WISEflow
Europe/Oslo(CEST)
03 Jul 2023

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

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Informasjon fra deltaker

Tittel *:	Empirical Analysis of Value and momentum strategies, evidence from Norway
Navn på veileder *:	Patrick konerman

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	332
Andre medlemmer i gruppen:	

BI Norwegian Business School
, Spring 2023

Empircal analysis of Value and Momentum strategies

Evidence from the Norwegian equity market

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Master thesis, Master of Science in Finance, Master of Science in Business

Major: Finance

BI Norwegian Business School

Acknowledgements

We wish to take this opportunity to thank our supervisor, for all the feedback he has given us. We also extend our appreciation to our fellow students, whose assistance and camaraderie have made this journey both productive and enjoyable.

BI Norwegian Business School

Oslo, June 2023

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Abstract

This thesis aims to examine whether investment strategies based on value and momentum in isolation and in combination are profitable in the Norwegian equity market between 1992 and 2022. Our research follows the methodology outlined in Asness Moskovitz and Pedersen (2013) and Jagadeesh and Titman (1993). We find evidence of a momentum premium but no value premium in our sample. Furthermore, we find statistically significant alpha in (75/25) portfolio, and not in the (50/50) combination of momentum and value, in that order.

Keywords – Value and Momentum Strategy, Zero Cost portfolio, Alpha, Fama french 3 factor, Carhart 4- factor, Carhart 4- factor plus Liquidity risk.

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1 Introduction

1.1 Introduction and motivation

The relationship between risk and return has always been a central topic for academics, investors, and other market participants alike in the financial world. The first model to explain the relationship between expected return and risk was the CAPM, which states that the expected return of an asset is a function of its beta. The CAPM, however, needs to explain the relationship between risk and return sufficiently. In 1992, Eugene Fama and Kenneth French added two additional risk factors to the market risk factor in the CAPM (size and value) and created the Fama French three-factor model. Their model showed that stocks of small companies and companies with a low book-to-market ratio tend to outperform large-cap stocks and growth stocks. Moreover, Fama and French showed that their model could explain up to 95% of the returns in a diversified portfolio (Fama & French, 1992). In 1997 a modification of the Fama French three-factor model was made by Mark Carhart. He added a risk factor, the cross-sectional momentum factor, proposing what is known today as the Carhart 4-factor model. Still, the existing body of research provides evidence that the relationship between risk and return is not always proportional, suggesting that generating abnormal returns above the market is possible. Such a possibility challenges the efficient market hypothesis (EMH) put forth by Eugene Fama in 1970

According to the EMH, security prices fully reflect all available information. To consistently achieve higher risk-adjusted returns over a long period than the market should therefore be impossible. However, several anomalies have been observed in the market, pointing to the fact that the EMH does not hold in practice and that it is possible to profit from them.

One such anomaly is value investing. Value investing is rooted in the idea of buying undervalued companies and short-selling overvalued companies. The book-to-market ratio is one commonly used indicator in the existing body of research to identify whether a company has been undervalued or overvalued. The market often undervalues companies with a low book-to-market ratio, while it often overvalues those with a high book-to-market ratio. Several studies in the existing literature present evidence that companies with low book-to-market ratios tend to outperform companies with high book-to-market ratios. Amongst these are Chen et al. (2006), Fama and French (1998), and Dimson et al. (2003).

A second anomaly is a momentum investing. Momentum investing is s based on buying past winners (stocks with high past returns) and short-selling losers (stocks with low past returns). Several previous studies have presented evidence of the existence of a momentum premium. Jegadeesh and Titman (1993) were the first to study a momentum strategy and found that it outperformed the US market on a risk-adjusted basis. Asness et al. (2013), Chan et al. (1999), and Griffin et al. (2003) are among the others who have provided evidence of a momentum premium both in the US and international equity market.

Investigating value and momentum is interesting, as these anomalies have persisted for decades. Moreover, research by Asness et al. (2013) demonstrates that a strategy combining value and momentum exhibits hedging characteristics due to the negative correlation between the two factors. Daniel and Moskowitz (2016) also provide further evidence that a value and momentum combination can partially hedge against momentum crashes.

The purpose of this paper is to investigate whether we can find positive and significant value and momentum premiums in the Norwegian equity market. We construct portfolios based on the past 11 months of realized returns (skipping the latest month) to investigate a pure momentum strategy and book-to-market ratios to investigate a pure value strategy. Moreover, we construct three different combination portfolios with different weightings between momentum and value; 50/50, 75/25, and 25/75, to investigate whether any of these combination strategies offer a higher alpha than the pure momentum and value strategies.

This paper unfolds across eight chapters. Chapter 2 delves into evidence from the existing body of research. Chapter 3 brings forth asset pricing theories and presents our hypotheses. Chapter 4 outlines the methodology we adopt for our research—chapter 5 details our data choice, collection, and filtering. Chapter 6 showcases our primary findings and results. Chapter 7 scrutinizes the limitations of our study. Finally, chapter 8 explores the potential for future studies.

2 Literature review and Theory

The efficient market hypothesis (EMH) is one of the most central theories in the financial world, which academics, investors, and market participants alike. Developed in 1970 by Eugene Fama, it states that security prices fully reflect all available information, and investors should thus not be able to consistently generate positive abnormal returns market (Fama, 1970). Despite this, over the years, there have been numerous cases of investors outperforming the market over an extended period by taking advantage of different anomalies. Value and momentum are two intriguing phenomena among the other factors studied over the years.

The concept of value investing, founded on purchasing undervalued companies, originates from the work of B. Graham and G. Dodd in the early 20th century. Companies with low prices relative to fundamental metrics - such as book value, cash flow, and earnings - will likely outperform in the long run. As such, value investors aim to acquire underpriced companies based on these fundamental metrics, intending to reap the rewards when the market self-corrects. Conversely, momentum investing is rooted in the observation that stocks which have shown robust performance in the past tend to sustain this strong performance over the short to intermediate term.

This literature review aims to consolidate and critically analyze critical findings from a diverse body of existing research, investigating the interactions, complementarities, and trade-offs between value and momentum.

2.1 Momentum

2.2 Momentum A momentum strategy is rooted in the idea of buying stocks that have performed well in the near past and shorting stocks that have performed poorly in the near past. It is expected that the best-performing stocks are going to continue outperforming the market, while the worst – performing stocks are going to continue to underperform the market.

Jegadeesh and Titman (1993) studied the US market for the period 1965 – 1989 and analyzed the performance of a momentum strategy where they sorted stocks into ten deciles portfolios based on their returns in the past 1, 2, 3, or 4 quarters, with each portfolio having a holding period which also varied between 1 – 4 quarters. They found that the best-performing zero–cost portfolio, which buys decile ten and sells decile 1, was the 12–month / 3- month portfolio, which yielded an average monthly return of 1.31% . (Jegadeesh & Titman, 1993).

Chan et al. (1999), who studied the US market from 1977 to 1993, confirm this. They constructed ten decile portfolios based on the past six-month returns of stocks. Following their formation of the portfolios at the end of the first year, they discovered a 15.4% difference between Portfolio 10 (Winners) and Portfolio 1 (Losers). (Chan, Jegadeesh & Lakonishok, 1999).

Apart from the US market, Griffin et al. (2003) investigated the performance of a zero-cost portfolio that purchases past winners and shorts past losers in 40 countries between 1975 and 1995. They scrutinized the top and bottom 20% of stock returns over a six-month ranking period and a six-month investing period, allowing a one-month gap between the ranking and investment periods. They found that momentum portfolio profits were high and positive across countries, with average monthly gains of 1.63% in Africa, 0.78% in the Americas (excluding the US), 0.32% in Asia, and 0.77% in Europe. These findings confirm that the momentum anomaly is not exclusive to the US; it appears worldwide. Furthermore, the authors discovered that macroeconomic factors, risk, and business cycles all contribute to the momentum premium (Griffin, Ji, & Martin, 2003

Such results corroborate with those of Rouwenhorst (1998). He studied 2,190 firms across 12 European countries, including Norway. Adopting the methodology of Jegadeesh and Titman (1993), he divided all stocks into ten decile portfolios and found that, regardless of the formation and holding periods, the tenth decile consistently outperformed the first. Additionally, he discovered that a zero-cost portfolio, which buys from the tenth decile and sells from the first, invariably generates positive and statistically significant mean monthly returns (Rouwenhorst, 1998)

Looking into Europe specifically, Bird & Whitaker (2003) examined the performance of a momentum strategy in the following countries: France, Germany, Italy, Netherlands, Spain, Switzerland, and the UK. They sorted the momentum portfolios based on either 6 – or 12–month past return. The authors found that the winners' portfolios outperformed the losers' portfolios for the optimum holding period of less than six months. By 4%. (Bird Whitaker, 2003). In 2012, Fama and French examined the momentum factor in North America, Europe, Japan, and Asia Pacific from 1989 – 2011. They find strong and consistent momentum premiums in all regions except Japan (Fama & French, 2012)

Like the value premium, many researchers have tried to explain the reason behind the momentum premium. Chordia & Shivakumar (2002) attribute the momentum premium to macroeconomic variables such as the lagged values of the value-weighted market dividend yield, default spread, term spread, and 3-month T- Bill yield. They report that once they controlled for these variables, the profits from momentum strategies disappear (Chordia & Shivakumar, 2002). Sagi & Seasholes (2007) argue that firm-specific characteristics explain the momentum premium and that firms with high revenue growth volatility, low costs, or valuable growth options experience higher momentum premiums than other firms (Sagi & Seashouse, 2007). Moskowitz & Grinblatt (1999) go down another route and argue that individual stock momentum profits are primarily attributable to industry momentum. Like Chordia & Shivakumar, they report that profits from a long/short momentum strategy become significantly lower once they control for industry momentum. (Moskowitz & Grinblatt, 1999)

2.2 Value

Value investing originated in the 1930s. Value investors uphold the belief that the market is inefficient, and therefore, by conducting thorough analyses of fundamental metrics and ratios such as B/E, B/M, P/E, P/S, and others, an investor should be able to outperform the market consistently.

