Department of Economics

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ALPHA ANALYSIS
- A MOMENTUM AND PERFORMANCE METRICS STUDY OF THE EFFICIENT MARKET HYPOTHESIS

Authors

Mikael Lindberg

Andreas Nilsson

Supervisor

Hossein Asgharian

Abstract

In this study the efficiency of the Nordic stock markets are tested. The evaluation period is 16 years, between 1995 and 2010. Monthly data on stock returns, D/Y, P/C, P/E, PTBV and EV/EBITDA are used to create six different single sorted portfolios. The portfolio evaluation periods and holding periods are set to six months. Our findings indicate that all of our single sorted portfolios could generate abnormal returns. These results are compared to that of the double sorted portfolios in order to investigate the profitability of different investment strategies. In the double sorted portfolios the momentum strategy is combined with each of the five performance metrics. In these regressions, the results indicate that the double sorted portfolios generate larger abnormal returns compared to that of the single sorted portfolios. These findings could have many causes, but the nature of the results indicates that the value based strategies aggravate the momentum effect, leading us to believe that the results could be emulated using a more extreme selection process based on the momentum effect.

Keywords: Momentum, Value strategies, Performance metrics, Abnormal returns, Efficient market hypothesis

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1. Introduction

Beating the market is said to be impossible in the long run, and the common belief is that stock markets obey a weak form of the efficient market hypothesis. This indicates that trading strategies based on predictive characteristics should be incapable of generating abnormal returns (actual returns minus expected returns) on a consistent basis, as all public information available is supposed to be accurately reflected in asset prices. With the assumption that markets are efficient, information is instantly and properly incorporated in stock prices and until new information has been introduced stock prices remain unchanged. Additionally, the pattern of stock prices are said to follow a random walk which further indicates that past returns lack explanatory power for future stock movements. Hence it should not be possible to reliably predict future stock returns by examining the past. Yet investors actively explore different venues with the purpose of beating the market on a consistent basis, and in recent years there have been a surge of studies giving their pursuit of profit validity. Results have shown that sorting portfolios based on past movement, for example, can continually generate significant returns above the mean, suggesting that the efficient market hypothesis as well as the random walk theory can be questioned. Moreover, the momentum effect is not contained to the stock market as both the commodity market and the currency market show similar patterns with persistent up and down periods.

Additionally, momentum in stock prices is not the only market anomaly that lends its support to question the efficient market hypothesis. Several studies suggest that value strategies based on performance metrics are capable of generating large abnormal returns. These strategies are based on buying stocks that are considered cheap, value stocks, while shorting stocks that are perceived as expensive, growth stocks. Identifying these stocks can be done using several different performance metrics. The underlying premises is that investors either overreact or underreact to news and information, ignoring fundamental data. As a result the current price may not accurately reflect the true value of the underlying asset.

1.1. Purpose of the paper

The goal with this paper is to test if the weak form of the efficient market hypothesis holds. Our null hypothesis is that past fundamental company data as well as stock returns should not contain predictive characteristics. That is, returns in the stock market should be independent of past returns with the rejection of the null hypothesis indicating that stock movements are, at least partly, predictable. In order to test the weak form of the efficient market hypothesis we

use investment strategies based on momentum and performance metrics, both on an individual basis and combined. If these strategies consistently generate abnormal returns, after controlling for variability in the sample characteristics, the null hypothesis can be rejected. Additionally, the combined portfolios are evaluated and compared to more extreme single sorted momentum portfolios in order to find indicative evidence of aggravated momentum effect when including value based strategies in the portfolios.

1.2 Outline of the essay

This brief introductory chapter has introduced the topic and the purpose of this essay. The following chapter will describe the underlying theory as well as previous research performed within the topics of momentum and value based investment strategies. Next, the third chapter describes data selection and the method used. In the first section of this chapter, the data and the different performance metrics are presented. The following section describes the portfolio creation process with two main portfolio strategies. The last part of the chapter provides a description of the portfolio evaluation methods used in this essay.

The fourth chapter provides the empirical results, obtained from the different portfolio strategies described in chapter three. The first section present the results in the absence of control variables. The next section adds control variables for market risk and in the final part of the chapter two more variables are added. Finally, chapter five, provides a brief summary of the analysis and concluding remarks.

2. Theory

2.1. The efficient market hypothesis

First introduced by Eugene Fama in the 1960s the efficient market hypothesis (EMH) states that information and news is correctly and instantaneously incorporated in asset prices. However this does not imply that all individual agents are rational. On the contrary, it is assumed that agents deviate from this model by reacting differently to new information. But on an aggregate level it is believed that these actions cancel each other out which results in efficient asset pricing. As long as the actions of these agents are considered random and follow a normal distribution the market is efficient. Hence the ability to predict stock prices based on past performance or fundamental data should not be possible after taking into account transaction costs and spreads.

There are three different forms of the efficient market hypothesis:

Weak form

According to the weak form of the efficient market hypothesis asset prices are not serially correlated and as a consequence follow a random walk. This implies that past price movements cannot predict future returns. Price movements are therefore exclusively results of news and information. However, private information is excluded and could therefore be used by "insiders" to generate abnormal returns. Moreover, there can be a time delay in the price adjustments as they respond to new information.

Semi strong form

Compared to the weak form of the efficient market hypothesis the semi strong form adds the assumption that all public information is instantaneously reflected in asset prices. However, private information is not accurately reflected in the prices and as a consequence it is possible to use this information in order to derive abnormal returns.

Strong form

In contrast to the semi strong form of the efficient market hypothesis asset prices reflects all asset information, both public and private in the strong form of the EHM. As a consequence it should be impossible to generate profit by using any information, even insider information.

2.2. Random walk

In order to explain the efficient market hypothesis, it is motivated to introduce the theoretical discussions around the concept of abnormal return. The EMH can be viewed upon as being a fair game, in where no player has any informational advantage to gain abnormal returns (Elton, *et al.* 2007:403). This is a central point, conceptualized in the Fair Game Model. In the model, there is no way that the information can be used to obtain above equilibrium returns. To test the return predictability of this model, different sets of information are used. In the strongest test, all information at the disposal of the investor is used. This assumption is relaxed in the semi strong test, in where only announcements of pieces of information are used.

The Fair Game Model does not require identical return distributions. This is in contrast to the restricted version, called the Random Walk Model, that states that the successive returns are independent and identically distributed (IID) over time. The Random Walk Model, much as the efficient market hypothesis, states that stock prices are unpredictable. A random walk is a mathematical explanation of a trajectory taking successive random steps. In 1973 Burton Malkiel popularized this term with the book "A random walk down wall street". However, the expression can be traced back to the mid 19th century in the book "Calcul des Chances et Philosophie" by the French economist Jules Augustes.

If the assumptions of the Random Walk Model holds, then the efficient market hypothesis must also hold in respect to past returns (Ibid:404). Therefore, evidence in favor of the Random Walk Model is also in favor of the efficient market hypothesis.

2.3. Previous research

2.3.1. Momentum

Dating back to 1937, Cowles and Jones found evidence for the occurrence of persistent stock prices and the momentum effect. Analyzing asset returns between the years 1835 and 1935 the authors concluded that: "the probability appeared to be .625 that, if the market had risen in any given month, it would rise in the succeeding month, or, if it had fallen, that it would continue to decline for another month." 30 years later Levy (1967) finds that basing trading strategies on the past 27 months stock returns yield considerable abnormal returns. Despite these earlier studies pointing towards persistence in stock prices, it was not until the 1990s the

momentum effect started to receive notable attention among academics. With an article in 1993, Jegadeesh, Narasimhan and Titman investigate the US stock market over the period 1965 to 1989 and conclude that applying the zero investment strategy, taking long positions in past winners while simultaneously shorting past losers, with stocks held over holdings periods of three to 12 months generate significant positive returns. Further, these return patterns were said to be unexplainable by systematic risk as well as delayed stock price reactions to common factors. In 1996 Chan, Jegadeesh and Lakonishok find significant momentum effects in the American stock market over the period 1977 to 1993. By sorting stock portfolios based on an evaluation and holding period of six months respectively the yield spread was found to be 8,8% on average. According to the authors this effect stems from the fact that the market responds to new information gradually. More recent studies have also been able to identify the momentum effect. Erb and Harvy (2006) found strong price persistence in the commodity future markets, where an evaluation period of 12 months and a holding period of one month generated abnormal profit. Miffre and Rallis (2007) extended this research and concluded how different momentum strategies, on average, were able to generate 9,38% annual return.

