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Applying Salience Theory to Momentum Strategies: Evidence from The Norwegian Equity Market 1992-2022

Master Thesis

by

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MSc in Business with Major in Finance

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ABSTRACT

This study examines whether conventional momentum strategies can be improved when different percentages of stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile portfolios in the Norwegian equity market spanning 1992-2022. By incorporating this, the strategy yields superior abnormal returns, measured by CAPM-, Fama-French three-factor-, and Carhart four-factor alphas, across all tested holding and formation periods. Performance improvements are primarily observed in the loser portfolio, accompanied by reduced drawdowns, less negative skewness, and decreased kurtosis. Accounting for transaction costs, numerous alphas vanish and longer holding periods surpass in performance, despite initial favouring of 1-month periods. Importantly, we find enhancements are restricted to microcaps and high-volatility environments, challenging the practical applicability of the strategy.

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Contents

List of Abbreviations

bps	Basis points
CAPM	Capital Asset Pricing Model
Carhart-4	Carhart four-factor model
EW	Equal weighted
FF3	Fama-French 3-factor model
HML	High minus low
LW	Liquidity weighted
MaxDD	Maximum drawdown
MKT	Market risk premium
MOM	Momentum
NIBIOR	Norwegian Interbank Offered Rate
OSE	Oslo Stock Exchange
OSEAX	Oslo Stock Exchange All Share Index
RET	Return
SMB	Small minus big
ST	Salience Theory
TC	Transaction cost
UMD	Up minus down
VW	Value weighted
WML	Winner minus loser

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List of Symbols

α	Abnormal returns
β	Beta coefficient
δ	Degree of salience perception
θ	Constant for adjusting zero-payoff scenarios
π_d	Objective probability
R_f	Risk-free rate
J	Formation period
K	Holding period
RCS	Roll's spread + commissions + short-sale cost

1. Introduction and motivation

Daniel Kahneman, winner of the Nobel Prize for Economics, once stated, "We have a very narrow view of what is going on. We don't see very far in the future, we are very focused on one idea at a time, one problem at a time, and all these are incompatible with rationality as economic theory assumes it." (NPR, 2011). This view is especially relevant to the complex world of today's financial markets. Due to the overwhelming amount of information combined with investors' cognitive limitations, their perception of stock prices may deviate from the actual fundamental values. This tendency, termed as "narrow framing" by Barberis and Huang (2001), notably influences how individuals evaluate risky investments. This idea directly relates to the salience theory put forth by Bordalo et al. (2012), which suggests that due to these cognitive limitations, investors pay particular attention to the most unusual or salient attributes of the available options.

Building on this theory, Cosemans and Frehen (2021) introduced a concrete measure for salience theory (ST)-values specifically tailored for stocks, using past return distributions. In their analysis, they observed a negative relationship between the ST measure and subsequent returns in the US equity market. Specifically, the equal-weighted high-low ST portfolio showcased a statistically significant mean monthly return of -1.28%, complemented by significant Fama-French five-factor and six-factor model alphas of -1.44% and -1.32%, respectively. This implies that investors tend to overestimate the importance of salient attributes in their decisions and therefore are attracted to stocks with salient upsides, leading to overvaluation and low future returns. Conversely, they tend to avoid stocks with salient downsides, which leads to undervaluation and high future returns.

This study aims to investigate whether the salience theory measure proposed by Cosemans and Frehen (2021) can be utilized to improve the abnormal returns, measured by CAPM-, FF3- and Carhart-4 alphas, of conventional momentum strategies. The conventional momentum approach involves buying stocks that have performed well in the past and selling those that have performed poorly (Jegadeesh & Titman, 1993). The idea is that by excluding stocks with the lowest ST-values from the loser portfolio and stocks with the highest ST-values from the winner portfolio, we can better capture the inherent momentum effect and avoid including overvalued "winner" stocks and undervalued "loser" stocks in our strategy. While this idea shows theoretical promise, empirical research in this domain remains limited. However, recent studies conducted in the US and Korea suggest the viability of this approach, demonstrating that stocks with extreme salient returns are more likely to reverse, which reduces the profitability of the momentum strategies (Sim et al., 2022; Sim & Kim, 2022). Building on the individually established effects of salience theory and momentum in the Norwegian equity market (Cakici & Zaremba, 2022; Chui et al., 2010; Rouwenhorst, 1998)), we are the first to investigate if Cosemans & Frehen's ST-measure can be incorporated to enhance momentum strategies in this market, thereby potentially extending the theory's broader validation. Thus, our research question becomes:

How is the performance, measured by CAPM-, Fama-French three-factor-, and Carhart four-factor alphas, of momentum strategies in the Norwegian equity market, affected when different percentages of stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile portfolios in the period 1992-2022?

Additionally, we investigate the impact of transaction costs, with the objective of gaining insights into the applicability of the findings in actual market scenarios. Existing research indicates that transaction costs have a significant influence on the profitability of momentum strategies, and some papers even suggest that incorporating transaction costs can eliminate the strategies' abnormal returns (Korajczyk & Sadka, 2004; Lesmond et al., 2004; Patton & Weller, 2020).

Our research contributes to the expanding literature on the implications of behavioral choice theories and investors' limited cognitive abilities on asset pricing. By considering investors' cognitive abilities and biases, it may be possible to design strategies that align with human decision-making processes and exploit market inefficiencies that can be leveraged to improve investment outcomes. In our analysis, we integrate this understanding of investors' cognitive abilities and biases into one of the most widely-researched and established investment strategies. Incorporating different measures for investor cognitive limitations and biases isn't restricted to this specific strategy or asset class; it can potentially enhance a broad spectrum of investment strategies. Beneficiaries of this improved understanding include individual investors, portfolio managers, financial advisors, hedge fund managers, and policymakers.

2. Literature review

2.1 Momentum

2.1.1 Evidence on the momentum premium

Jegadeesh and Titman (1993) paper "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency" was the first to discover persistent excess returns in an equity trading strategy consisting of buying previous winners and selling previous losers. To conduct their study, they created a total of 32 portfolios based on past returns ranging from 3- to 12-months and holding periods ranging from 3- to 12-months. They ranked all the stocks based on their returns from six months prior and held them for six months, resulting in ten equally weighted portfolios. The portfolio with the lowest past return decile was labeled P1, while the portfolio with the highest past return decile was labeled P10. Finally, they constructed a zero-cost long-short portfolio by subtracting P1 from P10. According to their findings, the optimal momentum strategy in the U.S. stock market in 1965-1989 selects stocks based on past 12-month returns and holds the securities for 3 months, rebalanced monthly. This strategy attained a significant monthly abnormal return of 1.31% on the zero-cost long-short portfolio, which was confirmed by a t-statistic of 3.74. To further confirm the robustness of these findings, Jegadeesh and Titman (2001) made the same conclusion using out-of-sample data from 1990-1997.

Rouwenhorst (1998) was the first to study momentum profits at individual country levels outside of the US market. The study focused on 12 European countries from 1978 to 1995. Utilizing the same methodology as Jegadeesh and Titman (1993), he also found similar results as the original paper, showing statistically significant positive results across all 32 zero-cost portfolios. The highest performing strategy was the 12-3 strategy without skip, which provided an average monthly return of 1.35%. Importantly, the momentum strategy yielded positive returns for all the studied countries, with Norway being one of the markets demonstrating success with 0.99% mean monthly returns for a 6-6 strategy.

In another international study, Chui et al. (2010) looked into the influence of cultural variances on momentum strategy returns by scrutinizing individual stock samples from 41 different global markets spanning from 1980 to 2003. They disregarded stocks with a market capitalization falling below the fifth percentile and created portfolios based on the past six-month returns, which they maintained for a six-month period, with each portfolio constituting 30% of their assets. Even though the strategy did not yield profits for four countries, it still produced average monthly returns of 0.93% when all stocks were considered. Notably, their analysis uncovered an average monthly return of 1.046% for stocks that were listed on the Oslo Stock Exchange, utilizing the 6-6 momentum strategy.

2.1.2 Explanations for momentum returns

There are two main stands in academic literature when explaining profits from momentum strategies: risk-based and behavioral-based explanations. Risk-based explanations propose that momentum profits are seen as compensation for risk, keeping the assumptions of rational investors and adhering to Fama and MacBeth (1973)'s efficient market hypothesis. The main risk-based explanation is that stocks that have done well (winners), inherently carry a higher risk than stocks that have done poorly (losers). Therefore, to balance this elevated risk, the winners persist in their success. The results from Johnson (2002) and Sagi and

Seasholes (2007) support this argument by showing an increased growth rate risk in companies following positive performances. Another risk-based explanation is that the momentum returns are compensation for liquidity risk. Results from Pástor and Stambaugh (2003) support this view, and their liquidity risk factor can explain approximately 50% of the returns coming from momentum.

On the other hand, behavioral-based explanations are based on assumptions of irrationality and biases from investors in the market. Daniel et al. (1998) suggests the returns from momentum strategies are explained by an irrational delayed overreaction to new information in the market. Barberis et al. (1998) argued that positive returns rather came from an initial underreaction from investors. Papers such as Hong and Stein (1999) have also concluded that both these phenomena are present in the market and are effective in explaining momentum returns.

Another behavioral explanation for momentum returns is an anchoring bias, introduced by George and Hwang (2004). This paper uses the distance from the 52-week high price to rank stocks and execute their momentum strategy. The returns from this strategy are almost double of a generic momentum strategy based on past returns. The results indicate that investors are irrationally drawn to a certain reference point. As supposed by Grinblatt and Han (2005), a disposition effect suggests that investors hold on to stocks too long after negative news and provide selling pressure on stocks after positive news drives momentum returns.

Skjeltorp (2000) discovered that both the US and Norwegian markets exhibit distinct fractal scaling behavior, deviating significantly from the outcomes of the random walk theory. These findings suggest the presence of patterns or trends in returns across various time periods. As a result, he concludes that the findings offer a theoretical basis for utilizing technical analysis and active trading strategies to achieve returns above the average in these markets.

2.2 Salience theory

According to Bordalo et al. (2012), decision-makers cognitive limitations cause them to focus on the most attention-seeking attributes of the options available to them, defined as salient. Consequently, these salient attributes are given greater weight in the decision-making process, while less prominent attributes are overlooked, leading to deviation from objective fundamental valuations. In essence, a lottery payoff is considered salient if its percentage differs significantly from the payoff of other available lotteries within the same state of the world. When the potential benefits of a lottery are salient, the decision-maker tends to become more risk-seeking. Conversely, when the potential losses are salient, the decision-maker tends to become more risk-averse.

Cosemans and Frehen (2021) introduced a Salient Theory (ST) measure for stock returns, building on the concept of salience from Bordalo et al. (2012). This measure involves daily ranking of the salience of payoffs for each equity and then deriving the monthly salience theory value for each stock, which we cover in greater detail in the methodology segment. Their model found that investors tend to give more weight to salient past returns when developing their expectations regarding future returns. This can result in a bias towards stocks with prominent potential gains, leading to overvaluation and subsequent low returns. Conversely, stocks with noticeable potential losses may be undervalued and yield higher future returns. According to their analysis, the mean monthly return for the EW high-low ST portfolio is -1.28%, with a Newey-West t-statistic of -10.73. Additionally, the salience effect is not eliminated when incorporating the Fame-French five-factor- or six-factor models, with a significant alpha of -1.44% and -1.32%, respectively. The return gap between the highest and lowest ST deciles is also significant for value-weighted portfolios.

Building on this concept, Sim and Kim (2022) used this ST measure to enhance the performance of a 12-1 momentum strategy in the US market. They found that excluding 5% of stocks with the highest (lowest) ST-values from the winner (loser) deciles increased their monthly Fama French three-factor alpha from 1.901% to 2.024% and Sharpe ratio from 0.852 to 0.927. Additionally, the returns from the refined momentum strategy persist across various firm characteristics (such as liquidity, volatility, and size), market states (including market liquidity and volatility), and sub-periods. Similarly, Sim et al. (2022) discovered supportive evidence for this phenomenon in the Korean market.