Chen et al. (2006) studied US stocks for 1941 – 2002 using a dynamic version of the method used by Fama & French (2002). They sorted stocks based on their B/M ratio, divided them into five different deciles, and found that portfolio 5 – 1 yielded, on average, a return of 5.8% annually. (Chen, Petkova & Zhang, 2006).

In one of the most essential papers on the topic from 1992, Eugene Fama and Kenneth French studied US stocks for the period 1963 – 1990. They sorted all stocks based on their B/M ratio using a 6 – month lagged book value into decile portfolios. They found that the highest decile portfolio yielded the highest average monthly return of 1.59%.

Moreover, the authors found that the B/M ratio has been one of the most crucial factors in explaining the cross–section of expected returns (Fama & French, 1992).

In 1998 Fama and French researched international data, including Europe, Australia, and the Far East, for 1974 – 1994. They sorted all stocks based on several fundamental metrics, amongst which the B/M ratio, and found that the High B/M ratio portfolio outperformed the global market portfolio by between 3.09% and 5.09% and the global growth portfolio by between 5.56% and 7.65%. This evidence indicated that the value premium is a global anomaly and cannot be found only in US stocks (Fama & French, 1998). Dimson et al. (2003) further confirmed this finding in their study of UK stocks from 1955 to 2011. Following the methodology of Fama and French (1992), they found that the average spread between the High B/M and Low B/M portfolio is 0.5% per month (Dimson, Nagel & Quigley, 2003.

Many researchers have tried to explain the reason behind the value premium anomaly. Chen and Zhang (1998) argue that the value premium results from higher risk, as value stocks are typically distressed companies with high leverage ratios and depressed earnings (Chen Zhang, 1998). Reinforcing Chen and Zhang's argument, Campbell and Vuolteenaho (2004) divided the beta of a firm into one that reflects news about market cash flow and one that reflects market discount rates. They found that value stocks have significantly higher cash-flow betas than growth stocks, suggesting that the cash flows of such value companies bear the more significant risk (Campbell Vuolteenaho, 2004). On the other hand, Fama and French (1992) attribute the value anomaly to behavioral reasons, arguing that investors tend to be overly optimistic about the growth possibilities of high B/M ratio stocks and overly pessimistic about the prospects of low B/M stocks. This perspective suggests that the value anomaly results from mispricing rather than risk (Fama & French, 1992)

2.3 Value and momentum

The value and momentum factors have been investigated and proven to hold multiple times. It is equally interesting to examine these two strategies in tandem. When investors combine these two strategies, they can gain exposure to both factors, potentially smoothing out performance and reducing volatility in the long run. This potential for reduced volatility mainly results from the fact that the performance of these two strategies depends on business cycles, and there is a negative correlation between them. Moreover, momentum and value strategies have an inverse relationship with liquidity risk.

The value premium transpires when prices develop in the opposite direction, while the momentum premium occurs when prices move in the same direction. More specifically, high momentum stocks are usually Low B/M stocks, and low momentum stocks are also High B/M stocks. As a result of this, investors can use the combination of the two strategies as a hedge against either value or momentum crashes. Some of the best examples are the burst of the dot-com bubble in 1999 and the Global Financial Crisis in 2007-2008. When the dot-com bubble busted, value stocks lost more than 30% of their value, while a combination of value and momentum gained 4%. In 2009 in the aftermath of the Global Financial Crisis, a momentum strategy lost around 30% of its value, while a combination strategy only lost 15%.

Bird and Whitaker (2004) examined the combination of value and momentum strategies in Europe from 1990 – 2002, with France, Germany, Italy, and Spain being some of the countries in their sample. Excluding financial companies and companies with negative book – value, they sorted all stocks based on B/M for the value portfolios and the past 6 – month return for the momentum portfolios. What they find is that there exists a significant negative correlation between the winners' portfolio and the High B/M portfolio. (Bird Whitaker, 2004).

Asness et al. (2013) confirm this after having studied the momentum and value factors across the US, UK, Continental Europe, and Japan from 1972 to 2011. They found that the correlation between the winners' portfolio and the High B/M portfolio is negative for all equity markets in the sample, and it ranges from -0.43 for the UK to -0.60 for Japan. Moreover, they found that a 50/50 combination portfolio between value and momentum strategies yields better returns, a higher Sharpe ratio, and higher alpha than a pure momentum or pure value strategy. (Asness, Moskowitz & Pedersen, 2013).

Asness et al. (2013) build upon this by showing that value and momentum have inverse correlations with liquidity risk. More precisely, a momentum strategy positively correlates with liquidity risk, while a value strategy negatively correlates with liquidity risk. As a result, investors would like to eliminate their momentum exposure but keep their exposure to the value factor.

Acharaya and Pedersen (2015) studied how liquidity risks affect a security's required rate of return. They studied. They researched US stocks for the period 1983 – 1992. They highlighted that a security's required rate of return depends on its expected liquidity and the covariance of its liquidity and return with the liquidity and return of the market. Kuan Lee (2011) confirmed this finding when he investigated Acharya and Pedersen's liquidity-adjusted capital asset pricing model from 2005 in 50 countries between January 1988 and December 2007. He concluded that international financial markets independently price liquidity risks apart from market risk Moreover, he found that the pricing of liquidity risk varies across different countries depending on their economic, geographic, and political environments. (Lee, 2011). Furthermore, Cakici and Tan (2013) found that momentum is less affected by liquidity risk than value (Cakici Tan, 2013).

There are notable between the data and methodologies used in the existing body of research—some, such as Chen et. Al (2006) and Fama French (1992) only use the B/M ratio as a measure of value, while others, such as Fama French (1998), use the B/M ratio in combination with other measures. Moreover, for momentum, some, such as Chan et al. (1999) and Griffin et al. (2003), rank stocks based on their past six months of return, while some, such as Jegadeesh and Titman (1993), utilize different ranking and holding periods. For our research, we have used only the B/M ratio as our value measure and a 12-month ranking period for our momentum portfolios. We have chosen the B/M ratio as our value measure as it is the original measure introduced by Fama and French in 1992, and we have chosen to use 12 months' returns to rank stocks as that is the most robust period overall in the existing body of research. In recent years, research has demonstrated that momentum strategies based on shorter ranking periods outperform those based on more extended ranking periods. Given that our sample returns to 1992, we believe a 12-month ranking period is most suitable.

Despite the numerous research studies on momentum and value, several areas still need to be explored to a certain degree. Such areas are how the strategies perform in extreme market conditions, how the strategies perform across asset classes, and how the strategies perform across different geographical regions. This paper focuses on the last area mentioned. It aims to examine the performance of value and momentum in a geographical region that has yet to be studied extensively, namely Norway.

3 Methodology

3.1 Hypothesis

Our objective is to investigate the effectiveness of pure value and pure momentum trading strategies in generating statistically significant alpha in the Norwegian equity market. A pure value strategy buys the highest book-to-market ratio decile portfolio and sells the lowest, while a pure momentum strategy buys the highest past-return decile and sells the lowest. We also aim to assess whether combining these strategies can enhance alpha generation, using three combination weights; (50/50, 75/25, and 25/75). Furthermore, we will analyze a 3x3 cross-sectional portfolio for momentum and value, categorized into high, average, and low for value and winners, neutral, and losers for momentum, yielding nine portfolios in total. These premises lead to four testable hypotheses.

H_0: A pure momentum strategy does not produce a positive and statistically significant alpha in the Norwegian equity market.

$\alpha_{\text{momentum}} \leq 0$

H_a: A pure momentum strategy produces a positive and statistically significant alpha in the Norwegian equity market.

$\alpha_{\text{momentum}} > 0$

H_0 (2): A pure value strategy does not produce a positive and statistically significant alpha in the Norwegian equity market.

$\alpha_{\text{value}} \leq 0$

H_a (2): A pure value strategy produces a positive and statistically significant alpha in the Norwegian equity market.

$\alpha_{\text{value}} > 0$

H_0 (3): None of the combination strategies between momentum and value produces a positive and statistically significant alpha which is higher than the alpha of both the pure value and pure momentum strategy in the Norwegian equity market.

$\alpha_{\text{combo (50/50)}}, \alpha_{\text{combo (75/25)}}, \alpha_{\text{combo (25/75)}} \leq \alpha_{\text{momentum}}$ and α_{value}

H_a (3): Any of the combination strategies between momentum and value produces a positive and statistically significant alpha which is higher than the alpha of both the pure value and pure momentum strategy in the Norwegian equity market.

$\alpha_{\text{combo (50/50)}}, \alpha_{\text{combo (75/25)}}, \alpha_{\text{combo (25/75)}} > \alpha_m$ and α_v

H_0 (4): None of the 3x3 Cross Section portfolios produce a positive and statistically significant alpha which is higher than the alpha of the pure value and pure momentum strategy in the Norwegian equity market.

$\alpha_{\text{(L/L)}}, \alpha_{\text{(L/N)}}, \alpha_{\text{(L/W)}}, \alpha_{\text{(A/L)}}, \alpha_{\text{(A/N)}}, \alpha_{\text{(A/W)}}, \alpha_{\text{(H/L)}}, \alpha_{\text{(H/N)}}, \alpha_{\text{(H/W)}} \leq \alpha_{\text{m}}$ and α_{v}

H_a (4): Any of the 3x3 Cross Section portfolios between value and momentum produces a positive and statistically significant alpha which is higher than the alpha of the pure value and pure momentum strategy in the Norwegian equity market.