Although many studies were made on the US markets this effect has proved to be a global phenomenon. Rouwenhorst (1998) concludes that an internationally diversified portfolio, with samples from 12 European countries, based on past winners outperforms a portfolio of past losers in the medium term. After adjusting for risk factors the difference between the two portfolio returns were more than one percent monthly during the period 1980-1995. In 2003 Hon and Tonks published compelling evidence for the momentum effect in the UK stock market. Even though the company size was able to partly explain the abnormal returns during the time period 1955-1996, the profit generated from stock price continuations remained significant.

2.3.2. Contrarian

Many indications points to the fact that the momentum effect is present in the short to medium run. However, in the long run stocks tend to a mean reversing pattern. Debont and Thaler (1985) found evidence for market inefficiency and discovered that contrarian strategies are applicable on longer investment horizons. By examining monthly return data on the US stock market they found that loser portfolios held over 36 months generated approximately 25% larger return compared to portfolios formed on past winners. More than a decade after Thaler's findings the contrarian effect received more attention when both Fama and French

(1998) and Poterba and Summers (1998) found evidence for mean reversal patterns among stocks in the US.

2.3.3. Performance metrics

Momentum and Contrarian strategies are not the sole options for predicting stock movements as similar results have been found in the field of performance metrics. Fama and French (1992) concluded that adding variables for both size and value improved the explanatory power of the famous capital asset pricing model proposed by Sharpe (1964), Lintner (1965) and Black (1972). Chan, Hamao and Lakonishok (1991) show, in a cross sectional study on the Japanese stock market, that firms with low price to cash flow yield higher returns than firms with a high price to cash flow ratio. Further, sorting portfolios based on the book-to-market ratio was proven to be even more significant and capable of generating higher average returns. Fama and French (1995) find that value (high B/M) stocks generate a larger average return compared to growth (low B/M) stocks. This characteristic is also documented by Piotroski (2002) where portfolio sorting based on the book-to-market ratio increases annual return by 7% on average. Moreover, applying the winner minus loser strategy on the US market yields a 23% annualized return between 1976 and 1996. This result also appears to be robust over time and when controlled against alternative investment strategies.

2.3.4. Combining momentum and value ratios

As of late there have been an increasing amount of studies investigating the link between performance metrics and the momentum effect based on stock prices. As both of these set of variables have shown predictive characteristics, the possibility of combining them have received increasing attention. Hong, Lim and Stein (2000) study the US stock market between 1980 and 1996, arriving at the conclusion that momentum profit sharply declines with firm size. Additional research based on double sorted portfolios is documented by Zhang (2006) where higher return volatility is the firm characteristic that amplifies momentum returns. Lee and Swaminathan (2000) make an analogous discovery for high turnover stocks. The stocks with a low (high) turnover ratio exhibit significantly higher (lower) returns over a two year holding period. Additionally they find that turnover rate have some explanatory power in determining how the momentum – mean reversal intertemporal pattern of stock prices unfolds. Avramov, Chordia, Jostova, and Philipov (2007) sort stocks after credit rating and conclude that stocks with low credit rating generate increased momentum profits as opposed to high credit rating firms where the momentum effect proved to be negligible. They further state that this effect is robust after controlling for other firm characteristics such as firm size, age, cash

flow volatility and leverage. Asness, Moskowitz and Pedersen (2009) arrives at the conclusion that both momentum and value strategies are profitable, and that the two are negatively correlated both within and across asset classes. The profit also increases after portfolios are double sorted based on both momentum and value. Additionally they find that said strategies are exhibiting a stronger negative correlation during more turbulent periods while showing a slight positive correlation when returns are noticeably smaller. Hence, when combining the two strategies investors can possibly alleviate the diversification problem that arises in extreme return periods where assets tend to become more positively correlated.

More recent studies indicate that the increased profitability from double sorting can be emulated by sorting portfolios based on more extreme past returns. Over a 45 year period (1964-2008) Bandarchuk and Hilshner (2011) show that abnormal returns generated by applying a double sorting strategy based on momentum and value does not exceed profit from sorting exclusively based on more extreme past returns. They conclude that the smaller percentiles the portfolios are sorted for, the more profitable the strategy is.

2.3.6. Behavioral finance

Standard economic theory is based on the assumption that individuals are rational and thus make rational decisions. However, this fails to explain the existence of stock price continuations. Behavioral economists are instead relaxing the assumption of rationality and build their models around social, cognitive and emotional factors which contradict the notion that agents are rational. Daniel, Hirschleifer, and Subrahmanyam (1998) explain short-lag autocorrelations with a behavior model using both overconfidence and self-attribution. Overconfidence is a well-established term in the field of behavior science. Studies within this area show that people tend to perceive their own abilities above average, including analyzing and interpreting commonly available information. In a study done by Svenson (1981) a group of people were asked about their relative driving skills; 77% perceived themselves as better drivers compared to the rest of the group. This is what Alicke, Vredenburg, Matthew and Olesya (2001) labeled "the better than average effect", showing that individuals fail to properly perceive their own relative skills. The second term, self-attribution, indicates that decisions and choices which generates positive outcomes are attributed to oneself , whereas negative outcomes are disregarded as bad luck (Bem 1965) . Using these two biases Daniel et al (1998) create a model displaying how investors overreact to private information and underreact to public information and how it aids to persistence in stock price movements.

More contributions include Barberis, Schleifner and Vishny (1998) attempt to explain investors' expectations on future earnings. They propose that agents pay too much attention to the strength of information while not focusing enough on the statistical weight of it. The study concludes that earning announcements from firms are of low strength and high statistical significance. This means that investors will underreact to earning-, and other performance metrics, announcements. On the other hand, a string of good announcements will have a low strength and a high statistical weight. The implication is that an agent will overreact to a sequence of good announcements, contributing to the momentum effect in the short to medium run, and the contrarian effect in the long run.

Another psychological factor that can explain the irrationality of agents is the "disposition effect". Odean (1998) finds that investors are more likely to sell stocks with a positive earning rather than selling stocks that have decreased in value. This is in stark contrast with the standard economic model that suggests that a rational investor should sell stocks with negative net returns since capital losses are tax deductible. Odean stresses the presence of irrationality further by showing how stocks that were sold subsequently showed larger returns compared to stocks that were bought.

The models described so far in this chapter are based on irrationality of agents in the financial markets. Crombez (1998) takes another approach, proposing that the explanation for momentum effects in stock price movements stems from noise in expert information and not from over- or under reacting investors. This explanation is consistent with rational investors and that of the efficient market, with the momentum effect being contributed to imperfections in information.

3. Method

In this chapter the methods used to calculate, construct and evaluate the different portfolios are described.

3.1. Data

The data are retrieved from Thompson Reuters Data Stream and consist of monthly data ranging from 1995 to 2010. 1856 different firms on the Nordic stock market are analyzed, with all the Nordic countries being represented. Additionally, liquidated firms are included in order to omit the potential problems occurring from survivorship bias. Apart from firm specific stock returns, we have retrieved data for five different performance metrics, these are:

- Dividend Yield (DY). This value is the dividend per share as a percentage of the share price. The dividend is based on anticipated annual dividend and is excluding special or once-of dividends. The Dividend yield is calculated on gross dividends which includes tax credits.
- Price-Cash flow (P/C), The P/C value is expressed as the share price divided by the cash earnings per share, were cash earnings are defined as "funds from operations".
- Price/earnings ratio (P/E). The P/E value is the share price divided by the earnings rate per share.
- Price-To-Book-Value (PTBV). PTBV is the share price divided by the book value per share. Book value is the value of an asset according to its balance sheet account balance and is comprised of total assets minus intangible assets and liabilities. This is the inverse to the commonly used Book-To-Market value.
- Enterprise Value divided by Earnings-Before-Interest, Taxes, Depreciation and Amortization (EV/EBITDA). Enterprise value is the market value of the entire business, and it is a sum of the aggregate claims of the security-holders.