Cakici and Zaremba (2022) conducted a study testing the salience theory on the cross-section of stock returns across 49 countries. One of the countries they researched was Norway, where they observed an average monthly return of -0.46 and a Fama-French six-factor alpha of -0.60, with respective t-statistics of -1.83 and -2.33. These results were derived from a zero-cost strategy, which entailed buying an equal-weighted quintile of the stocks with the highest Salience Theory (ST) values and selling those with the lowest ST values from the previous month.

The salience theory has also been criticized. Cakici and Zaremba (2022) identified three important limitations to the salience effect. Firstly, by dividing their sample into microcaps (smallest firms collectively accounting for 3% of total market cap), small firms (3%-10%), and big firms (remaining 90%), they find that the salience effect is only present in microcaps and small firms. Secondly, the premium is mainly observed during extreme market conditions, consisting of severe down markets and periods of high volatility. Thirdly, they found that a portion of the effect can be attributed to short-term reversals and that the salience effect shares characteristics with this measure.

2.3 Transaction costs in momentum strategies

The effect of transaction costs is important to consider as it can significantly affect the profitability of trading strategies. The precise estimation of transaction costs is a complex matter, sparking a debate in the finance world. Depending on the methods of estimation employed, the inclusion of transaction costs can turn formerly profitable trading strategies, like momentum, into less profitable or potentially unviable options. This has led to a debate about whether anomalies persist after properly accounting for transaction costs.

In their influential paper from 1993, Jegadeesh and Titman employed a fixed one-way 50 bps estimate to account for transaction costs. They recognized that real transaction costs might fluctuate, but they deemed this estimate a suitable proxy for costs. This paper has been foundational to momentum investing, and their utilization of a 50 bps estimate has been established as a standard measure for momentum strategies. Subsequent studies have also criticized this cost as too low and even proposed alternative fixed estimates and calculation techniques to more accurately capture the costs associated with transactions (Lesmond et al., 2004).

"What you see is not what you get: The costs of trading market anomalies" by Patton and Weller (2020) also adds to the existing research on evaluating trading strategies, particularly with regards to the momentum anomaly. The authors estimate that the all-in implementation costs of these strategies are between 7.2% and 7.6% per year, which significantly reduces the profits associated with momentum trading between 1970 and 2016. The authors conclude that momentum strategies are unprofitable for typical asset managers when taking into account a broader set of implementation costs, including those beyond just bid-ask spreads.

The research paper "Are Momentum Profits Robust to Trading Costs?" by

Korajczyk and Sadka (2004) evaluates four distinct trading cost measures: two proportional models based on quoted and effective spreads, independent of portfolio size, and two nonproportional models which account for the increasing price impact with larger traded positions. According to their analysis, the FF3 alphas for both EW and VW momentum strategies remain significant under both effective and quoted spread estimations, except for the VW 6-6 strategy with quoted spreads. For both the nonproportional models, the price impact drives away the profitability of EW strategies before $500 million is invested. VW strategies allow over $2 billion in both estimations before FF3 alpha becomes zero, while the LW strategy requires over $5 million before the alpha disappears. Although break-even sizes might appear large, they are indeed achievable for investors such as hedge funds, arbitrage hedge funds, and trend-follower hedge funds.

Additionally, researchers have found asymmetry in trading costs. Several papers hav found evidence for small-cap stocks having higher transaction costs than large-cap stocks due to less liquidity, which widens the spread and increases the market impact of trades, as well as greater information asymmetry. (Bessembinder & Kaufman, 1997; Chan & Lakonishok, 1997; Keim & Madhavan, 1997). For example, Chan and Lakonishok (1997) reports that an average one-way cost is 45 bps for large capitalization stocks and 166 bps for small capitalization stocks in the US. Moreover, traders have also found evidence for transaction costs being higher for short-selling than buying due to borrowing fees, dividend payments, risk, and short-sale constraints (Chan & Lakonishok, 1993; Holthausen et al., 1987; Keim & Madhavan, 1996; Kraus & Stoll, 1972).

In Ødegaard (2009)'s paper, trading equity costs at the Oslo Stock Exchange from 1980-2007 are empirically assessed. During this time, the exchange transitioned from period auctions to automated, continuous trading. Three trading cost measures were employed: the bid/ask spread, the Roll (1984) measure, and the Lesmond et al. (1999) measure. These measures largely agreed, showing high costs compared to the NYSE. He also finds that the trading costs in Norway varies in line with asset value, stock price, volatility and business cycles. Current trading costs are lower than before, but not significantly reduced from earlier periods.

3. Methodology

3.1 Testable hypothesis

We aim to investigate the effect of excluding different percentages of stocks with the highest (lowest) salience theory values from the top (bottom) decile portfolios on the performance, measured by CAPM-, Fama-French three-factor-, and Carhart four-factor alphas, in the Norwegian equity market between 1992-2022. To achieve this objective, we have developed three testable hypotheses. The first hypothesis studies whether the conventional momentum strategies proposed by Jegadeesh and Titman (1993), without ST-based exclusions, deliver positive and significant excess returns. The second hypothesis examines how the momentum strategies excluding stocks based on ST perform using the same performance measures as hypothesis 1. The results from the two first hypotheses are then compared in order to examine the effect of applying salience theory to momentum strategies in the Norwegian equity market. The third hypothesis considers whether the estimated excess returns remain significantly larger than zero after controlling for transaction costs.

The preliminary assessment is of the conventional momentum strategies, in line with Jegadeesh and Titman (1993)'s approach. Our objective is to test the null hypothesis; conventional momentum trading strategies has generated zero or negative abnormal returns (α) relative to the CAPM, Fama-French three-factor, and Carhart four-factor models in the Norwegian equity market 1992-2022. The CAPM, Fama-French three-factor, and Carhart four-factor models are all calculated in a Norwegian context and utilize the OSEAX index as a proxy for the market and the 1-month NIBOR as a proxy for the risk-free rate. The hypotheses are stated as follows:

Hypothesis 1:

$$H_0\text{: } \alpha_{mom} \leq 0$$

$$H_1\text{: } \alpha_{mom} > 0$$

Cosemans and Frehen (2021) found that salience theory has a negative relationship with subsequent returns. Sim and Kim (2022) concluded that excluding stocks based on the ST-measure led to elevated mean returns, Fama French three- and five-factor alphas, and Sharpe ratios, outperforming a conventional momentum strategy. Our null hypothesis states that when different percentages (1%,5%,10%) of stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile portfolios, the abnormal returns of the momentum strategies (α) in the Norwegian equity market 1992-2022 are negative or zero. The hypotheses are expressed as follows:

Hypothesis 2:

$$H_0\text{: } \alpha_{ST_{mom}} \leq 0$$

$$H_1\text{: } \alpha_{ST_{mom}} > 0$$

Subsequently, we compare our results with those of the conventional momentum strategy to assess if there's an enhancement in performance. Our analysis uses the CAPM-, FF3-, and Carhart-4 alphas due to their availability in Norwegian-specific calculations. Furthermore, we examine Sharpe ratios, drawdowns, skewness, and kurtosis to gain a comprehensive understanding of the impact of the ST-based exclusions.

To better mimic the real-world impact of our strategy, we incorporate a hypothesis that examines whether the abnormal returns remain significantly larger than zero after accounting for transaction costs. The transaction costs are estimates using Roll (1984)'s measure for effective spread plus commissions, including an additional short-sale cost. The null hypothesis we propose states that the momentum strategies utilizing ST-based exclusions delivers zero or negative abnormal returns after accounting for transaction costs in the Norwegian equity market 1992-2022. The hypotheses are then expressed as:

Hypothesis 3:

$$\mathrm{H}_0\text{: } \alpha^{TC}_{ST_{mom}} \leq 0$$

$$\mathrm{H}_1\text{: } \alpha^{TC}_{ST_{mom}} > 0$$

3.2 Momentum portfolio construction

In line with Jegadeesh and Titman (1993)'s methodology, we set up momentum portfolios through a strategy known as WML, which involves buying past high-performing stocks (winners) and selling past underperformers (losers). The process begins with ranking stocks according to their returns over the preceding J months, a period termed the "formation period." This method, known as cross-sectional momentum, gets its name from the way it uses comparisons across various stocks at single points in time. These stocks are then divided into ten equally weighted decile portfolios. Utilizing equally weighted portfolios and decile analysis is a common approach in academic research, enhancing the comparability across different studies.

The "winners" decile represents the top decile with the highest returns from the formation period, whereas the "losers" decile denotes the bottom portfolio. Each month at time t, stocks are ranked based on their J-month performance.

Subsequently, the strategy buys the "winners" and sells the "losers," maintaining these positions for K months, known as the "holding period." Simultaneously, the positions initiated in the previous month at t-K are concluded. This process means that each month, the strategy adjusts the weights of 1/K of the securities in the total portfolio while retaining the weights of the remaining stocks from the prior month.

In our study, we focus on strategies with formation periods of 6 and 12 (J = 6, 12) and holding periods of 1,3 and 6 (K = 1, 3, 6). This approach results in six distinct portfolios, each re-balanced monthly.

3.3 Salience theory measure

We closely follow the methodology from the paper "Salience theory and stock prices: empirical evidence" by Cosemans and Frehen (2021) from *the Journal of Financial Economics*. Firstly, we find the distance between stock returns and market returns using equation 3.1

$$\sigma\left(r_{i,d}\right) = \frac{|r_{i,d} - \bar{r}_d|}{|r_{i,d}| + |\bar{r}_d| + \theta} \tag{3.1}$$

The expression $r_{i,d}$ represents the daily return of stock i on day d, while $\bar{r}_d$ refers to the cross-sectional average stock return in the market on the given day. We select the OSE EW index as our representative market index $\bar{r}_d$ due to its inherent properties that maintain the ordering, diminishing sensitivity, and reflection properties of the salience function. We rank the results from equation 3.1, were k=1,...,N, where N is equal to days in the month and θ is a constant assumed to be equal to 0.1 based on the results of experimental evidence from long-short lotteries in Bordalo et al. (2012).

The salience function represented in equation 3.1 adheres to three primary conditions: ordering, diminishing sensitivity, and reflection. The ordering condition signifies that the salience of a given day d for a particular stock i amplifies with the increase in the distance between its payoff and the average lottery payoff in the same state s.

The second condition, diminishing sensitivity, means that the salience decreases when there is a uniform rise in absolute payoff levels across all stocks. Essentially, payoff variations become less impactful when they happen at elevated payoff levels.

The reflection condition suggests that salience relies solely on the size of payoffs and not on whether they are positive or negative. This means that reversing gains into losses doesn't alter the salience, as perception is attuned to differences in absolute values rather than their direction.

Then we utilize the ranking k to estimate weightings for the different stocks, were $\omega_{i,d}$ is the salience weight defined as:

$$\omega_{i,d} = \frac{\delta^{k_{i,d}}}{\sum_{d'} \delta^{k_{i,d'}} \cdot \pi_{d'}} \tag{3.2}$$

The objective probability is denoted by π'_d and is assumed to be equal to $\frac{1}{N}$. δ is a parameter that represents the level of salience distortion and is assumed to be equal to 0.7 based on evidence from Bordalo et al. (2012).

To calculate the salience theory (ST) value for a particular stock i in month m ($ST_{i,m}$), the covariance between the daily returns ($r_{i,d}$) and salience weights ($\omega_{i,d}$) is determined. If the highest (lowest) past returns of a stock are salient, then the ST value will be positive (negative). $ST_{i,m}$ is the salient theory value:

$$ST_{i,m} = cov[\omega_{i,d,m}, r_{i,d,m}] \tag{3.3}$$

After calculating a monthly ST-measure for all stocks, we apply the salience theory measure to momentum strategies. To achieve this, we construct new portfolios by excluding stocks with the 1%, 5%, and 10% highest (lowest) salience theory values from the top (bottom) decile portfolios.