$\alpha_{\text{(L/L)}}, \alpha_{\text{(L/M)}}, \alpha_{\text{(L/W)}}, \alpha_{\text{(A/L)}}, \alpha_{\text{(A/M)}}, \alpha_{\text{(A/W)}}, \alpha_{\text{(H/L)}}, \alpha_{\text{(H/A)}}, \alpha_{\text{(H/W)}} > \alpha_{\text{m}}$ and α_{v}

3.2 Momentum

To form our momentum portfolios, we follow a standard momentum signal procedure, where we rank each stock based on its cumulative return, skipping the most recent month to avoid short-term reversal, which is related to microstructure issues and liquidity dynamics (Jagadeesh, 1990; Ansess, Moskovitz & Pedersen 2013). The ranking period starts from the close price as of the last trading day $t-12$ up until the close price of the last trading day of $t-2$, where we are skipping the most recent month at $t-1$, where t is the formation period. Effectively, this indicates that as of the close price of the trading day of each month, we firms are ranking stocks based on their 12 months cumulative, Ansess et al., (2013). These portfolios are rebalanced each month at time t.

We sort into ten deciles, Jagadeesh and Titman (1993), contrary to Asness et al. (2013). Arranging for ten deciles will help capture the momentum effect better than three portfolios. The stocks with the highest–ranking period returns go into the 10th decile portfolio, and those with the lowest go into the first decile portfolio. We also evaluate zero–cost portfolio Winner – minus–loser (WML), which is the difference between the 10th and 1st decile each period. Zero cost portfolio is a strategy involving going long-winner portfolios and short-selling portfolios.

We assign the weights of the stocks using both value – and equal–weighted returns when measuring the portfolio performance. Jagadeesh and Titman (1993) utilize equal – weighted, while Asness et al. (2013) use value–weighted returns. However, most studies on momentum have assigned equal–weighted returns. The consequence of value-weighted performance measures is a tendency to favor stocks with large capitalization. This skew can then reflect itself in the returns. Hence, our primary will be on the equal–weighted approach, Jagadeesh and Titman (1993). Consequently, we will examine both performance characteristics of the pure play strategies, which will provide us with a nuanced understanding and can further validate the performance of the strategies.

3.3 Value

We construct the portfolios for our value strategy by sorting the stocks into ten deciles based on their book-to-market ratios on the last trading day of June t. We calculate these ratios using the book value per share from the previous fiscal year-end (December $t-1$) and the most recent market equity values from June in year t. We then measure the performance of these portfolios from July t to June in the subsequent year $(t+1)$

The lagged variable reflects that fiscal year-end book value data is unavailable immediately. Empirical evidence shows that 40 % of U.S. firms delayed the publication of their annual report until April. Therefore, to ensure that investors have access to the required fiscal year–end data, Fama and French (1992) suggest lagged book – value by six months, which also should be adequate for our analysis. Regarding the market values, we use the most current market value, meaning that the market value before the formation period starts at July t (Ansess, Moskovitz & Pedersen (2013)).
we use the following ratios the following ratio.

$$B/M_t = \frac{BE_{t-6}}{ME_t} \tag{1}$$

The implication of using this ratio is that following the release of fiscal year–end data, it is primarily the market values that will drive the change in the book–to–market ratio. This ex–post variation distinguishes our approach from Fama and French (1992), who choose to lag both variables in their calculations. In addition, this methodology suggests that the expected negative correlation will be more negative and potentially reduce the value premium. However, Asness et al. (2013) have demonstrated that regardless of the methodology, the result is not materially affected, reinforcing the value effect.

Each month at a time t, we construct ten decile portfolios based on their book–to–market ratios. The portfolio with the lowest ratio is termed Low Book–to–Market (LBM), while the one with the highest is termed High Book–to–Market (HBM). We further form a zero–cost portfolio, High Minus Low (HML), by going long on the HBM decile and short on the LBM decile. This approach departs from that of Asness et al. (2013), who sorted their portfolios into only three equal groups. As for the momentum strategy, we assign weights to the stocks in our portfolio using both equally – weight and value-weighted portfolios.

3.4 Weighted combination portfolio

We also perform tests on different weighted combinations of value and momentum strategies within the framework of equal-weighted Zero-cost portfolios. We examine the portfolio's allocation of (75%/25%, 50%/50%, and 25%/75%) for momentum/value, respectively. The goal is to observe what combination yields the highest Sharpe ratio compared to pure momentum or value play.

We drew inspiration for the weighted combinations of the two strategies from Ansess, Moskovitz & Pedersen (2013). They tested a (50%/50%) value/momentum allocation and found it to yield a negative correlation coefficient and a high Sharpe ratio. Our analysis tested the correlation between value and momentum within the zero-cost portfolio. We found a correlation coefficient of 0.03, indicating no linear relations. However, we do not find a negative correlation between pure value and pure momentum, as the correlation coefficients are positively correlated.

3.5 Cross-sectional Portfolio

Relative to examining pure momentum and pure value portfolios, we want to assess whether we would gain additional return in the cross-section of sorts of value and momentum.

Fama French (1993) presented a methodology for constructing a 5x5 cross-sectionally sorted based on size and value. We followed the same approach; however, we made some adjustments to fit our data and research purpose. We construct 3x3 portfolios and nine double-sorted portfolios based on the value and momentum, where we follow Fama French (2012) when sorting the momentum. We use a 3x3 portfolio rather than a 5x5 sort since we might end up with too few stock observations in some portfolios. Thereby making the results less reliable as the portfolios with few observations get a high level of importance in the portfolios.

Table 3.1: Table: 3x3 cross-sectional portfolios

First, we sort stocks based on their value, where we sort the stocks at the beginning of July t based on their book-to-market ratio in December t – 1, divided by their market values in June t. The stocks are then divided into three equal groups high, medium, and low book-to-market, using the percentiles 30th and 70th of the book–to–market as breakpoints. Consequently, we create the momentum factor by sorting stocks into a winner and neutral loser based on their cumulative return of the formation period of July t – 1 until May t, where we skip the most recent month of June.

		Momentum	
B/M	**Losers (L)**	**Neutral (N)**	**Winners (W)**
Low (L)	LxL	LxN	LxW
Medium (M)	MxL	MxN	MxW
High (H)	HxL	HxN	HxW

Notes: E.g., the L/L consist of the stocks with lowest book – to – market and lowest cumulative return. We held the portfolios for 12 months and calculate equal weighted monthly average returns. Only stocks with book value of equity in December t-1 and corresponding market value June t, are considered in the portfolio..

3.6 Value and Momentum Strategies and Asset Pricing Models

A pivotal aspect in assessing the value and momentum strategies involves determining whether the excess return generated over the market index is attributable to risk factors. In other words, examine the potential for these strategies to yield alpha.

Firstly, we use the three–factor pricing model of Fama French (1993), which explains strategy´s excess returns based on three risk factors: Market return minus risk-free rate, size factor (Small minus Big, SMB), and book-to-market factor (High minus Low), the following equation represents Fama French three-factor.

$$ri, t - rf, t = \alpha_i + \beta_i(rm, t - rf, t) + \beta_i SMB_t + \beta_i HML_t + e_{i,t} \tag{2}$$

The term β $(rm - rf)$ represents the proportion of the strategy´s excess return that compensation for its beta exposure, essentially reflecting the strategy´s risk relative to overall market risk; SMB accounts for the proportion of the strategy´s excess return that provides compensates for the risk associated with investments in small cap (i.e., lower capitalized firms); HML explains the proportion of the strategy´s excess return which compensates for the risk with investments in value firms.

We will also incorporate the four–factor model proposed by Carhart (1997), which supplements the existing three-factor models with an additional momentum risk factor (Up minus Down, UMD). These risk factors explain the proportion of the strategy's excess return, which compensates for investing in best-performing stocks and worst-performing stocks. The portfolios excess returns is treated as the dependent variable and, the risk factors are independent variables.

$$ri, t - rf, t = \alpha_i + \beta_i(rm, t - rf, t) + \beta_i SMB_t + \beta_i HML_t + \beta_i UMD_t + e_{i,t} \tag{3}$$

3.7 Liquidity risk factor

We also incorporate liquidity risk in our model as an additional factor. Liquidity risk is essential in asset pricing, acknowledging the risk associated with trading illiquid assets. Viral V, Lasse Heje Pedersen (2004) showed in their Liquidity adjusted Capm (LCAPM) that securities required return increases with their exposure to liquidity risk. Accordingly, it suggests that assets that underperform in times of reduced Liquidity, e.g., during a financial crisis, requires higher expected return as compensation for the additional risk factors. Sadka (2006) also mentioned that informed traders could drive the momentum effect by investing in stocks with liquidity risk. Ansess, Moskovitz, and Pedersen (2013) identified that liquidity risk negatively correlates with value strategies and positively correlates with momentum strategies. Consequently, we have incorporated liquidity risk as an additional factor in Carhart´s (1997) four–factor model. Our evaluation of the strategies´ excess return now leverages three asset pricing models, with the extended Carhart model accounting for liquidity risk as illustrated below.

$$ri,t - rf,t = \alpha_i + \beta_i(rm,t - rf,t) + \beta_i SMB_t + \beta_i HML_t + \beta_i UMD_t + \gamma_i ILLIQ_t + e_{i,t} \tag{4}$$

3.7.1 Measuring Liquidity Risk

There are several ways of measuring illiquidity, including the Amihud illiquidity factor (2002), trading volume, and bid–ask spread, where the latter is the difference between the asking price and the bid price of an asset. A widespread represents higher transaction cost and indicates higher liquidity risk. Despite its regular use as a straightforward measure of liquidity risk, the bid–ask spread. The methodology does encounter limitations. It often faces issues of data availability over extensive periods across markets. Furthermore, as highlighted by Virval V Acharya and Lasse Heje (2004), this approach does not adequately calculate selling costs when dealing with substantial volumes of assets. Therefore, we decide to use Amihud´s illiquidity; we construct the illiquidity factor in the following way.

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|r_{id,t}|}{V_{id,t}} \tag{5}$$

This measure of illiquidity calculates the daily ratio of absolute stock return to its dollar volume, where $r_{id,t}$ represents daily return and $V_{id,t}$ denotes the trading volume of stock i, on the day d and month t. D_i is the number of observations in month t. We use monthly frequency instead of daily absolute returns. Furthermore, together with securities market capitalization, we are constructing the ILLIQ factor, which is implemented as an additional risk factor, (see Table 3.2).