Furthermore, data for the market index (MKT), the risk-free rate (RF) and the variables controlling for size (SMB) and value (HML) have been downloaded from the Fama and French website. The market index we have chosen includes all NYSE, NASDAQ and AMEX firms, and the two control variables for size and value are derived from the same source.

3.2. Stock return derivation

Stock returns are calculated using monthly changes in stock prices. Changes in stock prices are calculated using the following formula:

$$R_i = LN \frac{P_t}{P_{t-1}}$$

Where R_i is the change in the stock price from month t-1 to t. P_t is the stock price in month t and P_{t-1} is the previous month's price.

The monthly stock price changes are accumulated over 6 months periods in order to rank, evaluate and sort portfolios:

$$\sum_{i=1}^{6} R_i$$

3.3. Portfolio formation

Our portfolios are created based on the performance of the firms in an evaluation period. At the end of the period the stocks are ranked and sorted into different percentiles. The lowest percentile contains the stocks with the worst performance during the evaluation period and the highest percentile includes the stocks with the highest performance. The worst performers are labeled the loser portfolio (L) and, consequently, the group of stocks with the highest returns is named the winner portfolio (W).

In order to take advantage of enduring stock movements two trading strategies are prevalent. In the long run stocks tend to reverse to their mean, which suggests that a contrarian strategy is applicable. In the short to medium run, which is the focus of this essay, asset returns tend to exhibit positive auto correlation, making momentum strategies applicable. The commonly used investment strategy for momentum portfolios is a so called zero investment strategy, where long (short) positions are taken in past winner (loser) stocks. Furthermore, asymmetric information creates a room for value investment portfolio strategies, which we create in the same manner as for the momentum portfolios.

The proceeding step involves holding the portfolio for a certain period of time and then analyze and compare the different returns of the stock portfolios at the end of the period. Both the evaluation and the holding period are set to six months, as several studies indicate that this choice historically has generated significant results for the momentum strategies[1]. For practical reasons, the same time periods are applied when evaluating value based strategies. At the end of each holding period the six month cumulative return of the different portfolios are evaluated. We use a method of overlapping portfolio creation which means the procedure

[1] See Levy (1967), Jegadeesh and Titman (1993), Rouwenhorst (1998).

above is reproduced every month, thus giving us the six month cumulative return on a monthly basis. This is a data generating process that outperforms non-overlapping methods, as it provides more data points. The effect is the possibility of significantly more robust results.

3.3.1. The momentum portfolios

The Momentum portfolio is formed by grouping firms into three different percentiles based on the six month cumulative return during the evaluation period. The stocks are then held for six month and at the end of the holding period the six month cumulative returns are derived. This is done monthly, producing a new set of six month cumulative returns derived on a monthly basis. Only the stocks that have monthly returns for both the evaluation and the holding period for a given month are emitted into the percentile groups. The percentile groups, or portfolios, are named High (H), Medium (M) and Low (L) depending on how they rank within each category. The final Momentum portfolio is created by taking a short position in the losing percentile portfolio and a long position in the winning percentile portfolio. This creates the Winner Minus Loser (WML) portfolio. The amount of companies in the different groups in the momentum strategy ranges from 169 to 325.

3.3.2. Performance metrics portfolios

The value portfolios based on the different performance metrics are formed in an analogous manner as the creation of the momentum portfolios. The amplitude of the performance metrics are used for measuring the performance of the portfolio. That is, for each month the firms are divided into three percentiles, High (H), Medium (M) and Low (L), where firms are sorted by their performance metric values in a descending rank from H to L. The proceeding step is equal to the one used when creating the Momentum portfolios. After stocks are sorted into portfolios based on their performance metrics, they are held for six months and the six month cumulative return is calculated. The overlapping method is once again applied, and the final WML portfolios are created by taking long positions in stocks in the Winner portfolio while simultaneously short selling the Loser portfolio. To be coherent with the Momentum portfolio the evaluation and holding period is set to six months.

Due to the fact that more than a third of the firms had no dividend payments during the period the portfolios based on DY could not be sorted into three equally large groups. Instead, firms with no dividend yield were sorted into one group while the remaining firms were distributed between two equally large groups. Then we apply the same procedure as earlier, to create the

WML portfolio. In the performance metrics strategies the amount of stocks in each of the percentiles is slightly less than in the momentum strategy and is ranging from 19-182.

3.3.3. The combined portfolios

The combined portfolios are created through the method of double sorting. This creates nine possible portfolio combinations for each of the performance strategies. Illustrated below, HH for example is consisting of firms that satisfy both the H percentile of the momentum strategy and the H percentile of the performance metrics strategy. Each of the performance metrics are combined with the momentum strategy in this fashion. Then we proceed with creating WML portfolios using the same technique as described earlier. Each group contains a number of stocks ranging from 10 to 182.

	Performance metrics			
Momentum		H	M	L
	H	HH	HM	HL
	M	MH	MM	ML
	L	LH	LM	LL

3.3.4. Extreme Momentum portfolios

In order to test if the double sorted portfolio returns can be emulated by more extreme sorted momentum portfolios, as proposed by Bandarchuk and Hilshner (2011), the stocks are divided into additional percentiles. Two new WML momentum portfolio strategies are applied to the data, using nine and 20 percentiles respectively. This can be compared to the three percentiles used up until this point. The returns from these portfolios are then tested for statistical significance, using the same procedure as earlier. Finally, the returns from these extreme momentum portfolios are compared to the performance of the combined portfolios.

3.4. Evaluation methods

3.4.1. Mean regression

In order to test whether the abnormal returns from the momentum, performance metrics and combined portfolios are significant, we run an OLS regression using only the asset return minus the risk free rate and the intercept.

$$R_i - R_f = \alpha_i$$

where R_i is the return of the portfolios and α_i is the intercept which represents the mean value of the returns. We run this regression on all portfolio combinations that are analyzed and evaluated in this paper.

3.4.2. Controlling for market risk

To control for market risk we apply the capital asset pricing model, CAPM, developed by Sharpe (1964), Lintner (1965) and Black (1972), to analyze the theoretical market returns. We then use Jensen's alpha to derive the abnormal return above the theoretical market return as defined by CAPM. By using this theoretical approach on the portfolios, returns originated from market movements are absorbed by the beta variable, leaving the alpha as the indicator of abnormal returns. The formula looks as following:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f)$$

Where $R_i - R_f$ = excess return of asset i, α_i = abnormal return of asset i, $R_m - R_f$ = excess return of the market.

3.4.3. Controlling for value and size in addition to market risk

In 1992 Fama and French proposed an alternative approach to measuring return performance of assets. By adding two additional variables to the commonly used CAPM, it is possible to account for the value and size characteristics which both have been proven to be relevant when explaining stock returns. These two variables are created by forming portfolios based on their book-to-market ratio and size respectively. Stocks with a large (small) book-to-market ratio are value (growth) stocks. After sorting stocks based on these criteria the loser portfolios' returns are subtracted from the winner portfolios' returns. The long short position for size based stocks is labeled small minus big (SMB) while high minus low (HML) is the acronym for value sorted portfolios. The formula looks as following:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2(SMB) + \beta_3(HML)$$

Where $R_i - R_f$ = excess return of asset i, α_i = abnormal return of asset i, $R_m - R_f$ = excess return of the market, SMB = small minus big portfolio and HML = high minus low portfolio.

4. Results/Analysis

In this chapter we present and analyze our results. The portfolio returns mentioned in this section are all derived on a six month basis.