3.4 Momentum performance

To examine the two first hypotheses, we perform several time-series regression analyses in order to examine the excess returns of the conventional and ST momentum strategies. We run regressions of the momentum WML portfolios excess returns of the 1-month NIBOR against the Norwegian equity market premium (OSEAX minus 1-month NIBOR) to determine the estimated CAPM alpha. We then incorporate SMB and HML factors to conduct a regression on the FF3 model. Finally, we include the UMD factor to calculate the estimated Carhart-4 alphas. We consider the OSEAX Index as a representative indicator of overall market performance because it covers the entire Norwegian stock market and incorporates a broad range of securities. The 1-month NIBOR is selected due to its liquidity, relevance as a local benchmark, and alignment with short-term market perspectives. The regression equation used for the estimated CAPM alphas are:

$$r_t^{mom_{J/K}} - r_f = \alpha + \beta_1 r_t^{mkt} + \epsilon \tag{3.4}$$

$$r_t^{ST\_mom_{J/K}} - r_f = \alpha + \beta_1 r_t^{mkt} + \epsilon \tag{3.5}$$

Additionally, we add to the CAPM regressions by introducing more risk factors. The regression equations for the estimated FF3 alphas become:

$$r_t^{mom_{J/K}} - r_f = \alpha + \beta_1 r_t^{mkt} + \beta_2 SMB + \beta_3 HML + \epsilon \tag{3.6}$$

$$r_t^{ST\_mom_{J/K}} - r_f = \alpha + \beta_1 r_t^{mkt} + \beta_2 SMB + \beta_3 HML + \epsilon \tag{3.7}$$

Finally, we add Carhart's UMD factor and get the regression equations we employ to estimate the Carhart-4 alphas:

$$r_t^{mom_{J/K}} - r_f = \alpha + \beta_1 r_t^{mkt} + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \epsilon \tag{3.8}$$

$$r_t^{ST\_mom_{J/K}} - r_f = \alpha + \beta_1 r_t^{mkt} + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \epsilon \tag{3.9}$$

All returns and alphas are expressed as percentages and accompanied by Newey and West (1987) adjusted t-statistics, which are presented in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Additionally, to further examine the findings, we compute Sharpe Ratios (SR), cumulative profits, drawdowns, standard deviations, skewness and kurtosis. Sharpe Ratios is calculated as $SR = \frac{R_p - R_f}{\sigma_p}$, where $R_p = Return$ of portfolio and $\sigma_p =$ Standard deviation of portfolio's excess return. The cumulative profit is calculated for the WML strategy after removing extreme salient returns (0%, 5%, 10%) on a logarithmic scale and represents the potential financial outcome of an initial investment of 10 NOK. The drawdown is measured as the ratio of the cumulative return of the strategy for a specific month t to the maximum cumulative return of the strategy up until the previous month t-1 (Blitz et al., 2011).

In order to measure the skewness, the Fisher-Pearson coefficient of skewness is calculated. This is achieved by raising each deviation from the mean to the third power, summing them, dividing by the number of observations minus one, and then dividing by the standard deviation cubed. Kurtosis is computed using Fisher's kurtosis calculation. This is implemented by raising each deviation from the mean to the fourth power, summing them, dividing by the number of observations minus one, and then dividing by the standard deviation to the power of four. Skewness quantifies the degree of asymmetry, while kurtosis measures the "fatness" of the tails of a distribution. These measures offer crucial insights into the form of the distributions, revealing how they deviate from a typical normal distribution.

3.5 Transaction costs

This paper presents two distinct methods for estimating transaction costs in financial markets. The first approach is based on the widely used method in the literature and was also employed in the seminal paper on momentum by Jegadeesh and Titman (1993), which estimates a one-way transaction cost of 50 basis points

$$TC_{FIXED} = 2 \cdot 50\, bsp \tag{3.10}$$

Despite its popularity, this method has received significant criticism for providing an underestimation of transaction costs (Lesmond et al., 2004). Therefore, in this paper, we also employ a second method to estimate transaction costs. This method utilizes Roll (1984)'s effective spread measure, commissions, and short-sale costs. Roll (1984)'s effective spread is calculated as $2\sqrt{-S_{\text{cov}}}$, where $S_{\text{cov}} = \text{cov}(\Delta p_t, \Delta p_{t-1})$, using price series data. Commissions are the fees charged by brokers for executing trades, which Stoll and Whaley (1983) estimated to be 30 bps. However, commissions have lowered substantially in the period since this paper, and we, therefore, use 20 bps as a measure for commissions in this paper. Additionally, we incorporate an estimate for short-sale costs, incorporating the cost of borrowing, which D'Avolio (2002) estimated to be under 1% annually for the vast majority of US stocks. For our strategy, where half of the stocks in our portfolio are shorted, we estimate a short sale cost of 10 bps per month. This estimate includes the borrowing cost and also the costs of paying dividends to the bondholders in the Norwegian market, which is likely a bit higher than the US (Ødegaard, 2009). This estimate is then computed as follows:

$$TC_{RCS} = RollSpread + 2 \cdot commission + shortsalecosts \tag{3.11}$$

Transaction costs are commonly estimated using spread plus commissions, offering a more cautious approximation than the fixed estimate suggested by Jegadeesh and Titman (1993) (Lesmond et al., 2004). Many studies have evidenced that a significant portion of trades is executed within the quoted bid-ask spread, and that quoted measures therefore likely are inaccurate (Lee & Ready, 1991; Petersen & Fialkowski, 1994). A number of techniques estimating the effective or realized spreads have therefore been employed instead (Lesmond et al., 2004). Considering this, and due to its appropriateness for the Norwegain market, we choose Roll's effective spread estimator plus commissions. It handles market microstructure elements such as price discreteness, dealer inventory effects, and information asymmetry, and applies well to both liquid and illiquid securities. Additionally, we factor in short-sale costs to provide a more complete portrayal of transaction costs. By illustrating this estimate combined with the fixed 50bps estimate, we achieve a broader understanding of the effect of transaction costs and the implications of different estimation methods.

3.6 Statistical significance

We conducted one-tailed t-tests to evaluate the significance of the hypotheses. We present selected thresholds for statistical significance at levels of 1%, 5%, and 10%. We used this formula to calculate the t-statistics:

$$t_{stat} = \frac{\bar{x} - \mu}{\frac{S}{\sqrt{n}}} \tag{3.12}$$

Where $\bar{x}$ represents the sample mean, μ is the hypothesized population mean, s is the sample standard error, and n is the sample size. After determining the t-value and degrees of freedom, we consult a table of values from a t-distribution to obtain the corresponding p-value. If the calculated p-value falls below the selected threshold for statistical significance, we reject the null hypothesis and accept the alternative hypothesis. Newey and West (1987) standard errors are employed throughout our analysis, using the automatic lag selection proposed in Newey and West (1994):

$$AutomaticLagSelection = 4(\frac{N}{100})^{\frac{2}{9}} \tag{3.13}$$

Newey-West standard errors are used to account for the presence of autocorrelation and potential heteroskedasticity in the time-series data.

3.7 Robustness checks

3.7.1 Sensitivity analysis: impact of varying $\mathtt{0}$ and δ

Our results may be influenced by the assumed values of $\mathtt{0}$ and δ used in estimating the ST-values. Hence, we aim to test the sensitivity of our results to changes in these parameters. The values of $\mathtt{0} = 0.1$ and $\delta = 0.7$ is based on the experimental evidence from long-short lotteries presented in Bordalo et al. (2012). However, real market conditions reveal differences in each investor's cognitive capabilities, resulting in varying degrees of salience perception. The proposed values may therefore not be appropriate in a Norwegian context.

For instance, professional investors, often displaying rational behavior, may have a δ value closer to 1, suggesting a more objective evaluation. On the other hand, non-rational investors, who tend to focus almost exclusively on the most noticeable lottery payoff while ignoring all others, might display a δ value closer to 0. Market environments characterized by distinct proportions of professional investors and unique features should be assigned different δ values in practice. The parameter plays a crucial role in determining the salience of situations that results in no payoff. Should θ be absent, conditions with zero payoffs would always exhibit the highest level of salience, regardless of the average payoff level represented by $\bar{r}_d$.

Hence, it is essential to investigate how variations in these assumed parameters could impact our analysis. Considering this, we will perform a sensitivity analysis, modifying the δ value from its initial 0.7 to 0.6 and 0.8, and adjusting the θ value from the original 0.1 to 0.05 and 0.15.

3.7.2 Extreme market conditions

To address Cakici and Zaremba (2022) criticism about salience theory only working under extreme market conditions, we draw from their methodology by dividing our sample into two parts based on volatility. Specifically, we calculate the past 12-months volatility each month using a rolling window and then split our sample into high and low-volatility stocks, divided on the median. This monthly filter allows us to compare the performance of the 12-1 momentum strategies and to assess if ST-based exclusions enhance the CAPM-, FF3, and Carhart-4 alphas in both scenarios.

3.7.3 Microcaps

In order to further incorporate Cakici and Zaremba (2022) critique into our analysis, we aim to investigate if the superior performance of ST-momentum strategies holds true for both large and small stocks. Specifically, they argued that the salience effect in high-minus-low-ST quantile portfolios is limited to microcaps and, to some extent, small stocks.

To examine this, we split our sample based on market capitalization. In the first sample, we select, on a monthly basis, companies with the smallest market capitalizations, which collectively represent 3% of the total market capitalization. Employing 3% as a threshold is commonly used to define microcaps, and this relatively small percentage of total market cap accounts for around 60% of all globally listed firms (Hanauer, 2020). Our second sample comprises the remaining companies, and we end up with approximately 50% of the total companies in each sample. Then, we apply the 12-1 momentum strategy, with and without ST based exclusions, to assess enhancements in mean returns, CAPM, FF3, and Carhart-4 factor estimated alphas across the various strategies and samples.

Moreover, momentum strategies have also faced criticism for being effective only with small stocks due to compensations for illiquidity- and information asymmetry- risks (Bessembinder & Kaufman, 1997; Chan & Lakonishok, 1997; Keim & Madhavan, 1997). This robustness test may provide some insights into this critique as well.

4. Data

4.1 Choice of market

The chosen market for this paper is the Norwegian equity market. Despite the established effects of momentum and salience theory in the Norwegian market, the focus is typically diluted in broader international studies (Cakici & Zaremba, 2022; Chui et al., 2010; Rouwenhorst, 1998). Moreover, research applying salience theory to momentum in the Norwegian context remains unexplored. Testing investment strategies in different markets is an essential aspect of developing a global investment perspective. Differences in education, cultural nuances, and the proportion of professional investors in the market could potentially influence the extent of salience-driven decision-making in Norway compared to the previously studied markets. By studying how a strategy performs in Norway, investors can gain a better understanding of the potential persistence of the results in markets with differentiating characteristics.

4.2 Time period

The data used in our analysis spans from 1992 to 2022. Previous research papers on the topic have used data spanning over similar lengths and concluded it provides a solid foundation for analyses and statistical tests (Asness et al., 2013; Jegadeesh & Titman, 1993). A 30-year sample period is long enough to encompass various market cycles, such as bull and bear markets or economic booms and recessions, thereby allowing a comprehensive assessment of momentum strategies' performance under different conditions. This timeframe also delivers a larger data set, enhancing the statistical significance and reliability of the results. While sample periods longer than 30 years can offer more data, they may also add irrelevant "noise" from outdated market conditions, regulations, and technologies, potentially leading to overfitting the model to conditions that no longer apply. A key consideration for our analysis is the shift from open outcry to electronic trading in the Norwegian stock market in 1988. Thus, we determined that 1992, a few years post-transition, would be an appropriate starting year for our study. The data is reported monthly for ease of comparison, as this format is predominantly used in other studies on the topic.

4.3 Data collection

This study obtained daily and monthly returns from Refinitiv Datastream. The directly available returns for download from Refinitiv do not factor in dividends, as it is simply calculated as $\frac{(EndPrice - StartPrice)}{StartPrice}$. We, therefore, downloaded the total return index instead, which consists of the theoretical growth of a stock holding over a given period, presuming dividends are reinvested to buy more equity or unit trust shares at the closing price on the ex-dividend date. Then, we calculated holding period returns as a percentage change in this index in order to obtain returns including dividends.

