Vaasan yliopisto
UNIVERSITY OF VAASA

Tommi Kukkonen

Effectiveness of the relative strength strategy over short and intermediate horizons

Evidence from the Nordic equity markets

School of Accounting and Finance
Master's Thesis in Finance
Master's Degree Programme in Finance

Vaasa 2023

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Tommi Kukkonen
Title of the Thesis: Effectiveness of the relative strength strategy over short and intermediate horizons: Evidence from the Nordic equity markets
Degree: Master of Science in Economics and Business Administration
Programme: Finance
Supervisor: Klaus Grobys
Year: 2023 **Pages:** 66

ABSTRACT:
This master's thesis studies the relative strength strategy in the Nordic stock markets by replicating the influential paper by Zhu, Duan and Tu (2019). Zhu et al. (2019) are the first to study the relative strength strategy in the US equity markets, and therefore this thesis aims to contribute to academic literature by testing the performance and robustness of the relative strength strategy in the Nordic markets by using data from the Danish, Finnish, Norwegian and Swedish stock markets between 1992–2021. The relative-strength measure proposed by Zhu et al. (2019) exploits both the short and intermediate-term past return information and thus it can be seen to share similar characteristics to the well-known short-term reversal and momentum strategies The average monthly returns of the relative strength strategy in the Nordics are calculated and further evaluated with a battery of robustness tests. The results indicate that the relative strength strategy does produce positive abnormal returns in the Nordic stock markets that behave more similarly to the momentum strategy rather than to the short-term reversal strategy. Robustness tests show that the relative strength does not perform as well in the Nordics as it does in the US. Even though the monthly average returns are positive and robust to different market conditions, alternative measures of past performance and the January-effect, the returns are not robust to Carhart's (1997) four-factor model or Fama and French's (2018) six-factor model. Also, the returns diminish significantly after during the post-2000 period, suggesting that the strategy would not be viable in the Nordic stock markets.

KEYWORDS: Short-term reversal, momentum, relative strength

Contents

Figures

Tables

1 Introduction

1.1 Previous studies

Multiple previous academic studies have been able to demonstrate that past performance predicts future performance. Jegadeesh and Titman (1993) show in their research that by buying stocks that have been showing an upward price trend and short-selling stocks that have been showing a downward price trend, an investor can capture robust abnormal returns. Moreover, momentum strategies that buy past winner stocks and sell past loser stocks based on the returns of the past 3–12 months are found to generate economically and statistically significant profits. Particularly, the momentum anomaly is one of the most researched return-based market anomalies and it is widely recognized across multiple asset classes and continents. For example, momentum premium is found to appear on equities (e.g., Jegadeesh & Titman, 1993; Rouwenhorst, 1998; Moskowitz, Ooi & Pedersen, 2012; Geczy & Samonov, 2016), equity indices (e.g., Asness, Liew & Stevens, 1997; Chan, Hameed & Tong, 2000; Moskowitz, et al., 2012), commodities (e.g., Moskowitz, et al., 2012; Asness, Moskowitz & Pedersen, 2013), equities (Baltas and Kosowski, 2013)**,** and bond futures (Moskowitz, et al., 2012), industry portfolios (Moskowitz & Grinblatt, 1999), currencies (e.g., Menkhoff, Sarno, Schmeling & Schrimpf, 2012; Moskowitz, et al., 2012), cryptocurrencies (e.g., Liu & Tsyvinski, 2018) as well as cross-asset momentum between bond market returns and equity market returns (Pitkäjärvi, Suominen & Vaittinen, 2020).

Another return-based phenomenon in the financial markets that has raised interest among academics is the short-term reversal effect. The short-term reversal effect is empirically acknowledged in the financial literature. The short-term reversal strategy is a contrarian strategy based on buying the short-term loser stocks and selling short-term winner stocks. Momentum strategies usually note the short-term reversal effect by ignoring the prior 1-month returns while constructing the momentum portfolio.

While there are conducted plenty of research considering both strategies respectively, there are not many research papers which attempt to combine both the strategies. First to do so were Zhu and Yung (2016), who research the interrelation between momentum and the short-term reversal phenomena. The authors notice a negative relation between medium-term performance and short-term price reversals. They note that stocks that have performed the best on medium-term are more likely to experience price continuation than stocks that have performed the best on short-term only. Moreover, by comparing the short-term reversal and momentum strategies, they conclude that stocks that belong to the momentum loser quintile tend to perform the best in short-term reversal strategies and vice versa. This same pattern can be noticed in firm sizes, during non-January months and during the post-2000 time period.

Han, Zhou and Zhu (2016) propose a trend factor with a cross-section regression approach aiming to simultaneously capture the short-term reversal, long-term reversal and the momentum effect. To do this, the authors exploit moving averages of past prices during multiple different time periods to recognize signals of the mentioned stock market anomalies. Particularly, the authors investigate moving averages from three days up to 1 000 days in their research to obtain the forecasted returns. Moreover, the trend factor is then constructed by buying the stocks with the highest forecasted returns and short selling the stocks with the lowest forecasted returns from the cross-section regression. The authors report statistically significant results for their trend factor strategy, earning an average monthly return of 1.63%. They also report the rend factor to be robust to different firm characteristics, such as size, book-to-market and trading turnover rate.

Zhu, Duan and Tu (2019) study the relation between short and intermediate term performance and propose a simple measure of relative strength over investment horizons by comparing the short-term price trend with the intermediate-term price trend. Specifically, the authors measure the relative strength as the difference between the prior 1-month returns and 1-month lagged prior 11-month returns of an individual stock. This straightforward measure they refer to as “DSI”. Moreover, a zero-cost strategy is composed by utilizing the DSI measure, by buying the stocks that have relatively low DSI and short-selling the stocks that have relatively high DSI measure. The authors refer to this strategy as the relative strength strategy or “DSI strategy”. This same terminology is used throughout this thesis. Furthermore, the authors report that their DSI strategy is able to generate an average monthly return of 2.34% which also outperforms the traditional short-term reversal and momentum strategies. They report that the DSI strategy is robust to different firm characteristics such as size, book-to-market and trading volume. Also, the strong performance is reported to remain robust even during the post-2000 period and different market conditions.

Motivated by the recent research regarding the strategies that aim to combine reversal and momentum effect (Zhu and Yung, 2016, Han et al. 2016, Zhu et al. 2019) the aim of this thesis is to explore whether the effects are evident in a different equity market setting. Specifically, this thesis uses Nordic stocks because while the momentum strategy has been researched in the Nordic markets, the DSI strategy has only been researched in the US equity markets. Additionally, the Nordic stock markets provides a unique sample of stock. As even though the Nordic stock markets are relatively new, the markets have developed significantly during the 1990s and especially the liquidity and size of the markets have increased to a level that the Nordic markets can nowadays be perceived as part of the European core (Grobys and Huhta-Halkola, 2019). Additionally, when compared to other emerging markets, such as Asian and African equity markets, the Nordic markets are widely known for the political stability of the Nordic economies which thus offers a relatively lower risk environment with moderate volatility and increased liquidity (Grobys and Huhta-Halkola, 2019).

All in all, it is extremely important to research the significance of different stock market phenomena with different market settings and samples as many of the anomalies have a possibility to be stock market specific as noted by Fama and French (2008). Therefore, Nordic stock markets provides valuable and insightful research endeavor for the academic research field of stock market anomalies.

1.2 Purpose of the thesis

The purpose of this thesis is to introduce the relative strength strategy over short and intermediate horizons and present its results in a Nordic equity market setting. As the previous research has only focused on the US equity markets, this thesis contributes to the existing literature by showing the effectiveness of the DSI strategy in the Nordic stock markets. Also, previous research regarding the DSI strategy has only been conducted with data until the end of 2017 while this thesis aims to study the effectiveness of the relative strength with the latest data, possibly ending up with different results. As of now this kind of study is yet to be conducted and therefore provides important insight to existing literature regarding relative strength strategies.

This thesis is a scientific replication of Zhu et al. (2019) study. Zhu et al. (2019) are the first to research the relative strength strategy as they utilize the US stock universe. There are few criteria that must be met in order for academic research to be a scientific replication of a prior study: Different (1) sample and (2) population as well as (3) similar but not identical methodology.

Different (1) sample and (2) population: In this thesis, there is used the Nordic stock universe and therefore, utilizes different sample and population.

(3) Similar but not identical methodology: This thesis implements the research with monthly data and therefore some measures such as daily moving average, 5-day max return, the average of five highest daily returns during a month, Amihud's (2002) stock illiquidity measure, and the trend factor by Han, Zhou and Zhu (2016) are not applied in this thesis in contrast to the research by Zhu et al. (2019). Additionally, the Fama and French short term reversal factor returns are not used in regression analysis due to the unavailability of the data, which is currently only available for the US stock universe and not for European or the Nordic stock universe.

1.3 Development of hypotheses

For the DSI-strategy to be valid empirically, its existence must be assessed by testing a set of hypotheses. As this thesis builds on to the prior research of Zhu et al. (2019) regarding their relative-strength strategy by combining the momentum and short-term reversal effects and researching this strategy in the US equity markets, the first hypothesis will be as follows:

H_1 = Relative-strength strategy does produce positive abnormal returns in the Nordics.