4.1. Mean regression

4.1.1. Single sorted portfolios

Table 1: mean values of single sorted portfolios					
Portfolios		**Coefficient**	**Std,error**	**t-value**	**p-value**
Momentum	W	0,011	0,031	0,356	0,722
	L	-0,070	0,041	-1,713	0,089(*)
	WML	0,081	0,020	4,055	0,000(***)
PE	W	0,028	0,029	0,949	0,344
	L	-0,019	0,033	-0,573	0,568
	WML	0,046	0,017	2,783	0,006(***)
DY	W	0,024	0,026	0,907	0,366
	L	-0,064	0,043	-1,486	0,139
	WML	0,088	0,026	3,400	0,001(***)
EV/EBITDA	W	0,034	0,028	1,226	0,222
	L	-0,029	0,034	-0,838	0,403
	WML	0,063	0,014	4,455	0,000(***)
PC	W	0,046	0,028	1,683	0,094(*)
	L	-0,078	0,043	-1,814	0,072(*)
	WML	0,125	0,025	5,016	0,000(***)
PTBV	W	0,023	0,030	0,776	0,439
	L	-0,072	0,041	-1,762	0,080(*)
	WML	0,096	0,025	3,802	0,000(***)

As can be seen in Table 1 the single sorted WML portfolios are exhibiting highly significant and positive abnormal returns, ranging from 4.6% for the PE portfolio up to 12,5% for the PC portfolio. The profit generated by the Momentum WML portfolio is in line with results from previous studies; Jegadeesh and Titman (1993). Similarly, results for the performance metrics sorted WML portfolios are also backed by previous research made by Fama and French (1992), Chan et al (1991) and Piotroski (2002). Additionally, profit generated by the momentum WML portfolio neither outperforms nor performs worse than the performance metrics based WML portfolios. Another interesting observation is that the returns generated by taking short positions in the L portfolios are overall much larger than the returns gained by the long positions in W portfolios. Additionally, returns generated by the W portfolios are in nearly all cases insignificant, whereas the loser portfolios are all significant on at least a 90% confidence level. This indicates that the short position in the L portfolios contributes more to the net profit than the long position in the W portfolios.

4.1.2. Double sorted portfolios

Table 2: mean values of the double sorted portfolios					
Portfolios		**Coefficient**	**Std,error**	**t-value**	**p-value**
Momentum and PE	W	0,043	0,029	1,490	0,138
	L	-0,059	0,040	-1,498	0,136
	WML	0,102	0,025	4,157	0,000(***)
Momentumand DY	W	0,029	0,027	1,077	0,283
	L	-0,106	0,048	-2,201	0,029
	WML	0,135	0,032	4,269	0,000(***)
Momentum and EV/EBITDA	W	0,046	0,028	1,659	0,099(*)
	L	-0,068	0,043	-1,607	0,110
	WML	0,115	0,024	4,725	0,000(***)
Momentum and PC	W	0,038	0,027	1,440	0,152
	L	-0,114	0,049	-2,332	0,021(**)
	WML	0,152	0,033	4,672	0,000(***)
Momentum and PTBV	W	0,041	0,030	1,385	0,168
	L	-0,133	0,045	-2,943	0,004(***)
	WML	0,174	0,032	5,375	0,000(***)

Table 2 presents the six months cumulative returns of double sorted portfolios. As in the case of the previous table the returns of the WML portfolios are highly significant and positive. Additionally, the results seem to indicate that higher returns can be achieved by combining momentum and performance strategies, compared to profits generated by single sorted portfolios. An interesting observation is that the single sorted momentum portfolio is outperformed by the complete range of double sorted portfolios. The combined momentum/PE WML portfolio has a six month return of 10,2% which is higher than the single sorted portfolios for both momentum and P/E, as their returns were 8,1% and 4,6% respectively. Similar results are observed in the remaining double sorted portfolios as the returns are consequently larger compared to their matching single sorted portfolio. The largest increase in returns comes from the Momentum/PTBV WML portfolio which is 7,8% larger than the PTBV WML portfolio and 9,3% larger than the Momentum WML portfolio. Similar to the previous scenario the returns from the L portfolios solely explains the majority of the profit.

4.2. Controlling for market risk

4.2.1. Single sorted portfolios

When controlling for market risk results are quite similar to the ones above, illustrated in Table 3. The WML portfolios are all showing highly significant values on the intercept, implying that abnormal returns can be achieved with strategies using a single sorting method based on either momentum or performance metrics. The momentum WML portfolio generates an abnormal semi annual return of 7.6% while the best performing performance metrics WML portfolio, PC, has a six month abnormal return of 12,2%. Analyzing the winners and losers portfolios in Table 3 there is, again, the short positions in the L portfolios that carry the majority of the profit. The L portfolios are showing large and significant negative returns, down to as much as minus 13% for the PC losers portfolio.

The observed coefficients for the MKTRF variable indicate that the L portfolios consistently display a larger exposure toward market movements. Additionally they are all, apart from the P/E based portfolio, highly significant. Due to the fact that the L portfolios also have higher market coefficients than their W portfolio counterparts the same coefficient for the WML portfolios turn slightly negative, around -0,4 on average. Despite coefficients for the market index being large and significant for the W and L portfolios, the abnormal returns generated by the WML portfolios are still prevalent but slightly lower across the board compared to the mean regression analyze of the single sorted portfolios.

Table 3: single sorted portfolios adjusted for market risk (CAPM)						
Portfolios		**Variable**	**Coefficient**	**Std,error**	**t-value**	**p-value**
Momentum	W	C	-0,030	0,018	-1,639	0,103
		MKTRF	1,111	0,122	9,094	0,000(***)
	L	C	-0,121	0,022	-5,509	0,000(***)
		MKTRF	1,547	0,125	12,360	0,000(***)
	WML	C	0,076	0,019	3,917	0,000(***)
		MKTRF	-0,435	0,125	-3,493	0,001(***)
PE	W	C	-0,012	0,018	-0,656	0,513
		MKTRF	1,068	0,151	7,059	0,000(***)
	L	C	-0,063	0,017	-3,699	0,000(***)
		MKTRF	1,259	0,105	11,991	0,000(***)
	WML	C	0,035	0,018	1,965	0,051
		MKTRF	-0,190	0,169	-1,125	0,262
DY	W	C	-0,014	0,016	-0,853	0,395
		MKTRF	0,980	0,119	8,238	0,000(***)
	L	C	-0,114	0,025	-4,616	0,000(***)
		MKTRF	1,535	0,161	9,542	0,000(***)
	WML	C	0,085	0,023	3,714	0,000(***)
		MKTRF	-0,555	0,191	-2,905	0,004(***)
EV/EBITDA	W	C	-0,004	0,018	-0,203	0,839
		MKTRF	0,974	0,133	7,350	0,000(***)
	L	C	-0,074	0,016	-4,545	0,000(***)
		MKTRF	1,336	0,098	13,604	0,000(***)
	WML	C	0,055	0,012	4,456	0,000(***)
		MKTRF	-0,361	0,102	-3,535	0,001(***)
PC	W	C	0,008	0,017	0,478	0,634
		MKTRF	1,005	0,129	7,783	0,000(***)
	L	C	-0,130	0,023	-5,587	0,000(***)
		MKTRF	1,579	0,155	10,185	0,000(***)
	WML	C	0,122	0,022	5,478	0,000(***)
		MKTRF	-0,574	0,193	-2,970	0,003(***)
PTBV	W	C	-0,016	0,019	-0,880	0,380
		MKTRF	1,083	0,140	7,727	0,000(***)
	L	C	-0,122	0,024	-5,166	0,000(***)
		MKTRF	1,507	0,176	8,572	0,000(***)
	WML	C	0,090	0,026	3,440	0,001(***)
		MKTRF	-0,424	0,242	-1,754	0,081(*)

4.22. Double sorted portfolios

Table 4 shows the results for the double sorted portfolios when controlling for market risk. The abnormal returns are consistent with what we have seen so far, they are increasing across the board compared to the single sorted equivalence. For example, the increase between the single sorted WML P/E portfolio and the double sorted WML portfolio is almost 300%, with

net return increasing from 3,5% on a 6 month basis to 9,8%. The WML EV/EBTDA portfolio is also showing a significant jump in abnormal returns moving from 5,5% to 11,6% compared to the single sorted EV/EBTDA portfolio. The coefficients for MKTRF are consistently more negative compared to the single sorted portfolios in the previous section. Thus the double sorted portfolios are more exposed to market risk, due to larger volatility associated with market movements. Similar to the mean regression analyzes the momentum portfolio, with a return of 7,6% semiannually, generates lower profit than any of the double sorted portfolios.

With the W portfolios not being able to produce significant alphas, we can arrive at a similar conclusion as we did earlier. L portfolios contributes with the significant part of the profit of zero investment strategies.