Additionally, we also downloaded monthly company market capitalizations from Refinitiv Datastream. We follow Lee and Ready (1991) by only including common stocks and allowing for both active and delisted companies in our sample to mitigate the effect of survivorship bias. Companies are often delisted due to poor performance or bankruptcy, and excluding these could potentially skew results and give an inaccurate representation. In line with Fong et al. (2017), we employ only the primary quotations of listed stocks for firms with multiple securities, choosing those with the highest market capitalization and liquidity. Moreover, our study exclusively considers domestic firms with stocks listed in Norway, discarding securities quoted in currencies differing from NOK following Griffin et al. (2010). In order to minimize the potential for spurious noise and reduce microstructure effects, the study excluded some of the most illiquid stocks from the sample. Specifically, we excluded returns with fewer than 3 return observations in the given month. To maintain data quality, daily returns over 100%, monthly returns over 300%, NaN, and duplicates were also removed from our sample.

We also gathered data from Bent Arne Ødegaard's website (Ødegaard, 2023). This included factors similar to those presented in the Fama French three-factor model (SMB and HML), and Carhart's momentum factor(UMD), all computed by Ødegaard specifically for the Norwegian context. To construct the market premium in these models, we acquired historical data from the same website for the OSEAX index, serving as a proxy for the Norwegian market, and the 1-month NIBOR was utilized as a proxy for the risk-free rate in the study's calculations. The additional factors from the Fama-French five-factor or Fama-French six-factor models were not accessible for download in Norwegian-specific calculations, thereby limiting our analysis to the presented factor models. Moreover, from Ødegaard's site, we downloaded the OSE EW index, which was used to calculate the ST values. From his site, we also gathered a monthly time series of Roll (1984)'s effective spread measure in the Norwegian market, which was employed in calculating transaction costs.

Table 4.1: *Summary statistics*

	Count	Mean	Std	min	max
Daily return	1324646	0.0006	0.031	-0.99	1.00
Monthly return	84361	0.0091	0.1988	-0.99	3.00
1-Month NIBOR	360	0.0032	0.0025	0.0001	0.0207
OSEAX	472	0.0115	0.0590	-0.2742	0.1744
OSE EW	516	0.0131	0.0698	-0.2375	0.2202
SMB	372	0.0138	0.0490	-0.2792	0.2754
HML	372	0.0008	0.0582	-0.2989	0.1804
UMD	372	0.0111	0.0622	-0.2686	0.2509
MktCap	113563	6521917149	30019123517	106668	1215252429849
Rolls spread	489	0.02070	0.0068	0.0056	0.0676

Table 4.1 reports summary statistics for the downloaded data used in this paper. All numbers are in decimals.

5. Results and analysis

This section presents the results from our hypothesis and the findings from the analysis conducted. Initially, we investigate the performance of momentum strategies employing various formation and holding periods in the Norwegian equity market. We then introduce the ST-momentum, a strategy that excludes different percentages of stocks with the highest (lowest) salience theory values from the top (bottom) deciles. We then assess whether this exclusion enhances the performance of the conventional momentum strategies. Moreover, we calculate Sharpe ratios, cumulative profits, drawdowns, standard deviations, skewness, and kurtosis to achieve a more comprehensive understanding of the results. Furthermore, to enhance the practical applicability of our findings, we incorporate transaction costs using two separate approaches and assess their impact on performance. Subsequently, we conduct robustness tests on our initial analysis, adjusting parameters and dividing the sample to address criticisms from literature, ensuring the validity and reliability of our results.

5.1 Performance of strategies

5.1.1 Conventional momentum performance

We begin by examining the results related to the initial hypothesis, which investigates whether conventional momentum strategies, as proposed by Jegadeesh and Titman (1993), generate significant positive abnormal returns when regressed on the CAPM, FF3, and Carhart-4. Our assessment involves the calculation of average monthly raw returns and estimated alphas for the mentioned factor models for various formation periods (J = 6,12) and holding periods (K = 1, 3, 6).

As shown in Table 5.1, all strategies display positive estimated alphas, significant at a 5% significance level or less. For the 6-month formation period strategies, all alphas are significant at a 1% level, with a consistent trend of performance decreasing with higher holding periods. The CAPM, FF3, and Carhart-4 alphas decrease by 0.39%, 0.38%, and 0.29%, respectively, as holding periods extend from 1 to 6 months. Strategies based on 12-month formation periods demonstrate significant alphas at a 1% level for 1- and 3-month holding periods, with the exception of Carhart-4 alphas at 5% levels. For the 6-month holding period strategy, the Carhart-4 alpha is only significant at a 10% level, while others maintain a 5% significance. The same decreasing trend with extended holding periods is seen for 12-month formation periods but with an even steeper decline.

Table 5.1: *Conventional Momentum*

J	6			12		
K	1	3	6	1	3	6
Ret_{mean}	1.76*** (3.39)	1.61*** (3.68)	1.39*** (3.56)	1.71*** (2.95)	1.29*** (2.34)	0.98** (1.80)
CAPM $\hat{\alpha}$	1.66*** (3.34)	1.52*** (3.75)	1.27*** (3.55)	1.65*** (3.00)	1.19*** (2.28)	0.86** (1.69)
FF3 $\hat{\alpha}$	1.99*** (3.87)	1.82*** (4.15)	1.61*** (4.21)	2.24*** (3.76)	1.78*** (3.22)	1.51*** (2.82)
Carhart4 $\hat{\alpha}$	1.23*** (2.46)	1.12*** (2.70)	0.94*** (2.68)	1.25** (2.28)	0.83** (1.69)	0.68* (1.42)
Sharpe	0.53	0.54	0.50	0.47	0.36	0.26

Table 5.1 presents the results of our analysis on winner-minus-loser (WML) momentum strategies in the Norwegian equity market, focusing on different formation- (J = 6,12) and holding periods (K = 1, 3, 6) spanning from 1992 to 2022. All values in the table are expressed in percentages. The mean monthly raw returns, Sharpe ratios, and the alphas from the CAPM, Fama-French three-factor model, and Carhart four-factor model are provided, with their corresponding Newey and West (1987) t-statistics enclosed in parentheses. The market premium factor (MKT) used in these models is the OSEAX Index in excess of the 1-month NIBOR. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The monthly mean return of 1.29% for the 12-3 strategy is close to the 1.31%

and 1.35% reported by Jegadeesh and Titman (1993) and Rouwenhorst (1998). More interestingly, compared to previous results in the Norwegian market, the mean monthly returns for the 6-6 strategy of 1.39% is higher than the 0.99% provided by Rouwenhorst (1998) and 1.046% reported by Chui et al. (2010). Therefore, the 6-6 momentum strategy appears more effective with recent data compared to the previously studied 1978-2003 period.

In summary, the strategy consistently yields significant alphas across all models and strategies, showing robust performance in the Norwegian market. Consequently, we reject the first null hypothesis of alphas being equal to or less than zero, accepting the alternative: conventional momentum strategy alphas exceed zero.

5.1.2 Momentum performance after salience-theory-based exclusions

Building on our initial investigation, we proceed to test our second hypothesis. This hypothesis seeks to examine if significant positive abnormal returns are found when different percentages of stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile. Similar to our first analysis, we employ the calculation of average monthly raw returns, CAPM alpha, Fama-French three-factor alpha, and the Carhart four-factor alpha, considering the same formation and holding periods. The results are presented in Table 5.2.

Comparing the results for the ST-based exclusion strategies in Table 5.2 to the conventional momentum in Table 5.1 reveals notable differences. With the removal of extreme ST stocks, all reported performance measures for all strategies are improved. This suggests that eliminating stocks with extreme ST values helps refine the momentum strategies and increases the effectiveness in generating abnormal returns. Additionally, the t-statistics also show an increase for all

Table 5.2: *ST-Momentum, excluding extreme 10% ST-stocks*

J	6			12		
K	1	3	6	1	3	6
Ret_{mean}	2.33*** (4.65)	1.77*** (4.45)	1.53*** (4.09)	2.02*** (3.40)	1.41*** (2.58)	1.00** (1.91)
CAPM $\hat{\alpha}$	2.20*** (4.64)	1.67*** (4.62)	1.41*** (4.17)	1.95*** (3.45)	1.31*** (2.59)	0.89** (1.84)
FF3 $\hat{\alpha}$	2.52*** (4.96)	2.00*** (4.97)	1.80*** (4.89)	2.57*** (4.11)	1.95*** (3.66)	1.57*** (3.09)
Carhart4 $\hat{\alpha}$	1.84*** (3.69)	1.39*** (3.59)	1.15*** (3.45)	1.63*** (2.75)	1.04** (2.15)	0.78** (1.70)
Sharpe	0.77	0.65	0.59	0.58	0.41	0.28

Table 5.2 presents the results of momentum strategies with ST-based exclusions, where the 10% stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile portfolios. The strategies showed include varying formation- (J = 6,12) and holding periods (K = 1, 3, 6) spanning from 1992 to 2022. Values in this table are represented in percentages. It shows the mean monthly raw returns (Mean RET), the alphas from the CAPM, Fama-French three-factor, and Carhart four-factor models, with their corresponding Newey and West (1987) t-statistics and Sharpe ratios. The market premium factor (MKT) employed in these models is the OSEAX Index in excess of the 1-month NIBOR. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

strategies, even elevating the 12-6 Carhart-4 alpha to a significant status at a 5% level. Furthermore, the 12-1 Carhart-4 alpha and 12-6 FF3 alpha transitions from being significant at 5% levels to achieving significance at 1% levels.

The performance increase is substantial for strategies utilizing 1-month holding periods, where the CAPM alphas increase by 0.53 and 0.30, FF3 by 0.53 and 0.33, and Carhart-4 increase by 0.61 and 0.38 for the 6- and 12-month formation periods respectively. For 6-month holding periods, the performance increase is still there, but only resulting in smaller improvements, especially for 12-month formations. This suggests that the ST effect is strongest for 1-month holding periods and fades out during longer holding periods, which is consistent with the findings of Cakici and Zaremba (2022).

Further in this paper, we chose to focus on examining the 12-1 strategy deeper. We opted for a 12-month formation period given its popularity in research and extensive data availability, while the 1-month holding period was chosen due to the demonstrated ST effect's diminishing presence over extended durations. These choices align with previous studies (Cakici & Zaremba, 2022; Jegadeesh & Titman, 1993; Sim & Kim, 2022).

Table 5.3: *Different exclusion percentages of ST-stocks in 12-1 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.56*** (4.68)	2.51*** (4.72)	2.53*** (4.73)	2.53*** (4.74)	-0.03
	CAPM $\hat{\alpha}$	1.40*** (4.06)	1.36*** (4.17)	1.37*** (4.16)	1.39*** (4.15)	0.01
	FF3 $\hat{\alpha}$	0.56** (2.15)	0.56** (2.23)	0.58** (2.26)	0.61*** (2.36)	0.05
	Carhart4 $\hat{\alpha}$	0.16 (0.67)	0.17 (0.75)	0.19 (0.81)	0.21 (0.90)	0.05
Loser	Ret_{mean}	0.85 (1.01)	0.60 (0.71)	0.59 (0.70)	0.51 (0.61)	-0.34
	CAPM $\hat{\alpha}$	-0.54 (-1.00)	-0.80* (-1.46)	-0.81* (-1.48)	-0.85* (-1.51)	-0.31
	FF3 $\hat{\alpha}$	-1.98*** (-3.86)	-2.22*** (-4.26)	-2.22*** (-4.23)	-2.25*** (-4.20)	-0.27
	Carhart4 $\hat{\alpha}$	-1.39*** (-2.73)	-1.69*** (-3.17)	-1.68*** (-3.12)	-1.72*** (-3.11)	-0.33
WML	Ret_{mean}	1.71*** (2.95)	1.92*** (3.25)	1.93*** (3.28)	2.02*** (3.40)	0.31
	CAPM $\hat{\alpha}$	1.65*** (3.00)	1.87*** (3.37)	1.89*** (3.41)	1.95*** (3.46)	0.30
	FF3 $\hat{\alpha}$	2.24*** (3.76)	2.49*** (4.06)	2.50*** (4.05)	2.57*** (4.11)	0.33
	Carhart4 $\hat{\alpha}$	1.25** (2.28)	1.56*** (2.70)	1.57*** (2.68)	1.63*** (2.75)	0.38
	Sharpe	0.47	0.54	0.54	0.58	0.11

The table displays the 12-1 momentum strategy under varying percantages of exclusions of stocks with the highest (lowest) salience theory values from the top (bottom) decile portfolios. Values in this table are represented in percentages. It shows the mean monthly raw returns (Mean RET), the alphas from the CAPM, Fama-French three-factor, and Carhart four-factor models, with their corresponding Newey and West (1987) t-statistics and Sharpe ratios. The market premium factor (MKT) employed in these models is the OSEAX Index in excess of the 1-month NIBOR. It illustrates the individual performance of both the winner and loser portfolios, along with the performance of the WML portfolio and its corresponding Sharpe ratios. The table also highlights the difference in results when excluding 10% versus excluding none of the extreme ST stocks. The data used is spanning from 1992 to 2022. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5.3 shows how different exclusion percentages affect the performance of the 12-1 WML strategy and the winner and loser portfolios individually. There is a consistent increase in mean returns, alphas, and Sharpe ratios with higher exclusion percentages for the WML portfolio, with the improvement from 0% to 10% exclusions ranging from 0.30%-0.38% for the mean returns and alphas, and the Sharpe ratio increasing by 0.11.