Table 3.2: Construction of the liquidty factor

We first sort stocks into two groups based on their market capitalizations at the beginning of July t. Stocks with market capitalization larger than the median are sorted into the big market cap group, and those with market capitalization smaller than the median are sorted into the small market cap group. Within each of these groups, stocks are then sorted into three equal groups (low, medium, high liquidity) based on their Amihud illiquidity measure, using the 30th and 70th percentiles as breakpoints. Consequently, six portfolios are created.

	Liquidity		
Market Cap	**Low (L)**	**Medium (M)**	**High (H)**
Small (S)	SxL	SxM	SxH
Big (B)	BxL	BxM	BxH

Notes: E.g., the S/L portfolio consists of stocks with small market cap and low liquidity. We compute equal-weighted average monthly returns for each portfolio. Only stocks with available market value data in June t and corresponding liquidity measures are considered in the portfolio.

3.8 Risk factors

In exploring the value and momentum dynamics in the Norwegian market, we have relied on Ødegaards (2022a) compilation of asset pricing risk factors, which are tailored to the Oslo Stock exchange and parallel the models developed by Fama French (1993); Carhart (1997) (see section 3.8.1 and tables 3.3 and 3.4) for a very brief explanation.

Although there were instances of missing market return data, i.e., OSEAX return data. We navigated this challenge by deriving value–weighted returns from our sample data. This adoption allowed us to fill the data gap and ensure continuity in our analysis. Our value–weighted less risk-free (i.e., market risk premium) showed a robust correlation coefficient of 95% with market risk premium computed with OSEAX returns less risk-free, which serves as our market risk premium proxy. This close alignment underscores the reliability of Ødegaards risk factors in the context of this research.

3.8.1 Construction of Risk factors

The Fama-French (1993) risk factors are constructed using six value-weighted portfolios based on size and book-to-market ratios. All stocks are allocated into two groups, small and big, using the median market capitalization as the breakpoint in June of year t. Subsequently, these groups are further classified based on their book-to-market values in December of year $t-1$, using the 30th and 70th percentiles as thresholds. $(rm - rf)$ is calculated as the difference between the value-weighted return of stocks in a particular universe and the preferred risk-free rate.

Table 3.3: Construction of SMB and HML

2x3 sorts which creates the risk factors SMB and HML.
SMB = 1/3(SxH + SxN + SxL) - 1/3(BxH + BxN + BxL)
HML = 1/2 (SH + BH) - 1/2 (SL + BL)

	B/M		
Size	**Low (L)**	**Neutral (N)**	**High (H)**
Small (S)	SxL	SxN	SxH
Big (B)	BxL	BxN	BxH

Table 3.4: Construction of Momentum

In similar manner as 3.3. All stocks are allocated into two groups, small and big, using the median market capitalization as the breakpoint in June of year t, subsequently these groups are further classified based on their return MOM 12-2, using the 30th and 70th percentiles as thresholds.
UMD = 1/2 (BW+SW) - 1/2 (BL+SL

	Momentum		
Size	**Low (L)**	**Neutral (N)**	**High (H)**
Small (S)	SxL	SxN	SxH
Big (B)	BxL	BxN	BxH

3.9 Fama Macbeth and momentum

To understand the momentum premiums in the context of various risk factors and macroeconomic factors, we employ the Fama-MacBeth (1973) two-stage regression methodology. We aim to see whether our selected independent variables can adequately explain the observed momentum premiums. Specifically, we are interested in estimating the risk premiums associated with each factor and understanding how these premiums contribute to the momentum returns.

Our independent factors for our study include size (SMB), book-to-market value (HML), our constructed illiquidity factor (ILLIQ), term structure (TERM, 10 yr Norwegian yield minus three months Norwegian yield), as our default risk (DEF) proxy we used (US corporate AAA yield minus three months US treasury Yield, Norwegian GDP growth (growth), and recession indicator (REC), which is an OECD based recession dummy variable for Norway, indicating expansion = 0 and recession = 1.

In the first stage of our analysis, we conduct time-series regressions using the average excess returns from 20 momentum portfolios as the dependent variables. These returns are derived from 10 value-weighted and ten equally-weighted portfolios. The independent variables in these regressions are a set of selected market factors.

$$
\begin{aligned}
&R_{1,t} = \alpha_1 + \beta_{1,\mathrm{smb}_1} F_{1,t} + \beta_{1,\mathrm{hml}_2} F_{2,t} + \beta_{1,\mathrm{illiq}_3} F_{3,t} + \\
&\beta_{1,\mathrm{term}_4} F_{4,t} + \beta_{1,\mathrm{def}_5} F_{5,t} + \beta_{1,\mathrm{GdpGrowth}_6} F_{6,t} + \beta_{1,\mathrm{Rec}_7} F_{7,t} + \epsilon_{1,t} \\
&R_{2,t} = \alpha_2 + \beta_{2,\mathrm{smb}_1} F_{1,t} + \beta_{2,\mathrm{hml}_2} F_{2,t} + \beta_{2,\mathrm{illiq}_3} F_{3,t} + \\
&\beta_{2,\mathrm{term}_4} F_{4,t} + \beta_{2,\mathrm{def}_5} F_{5,t} + \beta_{2,\mathrm{GdpGrowth}_6} F_{6,t} + \beta_{2,\mathrm{Rec}_7} F_{7,t} + \epsilon_{2,t} \\
&\vdots \\
&R_{n,t} = \alpha_n + \beta_{n,\mathrm{smb}_1} F_{1,t} + \beta_{n,\mathrm{hml}_2} F_{2,t} + \beta_{n,\mathrm{illiq}_3} F_{3,t} + \\
&\beta_{n,\mathrm{term}_4} F_{4,t} + \beta_{n,\mathrm{def}_5} F_{5,t} + \beta_{n,\mathrm{GdpGrowth}_6} F_{6,t} + \beta_{n,\mathrm{Rec}_7} F_{7,t} + \epsilon_{n,t}
\end{aligned}
\tag{6}
$$

In the equation above, R_t represents the average excess return of the portfolio at time t, α is the portfolio's alpha, β_{F_j} is the sensitivity of the portfolio's return to factor F_j , and

ϵ_t is the error term. When $\beta_{F_{\text{smb}}}$ is 0.2, it implies that a 1% increase in the SMB factor will likely lead to a corresponding 0.2% increase in the portfolio's excess return, assuming all other factors remain constant. We used a rolling window of 60 months over the past period. This approach is consistent with the approach Fama and Macbeth (1973) used and allows us to account for time-varying market conditions, enhancing the robustness of our analysis.

After obtaining the betas from these first-stage time-series regressions, we proceed to the second step of the Fama-MacBeth procedure. In this step, cross-sectional regressions with the estimated betas serving as independent variables and the average excess return R_t of the portfolios at time t as dependent variables:

$$E(r_i, 1) = \lambda_0 + \lambda_1 \hat{\beta}_{i,\text{smb}} + \lambda_2 \hat{\beta}_{i,\text{hml}} + \epsilon_{i,1} \tag{7}$$

$$E(r_i, 2) = \lambda_0 + \lambda_1 \hat{\beta}_{i,\text{smb}} + \lambda_2 \hat{\beta}_{i,\text{hml}} + \lambda_3 \hat{\beta}_{i,\text{illiq}} + \epsilon_{i,2} \tag{8}$$

$$E(r_i, 3) = \lambda_0 + \lambda_1 \hat{\beta}_{i,\text{smb}} + \lambda_2 \hat{\beta}_{i,\text{hml}} + \lambda_3 \hat{\beta}_{i,\text{illiq}} + \lambda_4 \hat{\beta}_{i,\text{term}} + \epsilon_{i,3} \tag{9}$$

$$E(r_i, 4) = \lambda_0 + \lambda_1 \hat{\beta}_{i,\text{smb}} + \lambda_2 \hat{\beta}_{i,\text{hml}} + \lambda_3 \hat{\beta}_{i,\text{illiq}} + \lambda_4 \hat{\beta}_{i,\text{term}} + \lambda_5 \hat{\beta}_{i,\text{def}} + \lambda_6 \hat{\beta}_{i,\text{GdpGrowth}} + \lambda_7 \hat{\beta}_{i,\text{Rec}} + \epsilon_{i,4} \tag{10}$$

We perform a two-stage Fama-MacBeth regression using four separate cross-sectional regressions. These regressions aim to estimate the risk premiums (λ) associated with each factor at each time t. We use the estimated factor sensitivities ($\hat{\beta}_{i,F}$) obtained from the first stage of the Fama-MacBeth procedure as independent variables in these regressions. Each portfolio's expected return $E(ri)$ is the dependent variable. We obtain four different intercepts from these regressions, which reflect the portion of the average expected returns on the portfolios not explained by exposure. However, Fama Macbeth's (1973) procedure assumes an alpha to be zero for the second stage; under this assumption, any expected returns not associated with the risk factors should be zero.

In econometric modeling, heteroscedasticity can present challenges when obtaining valid inference tests. Heteroscedasticity refers to the condition where the variance of the errors, or residuals, from a regression model, is not constant. If heteroscedasticity is present in the data, where the variance is non-constant, it can result in distorted standard errors.

These distorted standard errors, in turn, can make inference tests misleading.