Table 4: double sorted portfolios adjusted for market risk (CAPM)

Portfolios		Variable	Coefficient	Std,error	t-value	p-value
Momentum and PE	W	C	0,005	0,020	0,273	0,785
		MKTRF	0,974	0,147	6,609	0,000(***)
	L	C	-0,108	0,024	-4,552	0,000(***)
		MKTRF	1,459	0,141	10,360	0,000(***)
	WML	C	0,098	0,025	3,898	0,000(***)
		MKTRF	-0,484	0,208	-2,326	0,021(**)
Momentum and DY	W	C	-0,007	0,018	-0,403	0,688
		MKTRF	0,931	0,122	7,619	0,000(***)
	L	C	-0,159	0,029	-5,485	0,000(***)
		MKTRF	1,682	0,186	9,047	0,000(***)
	WML	C	0,137	0,028	4,831	0,000(***)
		MKTRF	-0,751	0,216	-3,475	0,001(***)
Momentum and EV/EBITDA	W	C	0,010	0,019	0,532	0,595
		MKTRF	0,914	0,131	7,002	0,000(***)
	L	C	-0,121	0,022	-5,599	0,000(***)
		MKTRF	1,655	0,116	14,213	0,000(***)
	WML	C	0,116	0,020	5,953	0,000(***)
		MKTRF	-0,740	0,133	-5,556	0,000(***)
Momentum and PC	W	C	0,001	0,017	0,068	0,946
		MKTRF	0,956	0,133	7,185	0,000(***)
	L	C	-0,170	0,028	-6,152	0,000(***)
		MKTRF	1,779	0,177	10,025	0,000(***)
	WML	C	0,156	0,029	5,405	0,000(***)
		MKTRF	-0,822	0,239	-3,437	0,001(***)
Momentum and PTVB	W	C	0,004	0,021	0,203	0,840
		MKTRF	0,939	0,163	5,750	0,000(***)
	L	C	-0,185	0,029	-6,419	0,000(***)
		MKTRF	1,591	0,211	7,535	0,000(***)
	WML	C	0,174	0,033	5,270	0,000(***)
		MKTRF	-0,652	0,288	-2,269	0,025(**)

4.3. Controlling for market risk, size and value

4.3.1. Single sorted portfolios

In this part we examine the results from the FF three factor model where returns are controlled for market risk, size and value. Starting with the abnormal returns for the WML portfolios, they are highly significant and positive and this is a result consistent with our previous findings. However, each of these values are notably lower than their equivalence found in the CAPM regression analyzes. This indicates that size and value play a role when determining the profits from momentum and performance metrics strategies.

The MKTRF coefficients for the WML portfolios are significant in all cases with negative values. This is similar to our findings in the CAPM regressions.

When controlling for size using the SMB variable, all but one WML portfolio coefficients are insignificant, therefore size cannot explain profit generated by the single sorted WML portfolios. A possible reason for why the D/Y sorted WML portfolios have a significant and positive loading on the size variable is that, intuitionally, dividends are positively correlated with the company size.

The entire range of W and L portfolios in table 4 have significant and positive size coefficients, indicating that there is an overrepresentation of small firms in these portfolios. This implies that small firms have both the possibility to generate high abnormal returns while simultaneously carrying the risk of large declines. This is in line with previous research, as small firms in general have larger volatility than large firms. From the results from table 4 it also seems like the portfolios with the highest positive loadings to small firms seems to show the highest volatility in their abnormal returns. This is all supported by studies like Hong, Lim and Stein (2000) and Zhang (2006), where the former concludes that momentum profits decline with increasing firm size and the latter proposes that it is volatility that amplifies momentum profits.

The value variable HML shows significant and positive coefficients for the performance metrics WML portfolios, implying that they can explain parts of the abnormal returns they are showing and that they are consisting more heavily of value stocks. The HML beta for the momentum portfolio is insignificant and hence nothing can be said about whether HML accounts for parts of the abnormal returns derived from the momentum WML portfolio. All the HML coefficients for the W performance metrics portfolios show positive and significant

values, indicating that the W portfolios largely consists of value stocks. The performance metrics L portfolios show insignificant HML coefficients, again limiting the conclusions to be made. However, the majority show negative coefficients and that in turn can point to heavy load on growth stocks.

Table 5: single sorted portfolios adjusted for market risk, size and value (FF three factor model)

Portfolios		Variable	Coefficient	Std,error	t-value	p-value	Portfolios		Variable	Coefficient	Std,error	t-value	p-value
Momentum	W	C	-0,042	0,018	-2,387	0,018	EV/EBITDA	W	C	-0,022	0,017	-1,352	0,178
		MKTRF	1,087	0,128	8,525	0,000			MKTRF	0,985	0,118	8,384	0,000
		SMB	0,500	0,205	2,435	0,016			SMB	0,444	0,198	2,245	0,026
		HML	0,209	0,154	1,359	0,176			HML	0,518	0,124	4,179	0,000
	L	C	-0,129	0,023	-5,534	0,000		L	C	-0,084	0,018	-4,769	0,000
		MKTRF	1,502	0,127	11,835	0,000			MKTRF	1,311	0,107	12,255	0,000
		SMB	0,527	0,281	1,875	0,063			SMB	0,414	0,221	1,871	0,063
		HML	0,014	0,208	0,068	0,946			HML	0,117	0,154	0,759	0,449
	WML	C	0,071	0,018	4,069	0,000		WML	C	0,045	0,010	4,481	0,000
		MKTRF	-0,418	0,110	-3,791	0,000			MKTRF	-0,329	0,068	-4,807	0,000
		SMB	0,010	0,168	0,061	0,951			SMB	0,068	0,131	0,517	0,606
		HML	0,189	0,170	1,109	0,269			HML	0,394	0,092	4,289	0,000
PE	W	C	-0,031	0,015	-2,054	0,042	PC	W	C	-0,011	0,015	-0,727	0,469
		MKTRF	1,091	0,115	9,476	0,000			MKTRF	1,019	0,106	9,596	0,000
		SMB	0,383	0,181	2,112	0,036			SMB	0,441	0,180	2,447	0,015
		HML	0,591	0,104	5,674	0,000			HML	0,549	0,114	4,834	0,000
	L	C	-0,068	0,018	-3,679	0,000		L	C	-0,135	0,025	-5,444	0,000
		MKTRF	1,213	0,107	11,342	0,000			MKTRF	1,529	0,154	9,928	0,000
		SMB	0,428	0,226	1,894	0,060			SMB	0,470	0,277	1,694	0,092
		HML	-0,079	0,162	-0,487	0,627			HML	-0,089	0,214	-0,415	0,679
	WML	C	0,021	0,012	1,657	0,099		WML	C	0,108	0,019	5,754	0,000
		MKTRF	-0,125	0,095	-1,324	0,187			MKTRF	-0,513	0,136	-3,771	0,000
		SMB	-0,008	0,131	-0,059	0,953			SMB	0,008	0,164	0,051	0,960
		HML	0,663	0,087	7,662	0,000			HML	0,631	0,139	4,552	0,000
DY	W	C	-0,031	0,014	-2,156	0,033	PTBV	W	C	-0,038	0,016	-2,403	0,017
		MKTRF	0,992	0,098	10,097	0,000			MKTRF	1,098	0,112	9,833	0,000
		SMB	0,388	0,179	2,171	0,031			SMB	0,481	0,192	2,501	0,013
		HML	0,487	0,104	4,683	0,000			HML	0,601	0,118	5,070	0,000
	L	C	-0,123	0,026	-4,813	0,000		L	C	-0,121	0,024	-5,125	0,000
		MKTRF	1,450	0,150	9,639	0,000			MKTRF	1,429	0,142	10,062	0,000
		SMB	0,770	0,318	2,423	0,017			SMB	0,460	0,278	1,651	0,101
		HML	-0,173	0,228	-0,758	0,450			HML	-0,382	0,212	-1,805	0,073
	WML	C	0,076	0,019	4,064	0,000		WML	C	0,067	0,017	3,887	0,000
		MKTRF	-0,461	0,125	-3,686	0,000			MKTRF	-0,335	0,131	-2,557	0,011
		SMB	-0,344	0,204	-1,684	0,094			SMB	0,059	0,202	0,294	0,769
		HML	0,652	0,159	4,094	0,000			HML	0,976	0,127	7,687	0,000

4.3.2 Double sorted portfolios

When controlling the double sorted portfolios for market risk, size and value (table 6) it is evident that the WML portfolios perform better than their single sorted counterparts, including the Momentum portfolio. The WML portfolios' abnormal returns are significant and large, with the highest return produced by the PTBV/Momentum portfolio at 15,2% on a semiannual basis. This can be compared to their single sorted counterparts managing 7,1% and 6,7% respectively.