Additionally, we are curious to examine whether the improvement in performance is attributed to either the winner or loser portfolios within the WML momentum strategy. Upon reviewing the winner portfolio of the 12-1 strategy, it's clear that excluding 10% instead of 0% of stocks results in minimal changes in performance. There is a decrease of -0.03% in mean returns, only a minimal 0.01 enhancement in the CAPM alpha, and the FF3 and Carhart-4 alphas both increase by a modest 0.05%.

Conversely, the loser portfolio showcases more substantial shifts in the presented performance measures. With the exclusion of 10% of stocks, the mean return notably drops from 0.85% to 0.51%. However, none of the mean returns are significantly different from zero, so this should be taken into account. A similar trend is observed in the CAPM alpha, decreasing from -0.54% to -0.85%. Furthermore, the FF3 alpha transitions from -1.98% to -2.25%, and the Carhart-4 alpha experiences a decline of 0.33%. It's essential to note that a decline in the performance of the loser portfolio results in a performance increase in the WML portfolio because the strategy short-sells this portfolio.

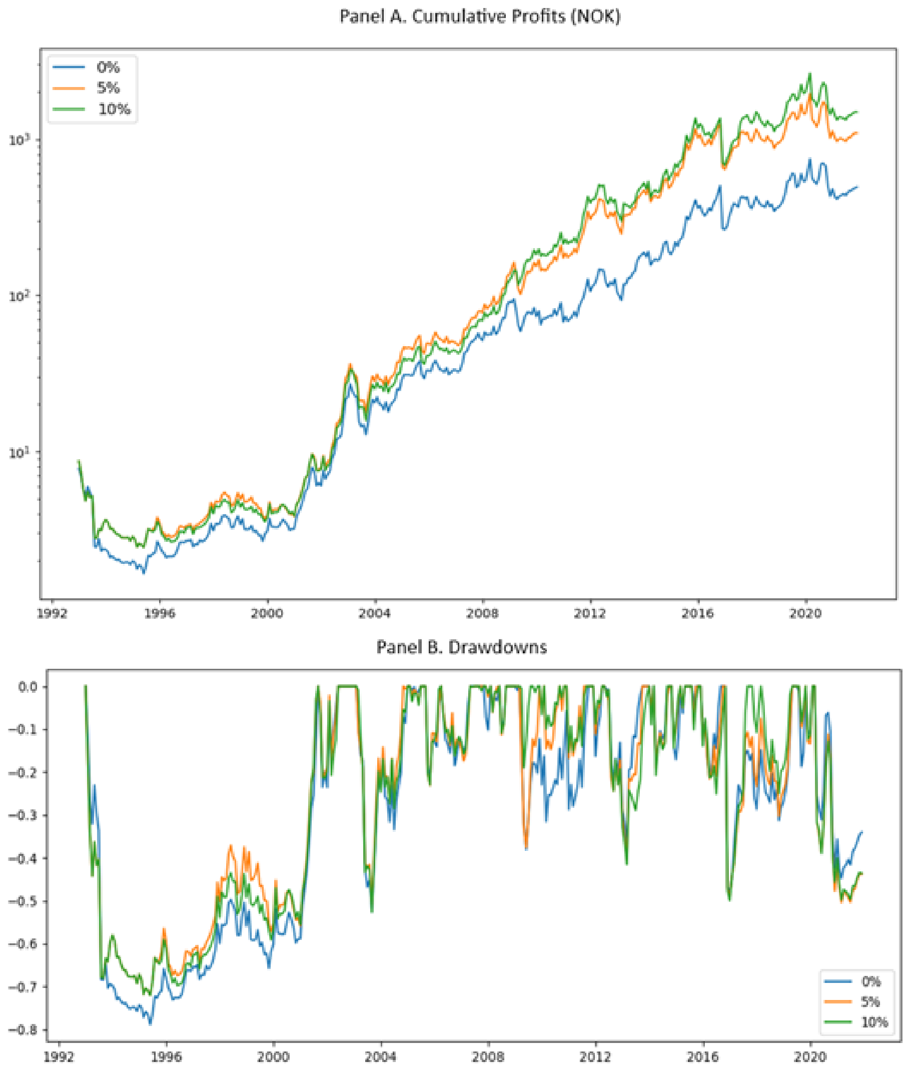
The more pronounced changes for loser portfolios compared to winners can be attributed to a couple of market phenomena. Firstly, market underreaction to negative (positive) news tends to result in the overvaluation (undervaluation) of loser (winner) stocks. Secondly, the existence of short-sale constraints and costs often makes stock overvaluation more widespread than undervaluation (Miller, 1977; Stambaugh et al., 2012). Consequently, loser stocks are more susceptible to yielding lower future returns than winners are to producing higher future returns (Hong & Stein, 1999; Stambaugh et al., 2012). The strategy of excluding stocks with extreme salient returns successfully amplifies the inherent momentum effect, primarily due to the short selling of loser stocks becoming more lucrative.

From the analysis, we can conclude that we reject our second null hypothesis. This hypothesis states that there would be no, or zero, abnormal returns after removing stocks with extremely salient returns from the momentum strategy. However, the collected data clearly shows that this strategy generates abnormal returns across all tested strategies, factor models, and exclusion percentages. Therefore, we accept the alternative hypothesis, which states that; when different percentages (1%,5%,10%) of stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile portfolios, the abnormal returns of the momentum strategies (α) in the Norwegian equity market 1992-2022 exceeds zero. Furthermore, upon comparing the performance of the ST-momentum strategies with the conventional momentum strategies, it becomes evident that the ST-momentum consistently demonstrates superior performance across all tested areas.

5.1.3 Cumulative profits and drawdowns

To further examine the effectiveness of the improved momentum strategies, we illustrate the cumulative profits and drawdowns of the 12-1 strategy, omitting 0%, 5%, and 10% of the stocks with the highest (lowest) salience theory values from the top (bottom) decile portfolios. It's clear from figure 5.1 Panel A that the WML portfolios excluding extreme ST consistently yield greater cumulative profits during the selected timeframe. The strategy that excludes the top and bottom 10% of extreme ST stocks, starting with a 10 NOK investment, results in an end-period total of 1490 NOK, which is higher compared to the conventional momentum strategy's outcome of 493 NOK.

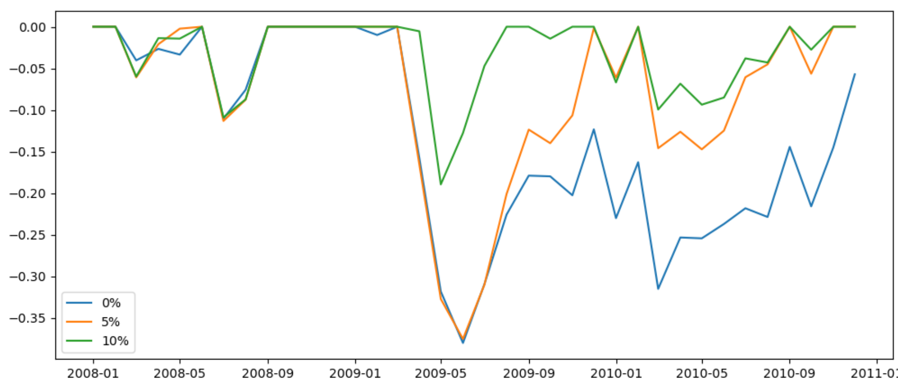
Figure 5.1: *Cumulative profits and drawdowns of the 12-1 WML momentum strategy excluding different percentages of extreme ST stocks*



This figure displays the cumulative profits (Panel A) and drawdowns (Panel B) of the 12-1 WML portfolio over time, after the removal of stocks with highest (lowest) salience theory values from the top (bottom) decile portfolios at levels of 0% (blue), 5% (orange), and 10% (green). The cumulative profit signifies the resulting NOK amount from an initial 10 NOK investment made at the start of 1992 to 2022, represented on a logarithmic scale. Drawdowns are measured as the ratio of the cumulative return of the strategy for a specific month t to the maximum cumulative return of the strategy up until the previous month t-1.

Observing the drawdowns for the same portfolios in figure 5.1 Panel B, it's evident that the conventional momentum strategy, represented in blue, generally suffers greater drawdowns than the strategies that exclude extreme ST stocks. The strategies omitting 5% and 10% of the most extreme ST stocks are alternating in producing the lowest downturns. Interestingly, as shown in figure 5.2, the strategy omitting 10% of extreme ST stocks sees considerably less severe drawdowns in the period following the 2008 financial crisis. Specifically, the conventional momentum strategy sees a maximum drawdown of 38.02% during 2008-2010, while the strategy that excludes the top 10% of ST-Momentum stocks suffers only a 18.95% drawdown. The strategy utilizing 5% ST based exclusions undergoes a drawdown nearly as pronounced as that of the conventional approach just after the crisis, yet it shows a quicker recovery.

Figure 5.2: *Drawdowns after 2008 financial crisis*

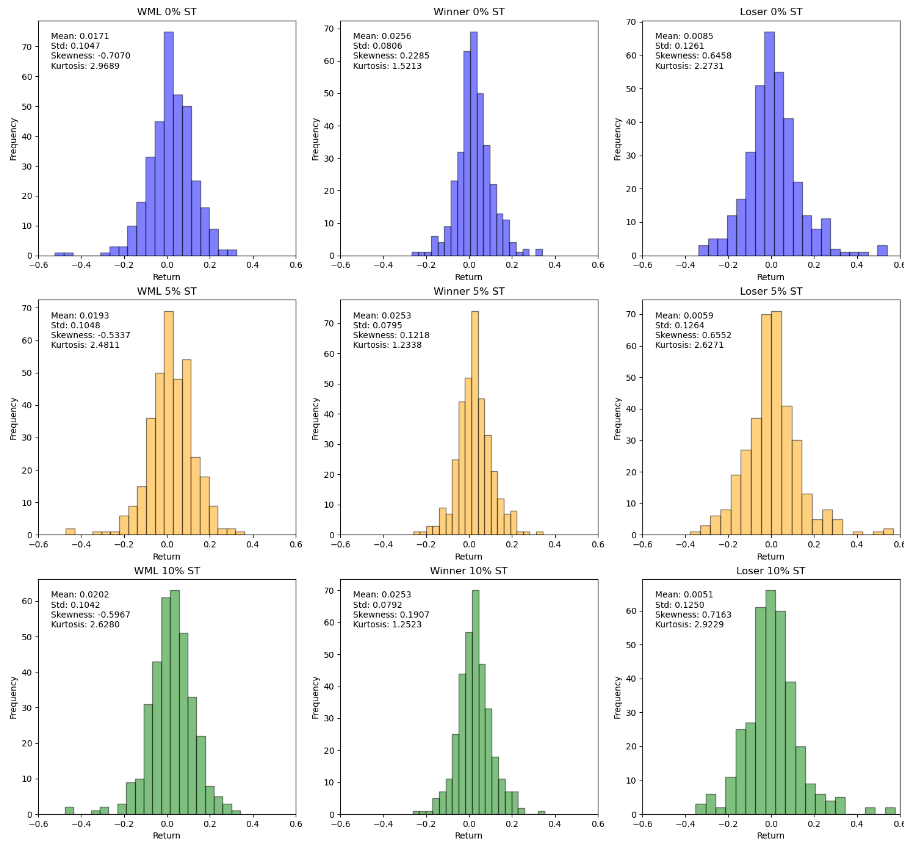


This figure displays the drawdown during the aftermath of the 2008 financial crisis for the 12-1 WML portfolio, after the removal of extreme salience theory (ST) stocks at levels of 0% (blue), 5% (orange), and 10% (green). Drawdowns are measured as the ratio of the cumulative return of the strategy for a specific month t to the maximum cumulative return of the strategy up until the previous month t-1.