Running a time-series regression and then a cross-sectional regression can introduce estimation error. To address this, we performed a White test for heteroscedasticity. The first step is to run the initial ordinary least squares (OLS) regression on a rolling window from April 2014 to August 2022, as illustrated in equation (11):

3.9.1 Diagnostic test for heteroscedasticity

In econometric modeling, heteroscedasticity can be a concern for obtaining valid inference testing. If there is some heteroscedasticity in the data, the variance is non-constant and may result in distorted standard errors. Hence inference tests are misleading. Running a time-series regression and then running a Cross-sectional regression can introduce estimation error. To address this, we performed a White test for heteroscedasticity. The first step is to run the initial ordinary least squares (OLS) regression on the rolling window from April 2014 to August 2022. As illustrated in the equation(11))

$$y_t = \beta_1 + \beta_2 x_{2,t} + \beta_3 x_{3,t} + \ldots + \beta_n x_{n,t} + u_t \tag{11}$$

Here, y_t represents the average excess return of 20 Momentum portfolios. The β coefficients (β_1, β_2, β_3, ..., β_n) are associated with the independent variables $x_{2,t}$, $x_{3,t}$, ..., $x_{n,t}$. The error term, represented by u_t, captures the unobserved factors affecting the average excess return but is not explicitly included in the model.

The second step is to run an auxiliary regression as shown in equation (12):

$$\hat{u}_t^2 = \alpha_0 + \alpha_1 x_t + \alpha_2 x_t^2 + \alpha_3 x_{2,t} + \alpha_4 x_{2,t}^2 + \alpha_5 x_t x_{2,t} + v_t \tag{12}$$

In this equation, u^2 refers to the squared residuals obtained from the initial OLS regression, while x_t, x_t^2, $x_{2,t}$, $x_{2,t}^2$, and $x_t x_{2,t}$ represent the independent variables and their interactions.

The inference test results showed that we reject the null hypothesis (H0) at a 5% significance level, i.e., heteroscedasticity is present in the residuals. In response to this, we apply a robust standard error (VCOV) Variance-Covariance matrix adjustment to correct for the heteroscedasticity.

4 Data

4.1 Collection of data

4.1.1 Collection of data

For our empirical study, we collect data from Thomas Reuters Datastream and macroeconomic data from FRED(Federal Reserve economic data). For our RHS risk factors, value weighted index(oseax), and the risk-free rate, we are collecting the data from Ødeagaard B.A (2022a). All data we download are monthly historical indicators, except for real GDP, which is quarterly.

4.1.2 Data types

We are collecting data from Datastream from OSEAX (Oslo All–Share index). This dataset includes indicators such as closing prices, outstanding shares, and each stock's book equity per share and volume. We are computing key variables such as market capitalization and stock return using Excel. The accounting ratio Book equity pr share is calculated in R by multiple with number of shares. These variables will be important when constructing value and momentum portfolios which will serve as the dependent variables when conducting regressions. Volume variables are needed when constructing. For our risk-free rate, we use 1 – month forward-looking interest rate estimated from government securities and Nibor.

From FRED, we are collecting independent variables such as; ten-year government bond yields, 3-month government bond yields, which will serve as our term structure spread; AAA corporate bond yield, three-month treasury bills, which will serve as our Default spread proxy; OCED-based recession indicator for Norway which is a dummy variable, expansion= 0, recession =1; Quarterly based real GDP, which will serve as our GDP growth proxy. We made this monthly by extrapolating after computing the log difference between t and $t-1$.

We must also disclose that we are windzorising the outliers in the return data. We are cutting the 0.01 and 0.99 percentiles of the monthly returns mainly because we have some abnormally high and low returns for some companies, which could skew results. When constructing the momentum and combination portfolios, we ensure each asset has a minimum of six months' returns. However, this six-month data requirement is not applied to all assets within the cross-sectional portfolio.

4.1.3 Choice of Market

We've chosen to examine companies listed on the Oslo Stock Exchange (OSE) in the Norwegian market for our research, for several compelling reasons. Firstly, Norway's equity market provides an interesting study because it is heavily influenced by two sectors - shipping and energy, which together account for over 50% of the market's capitalization Ødegaard (2008). Secondly, prior research on similar topics predominantly focuses on the US equity market, with few exploring Norwegian markets. Consequently, we see an opportunity to broaden the research scope and contribute a unique analysis to this field.

Moreover, comparing our findings with established studies such as those by Jegadeesh Titman (1993) and Fama French (1992) on the US market can provide new insights. As Fama and French (2008) suggest, equity market phenomena can be sample specific, making it intriguing to see if the Norwegian markets exhibit similar or different trends.

4.1.4 Choice of time period

Our empirical data covers January 1992 to December 2022, providing a robust sample size of 30 years. A large timescale serves two purposes. Firstly it ensures a representative sample of market behavior. Secondly, the chosen period enables us to conduct a thorough analysis and statistical tests. The adoption of a roughly 30–year timeframe is consistent with previous studies such as (Jagadeesh & Titman, 1993; Ansess et al. 2013)

It is essential to clarify that despite our initial data span, we made subsequent adjustments due to missing data and the unavailability of certain risk factors. Consequently, this narrowed our coverage period from August 1994 to October 2022.

4.2 Data filtering

4.2.1 Error in the data sample

During our data retrieval process, some companies exhibited errors due to the absence of certain requested variables. To ensure the accuracy of our analysis, we made the decision to exclude these companies. This does present a limitation in our research due to the potential for missing company data. In some cases, companies had error messages for just one or two variables, despite having data for other variables. To maintain consistency across our portfolios, we decided to remove these companies as well.

4.2.2 Stock Class Filtering

We also considered excluding firms listed multiple times under different stock classes. These often involve Class A and B stocks, resulting in dual listings like Odfjell Drilling A and B. The handling of such cases varies in literature. Given our research doesn't focus on trading frequency, which would be affected by exclusion, we decided to retain both listings. This also aligns with our aim to maximize our stock sample size. Considering our research doesn't concentrate on trading frequency, which dual stock class exclusion would impact, we opted to keep both listings. This decision supports our goal of maximizing the stock sample size and also accommodates the liquidity risk factor, an integral aspect of our study.

4.2.3 Sector Filtering

To focus on ordinary stocks, we've excluded preference shares, ETFs, closed-end funds, warrants, and exchange-traded notes, aligning with Assess et al. (2013) and Fama & French (1992) who similarly omitted ADRs, REITs, and others. This ensures the exclusion of firms investing in our sample companies, thereby avoiding double registration.

4.2.4 Parent Companies with Subsidiaries

Certain firms on the Oslo Børs, like Aker, have listed subsidiaries such as Aker Solutions and Aker Drilling. We considered excluding all related companies, just the parent, or only subsidiaries to avoid correlation effects. However, we've decided to include them as each entity is unique and influenced by varying factors, despite the shared parent company. This also prevents the oddity of excluding a major entity like Aker.

4.2.5 Dead and Delisted Companies

A significant portion of our sample includes inactive companies, either delisted or dead. We've chosen to include these for two reasons. First, excluding them would notably diminish our sample size. Second, excluding such companies would introduce survivorship bias, potentially skewing results upwards by omitting poorly performing entities. Post delisting or closure, a company's remaining returns are marked as N/A. From Datastream we could read that we included 729 dead, and 345 active companies are in our dataset.

4.3 Descriptive Statistics

In table 4.1 we report the descriptive statistics of the our data stretching from January 1992 to December 2022, including the NA´s. This is the data we have acquired after we have done the necessary stock filtering and sector filtering, which we did in Datastream. In panel B Shows the primary time period for which we are conducting analysis on. We had to restrict the data sample because of data availability when constructing the value strategy, which requires the Book to equity, shares outstanding and market capitalization. And if we don´t have any of these variables at the specific dates, that is December $t-1$ for the book equity and shares outstanding, and market capitalization at June t, we to removed those observations. This creates an data limitations specially when conducting the pure value analysis.

Table 4.1: Our data sample

Panels below, we report the descriptive statistics of our empirical data from January 1992 to December 2022. Panel A shows the raw data we first downloaded from Datastream. Panel B presents the same dataset as Panel A, albeit with modifications; it restricts the sample period to August 1994 to October 2022, excludes the NA values, and incorporates the application of Winsorization to the returns.

Panel A: Raw data				
	Market cap	Rets	Book equity pr share	Volume
min	0.1	-1.00	0.00	0.10
first quartile	182.10	0.00	6.00	7.10
median	750.30	0.00	20.00	54.30
mean	4527.40	0.05	423700.00	650.00
third quartile	2374.40	0.00	63.00	311.80
max	1215251.00	1105.00	1375000000	677536.40
NA's	120892.00	121321.00	168071.00	200356.00

Panel B: Restricting the data sample, Excluding NA's and Winsorizing				
	Market cap	Rets	be	volume
min	0.2	-0.19	0.00	0.1
first quartile	387.9	-0.06	6	6
median	1260	0.0	19	43.9
mean	8863.4	0.001	44640	603.78
third quartile	4204.2	0.06	55	254.3
max	1215251	0.19	10790	121465.4

4.3.1 Correlations of the independent variables

In this section, we aim to discover whether there are correlations between independent variables. A high linear relationship between the independent variables can result in multicollinearity. The presence of near and perfect multicollinearity will increase the R squared and standard errors.

We detect no near or perfect collinearity among our independent variables. The independent variables with some correlation are between the Risk-free rate and Norwegian term structure and between GDP growth and recession indicator, indicating an inverse relationship. -0.49 and -0.46, respectively.

Table 4.2: Correlation Matrix

Reported are the correlation coefficients of the independent variables; Mktrf (oseax - rf,) SMB (small minus big,) HML (high minus low,) UMD (up minus down), Rf (1 – month forward-looking interest rate estimated from government securities and Nibor,) Illiq (Liquidity factor Amihud, 2002), Term(Norwegian 10 yr yield minus three month yield,) DEF (US AAA corporate bond yield minus three month treasury bill), GDP growth (log difference between t and $t-1$ of Real GDP,) REC (OCED-based recession indicator for Norway which is a dummy variable, expansion= 0, recession =1).