Further robustness of the earlier results regarding the market index coefficients are provided, as they are negative and significant for the WML portfolios. The coefficient for size is not significant for any of the WML portfolios, making it hard to draw any real conclusions about

the size distribution of stocks. However, the HML coefficients are significant and positive for the WML portfolios indicating that they consist of value stocks. These findings are similar to the results of the single sorted portfolio regressions. Additionally, the market index coefficients for the W and L portfolios are positive and significant. Similar to before the coefficients for the L portfolios are larger, explaining the sign of the WML portfolios coefficients.

As noted previously, the W portfolios do not show significant alpha values. The L portfolios on the other hand generate considerable abnormal returns. This result, together with the earlier observations, strengthen the claim that the L portfolios stand for the majority of the profits in the WML portfolios. The SMB beta in the W portfolio and L portfolios in table 5 are showing significant and positive betas over the board, thus pointing to the fact that both the W portfolio and the L portfolios load heavily on small firms. In all of the W portfolios in table 5 the HML betas are significant and positive, indicating that the winner portfolios is loading heavily on value stocks. The L portfolios however are not significant at a 5% level and there cannot be any real conclusions drawn about them.

Table 6: double sorted portfolios adjusted for market risk, size and value (FF three factor model)

Portfolios		Variable	Coefficient	Std,error	t-value	p-value	Portfolios		Variable	Coefficient	Std,error	t-value	p-value
Momentum and PE	W	C	-0,016	0,017	-0,942	0,347	Momentumand PC	W	C	-0,018	0,014	-1,230	0,221
		MKTRF	0,992	0,116	8,535	0,000			MKTRF	0,973	0,106	9,163	0,000
		SMB	0,459	0,187	2,448	0,015			SMB	0,409	0,164	2,498	0,014
		HML	0,603	0,117	5,132	0,000			HML	0,551	0,097	5,706	0,000
	L	C	-0,114	0,025	-4,544	0,000		L	C	-0,175	0,029	-6,088	0,000
		MKTRF	1,394	0,135	10,357	0,000			MKTRF	1,704	0,159	10,693	0,000
		SMB	0,566	0,301	1,879	0,062			SMB	0,601	0,332	1,813	0,072
		HML	-0,148	0,208	-0,709	0,480			HML	-0,225	0,253	-0,890	0,375
	WML	C	0,082	0,019	4,272	0,000		WML	C	0,141	0,025	5,733	0,000
		MKTRF	-0,406	0,134	-3,038	0,003			MKTRF	-0,734	0,163	-4,507	0,000
		SMB	-0,069	0,188	-0,369	0,712			SMB	-0,155	0,248	-0,625	0,533
		HML	0,744	0,148	5,014	0,000			HML	0,769	0,201	3,834	0,000
Momentum and DY	W	C	-0,024	0,017	-1,472	0,143	Momentum and PTBV	W	C	-0,018	0,017	-1,065	0,289
		MKTRF	0,931	0,107	8,680	0,000			MKTRF	0,960	0,139	6,925	0,000
		SMB	0,467	0,196	2,380	0,019			SMB	0,471	0,200	2,349	0,020
		HML	0,431	0,129	3,351	0,001			HML	0,654	0,123	5,328	0,000
	L	C	-0,168	0,029	-5,832	0,000		L	C	-0,186	0,028	-6,731	0,000
		MKTRF	1,580	0,160	9,875	0,000			MKTRF	1,490	0,165	9,013	0,000
		SMB	0,882	0,350	2,518	0,013			SMB	0,677	0,318	2,131	0,035
		HML	-0,251	0,249	-1,008	0,315			HML	-0,430	0,250	-1,722	0,087
	WML	C	0,127	0,024	5,403	0,000		WML	C	0,152	0,023	6,523	0,000
		MKTRF	-0,652	0,138	-4,739	0,000			MKTRF	-0,533	0,168	-3,173	0,002
		SMB	-0,378	0,248	-1,525	0,129			SMB	-0,168	0,218	-0,772	0,441
		HML	0,675	0,203	3,323	0,001			HML	1,078	0,179	6,029	0,000
Momentum and EV/EBITDA	W	C	-0,010	0,018	-0,538	0,591							
		MKTRF	0,918	0,120	7,631	0,000							
		SMB	0,515	0,211	2,444	0,016							
		HML	0,515	0,133	3,864	0,000							
	L	C	-0,130	0,022	-5,789	0,000							
		MKTRF	1,612	0,119	13,527	0,000							
		SMB	0,517	0,280	1,845	0,067							
		HML	0,028	0,194	0,143	0,886							
	WML	C	0,105	0,016	6,687	0,000							
		MKTRF	-0,697	0,103	-6,784	0,000							
		SMB	0,036	0,162	0,221	0,826							
		HML	0,480	0,126	3,805	0,000							

4.4. Extreme momentum portfolios

Table 7 shows that, while double sorting momentum and performance metrics will give larger returns then either momentum or performance metrics will do alone, so will increasing the number of percentiles when constructing the momentum portfolio.

WML9 is constructed using the same amount of percentiles as the double sorting portfolios, which is nine. This generates a six month return of 13.2% which is considerably larger than the 8.1% from the three percentile Momentum WML portfolio. When increasing the amount of percentiles to 20 the results in the WML portfolios become even larger, 16.5% return on a semiannual basis. This implies that increasing the amount of percentiles when creating the portfolios lead to larger returns. Thus it is likely that this is one of the main contributing factors to the large abnormal returns generated by the double sorted WML portfolios.

Table 7: Extreme momentum portfolios

Portfolios	Mean	std error	T-stat	P-value
W9	0,016	0,035	0,442	0,659
L9	-0,116	0,051	-2,290	0,023(**)
WML9	0,132	0,028	4,679	0,000(***)
W20	0,027	0,033	0,824	0,411
L20	-0,138	0,058	-2,388	0,018(**)
WML20	0,165	0,037	4,493	0,000(***)

4.5. Robustness test

In this section we have divided our data into seven sub periods, illustrated in Table 8. This is done to examine whether or not the investment strategies are consistent over time. There are reasons to believe that markets behave differently in times of great turbulence, and considering our data period includes two major financial crisis it is of great importance to analyze eventual incoherencies. Time period one and three covers the time between financial crisis while sub period two and four are created in order to capture the entirety of the financial crises. Sub period five excludes the first financial crisis while sub period six also excludes the financial crisis in 2008. Finally period seven represents the entire time period of our study.

Table 8: Time periods	
1	1996m12-1999m12
2	2000m01-2002m12
3	2003m01-2008m08
4	2008m09 2010m12
5	1996m12-1999m12, 2003m01-2010m12
6	1996m12-1999m12, 2003m01-2008m08
7	1996m12-2010m12

Table 8 provides the results for the single sorted portfolios. The table reveals that the largest returns from all portfolios can be found in sub period two. During the first financial crisis, the returns for both the momentum based portfolios and the value based portfolios are two to three times larger than the returns throughout the entire period. In sub period four, illustrating the second financial crisis, only the D/Y and EV/EBITDA sorted portfolios achieve similar returns. The loser portfolios display significant negative returns during the financial crisis. This adds to the intuition, given the above results, that the short positions in the loser portfolios constitutes the lion's share of the large abnormal returns.

The general conclusion , from the table below, is that the WML portfolios generate positive abnormal returns throughout all the sub periods.

