picture. Lettau and Watcher's (2007) duration based explanation of the value premium, present that short duration assets are riskier than long duration assets and therefor have higher required returns. However, Novy-Marx (2012) finds that high gross profitable firms are associated with long run growth in profits, earnings, cash flows and dividends. As such, these firms are on average longer duration, yet still generate higher returns.

Why gross profitability is able to generate abnormal returns is yet up for interpretation. Gross profitability scaled by book assets in one sense, seeks to capture the same firm characteristics as book-to-market. Both strategies' goal is to capture productivity at a valuable price. While book-to-market achieves this through buying cheap assets, gross profitability achieves the same through buying highly productive assets (Novy-Marx, 2012). Finance theory suggests that this productivity should be reflected in investors required returns. However, our findings suggests differently. Asness, Frazzini and Pedersen (2013), finds that there is a price of quality. Where firms with quality characteristics such as gross profitability on average trades on higher book-to-markets. This is consistent with our findings, where we can observe a monotonically decrease in HML loadings with higher profitability in our portfolio sorts. Yet, this price premium is apparently not high enough for gross profitability. As our portfolio sorts has negative loadings in all the risk factors in the FF3 model, and it performs well during downturns, a risk based explanation proves hard to present. There is no evidence to suggest that a liquidity premium can be presented as an explanation. We have value weighted in our return calculations, avoiding to put large weight on micro- and nanocap stocks. Additionally, Novy-Marx (2012) has presented similar findings, while only employing data from large cap stocks. As we utilize data from the year of 1963, another possible explanation may be that quantitative strategies such as this one may not have been possible due to a lack of computing power (Richardson, Tuna, Wysocki, 2010). This does not necessarily imply that markets were inefficient at that point in time, as investors did not have the capability to complete a similar analysis. Another point to be made is that we have not adjusted for transaction costs in our analysis. Richardson, Tuna and Wysocki (2010) suggests adjusting for transaction costs with 1.5% yearly. This is based upon an average, as transaction costs has decreased with time. As our strategy yields a monthly alpha of 0.48%, we should still be able to conclude that the gross profitability strategy yields abnormal returns.

As an alternative explanation for the abnormal returns we present the sector betting effect. By sector betting, we are referring to how portfolio sorts on gross profitability to assets will over- and underweight sectors substantially, as proved in section 4.3. As the portfolio is demeaned by the sector average, we observe that sector betting is eliminated to a large degree. Furthermore, demeaning clearly reduces the performance of the portfolio. The alphas are reduced in all the models employed, and is no longer significant in the FF5 model. We can also observe that the returns of the demeaned portfolio is relatively reduced by 60%. The volatility of the portfolio is slightly reduced, probably explained by increased diversification as sector betting is eliminated. We also prove that sorting on gross profitability on assets, does not generate abnormal returns in seven out of nine sectors individually. Lastly, a portfolio of selling more profitable stocks and buying less profitable stocks in different sectors, exhibits a significant alpha.

All of our three investment strategies point towards sector betting explaining the abnormal returns of the gross profitability portfolio sort. Yet, there is still some relationship between gross profitability and higher returns. Our demeaned portfolio still generates significant alphas in the FF3- and C4FM models. Additionally, nearly all of the alphas are positive yet not significant in the regressions within the sectors. However, there are clear grounds to conclude that sector betting is a significant contributor to the abnormal returns of the original gross profitability portfolio.

As is, we present sector betting as a partial explanation for the gross profitability anomaly, where there has been lack of sound explanations in previous literature. This might also present as a weak risk explanation, as the reduced diversification due to sector betting leads to higher volatility in the portfolio. However, the largest contributor is the sector outperformance one indirectly makes use of while sorting on gross profitability to assets. The most profitable sectors on average displays higher average returns than the least profitable sectors. What proves puzzling is that gross profitability is not necessarily the driver behind this sector return outperformance. Portfolio sorts within these sectors works poorly, and our "long sector – short profitability" portfolio generates an alpha of 0.48% monthly. Yet, in the original portfolio, one ends up tilting the portfolio towards these sectors due to their naturally high gross profitability, and thus gains abnormal returns due to sector outperformance. Why certain sectors outperform others, we leave up to others to explain. However, it seems that gross profitability is a proxy for some unknown effect that leads to sector outperformance.