As evidenced by Zhu et al. (2019), the short-term reversal, momentum and DSI strategy are very similar in nature since all of the strategies exploit prior price information. Therefore, the performance of the DSI must be tested against the other two strategies. Particularly the performance will be measured in terms of abnormal returns. This leads to the next hypothesis which goes as follows:

H_2= DSI strategy produces higher abnormal returns than the combination of short-term reversal and cross-sectional momentum strategies in the Nordics

Lastly, the robustness of the DSI strategy must be tested and especially its robustness to traditional factor models, different market conditions, January-effect, performance during the post-2000 period and with alternative measures of past performance. This leads to the final hypothesis of this thesis which goes as follows:

H_3 = DSI strategy is robust to traditional factor models, different market conditions, January-effect, performance during the post-2000 period and with alternative measures of past performance

1.4 Structure of the thesis

This thesis is structured as follows. In section 2 there is presented background information regarding momentum, reversal effect, efficient-market hypothesis and various asset pricing models. These previous influential studies and findings are presented to support the reader to thoroughly understand the methodology used in this thesis. Section 3 includes a literature review focusing on previous studies and findings regarding relative strength strategies. Next, in section 4, there is presented the used data and methodology of this thesis. Section 5 presents the results of the empirical analysis. Lastly, section 6 concludes this thesis.

2 Theoretical background

In this section we go through the basic underlying theory regarding the methodology of this thesis. For the reader, it is important to understand the topics presented in this section in order to fully comprehend the analysis and methodology applied in this thesis. First is introduced comprehensive theory regarding market efficiency as well as momentum and reversal effects. After that, there is presented some commonly used asset pricing models.

2.1 Efficient-market hypothesis

Eugene Fama revolutionizes the academic research field of finance being the pioneer to question the so-called equilibrium of capital markets as he published his research of efficient capital markets in 1970. With his empirical work, Fama (1970) found that there can be recognized different forms of market efficiency, and when it is possible to say that markets fully reflect all available information. Fama's (1970) efficient-market hypothesis is simplified to extremity for it to provide a more realistic picture of the informative distribution at the capital markets. Assumptions made in the efficient-market hypothesis are that there are no transaction costs or taxes while also assuming perfect liquidity of securities (Ball, 2009).

Fama (1970) divides his findings of market efficiency to three forms: weak form, semi-strong form, and strong form. The weak form is satisfied when the security prices reflect all historical data, here being past prices and returns (Fama 1970). The semi-strong form is satisfied when the security prices reflect all publicly available information, here being concerned as annual reports together with announcements of results and stock splits, etc. (Fama 1970). The criteria for strong form to hold, is that the security prices should reflect all the relevant information there can possibly be, including inside information (Fama, 1970). This would suggest that all parties in the capital markets would have equal access to equal resources of information and therefore all securities would always be priced as efficient as possible.

Needless to say, that the academic literature opposes the efficient-market hypothesis. While individual investors are responsible for their own investment decisions, whether they are institutional or private investors, they usually have to weigh between their beliefs whether to trust or not, that the market price of the security is accurate. Fama (1991) addresses the efficient-market hypothesis by suggesting that after the construction of the hypothesis, there have appeared anomalies in the capital markets which are against the notion of efficient markets. Fama (1991) also suggests that to dodge the joint-hypothesis problem of the efficient market hypothesis, there must be utilized asset pricing models to jointly test the existence of perfect financial markets.

2.2 Asset pricing models

The efficient-market hypothesis suggests that information should already be reflected in asset prices. However, academics quickly noticed that the theorem is not completely exhaustive and that the market-efficiency and price formation in the financial markets should be researched more thoroughly. Objective of asset pricing models is to fill this void. Asset pricing models are composed to capture the relationship between risk and return of an asset and estimate on how investors price the risk of an asset.

In this sub-section, there is presented the most commonly used asset pricing models in the finance literature. First the capital asset pricing model, hereinafter as the CAPM, by Sharpe (1964), Lintner (1965) and Mossin (1966) is introduced. To build on to that, the CAPM is followed by the three-factor, five-factor and six-factor models by Fama and French (1993, 2015, 2018). These asset pricing models have been picked for this thesis since they are the most popular and commonly used models among academics and also these are the models that are applied in the research methodology of this thesis. Therefore, a thorough understanding of the models is required.

2.2.1 The capital asset pricing model

The CAPM was the first asset pricing model aiming to explain stocks returns in relation to systematic risk. The model is widely recognized among researchers and academics. The CAPM is built up on Markowitz' (1952) modern portfolio theory. The CAPM predicts security's expected excess returns are in a positive linear relation to its systematic risk. The model shows on how risk and return affect each other. In CAPM, the systematic risk of an asset is measured with beta (β). Moreover, the expected return of an asset is purely measured by the excess expected market return scaled with the asset's beta. The equation of CAPM goes as follows.

$$E(R_i) = R_f + \beta_i[E(R_M) - R_f] \tag{1}$$

Where:

$E(R_i)$	=	the expected return of security i,
R_f	=	the risk-free rate,
β_i	=	the beta of security i,
$E(R_M)$	=	the expected market return

While the CAPM is already an overly simplified implementation of asset's risk and return relationship in well-functioning financial markets, the model also poses some assumptions regarding investor behavior and markets structure. The assumptions of the CAPM goes as follows (Bodie, Kane and Marcus, 2018: p. 278).

1. Individual behavior
    a. Investors are rational, mean-variance optimizers.
    b. Their common planning horizon is a single period.

   c. Investors all use identical input lists, an assumption often termed homogeneous expectations. Homogeneous expectations are consistent with the assumption that all relevant information is publicly available.

2. Market structure
   a. All assets are publicly held and trade on public exchanges.
   b. Investors can borrow or lend at a common risk-free rate, and they can take short positions on traded securities.
   c. No taxes.
   d. No transaction costs.

As the CAPM provides insight about the risk and return relationship of stocks, it can still be seen to provide a restrictive outlook of financial markets and the investor behavior. Even though the CAPM is an excellent framework, it has received a lot of critique mainly due to its simplicity. It is argued that there is more to the asset pricing than risk-free rate, asset beta and the market risk premium, and therefore it can be seen that the CAPM oversimplifies the complex relationship between risk and return. Also, the CAPM is originally designed to capture the expected return during a certain time period. However, it was noticed that the framework could also suit for estimating the expected returns over multiple time periods by utilizing time series data. All in all, the critique towards CAPM created the research field of asset pricing models. The more current asset pricing models presented in this thesis are built upon the structure of the CAPM.

2.2.2 Fama-French three-factor model

As the research of asset pricing models evolved, academics started to look for solutions to explain anomalies and phenomena. Research started to focus more on trying to define and specify firm characteristics that could enhance the CAPM as well as to explain more accurately the relationship of risk and expected returns of an asset.

Fama and French (1992, 1993) attempt to explain the cross-sectional variation in average stock returns. Fama and French (1993) notice that there lies little relation between the cross-section of US stock market returns and market betas. The authors present two variables that can be used to capture the risk in stocks. These two variables are the size, which is measured by the market capitalization of a company, and value, which is measured by book-to-market equity. Fama and French (1993) show in their research that these two variables cannot be explained with the CAPM. Therefore, they form their own factor model, called the three-factor model, which includes the size and value factor as well as the market factor from the CAPM. Fama and French (2015) present their three-factor model as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + \epsilon_{it} \tag{2}$$

Where:

R_{it}	=	the return on security or portfolio i at time t,
R_{ft}	=	the risk-free return,
α_i	=	the intercept term,
R_{Mt}	=	the return on the value-weight market portfolio
SMB_t	=	the difference between the returns on diversified portfolios of small and big stocks,
HML_t	=	the difference between the returns on diversified portfolios of high and low B/M stocks,
ϵ_{it}	=	a zero-mean residual.

Treating the parameters as true values rather than estimates. Therefore, if the factor exposures β_i, s_i, and h_i are to capture all variation in expected returns, the intercept term α_i is equal to zero for all securities and portfolios i during time t.

2.2.3 Carhart's four-factor model

Carhart was first to introduce momentum effect into the asset pricing models. Carhart (1997) studies mutual fund performance and notices that the one-year momentum effect can be seen as a performance driver for multiple mutual funds. Thus, Carhart analyzes the effect of the prior one-year returns effect to stock overall performance. Motivated by Fama and French's (1993) three-factor model, Carhart (1997) extends the model by adding a momentum factor (winner minus loser, WML) into it. The Carhart's four-factor model goes as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + w_i WML_t + \epsilon_{it} \qquad (3)$$

Where:

WML_t = the difference between the returns on diversified portfolios of winner and loser stocks of the prior one-year time period.

While the other factors presented are defined as previously. Also, the parameters are treated as true values rather than estimates. Therefore, if the factor exposures β_i, s_i, h_i and w_i are to capture all variation in expected returns, the intercept term α_i is equal to zero for all securities and portfolios i during time t.