	Mktrf	smb	hml	umd	rf	illiq	term	def	GDP-grwth	REC
Mktrf		0.04	0.09	-0.15	-0.21	0.38	0.19	-0.19	0.11	-0.22
smb	0.04		-0.18	-0.08	-0.06	0.19	0.21	0.01	0.09	-0.08
hml	0.09	-0.18		-0.02	-0.02	0.11	0.18	-0.04	0.07	-0.08
umd	-0.15	-0.08	-0.02		-0.11	-0.24	0.02	-0.03	0.06	-0.02
rf	-0.21	-0.06	-0.02	-0.11		-0.11	-0.49	0.11	0.00	0.08
illiq	0.38	0.19	0.11	-0.24	-0.11		0.16	-0.09	0.12	-0.07
term	0.19	0.21	0.18	0.02	-0.49	0.16		0.02	0.08	-0.16
def	-0.19	0.01	-0.04	-0.03	0.11	-0.09	0.02		-0.09	0.14
Gdp_growth	0.11	0.09	0.07	0.06	0.00	0.12	0.08	-0.09		-0.46
REC	-0.22	-0.08	-0.08	-0.02	0.08	-0.07	-0.16	0.14	-0.46	

5 Results and Analysis

5.1 Momentum

We want to determine whether the pure play momentum zero-cost (WML) momentum portfolio yields a statistically significant alpha after controlling for three asset pricing models: Fama French - 3 factors, Carhart 4 - factor, and Carhart 4 - factor plus a liquidity factor. We are considering both equal-weighted and value-weighted returns of the momentum strategies. This approach allows us to evaluate the potential for portfolio performance enhancement by varying the weighting scheme

Table 5.1 presents an overview of the portfolio statistics for the value-weighted portfolios, while Table 5.2 shows the corresponding alpha values and their t-statistics. Additionally, Table 5.3 provides the statistics for the equal-weighted portfolios, and Table 5.4 displays their respective alpha values and t-statistics.

Upon examining Table 5.1, it becomes evident that there is an observable upward trend in the mean monthly returns for value-weighted portfolios, specifically transitioning from the 'loser' to the 'winner' portfolios. This observation initially suggests a significant momentum effect within the Norwegian equity market; however, most alphas are not statistically significant when these returns are controlled for using asset pricing models (as shown in Table 5.2). Only the lower deciles generate negative and statistically significant alphas when evaluated under Fama French 3 factor. However, it is noteworthy that the zero-cost momentum portfolio (WML) produces a positive and statistically significant alpha across all considered asset pricing models, also with the inclusion of the liquidity risk factor. Meaning that WML generates an excess return of 0.1 or (10% annualy) despite the fluctuations in market liquidity conditions.

In contrast to the value-weighted portfolios, seven of the ten equal-weighted decile portfolios, as presented in Table 5.4, show negative and statistically significant alpha. This pattern extends to the seventh decile. These significant alphas are derived using the Fama-French 3-factor model, Carhart's 4-factor model, and an augmented Carhart model incorporating a liquidity factor. While these findings deviate from the outcomes observed for the value-weighted portfolios, the alphas' negative sign remains consistent. However, the consistency of the zero-cost portfolio is maintained, as it continues to generate a positive and statistically significant alpha across all asset pricing models, mirroring the findings observed in the value-weighted portfolios.

Furthermore, we observe that the WML equal- weighted outperform WML value-weighted portfolio in terms of raw returns and risk adjusted returns. Which is coherent with financial research, Yuliya Plyakha(2016), and one can argue that in a real life scenario the cost of owning the value-weighted if higher than equal-weighted. Moreover,The Zero cost findings align with those of Asness et al. (2013) as they identified a positive and statistically significant alpha for the zero-cost portfolio.

Table 5.1: Momentum: Value - Weighted Portfolios Statistics

In Tables 5.1 and 5.3 We present the average monthly return (in percentage) for ten value-weighted and ten equal-weighted (respectively in that order) decile portfolios, including zero-cost portfolios (WML), together with skewness, kurtosis, maximum Drawdown, and Sharpe ratios for the period between August 1994 to October 2022. These 20 decile portfolios are constructed and rebalanced at each month t. We rank the stocks based on their 12 months past cumulative return, skipping the most recent month between the holding and formation periods. WML is constructed by long stocks in the 10th decile [Winners] and short-selling stocks in the first decile [Losers].

Decile	1	2	3	4	5	6	7	8	9	10	WML
Mean	-1.07	0.06	0.47	0.07	0.05	0.35	0.66	0.74	0.72	1.06	2.12
Skewness	-0.01	0.12	-0.06	-0.32	-0.43	-0.10	-0.36	-0.30	-0.31	-0.40	0.22
Kurtosis	2.52	3.11	3.17	3.59	3.66	3.10	3.88	3.71	2.74	3.65	-0.05
Max Drawdown	0.96	0.76	0.56	0.59	0.48	0.67	0.53	0.41	0.45	0.60	0.44
Sharpe Ratio	-0.12	0.01	0.07	0.01	0.01	0.05	0.10	0.11	0.10	0.15	0.25

Skewness defines the shape of the distrubutions (normally distributed at zero). Kurtosis measures the fatness of the tail (normally distributed at three). Sharpe ratio, risk adjusted returns. Maximum drawdown, maximum fall of an value of the investments.

Table 5.3: Momentum: Equal - Weighted Portfolios Statistics

Decile	1	2	3	4	5	6	7	8	9	10	WML
Mean	-1.50	-0.62	-0.13	-0.38	0.07	-0.11	0.10	0.46	0.54	0.97	2.47
Skewness	0.07	0.01	-0.17	-0.31	-0.61	-0.69	-0.60	-0.77	-0.33	-0.57	0.35
Kurtosis	3.09	3.17	3.23	3.93	3.75	4.09	3.71	4.48	3.37	4.14	0.57
Max Drawdown	0.98	0.89	0.74	0.80	0.65	0.63	0.64	0.55	0.61	0.51	0.22
Sharpe Ratio	-0.21	-0.10	-0.02	-0.07	0.01	-0.02	0.02	0.09	0.10	0.18	0.44

Table 5.2: Momentum: Value - Weighted Portfolio alphas

In Tables 5.2 and 5.4 We present alpha estimations derived from the Value - Weighted and Equal-weighted Momentum portfolios, respectively, from August 1994 to October 2022. The alphas are computed based on three different asset pricing models: the Fama French 3-factor model, the Carhart 4-factor model, and a modified Carhart 4- factor model with an additional liquidity factor (5-factor model). The corresponding t-statistics in (parentheses).

Decile	1	2	3	4	5	6	7	8	9	10	WML
3 Factor	-0.02	-0.01	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.02
	(-4.56)**	(-2.60)*	(-0.99)	(-2.25)*	(-2.20)*	(-1.28)	(-0.42)	(0.47)	(-0.28)	(0.07)	(3.22)**
4 factor	-0.02	-0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.01
	(-3.75)***	(-1.56)	(-0.11)	(-1.14)	(-2.16)*	(-1.19)	(-1.01)	(0.31)	(-1.03)	(-0.77)	(2.13)*
5 factor	-0.02	-0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.01
	(-3.47)***	(-1.62)	(0.05)	(-0.60)	(-1.89)	(-0.96)	(-0.82)	(0.71)	(-0.60)	(-0.18)	(2.30)*

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

Table 5.4: Momentum: Equal - Weighted Portfolio alphas

Decile	1	2	3	4	5	6	7	8	9	10	WML
3 Factor	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.02
	(-7.28)***	(-5.74)***	(-3.62)***	(-6.17)***	(-3.86)***	(-3.77)***	(-2.94)**	(-1.19)	(-1.52)	(0.10)	(5.73)***
4 factor	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.02
	(-6.45)***	(-4.84)***	(-2.73)**	(-5.42)***	(-3.34)***	(-3.57)***	(-2.84)**	(-1.35)	(-2.02)*	(-0.55)	(4.74)***
5 factor	0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.02
	(4.93)***	(-4.51)***	(-2.28)*	(-4.74)***	(-2.75)**	(-3.20)***	(-2.09)*	(-0.76)	(-1.05)	(0.31)	(4.93)***

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

5.2 Value

We want to determine whether the pure play value and zero-cost (WML) value portfolio yields a statistically significant alpha after controlling for three asset pricing models: Fama French - 3 factors and Carhart 4 – factor. We are considering both equal-weighted and value-weighted returns of the momentum strategies. This approach allows us to evaluate the potential for portfolio performance enhancement by varying the weighting scheme Table 5.5 5.5 presents an overview of the portfolio statistics for the value-weighted portfolios, while Table 5.6 5.6 shows the corresponding alpha values and their t-statistics. Additionally, Table 5.7 5.7 provides the statistics for the equal-weighted portfolios, and Table 5.8 5.6 displays their respective alpha values and t-statistics.

Upon examining 5.5, it becomes evident that contrary to the momentum strategy, for the value strategy there is a downward trend in the mean monthly returns for value-weighted portfolios. It can also be observed that the low B/M portfolio which has a return of 0.14 outperforms the high B/M portfolio which has a return of -0.42%. Similarly, from Table 5.7 it can be observed that when portfolios are constructed equally weighted, once again the low B/M portfolio outperforms the high B/M portfolio.

These findings are in contradiction with Fama and French (1998) and Chen et. al (2006) amongst others, who found that the high B/M portfolio outperforms the low B/M portfolio in terms of mean returns.

Upon examining the regression results from Table 5.6 and 5.8 5.8 we find that when portfolios all 11 portfolios either yield a negative alpha or an alpha equal to zero, with most being statistically insignificant. These results are consistent across both asset pricing models.

What´s of most interest to us is to examine the performance of the zero-cost (HML) portfolio that buys decile ten and sells decile one. From the results in Table 5.5 we find that when value-weighted the zero-cost portfolio yields a negative mean monthly return of -0.57%. When equally weighted the performance of the HML portfolio is even worse and its mean monthly return decreases to -0.81%. Upon examining Tables 5.6 5.6 and 5.8 5.8 we find that when value-weighted, the HML portfolio yields a negative but not statistically significant alpha for both asset pricing models. When equally weighted once again the alpha is negative and statistically significant.

One possible reason for our discrepancies between our findings and those in the existing literature could be the fragmented nature of our dataset when constructing the value portfolios. We have missing data for several years. This holds true specially for the the period between 1996 and 2011, where we can count 32 observations, indicating we are losing several markets cycles. This reduces the validity for the value results.