As to why gross profitability generates abnormal returns in a few selected sectors is up for discussion. Yet, as explained in section 4.3.2, we suspect that gross profitability is more related to returns in certain sectors. If a large part of costs are categorized under COGS, one would think that gross profitability is more related to returns. This will of course differ in the individual sectors. An interesting approach would be to test several different measures of profitability within the individual sectors to see which accounting measure that predicts returns with most power within the sectors. As a consequence, one could choose stock picking criteria that would suit the respective sectors the most, and possibly achieve higher abnormal returns.

Quality investing still stands strong in financial literature and practice, and has been proven to be best combined with some value characteristic. Both Asness, Frazzini and Pedersen (2013) and Novy-Marx (2012) finds that combining quality characteristics with book-to-market improves performance. We present similar results, where combining book-to-market and profitability reduces the risk of the portfolio significantly. We present sector betting as a possible partial explanation for the negative correlation of book-to-market and gross profitability, as they over- and underweight different sectors, and balance eachother when combined.

Asness, Frazzini and Pedersen (2013) use a different methodology employing 21 different proxies for quality, similarly to Piotroski (2000). One would think this should lead, but not necessarily, to less sector betting. A similar analysis of sector betting on the Asness, Frazzini and Pedersen or Piotroski methodology would be interesting for comparison reasons.

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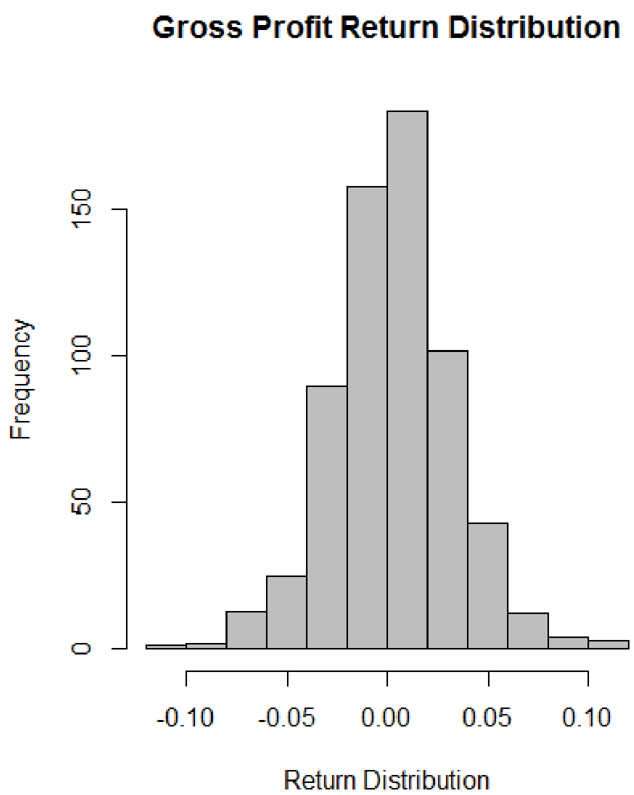
A Appendix