5.1.4 Skewness and kurtosis

To further dive into the risk profile of the returns, we calculate and evaluate the skewness and kurtosis of the 12-1 WML strategy with 0%, 5%, and 10% ST-based exclusions. Results for the winner portfolio and loser portfolio are also shown individually in order to get a broader understanding of the return distributions. Notably, these statistics help us better understand the nature of the distribution tail risks, providing insights into potential extreme losses (negative skewness) and potential for extreme outcomes (high kurtosis). The results are shown in figure 5.3.

Figure 5.3: *Return distributions*



This figure displays the time series return distributions of WML, winner, and loser portfolios for 12-1 ST-momentum strategies excluding 0% (blue), 5% (orange), and 10% (green) of stocks based on ST-values. Additionally, the mean, standard deviations, skewness, and kurtosis are presented for the different return distributions

With 0% exclusions based on Salience Theory (ST) values, our Winner-Minus-Loser (WML) portfolio shows negative skewness (-0.7070), implying a left-skewed distribution with a risk of substantial negative returns. As we exclude stocks based on ST values, we see an interesting shift towards a less negatively skewed distribution: -0.5337 with 5% exclusions and -0.5967 with 10% exclusions. This shift indicates that as we incorporate the ST based exclusions, the risk of large negative returns decreases. Simultaneously, we observe a reduction in kurtosis from 2.9689 to 2.4811 and 2.6280 for 5% and 10% exclusions, respectively. This drop in kurtosis suggests less extreme outcomes or less tail risk with the incorporation of ST exclusions. The results indicates that the strategy excluding the initial 5% of stocks more effectively mitigates risk than the subsequent 5% exclusion, while this still delivers superior performance compared to the 0% exclusion strategy.

Separately, our analysis of the winner and loser portfolios reveals different dynamics. The winner portfolio presents relatively stable skewness and kurtosis, regardless of the ST exclusions, suggesting a fairly consistent risk profile. However, the loser portfolio, which we short-sell in our WML strategy, displays positive skewness, from 0.6458 with no exclusions to 0.7163 with 10% exclusions. This heightened skewness in the loser portfolio indicates an increased risk of large positive returns, which is unfavorable for the overall strategy which short-sells this portfolio. Notably, the kurtosis also increases, implying more extreme returns might be expected in the loser portfolio. The higher returns observed in the loser portfolio can be attributed to its inherent riskier profile, showed by a rise in skewness and kurtosis.

In summary, the integration of the ST-based exclusions seems to reduce left tail risk in the WML strategy, reducing the possibilities for large negative returns and momentum crashes. However, the increased risk observed in the loser portfolio highlights the need for further risk management considerations.

5.2 Transaction costs

To further investigate our strategies and scrutinize their potential to deliver abnormal returns in a real-world setting, we take into consideration the impact of transaction costs. These costs are accounted for by implementing two distinct methodologies.

The first method, frequently utilized by Jegadeesh and Titman along with various other researchers, employs a one-way fixed transaction cost of 50 bps. While this method is frequently used, it has been critiqued for understating the actual transaction costs (Lesmond et al., 2004).

Addressing this critique, we introduce a second, alternative calculation that employs Roll (1984)'s effective spread, commissions, and short-sale costs in order to get a more accurate estimation for the Norwegian market.

Table 5.4: *Effect of transaction costs, fixed and RCS*

ST		10%		
		Without transaction cost	Wtih transaction cost (TC_{fixed})	With transaction cost(TC_{RCS})
WML	Ret_{mean}	2.02*** (3.40)	1.11** (1.83)	-0.47 (-0.78)
	CAPM $\hat{\alpha}$	1.95*** (3.45)	1.01** (1.74)	-0.60 (-1.04)
	FF3 $\hat{\alpha}$	2.57*** (4.11)	1.78*** (2.81)	0.17 (0.27)
	Carhart4 $\hat{\alpha}$	1.63*** (2.75)	0.80* (1.31)	-0.82* (-1.36)
	Sharpe	0.58	0.27	-0.25

Table 5.4 shows the effect of incorporating transaction costs in a 12-1 momentum strategy with a 10% ST-based exclusion percentage. The table shows the monthly mean raw return, CAPM, Fama-French three-factor, and Carhart four-factor models, and Sharpe ratios. It is presented for the fixed transaction cost method used by Jegadeesh and Titman (1993) and our proposed estimate utilizing Roll (1984)'s effective spread measure, commissions, and short-sale costs. All returns are expressed in percentages, with t-statistics enclosed in parentheses, computed utilizing Newey and West (1987) standard errors. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Analyzing the 12-1 momentum strategy with a 10% ST-based exclusion percentage, as shown in table 5.4, we observe notable differences in reductions in alphas using the two transaction cost estimation methods. Using the spread, commissions, and short-sale costs method, we observe insignificant or negative alphas. For the fixed 50bps transaction costs, we still obtain positive alphas which are significantly different from zero, at least at a 10% level. Given these observations, we have extended our analysis to assess the effect of transaction costs on strategies involving longer holding periods.

Table 5.5: *Transaction costs for different formation- and holding-periods*

Fixed transaction cost						
J	6			12		
K	1	3	6	1	3	6
TC_{bps}	100	33	17	100	33	17
Ret_{mean}	1.38*** (2.68)	1.43*** (3.52)	1.38*** (3.62)	1.11** (1.83)	1.15** (2.07)	0.90** (1.71)
CAPM $\hat{\alpha}$	1.22*** (2.51)	1.31*** (3.52)	1.24*** (3.55)	1.01** (1.74)	1.02** (1.97)	0.77* (1.55)
FF3 $\hat{\alpha}$	1.65*** (3.22)	1.74*** (4.23)	1.71*** (4.54)	1.78*** (2.81)	1.83*** (3.43)	1.63*** (3.27)
Carhart4 $\hat{\alpha}$	0.95** (1.84)	1.11*** (2.75)	1.03*** (2.98)	0.80* (1.31)	0.87** (1.78)	0.80** (1.76)
Sharpe	0.40	0.49	0.51	0.27	0.31	0.23
Roll's Spread + commissions + short-sale costs						
J	6			12		
K	1	3	6	1	3	6
TC_{bps}	240	80	40	240	80	40
Ret_{mean}	-0.23 (-0.45)	0.89** (2.21)	1.11*** (2.91)	-0.47 (-0.78)	0.62 (1.12)	0.64 (1.21)
CAPM $\hat{\alpha}$	-0.41 (-0.84)	0.76** (2.04)	0.97*** (2.76)	-0.60 (-1.04)	0.48 (0.93)	0.50 (1.00)
FF3 $\hat{\alpha}$	0.02 (0.03)	1.20*** (2.88)	1.44*** (3.79)	0.17 (0.27)	1.30*** (2.41)	1.36*** (2.72)
Carhart4 $\hat{\alpha}$	-0.70* (-1.38)	0.55* (1.37)	0.75** (2.18)	-0.82* (-1.36)	0.33 (0.67)	0.53 (1.16)
Sharpe	-0.20	0.25	0.38	-0.26	0.12	0.13

This table displays monthly average transaction costs, represented in basis points, alongside mean returns, alphas from CAPM-, FF3, and Carhart-4 regression models, and Sharpe ratios. This is reported for various strategies with different formation periods (J=6,12) and holding periods (K=1,3,6) utilizing a 10% ST-based exclusion percentage. Two different transaction cost estimation methods are used, one based on Jegadeesh and Titman (1993)'s fixed one-way costs and one utilizing Roll (1984)'s effective spread measure, commissions and short-sale costs. All returns are expressed in percentages, with t-statistics enclosed in parentheses, computed utilizing Newey and West (1987) standard errors. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5.5 shows the downward trend of transaction costs with increasing holding periods across both estimation methods. With the fixed transaction cost method, monthly transaction costs decrease from 100 bps for a 1-month holding period to 33 bps and 17 bps for the 3-month and 6-month holding periods, respectively. Meanwhile, using the spread, commissions, and short-sale costs method, we see monthly averages decrease from 240 bps for 1-month holding periods to 80 bps for 3-month periods and finally to 40 bps for 6-month periods.

It's noteworthy that, for the fixed transaction cost method, all strategies employing a 6-month formation period generate significant returns at the 1% level, except for the 1-month holding period Carhart four-factor model. This model only achieves significance at a 5% level. For the 12-month formation period strategies, a similar trend is observed, except that the 12-1 Carhart-4 alpha is only significant at 10% level. However, the two strategies with longer holding periods are significant at the 5% level. In general, for the fixed transaction costs, all values remain significantly positive.

The spread, commissions, and short-sale costs method reveals a more pronounced difference in holding periods. For 1-month holding periods, all performance measures are not significantly different from zero or negatively different from zero. However, for 3-month holding periods, the 6-3 delivers positive alphas, all significant at a minimum of 10%, while the 12-3 strategy only delivers a significantly positive result for the FF3 alpha, even significant at a 1% level. The 6-6 strategy performs the best when employing this transaction cost estimation, as both CAPM and FF3 factor alphas are significantly positive at a 1% level, coupled with a Carhart-4 alpha significant at a 5% level and a Sharpe ratio of 0.38. The 12-6 strategy achieves positive values across the board, but only the FF3 alpha is significantly different from zero.

The continued presence of some positive and significant alphas, particularly considering the 6-6 strategy, leads us to reject the third null hypothesis. This analysis highlights the importance of selecting optimal holding periods to preserve returns against transaction costs and illustrates how the choice of cost estimation method can significantly impact strategy performance perceptions. While initial data favor 1-month periods, longer holding periods perform better when considering transaction costs. Despite the substantial costs associated with trading, the potential for positive alphas remains evident in our analysis.

5.3 Robustness checks

5.3.1 Impact of varying $\mathtt{0}$ and δ in the ST-calculation

The conducted sensitivity analysis provides an insightful perspective into the implications of adjusting the parameters $\mathtt{0}$ and δ, demonstrating how these changes influence the results. Table 5.6 exposes a slight upward trend in all three alpha values as δ increases from 0.6 to 0.8, holding $\mathtt{0}$ at a constant value of 0.1. The maximum change in alphas here is 0.03%, which implies a minimal, insignificant enhancement in risk-adjusted performance as we lean towards a more objective evaluation (higher δ value), illustrating the model's sensitivity to variations in salience perception.

Table 5.6: *Impact of varying* 0 *and* δ

Changing parameters						
0		0.1		0.05	0.1	0.15
δ	0.6	0.7	0.8		0.7	
Ret_{mean}	2.01*** (3.42)	2.02*** (3.40)	2.03*** (3.44)	1.99*** (3.43)	2.02*** (3.40)	2.05*** (3.45)
CAPM $\hat{\alpha}$	1.94*** (3.48)	1.95*** (3.46)	1.97*** (3.55)	1.93*** (3.52)	1.95*** (4.46)	1.97*** (3.48)
3-factor model $\hat{\alpha}$	2.55*** (4.16)	2.57*** (4.11)	2.58*** (4.18)	2.57*** (4.14)	2.57*** (4.11)	2.58*** (4.11)
4-factor model $\hat{\alpha}$	1.61*** (2.78)	1.63*** (2.75)	1.62*** (2.78)	1.66*** (2.83)	1.63*** (2.75)	1.64*** (2.77)
Sharpe	0.57	0.58	0.58	0.56	0.58	0.58

The table presents the results of the sensitivity analysis conducted for varying values of 0 and δ in the 12-1 momentum strategy with 10% ST-based exclusions. Each row represents a different combination of the parameters 0 and δ, to the left where 0 stays fixed and to the right where δ stays fixed at the suggested values from Bordalo et al. (2012). The mean monthly raw returns, Sharpe ratios, and the alphas from the CAPM, Fama-French three-factor model, and Carhart four-factor model are provided. T-statistics are enclosed in parentheses, computed utilizing Newey and West (1987) standard errors. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Altering 0, while keeping δ constant at 0.7, also resulted in minor changes in the alpha values. When 0 increases, we see a positive enhancement in all alphas except the Carhart-4 model, which has a downward trend. However, the shifts are minimal here as well, and all performance measures stays within their original given significance levels. Therefore, our results seem robust to small changes in the 0 parameter, which adjusts for the salience of zero-payoff situations.

