Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	16-01-2022 09:00	**Termin:**	202210
Sluttdato:	01-07-2022 12:00	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202210||10936||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	Ole Toralfsøn Brunæs og Espen Fagtun Kjærnli

Informasjon fra deltaker

Tittel *:	Momentum Profits and Investor Sentiment
Navn på veileder *:	Patrick Konermann

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

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	163
Andre medlemmer i gruppen:	

MOMENTUM PROFITS AND INVESTOR SENTIMENT

Master Thesis

by
Espen Fagtun Kjærnli and Ole Toralfsøn Brunæs
Master of Science in Business with Major Finance

Oslo, July 1, 2022

ABSTRACT

This paper studies investor sentiment as a predictive factor of momentum profits and evaluates momentum trading profitability for investors. We identify momentum profits on the Norwegian stock market by recreating the momentum strategy presented by Jegadeesh and Titman (1993). Next, we propose a sentiment-based momentum strategy that relies on the ability of investor sentiment to predict future momentum profits. Our findings show that the sentiment-based strategy outperforms the conventional momentum strategy across several different strategy variations. However, we observe the significance of the strategies' risk-adjusted returns to drastically depend on the estimation of transaction costs. Lastly, we identify a clear pattern in the ability of investor sentiment to predict momentum profits across different time horizons.

Keywords. momentum, sentiment, portfolio performance, transaction costs

Acknowledgements

This thesis ends our journey at the Master of Science program in Business with a major in Finance at BI Norwegian Business School. We want to express our gratitude to BI and our supervisor Patrick Konermann for facilitating and guiding us through this thesis. Finally, we would like to thank Geir Linløkken and Investtech for contributing with data and market insights essential for this paper.

Contents

List of Figures

List of Tables

List of Abbreviations

CAPM	Capital Asset Pricing Model
FF3	Fama-French 3-factor model
HI	Hausseindex
HML	High-Minus-Low
HWM	High-Water Mark
MDD	Maximum Drawdown
MOM	Conventional Momentum Strategy
NYSE	New York Stock Exchange
OBI	Oslo Børs Informasjon (Oslo Stock Information)
OSEBX	Oslo Stock Exchange Benchmark Index
S + C	Spread + Commission
SMB	Small-Minus-Big
SMOM	Sentiment-based Momentum Strategy
SR	Sharpe Ratio
TC	Transaction costs
VIX	CBOE Volatility Index
X-Y Strategy	X-month formation and Y-month holding strategy

1 Introduction and motivation

Does investor sentiment play a role in financial asset pricing? This issue has long been debated in financial economics and has taken on renewed significance in the context of dramatic fluctuations in global stock markets this decade. We address this issue by investigating the relationship between investor sentiment and stock price momentum: one of the most pervasive asset pricing anomalies documented in the financial literature.

Momentum investing refers to the trading strategy in which investors buy winner-stocks and sell losing-stocks, which implies betting on the ability of past returns to predict future returns. Jegadeesh and Titman (1993) found the strategy to realize a compounded excess return of a significant 12.01% per year on average and the strategy to be robust across more extended periods. Furthermore, Rouwenhorst (1998) and Griffin et al. (2003) found the strategy robust across continents and assets, respectively, yet researchers cannot seem to agree upon what drives its profitability. A significant study by Cooper et al. (2004) tested whether conditioning on the state of the market could benefit the profitability of momentum strategies and concluded that short-run momentum profits exclusively follow periods of market gain. These findings have since then been supported and built upon by several studies conducted on different markets, time periods and asset classes (Stambaugh et al. (2012), Antoniou et al. (2013), Lansing et al. (2018)). As today's financial unpredictability has left investors with more questions than answers, our study endeavours to contribute to this literature by shedding light on the predictability power of investor sentiment in the Norwegian stock market.

As a preliminary analysis, we investigate whether abnormal momentum returns can be found on the Oslo Stock Exchange (OSE) from 1997 to 2021, following the methodology of Jegadeesh and Titman (1993). We find the strategy to outperform the benchmark index across several different portfolio variations when controlling for common risk factors. Next, we analyze whether the conventional momentum strategy can be enhanced by using a market sentiment indicator as a signal to customize the portfolio weights monthly. We develop a momentum strategy that relies on the statement that sentiment is a leading factor of momentum profits and find that the sentiment-based strategy offers returns above the conventional strategy at the same level of risk, supporting the findings of Stambaugh et al. (2012). Lastly, we evaluate how the sentiment-based momentum strategy performs relative to the benchmark when incorporating the aspect of transaction costs. Our results show that the strategy highly depends on the estimation of transaction costs, yielding non-significant abnormal returns when applying a conservative estimate and significant abnormal returns when applying a less conservative estimate. In summary, we address the following research questions:

1. *Does conventional stock momentum strategy outperform OSEBX?*

2. *Can market sentiment be used to optimize momentum profits?*

3. *How do transaction costs affect momentum profits?*

This paper contributes to the existing literature in several ways. A number of studies have been conducted on sentiment and momentum profits; however, contrasting with most papers, our study presents a sentiment-based momentum strategy that is easily implementable for investors concerning the necessity of data and calculations. These features make the profit opportunities from the sentiment-based momentum strategy exploitable for all types of investors. Furthermore, there are no studies conducted on market sentiment and momentum trading in Norway. In contrast to a significant part of existing literature, this paper also analyzes momentum strategies net of transaction costs, making the strategy more comparable to alternative investment methods.

2 Literature review

This section surveys the current literature on the momentum anomaly and the driving forces behind its profitability. We also review the existing studies on how market sentiment affects the profitability of momentum and the role of transaction costs in relative strength strategies. Table 3 in the Appendix summarizes the most relevant papers' methodologies, data features and conclusions.

2.1 Conventional Momentum Strategy

Jegadeesh and Titman (1993) documented that buying stocks based on recent high returns and selling stock based on recent low returns produced a profitable trading strategy. The strategy has continued to perform well over multiple decades (Jegadeesh and Titman (1993), Jegadeesh and Titman (2001) and Jegadeesh and Titman (2011)), as well as across several different asset classes (Asness et al., 2014) and national financial markets (see, e.g., Rouwenhorst (1998), and Griffin et al. (2003)). Over time, the momentum effect has grown to become one of the most thoroughly researched trading strategies in academic finance, and its existence a well-established empirical fact (Asness et al., 2014). Nevertheless, momentum is still considered an anomaly, warranting further research.

Numerous explanations have been put forward to jointly explain the long-run cross-sectional momentum reversal in stock returns documented by De Bondt and Thaler (1985) and the short-run cross-sectional momentum returns identified by Jegadeesh and Titman (1993). The empirically proven performance of momentum has left researchers discordant concerning its underlying theory. The most consented explanations have emerged from both rational perspectives, inducing explanations such as time-varying expected returns (Johnson (2002)) and market frictions and behavioural perspectives related to investor psychology (Hong and Stein (1999)). On the theoretical side, exponents of the efficient market hypothesis argue that rational investors arbitrage away any sentiment-induced mispricing, leaving the impact of sentiment negligible at most. However, several theorists from the behavioural side claim that sentiment causes systematic deviations from fundamental values, owing to the "limit to arbitrage" argument De Long et al. (1990). Shiller (2000) explains that if stock prices start to rise, some investors' success may attract public attention, leading to market enthusiasm. When new investors enter the market and start bidding up the prices, this creates expectations of further price increases where "irrational exuberance" cause prices to exceed above levels justified by fundamentals. Both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) highlight that momentum strategies can experience infrequent and persistent strings of negative returns, resulting in momentum crashes. However, they find these crashes to occur in panic states and times of market stress habitually, making the crashes somewhat predictable. This finding further motivates us to investigate whether the momentum strategy can be altered to avert such crashes.

2.2 Sentiment-based Momentum Strategy

The phrase "sentiment" refers to whether an agent possesses excessively positive or negative affect. Several psychology studies have found that peoples' current sentiment affects their judgement and to what extent they regard future events optimistically (Johnson and Tversky (1983), Bower (1981), among others). Hong and Stein (1999) build upon this line of thought and draw a parallel between the momentum anomaly and investor psychology by inferring that news diffuses slowly through the actions of different sets of "newswatchers" that reacts to news sequentially, which in turn creates momentum. Some momentum traders mistake price movements for fundamental news movements due to previous momentum trades. An overreaction is set off by their reactive trades, which is corrected when the momentum positions in time are reversed. Hong and Stein theorize that "newswatchers" will underreact more strongly if the information they receive contradicts their sentiment. This is due to cognitive dissonance Festinger (1957) and implies that bad (good) news among losers (winners) will tend to diffuse more slowly when the sentiment is optimistic (pessimistic) and will, in consequence, lead to momentum.

In the existing literature, sentiment has been linked to both the rational risk-return tradeoff and investment anomalies left unexplained by rational pricing models. Chordia and Shivakumar (2002) present evidence that momentum profits are only significant during periods when the economy is expanding. A related and significant paper, Cooper et al. (2004), find that investor biases are more accentuated in periods following market gains and conclude that momentum is exclusively profitable after a market increase. The researchers define two market states: (1) "UP" is defined when the three-year lagged market return is non-negative, and (2) "DOWN" is defined when the three-year lagged market return is negative. Using these market states in a six-month momentum strategy, they find highly significant monthly mean profit after three-year UP markets and insignificant profit after DOWN markets. A more recent paper by Antoniou et al. (2013) builds upon this argument of Cooper et al. (2004) and finds that momentum profits only arise during periods of optimism.

Stambaugh et al. (2012) investigate the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns. The researchers apply the methodology of Jegadeesh and Titman (1993), using a sample period spanning over 42 years, from 1965 to 2007, on the New York Stock Exchange. By employing the sentiment index constructed by Baker and Wurgler (2006)[1],

[1] Baker and Wurgler (2006) constructed an investor sentiment index based on five metrics: the value-weighted dividend premium, the first-day returns on initial public offerings (IPOs), IPO volume, the closed-end fund discount, and the equity share in new issues.

they find that each of the 11 anomalies, including the momentum effect, is stronger following high levels of investor sentiment. Moreover, a paper by the Federal Reserve Bank of San Francisco presents evidence that the combination of sentiment and momentum can help predict the return on the Standard & Poor's 500 stock index over the next month, Lansing et al. (2018). No studies on the Oslo Stock Exchange have examined whether sentiment can help investors forecast momentum profits. In this respect, further work on the relationship is warranted.

2.3 Momentum Strategy and Transaction Costs

This paper evaluates momentum trading as a viable investment alternative to the market index. In this respect, we account for realistic market conditions by introducing frictions induced by trading. When assessing the profitability of relative strength trading strategies, it is crucial to assess the investors' trading costs (Grundy and Martin (2001)). This generally comprises applicable commissions, taxes, bid-ask spread, and the market impact of trades. Today's literature offers a menu of different trading cost procedures, each with different advantages and limitations.

Jegadeesh and Titman (1993), Lui et al. (2003) and DeMiguel et al. (2009) all assume one-way transaction costs of 0.5%. This is historically the most widespread implication of transaction costs; however, Lesmond et al. (2004) argue that these estimates substantially underestimate the true costs of execution. According to Lesmond et al. (1999), the most direct estimate of transaction costs is the spread plus commission (hereafter S + C), which first was applied by Stoll and Whaley (1983). Lesmond further augmented the S + C estimation method by assuming that the marginal informed investor only will trade if the information's value exceeds transaction costs. While the two estimates are highly correlated, S + C was found to be the more conservative estimate in that it returns slightly higher transaction costs than that of Lesmond. Applying Lesmond's estimation method will affect the momentum strategy's portfolio composition and make our results less comparable to existing literature. Therefore, we rule out this estimation approach and focus on the two methods discussed; proportional bid-ask spread plus commission (S + C) and fixed one-way transaction costs of 50 basis points.

Transaction costs are especially crucial for equally-weighted strategies since their performance measures decrease dramatically even when a relatively small investment is considered (Korajczyk and Sadka (2004)). Grundy and Martin (2001) present evidence that the profits on a long-short momentum strategy become statistically insignificant when incorporating round-trip transaction costs of 1.5%. This finding is consistent with Lesmond et al. (2004), who argue that momentum strategies require frequent trading in disproportionately high-cost securities such that trading costs prevent profitable strategy execution. Patton and Weller (2020) test whether there is a gap between the profitability of a trading strategy on paper and that achieved in practice. Similar to Lesmond et al. (2004), their results paint a sobering picture of the strategy's real-life returns by concluding that momentum strategies are unprofitable for typical asset managers when a broader set of implementation costs are considered. Moreover, the researchers stress the importance of considering variations in implementation costs when evaluating the profitability and implementability of factor strategies. In light of these studies, we consider the implication of transaction costs vital for observing momentum strategies' actual performance.