2.2.4 Fama-French five-factor model

The three-factor model by Fama and French (1993) evolved research field of asset pricing models. While the relation between market risk, firm size and book-to-market ratio to stock returns were evident, the three-factor model raised discussion on whether it should also include other additional risk factors. It was argued that the three-factor model was still a rather simplified depiction of risk and return and therefore firm profitability and investment profile of a company could serve as a potential new risk factors and enhance the predictive power of the three-factor model (see e.g., Titman, Wei and Xie, 2004; Fama and French, 2006; Aharoni, Grundy and Zeng, 2013; Novy-Marx, 2013).

Motivated by the challenge the three-factor model had received, Fama and French (2015) propose an extended factor model including the two new risk factors: the profitability factor (RMW, robust minus weak) and investment factor (CMA, conservative minus aggressive). The new and enhanced factor model was named as the five-factor model. The equation of the five-factor model goes as follows (Fama and French, 2015).

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t \\ + c_i CMA_t + \epsilon_{it} \end{aligned} \tag{4}$$

Where:

RMW_t = the difference between the returns on diversified portfolios of stocks with robust and weak profitability,

CMA_t = the difference between the returns on diversified portfolios of the stocks of low and high investment firms.

While the other factors presented are defined as previously. Also, the parameters are treated as true values rather than estimates. Therefore, if the factor exposures β_i, s_i, h_i, r_i, and c_i capture all variation in expected returns, the intercept term α_i is equal to zero for all securities and portfolios i during time t.

2.2.5 Fama-French six-factor model

Due to a popular demand, Fama and French (2018) extend their factor model with the momentum factor, WML (winners minus losers). Fama and French (2018) define WML similarly to the value factor, HML, except WML is updated monthly instead of annually, and the sort for portfolios formed at the end of month t −1 is on average return from t −12 to t −2. Fama and French (2018) are skeptical of whether to include the momentum factor into their factor model, due to momentum's lack of theoretical motivation. Eventually, Fama and French (2018) present their six-factor model as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t \\ + c_i CMA_t + w_i WML_t + \epsilon_{it} \tag{5}$$

Where:

WML_t = the difference between the returns on diversified portfolios of winner and loser stocks of the prior one-year time period.

While the other factors presented are defined as previously. Also, the parameters are treated as true values rather than estimates. Therefore, if the factor exposures β_i, s_i, h_i, r_i, c_i and w_i capture all variation in expected returns, the intercept term α_i is equal to zero for all securities and portfolios i during time t.

In spite of Fama and French's (2018) reluctancy of including the momentum factor into their factor model, the six-factor model will be in great use in this thesis. Previous studies have not observed relative strength strategies with the six-factor model. Therefore, the inclusion of the six-factor model provides even more academic insight to this research.

2.3 Stock market anomalies

Securities do not always perform according to the traditional asset pricing models and efficient market hypothesis. These deviations from expected behavior that cannot be explained by traditional theorems and models are referred to as anomalies. The terminology and definition of stock market anomalies were first reported by Thomas Kuhn (1970). As the scientific research evolves all the time, more anomalies occur all the time as well. For instance, Hou, Xue, and Zhang (2020) evidence the number of different stock market anomalies in their research where they test a total of 447 stock market anomalies.

In this sub-section we go through a couple of anomalies that are argued not to be explained by the conventional asset pricing models and are also closely related to the methodology of the relative strength strategy and thus the methodology of this thesis. The presented anomalies in this sub-section are the long and short-term reversal effects and the traditional cross-sectional momentum anomaly.

2.3.1 Long-term reversals

Fama's (1970) efficient-market hypothesis formed the research field of finance towards factor-based asset pricing models but also towards behavioral finance. The efficent-market hypothesis suggests that prices should reflect all the information in the efficient markets. Also, the random walk theory famously documented by Malkiel (1973) suggests that stock prices move randomly and thus the future performance of the stock cannot be predicted from its past performance. Both of these theories ended up being highly contradictive as researchers started to find major fallacies in them and noticed patterns in stock returns and prices that could not be explained by either theory.

In their influential research, De Bondt and Thaler (1985) study market efficiency and investor behavior. The authors report that unexpected events and news cause investors to overreact to the new emerged information. As a consequence, stock prices are reported to reverse over time on the long-term. Specifically, DeBondt and Thaler (1985) notice stocks that have reported prior returns during the last 3 to-5 years, also tend report higher returns over the next 3-to-5-year time period. The authors also suggest a contrarian strategy in which by buying past losers and selling past winners an investor is able to capture robust abnormal returns over 3 to 5-year holding periods.

In their following study, De Bondt and Thaler (1987) continue to find more empirical evidence for long-term reversals. They report that the long-term reversal effect is especially strong during January. The authors show that in terms of risk the long-term reversal strategy cannot be explained by the CAPM. They also note that the long-term reversal effect is not primarily a size effect, even though it can be seen to produce slightly higher returns with small companies especially in the “loser” portfolio.

2.3.2 Short-term reversals

Jegadeesh (1990) contributes to the literature by showing strong evidence of predictable behavior in stock returns based on its past 1-month performance. Particularly, Jegadeesh (1990) reports in hiss study that the worst preforming stocks of the past month tend to earn positive abnormal returns in the following month or week. Concurrently, stocks that have performed the best during the last month usually generate negative abnormal returns in the following month or week. Based on this observation, Jegadeesh (1990) builds a zero-cost portfolio by first sorting stocks to deciles based on their past month’s performance, and then buying the stocks belonging to the lowest decile and short selling the stocks belonging to the highest decile. Evidently, Jegadeesh (1990) was able to find the same reversal effect that De Bondt and Thaler (1985, 1987) were able to capture on long term but with the period being only one month. Based on the reversal effect of the stock’s price trend in a short-term period, Jegadeesh’ (1990) named its strategy as the short-term reversal strategy and since then the short-term reversal effect has attracted a lot of interest among academics and even become one of the most studied return-based market anomalies.

Jeageesh (1990) reported the short-term reversal strategy to be robust to seasonality aspects and the returns to be especially high during January-months, similary to DeBondt and Thaler’s findings (1985, 1987) long-term reversal strategy. Jegadeesh (1990) recorded an average monthly return of 2.20% for its long-short portfolio and as high as 4.37% average monthly return during January-months. As Jegadeesh (1990) recorded the short-term reversal on a one-month period, Lehmann (1990) was able to capture the reversal effect on even a one-week period, suggesting robust performance for the short-term reversal effect.

There has been noted two possible explanations for the short-term reversal strategy: investor overreaction (Jegadeesh and Titman, 1995a; Subrahmanyam, 2005) and asset’s liquidity (Grossman and Miller, 1988; Jegadeesh and Titman, 1995b). The behavioral explanation of investor overreaction is argued to originate from investors’ tendency to excessively interpret new firm specific information such as earnings announcements. The liquidity-based explanation is based on to the notion that market makers influence the liquidity of an individual asset and therefore manipulate its performance (Grossman and Miller, 1988; Jegadeesh and Titman, 1995b). Additionally, small and liquid stocks are found to contribute the most to short-term reversal’s abnormal returns (Avramov, Chordia and Goyal, 2006).

2.3.3 Momentum

The momentum anomaly was first introduced by Jegadeesh and Titman in 1993. Their influential research proposes that investors are able to generate abnormal returns by buying stocks that have performed well in the recent past (winners) and selling stocks that have performed poorly in the recent past (losers). To be specific, Jegadeesh and Titman (1993) divide the sample stocks into decile portfolios on the basis of their performances over the past 3–12 months. Then, based on their recent performance a zero-cost strategy is implemented by buying the recent winners and selling the recent losers. The strategy is based on the idea that stocks that have performed well are likely to continue performing well, while stocks that have performed poorly are likely to continue underperforming. The authors examine the performance of the momentum strategy using data from the US stock market over a period of more than 60 years. To avoid the short-term reversal effect, Jegadeesh and Titman (1993) account for one-month lagged returns when formatting the portfolios.

Jegadeesh and Titman (1993) record statistically significant abnormal returns for their momentum strategies. For example, the average monthly excess returns of their zero-cost strategy based on the prior 12-month performance with a 3-month holding perdio was reported as high as 1.49%. The authors also record the highest average yearly excess returns of 12.01% by selecting stocks based on their previous 6 months performance and holding them for 6 months. In their subsequent work, Jegadeesh and Titman (2001) provide out-of-sample results that were found to be similar to their initial proposition presented in 1993 suggesting robustness of momentum profitability in the US stock market.

Momentum in stock returns presents one of the strongest challenges to the efficiency and rationality of financial markets. Why does buying stocks with the highest returns over the prior six to twelve months and shorting stocks with the lowest returns generate robust profits? As a consequence, most theories of momentum rely on behavioral and cognitive biases of investors.

2.3.4 Behavioral explanations to return-based anomalies

Return-based anomalies, such as the reversal and momentum effect, are generally understood to be generated mostly by irrational behavior, emotional reactions and biases of investors. Two of the main hypotheses which are usually stated as the main explanations for the emergence of the return-based anomalies are overreaction and underreaction of investors.