Table 5.5: Value: Value - Weighted Portfolios Statistics

In Tables 5.5 and 5.7 We present the average monthly return (in percentage) for ten value-weighted and ten equal-weighted (respectively in that order) decile portfolios, including zero-cost portfolios (HML), together with skewness, kurtosis, maximum Drawdown, and Sharpe ratios for the period between August 1994 to October 2022. We construct these 20 decile portfolios by sorting stocks based on their book-to-equity ratio in December $(t-1)$ relative to the market values in June t. HML is constructed by long stocks in 10 decile [High-book- to-market] and short selling stocks with [Low-book-to-market]

Decile	1	2	3	4	5	6	7	8	9	10	HML
Mean	0.14	1.73	0.79	0.21	0.83	1.23	0.89	0.27	1.63	-0.42	-0.57
Skewness	0.05	-0.28	0.15	-0.43	0.14	-0.24	-0.19	-0.26	0.32	-0.02	-0.21
Kurtosis	3.23	3.18	3.11	4.12	2.95	2.90	3.01	3.57	3.10	3.24	2.63
Max Drawdown	0.42	0.27	0.18	0.28	0.15	0.19	0.26	0.41	0.31	0.56	0.60
Sharpe Ratio	0.02	0.26	0.14	0.04	0.19	0.23	0.17	0.04	0.21	-0.06	-0.08

Skewness defines the shape of the distributions (normally distributed at zero). Kurtosis measures the fatness of the tail (normally distributed at three). Sharpe ratio, risk adjusted returns. Maximum drawdown, maximum fall of an value of the investments.

Table 5.7: Value: Equal Weighted portfolios statistics

Decile	1	2	3	4	5	6	7	8	9	10	HML
Mean	0.29	1.34	0.86	0.44	1.02	0.81	0.61	0.45	0.35	-0.51	-0.81
Skewness	-0.20	-0.27	-0.49	-0.56	-0.32	-0.41	-0.87	-0.40	0.23	0.25	0.17
Kurtosis	3.41	3.32	3.50	3.28	3.09	3.22	5.13	3.67	3.27	2.45	2.31
Max Drawdown	0.33	0.27	0.16	0.47	0.17	0.20	0.35	0.22	0.31	0.31	0.73
Sharpe Ratio	0.05	0.22	0.20	0.08	0.22	0.17	0.13	0.09	0.06	-0.09	-0.13

Table 5.6: Value: Value - Weighted Portfolio alphas

In Tables 5.6 and 5.8 We present alpha estimations derived from the Value - Weighted and Equal - Weighted Value portfolios, respectively, from August 1994 to October 2022. The alphas are computed based on two different asset pricing models: the Fama French 3-factor model and the Carhart 4-factor model. The corresponding t-statistics are reported in (parentheses).

Decile	1	2	3	4	5	6	7	8	9	10	HML
3 Factor	-0.02	0.00	0.00	-0.01	0.00	-0.01	-0.01	-0.01	0.00	-0.03	-0.01
	(-2.71)**	(0.43)	(0.39)	(-2.17)*	(0.19)	(-1.02)	(-0.92)	(-1.81)	(-0.53)	(-4.02)***	(-1.29)
4 factor	-0.02	0.00	0.00	-0.01	0.00	-0.01	-0.01	-0.01	0.00	-0.03	-0.01
	(-2.82)**	(0.37)	(0.08)	(-1.45)	(0.30)	(-1.60)	(-0.92)	(-1.76)	(-0.44)	(-3.67***)	(-0.94)

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

Table 5.8: Value: Equal - Weighted Portfolios alphas

Decile	1	2	3	4	5	6	7	8	9	10	HML
3 Factor	-0.02	-0.01	0.00	-0.01	0.00	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01
	(-3.39)**	(-0.95)	(-0.95)	(-3.03)**	(-0.87)	(-1.94)	(-2.50)*	(-2.52)*	(-2.88)**	(-3.01)**	(-0.42)
4 factor	-0.02	0.00	-0.01	-0.01	0.00	-0.01	0.00	-0.02	-0.01	-0.02	0.00
	(-3.19)**	(-0.75)	(-1.16)	(-2.63)*	(-0.30)	(-1.60)	(-1.01)	(-2.88)**	(-2.54)*	(-2.76)**	(-0.35)

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

5.3 Weighted combinations

Table 5.9 showcases the estimated alpha, returns, and Sharpe ratio for three different weighted combinations (50/50, 75/25, and 25/75). These figures are derived from running regressions with the Fama French 3-factor, Carhart 4-factor, and Carhart 4-factor plus a liquidity factor asset pricing models. This analysis aim to examine whether weighted combination yields higher alpha than zero cost portfolios value weighted or equal weighted portfolios.

Table 5.9 shows that the 75/25 portfolio outperforms with a mean monthly return of 1.34%, while the 25/75 portfolio lags behind at 0.06%. However, all combinations surpass the zero-cost value portfolio in returns, yet none outperforms the zero-cost momentum portfolio.

From Panel B, we find that the weighted combination with more emphasis on momentum return yields a positive and statistically significant alpha across all asset pricing models. Interestingly, when we control for the up-minus-down factor, alpha diminishes. This decrease suggests that the up-minus-down risk factor accounts for a portion of the returns, hence its inclusion in the model reduces the alpha, which helps us better identify where these returns are coming from. Although the Portfolio risk adjusted returns are aligned with the Zero-cost portfolios of the momentum strategy.

The 50/50 do not generate any statistically significant alpha among any of the three asset pricing models. This is not aligned with the finding of Asness et al. (2013). Which found a Sharpe ratio of 1.20 and a significant alpha when regression factor models for European stocks. The explanation could lie in the correlation between value strategy and the momentum strategy which is quite the opposite. When we put more weight on the value portfolio we find non statistically significant alpha.

Table 5.9: Different weighted combinations on Zero Cost portfolio

Table 5.9 presents average returns, Sharpe ratio, and alpha estimations from three asset pricing models. We apply the models to different weighting combinations within the equal-weighted Zero-cost portfolio of the Norwegian equity market from August 1994 to October 2022. Panel A: presents a balanced (50/50) combination of momentum and value, Panel B: emphasizes momentum over value (75/25), and Panel C: places greater emphasis on value over momentum (25/75), respectively.

Panel A: 50/50	
Average return	0.70
Sharpe ratio	0.10
3-Factor	0.01
	(1.73)
4-Factor	0.01
	(1.039)
5-Factor	0.01
	(1.101)
Panel B: 75/25	
Average return	1.34
Sharpe ratio	0.25
3-Factor	0.02
	(2.95)**
4-Factor	0.01
	(2.07)*
5-Factor	0.01
	(2.16)*
Panel C: 25/75	
Average return	0.06
Sharpe ratio	0.05
3-Factor	0.002
	(0.37)
4-Factor	0.001
	(0.08)
5-Factor	0.001
	(0.11)

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

5.4 Cross-sectional portfolio

In table 5.10, We present the returns of the 3x3 cross-sectional portfolio, and in 5.11 to 5.13, we present their alphas based on three asset pricing models. In 5.10, we detect that six out of nine portfolios generate positive returns, whereas only three have significant returns. Winner/ LBM yields the highest return of 2.33%.

Six of nine portfolios generate statistically significant alphas when applying asset pricing models. Interestingly, the three portfolios that generate the highest returns do not yield statistically significant alphas. This outcome is not aligned with our initial expectations that portfolios with high past cumulative returns and the progression from low to high book-to-market ratios would yield significant alphas. Additionally, when adding more variables, the significant alphas increase towards zero.

Furthermore, we find no reel statistical evidence that the cross-sectional portfolios are superior to pure value, pure momentum strategies, or the zero-cost portfolio. One explanation may be the high correlation between the two strategies, and combining them might not provide diversification benefits or performance enhancement. The other explanation is the fragmented nature of our data over several years, which presents a potential challenge. This could introduce biases and skew the portfolio performance results.

Table 5.10: Returns of 3x3 Cross sectional portfolios

In Table 5.10 We report the monthly average return of nine double-sorted portfolios based on value and momentum factors constructed from the Norwegian equity market from May 1995 to October 2022. We sorted the process on two criteria: "Book - to - market" ratios and past cumulative returns. During the sorting process, we initially classify stocks into "High," "Medium," and "Low" groups based on their book-to-market ratios as of December $t-1$ relative to their market value in June t using the percentiles 30th and 70th as breakpoints. Further, we sub-classify these stocks within each group as "Winners," "Neutral," or "Losers," determined by their cumulative returns from July $t-1$ to May t, skipping the recent month June. The t-statistics for each average return are in (parentheses).

B/M	Momentum		
	Loser	Neutral	Winner
Low	-0.45	0.92	2.33
	(-0.89)	(2.02)*	(4.93)***
Medium	-0.75	0.61	2.03
	(-1.65)	(1.48)	(4.70)***
High	-1.26	0.11	1.53
	(-2.70)*	(0.26)	(3.43)**

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

Table 5.11: Fama French 3 - Factor

In Tables 5.11, 5.12, and 5.13: We present alpha estimations from three asset pricing models applied to nine double-sorted portfolios based on book-to-market ratios and past cumulative returns. These portfolios span from May 1995 to October 2022. In all three tables, the reported alphas represent the excess returns not explained by the asset pricing models. Table 5.11 showcases the results from the Fama French 3-factor model. Table 5.12 provides alpha estimations derived from the Carhart 4-factor model. In Table 5.13, we extend the Carhart 4-factor with an augmented liquidity factor and report the resulting alphas. During the sorting process, we initially classify stocks into "High," "Medium," and "Low" groups based on their book-to-market ratios as of December $t-1$ relative to their market value in June t. Further, we sub-classify these stocks within each group as "Winners," "Neutral," or "Losers," determined by their cumulative returns from July $t-1$ to May t, skipping the recent month June. The t-statistics for each alpha are in (parentheses).