Table A.1: Spearman Correlation Matrix

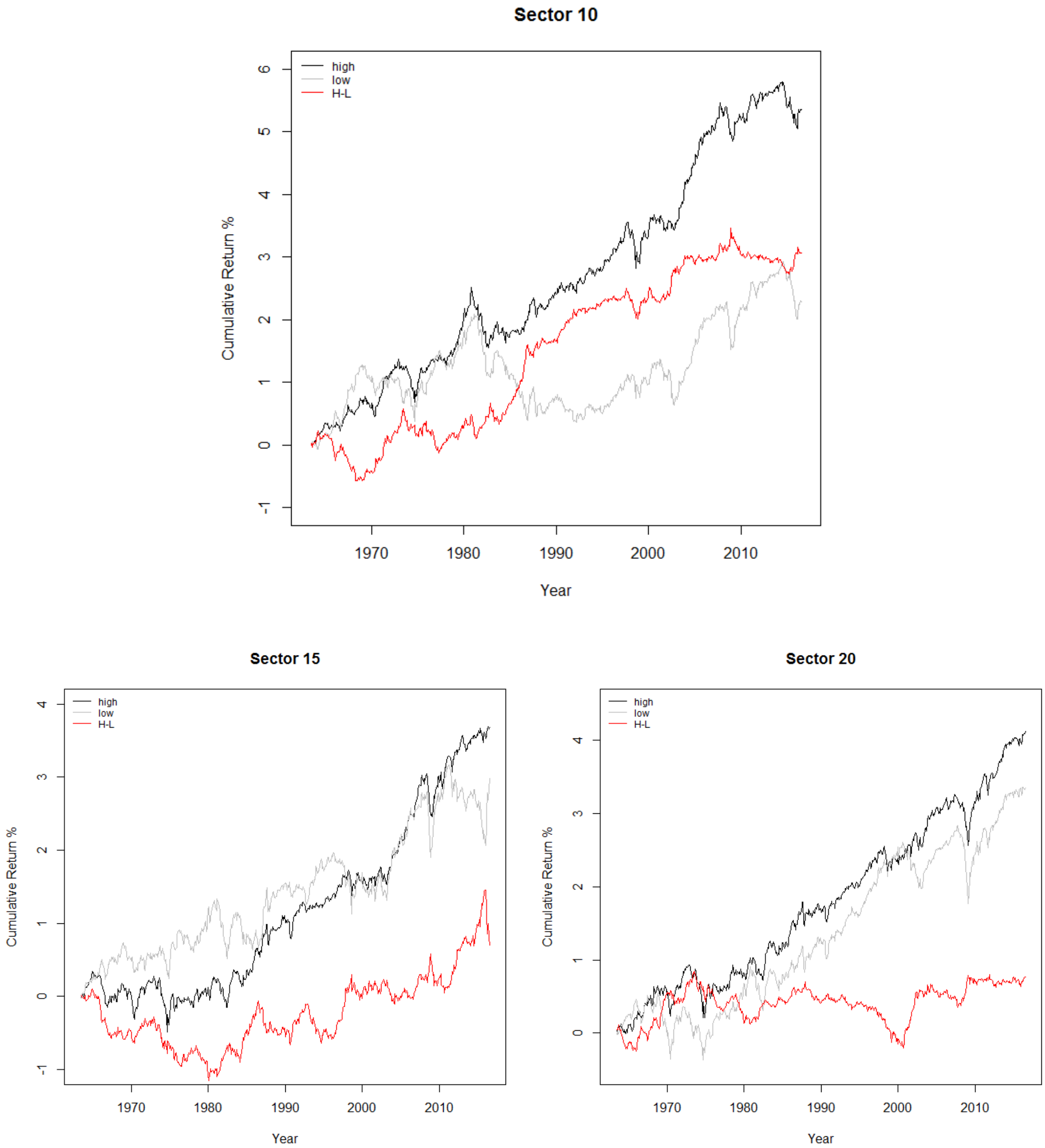
	GP	Mkt.RF	SMB	HML	RMW	CMA
GP	1	0.063	-0.040	-0.409	0.441	-0.335
Mkt.RF	0.063	1	0.255	-0.253	-0.205	-0.336
SMB	-0.040	0.255	1	-0.062	-0.250	-0.115
HML	-0.409	-0.253	-0.062	1	-0.211	0.678
RMW	0.441	-0.205	-0.250	-0.211	1	-0.213
CMA	-0.335	-0.336	-0.115	0.678	-0.213	1