As new information emerges in the markets, such as news, investors tend to overexaggerate it. This overreaction of investors creates a temporary mispricing of stocks, a continuation pattern in short-term. When more information is received, the returns of the overreacted stocks usually then reverse in the long run and therefore correct over time (Daniel, Hirshleifer and Subrahmanyam, 1998). On the other hand, studies have shown that investors also tend to underreact to different news and events leading to delayed price movements in the stock markets (see e.g., Barberis, Shleifer and Vishny, 1998; Hong and Stein, 1999). According to the underreaction hypothesis, investors do not fully incorporate the new information into the valuation of the company right away.

However, as with the overreaction in hypotheses, the delayed price movements tend to correct over time as more information emerges in the markets.

One would think that this irrational behavior would only occur among private individual investors. However, this is not the case, as there have been studied that both the overreaction and underreaction have been reported among institutional investors as well. Gutierrez and Pinsky (2007) argue that overreaction and underreaction among institutional investors is due to the possible incentives of portfolio managers, which influence their behavior maintain the portfolio returns close to or deviate from market index returns. In the case where the portfolio manager aims their portfolios to perform similarly to the market index they might neglect the firm-specific information they have as generating positive alpha might require them to shift their positions towards individual stocks.

3 Literature review

In this section there is presented previous literature regarding short-term reversals, momentum, and relative strength strategies which all relate closely to the relative strength strategy proposed by Zhu, et al. (2019) and thus the research setting and methodology of this thesis as well.

3.1 Replicating anomalies

Hou, et al. (2020) examine the robustness and replicability of various stock market anomalies. The authors analyze 447 previously documented anomalies across global stock markets and find that the vast majority of these anomalies are not statistically significant after taking into account various factors such as data snooping and publication bias. To address potential data snooping biases, the authors implement a number of statistical tests that correct for multiple testing and other data-mining issues. Their results show that only a small number of previously documented anomalies hold up to these tests, and even those that do have economically small effects.

Hou et al. (2020) conclude that most anomalies in the stock market are likely the result of data snooping biases or other statistical artifacts, rather than true market inefficiencies that can be exploited by investors. They suggest that future research should focus on developing more robust methods for identifying genuine market anomalies, and caution against relying on the results of studies that do not account for data snooping biases.

Overall, Hou et al. (2020) research provides a comprehensive analysis of the replicability of anomalies in global stock markets and highlights the importance of careful statistical methods in financial research. Relatedly, Grobys (2021) argues that research results in finance are subject to sample-specificity because the variance of variance remains undefined. Statistically significant investment strategies could be simply a noise that is mistaken for some signal. Hence, it is important to explore whether reported research results are specific to some sample.

3.2 Combining reversals with momentum

As plain momentum aims to capture the price trend from an intermediate horizon and reversal effects do this over short and long-term horizons, researchers have been desperate on trying to form strategies to capture those returns from all three price trends.

Zhu and Yung (2016) investigate the interaction between short-term reversal (Jegadeesh, 1990) and momentum trading strategies (Jegadeesh and Titman, 1993) by researching how the two strategies interrelate with each other and if a joint strategy would generate significant returns. The authors conduct their study all common stocks listed on the NYSE, AMEX and Nasdaq with an observation period running from January 1965 until December 2013. The main finding of their research is that short-term reversal returns are heavily influenced by the stocks' past medium term performance. In fact, they report that stocks that have performed the best during the past 1-month period experience larger price reversals if they have also performed the worst during the previous 6-12 months' time period. In other words, the momentum loser stocks record the highest short-term reversal returns whereas short-term winner stocks record the highest short-term reversal returns. They also test the robustness of their findings and notice that size, different market states, and non-January periods do not affect the performance. Moreover, their findings are also robust during the post-2000 period. These findings suggest that the momentum and short-term reversal strategies can be seen as more unified than previous literature has been able to show.

Han, Zhou and Zhu (2016) present a trend factor based on utilizing the information in moving averages prices. The authors report that their trend factor strategy is able to outperform the well-known short-term reversal (Jegadeesh, 1990), momentum

(Jegadeesh and Titman, 1993), and long-term reversal factors (DeBondt and Thaler, 1985). They incorporate a unique framework based on daily data of moving averages prices of all common stocks listed on the NYSE, AMEX and Nasdaq with an observation period running through from January 1926 until December 2014. Their trend factor is constructed by first calculating the stocks moving average prices on the last trading day of the month and then by normalizing the moving average price with the closing price of the last trading day of the month. Then the authors run a cross section regression on the trend signals, normalized moving average prices, to obtain time-series of the coefficients. Lastly, they implement a predictive model based on the estimated expected coefficient of the trend signal which they calculate as the 12-month average of the estimated loadings on the trend signal. The author report that with this framework they are able to detect stocks that will perform better in the future. As they form quintile portfolios based on the trend signal, they report a zero-cost strategy to record an average monthly raw return of 1.63 over the observation period., which also outperforms the short-term reversal, long-term reversal and momentum strategies. Han et al. (2016) also report significantly higher returns for their trend factor during the financial crisis period. They also find their trend factor to be robust after controlling for various explanatory variables, such as size, value, trading turnover and alternative formations.

3.3 Relative strength strategy

Relative strength strategy is similar to the more traditional momentum strategy of cross-sectional momentum, and time-series momentum, but there are some underlying differences between them. As in cross-sectional momentum by Jegadeesh and Titman (1993), the returns are measured based on the relative performance over some prior period and in time-series momentum strategies the returns are measured in absolute basis. Moreover, the relative strength strategy proposed by Zhu et al. (2019) combines the short-term reversal and the cross-sectional momentum strategies on prior short and intermediate horizons.

Zhu et al. (2019) study the relative strength over short and intermediate horizons. The authors propose a simplified and straightforward measure for relative strength which they call as the DSI measure. The DSI measure is based on the stock's past short and intermediate term returns and is calculated as the difference between the past 1-month and lagged past 11-month (from month t – 12 to t – 2) cumulative returns. By first dividing the stocks into two groups based on whether the stocks DSI is positive or negative. Then, by sorting the stocks based on the magnitude of DSI, the authors compose a strategy which takes a long position in stocks with the lowest DSI and short sells those with the highest DSI. The authors find their DSI strategy as a simplified version of previous studies, as for example strategies proposed by Han et al. (2016), and Zhu and Yung (2016) rely on sophisticated statistical models whereas the DSI strategy only relies on simple return data of an individual stock. Another advantage that arises from the simplicity of the strategy is that it does not require double-sorting as the DSI is calculated by deducting the past 11-month cumulative returns from the past 1-month return.

The DSI strategy by Zhu et al. (2019) provides intriguing evidence that relative strength over short and intermediate horizons can significantly predict future returns. Zhu et al. (2019) conduct their research with a comprehensive dataset consisting of all common stocks listed in the NYSE, AMEX and Nasdaq running from January 1967 until December 2017. The authors report their DSI strategy to record an average month raw return of 2.34% with a t-stat of 11.23. This robust monthly return also outperforms the simple cross-sectional momentum strategy (Jegadeesh and Titman, 1993) and short-term reversal strategy (Jegadeesh, 1990) which they report to record average monthly raw returns of 1.06% (t-stat of 5.92) and 1.10% (t-stat of 4.51) respectively, over the observation period. Moreover, Zhu the return of the DSI strategy is reported to be larger than the simple sum of the momentum and short-term reversal strategies' returns, which thus suggests that the DSI measure holds more predictive power over future returns than prior 1-month return and 1-month lagged cumulative 11-month returns do on their own.

Prior behavioral finance studies inspired Zhu et al. (2019) in their composition of the DSI measure and basing it to the prior short and intermediate-term stock returns as it is widely recognized that investors tend to underreact to new information (see e.g., Edwards, 1968; Lord, Ross and Lepper, 1979; Daniel et al., 1998). Zhu et al. (2019) suggest that temporary market shocks and short squeezes create temporary price pressure on stocks. This price pressure, whether it is up or down, is then neglected by conservative and underreacting investors which then consequently steer prices towards their long-term trend. Moreover, the authors conclude that it is sensible to assume that conservative investors would follow the long-term price trend and therefore buy the stocks with the lowest DSI and short sell the stocks with the highest DSI.

However, as Zhu et al. (2019) conduct their analysis with only stocks listed in the United States and also report for major drawdowns with their strategy during the financial crisis period, their DSI strategy calls for more empirical evidence.

4 Data and methodology

In this section there are presented the data and methodologies that are applied in this thesis providing a comprehensive overview of the research design, data sources, data collection techniques, sample selection, and statistical tools used to format the portfolios and research the performance of the relative strength strategy in the Nordics. Since this thesis is a scientific replication of the research paper "Relative strength over investment horizons and stock returns" by Zhu et al. (2019), especially the methodologies are designed to keep fairly similar to their research in order for this thesis to be in line and as comparable as possible. However, for some parts, the research methodologies of this thesis are improved or adjusted accordingly compared to Zhu et al. (2019) research. These dissimilarities are acknowledged throughout this section.

This section consists of two parts. First, the gathered data sample and descriptive statistics of it is presented thoroughly. Next, the methodologies of portfolio formation and performance are presented.