3 Testable hypotheses

The goal of this paper is to assess the role of investor sentiment in momentum trading comprehensively. We develop three testable hypotheses corresponding to the three research questions stated in the introduction. These are constructed to jointly paint a picture of a sentiment-based strategy's profitability, risk, and overall attractiveness. The first hypothesis studies whether a conventional stock momentum strategy outperforms the benchmark. The second hypothesis aims to provide investors with insights on whether the market sentiment can help predict momentum returns. In the last hypothesis, we disclose the actual performance of momentum strategies relative to the market by incurring transaction costs.

Before studying how investor sentiment's employment affects momentum trading's profitability, we run a preliminary analysis of the conventional momentum strategy, following Jegadeesh and Titman (1993). Specifically, we test the null hypothesis that historically, individual stock momentum trading strategy has outperformed the Norwegian benchmark index by generating abnormal returns, denoted as α. The corresponding hypothesis is presented below:

$$H_1 \begin{cases} H_0 : \alpha \leq 0 \\ H_A : \alpha > 0 \end{cases}$$

Next, we construct a sentiment-based momentum strategy to test the theory that investor sentiment can help predict momentum profits. We augment the conventional momentum strategy by altering the portfolios' exposure following the recent market sentiment; higher sentiment implies higher portfolio weights and vice versa. Then we test whether our sentiment-based momentum strategy yields any abnormal return above the market index before comparing it thoroughly to the conventional momentum strategy and its risk-adjusted returns.

Consequently, if the abnormal return of the sentiment-based momentum strategy is observed across the different strategy variations, we discard the null hypothesis. Hence, our second hypothesis follows:

$$H_2 \begin{cases} H_0 : \alpha_{SMOM} \leq 0 \\ H_A : \alpha_{SMOM} > 0 \end{cases}$$

Lastly, we test how the sentiment-based momentum strategy performs relative to the market after incorporating transaction costs. Several studies have found transaction costs to wipe out most, if not all, of momentum trading strategy's excess returns, making us believe the inclusion of transaction costs is essential to obtain robust results. We test the null hypothesis that the sentiment-based momentum strategy generates abnormal returns:

$$H_3 \begin{cases} H_0 : \alpha^{TC}_{SMOM} \leq 0 \\ H_A : \alpha^{TC}_{SMOM} > 0 \end{cases}$$

Rejection of all three null hypotheses would leave us with the conclusion that investors can expect higher net returns from our sentiment-based momentum strategy than both conventional momentum and the benchmark index, implicitly indicating that investor sentiment can help predict momentum returns.

4 Research methodology

4.1 Conventional Momentum Strategy

We test our first hypothesis by constructing momentum portfolios on the Norwegian stock market following the methodology of Jegadeesh and Titman (1993). Table 3 (Appendix) shows this is momentum literature's most accepted and broadly applied methodology.

As for each month t, we rank all stocks in ascending order based on their accumulated returns past J months, where J denotes the strategy's formation period. The stocks are divided into ten equally weighted portfolios using deciles, whereas the tenth decile is termed "winner portfolio" and the first decile "loser portfolio." Considering our relatively small data set, we construct only equally-weighted portfolios as we expect a value-weighted portfolio to be disproportionally influenced by the corporate giants on OSE. Each month, the momentum portfolio is formed by going long the winner and short the loser portfolios, and this long-short portfolio is held for K months. Since the portfolio compositions are rebalanced each month, we create overlapping portfolios. This is performed by revising $1/K$ of the stocks each month, meaning that we close our positions initiated in month $t-K$ in the winner and loser portfolios, open those positions initiated in month $t-1$, and lastly, carry the rest over from the previous month. The momentum returns (referred to as MOM) in month t are thus calculated as

$$R_{\text{MOM},t} = \frac{1}{K}\sum_{k=1}^{K}\left[R10_{t-k,k} - R1_{t-k,k}\right] \tag{1}$$

where $R10_{t,k}(R1_{t,k})$ denotes the return at time $t+k$ of the tenth (first) decile portfolio formed at time t. In our study, we consider six different portfolio variations: $J = 6, 12$ and $K = 1, 3, 6$.

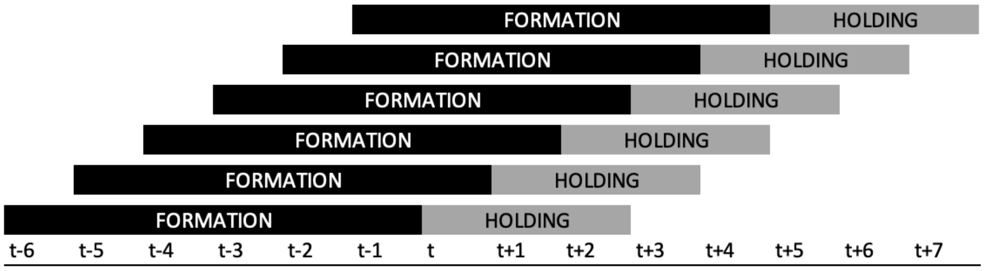

Figure 1: Momentum Portfolio Construction

Figure 1 is a visual overview of six momentum portfolios and their creation. The figure illustrates portfolios created using a formation period of six months and a holding period of three months. The first investment is made in period t, using the price history of the preceding six $(t-6)$ months. Then we hold that investment for three months $(t+3)$. This procedure is repeated every month.

By applying this methodology, we can estimate the momentum effect on the Norwegian stock market and make comparisons to existing literature. Successively, we run a CAPM regression and a Fama French 3-factor regression to observe if the momentum strategies yield any abnormal return above the benchmark. In the occurrence of abnormal returns, we would reject the null hypothesis and conclude that a conventional momentum strategy does outperform the OSEBX.

4.2 Sentiment-based Momentum Strategy

Despite the impressive historical performance of momentum strategies, researchers have identified several drawbacks, whereas the most prominent one is the risk of momentum crashes (Daniel and Moskowitz (2016)). A large body of literature has found these crashes to be partly forecastable, as they habitually occur following market declines and increased volatility. In light of these findings, we test whether these crashes can be avoided through a sentiment-based momentum strategy. Existing papers examining the sentiment-momentum relationship have used various methodologies (see Table 3, Appendix); however, they share certain features. They all measure investor sentiment by employing a sentiment index on their respective analyzed market and categorize the sentiment scores based on particular cut-offs - an approach we follow.

Our methodology is inspired by Barroso and Santa-Clara (2015), who created a risk-managed momentum strategy based on an international sample of 21 countries. The researchers theorized that momentum risk is highly variable over time and predictable and scaled their long-short portfolios by its realized variance of daily returns. Their study showed that scaling the portfolios to have constant volatility over time resulted in a momentum strategy with significantly higher risk-adjusted returns. Instead of using volatility to scale the portfolios, we theorize that momentum returns are affected by the level of optimism in the market and employ investor sentiment as a predictive factor.

In other words, we create an adjusted momentum strategy that relies on the argument that market sentiment affects momentum profits. Our strategy exploits this proposed relationship by using data from the Hausseindex, an indicator of investor optimism on the Oslo Stock Exchange, as a sentiment signal to determine our portfolio's market exposure monthly. Compared to the regular momentum strategy, the portfolio weight increases (decreases) with optimistic (pessimistic) sentiment signals. By assigning higher weightings to the more recent sentiment information, we calculate a weighted-rolling average of the sentiment level for the prior three months, in accordance with Lakonishok et al. (1994)[2]. The sentiment index is restricted between 0 and 100 and conveys the proportion of investors that are optimistic about the market from a mid-to-long-term perspective. We classify the current sentiment into three states; if the sentiment index value in month t exceeds 75, the month is classified as a "high" (H) sentiment period. Contrarily, the sentiment period is classified as "low" (L) if the sentiment index value in month t is less than 25.

[2] Lakonishok et al. (1994) assigned more weight on the more recent sentiment observation by calculating a weighted rolling average of the sentiment level. Correspondingly, we give weights of 3, 2 and 1 to sentiments in the prior month (month t-1), month t-2 and month $t-3$, respectively.

The remaining sentiment periods are classified as "medium" (M) sentiment periods. In the cases of high (low) sentiment periods, we use the calculated sentiment signal from the prior month to determine to which extent we invest more (less) in the current month. When the sentiment state is medium, in that the market is somewhat neutral, we do not alter the portfolio weights. Specifically, the new momentum portfolio return is calculated as

$$R_{SMOM,t} = \frac{1}{K} \sum_{k=1}^{K} (1 + \delta_{t-1} D_t) \left(R10_{t-k,k} - R1_{t-k,k} \right) \tag{2}$$

with

$$\delta_t = \frac{WHI_t - \mu}{\sigma} \in [-1, 1], \tag{3}$$

$$WHI_t = HI_t * \frac{3}{6} + HI_{t-1} * \frac{2}{6} + HI_{t-2} * \frac{1}{6} \tag{4}$$

where WHI_t denotes the weighted sentiment indicator, and δ is our standard normally distributed variable, which denotes our portfolio-weight increase (decrease) during periods of market optimism (pessimism). The dummy variable D_t takes the value 1 if the sentiment in month t is low or high and 0 if the sentiment is medium. We restrict the δ within $[-1, 1]$ to maintain stability in the analysis. As graphically displayed in Figure 2, these alternations of the momentum strategy would have instructed investors to lower their market exposure significantly during historical periods of financial recessions.

From the graph below, we observe that the investment weights are altered relatively infrequent, which is an intentional feature to keep the strategy implementable to investors. The strategy only suggests weight adjustments when the Hausseindex express significant levels of optimism or pessimism among the investors. In this respect, we expect the returns of the sentiment-based momentum strategy (hereby referred to as SMOM) to be highly correlated to

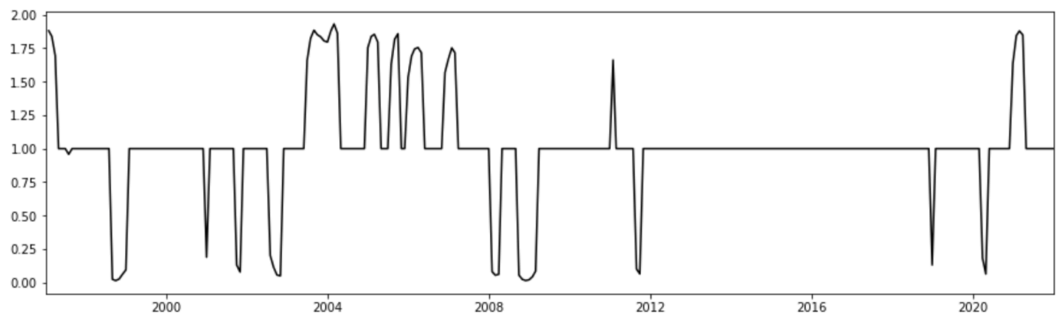

Figure 2: Customized Portfolio Weights Induced by Sentiment Signal

The figure displays how the sentiment-based strategy uses the sentiment signal, $(1 + \delta_{t-1} * D_t)$, to alter the effective investment weights each month. Expectedly, the strategy reduces the market exposure in periods of financial recession, such as the stock market crash of 2008 and the Covid pandemic, 2020.

that of conventional momentum (MOM). We implement the sentiment-based methodology on the six different strategy variations and obtain new returns comparable to the previous conventional momentum returns. By studying the difference in abnormal returns between SMOM and MOM, we can observe how the investor sentiment has covaried with the momentum returns on the Norwegian stock market.

Barroso and Santa-Clara (2015) emphasise that momentum strategies are zero-investment and self-financing strategies, entailing that they are scaleable without constraints. However, one risk associated with this methodology is that SMOM allows higher market exposure than conventional strategies. Consequently, any increase in profitability could merely be compensation for higher risk. We, therefore, need to compare the risk-adjusted returns of the two strategies.