Figures A.1: Gross profit return distribution

B Appendix

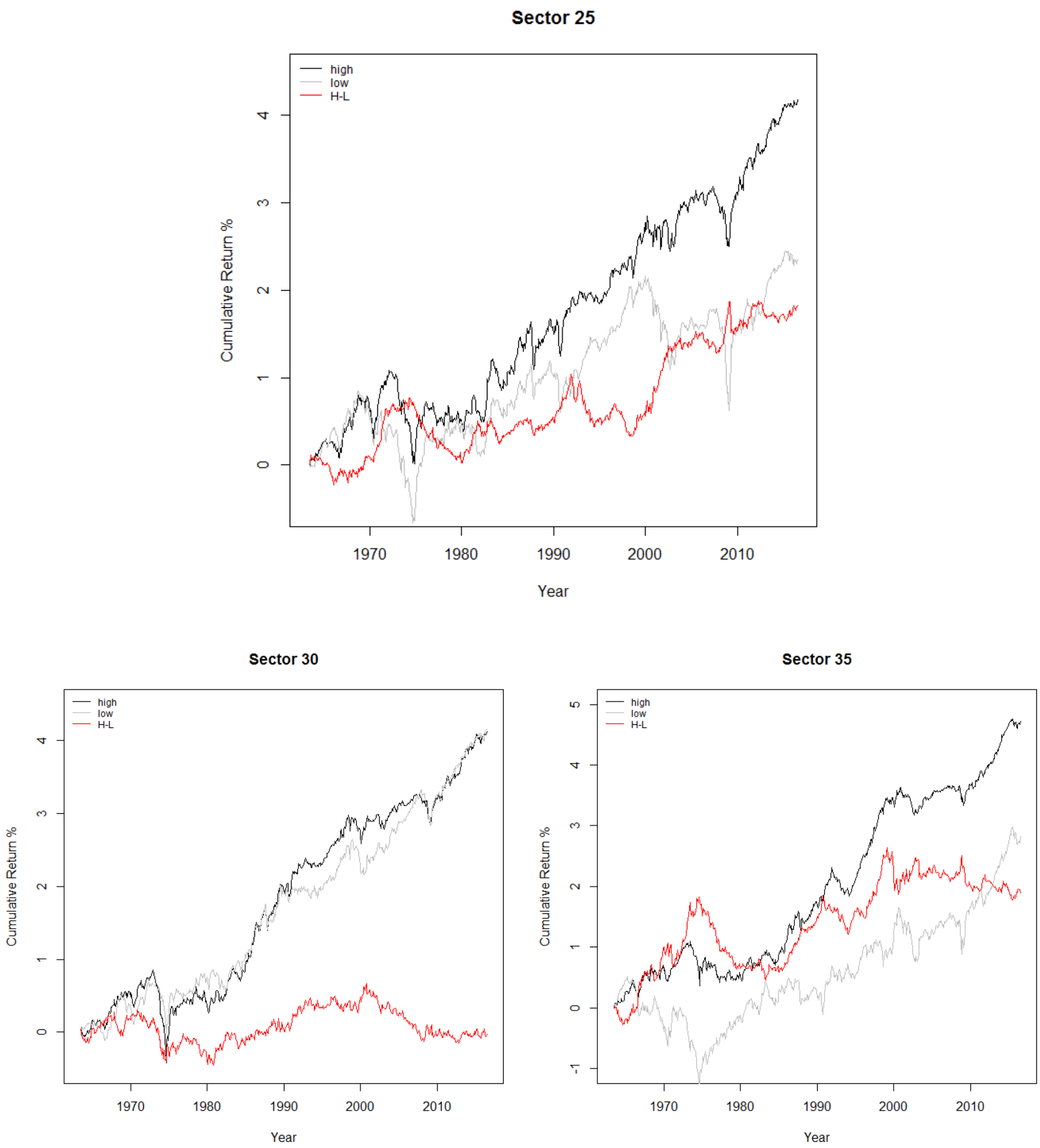
[1]