In summary, the sensitivity analysis affirms the robustness of the model, as evidenced by the consistent small and insignificant changes in the alpha values under various parameter adjustments. This suggests that the model appropriately accounts for different market dynamics, offering a reliable tool to gauge risk-adjusted returns in markets with diverse cognitive abilities and salience perceptions. Given that the case with $0 = 1$ and $\delta = 0.7$ did not distinctly outperform the others, the results alleviate concerns about overfitting bias arising from the selected parameters for computing ST. Moreover, the statistical significance of the alpha values remains consistent and high across all scenarios, reinforcing the model's resilience and dependability amidst these changes.

5.3.2 Extreme market conditions

Having confirmed the ST-based exclusion strategy's improved performance across our entire sample, we will now investigate whether this performance improvement is consistent across all segments of our sample or if it's largely driven by specific segments. This will help us understand any potential implications for different sections of our sample. In this robustness test, we will specifically assess whether the strategy continues to perform well and show improvements in both high-volatility and low-volatility stocks.

Table 5.7: *High and low volatility*

	High volatility		Low volatility	
ST	0%	10%	0%	10%
Ret_{mean}	2.18*** (2.70)	2.23** (2.29)	2.05*** (5.79)	2.02*** (5.18)
CAPM $\hat{\alpha}$	1.92*** (2.38)	2.02** (2.08)	1.83*** (5.04)	1.81*** (4.43)
FF3 $\hat{\alpha}$	2.16*** (2.35)	2.30** (2.09)	1.96*** (5.66)	1.89*** (4.80)
Carhart4 $\hat{\alpha}$	0.88 (0.99)	1.18 (1.07)	1.59*** (4.92)	1.51*** (4.08)
Sharpe	0.40	0.38	1.13	1.02

This table presents the results of a robustness check where the sample is divided into high- and low-volatility stocks in 12-1 momentum strategies utilizing 0% and 10% ST-based exclusions. This is calculated using a rolling window utilizing the stock's past 12-month volatility, and each month split the sample on the median. Values in this table are represented in percentages. It shows the mean monthly raw returns (Mean RET) and the estimated alphas from the CAPM, Fama-French three-factor, and Carhart four-factor models, with their corresponding Newey and West (1987) t-statistics and Sharpe ratios. The market premium factor (MKT) employed in these models is the OSE EW Index in excess of the 1-month NIBOR. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The findings from table 5.7 indicate that performance improvements are exclusive to the sample's high volatility sector, where all the recorded performance metrics, with the exception of the Sharpe ratio, experience an increase. Conversely, for the low volatility sample, the exclusion of extreme ST-stocks negatively impacts all performance measures. This aligns with Cakici and Zaremba (2022) critique, implying that the ST-effect is only operational within high volatility circumstances in the Norwegian market as well.

Momentum strategies have been found to sometimes have detrimental results under market turmoil, often referred to as momentum crashes (Barroso & Santa-Clara, 2015). The exclusion of stocks based on ST could potentially aid in reducing such crashes, given that this effect becomes more pronounced during periods of high volatility. However, in times of market uncertainty when liquidity may dry up, trading costs are often high and the returns may therefore be much lower in actual market settings than it is perceived here.

5.3.3 Microcaps

Additionally, we aim to assess whether the observed performance improvement applies equally to microcaps and larger-cap stocks. Therefore, we split our sample and evaluate the performance measures of the ST-momentum strategy under both these scenarios.

Table 5.8: *Microcaps vs. Larger Cap Stocks*

	Microcaps		Larger Cap Stocks	
ST	0%	10%	0%	10%
Ret_{mean}	1.77*** (2.36)	2.43*** (3.05)	1.74*** (3.18)	1.21*** (2.41)
CAPM $\hat{\alpha}$	1.74*** (2.47)	2.35*** (3.07)	1.64*** (3.20)	1.19*** (2.40)
FF3$\hat{\alpha}$	2.10*** (2.86)	2.67*** (3.19)	1.77*** (3.41)	1.44*** (2.68)
Carhart4 $\hat{\alpha}$	1.20** (1.66)	2.06*** (2.44)	0.59* (1.32)	0.32 (0.70)
Sharpe	0.34	0.50	0.47	0.32

This table presents the results of a robustness check where the sample is divided into microcaps and larger cap stocks in 12-1 momentum strategies utilizing 0% and 10% ST-based exclusions. Microcaps are defined as the lowest market capitalization stocks, which collectively contribute to 3% of total market capitalization. In our sample, this results in an approximately equal number of stocks in each section. Values in this table are represented in percentages. It shows the mean monthly raw returns (Mean RET) and the estimated alphas from the CAPM, Fama-French three-factor, and Carhart four-factor models, with their corresponding Newey and West (1987) t-statistics and Sharpe ratios. The market premium factor (MKT) employed in these models is the OSEAX Index in excess of the 1-month NIBOR. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The data presented in table 5.8 reveals that performance enhancements are solely observable in the microcaps segment of our sample. The 10% exclusions based on ST result in solid performance gains in this segment, with CAPM-, FF3-, and Carhart-4 alphas increasing by 0.61%, 0.57%, and 0.86%, respectively. In contrast, performance measures for larger cap stocks exhibit a downward trend when excluding stocks based on ST. Interestingly, the microcaps segment also demonstrates slightly better results for the overall momentum strategy compared to larger cap stocks. The findings raise concerns regarding the strategy's applicability, given that the effective sector only represents 3% of the total market cap and is characterized by considerably higher transaction costs.

It could be argued that smaller firms, characterized by higher price volatility and limited news coverage, provide more opportunities for salient thinking. Numerous standout prices grab the limited attention of investors, while plausible risk-based explanations for significant price fluctuations often fail to reach them. Furthermore, the elevated returns observed for small-cap stocks might serve as a counterbalance for the increased trading costs typically associated with this segment of the market in practical settings. This concept aligns with Hou et al. (2018), who argues that many recognized anomalies cease to exist when proper adjustments for microcaps are made.

It's crucial to note, however, that there were approximately 20% of companies for which MKT CAP data wasn't available in Refinitiv. Therefore, the two samples collectively represent only around 80% of the total sample. Nevertheless, the majority of the data remains intact, suggesting that the results should largely maintain their reliability.

6. Conclusion

Our research initially demonstrates the promise and potential of a refined momentum strategy where different percentages of stocks with the highest (lowest) salience theory values are removed from the top (bottom) decile portfolios in the Norwegian equity market from 1992-2022. This strategy consistently delivers superior performance, measured by estimated CAPM-, FF3-, and Carhart-4 alphas, compared to the conventional momentum strategies. Interestingly, the enhancements were most notable in the loser portfolio. Moreover, the ST-based exclusions contributes to a decrease in drawdowns, less negative skewness and a drop in kurtosis. The refined strategy therefore seems to reduce the possibilities for large negative returns and momentum crashes.

When considering the practical application of these strategies, we accounted for transaction costs. Despite the superior performance measures for 1-month holding periods, longer holding periods performed better once these costs were factored in. While transaction costs wipe out alphas for several portfolios, our analysis demonstrates some persists, highlighting the importance of selecting an optimal holding period and the significant role cost estimation methods play in shaping perceptions of strategy performance.

Through our robustness checks, we highlight that the enhancements in performance originate mainly from microcaps and occur in high volatility environments. Even though we earlier established considerable improvements in the conventional momentum strategy, the effect only exists where trading is the most difficult and costly. This indicates that implementing these strategies profitably in the Norwegian market could prove difficult, if not impossible, in a practical setting.

For further research, we recommend a deeper investigation into the effects of salience theory in the Norwegian context. Due to the different characteristics of the Norwegian market, another measure of salience may be more appropriate. Another interesting point of interest would be to assess which transaction cost method best mirrors actual costs in Norway, given the limited research and significant impacts on the evaluation of potential strategies. Further deep dives into why it works exclusively for microcaps and high volatility events may also be researched further. Additionally, future research could also consider examining the implications of our findings for value-weighted momentum strategies, which could potentially offer a different perspective on the effectiveness of the ST-based exclusion strategy.

Our research incorporates insights from behavioral finance, considering investors' cognitive limitations as defined by the salience theory. The combination of cognitive biases and momentum investing provides a new perspective on the market phenomena in the Norwegian equity market. This approach provides a stepping stone to exploring more nuanced momentum strategies, pushing the boundaries of our understanding of market dynamics, and improving the practical applicability of investment strategies.

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A. Appendix

Table A.1: *ST-Momentum, excluding extreme 1% ST-stocks*

J	6			12		
K	1	3	6	1	3	6
Ret_{mean}	2.14*** (4.27)	1.77*** (4.14)	1.49*** (3.85)	1.91*** (3.25)	1.41*** (2.55)	1.01** (1.88)
CAPM $\hat{\alpha}$	2.25*** (5.05)	1.68*** (4.25)	1.36*** (3.85)	1.87*** (3.37)	1.32*** (2.55)	0.90** (1.78)
FF3 $\hat{\alpha}$	2.41*** (4.71)	1.99*** (4.67)	1.73*** (4.56)	2.49*** (4.06)	1.91*** (3.51)	1.55*** (2.93)
Carhart4 $\hat{\alpha}$	1.74*** (3.41)	1.34*** (3.28)	1.07*** (3.07)	1.56*** (2.70)	0.99** (2.04)	0.73* (1.55)
Sharpe	0.69	0.62	0.55	0.54	0.40	0.27

Table A.2: *ST-Momentum, excluding extreme 5% ST-stocks*

J	6			12		
K	1	3	6	1	3	6
Ret_{mean}	2.14*** (4.28)	1.77*** (4.39)	1.49*** (3.94)	1.93*** (3.28)	1.46*** (2.64)	1.03** (1.94)
CAPM $\hat{\alpha}$	2.04*** (4.28)	1.68*** (4.59)	1.36*** (3.97)	1.89*** (3.41)	1.37*** (2.67)	0.93** (1.86)
FF3 $\hat{\alpha}$	2.38*** (4.63)	2.00*** (4.89)	1.74*** (4.66)	2.50*** (4.05)	1.99*** (3.68)	1.59*** (3.03)
Carhart4 $\hat{\alpha}$	1.72*** (3.33)	1.35*** (3.46)	1.09*** (3.20)	1.57*** (2.68)	1.08** (2.20)	0.78** (1.67)
Sharpe	0.69	0.64	0.56	0.54	0.42	0.28

Table A.3: *ST-Momentum, excluding extreme 10% ST-stocks*

J	6			12		
K	1	3	6	1	3	6
Ret_{mean}	2.33*** (4.65)	1.77*** (4.45)	1.53*** (4.09)	2.02*** (3.40)	1.41*** (2.58)	1.00** (1.91)
CAPM $\hat{\alpha}$	2.20*** (4.64)	1.67*** (4.62)	1.41*** (4.17)	1.95*** (3.45)	1.31*** (2.59)	0.89** (1.84)
FF3 $\hat{\alpha}$	2.52*** (4.96)	2.00*** (4.97)	1.80*** (4.89)	2.57*** (4.11)	1.95*** (3.66)	1.57*** (3.09)
Carhart4 $\hat{\alpha}$	1.84*** (3.69)	1.39*** (3.59)	1.15*** (3.45)	1.63*** (2.75)	1.04** (2.15)	0.78** (1.70)
Sharpe	0.77	0.65	0.59	0.58	0.41	0.28