4.3 Controlling for Risk

To evaluate the momentum strategy from an investor perspective, consistent with the likes of Cooper et al. (2004), Lesmond et al. (2004), and Daniel and Moskowitz (2016), we need to measure the strategy's inherent level of risk. Hence, to measure the risk-adjusted return of the strategies with varying holding and formation periods, we calculate and compare each strategy's Sharpe ratio[3] and maximum drawdown[4]. We further control for risk by using a standard capital asset pricing model (CAPM) and the Fama-French 3-factor model (FF3). These are the most widespread and mutually agreed upon risk estimation methods, making our results comparable to existing literature (Stambaugh et al. (2012), Daniel and Moskowitz (2016), Antoniou et al. (2013)). We estimate the risk-adjusted abnormal return as the intercept from the CAPM regression model:

$$R^e_{i,t} = a_i + \beta_1 R^e_{m,t} \tag{5}$$

where $R^e_{i,t}$ is the portfolio return, α_i is the abnormal returns earned above the benchmark, and $R^e_{m,t}$ is the market risk premium. Next, we introduce the Fama-French 3-factor model to test whether the returns of momentum strategies reflect significant loadings on economic factors. The risk-adjusted abnormal returns based on the 3-factor model are estimated as:

$$R^e_{i,t} = \alpha_i + \beta_1 R^e_{m,t} + \beta_2 R^e_{SMB,t} + \beta_3 R^e_{HML,t} \tag{6}$$

where $R^e_{SMB,t}$ denotes the return of small-cap vs large-cap companies, and $R^e_{HML,t}$ denotes the return of value stocks vs growth stocks. If the portfolio returns are compensation for risk to some extent, we expect the abnormal returns to shrink when adjusting for these common risk factors.

4.4 Transaction Costs

To compare the performance of the sentiment-based momentum strategy to the performance of our benchmark, we introduce the effect of transaction costs.

[3]Sharpe Ratio is calculated as $SR = \frac{R_i - R_f}{\sigma_i}$

[4]Max Drawdown is calculated as $MDD_T = \max_{t \leq T} \left\{ \frac{HWM_t - P_t}{HMW_t} \right\}$

Transaction cost is disputed in the previous research literature, as many papers use different approaches and techniques. In this paper, we will explore two different methods. First, a method where we use the bid-ask spread and a fixed one-way commission of 20 basis points, referred to as S+C. This estimation is often considered conservative since it tends to overestimate the effect of transaction costs rather than underestimate them Lesmond et al. (1999). For this reason, we also apply a second estimation of effective transaction costs consisting of a fixed one-way transaction cost of 50 basis points (τ), employed by the likes of Jegadeesh and Titman (1993) and DeMiguel et al. (2009)

Our strategy consists of different holding periods, so we need to adjust the transaction costs accordingly. For instance, the transaction costs would be highest in the case of a 1-month holding period. This is because we reallocate the entire investment each month, contrasting to the 3- and 6-month holding period, where we only reallocate 1/3 and 1/6 each month, respectively. Additionally, since the commission and the fixed transaction cost are one-way transactions, we multiply these by two to provide for buying and selling each month. The calculations of the transaction cost for each method are presented below:

$$TC_{S+C} = Spread + 2 * Commission \tag{7}$$

$$TC_f = \tau * 2 \tag{8}$$

where τ denotes the fixed one-way transaction costs of 50 basis points. This methodology will provide us with a total of twelve momentum returns, six controlled for the S+C transaction cost and six momentum returns controlled for the fixed transaction cost. By regressing the CAPM and Fama French 3-factor model with the two different approaches, we can observe whether these strategies still yield any abnormal returns and, in that case, reject the null hypothesis (H3).

We emphasize that the spread can be significantly affected if trades are sufficiently large, known as the price impact. Like Lesmond et al. (2004), our trading cost measures do not explicitly include price impact costs, making the relative spread the minimum spread for the strategy. Moreover, as the sentiment-based momentum portfolio requires us to weigh the portfolio based on different sentiment levels each month, the transaction costs could, to some extent, be higher for the sentiment-based portfolio than for the conventional momentum strategy. Additionally, we assume that we reallocate the entire portfolio every month. However, there is a possibility that some stocks stay in the portfolio for periods longer than the holding period due to high or poor performance pasts months. This would indicate that we reallocate fewer stocks in the portfolio, decreasing the transaction costs. As a result, we expect our analysis to overestimate rather than underestimate the monthly transaction costs.

5 Data

To ensure a sufficiently large dataset, we test for momentum profits on Oslo Stock Exchange on a 25-year sample period, from 31st Jan 1997 to 31st Dec 2021. The size of our sample period is comparable to other relevant literature (e.g., Jegadeesh and Titman (1993), Cooper et al. (2004)).

5.1 Data Collection

The data we have used is primarily the historical adjusted returns for each stock on the Oslo Stock Exchange during the period of interest. This is collected from a document called "Oslo Børs Informasjon[5]", hereafter referred to as OBI, which provides us with information about the stocks on OSE in our desired period. OBI provides all listed and delisted companies on Oslo Stock Exchange from January 1997 until June 2020, with corresponding adjusted monthly returns, prices, dividends, and shares. We have collected the missing data from July 2020 to December 2021 from Yahoo Finance. Additionally, we calculated the market capitalization for each company each month by multiplying the monthly price by the number of shares each month. The number of stocks on the Oslo Stock Exchange varies from a minimum of 180 stocks in 1997 to a maximum of 274 stocks in 2008, as displayed in Figure 7 (Appendix). Our methodology divides the sample into ten equal portfolios, suggesting we end up with a collection of 18 to 28 stocks in each portfolio, depending on the period.

To run the regression analysis, we are dependent on additional information such as the returns of OSEBX, the Fama French 3-factor model factors, and the risk-free rate. We use the NIBOR-3M as a risk-free rate. Both the data on OSEBX and NIBOR-3M are collected for Bloomberg. The factor returns for

[5] ≪Oslo Børs Informasjon≫ (Oslo Stock Information) is a Norwegian provider of daily stock information for all listed and delisted securities on Oslo Stock Exchange.

size (SMB) and value (HML), used in the regression analysis, are collected from Bernt Arne ødegaard's homepage[6]. The size and value factors are calculated similarly to Fama and French (1996), only using Norwegian stock data.

In addition, we need data that communicate the investor sentiment on Oslo Stock Exchange. Based on the availability of historical sentiment data, we employ data from the Hausseindex: an indicator of investor optimism on OSE constructed by Investtech. The index expresses the share of bullish or bearish investors towards the stock market. More specifically, stocks are ascribed with a buy, hold, or sell recommendation based on investors' willingness to pay for the stock. As a result, the index shows the proportion of stocks given a buy recommendation relative to the total number of shares. The index is distributed between 0 and 100, where a value equal to 100 implies that every company recently were assigned a buy recommendation. Hence, if the index is above 50, it tells us that most investors are optimistic about the market.

Investtech operates with two different Hausseindices: one for short-term investors and one for long-term investors. In this paper, we use the long-term index exclusively, which shows the sentiment of investors that holds their positions for several months or even years. Investtech publishes the Hausseindex daily, meaning that investors can use the sentiment of the previous month to weigh their investment today. Hence, updating the index daily is pivotal in making the sentiment-based strategy feasible. Below, we have presented the graph of the Hausseindex from 1997 to 2021 and highlighted the most important historical events.

To investigate whether the relationship between sentiment and momentum profits is robust to other sentiment indices, we consider the U.S. Volatility Index, referred to as VIX[7]. Contrarily to the Hausseindex, a high (low) VIX

[6]Homepage: `https://ba-odegaard.no`

[7]The Cboe Volatility Index (VIX) measures the 30-day expected volatility of the S&P500, based on mid-quote prices of S&P500 index call and put options.

Figure 3: Hausseindex 1997 - 2021

The graph displays the Hausseindex from 1997 till the end of 2021. The Hausseindex is an indicator of optimism and represents the investor sentiment on Oslo Stock Exchange. In the graph, we have highlighted important events like the dot-com bubble in 2001, the financial crises of 2008 and the Covid pandemic at the beginning of March 2020.

value is associated with market pessimism (optimism). The data from the Volatility Index is collected from Bloomberg. Below, we have displayed the VIX from 1997 to 2021 and highlighted the most important historical events.

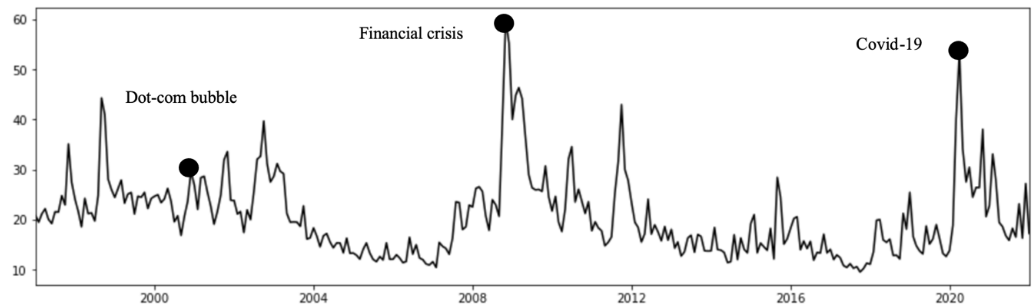

Figure 4: Volatility Index (VIX) 1997 - 2021

The graph displays the Volatility Index (VIX) from 1997 till the end of 2021. In the graph, we can observe spikes in the financial crisis of 2008 and the Covid pandemic in March 2020, indicating a high level of pessimism from the investors.

We can observe a clear pattern between the two sentiment indices. Both exhibit a high level of pessimism in recession periods like the dot-com bubble, the financial crisis of 2008, and the Covid pandemic in 2020. Furthermore, the correlation between the two indices is -61%, which is significantly high and confirms their inverted relationship.

Finally, we apply two different estimation methods of transaction costs; spread plus commission and a fixed one-way transaction cost. The monthly relative spread on Oslo Stock Exchange from 1997 till 2021 is collected from Bernt Arne ødegaard's homepage. The relative spread is the difference between the closing bid and ask price divided by the mid-price. The commission of 0.2%, and the fixed transaction cost of 0.5% are based on Jegadeesh and Titman (1993) and Lesmond et al. (1999).

5.2 Filtering the Data

To get a representative dataset for our study, we reduce the chances of obtaining inflated or spurious results by filtering the data according to specific criteria. We started with the stock returns of all companies from 1985 till 2021, corresponding to 87070 observations. Companies with fewer than 12 months of observation are removed to enable for 12-month formation period. Following Asness et al. (2013), we remove the most illiquid companies to avoid potential issues related to illiquidity and transaction costs. According to Hou et al. (2020), the smallest stocks, or "microcaps", present especially challenging environments for investors due to their low carrying capacities and high transaction costs. We build upon this theory by filtering the data and removing the observations of companies with a market cap of less than NOK 10 million from our dataset. This makes our estimation of transaction costs more conservative and enables us to keep a larger portion of the dataset than if we applied a lower limit on stock prices. Both A and B shares are included in the dataset, as both types of shares are tradable for investors. Further, due to the limitations of the Hausseindex sample period, we restrict the analyses to the time period 1997 till 2021.

The finished data sample of stocks consists of 66 211 observations divided between 621 companies on Oslo Stock Exchange between 1997 and 2021. We include both listed and delisted stocks in our data sample to avoid survivorship bias. Moreover, Pástor and Stambaugh (2003) and Sadka (2006) find that measures of liquidity risk are positively related to momentum in U.S. individual stocks. Since we are filtering out these most illiquid stocks, we can presume that our data selection does not contribute to the effect of survivorship bias but rather promote more conservative results. In Table 5 (Appendix), we present the summary statistics of our data collection, while Tables 6 and 7 (both in Appendix) present the summary statistics for the conventional and sentiment-based momentum strategy, respectively, prior and net of transaction costs. We construct a correlation matrix to understand better the relationship between the input variables used in our model (Table 8, Appendix). The matrix includes the conventional momentum returns based on the entire dataset from 1997 to 2021. Additionally, we have calculated the correlation between OSEBX and the Hausseindex, which, not surprisingly, shows a significant correlation of 50%.

Lastly, we test for stationarity in the time series to ensure that our data is applicable, as stationary time series are easier for statistical models to predict effectively and precisely. This is done by running both an Augmented Dickey-Fuller[8] (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin[9] (KPSS) test. To further study our regression's statistical validity, we check whether the Classic Linear Regression Model (CLRM) assumptions are upheld. Consequently, we control for both homoscedasticity and autocorrelation in the regression models.

[8]An ADF test is a common statistical test used to test whether a given time series is stationary or not.

[9]A KPSS test is a statistical test to check for stationarity of a time series around a deterministic trend.