Figures B.1: Sector 10 - 20 cumulative returns

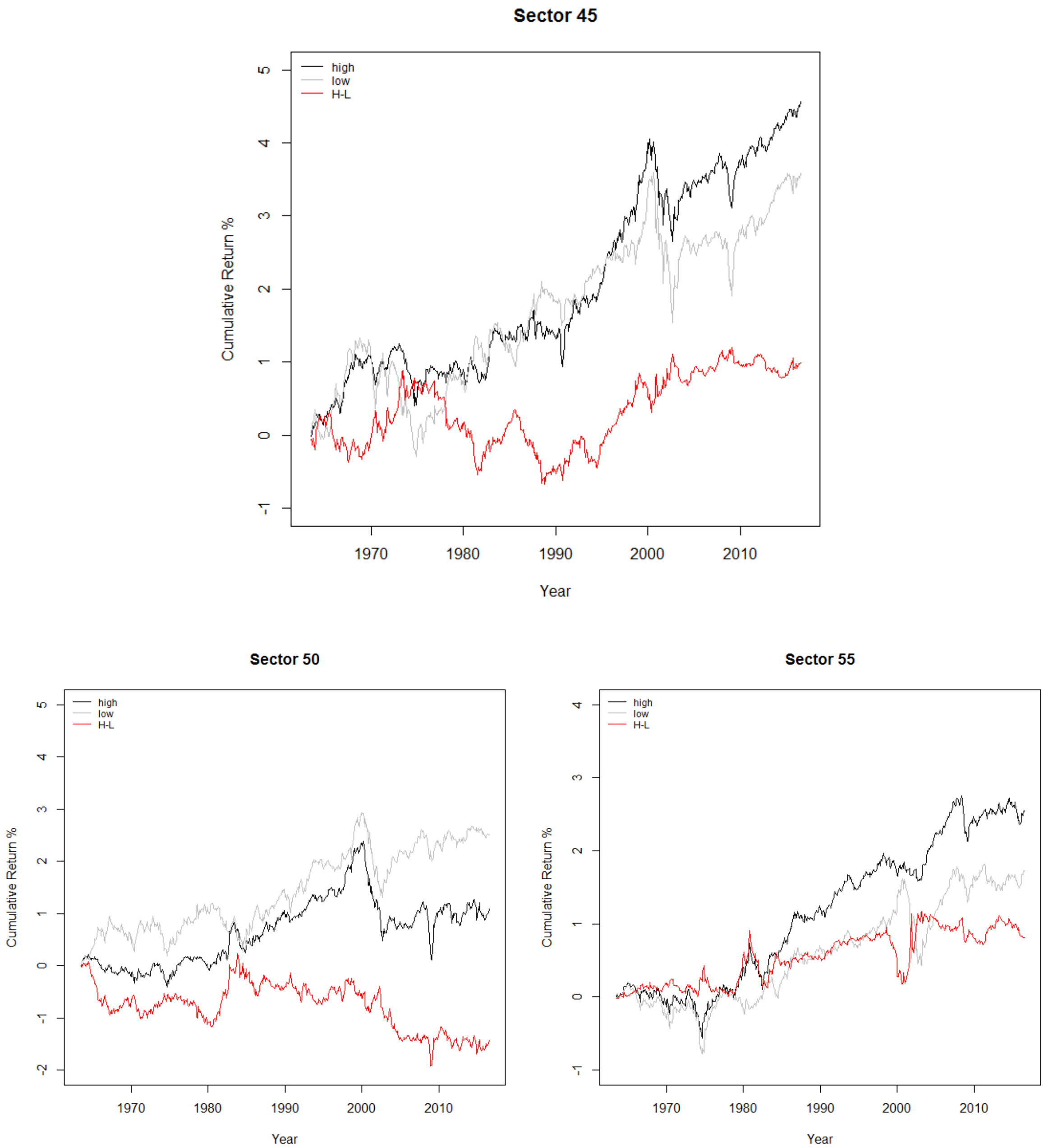
[1]Black = 5th quintile GP, Grey = 1st quintile GP, Red = High minus low portfolio

2



Figures B.2: Sector 25 - 35 cumulative returns

[2]Black = 5th quintile GP, Grey = 1st quintile GP, Red = High minus low portfolio