4.1 Data

The empirical analysis of this thesis focuses on the Nordic stock markets of Denmark, Finland, Norway, and Sweden. The Icelandic stock market is excluded from this thesis due to the relatively smaller size of the market compared to other Nordic countries. Nordic stock markets provide an interesting universe for research since it is often neglected in financial literature as most of the research focuses on the US. and European stock markets. Thus, some of the originality of this thesis is provided by its focus on the Nordic stock markets.

The gathered data set comprises of monthly returns, market values, trading volumes and book-to-market ratios. Additionally, number of shares outstanding is recorded for all stocks but only on annual basis due to limited availability of the data. All observations are recorded from January 1992 to December 2021, resulting in total of 29 years' worth of data. In terms of the length of the time series, the amount can be considered sufficient as previous studies by Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), and Asness et al. (2013) utilize data for over 24, 32, and 39 years of time periods, respectively.

The universe of stocks comprises of all primarily listed stocks of Nasdaq OMX Copenhagen, Helsinki, Oslo, and Stockholm. Stocks listed on Nasdaq OMX first North Growth market are excluded from the scope of this research since due to their generally smaller size and lower liquidity. Additionally, financial companies are excluded from the sample and companies with no observations in one or more variables during the last twelve months of the time series are excluded from the total sample, as these are unusable in this thesis. Furthermore, stocks that are delisted during the observations period are given NA values after the date of delisting, thus sold at its closing price. Stocks that have gone bankrupt are reported with -100% returns at the end of the holding period. This differs slightly from Zhu et al. (2019 study where they set -30% delisting returns for stocks listed on NYSE and AMEX and -50% delisting returns for stocks listed on NASDAQ. Lastly, both A and B shares are included in the sample, as these are both tradable stocks, even though they do increase the correlation between companies.

All in all, this data set provides us with a robust view of the Nordic stock markets comprising of more than 1500 stocks during the total time period. In table 1 there is presented descriptive statistics of the stocks in the total sample. It is worth noting that Sweden contributes to the majority of the sample as it holds the most stocks during the whole time period and its average market value in total is almost double the average market value of Denmark, Finland and Norway, respectively. Therefore, Swedish stocks have a significant impact on the research results.

All stock-related, interest rate and market index data are gathered from Thomson Reuters Datastream. Fama-French factor data for European stocks is gathered from Fama and French website. As the factor returns are calculated withs US dollars, the returns of the Nordic stocks in the sample are calculated in US dollars as well. Baker and Wurgler (2006) investor sentiment index data is gathered from Jeffrey Wurgler's (2023) website.

To alleviate the effects of illiquidity, the stocks listed on the First North Growth Market are excluded from the sample, which tend to be much smaller on size and trading volume than he stocks listed on the main lists of the Nordic stock exchanges. Lastly, to ensure consistency in the research between Nordic markets, all returns and other stock-related data are noted in US dollars.

Table 1. Descriptive statistics of the total sample

This table reports the descriptive statistics of the total sample of the Nordic stocks. The maximum, minimum and average number of stocks as well as the average market value in total (noted in US dollars) are reported on this table. The data samples all main listed companies from the Danish, Finnish, Norwegian and Swedish stock markets. The data period is from January 1993 to December 2021.

Measure	Denmark	Finland	Norway	Sweden	Total
Max # of stocks	146	141	221	381	825
Min # of stocks	97	37	63	112	316
Average # of stocks	118	115	145	264	643
Average market value in total ($M)	151 190	171 492	147 001	300 763	770 447

Since the thesis requires to combine four different markets into one entity, a combined market index is created to depict the Nordic market. Following Grobys and Huhta-Halkola (2019), a combined market index is created by equally weighting the monthly returns of the all-share indexes of Nasdaq OMX Copenhagen, Helsinki, Oslo, and Stockholm. To account for dividend payments and cash contributions, there is primarily used the total return indexes of the respective stock exchanges. Due to limited data availability, the price indices are used instead. Additionally, as all stock returns are adjusted with the USD foreign exchange rate changes, the same adjustment is also done to the Nordic market index returns.

Below in Figure 1, there is presented the indexed returns of all four Nordic stock exchanges and the equally weighted average, the Nordic market index, from the beginning of 1992 until the end of 2021.

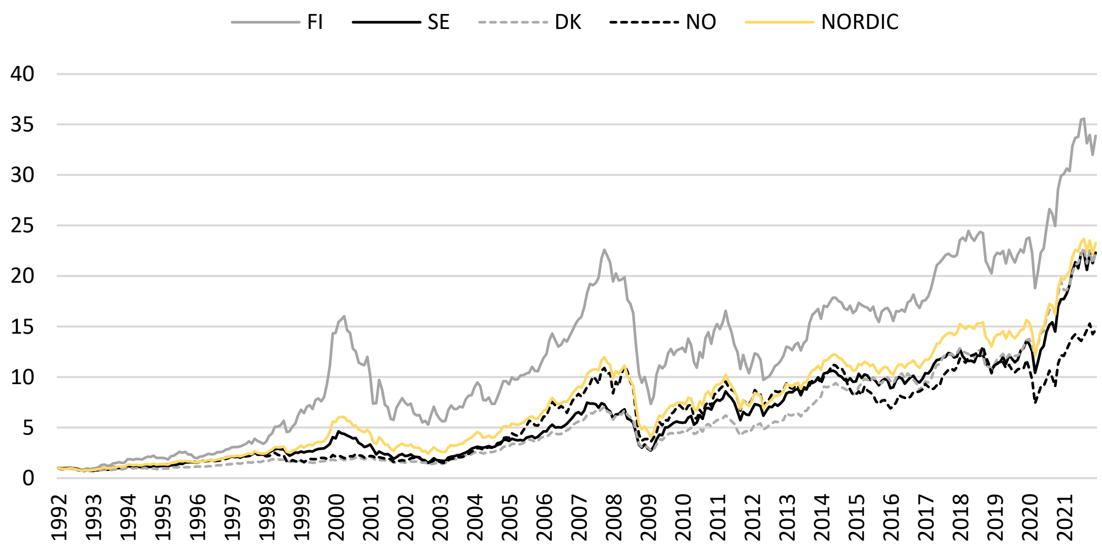

Figure 1. Historical indexed returns of Nordic stock indices

The indexed returns show that Finnish stock market has performed the best whereas the other three markets, Denmark, Norway and Sweden, have performed more similarly to each other. Therefore, the Nordic market index returns also sets to a that level.

4.2 Methodology

The purpose of this thesis is to test the performance and robustness of the relative strength strategy by Zhu et al. (2019) in the Nordic stock markets. Zhu et al. (2019) introduced the relative strength strategy to academia by researching it in the US stock markets. The main goal of this thesis is to test whether the similar return anomaly can be recognized in the Nordic stock markets and whether the strategy can provide robust returns in spite of the underlying market sentiment. This thesis follows a similar methodology to the Zhu et al. (2019) study, but some adjustments are applied due to the limitation of the available data. For example, as there is used monthly data to conduct this thesis, opposed to the daily data that Zhu et al. (2019) use, some measures such as daily moving average, 5-day max return, the average of five highest daily returns during a month, Amihud's (2002) stock illiquidity measure, and the trend factor by Han, Zhou and Zhu (2016) are not applied in this thesis. Additionally, the Fama and French short-term reversal factor returns are not used in the regression analysis of this thesis due to the unavailability of the data, which is currently only available for the US stock universe and not for European stock universe and also due to the fact that Zhu et al. (2019) did not find statistical significance between the DSI returns and short-term reversal factor returns.

In this thesis the main comparison is done between three different strategies: the DSI, momentum and the short-term reversal strategy. The comparison is done between these three strategies because, Zhu et al. (2019) focus their research on the same three strategies and this thesis aims to follow their methodology as accurately as possible. Similarly, the returns for the momentum strategy are calculated in a similar manner to how Jegadeesh and Titman (1993) conducted their research. Particularly, the effect of the limitations of using the monthly stock data instead of daily data are minimized by focusing on the three strategies as they all can be conducted with monthly data as well. Momentum returns are calculated by first sorting each individual stock by their one-month lagged 11-month returns. Then, the sorted stocks are divided into quartile portfolios based on the calculated 11-month returns. A zero-cost strategy is performed by buying the stocks that belong to the lowest quartile or, in other words, that have had the highest past lagged 11-month returns and selling the stocks that belong to the highest quartile. The short-term reversal strategy is conducted similarly but there the stocks are first sorted based on their past 1-month returns and the zero-cost strategy buys the recent loser stocks and sells the recent winner stocks.

The relative strength measure, here-in after as the DSI measure, constructs of two parts and takes into account the stock's performance during a short and intermediate time-period. The DSI measure is calculated as the difference between past 1-month return (t–1) and lagged past 11-month (from month $t - 12$ to $t - 2$) cumulative return, as presented in equation 6.

$$DSI_{t-1} = Ret_{t-1} - \sum_{t=2}^{12} Ret_t \tag{6}$$

After calculating the DSI measures of each individual stock, all sample stocks are divided to two groups based on whether the DSI is positive or negative. Then, within each group, all stocks are equally sorted into two groups based on the magnitude of DSI measure. This leads us to a total of 4 portfolios.