6 Results and analysis

This section presents the results of our hypotheses tests and analyses. We start by diving into the first hypothesis, where we present the results from the conventional momentum strategy and compare it with the OSEBX (H_1). The next hypothesis we examine is whether we can optimize the momentum profits with the help of the investor sentiment (H_2). In the last hypothesis, we study the effect of two different transaction cost measures on momentum profits (H_3). To validate the robustness of the model, we run several alternative methods where we alter the restrictions and features of the model. Also, we study the sentiment index's predictability of momentum profits by lagging the sentiment variable.

6.1 Conventional Momentum Performance

We start by discussing the results of our first hypothesis; does conventional momentum strategy outperform OSEBX. Similar to the findings of Jegadeesh and Titman (1993), we find the conventional MOM strategy outperforming the benchmark index. Specifically, the strategy yields mean returns higher than the benchmark index in every strategy variation. Similar to Jegadeesh, the highest yielding strategy is 12-3, and our strategy generates monthly mean returns of 1.92%, which is significantly higher than the 0.88% monthly mean returns of the benchmark index. The 6-6 strategy yields a compounded excess return of 1.65% per month on average, comparable to Jegadeesh's 0.95% per month. Griffin et al. (2003) found that a 6-6 momentum strategy generated monthly returns of 1.11% on the Norwegian stock market from 1982 to 2000. The higher returns of our analysis could be explained by the increased momentum effect observed on Oslo Stock Exchange in the last decade, as shown in Figure 8 (Appendix).

The MOM strategy also returns a higher Sharpe ratio in every case except for the 6-1 strategy. According to Jegadeesh and Titman (1993) and Fama and French (1996), the first month after the holding period could be prone to spurious negative autocorrelation due to bid-ask bounce, which can affect the momentum effect in the first holding period month. For the analysis's purpose and validity, we disregard the 1-month holding period strategies going forward. The CAPM and 3-factor alpha also represent the strategy's outperformance; every strategy variation returns statistically significant alphas at a 5% significance level. Specifically, the 6-6 strategy generates monthly abnormal returns of 1.60% - comparable to the 1.77% Stambaugh et al. (2012) and 1.15% Jegadeesh and Titman (1993) identify in the U.S. stock market. All portfolios are negatively correlated with the market risk premium, defined as $R^e_{m,t}$, implying that a market drop would result in positive returns for the portfolios, all else equal. None of the remaining risk factors are statistically significant on any strategy variation.

Figure 8 in the Appendix displays that the conventional momentum strategy outperforms the OSEBX during the entire period; however, the strategy yields quite similar returns at the beginning of the period. Notably, we detect that the momentum strategy overtakes the index in the wake of the financial crisis of 2008 and yields substantially higher returns than the benchmark. In summary, the conventional momentum strategy outperforms the benchmark in terms of both average and abnormal returns for the portfolios, which is consistent with existing literature.

6.2 Sentiment-based vs Conventional Momentum

This subsection presents portfolio performances of the new sentiment-based momentum strategy (SMOM) and makes comparisons to the conventional momentum strategy (MOM). As reported in Table 1, both strategies generate significantly positive monthly mean returns in every strategy variation; however, the SMOM strategy yields higher mean returns at the same level of volatility. Consequently, the sentiment-based strategy generates a higher Sharpe ratio in every portfolio variation, excluding 1-month holding period strategies, which are included in the table for completeness only.

		Conventional Stock Momentum						**Sentiment-based Stock Momentum**					
	Portfolio	Zero-cost (Winners - Losers)						Zero-cost (Winners - Losers)					
	Formation	6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6
Oslo Stock Exchange (January 1997 to December 2021)	Mean R (%)	1.36%	1.75%	1.65%	1.73%	1.92%	1.66%	1.69%	1.96%	1.98%	1.79%	2.05%	1.72%
		(2.28)	(3.31)	(3.42)	(2.72)	(3.39)	(3.11)	(2.83)	(3.77)	(4.19)	(2.72)	(3.51)	(3.15)
	CMGR (%)	0.82%	1.33%	1.30%	1.09%	1.42%	1.21%	1.15%	1.56%	1.64%	1.10%	1.51%	1.25%
	Std. Dev.	0.10	0.09	0.08	0.11	0.10	0.09	0.10	0.09	0.08	0.11	0.10	0.09
	Annualized Sharpe	0.37	0.56	0.58	0.46	0.59	0.52	0.48	0.65	0.73	0.46	0.61	0.54
	CAPM	0.013	0.017	0.016	0.017	0.019	0.016	0.016	0.018	0.019	0.017	0.019	0.016
	alpha	(2.29)	(3.51)	(3.63)	(2.81)	(3.36)	(3.09)	(2.63)	(3.78)	(4.13)	(2.61)	(3.32)	(2.94)
	3-factor	0.013	0.018	0.016	0.017	0.019	0.016	0.015	0.019	0.019	0.017	0.020	0.016
	alpha	(2.24)	(3.71)	(3.61)	(2.82)	(3.51)	(3.18)	(2.68)	(3.90)	(4.04)	(2.70)	(3.42)	(2.97)
	MKT-RF	-0.37	-0.42	-0.37	-0.44	-0.42	-0.36	-0.23	-0.26	-0.24	-0.27	-0.27	-0.25
		(-2.83)	(-3.47)	(-3.01)	(-2.82)	(-2.69)	(2.28)	(-1.82)	(-2.39)	(-2.10)	(-1.73)	(-1.74)	(-1.59)
	SMB	0.07	-0.08	-0.03	0.01	-0.14	-0.14	-0.02	-0.08	-0.04	-0.10	-0.11	-0.07
		(0.31)	(-0.50)	(-0.18)	(0.03)	(-0.68)	(-0.72)	(0.12)	(-0.50)	(-0.28)	(-0.42)	(-0.53)	(-0.42)
	HML	-0.21	-0.16	-0.13	-0.31	-0.31	-0.29	-0.27	-0.17	-0.15	-0.28	-0.24	-0.23
		(-1.25)	(-0.98)	(-0.96)	(-1.70)	(-1.84)	(-1.81)	(-1.68)	(-1.09)	(-1.06)	(-1.53)	(-1.42)	(-1.41)
	Max DD (%)	80%	56%	53%	83%	66%	63%	71%	47%	43%	86%	69%	72%

Table 1: Portfolio Performance - Conventional vs Sentiment-based Momentum

Reported are the mean returns, compounded monthly growth rate (CMGR)[10], standard deviation, and annualized Sharpe ratio for both the conventional and sentiment-based momentum strategy from 1997 till 2021. The table reports the results of both strategies over 6- and 12-month formation periods and 1,3- and 6-month holding periods. Also reported are the alphas from CAPM and the 3-factor model of Fama and French, and lastly, the maximum drawdown (Max DD) for each strategy. The regression equation for CAPM and Fama French is presented in part 4 (Research Methodology). T-statistics are reported in parathesis.

The mean returns increase in every SMOM variation compared to the MOM strategy. This alone indicates a positive relationship between investor sentiment and momentum, supporting the findings of Stambaugh et al. (2012). The 12-3 strategy yields the highest return with a monthly average of 2.05%, equaling a mean return of a significant 1.17% above the market index per month. In resemblance with Antoniou et al. (2013), we find that the momentum effect

[10]The CMGR is calculated as $1 + HPR$ raised to the power of 1 divided by number of months (300) $\left((1 + HPR)^{1/300} - 1\right)$.

is more substantial when adjusting for the investor sentiment. Despite the increased mean returns, we observe relatively small differences in abnormal returns between SMOM and MOM in every strategy variation. This suggests that the higher returns of SMOM primarily are due to higher loadings on risk factors.

The two strategies are highly correlated throughout the observation period, as shown in Figure 9 (Appendix). From Table 5, however, we can observe that the maximum drawdown is lower for a 6-month than a 12-month formation period, indicating a lower risk when basing the investment on a smaller formation period. When comparing the sentiment-based- and conventional momentum strategy, we detect a similar pattern: SMOM returns a lower maximum drawdown with a 6-month formation and higher with a 12-month formation. Per the discussed results, these findings suggest that a sentiment-based strategy with a short formation period offers higher returns at a lower level of volatility than the conventional momentum strategy.

We observe that all SMOM variations yield significant abnormal returns, implying that we can reject our null hypothesis (H2). In comparison, Stambaugh et al. (2012) also report a positive abnormal return for a sentiment-based momentum strategy. Furthermore, the CAPM and 3-factor alpha of the 6-month formation period strategies increase slightly with the new strategy. This may indicate sentiment to be a better predictor of future momentum returns for shorter formation periods rather than longer. The SMOM strategy tends to invest slightly more in larger companies, but we observe a more significant shift in the strategy's correlation with the market. The less negative market coefficient of SMOM indicates a positive correlation between the market and the previous month's investor sentiment, consistent with the findings of Antoniou et al. (2013) and Lansing et al. (2018). In summary, these findings exhibit tendencies of sentiment to predict momentum returns, but most of all, they indicate that the higher profits of SMOM are primarily compensation for risk.

Similar to Jegadeesh and Titman (1993), we run a sub-period analysis to substantiate our comparison results between conventional and sentiment-based strategies. This analysis is performed to check whether SMOM outperforms MOM throughout the sample period or if the strategy's impressive performance merely is driven by shorter periods of outperformance. Our sample is split into four equally-sized subperiods, intentionally chosen to split up the most significant historical financial crises and thereby observe the performance of SMOM versus MOM through each major event. As Figure 10 (Appendix) shows, SMOM outperforms MOM in terms of average returns for close to every formation- and holding period variation. The only subperiod where SMOM does not yield higher average returns is subperiod 1 (1997-2003) for the 6-6 and 12-6 strategies. Said differently, the sentiment-based strategy yields higher returns in 14 of the 16 subperiods examined across four different strategy variations. We conclude that the results are robust across subsamples and are not driven entirely by single events. These results substantiate our hypothesis that sentiment can help predict momentum returns.

To summarize, the sentiment-based momentum strategy does outperform the conventional momentum strategy in terms of both average and abnormal returns. Our results are analogous to existing literature, suggesting a positive relationship between investor sentiment and momentum profits. Since SMOM generates higher mean returns for every strategy and higher abnormal returns in three of the four cases, we can conclude that the employment of investor sentiment has historically positively impacted momentum profits on the Norwegian stock market.

6.3 Impact of Transactions Costs

In our above analysis, we have not considered the effects of transaction costs on the momentum strategies. However, several papers find momentum profits to become insignificant when accounting for the high transaction costs induced by execution. We, therefore, implement two estimates of trading costs in accordance with existing literature: (1) spread plus commission (S+C) and (2) a fixed one-way transaction cost of 0.50%. The latter is the most widely applied approach in existing literature, while the former is considered a more conservative estimation method. Table 2 reports the returns and risk-adjusted returns for conventional and sentiment-based momentum strategies, adjusted for transaction costs.

		Conventional Stock Momentum				**Sentiment-based Stock Momentum**				**OSEBX**
	Portfolio	Zero-cost (Winners - Losers)				Zero-cost (Winners - Losers)				
	Formation	6		12		6		12		
	Holding	3	6	3	6	3	6	3	6	
		PANEL A: BID-ASK SPREAD + COMMISSION								
Oslo Stock Exchange (January 1997 to December 2021)	Transaction costs	0.011	0.006	0.011	0.006	0.011	0.006	0.011	0.006	
	Mean R (%)	0.61%	1.08%	0.78%	1.09%	0.82%	1.40%	0.91%	1.15%	0.88%
		(1.15)	(2.23)	(1.37)	(2.04)	(1.57)	(2.97)	(1.55)	(2.10)	(2.63)
	Annualized Sharpe	0.13	0.34	0.18	0.31	0.21	0.48	0.22	0.33	0.37
	CAPM alpha	0.006	0.010	0.007	0.010	0.007	0.013	0.008	0.010	
		(1.14)	(2.29)	(1.28)	(1.94)	(1.38)	(2.79)	(1.31)	(1.85)	
	3-factor alpha	0.006	0.010	0.008	0.010	0.007	0.013	0.008	0.010	
		(1.23)	(2.26)	(1.36)	(2.02)	(1.43)	(2.72)	(1.36)	(1.86)	
		PANEL B: 0.50% ONE-WAY TRANSACTION COSTS								
	Transaction costs	0.003	0.002	0.003	0.002	0.003	0.002	0.003	0.002	
	Mean R (%)	1.42%	1.48%	1.59%	1.49%	1.63%	1.81%	1.72%	1.56%	0.88%
		(2.68)	(3.07)	(2.80)	(2.80)	(3.13)	(3.82)	(2.94)	(2.85)	(2.63)
	Annualized Sharpe	0.44	0.51	0.47	0.46	0.53	0.66	0.50	0.47	0.37
	CAPM alpha	0.014	0.014	0.015	0.014	0.015	0.017	0.016	0.014	
		(2.83)	(3.25)	(2.77)	(2.76)	(3.10)	(3.76)	(2.75)	(2.63)	
	3-factor alpha	0.014	0.014	0.016	0.015	0.015	0.017	0.016	0.014	
		(3.00)	(3.23)	(2.90)	(2.85)	(3.20)	(3.67)	(2.84)	(2.66)	

Table 2: Portfolio Performance Net of Transaction Costs - SMOM vs. MOM

The portfolio performances for both the conventional and the sentiment-based momentum strategies net of transaction costs are reported. We have employed two different estimates of transaction costs; bid-ask spread plus commission (S + C) in Panel A and a fixed one-way cost of 50 basis points in Panel B. Transaction costs are defined as the mean of total transaction cost over the sample period. The mean R is the monthly return of the portfolios incorporating transaction costs. Lastly, we have reported the annualized Sharpe ratios for the respective strategies and the monthly abnormal returns (CAPM alpha and 3-factor alpha). For comparison, we have reported the mean return and annualized Sharpe ratio of OSEBX on the table's right-hand side.