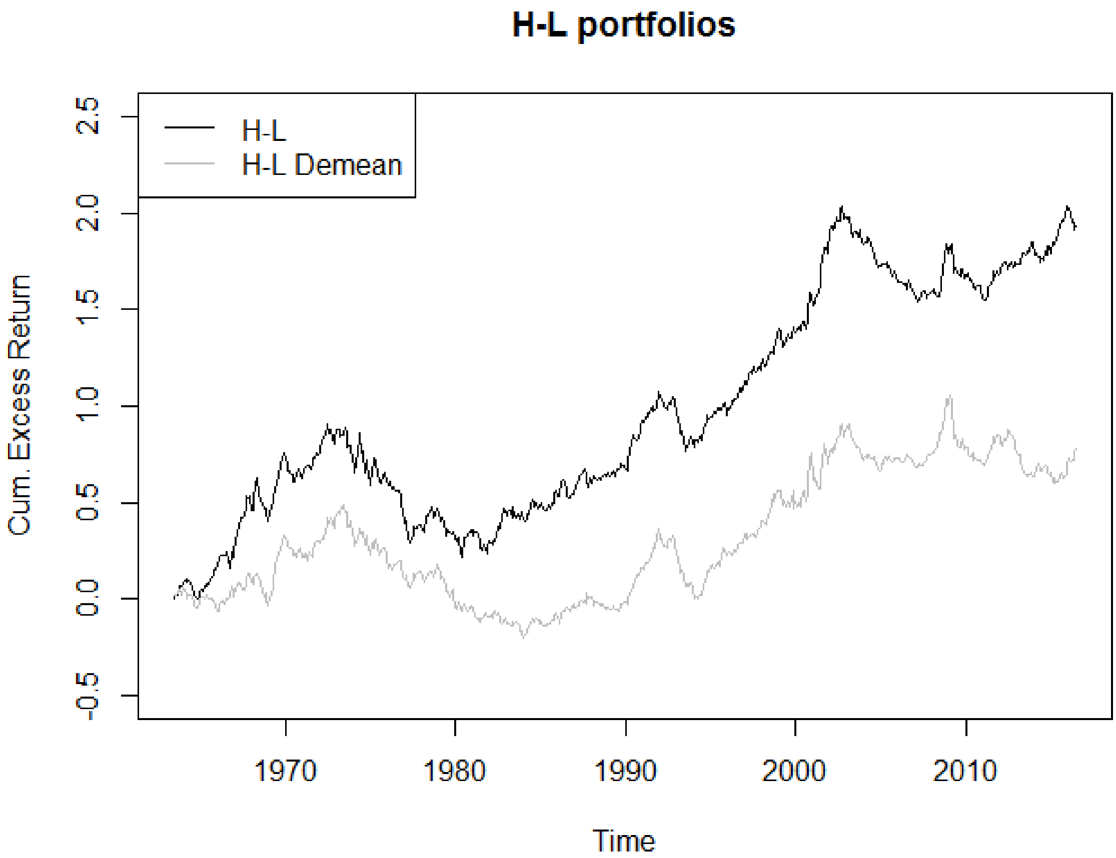


Figures B.3: Sector 45 - 55 cumulative returns

[3]

[3]Black = 5th quintile GP, Grey = 1st quintile GP, Red = High minus low portfolio

C Appendix

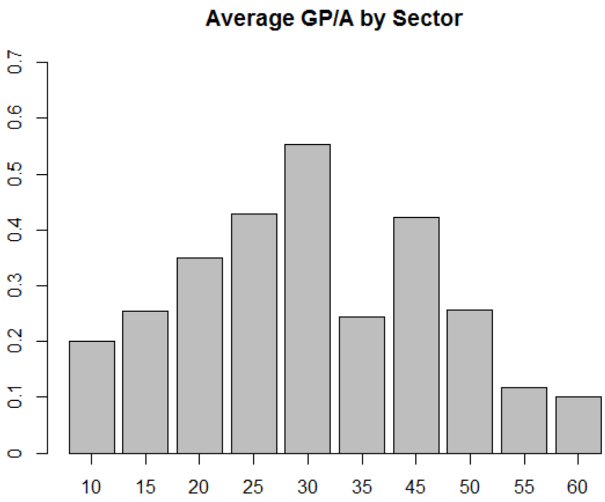


Figures C.1: H-L portfolios, non-demean vs. demean

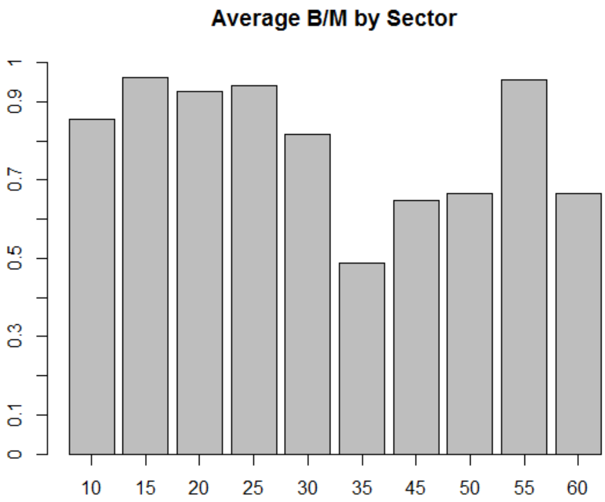
[1]

[1] Grey = Demeaned profitability return, Black = Straight profitability return

D Appendix



Figures D.1: Average GP/A by Sector



Figures D.2: Average B/M by Sector