To evaluate the performance of the DSI strategy, asset pricing models, including CAPM (Sharpe, 1964, Lintner, 1965, Mossin, 1966), Fama-French three-factor model (Fama & French, 1993), Carhart's four-factor model (1997), Fama-French five-factor model (Fama & French, 2015) and Fama-French six-factor model (Fama & French, 2018) are used to test whether momentum, short-term reversal or DSI-strategy produce abnormal returns, using the OLS regression.

A battery of robustness tests is applied to the DSI strategy to evaluate its performance. DSI strategy's portfolio returns are calculated for different sub-periods, for January and Non-January months and with alternative measures of intermediate-term returns. Additionally, the DSI, momentum and short-term reversal strategies' returns' longevity is estimated with an event study as well as the top 20 worst monthly performances of the DSI and momentum strategy are calculated in order to study the robustness of the returns.

In order to assess the performance of the DSI strategy and control for different market conditions, a predictive regressions model is applied similarly to the methodology of the Zhu, et al. (2019) research. Two different estimates for the market conditions are thus applied in a predictive setting, a down-market dummy variable and Baker and Wurgler's (2006) composite investor sentiment index. The down-market dummy variable is set to take a value of 1 if the past three-month Nordic market index returns are negative during the portfolio formation period, and 0 if the return is positive. The applied predictive regression model is presented in equation 7.

$$RDSI_{it} = \alpha_i + \beta_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + w_i WML_t + b_i SNTM_{t-1} + d_i DOWN_{t-a} + \epsilon_{it} \tag{7}$$

Where:

$RDSI_t$ = the returns of the long-short portfolio based on DSI

$SNTM_{t-1}$ = the Baker and Wurgler (2006) composite investor sentiment index,

$DOWN_{t-1}$ = the down-market dummy variable.

5 Results

In this section, there is presented the findings of the empirical analysis. The section starts with presenting the portfolio returns of the DSI, short-term reversal and momentum strategies. Furthermore, the characteristics of the DSI portfolio firms are presented. After that, the performance of the DSI strategy against different market conditions is assessed. This is then followed by the robustness tests and performance evaluation of the DSI strategy in comparison to the short-term reversal and momentum strategies.

5.1 Portfolio returns

In Table 2, we can see that the returns of the sorted DSI portfolios monotonically and negatively vary with DSI, suggesting a linear relation between DSI and portfolio returns. The highest DSI portfolio records the lowest average monthly return of -1.80% and the lowest DSI portfolio records the highest average monthly return of -0.22%. The zero-cost portfolio (Low-High) thus records statistically significant average monthly return of 1.58% with a t-statistic of 6.36. Also, we can see that the volatility of the returns is also the lowest for the low-high portfolio, with a value of 4.64%. This suggests that the DSI strategy can significantly predict future returns in the Nordic stock market.

In terms of risk-adjusted returns, the Sharpe ratio of the low-high portfolio's average monthly return is only 0.34, suggesting that the risk-adjusted return of the DSI strategy is rather weak, however, Zhu et al. (2019) record a similar level of Sharpe ratio of 0.48. Both the low and high as well as low-high portfolios generate statistically significant alphas for various factor models, suggesting that the used factor models of CAPM, FF3, Ff4, FF5 or FF6 cannot statistically explain the predictability of the returns generated by the DSI strategy.

Table 2. Returns on portfolios of stocks sorted by DSI (equal-weighted)

This table reports the minimum, maximum and average monthly raw returns, average monthly factor-adjusted returns, as well as descriptive statistics related to the raw returns on equal-weighted portfolios of stocks sorted by DSI. Measures are recorded for all four quartile portfolios, low denoting the lowest quartile and high denoting the highest quartile, and for the zero-cost portfolio, low-high. CAPM denotes the market-adjusted returns according to the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966), FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the Carhart's (1997) four-factor model, FF5 denotes the alphas with respect to the Fama-French (2015) five-factor model, and FF6 denotes the alphas with respect to the Fama-French six-factor model. Newey and West (1987) t-statistics are reported in parentheses.

Measure	**Low**	**2**	**3**	**High**	**Low–High**
Min	-26.76	-25.43	-27.13	-27.87	-20.87
Max	45.34	19.39	18.18	28.39	24.85
Mean	-0.22	-0.84	-1.32	-1.80	1.58
	(-0.59)	(-2.74)	(-4.13)	(-4.37)	(6.36)
Std. Dev.	6.77	5.72	5.95	7.68	4.64
Sharpe ratio	-0.03	-0.15	-0.22	-0.23	0.34
Skewness	0.61	-0.16	-0.12	0.31	-0.16
Kurtosis	6.48	1.62	1.88	1.68	4.19
CAPM	-0.87	-1.41	-1.91	-2.52	1.65
	(-3.58)	(-7.01)	(-9.25)	(-8.86)	(6.61)
FF3	-0.96	-1.52	-2.04	-2.68	1.72
	(-4.60)	(-9.00)	(-11.52)	(-10.72)	(6.92)
FF4	-1.21	-1.66	-1.89	-2.24	1.03
	(-5.66)	(-9.48)	(-10.31)	(-9.01)	(4.55)
FF5	-1.06	-1.58	-1.97	-2.34	1.28
	(-4.80)	(-8.87)	(-10.48)	(-9.04)	(5.00)
FF6	-1.23	-1.67	-1.87	-2.07	0.84
	(-5.56)	(-9.27)	(-9.84)	(-8.15)	(3.61)

Table 3 is constructed in the same manner as table 2, but it represents the value-weighted portfolios. In contrast to the equal-weighted portfolios, the value-weighted high DSI portfolio does not record the lowest monthly average returns, but in this case the 3rd quartile portfolio records the lowest average monthly returns, suggesting that the DSI does not optimize the returns of the zero-cost strategy as efficiently as in the equal weighted portfolio setting. However, the low-high portfolio still records a positive monthly average return of 1.02% with a t-statistic of 2.78, implying that the return is statistically significant, similarly to the equal-weighted low-high portfolio. Again, the

Sharpe ratio of the low-high portfolio is fairly small (0.15) but here the Carhart's four factor model (FF4) and the Fama and French six-factor model record alphas significantly closer to zero, 0.16% and 0.05% respectively, implying that those regression models and especially the momentum factor can statistically predict the returns of the DSI strategy. This is contrary to the findings of Zhu et al. (2019) research, which did not find the traditional factor-models to predict DSI returns.

Table 3. Returns on portfolios of stocks sorted by DSI (value-weighted)

This table reports the minimum, maximum and average monthly raw returns, average monthly factor-adjusted returns, as well as descriptive statistics related to the raw returns on value-weighted portfolios of stocks sorted by DSI. Measures are recorded for all four quartile portfolios, low denoting the lowest quartile and high denoting the highest quartile, and for the zero-cost portfolio, low-high. CAPM denotes the market-adjusted returns according to the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966), FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the Carhart's (1997) four-factor model, FF5 denotes the alphas with respect to the Fama-French (2015) five-factor model, and FF6 denotes the alphas with respect to the Fama-French six-factor model. Newey and West (1987) t-statistics are reported in parentheses.

Measure	Low	2	3	High	Low–High
Min	-25.92	-30.49	-24.75	-25.51	-27.72
Max	37.12	55.75	32.96	39.65	23.51
Mean	0.26	-0.48	-1.06	-0.76	1.02
	(0.69)	(-1.33)	(-2.79)	(-1.69)	(2.78)
Std.Dev	7.03	6.73	7.07	8.39	6.84
Sharpe ratio	0.04	-0.07	-0.15	-0.09	0.15
Skewness	0.29	1.33	0.12	0.40	-0.15
Kurtosis	2.87	14.62	2.38	2.11	2.40
CAPM	-0.41	-1.06	-1.74	-1.56	1.15
	(-1.59)	(-3.87)	(-6.78)	(-5.05)	(3.13)
FF3	-0.37	-1.05	-1.73	-1.59	1.21
	(-1.54)	(-3.95)	(-6.81)	(-5.20)	(3.32)
FF4	-0.84	-1.16	-1.52	-0.99	0.16
	(-3.50)	(-4.16)	(-5.76)	(-3.31)	(0.47)
FF5	-0.60	-1.11	-1.63	-1.37	0.76
	(-2.36)	(-3.91)	(-6.04)	(-4.24)	(1.99)
FF6	-0.92	-1.18	-1.49	-0.97	0.05
	(-3.69)	(-4.08)	(-5.43)	(-3.11)	(0.16)

In table 4, there is reported the same measures as in table 2 and 3 but for the value-weighted momentum and short-term reversal portfolios. First, we can conclude that neither the short-term reversal nor the momentum strategy record statistically significant positive average monthly returns overs the time period as the momentum strategy records average monthly return of 0.69% with a t-statistic of 1.77 and the short-term reversal strategy records average monthly return of 0.26% with a t-statistic of 0.85. Thus, we can conclude that the DSI strategy outperforms the momentum and the short-term reversal strategy over the sample period. Also, the FF4 and FF5 factor-adjusted alphas are statistically insignificant for the momentum strategy, implying that the FF4 and FF5 model hold predictive over the momentum strategy's returns. For short-term reversal, all of the factor models record statistically insignificant alphas, meaning that all of the used factor models can predict the returns of the short-term reversal strategy.