We observe the performance of both conventional and sentiment-based momentum strategies to depend drastically on the estimation of transaction costs. Notably, the S + C approach estimates transaction costs more than three times that of the fixed fee approach. Consequently, we observe that the mean return of all 3-month holding period strategies falls below that of OSEBX when assuming S + C costs. As previously addressed, this is not surprising, considering that a lower holding period implies more frequent trading and thus higher effective transaction costs. Contrarily, both 6-month holding period SMOM strategies yield higher mean returns than the benchmark and statistically significant CAPM- and 3-factor alphas on a 5% significance level. Isolated, these findings should encourage momentum traders to increase their holding periods. Similar to Jegadeesh and Titman (1993), our 6-6 strategy is the best performing.

When applying the transaction costs consistent with Jegadeesh and Titman (1993), Lui et al. (2003), and DeMiguel et al. (2009), we observe, however, that the risk-adjusted returns stay significant for every strategy variation. For example, the monthly 3-factor alpha of strategy 6-6 moves from 1.9% to 1.7% when transaction costs are incorporated. Further, Figure 5 displays the cumulative returns of SMOM net of the two transaction cost estimates compared to the benchmark index.

Figure 5 supports the findings of Lesmond et al. (1999); S + C tends to overestimate the effective transaction costs and act as an upper bound for the total effective transaction costs for the marginal investor. As a result, from Table 2, Panel A, we observe that the risk-adjusted returns, meaning the CAPM alphas and 3-factor alphas, stay significant for only one of four SMOM strategies.

From the above analysis, we can conclude that momentum strategies are highly predisposed to changes in transaction costs. Considering that S + C and the fixed one-way cost are found to overestimate and underestimate the effect of

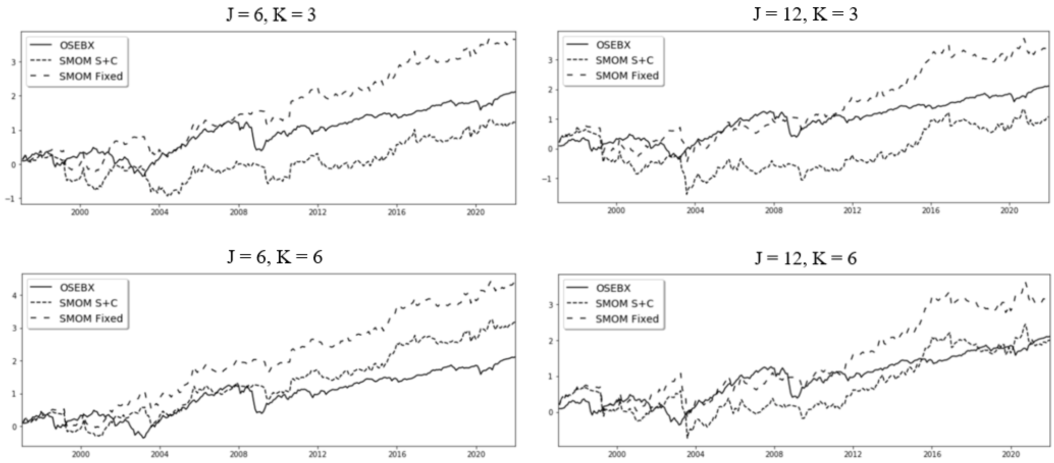

Figure 5: Cumulative Returns Net of Transaction Costs - SMOM vs. OSEBX

The figures display the performance of the sentiment-based momentum strategy after implementing two different estimates of transaction costs; spread and commission (SMOM S + C) and a fixed one-way transaction cost (SMOM Fixed).

transaction costs, respectively, we believe the true transaction costs of the momentum strategies lie somewhere in between. Moreover, transaction costs on the Norwegian stock market have gradually decreased over the last decades, suggesting that the strategy going forward would incur relatively lower transaction costs. However, the actual effect of transaction costs is hard to estimate, as the data on such a long observation period is limited and partly inaccessible. Furthermore, transaction costs are both market and investor-dependent.

Although our results expose the hefty impact transaction costs can have on momentum strategies, we also observe how risk management can help protect momentum profits from being entirely eaten up by transaction costs. In fact, we find that the transaction costs needed to remove the significance of the 6-6 sentiment-based strategy are 52% higher than for conventional momentum, applying the fixed transaction costs. For comparisons, Barroso and Santa-Clara (2015), who used the realized variance of daily returns to scale their long-short portfolio weights, found that the costs needed to remove the significance of their risk-managed momentum strategy were 40% higher than for conventional momentum. If we isolate the purpose of the study, which is to examine the role of investor sentiment on momentum profits, these findings support the argument that sentiment can help predict momentum.

6.4 Robustness Analyses

6.4.1 Alternative Portfolio Scaling

We run some robustness analyses to substantiate our sentiment-based momentum strategy findings. We start by altering the strategy's boundaries on investment weights. Instead of restricting the extra (less) investment weights (δ) induced by investor sentiment within $[-1, 1]$, we restrict δ between $[-0.5, 0.5]$. This is to maintain stability and ensure that we never exceed 150 percent exposure in periods of optimism and never fall below 50 percent in periods of pessimism. This strategy adjustment consequently lessens the differences between the conventional and sentiment-based strategies. The corresponding results, reported in Table 9 (Appendix), show that this alteration affects the strategies' overall performance to a small degree. While the risk-adjusted returns of the 6-month formation period strategies decrease marginally, it marginally increases the risk-adjusted returns of the 12-month strategies. These relatively small changes in strategy performance indicate that the SMOM profits are robust to changes. Consequently, according to the results of Table 9, the SMOM strategy still outperforms the MOM strategy using alternative cut-offs. The cumulative returns relative to conventional momentum are shown in Figure 11 (Appendix).

6.4.2 Alternative Sentiment Cut-Offs

Our principal analysis employed the sentiment cut-offs 75 and 25 to adjust the portfolio weights. Specifically, we increased the investment weights when the sentiment in month $t-1$ surpassed 75 and decreased the investment weights in the case of sentiment below 25. As a robustness check, we test the strategy when applying new cut-offs of 66 and 33. Hence, this involves adjusting the portfolio weights more frequently than the original 75/25 strategy. The results of this modified strategy are reported in Table 10 (Appendix) and show arbitrarily small performance changes. The best performing strategy's mean return is reduced from 2.05% to 1.99% per month, yielding identical abnormal returns of 2%. Antoniou et al. (2013) ran a similar robustness test and confirmed that the cut-off point for optimistic and pessimistic sentiment did not materially affect their conclusions. As our results testify, we come to the same conclusion. In summary, both strategies (75/25 and 66/33) yield approximately the same results, indicating that our model is robust to changes.

6.4.3 Alternative Sentiment Index

To check if our model is robust towards other sentiment measures, we run an analysis where we change the sentiment index, inspired by Antoniou et al. (2013). As there are no other sentiment indices on the Norwegian stock market dating back to 1997, we test the sentiment-based strategy using the U.S. Volatility Index. Since the two indices differ in construction and thresholds, we adjust the definitions of high- and low sentiment to make them comparable. The results obtained from the two indices are very similar, substantiating that our model applies to other sentiment measures. Once we alternate to the VIX, we observe that every strategy returns higher mean returns compared to the use of the Hausseindex. The sentiment-based momentum strategy using VIX either equalises or outperforms the original sentiment-based strategy regarding both CAPM and Fama French 3-factor alpha, as observed in Table 11 (Appendix). Even though the VIX is based on the U.S. market, it turns out to be a helpful predictor of momentum returns on the Oslo Stock Exchange. This could be explained by investor sentiment being, to some degree, universal across markets and continents, however, the relationship is worth examining more closely in future research.

6.4.4 Sentiment Predictability

Contrarily to the MOM strategy, SMOM enables the investor to increase (decrease) the portfolio weights each month. As documented in section 6.2, the increase in monthly market exposure seems to be a contributing factor to why SMOM outperforms MOM in terms of monthly returns. Up until this point, we have, in conformity with existing literature, Lansing et al. (2018) and Antoniou et al. (2013), focused on the predictability of sentiment signal in month $t-1$ to explain future momentum returns. As an additional robustness analysis, we want to study the lead-lag relationship between sentiment and momentum profits more closely by varying the number of lags of the sentiment signal. In other words, we test whether today's momentum returns can be predicted by the investor sentiment of any other prior months. Figure 6 displays the correlation between the weighted rolling sentiment signal (WHI) in month $t-k$ and momentum profits in month t, where $k \in [1, 10]$.

The Figure exhibits a somewhat surprising relationship between investor sentiment and momentum profits. According to the correlation, the one-month lagged sentiment signal turns out to be a poor predictor of momentum returns compared to the other months. Although the correlation differs substantially between the strategy variations, we can observe clear patterns across the strategies, which is that the momentum trend is positive for the eight first consecutive months, whereas the sentiment signal for month $t-6$ holds the all-over highest correlation. These observations encourage us to deviate from the methodology of existing literature and test the sentiment-based momentum strategy using the six-month lagged sentiment signal. The corresponding results are reported in Table 11.

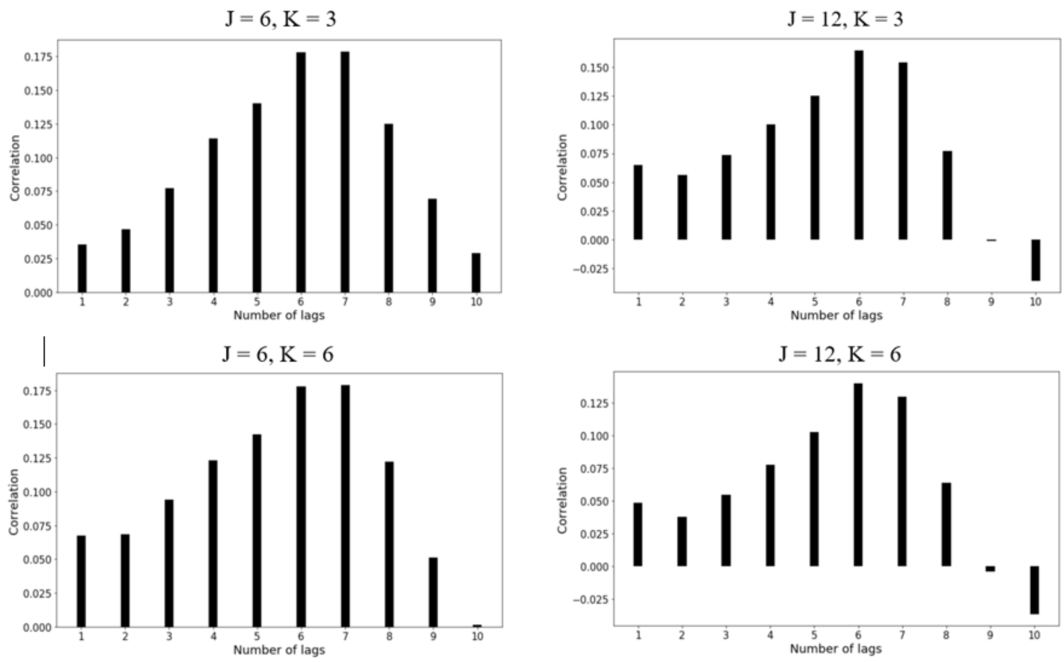

Figure 6: Correlation Between MOM and Investor Sentiment

The figures display the correlation between the sentiment-based momentum strategy and the weighted rolling sentiment signal (WHI). We vary the lags between 1 and 10, and we can observe that the sentiment index $t-6$ has the highest correlation with the conventional momentum strategy.