Table A.4: *Different exclusion percentages of ST-stocks in 6-1 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.41*** (4.27)	2.34*** (4.14)	2.37*** (4.19)	2.44*** (4.30)	0.03
	CAPM $\hat{\alpha}$	1.32*** (3.76)	1.23*** (3.63)	1.26*** (3.72)	1.34*** (3.88)	0.02
	FF3 $\hat{\alpha}$	0.38* (1.48)	0.34* (1.34)	0.36* (1.44)	0.42* (1.62)	0.04
	Carhart4 $\hat{\alpha}$	0.02 (0.91)	-0.01 (-0.01)	0.02 (0.92)	0.01 (0.25)	-0.01
Loser	Ret_{mean}	0.65 (0.82)	0.21 (0.26)	0.22 (0.28)	0.11 (0.13)	-0.54
	CAPM $\hat{\alpha}$	-0.66* (-1.29)	-1.11* (-2.14)	-1.09** (-2.09)	-1.18** (-2.25)	-0.52
	FF3 $\hat{\alpha}$	-1.93*** (-3.92)	-2.39*** (-4.75)	-2.34*** (-4.64)	-2.42*** (-4.78)	-0.49
	Carhart4 $\hat{\alpha}$	-1.53*** (-3.00)	-2.07*** (-3.87)	-2.02*** (-3.77)	-2.11*** (-3.96)	-0.58
WML	Ret_{mean}	1.76*** (3.39)	2.14*** (4.27)	2.14*** (4.28)	2.33*** (4.65)	0.57
	CAPM	1.66*** (3.34)	2.03*** (4.28)	2.04*** (4.28)	2.20*** (4.64)	0.54
	FF3 $\hat{\alpha}$	1.99*** (3.87)	2.41*** (4.71)	2.38*** (4.63)	2.52*** (4.96)	0.53
	Carhart4 $\hat{\alpha}$	1.23*** (2.46)	1.74*** (3.41)	1.72*** (3.33)	1.84*** (3.69)	0.61
	Sharpe	0.53	0.69	0.69	0.77	0.24

Table A.5: *Different exclusion percentages of ST-stocks in 6-3 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.26*** (4.21)	2.25*** (4.17)	2.23*** (4.18)	2.17*** (4.06)	-0.09
	CAPM $\hat{\alpha}$	1.17*** (3.76)	1.15*** (3.75)	1.13*** (3.81)	1.07*** (3.65)	-0.10
	FF3 $\hat{\alpha}$	0.27 (1.14)	0.26 (1.13)	0.26 (1.15)	0.22 (0.95)	-0.05
	Carhart4 $\hat{\alpha}$	-0.01 (-0.23)	-0.05 (-0.21)	-0.05 (-0.22)	-0.07 (-0.32)	-0.06
Loser	Ret_{mean}	0.65 (0.88)	0.48 (0.65)	0.46 (0.62)	0.40 (0.54)	-0.25
	CAPM $\hat{\alpha}$	-0.67* (-1.58)	-0.84** (-1.98)	-0.86** (-2.10)	-0.92** (-2.22)	-0.25
	FF3 $\hat{\alpha}$	-1.87*** (-4.47)	-2.05*** (-4.91)	-2.06*** (-5.06)	-2.10*** (-5.21)	-0.23
	Carhart4 $\hat{\alpha}$	-1.50*** (-3.48)	-1.71*** (-3.98)	-1.73*** (-4.12)	-1.78*** (-4.31)	-0.28
WML	Ret_{mean}	1.61*** (3.68)	1.77*** (4.14)	1.77*** (4.39)	1.77*** (4.45)	0.16
	CAPM $\hat{\alpha}$	1.52*** (3.75)	1.68*** (4.25)	1.68*** (4.59)	1.67*** (4.62)	0.15
	FF3 $\hat{\alpha}$	1.82*** (4.15)	1.99*** (4.67)	2.00*** (4.89)	2.00*** (4.97)	0.18
	Carhart4 $\hat{\alpha}$	1.12*** (2.70)	1.34*** (3.28)	1.35*** (3.46)	1.39*** (3.59)	0.27
	Sharpe	0.54	0.62	0.64	0.65	0.11

Table A.6: *Different exclusion percentages of ST-stocks in 6-6 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.21*** (4.15)	2.20*** (4.13)	2.19*** (4.15)	2.18*** (4.16)	-0.03
	CAPM $\hat{\alpha}$	1.10*** (3.81)	1.09*** (3.81)	1.08*** (3.85)	1.08*** (3.89)	-0.02
	FF3 $\hat{\alpha}$	0.20 (0.99)	0.20 (1.01)	0.21 (1.04)	0.22 (1.09)	0.02
	Carhart4 $\hat{\alpha}$	-0.05 (-0.27)	-0.06 (-0.28)	-0.05 (-0.23)	-0.03 (-0.15)	0.02
Loser	Ret_{mean}	0.81 (1.14)	0.71 (0.99)	0.70 (0.99)	0.65 (0.92)	-0.16
	CAPM $\hat{\alpha}$	-0.48* (-1.23)	-0.58* (-1.45)	-0.59* (-1.52)	-0.65** (-1.66)	-0.17
	FF3 $\hat{\alpha}$	-1.73*** (-4.55)	-1.84*** (-4.82)	-1.85*** (-4.91)	-1.90*** (-5.15)	-0.17
	Carhart4 $\hat{\alpha}$	-1.32*** (-3.48)	-1.45*** (-3.78)	-1.46*** (-3.88)	-1.50*** (-4.11)	-0.18
WML	Ret_{mean}	1.39*** (3.56)	1.49*** (3.85)	1.49*** (3.94)	1.53*** (4.09)	0.14
	CAPM $\hat{\alpha}$	1.27*** (3.55)	1.36*** (3.85)	1.36*** (3.97)	1.41*** (4.17)	0.14
	FF3 $\hat{\alpha}$	1.61*** (4.21)	1.73*** (4.56)	1.74*** (4.66)	1.80*** (4.89)	0.19
	Carhart4 $\hat{\alpha}$	0.94*** (2.68)	1.07*** (3.08)	1.09*** (3.20)	1.15*** (3.45)	0.21
	Sharpe	0.50	0.55	0.56	0.59	0.09

Table A.7: *Different exclusion percentages of ST-stocks in 12-1 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.56*** (4.68)	2.51*** (4.72)	2.53*** (4.73)	2.53*** (4.74)	-0.03
	CAPM $\hat{\alpha}$	1.40*** (4.06)	1.36*** (4.17)	1.37*** (4.16)	1.39*** (4.15)	0.01
	FF3 $\hat{\alpha}$	0.56** (2.15)	0.56** (2.23)	0.58** (2.26)	0.61*** (2.36)	0.05
	Carhart4 $\hat{\alpha}$	0.16 (0.67)	0.17 (0.75)	0.19 (0.81)	0.21 (0.90)	0.05
Loser	Ret_{mean}	0.85 (1.01)	0.60 (0.71)	0.59 (0.70)	0.51 (0.61)	-0.34
	CAPM $\hat{\alpha}$	-0.54 (-1.00)	-0.80* (-1.46)	-0.81* (-1.48)	-0.85* (-1.51)	-0.31
	FF3 $\hat{\alpha}$	-1.98*** (-3.86)	-2.22*** (-4.26)	-2.22*** (-4.23)	-2.25*** (-4.20)	-0.27
	Carhart4 $\hat{\alpha}$	-1.39*** (-2.73)	-1.69*** (-3.17)	-1.68*** (-3.12)	-1.72*** (-3.11)	-0.33
WML	Ret_{mean}	1.71*** (2.95)	1.92*** (3.25)	1.93*** (3.28)	2.02*** (3.40)	0.31
	CAPM $\hat{\alpha}$	1.65*** (3.00)	1.87*** (3.37)	1.89*** (3.41)	1.95*** (3.46)	0.30
	FF3 $\hat{\alpha}$	2.24*** (3.76)	2.49*** (4.06)	2.50*** (4.05)	2.57*** (4.11)	0.33
	Carhart4 $\hat{\alpha}$	1.25** (2.28)	1.56*** (2.70)	1.57*** (2.68)	1.63*** (2.75)	0.38
	Sharpe	0.47	0.54	0.54	0.58	0.11

Table A.8: *Different exclusion percentages of ST-stocks in 12-3 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.25*** (4.22)	2.27*** (4.28)	2.24*** (4.26)	2.21*** (4.30)	-0.04
	CAPM $\hat{\alpha}$	1.09*** (3.38)	1.11*** (3.47)	1.08*** (3.45)	1.06*** (3.47)	-0.03
	FF3 $\hat{\alpha}$	0.27 (1.11)	0.31* (1.28)	0.29 (1.27)	0.32* (1.38)	0.05
	Carhart4 $\hat{\alpha}$	-0.15 (-0.68)	-0.10 (-0.49)	-0.10 (-0.49)	-0.06 (-0.27)	0.09
Loser	Ret_{mean}	0.96 (1.20)	0.86 (1.09)	0.78 (0.97)	0.80 (1.01)	-0.16
	CAPM $\hat{\alpha}$	-0.39 (-0.78)	-0.50 (-1-02)	-0.58 (-1.17)	-0.54 (-1.10)	-0.15
	FF3 $\hat{\alpha}$	-1.81*** (-3.76)	-1.90*** (-4.06)	-1.99*** (-4.23)	-1.93*** (-4.18)	-0.12
	Carhart4 $\hat{\alpha}$	-1.28*** (-2.71)	-1.39*** (-3.03)	-1.48*** (-3.18)	-1.40*** (-3.05)	-0.12
WML	Ret_{mean}	1.29*** (2.34)	1.41*** (2.55)	1.46*** (2.64)	1.41*** (2.58)	0.12
	CAPM $\hat{\alpha}$	1.19*** (2.28)	1.32*** (2.55)	1.37*** (2.67)	1.31*** (2.59)	0.12
	FF3 $\hat{\alpha}$	1.78*** (3.22)	1.91*** (3.51)	1.99*** (3.68)	1.95*** (3.66)	0.17
	Carhart4 $\hat{\alpha}$	0.83** (1.69)	0.99** (2.03)	1.08** (2.20)	1.04** (2.15)	0.21
	Sharpe	0.36	0.40	0.42	0.41	0.05

Table A.9: *Different exclusion percentages of ST-stocks in 12-6 momentum strategy*

	ST	0%	1%	5%	10%	Diff 10%-0%
Winner	Ret_{mean}	2.09*** (3.98)	2.08*** (3.99)	2.05*** (4.02)	2.05*** (4.06)	-0.04
	CAPM $\hat{\alpha}$	0.93*** (3.02)	0.93*** (3.03)	0.91*** (3.07)	0.91*** (3.13)	-0.01
	FF3 $\hat{\alpha}$	0.14 (0.60)	0.14 (0.62)	0.15 (0.69)	0.18 (0.81)	0.04
	Carhart4 $\hat{\alpha}$	-0.19 (-0.86)	-0.19 (-0.86)	-0.16 (-0.76)	-0.12 (-0.58)	0.07
Loser	Ret_{mean}	1.11* (1.41)	1.07* (1.37)	1.02* (1.32)	1.05* (1.35)	-0.06
	CAPM $\hat{\alpha}$	-0.22 (-0.46)	-0.27 (-0.56)	-0.31 (-0.66)	-0.28 (-0.60)	-0.06
	FF3 $\hat{\alpha}$	-1.67*** (-3-61)	-1.71*** (-3.75)	-1.73*** (-3.83)	-1.69*** (-3.83)	-0.02
	Carhart4 $\hat{\alpha}$	-1.17*** (-2.62)	-1.21*** (-2.77)	-1.24*** (-2.84)	-1.20*** (-2.79)	-0.03
WML	Ret_{mean}	0.98** (1.80)	1.01** (1.88)	1.03** (1.94)	1.00** (1.91)	0.02
	CAPM $\hat{\alpha}$	0.86** (1.69)	0.90** (1.78)	0.93** (1.86)	0.89** (1.84)	0.03
	FF3 $\hat{\alpha}$	1.51*** (2.82)	1.55*** (2.93)	1.59*** (3.04)	1.57*** (3.09)	0.06
	Carhart4 $\hat{\alpha}$	0.68* (1.42)	0.73* (1.55)	0.78** (1.67)	0.78** (1.70)	0.10
	Sharpe	0.26	0.27	0.28	0.28	0.02