B/M	Momentum		
	Loser	Neutral	Winner
Low	-0.03	-0.01	0.01
	(-6.65)***	(-2.86)**	(1.47)
Medium	-0.03	-0.01	0.003
	(-7.97)***	(-3.84)***	(0.91)
High	-0.03	-0.02	0.001
	(-8.90)***	(-5.24)***	(-0.32)

*Significant at the 0.05 level **Significant at the 0.01 level ***Significant at the 0.001 level

Table 5.12: Carhart 4 - Factor

B/M	Momentum		
	Loser	Neutral	Winner
Low	-0.03	-0.01	0.004
	(-6.24)***	(-2.65)*	(1.15)
Medium	-0.03	-0.01	0.004
	(-7.33)***	(-3.27)**	(0.97)
High	-0.03	-0.02	-0.002
	(-8.35)***	(-4.87)***	-0.53

Table 5.13: Carhart 4 Factor plus liquidity factor

B/M	Momentum		
	Loser	Neutral	Winner
Low	-0.02	-0.01	0.01
	(-6.08)***	(-2.44)*	(1.42)
Medium	-0.03	-0.01	0.005
	(-7.23)***	(-3.06)**	(1.27)
High	-0.03	-0.02	-0.001
	(-8.23)***	(-4.70)***	(-0.29)

5.5 Fama Macbeth regressions

We use Fama Macbeth's two-stage regression to identify momentum premium in the Norwegian equity market. This approach allows us to estimate betas and risk premiums associated with risk factors, which could influence asset prices. As our independent macroeconomic factors, we use Norwegian term structure, US default spread, and GDP growth; other "domestic" independent factors are SMB, HML, and Norwegian recession indicator.

The outcome of a time-series regression with 20 average momentum excess returns as the dependent variable, and a rolling window of the past 60 months, is presented in Table 5.14. The regression analysis includes those, as mentioned above, seven independent factors . The Table shows that global macroeconomic variables are generally not significantly related to momentum returns, with a couple of exceptions. A negative and statistically significant coefficient indicates the default spread and exhibits a negative relationship with momentum premiums. This finding aligns with the regression results Asness et al.(2013) reported for both US and Global stocks. We also find that the Size and Norwegian term structure factors have a positive and adverse relationship with the momentum premium, respectively. Asness et al. (2013) reported no significant impact of the US term structure on US momentum stocks, contrasting our results. Additionally we find liquidity risk to affect momentum returns, indicating that asset with high liquidity risk may affect momentum premium.

In table 5.15, we report the results from the second stage of the Fama Macbeth (1973), where regress the average momentum premium in four stages against the betas obtained in step 1 using the time series approach. We do not find any of the betas to be statistically significant when applying a 60-month rolling window. However, for sensitivity analysis, we reduced the rolling window to 36 months, where find that the average beta of SMB to be statistically significant at a 5% significance level, indicating that the size effect is a relevant risk factor in explaining the cross-sectional variation in momentum premium, primarily when focusing on a shorter term basis within the 36 months window. However, this is in contrast in with the findings of Asness et al. (2013), which find there to risk premium in the liquidity risk factor. One explantion here, could be the pricing of liquidity risk varies across countires and markets Kuan lee (2011)

Table 5.14: Fama Machbeth 1 stage Time-series regression

Reported are the beta estimates derived from the first stage of the Fama Macbeth regression (1973). We regress the average monthly excess returns of 20 momentum premium as our dependent variable on seven factors as our independent variables: SMB(Small minus Big), HML(High minus Low), ILLIQ(liquidity), TERM(10 yr Norwegian bond minus three months Norwegian bond), DEF (US corporate AAA yield minus three month US treasury yield), GDP-growth(log difference Real Gdp t and t-1), and REC(recession dummy, Recession= 1, expansion=0). The regression spans the period from April 2014 to August 2022, the rolling window period. The t-statistics for each independent variable are in parentheses; we also report R-squared and adjusted R-squared.

	α Intercept	β SMB	β HML	β ILLIQ	β TERM	β DEF	β GDP Growth	β REC
Estimate	0.00	0.31	0.05	0.16	0.07	-0.05	0.00	0.00
	(-0.46)	(2.92)**	(0.73)	(2.10)*	(2.43)*	(-4.08)**	-0.20	-0.27

*Significant at the 0.05 level
**Significant at the 0.01 level ***Significant at the 0.001 level R^2: 0.49, $\overline{R^2}$: 0.42

Table 5.15: Fama Macbeth second stage cross-sectional regression

We report the estimated coefficient form the cross-sectional regression from the second stage. We run in four separate regressions, where average excess return across 20 portfolios as our dependent variable, and seven factors are independent variables.

	(1)	(2)	(3)	(4)
Intercept	0.000	0.02	-0.02	-0.04
	(0.11)	(0.96)	(-0.66)	(-0.86)
β SMB	-0.01	-0.01	0.03	0.03
	(-0.44)	(0.96)	(0.67)	(0.60)
β HML	-0.04	-0.07	-0.07	-0.05
	(-1.11)	(-1.36)	(-1.21)	(-0.72)
β ILLIQ		-0.06	0.02	-0.07
		(-0.95)	(0.20)	(-0.64)
β TERM			0.26	0.20
			(1.41)	(1.09)
β DEF				0.20
				(-0.81)
β GDP				-0.95
				(-0.72)
β REC				(–1.61)
				(-1.85)

6 Discussion

6.1 Limitations of our study

In this thesis we are making several assumption, these assumption would probably affect the performance of the portfolios . Firstly we are not inducing any transactions cost, or any taxes. We observe that not adjusting for transaction cost when researching within finance topics. In a real life scenario this would affect the profitability of our portfolios, especially since the portfolios are rebalancing on a monthly basis. We are also not adjusting for taxes, Norway are required to pay 37.84% taxes on all capital gains (Skatteetaten, 2023), thus decreasing the degree of profitability of the strategies we have studied.

The zero–cost strategy studied in this paper requires short-selling companies. We have thus assumed that short selling is available and cost-free for investors. This is an unrealistic assumption as firstly, there is a cost associated with shorting stocks and secondly, not all stocks are even available for shorting. Considering these two factors is certainly going to affect the performance of the strategies studied and decrease their profitability.

We have also not considered firm-specific characteristics such as profitability, assets, asset growth, leverage, and so on. Accounting for these firm-specific characteristics may change and affect the performance of the strategies and lead to different conclusions.

For the momentum strategy, we could have also studied and considered industry momentum. Previous studies, amongst which Moskowitz and Grinblatt (1999) showed that industry momentum explains a lot of the individual stock momentum.

An important limitation to acknowledge in our analysis is the fragmented nature of our dataset, especially when constructing the value portfolios. For the portfolios we are dependent on having observation of book equity per share, market capitalization and share outstanding at specific dates, i.e., December $t - 1$ and June t. The missing data could potentially introduce bias into our analysis, as we cannot be sure whether the data we have is representative of the missing years. Consequently, our understanding of the portfolios' performance dynamics over the entire period could be skewed. These gaps in the dataset might will most likely affect the robustness of our results. We could potentially have used accounting data, in which we had to download more variables like total asset less total liabilities and deferred taxes.

Another potential improvements in accordance with the momentum premium and Fama Macbeth (1973) two step procedure, one could have conducted the portfolio constructed of Jagadeesh and Titman (1993) and introduced several holding periods, and found the the holding period and formation period that had the highest significant of returns.

6.2 Potential for future studies

As stated in the previous chapter of this paper, the focus of this study has been to find out whether trading based on momentum and value in the Norwegian equity market is theoretically profitable. Given the time constraints when conducting our study, we have had to make some major assumptions which have limited the applicability of our results. Based on this, we have some recommendations for further research.

Given that our study focused on profitability in theory, it would be interesting to conduct a study on the profitability of these strategies in practice. This would entail including the effect of taxes and transaction costs as well as shorting and liquidity constraints.

Furthermore, our study focuses on the Norwegian equity market as a whole. Given that there are companies from different industries in our sample, it would be interesting to conduct a study that further entangles the momentum and value effect on an industry level.

7 Conclusion

We provide evidence that both zero cost momentum portfolios between the period of August 1994 to December 2022 do generate positive and statistical significant alpha, when we run regression with 3 asset pricing factors, Fama French 3 - factor, Carhart 4 - factor and Carhart 4 - factor plus an liquidity risk factor. They are also superior in terms of risk adjusted return and returns. We found that equal weighted WMl equal weighted attributed to higher premium than value weighted WML. These finding are in line with what disovered by Asness et al. (2013)

For our value strategy, we find that the none of the Zero cost portfolios generated abnormal return, which holds true for the asset pricing models Fama French 3-factor and Carhart 4-factor. This is contradicting to existing literature, where premium can be made by buying undervalued companies. However, the analysis introduces an significant problem. Due to missing several years of data, this gaps might have impacted the results.

For our cross sectional portfolio we find a general trend that returns are increasing from loser to winner. And that LBM and Winner portfolio generate the second most highest return, only beaten by equal weighted WML momentum portfolio. LBM/Winner showed significant return, however when running the three asset pricing factors, all alpha turned insignificant. Moreover, the zero-cost combination portfolio that prompt positive and significant alpha was across all three asset pricing models was (75/25) where momentum weight was prominent.

Finally, using the Fama-MacBeth two-stage regression, we found liquidity risk, default spread, and size to significantly influence momentum returns. However, no liquidity risk premium was detected for any of the independent variables, except when adjusting the rolling window from 60 months to 36 months, which showed a risk premium in the context of momentum premiums for the "Small Minus Big" (SMB) factor. This suggests a potentially complex relationship between liquidity risk and momentum returns that may be worth exploring in further research

Interestingly, our study showed that while the value strategy did not yield abnormal returns, the momentum strategy performed well, particularly for the equal-weighted WML portfolio. This raises questions about the effectiveness of different investment strategies in various market conditions and suggests the need for further investigation.

Appendices

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Appendices