As expected from the higher correlation, the SMOM strategy using a 6-month lagged sentiment signal yields higher mean returns, Sharpe ratios, and abnormal returns than the 1-month lagged SMOM strategy. The best performing strategy, 12-month formation, and 3-month holding generate monthly abnormal returns of 2.3% and 2.4% according to the CAPM and Fama French 3-factor model, respectively. Considering the relatively small differences in risk factor loadings, we can interpret the increased profits as not being a compensation for risk. However, we have to be careful when drawing inferences from these findings. Although the investor sentiment gets the future market direction correct over the short investor horizon, it is difficult to explain the observed correlation pattern from this limited analysis.

7 Conclusion

We study whether momentum profits can be predicted by investor sentiment and to what extent this relationship is exploitable for investors. We tackle this subject by examining three research questions. First, we examine the presence of momentum profits on the Oslo Stock Exchange. Next, we study the relationship between investor sentiment and momentum profits by creating a sentiment-based momentum strategy. Finally, we analyze how transaction costs affect the profitability of momentum trading.

We establish the presence of momentum return on the Oslo Stock Exchange by running a preliminary analysis of conventional momentum in accordance with Jegadeesh and Titman (1993). The strategy outperforms the market in six out of six portfolio variations, whereas the 6-6 strategy generates monthly abnormal returns of 1.60%, comparable to the 1.15% and 1.77% Jegadeesh and Titman (1993) and Stambaugh et al. (2012) found on the U.S. stock market, respectively. Second, we propose a sentiment-based momentum strategy by scaling the long-short portfolios proportional to the current investor sentiment. Hence, the strategy prescribes decisions to invest more (less) with optimistic (pessimistic) sentiments. Three out of six portfolio variations generate higher risk-adjusted returns, whereas the best performing strategy, 6-6, generates monthly abnormal returns of a significant 1.90%. The results seem robust to alternative portfolio scaling, cut-offs, and alternative sentiment indices. In conformity with Stambaugh et al. (2012) and Antoniou et al. (2013), these results substantiate the argument that investor sentiment help predict momentum profits. Lastly, we study the performance of the sentiment-based momentum strategy net of transaction costs. Our results reveal that the profitability of momentum strategies highly depends on the size of transaction costs, consistent with the findings of Grundy and Martin (2001). We find the risk-adjusted returns to become insignificant in three of four strategy variations when shifting to a conservative estimation of transaction costs. Still, we observe that the transaction costs needed to remove the significance of the 6-6 sentiment-based strategy are 52% higher than for conventional momentum.

In summary, our study reveals a significant relationship between sentiment and momentum while demonstrating the harsh impact of transaction costs in relative strength strategies. We also discover a somewhat surprising correlation pattern between the weighted sentiment index and future momentum profits: a 6-month lagged sentiment signal has the highest predictability of future momentum profits. Whether these findings are specific to the Norwegian stock market or could be found across different markets is worth exploring in future research.

REFERENCES

Antoniou, C., J. A. Doukas, and A. Subrahmanyam. 2013. Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis* 48:245–275.

Asness, C., A. Frazzini, R. Israel, and T. Moskowitz. 2014. Fact, fiction, and momentum investing. *The Journal of Portfolio Management* 40:75–92.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *The Journal of Finance* 68:929–985.

Baker, M., and J. Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *The journal of Finance* 61:1645–1680.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its moments. *Journal of Financial Economics* 116:111–120.

Bower, G. 1981. American Psychologist. *Mood and Memory* 36:129–148.

Chordia, T., and L. Shivakumar. 2002. Momentum, business cycle, and time-varying expected returns. *The journal of Finance* 57:985–1019.

Cooper, M. J., R. C. Gutierrez Jr, and A. Hameed. 2004. Market states and momentum. *The journal of Finance* 59:1345–1365.

Daniel, K., and T. J. Moskowitz. 2016. Momentum crashes. *Journal of Financial economics* 122:221–247.

De Bondt, W. F., and R. Thaler. 1985. Does the stock market overreact? *The Journal of finance* 40:793–805.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Noise trader risk in financial markets. *Journal of political Economy* 98:703–738.

DeMiguel, V., L. Garlappi, and R. Uppal. 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *The review of Financial studies* 22:1915–1953.

Fama, E. F., and K. R. French. 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance* 51:55–84.

Festinger, L. 1957. *A theory of cognitive dissonance*, vol. 2. Stanford university press.

Griffin, J. M., X. Ji, and J. S. Martin. 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of finance* 58:2515–2547.

Grundy, B. D., and J. S. M. Martin. 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *The Review of Financial Studies* 14:29–78.

Hong, H., and J. C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance* 54:2143–2184.

Hou, K., C. Xue, and L. Zhang. 2020. Replicating anomalies. *The Review of Financial Studies* 33:2019–2133.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance* 48:65–91.

Jegadeesh, N., and S. Titman. 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance* 56:699–720.

Jegadeesh, N., and S. Titman. 2011. Momentum. *Annual Review of Financial Economics* 3:493–509.

Johnson, E. J., and A. Tversky. 1983. Affect, generalization, and the perception of risk. *Journal of personality and social psychology* 45:20.

Johnson, T. C. 2002. Rational momentum effects. *The Journal of Finance* 57:585–608.

Korajczyk, R. A., and R. Sadka. 2004. Are momentum profits robust to trading costs? *The Journal of Finance* 59:1039–1082.

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian investment, extrapolation, and risk. *The journal of finance* 49:1541–1578.

Lansing, K. J., M. Tubbs, et al. 2018. Using sentiment and momentum to predict stock returns. *FRBSF Economic Letter* 2018:29.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka. 1999. A new estimate of transaction costs. *The review of financial studies* 12:1113–1141.

Lesmond, D. A., M. J. Schill, and C. Zhou. 2004. The illusory nature of momentum profits. *Journal of financial economics* 71:349–380.

Lui, W., N. Strong, and X. Xu. 2003. The profitability of momentum investing. *Journal of Business Finance & Accounting* 26:1043–1091.

Pástor, L., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political economy* 111:642–685.

Patton, A. J., and B. M. Weller. 2020. What you see is not what you get: The costs of trading market anomalies. *Journal of Financial Economics* 137:515–549.

Rouwenhorst, K. G. 1998. International momentum strategies. *The journal of finance* 53:267–284.

Sadka, R. 2006. Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics* 80:309–349.

Shiller, R. J. 2000. Irrational Exuberance, Princeton Univ.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics* 104:288–302.

Stoll, H. R., and R. E. Whaley. 1983. Transaction costs and the small firm effect. *Journal of Financial Economics* 12:57–79.

APPENDIX

Author	Year	Sample period	Data	Methodology	Conclusion
			Individual Stock Momentum		
Jegadeesh & Titman	1993	1965 - 1989	NYSE-and AMEX-listed stocks	Formed ten equally-weighted portfolios ranked in ascending order based on past returns.	Documents that strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significantly positive returns over 3- to 12-month holding periods.
Rouwenhorst	1998	1980-1995	12 European countries	Constructed relative strength portfolios following the methodology of Jegadeesh (1993).	Find that an internationally diversified portfolio of past medium-term Winners outperforms a portfolio of medium-term Losers after correcting for risk by more than 1 percent per month. Return continuation is present in all twelve sample countries.
Griffin & Martin	2002	1975-2000	NYSE- and AMEX-listed stocks, totalling 40 countries	Constructed relative strength portfolios following the methodology of Jegadeesh (1993).	Momentum profits around the world are economically large and statistically reliable in both good and bad economic states.
Asness et al.	2013	1972-2011	The United States, The United Kingdom, continental Europe, and Japan	Constructed relative strength portfolios following the methodology of Jegadeesh (1993).	Identify consistent value and momentum return premia across eight diverse markets and asset classes and a strong common factor structure among their returns.
			Momentum and Investor Sentiment		
Cooper et al.	2004	1963-1994	NYSE- and AMEX-listed stocks	Use recent market returns to construct momentum portfolios (in accordance with Jegadeesh (1993)) dependent on different market states.	Uncover that momentum profits critically depend on the state of the market. The mean monthly momentum profit following positive market returns is 0.93%, whereas the mean profit following negative market returns is -0.37%.
Stambaugh et al.	2012	1965-2008	NYSE-listed stocks	Construct momentum portfolios based on recent investor sentiment in the market. Applies the Baker and Wurgler (2006) sentiment index.	Identifies a positive relationship between investor sentiment and future momentum profits, as well as ten other asset-pricing anomalies.

Antoniou et al.	2013	1967-2008	NYSE- and AMEX-listed stocks, in addition to stock data from 39 non-U.S. countries	Use recent market returns to construct momentum portfolios (in accordance with Jegadeesh (1993)) dependent on different sentiment states. Sentiment index applied is the Consumer Confidence Index.	Find momentum profits to exclusively arise during periods of optimism. Even after controlling for variability captured by the model, winner stocks earn economically and statistically larger future returns than loser stocks internationally.
Momentum and Transaction Costs					
Lesmond et al.	2003	1980-1998	NYSE-, AMEX- and NASDAQ-listed stocks	Construct momentum portfolios following Jegadeesh (1993) and applies various transaction cost measures, including Roll (1984), spread + commission, and LDV measure (Lesmond 1999).	Find that those stocks that generate significant momentum returns are precisely those stocks with high trading costs. They also conclude that the magnitude of the abnormal returns associated with these trading strategies creates an illusion of profit opportunity when, in fact, none exists.
Grundy & Martin	2004	1926-1995	NYSE- and AMEX-listed stocks	Construct momentum portfolios following Jegadeesh (1993) and calculate the level of round-trip transaction costs that wipes out net momentum profits.	Uncovers that only an investor whose round-trip costs were less than 1.5% could expect statistically significant net profits when undertaking a momentum strategy.
Patton & Weller	2020	1970-2016	4267 United States equity mutual fund groups	Estimate the "implementation gap" using augmented Fama and McBeth (1973) two-stage regressions for the Carhart	Their findings imply that implementation costs erode almost the entirety of the return to value and momentum strategies for typical mutual funds but have little effect on market and size factor strategies.

Table 3: Literature Overview

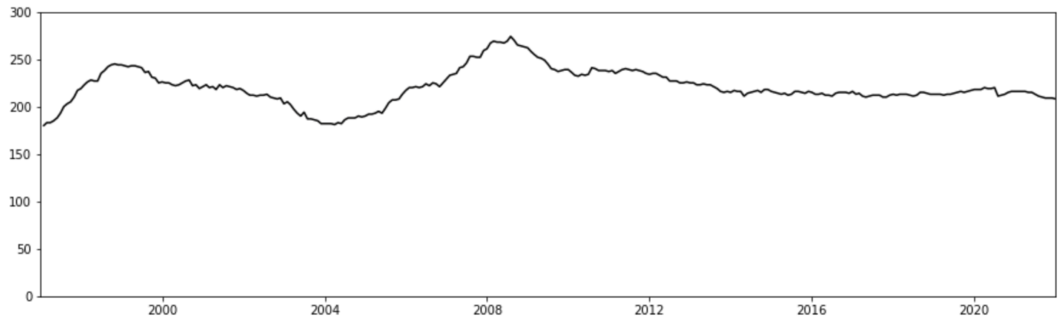

Figure 7: Number of Stocks on the Oslo Stock Exchange 1997 - 2021

The figure above displays the number of stocks on the Oslo Stock Exchange from 1997 to 2021. As we can observe, the average number of stocks is centred around 200, the minimum number is equal to 180, and the maximum number is equal to 274. As we divide our sample into ten equally portfolios, each portfolio consists of between 18 and 27 stocks.

Variables	N (observations)	Mean	Standard deviation
Stocks	66211	1.02%	22.47%
$R^e_{m,t}$	300	0.62%	5.84%
$R^e_{SMB,t}$	300	0.41%	3.86%
$R^e_{HML,t}$	300	-0.22%	4.73%

Table 4: Summary Statistics - Data

The table presents the summary statistics for all stock observations, the market risk premium ($R^e_{m,t}$), and the factors for Fama and French ($R^e_{SMB,t}$ and $R^e_{HML,t}$).