Table 9: mean values of the single sorted portfolios in different time periods								
Portfolio		Period						
		1	2	3	4	5	6	7
Mom	c	0,053	0,148	0,068	0,064	0,063	0,063	0,081
	stdv	0,023	0,069	0,014	0,039	0,013	0,013	0,020
	t-value	2,326	2,151	4,849	1,662	4,802	4,920	4,055
	p-value	0,026	0,038	0,000	0,108	0,000	0,000	0,000
PE	c	0,014	0,141	0,028	0,014	0,021	0,023	0,046
	stdv	0,013	0,054	0,008	0,025	0,008	0,007	0,017
	t-value	1,063	2,624	3,492	0,576	2,645	3,188	2,783
	p-value	0,295	0,013	0,001	0,569	0,009	0,002	0,006
PC	c	0,029	0,279	0,067	0,194	0,083	0,054	0,125
	stdv	0,015	0,069	0,016	0,013	0,015	0,013	0,025
	t-value	1,875	4,033	4,270	15,436	5,511	4,199	5,016
	p-value	0,069	0,000	0,000	0,000	0,000	0,000	0,000
EV	c	0,003	0,144	0,047	0,074	0,041	0,032	0,063
	stdv	0,010	0,043	0,007	0,014	0,007	0,007	0,014
	t-value	0,262	3,308	7,019	5,304	5,571	4,355	4,455
	p-value	0,794	0,002	0,000	0,000	0,000	0,000	0,000
DY	c	0,046	0,212	0,019	0,152	0,054	0,028	0,088
	stdv	0,022	0,081	0,020	0,013	0,016	0,017	0,026
	t-value	2,106	2,636	0,940	11,518	3,312	1,711	3,400
	p-value	0,042	0,012	0,351	0,000	0,001	0,090	0,001
PTBV	c	0,009	0,246	0,082	0,050	0,055	0,056	0,096
	stdv	0,016	0,081	0,011	0,022	0,010	0,012	0,025
	t-value	0,593	3,034	7,381	2,271	5,263	4,790	3,802
	p-value	0,557	0,005	0,000	0,031	0,000	0,000	0,000

In the double sorted portfolios in table 10 we see the same pattern as above, peaking with the momentum and PTBV based portfolio with a six month return of 34,7% in sub period two. There is no clear difference between the single sorted portfolios and the double sorted counterparts, both are showing the same pattern with positive returns in all periods and in all of the metrics measure portfolios.

Table 10: mean values of the double sorted portfolios in different time periods								
Portfolio		Period						
		1	2	3	4	5	6	7
MPE	C	0,061	0,222	0,081	0,054	0,070	0,074	0,102
	Stdv	0,025	0,081	0,014	0,040	0,013	0,013	0,025
	t-value	2,451	2,754	5,903	1,362	5,188	5,701	4,157
	p-value	0,019	0,009	0,000	0,185	0,000	0,000	0,000
MPC	C	0,040	0,314	0,098	0,225	0,109	0,078	0,152
	Stdv	0,032	0,103	0,019	0,023	0,019	0,018	0,033
	t-value	1,220	3,065	5,210	9,752	5,706	4,215	4,672
	p-value	0,230	0,004	0,000	0,000	0,000	0,000	0,000
MEV	C	0,033	0,243	0,093	0,112	0,080	0,072	0,115
	Stdv	0,027	0,071	0,015	0,051	0,016	0,015	0,024
	t-value	1,209	3,411	6,164	2,192	4,870	4,697	4,725
	p-value	0,235	0,002	0,000	0,037	0,000	0,000	0,000
MDY	C	0,087	0,255	0,077	0,184	0,102	0,081	0,135
	Stdv	0,032	0,105	0,025	0,037	0,020	0,021	0,032
	t-value	2,701	2,432	3,122	4,928	5,154	3,847	4,269
	p-value	0,011	0,020	0,003	0,000	0,000	0,000	0,000
MPTBV	C	0,091	0,347	0,151	0,119	0,128	0,130	0,174
	Stdv	0,025	0,108	0,015	0,035	0,014	0,015	0,032
	t-value	3,622	3,206	9,868	3,428	9,255	8,792	5,375
	p-value	0,001	0,003	0,000	0,002	0,000	0,000	0,000

These results point to the fact that the financial crisis affect the profitability of momentum and performance metrics strategies in a positive way. They also suggest that the crisis of 2000 had a larger effect than the more recent crisis of 2008.

5. Conclusion

The final chapter of this essay contains a brief summary and some concluding remarks around our empirical results. This essay has evaluated the efficiency of the Nordic stock markets by using investment strategies based on selected market variables. The individual stocks are ranked according to their past six month relative performance, and sorted by the use of overlapping six month periods. Based on the stocks relative ranking, they have then been placed in three different portfolios for each of the selected variables. The worst performing portfolio has been subtracted from the best performing portfolio, creating the winner minus loser portfolio (WML) investment strategy. Using these constructed portfolios, this study examines the possibility of reaching elevated levels of profitability by using both single sorted portfolios and double sorted portfolios based on the momentum effect and one additional performance metrics. Finally the performance of the portfolios are compared to a single sorted momentum strategy which employs a more extreme sorting process, using more and smaller percentile groups in the evaluation of the stocks.

From section 4.1, using the mean regression analysis, we can see that the entire range of evaluated single sorted WML portfolios generate abnormal returns. The return based momentum portfolios, compared to all portfolios, is in the medium range with regards to profitability. It has a semiannual return of 8,1 percent which can be compared to the value based portfolios P/C that attained the highest abnormal return, 12,5 percent. The P/E portfolio proved to be the least profitable with a return of 4,6 percent. So we cannot say that the classic momentum strategy in general is outperformed by all of the other measures used in the study, but the mean regression analysis indicates that strategies based on the performance metrics D/Y,P/C and PTBV arguably perform better than the strategies based on stock returns.

The mean regression analysis of the double sorted portfolios also came out all positive and significant. They all beat their counterparts in the single sorted portfolios, and even more interesting, all of them also showed higher returns compared to the momentum strategy. Thus the mean regression analysis indicates that by using any one of the five measures presented in the paper, combined with stock returns for the basis of the creation of the WML portfolios, higher profitability can be achieved compared to the single sorted momentum strategy based solely on stock returns.

After controlling for market risk by using the CAPM model, the abnormal returns observed earlier are persistent, while the abnormal returns were in general lower compared to the

results from the mean regression analysis, they were still present and rather large. This indicates that even if market risk can explain parts of the abnormal returns, it is not capable of fully encapsulating stock returns based on these strategies.

In the Fama and French three factor model analysis the abnormal returns persist, albeit on a smaller scale compared to the results from the CAPM analysis. This indicates that size and value can partly explain the large abnormal profits. But considering the abnormal profits are still significant it is not fully capable of explaining this profitability. Further, it seems like the winner and loser portfolios load heavy on size, which point to the fact that the profits is somewhat correlated to the size of the firms. However the size coefficients for the WML portfolios are insignificant so it is hard to say anything definite. It also seems like the portfolios with the largest concentration of small firms are also the ones with the highest volatility, indicating that volatility affects the final return. It seems that value firms can explain a small part of the return of the performance metrics strategies, which does not come as a surprise considering these strategies are created based on value based variables.

We also arrived at the conclusion that it is the short position in the loser portfolio that has the largest contribution to the abnormal returns based on our portfolio strategies. Our numbers showed large negative and significant returns on the loser portfolios. This conclusion is also strengthened by the fact that periods of financial crisis increase the profits from momentum and performance metric strategies.

The fact that the double sorted portfolios seem to outperform their counter parts in the single sorted strategies, it is not necessarily due to being a dominant investment strategy. A possible explanation is that there are less firms in the double sorted portfolios and these firms are more extreme within the various characteristics presented in this paper. Our extreme momentum test display that larger profits can be achieved solely by elevating the ranking process.

As neither market-risk, size nor value are able to explain the difference in returns between performance metrics or the large abnormal returns achieved, it is highly probable that the answers are found in the field of behavioral finance. Our conclusion is that the efficient market hypothesis does not hold, and that the large abnormal returns can possibly be explained by the actions of irrational agents, where attributes such as overconfidence and self-attribution combined with ambiguous interpretation of news and information is causing investors to react differently. Experimental evidence has been found in the study by Daniel, K., D. et.al (1998), where over and under reaction of both private and public information is

the underlying reason for the profitability of momentum and value based investment strategies. However, the possibility that investors in fact are rational cannot be ruled out. Crombez (1998) proposes that the source for these market anomalies can be explained by noise in expert information. Either way, our study indicates that conventional economic theory fails to explain the large abnormal returns derived from persistent stock price continuations and value based investment strategies.

6. References

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Appendix 1: Stationarity

In order to test our data for Stationarity we employ the Phillips-Perron test, which tests for a unit root in the data. All the regressions has P-values that show significance at a 10% level and all except one shows significance at a 5% level. This means that the null of a unit root in the data is rejected and we conclude that the data is stationary.