Table 4. Value-weighted returns of momentum and short-term reversal portfolios

This table reports the minimum, maximum and average monthly raw returns, average monthly factor-adjusted returns, as well as descriptive statistics related to the raw returns of momentum and short-term reversal portfolios. Returns of the momentum portfolio are calculated as the cumulative 1-month lagged 11-month returns of the simple momentum strategy by Jegadeesh and Titman (1993). Returns of the short-term reversal portfolio are calculated as 1-month lagged monthly returns of a traditional short-term reversal strategy by Jegadeesh (1990). Measures are recorded for two quartile portfolios, Long denoting the long-leg of the portfolio and Short denoting short-leg of the portfolio and L-S denoting the zero-cost portfolio, long-short. CAPM denotes the market-adjusted returns according to the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966), FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the Carhart's (1997) four-factor model, FF5 denotes the alphas with respect to the Fama-French (2015) five-factor model, and FF6 denotes the alphas with respect to the Fama-French six-factor model. Newey and West (1987) t-statistics are reported in parentheses.

	Momentum			**Short-term reversal**		
Measure	**Long**	**Short**	**L-S**	**Long**	**Short**	**L-S**
Min	-24.02	-29.00	-42.79	-35.64	-22.10	-24.31
Max	25.63	46.78	25.30	44.18	26.98	27.32
Mean	0.16	-0.53	0.69	0.02	-0.24	0.26
	(0.44)	(-1.09)	(1.77)	(0.05)	(-0.64)	(0.85)
Std.Dev	6.72	9.07	7.25	8.18	7.04	5.81
Sharpe ratio	0.02	-0.06	0.09	0.00	-0.03	0.05
Skewness	-0.06	0.65	-0.74	0.40	0.47	0.28
Kurtosis	0.98	3.77	4.98	3.90	1.37	4.46
CAPM	-0.51	-1.39	0.88	-0.76	-0.96	0.20
	(-2.16)	(-4.12)	(2.29)	(-2.53)	(-4.06)	(0.64)
FF3	-0.48	-1.37	0.89	-0.76	-0.88	0.11
	(-2.17)	(-4.11)	(2.31)	(-2.62)	(-3.91)	(0.37)
FF4	-0.97	-0.45	-0.52	-0.52	-0.96	0.44
	(-4.51)	(-1.48)	(-1.67)	(-1.71)	(-4.07)	(1.37)
FF5	-0.70	-0.91	0.21	-0.51	-0.86	0.35
	(-2.99)	(-2.62)	(0.53)	(-1.67)	(-3.59)	(1.05)
FF6	-1.03	-0.31	-0.72	-0.38	-0.93	0.55
	(-4.63)	(-0.98)	(-2.27)	(-1.21)	(-3.79)	(1.65)

5.2 Characteristics of the DSI portfolio firms

To understand more thoroughly the relative strength over short and intermediate horizons, the characteristics of the four DSI portfolios' firms are presented in table 5. A linear relation between DSI and size, value, prior 1-month, 11-month and 6-month returns, respectively, can be seen throughout the four portfolios sorted on DSI. The low-DSI portfolio firms include the largest sized companies, with the lowest book-to-market ratios and past 1-month returns, as well as the highest 1-month lagged past 11-month and 6-month returns and the highest number of shares outstanding and turnover by volume, on average. In other words, the low-DSI firms are generally the most liquid, large-sized and high-value firms with relatively strong intermediate-term performance and poor short-term performance. Whereas the high-DSI firms are in general the exact opposite. Interestingly, Zhu et al. (2019) record similar results, but they note that the low-DSI stocks have generally higher book-to-market ratios than high-DSI stocks.

Table 5. Characteristics of the DSI portfolio firms

This table reports the firm characteristics of the stock in the four DSI portfolios. Particularly, the average monthly mean values of DSI, size, book-to-market ratio (BM), past one-month returns (Ret 1m), one-month lagged past 11-month returns (Ret 11m), lagged past six-month returns (Ret 6m), number of shares outstanding (S/O), turnover by volume (VOL) and the average number of stocks across each portfolio in each month are reported

Portfolio	**DSI**	**SIZE**	**BM**	**Ret 1m**	**Ret 11m**	**Ret 6m**	**S/O**	**VOL**	**N**
Low	-80.12	1 410	0.60	-3.54	76.49	39.31	165 326	3 341	170
2	-14.69	1 509	0.72	-2.86	11.82	7.24	178 853	3 212	169
3	10.94	1 002	0.83	-1.70	-12.60	-5.50	143 817	3 175	133
High	46.71	439	1.07	5.93	-40.79	-22.69	101 687	2 707	134

The high (low) intermediate-term past returns of the low-DSI (high-DSI) portfolio suggest that those same stocks would typically be included into the long leg (short leg) of the momentum portfolio as well, suggesting that the firm characteristics between the two strategies are rather similar. Additionally, as the past 1-month returns are the smallest (highest) for the low-DSI (high-DSI) portfolio, this suggests that these stocks would also be included into the long-leg (short-leg) of a short-term reversal strategy and thus explains the efficiency of the DSI strategy capturing short and intermediate term information in portfolio formation.

5.3 Sensitivity to different market conditions

Previous academic research has shown that momentum strategies generate higher returns after periods of high investor sentiment and upward-trend markets (see e.g., Antoniou, Doukas and Subrahmanyam, 2013; Cooper, Gutierrez and Hameed, 2004; Wang and Xu, 2015). Also, short-term reversal strategies have been shown to perform better following down markets and that investor sentiment significantly explains the reversal of short-term winners (see e.g., Hameed, Kang and Viswanathan, 2010; Da, Liu and Schaumburg, 2014). Since the DSI captures both the short-term and intermediate-term performance, it is important to test whether it possesses similar traits to momentum and short-term strategies.

Table 6. DSI performance and market conditions

This table reports the results of a predictive regression (presented in equation 7), where the returns of the zero-cost DSI strategy are regressed against the Baker and Wurgler (2006) investor sentiment index "Sentiment" and a down-market dummy variable "Down" that captures the shifts of the Nordic market index returns. Additionally, Fama and French six-factor model parameters are regressed against the DSI returns. The "Intercept" presents the alpha of the predictive regression result, "Sentiment" denotes the exposure against the investor sentiment index, "Down" denotes the exposure against the down-market dummy, and MKT, SMB, HML RMW CMA and WML denote factor exposures against the Fama and French factors of the six-factor model (2018). All coefficients are recorded for all four DSI portfolios as well as for the zero-cost strategy "Low-High". Newey and West (1987) adjusted t-statistics are reported in parentheses.

Measure	**Low**	**2**	**3**	**High**	**Low–High**
Intercept	-1.05	-1.68	-1.93	-1.16	0.11
	(-3.53)	(-4.91)	(-6.00)	(-3.11)	(0.26)
Sentiment	-0.71	-1.10	-1.17	-0.69	-0.02
	(-1.91)	(-2.57)	(-2.90)	(-1.48)	(-0.05)
Down	0.57	1.67	1.49	0.87	-0.29
	(1.14)	(2.88)	(2.73)	(1.38)	(-0.42)
MKT	1.22	1.00	1.10	1.15	0.08
	(21.25)	(15.15)	(17.64)	(15.94)	(0.97)
SMB	0.43	0.47	0.31	0.53	-0.10
	(3.90)	(3.71)	(2.66)	(3.88)	(-0.68)
HML	-0.15	-0.25	-0.34	-0.33	0.18
	(-1.03)	(-1.49)	(-2.18)	(-1.81)	(0.89)
RMW	0.26	0.03	-0.05	-0.07	0.33
	(1.40)	(0.14)	(-0.27)	(-0.32)	(1.31)
CMA	-0.20	0.05	0.18	-0.16	-0.04
	(-1.12)	(0.24)	(0.97)	(-0.74)	(-0.14)
WML	0.41	0.15	-0.14	-0.52	0.93
	(6.19)	(1.94)	(-2.03)	(-6.30)	(10.20)

From table 6, we can see that the investor sentiment index does hold predictive power for only the high-DSI portfolio, and the zero-cost portfolio returns. However, the down-market dummy holds predictive power for the low-DSI portfolio returns as well. In terms of Fama and French six-factor exposures, the size factor (HML), profitability factor (RMW) and the investment factor (CMA) seem to hold the most predictive power across the DSI portfolio returns. As the intercept-term, sentiment and down-market dummy coefficients are all statistically insignificant regarding the low-high-portfolio, we can conclude that they hold predictive power against the returns of the DSI strategy and thus the performance is robust to different market conditions.

5.4 Robustness tests

In this section there are presented the results to a battery of robustness tests of the performance of DSI strategy. Robustness tests focus on researching the DSI strategy performance over different sub-periods, especially the post-2000 era, the January effect, alternative measures of past intermediate-term performance, long-term performance as well as the performance evaluation of the DSI and momentum strategies during their respectively top 20 worst performing months.