Variables	Formation period	Holding period	N (observations)	Mean	Standard deviation	Mean (after TC_{Fixed})	Mean (after $TC_{\text{S+C}}$)
$R^{6,1}_{MOM,t}$	6 months	1 month	300	1.36%	10%	0.36%	-2.07%
$R^{6,3}_{MOM,t}$	6 months	3 months	300	1.75%	9%	1.42%	0.61%
$R^{6,6}_{MOM,t}$	6 months	6 months	300	1.65%	8%	1.48%	1.08%
$R^{12,1}_{MOM,t}$	12 months	1 month	300	1.73%	11%	0.73%	-1.69%
$R^{12,3}_{MOM,t}$	12 months	3 months	300	1.92%	10%	1.59%	0.78%
$R^{12,6}_{MOM,t}$	12 months	6 months	300	1.66%	9%	1.49%	1.09%

Table 5: Summary Statistics - MOM

The table presents the summary statistics of the conventional momentum returns for all the formation and holding periods. Additionally, we have reported the mean controlled for transaction costs, both the S+C and the fixed.

Variables	Formation period	Holding period	N (observations)	Mean	Standard deviation	Mean (after TC_{Fixed})	Mean (after $TC_{\text{S+C}}$)
$R^{6,1}_{SMOM,t}$	6 months	1 month	300	1.69%	10%	0.69%	-1.73%
$R^{6,3}_{SMOM,t}$	6 months	3 months	300	1.96%	9%	1.63%	0.82%
$R^{6,6}_{SMOM,t}$	6 months	6 months	300	1.98%	8%	1.81%	1.40%
$R^{12,1}_{SMOM,t}$	12 months	1 month	300	1.79%	11%	0.79%	-1.64%
$R^{12,3}_{SMOM,t}$	12 months	3 months	300	2.05%	10%	1.72%	0.91%
$R^{12,6}_{SMOM,t}$	12 months	6 months	300	1.72%	9%	1.56%	1.15%

Table 6: Summary Statistics - SMOM

The table presents the summary statistics of the sentiment-based momentum returns for all the different formation and holding periods. Additionally, we have reported the mean controlled for transaction costs, both the S+C and the fixed.

	$R^e_{m,t}$	$R^e_{SMB,t}$	$R^e_{HML,t}$	$R^{6,1}_{MOM,t}$	$R^{6,3}_{MOM,t}$	$R^{6,6}_{MOM,t}$	$R^{12,1}_{MOM,t}$	$R^{12,3}_{MOM,t}$	$R^{12,6}_{MOM,t}$	δ_t
$R^e_{m,t}$	1									
$R^e_{SMB,t}$	-0.45	1								
$R^e_{HML,t}$	-0.15	-0.24	1							
$R^{6,1}_{MOM,t}$	-0.20	0.14	-0.07	1						
$R^{6,3}_{MOM,t}$	-0.24	0.11	-0.03	0.92	1					
$R^{6,6}_{MOM,t}$	-0.24	0.12	-0.03	0.82	0.93	1				
$R^{12,1}_{MOM,t}$	-0.21	0.14	-0.10	0.70	0.73	0.75	1			
$R^{12,3}_{MOM,t}$	-0.20	0.09	0.10	0.67	0.74	0.79	0.94	1		
$R^{12,6}_{MOM,t}$	-0.18	0.08	-0.10	0.58	0.67	0.76	0.87	0.96	1	
δ_t	0.33	0.02	0.07	-0.02	-0.03	0.00	0.01	0.01	0.01	1

Table 7: Correlation Matrix

In the table above, we have reported the correlation between our input variables.

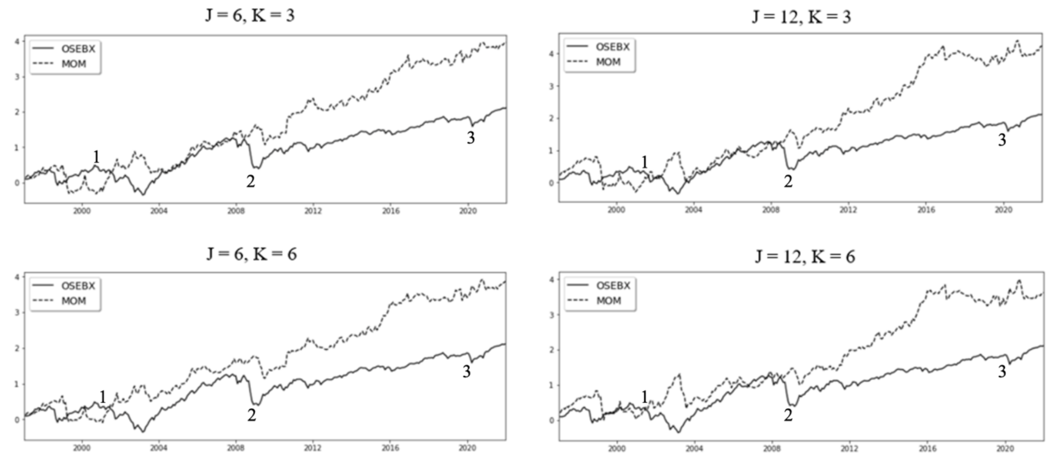

Figure 8: Cumulative Returns - Conventional Momentum vs. OSEBX

The figures above display the performance of conventional momentum strategies with 6- and 12-month formation periods and 3- and 6-month holding periods compared to OSEBX. The y-axis represents the log of cumulative returns. In the figures, we have highlighted the following recession periods: 1) the Dot-com bubble, 2) the financial crisis of 2008, and 3) Covid-19.

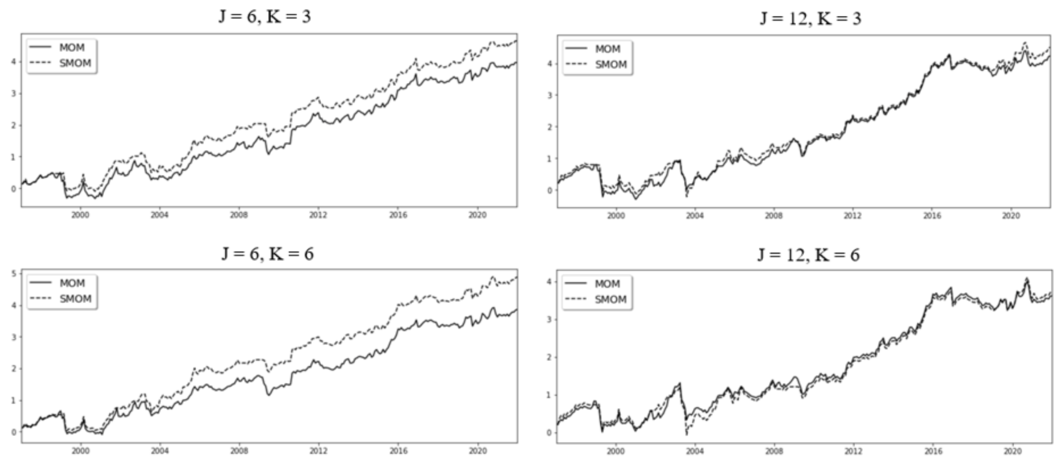

Figure 9: Cumulative Returns - Conventional vs. Sentiment-based Momentum

The figures above show the conventional momentum returns compared to the sentiment-based momentum returns for the 6- and 12-month formation and 3- and 6-month holding periods. The y-axis represents the log of cumulative returns.

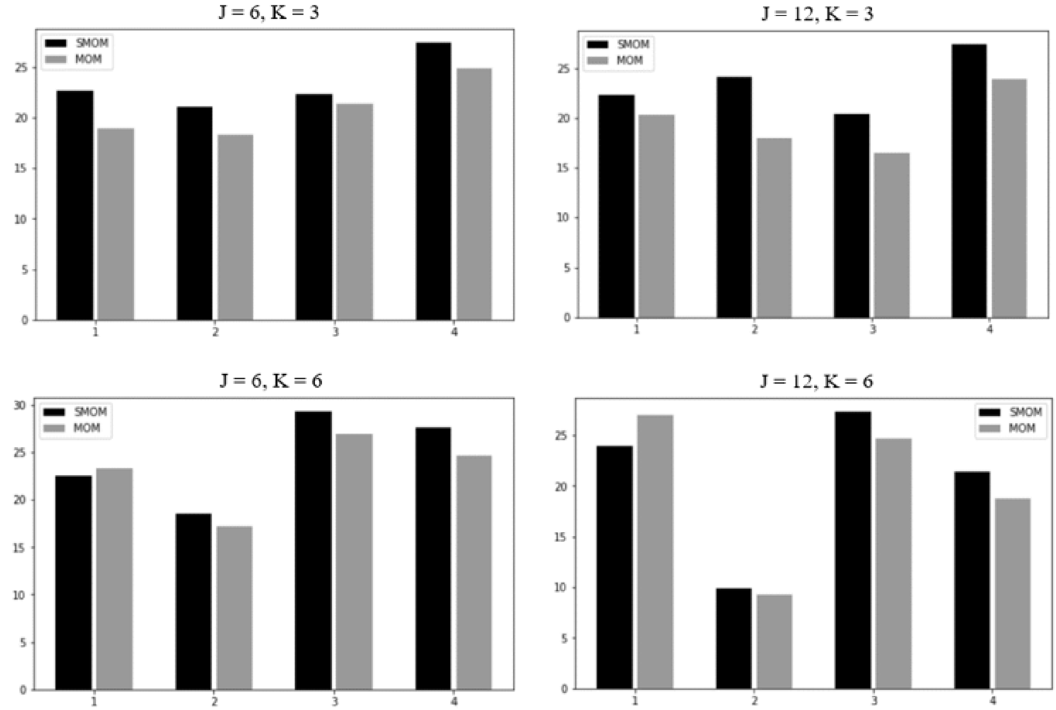

Figure 10: Subperiod Analysis - Conventional vs. Sentiment-based Momentum

The figures show the annualized average returns (%) of the conventional momentum (MOM) and sentiment-based momentum (SMOM) strategy for each subperiod. We divide the sample period into four 6-year subperiods: 1997-2003 (subperiod 1), 2003-2009 (subperiod 2), 2009-2015 (subperiod 3), and 2015-2021 (subperiod 4). The x-axis indicates four 6-year subperiods. Four different momentum strategies are considered with a J-month formation and K-month holding periods.

		Sentiment-based Stock Momentum [-1.0, 1.0]						**Sentiment-based Stock Momentum [-0.5, 0.5]**					
	Portfolio	Zero-cost (Winners - Losers)						Zero-cost (Winners - Losers)					
	Formation	6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6
Oslo Stock Exchange (January 1997 to December 2021)	Mean R (%)	1.69%	1.96%	1.98%	1.79%	2.05%	1.72%	1.53%	1.86%	1.81%	1.76%	1.99%	1.69%
		(2.83)	(3.77)	(4.19)	(2.72)	(3.51)	(3.15)	(2.61)	(3.61)	(3.88)	(2.77)	(3.51)	(3.18)
	CMGR (%)	1.15%	1.56%	1.64%	1.10%	1.51%	1.25%	1.01%	1.46%	1.48%	1.12%	1.49%	1.24%
	Std. Dev.	0.10	0.09	0.08	0.11	0.10	0.09	0.10	0.09	0.08	0.11	0.10	0.09
	Annualized Sharpe	0.48	0.65	0.73	0.46	0.61	0.54	0.43	0.62	0.66	0.47	0.61	0.54
	CAPM alpha	0.016	0.018	0.019	0.017	0.019	0.016	0.014	0.018	0.017	0.017	0.019	0.016
		(2.63)	(3.78)	(4.13)	(2.61)	(3.32)	(2.94)	(2.51)	(3.69)	(3.92)	(2.76)	(3.39)	(3.05)
	3-factor alpha	0.015	0.019	0.019	0.017	0.020	0.016	0.014	0.018	0.017	0.017	0.019	0.016
		(2.68)	(3.90)	(4.04)	(2.70)	(3.42)	(2.97)	(2.53)	(3.87)	(3.87)	(2.82)	(3.51)	(3.11)
	MKT-RF	-0.23	-0.26	-0.24	-0.27	-0.27	-0.25	-0.30	-0.34	-0.31	-0.36	-0.35	-0.30
		(-1.82)	(-2.39)	(-2.10)	(-1.73)	(-1.74)	(-1.59)	(-2.40)	(-3.06)	(-2.63)	(-2.31)	(-2.25)	(-1.95)
	SMB	-0.02	-0.08	-0.04	-0.10	-0.11	-0.07	0.02	-0.08	-0.03	-0.04	-0.12	-0.10
		(0.12)	(-0.50)	(-0.28)	(-0.42)	(-0.53)	(-0.42)	(0.11)	(-0.53)	(-0.23)	(-0.20)	(-0.62)	(-0.59)
	HML	-0.27	-0.17	-0.15	-0.28	-0.24	-0.23	-0.24	-0.16	-0.14	-0.29	-0.27	-0.26
		(-1.68)	(-1.09)	(-1.06)	(-1.53)	(-1.42)	(-1.41)	(-1.49)	(-1.05)	(-1.02)	(-1.63)	(-1.65)	(-1.62)
	Max DD (%)	71%	47%	43%	86%	69%	72%	75%	50%	46%	84%	65%	67%

Table 8: Portfolio Performance - Alternative Investor Sentiment Cut-Offs

Above, we have reported the table for the robustness check when changing the restrictions of the δ to $[-0.5, 0.5]$ from $[-1, 1]$. The mean returns, compounded monthly growth rate (CMGR)[11], standard deviation, and annualized Sharpe ratio for the sentiment-based momentum strategy from 1997 to 2021 are reported. The table reports the results of both strategies over 6- and 12-month formation periods and 1,3- and 6-month holding periods. Also reported are the alphas from CAPM and the 3-factor model of Fama and French, and lastly, the maximum drawdown (Max DD) for each strategy. The regression equation for CAPM and Fama French is presented in part 4 (Research Methodology). T-statistics are reported in parathesis.