Phillips-Perron test for stationarity							
		T-statistic	P-value			T-statistic	P-value
Momentum	W	-3.601945	0.0067	**MPE**	W	-3.354546	0.0140
	L	-3.424896	0.0114		L	-3.556793	0.0077
	WML	-3.962314	0.0021		W-L	-3.737395	0.0043
PE	W	-3.403272	0.0122	**MPC**	W	-3.415064	0.0118
	L	-3.446125	0.0107		L	-3.362726	0.0137
	WML	-3.367052	0.0135		W-L	-3.208815	0.0212
DY	W	-3.470577	0.0100	**MDY**	W	-3.520619	0.0086
	L	-3.446958	0.0107		L	-3.462822	0.0102
	WML	-3.192927	0.0221		W-L	-3.435793	0.0111
EV/EBITDA	W	-3.498692	0.0092	**MEV**	W	-3.423104	0.0115
	L	-3.428213	0.0113		L	-3.570109	0.0074
	WML	-3.388749	0.0127		W-L	-4.009017	0.0018
PC	W	-3.436370	0.0110	**MPTBV**	W	-3.338866	0.0147
	L	-3.272120	0.0178		L	-3.427512	0.0113
	WML	-2.825090	0.0569		W-L	-3.388821	0.0127
PTBV	W	-3.369469	0.0134	**HML**		-3.753731	0.0041
	L	-3.379105	0.0131	**SMB**		-4.644009	0.0002
	WML	-3.186843	0.0225	**MKRF**		-3.905930	0.0025

2: OLS assumptions

In order to use OLS for statistical testing we need to make sure that:

1. The expected value of the error terms are always zero. This is fulfilled as we have a constant included in all the equations we are using in the regressions.

2. That the errors are normally distributed. To test for normality, the Jarque-Bera test is used. If the P-values in the Jarque-Berra test is smaller than 0,05, it means that the null of normality at a 5% level is rejected. We can however still use this data in our analysis and get unbiased results due to the large data samples we employ.

Jarque-bera normality test							
		Constant		CAPM		FF	
		Jarque-bera	P-value	Jarque-bera	P-value	Jarque-bera	P-value
Momentum	W	23.25	0	5.28	0.7	1,96	0,38
	L	11.33	0	10.89	0	6,97	0,03
	W-L	24.65	0	27,83	0	49,46	0
PE	W	147,06	0	45,42	0	27,51	0
	L	13,86	0	1,58	0,45	0,37	0,83
	W-L	38,79	0	14,08	0	5,2	0,07
DY	W	83,64	0	51,38	0	20,1	0
	L	2,71	0,26	1,86	0,4	0,03	0,98
	W-L	13,83	0	10,49	0	2,31	0,32
EV/EBITDA	W	74,3	0	49,71	0	11,39	0
	L	22,94	0	9,15	0,01	1,74	0,42
	W-L	40,69	0	13,01	0	1,37	0,5
PC	W	73,26	0	48,41	0	12	0
	L	10,31	0,01	2,15	0,34	1,73	0,42
	W-L	18,6	0	4,9	0,09	8,92	0,01
PTBV	W	63,03	0	31,05	0	8,72	0,01
	L	8,47	0,01	0,29	0,86	0,8	0,67
	W-L	61,52	0	10,2	0,01	0,64	0,73
MPE	W	65,87	0	12,61	0	4,96	0,08
	L	13,97	0	13,6	0	14,59	0
	W-L	57,69	0	17,11	0	23,36	0
MPC	W	97,87	0	22,72	0	9,6	0,01
	L	8,03	0,02	0,89	0,64	2,2	0,33
	W-L	16,17	0	0,96	0,62	3,04	0,22
MDY	W	36,6	0	16,26	0	8,31	0,02
	L	2,86	0,24	0,33	0,84	0,7	0,7
	W-L	6,9	0,032	4,23	0,12	3,57	0,17
MEV	W	29,85	0	16,98	0	2,44	0,3
	L	21,22	0	17,56	0	15,68	0
	W-L	31,79	0	18,21	0	16,68	0
MPTBV	W	42,83	0	4,09	0,13	4,34	0,11
	L	7,89	0,02	1,74	0,41	4,78	0,09
	W-L	41,55	0	5,09	0,08	1,96	0,38

3. The variance of the error terms should be constant, that is an assumption of homoscedasticity. To test for this we use White´s test, one advantage with this test is that it do not require normality in the error terms.

White´s test for homoscedasticity					
		CAPM		FF	
		Obs*R-squared	Prob. Chi-Square(2)	Obs*R-squared	Prob. Chi-Square(2)
Momentum	W	9.564454	0.0084	29.86734	0.0005
	L	2.702320	0.2589	25.87159	0.0021
	WML	10.85005	0.0044	17.33116	0.0438
PE	W	5.807327	0.0548	41.06725	0.0000
	L	8.919031	0.0116	30.42099	0.0004
	WML	30.28153	0.0000	22.28182	0.0080
DY	W	1.754526	0.4159	38.11954	0.0000
	L	15.27945	0.0005	29.58222	0.0005
	WML	10.17549	0.0062	10.50073	0.3115
EV/EBITDA	W	2.042814	0.3601	44.10119	0.0000
	L	9.912847	0.0070	31.79219	0.0002
	WML	7.329331	0.0256	43.44720	0.0000
PC	W	2.139842	0.3430	42.63383	0.0000
	L	19.85871	0.0000	32.44860	0.0002
	WML	21.50421	0.0000	14.34115	0.1107
PTBV	W	4.350319	0.1136	38.67346	0.0000
	L	9.084159	0.0107	22.21455	0.0082
	WML	31.06216	0.0000	29.25290	0.0006
MPE	W	2.852203	0.2402	22.38219	0.0077
	L	0.132511	0.9359	21.12357	0.0121
	W-L	21.43556	0.0000	11.92570	0.2175
MPC	W	3.365906	0.1858	38.55022	0.0000
	L	7.980646	0.0185	24.84292	0.0031
	W-L	11.98469	0.0025	11.97293	0.2148
MDY	W	0.796189	0.6716	21.12061	0.0121
	L	7.817862	0.0201	21.70411	0.0099
	W-L	4.778290	0.0917	7.315357	0.6043
MEV	W	3.590483	0.1661	34.16853	0.0001
	L	1.065248	0.5871	18.79733	0.0270
	W-L	6.024148	0.0492	8.556468	0.4792
MPTBV	W	7.967236	0.0186	38.81175	0.0000
	L	4.436411	0.1088	21.65515	0.0100
	W-L	30.43931	0.0000	20.43704	0.0154

4. That there is no presence of autocorrelation. That is that the error terms are uncorrelated over time. To test for this we use the Durbin-Watson test, which test for first order autocorrelation. The lower and upper bounds are for CAPM 1,664-1,684 and for FF 1,643-1,704. If the DW statistical value is less than the lower bound there is a problem with autocorrelation.

Durbin-Watson, test for first order autocorrelation				
			CAPM	FF
Momentum	W		0.315497	0.388558
	L		0.339023	0.368829
	WML		0.341567	0.347731
PE	W		0.241965	0.410312
	L		0.316604	0.344792
	WML		0.185464	0.259402
DY	W		0.247904	0.401526
	L		0.280007	0.344155
	WML		0.201003	0.254769
EV/EBITDA	W		0.224706	0.367443
	L		0.346102	0.387225
	WML		0.254143	0.311146
PC	W		0.228612	0.386581
	L		0.309234	0.327903
	WML		0.212293	0.234872
PTBV	W		0.230035	0.410886
	L		0.295186	0.323187
	WML		0.167313	0.266971
MPE	W		0.281035	0.429689
	L		0.352112	0.371128
	W-L		0.338503	0.409488
MPC	W		0.262837	0.447728
	L		0.360292	0.379290
	W-L		0.302991	0.324362
MDY	W		0.252814	0.371686
	L		0.319163	0.382092
	W-L		0.310677	0.354042
MEV	W		0.239473	0.370723
	L		0.441395	0.465858
	W-L		0.481881	0.539019
MPTBV	W		0.215483	0.366804
	L		0.318078	0.342847
	W-L		0.261119	0.387878

5. That the data is non-stochastic, this however is not a problem in our analysis since the regression estimators are consistent and unbiased even in the presence of stochastic regressors.

To correct the effects of hetroskedasticity and autocorrelation in the error terms we use the Newey-West estimator to get HAC consistent covariances for all our regressions.