[11]The CMGR is calculated as $1 + HPR$ raised to the power of 1 divided by number of months (300) $\big((1 + HPR)^{1/300} - 1\big)$.

		Sentiment-based Stock Momentum (75/25)						Sentiment-based Stock Momentum (66/33)					
	Portfolio	Zero-cost (Winners - Losers)						Zero-cost (Winners - Losers)					
	Formation	6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6
Oslo Stock Exchange (January 1997 to December 2021)	Mean R (%)	1.69%	1.96%	1.98%	1.79%	2.05%	1.72%	1.64%	1.85%	1.85%	1.97%	2.20%	1.86%
		(2.83)	(3.77)	(4.19)	(2.72)	(3.51)	(3.15)	(2.68)	(3.57)	(3.91)	(2.95)	(3.64)	(3.29)
	CMGR (%)	1.15%	1.56%	1.64%	1.10%	1.51%	1.25%	1.05%	1.43%	1.51%	1.28%	1.64%	1.36%
	Std. Dev.	0.10	0.09	0.08	0.11	0.10	0.09	0.11	0.09	0.08	0.12	0.10	0.10
	Annualized Sharpe	0.48	0.65	0.73	0.46	0.61	0.54	0.45	0.61	0.67	0.51	0.64	0.57
	CAPM alpha	0.016	0.018	0.019	0.017	0.019	0.016	0.015	0.017	0.017	0.018	0.020	0.017
		(2.63)	(3.78)	(4.13)	(2.61)	(3.32)	(2.94)	(2.42)	(3.50)	(3.76)	(2.73)	(3.35)	(3.02)
	3-factor alpha	0.015	0.019	0.019	0.017	0.020	0.016	0.014	0.017	0.017	0.018	0.020	0.017
		(2.68)	(3.90)	(4.04)	(2.70)	(3.42)	(2.97)	(2.46)	(3.54)	(3.59)	(2.83)	(3.43)	(2.98)
	MKT-RF	-0.23	-0.26	-0.24	-0.27	-0.27	-0.25	-0.16	-0.19	-0.16	-0.15	-0.15	-0.14
		(-1.82)	(-2.39)	(-2.10)	(-1.73)	(-1.74)	(-1.59)	(-1.21)	(-1.57)	(-1.39)	(-1.91)	(-0.93)	(-0.89)
	SMB	-0.02	-0.08	-0.04	-0.10	-0.11	-0.07	-0.00	-0.07	-0.05	-0.05	-0.06	-0.03
		(0.12)	(-0.50)	(-0.28)	(-0.42)	(-0.53)	(-0.42)	(-0.01)	(-0.37)	(-0.33)	(-0.18)	(-0.27)	(-0.17)
	HML	-0.27	-0.17	-0.15	-0.28	-0.24	-0.23	-0.28	-0.20	-0.13	-0.24	-0.19	-0.18
		(-1.68)	(-1.09)	(-1.06)	(-1.53)	(-1.42)	(-1.41)	(-1.56)	(-1.16)	(-0.80)	(-1.20)	(-1.00)	(-0.96)
	Max DD (%)	71%	47%	43%	86%	69%	72%	73%	54%	49%	83%	64%	61%

Table 9: Portfolio Performance - Varying Threshold for Sentiment Signal

Above, we have reported the table for the robustness check altering the investor sentiment cut-offs. The table compares the strategies when investing more when the sentiment index is above 66 and less when the sentiment is below 33, contrasting the previous cut-offs of 75 and 25. The mean returns, compounded monthly growth rate (CMGR)[12], standard deviation, and annualized Sharpe ratio for the sentiment-based momentum strategy from 1997 to 2021 are reported. The table reports the results of both strategies over 6- and 12-month formation periods and 1,3- and 6-month holding periods. Also reported are the alphas from CAPM and the 3-factor model of Fama and French, and lastly, the maximum drawdown (Max DD) for each strategy. The regression equation for CAPM and Fama French is presented in part 4 (Research Methodology). T-statistics are reported in parathesis.

[12]The CMGR is calculated as $1 + HPR$ raised to the power of 1 divided by number of months (300) $\big((1 + HPR)^{1/300} - 1\big)$.

		Sentiment-based Stock Momentum (Hausseindex)						**Sentiment-based Stock Momentum (VIX)**					
	Portfolio	Zero-cost (Winners - Losers)						Zero-cost (Winners - Losers)					
	Formation	6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6
Oslo Stock Exchange (January 1997 to December 2021)	Mean R (%)	1.69%	1.96%	1.98%	1.79%	2.05%	1.72%	1.78%	2.02%	2.01%	2.01%	2.22%	1.89%
		(2.83)	(3.77)	(4.19)	(2.72)	(3.51)	(3.15)	(3.04)	(3.85)	(4.27)	(3.16)	(3.92)	(3.58)
	CMGR (%)	1.15%	1.56%	1.64%	1.10%	1.51%	1.25%	1.27%	1.61%	1.68%	1.38%	1.73%	1.46%
	Std. Dev.	0.10	0.09	0.08	0.11	0.10	0.09	0.10	0.09	0.08	0.11	0.10	0.09
	Annualized Sharpe	0.48	0.65	0.73	0.46	0.61	0.54	0.52	0.67	0.74	0.55	0.69	0.62
	CAPM	0.016	0.018	0.019	0.017	0.019	0.016	0.017	0.019	0.019	0.019	0.021	0.017
	alpha	(2.63)	(3.78)	(4.13)	(2.61)	(3.32)	(2.94)	(2.88)	(3.89)	(4.15)	(3.02)	(3.67)	(3.33)
	3-factor	0.015	0.019	0.019	0.017	0.020	0.016	0.016	0.019	0.019	0.018	0.021	0.017
	alpha	(2.68)	(3.90)	(4.04)	(2.70)	(3.42)	(2.97)	(2.92)	(4.03)	(4.14)	(3.05)	(3.77)	(3.36)
	MKT-RF	-0.23	-0.26	-0.24	-0.27	-0.27	-0.25	-0.22	-0.25	-0.19	-0.21	-0.19	-0.16
		(-1.82)	(-2.39)	(-2.10)	(-1.73)	(-1.74)	(-1.59)	(-1.95)	(-2.37)	(-1.96)	(-1.50)	(-1.41)	(-1.71)
	SMB	-0.02	-0.08	-0.04	-0.10	-0.11	-0.07	-0.00	-0.06	-0.03	-0.01	-0.05	-0.02
		(0.12)	(-0.50)	(-0.28)	(-0.42)	(-0.53)	(-0.42)	(-0.01)	(-0.35)	(-0.20)	(-0.06)	(-0.24)	(-0.12)
	HML	-0.27	-0.17	-0.15	-0.28	-0.24	-0.23	-0.18	-0.11	-0.09	-0.22	-0.20	-0.19
		(-1.68)	(-1.09)	(-1.06)	(-1.53)	(-1.42)	(-1.41)	(-1.11)	(-0.71)	(-0.71)	(-1.28)	(-1.27)	(-1.28)
	Max DD (%)	71%	47%	43%	86%	69%	72%	71%	56%	53%	83%	66%	63%

Table 10: Portfolio Performance - Hausseindex vs. VIX

Above, we compare the portfolio performance of the SMOM strategy when employing the VIX as an alternative sentiment index. The mean returns, compounded monthly growth rate (CMGR)[13], standard deviation, and annualized Sharpe ratio for the sentiment-based momentum strategy from 1997 to 2021 are reported. The table reports the results of both strategies over 6- and 12-month formation periods and 1,3- and 6-month holding periods. Also reported are the alphas from CAPM and the 3-factor model of Fama and French, and lastly, the maximum drawdown (Max DD) for each strategy. The regression equation for CAPM and Fama French is presented in part 4 (Research Methodology). T-statistics are reported in parathesis.

[13]The CMGR is calculated as $1 + HPR$ raised to the power of 1 divided by number of months (300) $\big((1 + HPR)^{1/300} - 1\big)$.

		Sentiment-based Stock Momentum - Lag 1				Sentiment-based Stock Momentum - Lag 6			
	Portfolio	Zero-cost (Winners - Losers)				Zero-cost (Winners - Losers)			
	Formation	6		12		6		12	
	Holding	3	6	3	6	3	6	3	6
Oslo Stock Exchange (January 1997 to December 2021)	Mean R (%)	1.96%	1.98%	2.05%	1.72%	2.25%	2.13%	2.47%	2.09%
		(3.77)	(4.19)	(3.51)	(3.15)	(4.35)	(4.52)	(4.63)	(4.17)
	CMGR (%)	1.56%	1.64%	1.51%	1.25%	1.86%	1.80%	2.05%	1.71%
	Std. Dev.	0.09	0.08	0.10	0.09	0.09	0.08	0.09	0.09
	Annualized Sharpe	0.65	0.73	0.61	0.54	0.77	0.79	0.83	0.73
	CAPM alpha	0.018	0.019	0.019	0.016	0.021	0.020	0.023	0.019
		(3.78)	(4.13)	(3.32)	(2.94)	(4.42)	(4.67)	(4.30)	(3.88)
	3-factor alpha	0.019	0.019	0.020	0.016	0.022	0.020	0.024	0.020
		(3.90)	(4.04)	(3.42)	(2.97)	(4.59)	(4.64)	(4.51)	(4.07)
	MKT-RF	-0.26	-0.24	-0.27	-0.25	-0.27	-0.23	-0.23	-0.22
		(-2.39)	(-2.10)	(-1.74)	(-1.59)	(-2.30)	(-1.96)	(-1.57)	(-1.46)
	SMB	-0.08	-0.04	-0.11	-0.07	-0.10	-0.11	-0.18	-0.20
		(-0.50)	(-0.28)	(-0.53)	(-0.42)	(-0.54)	(-0.65)	(-0.89)	(-1.08)
	HML	-0.17	-0.15	-0.24	-0.23	-0.18	-0.17	-0.28	-0.26
		(-1.09)	(-1.06)	(-1.42)	(-1.41)	(-1.12)	(-1.17)	(-1.71)	(-1.66)
	Max DD (%)	47%	43%	69%	72%	42%	37%	48%	45%

Table 11: Portfolio Performance - 1-month vs 6-months Lagged Investor Sentiment

In Table 11, we have compared the sentiment-based momentum strategy with one lag alongside the sentiment-based momentum strategy with six lags. We can observe a clear pattern that the six-month lag strategy outperforms the 1-month lag. Reported are the mean returns, compounded monthly growth rate (CMGR)[14], standard deviation, and annualized Sharpe ratio for sentiment-based momentum strategy with 1- and 6-months lag. The table reports the results of both strategies over 6- and 12-month formation periods and 3- and 6-month holding periods. Also reported are the alphas from CAPM and the 3-factor model of Fama and French, and lastly, the maximum drawdown (Max DD) for each strategy. T-statistics are reported in parathesis.

[14] The CMGR is calculated as $1 + HPR$ raised to the power of 1 divided by number of months (300) $\left((1 + HPR)^{1/300} - 1\right)$.