From table 7, we can see that the highest average monthly raw returns of are recorded during the years 1993-2001. During that period, the zero-cost strategy records a monthly average raw return of 1.71% which is also statistically significant with a t-statistic of 2.52. The FF4 and FF6 factor-adjusted returns are the only ones that are statistically insignificant, meaning that those factor-models can capture the predictive power of the DSI strategy. From 2002 to 2011, the average monthly raw return of the DSI strategy of 1.19% is still statistically significant with a t-statistic of 1.95. Here again, the factor models including the momentum factor, FF4 and FF6, are able to predict the future returns of DSI strategy but now also the FF5 model records statistically insignificant average monthly factor-adjusted returns. Finally, during the years 2012-2021, the DSI strategy does not record statistically significant raw returns as the average monthly average raw return is only 0.22% with a t-statistic of 0.42. Additionally, all used factor models show that they can predict the returns of the DSI strategy during the latest subperiod.

As a conclusion, persistence and efficiency of the DSI strategy seems to diminish slowly during the 21st century. This finding is in line with the previous academic findings regarding the diminishing performance of momentum and short term-reversal strategies. However, Zhu et al. (2019) report statistically significant monthly raw returns of 1.19% for their DSI strategy in the US stock markets during 2001-2017.

Table 7. DSI performance during different subperiods

This table reports the average monthly raw and factor-adjusted returns of all four DSI portfolios and the zero-cost strategy during three different time periods: 1993–2001, 2002–2011 and 2012–2021. Raw denotes the raw returns, CAPM denotes the market-adjusted returns according to the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966), FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the Carhart's (1997) four-factor model, FF5 denotes the alphas with respect to the Fama-French (2015) five-factor model, and FF6 denotes the alphas with respect to the Fama-French six-factor model. Newey and West (1987) adjusted t-statistics are reported in parentheses.

Period	Measure	Low	2	3	High	Low-High	t-Stat
1993–2001	Raw	-1.06	-2.89	-3.15	-2.77	1.71	(2.25)
	CAPM	-1.75	-3.53	-3.76	-3.58	1.83	(2.37)
	FF3	-1.47	-3.50	-3.91	-3.57	2.10	(2.63)
	FF4	-1.97	-3.51	-3.87	-2.82	0.84	(1.22)
	FF5	-1.85	-3.58	-3.97	-3.40	1.55	(1.85)
	FF6	-2.16	-3.58	-3.94	-2.87	0.71	(0.99)
2002–2011	Raw	0.35	0.21	-0.69	-0.84	1.19	(1.95)
	CAPM	-0.19	-0.20	-1.23	-1.45	1.27	(2.09)
	FF3	-0.20	-0.23	-1.05	-1.46	1.26	(2.09)
	FF4	-0.63	-0.35	-0.68	-0.96	0.33	(0.62)
	FF5	-0.56	-0.07	-0.47	-1.17	0.61	(0.94)
	FF6	-0.68	-0.13	-0.39	-1.02	0.34	(0.61)
2012–2021	Raw	1.35	1.01	0.46	1.13	0.22	(0.42)
	CAPM	0.57	0.23	-0.44	0.12	0.46	(0.85)
	FF3	0.28	0.07	-0.59	0.04	0.25	(0.46)
	FF4	-0.05	-0.06	-0.51	0.49	-0.53	(-1.07)
	FF5	0.29	0.04	-0.71	-0.01	0.30	(0.56)
	FF6	-0.08	-0.09	-0.62	0.44	-0.52	(-1.01)

Short-term reversal strategies are reported to perform the best in January, but oh the other hand, price momentum reported to perform the worst in January (Jegadeesh, 1990; Jegadeesh and Titman, 1993). By testing the performance of the DSI strategy during January and non-January months thus brings interesting insight whether the DSI strategy's returns behave the similarly to traditional momentum or short-term reversal strategy.

In table 8, there is recorded the average monthly returns during January and non-January months for all four DSI quartile portfolios as well as for the zero-cost portfolio. All returns are also, regressed against the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966), Fama and French's (2015) three-factor model, Carhart's (1997) four-factor model, Fama and French's (2015) five-factor model and Fama and French's (2018 six-factor model, with the Newey and West (1987) t-statistics reported in parentheses. It can be seen that the DSI strategy performs much better during non-January months and thus a statistically significant January effect is not detected after controlling for risk factors. Zhu et al. (2019) report similar findings with US stocks.

Table 8. DSI performance during January vs non-January months

This table reports the average monthly raw and factor-adjusted returns of all four DSI portfolios and the zero-cost strategy during January and non-January months. Raw denotes the raw returns, CAPM denotes the market-adjusted returns according to the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966), FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the Carhart's (1997) four-factor model, FF5 denotes the alphas with respect to the Fama-French (2015) five-factor model, and FF6 denotes the alphas with respect to the Fama-French six-factor model.and factor adjusted returns. Newey and West (1987) adjusted t-statistics are reported in parentheses.

Period	Measure	Low	2	3	High	Low-High	t-Stat
January	RAW	0.72	0.98	-1.12	0.30	0.42	(0.36)
	CAPM	0.97	0.94	-0.92	0.61	0.35	(0.30)
	FF3	-0.47	-1.37	-2.44	-1.52	1.05	(0.67)
	FF4	-1.07	-1.35	-2.64	-1.13	0.06	(0.04)
	FF5	-0.63	-1.16	-2.60	-1.39	0.76	(0.48)
	FF6	-1.12	-1.27	-2.70	-1.11	0.00	(0.00)
non-January	RAW	0.22	-0.61	-1.05	-0.86	1.07	(2.78)
	CAPM	-0.56	-1.34	-1.85	-1.78	1.22	(3.15)
	FF3	-0.46	-1.28	-1.81	-1.73	1.28	(3.31)
	FF4	-0.91	-1.42	-1.57	-1.13	0.21	(0.61)
	FF5	-0.74	-1.42	-1.69	-1.55	0.82	(1.99)
	FF6	-1.02	-1.49	-1.54	-1.16	0.14	(0.38)

Previous studies show that 1-month lagged 11-month returns might not be the most optimal measure of past intermediate-term performance. For example, Cheng et al. (2017) report in their study that the short-term reversal effect is actually stronger among stocks that have performed the worst during the last three months. Moreover, Novy-Marx (2012) reports that the 6 months lagged 6-month ($t-7$ to $t-12$) returns present more predictive power than prior one month lagged 5-month returns ($t-2$ to $t-6$), or in other words the recent past performance. As the empirical analysis of this thesis relies on the past 11-month returns ($t-2$ to $t-12$) it is interesting to see whether the performance of the DSI strategy enhances after constructing the portfolios with alternative measure of past performance.

Table 9 reports the average monthly raw and factor adjusted returns of four DSI quartile portfolios and respective the zero-cost strategy. Three alternative measures of past performance are used, one month lagged 3-month returns ($t-2$ to $t-4$), one month lagged prior 6-month returns ($t-2$ to $t-7$), herein after as the recent past performance, and 6 months lagged 6 month returns ($t-7$ to $t-12$), herein after denoted as intermediate-term past performance. The alternative DSI's are calculated by subtracting the prior 1-month return ($t-1$). Newey and West (1987) t-statistics are reported in parentheses regarding respective zero-cost strategies.

In terms of monthly average raw returns, all three different measures of DSI report statistically significant and positive returns of 0.58% (t-stat 1.91), 0.72% (t-stat 2.04) and 1.00% (t-stat 2.43) for lagged 3-month, recent past performance, and intermediate-term past performance zero-cost portfolios, respectively. For all portfolio's, the FF4 and FF6 factor adjusted monthly average returns are statistically insignificant, implying that the FF4 and FF6 models can predict the returns of the alternative DSI portfolios. To summarize, we can conclude that as the measure of past performance is longer, and thus there contain more information, the DSI measure becomes more efficient on predicting future returns. Hence the lagged 11-month returns also seem as the most efficient measure as it reports an average monthly raw return of 1.02% (t-stat 2.78), reported in table 3. These findings in line with the findings of Zhu et al. (2019) study with US stocks.

Table 9. DSI performance with alternative measures of past returns

This table reports the average monthly raw and factor-adjusted returns of all four DSI portfolios and the zero-cost strategy. The DSI portfolio returns are calculated similarly to in equation 6 but with three different variations of the intermediate-term returns replacing past 11-month cumulative returns in the equation. MOM 4-2 denotes one month lagged 3-month returns ($t-2$ to $t-4$), MOM 7-2 denotes one month lagged prior 6-month returns ($t-2$ to $t-7$), herein after as the recent past performance, and 6 months lagged 6 month returns ($t-7$ to $t-12$), herein after denoted as intermediate-term past performance. The alternative DSI's are calculated by subtracting the respective return from the prior 1-month return ($t-1$). Moreover, Raw denotes the raw returns, CAPM denotes the market-adjusted returns according to the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966), FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the Carhart's (1997) four-factor model, FF5 denotes the alphas with respect to the Fama-French (2015) five-factor model, and FF6 denotes the alphas with respect to the Fama-French six-factor model.and factor adjusted returns. Newey and West (1987) adjusted t-statistics are reported in parentheses.

Period	Measure	Low	2	3	High	Low-High	t-Stat
MOM 4-2	Raw	-0.04	-0.09	-0.66	-0.62	0.58	(1.91)
	CAPM	-0.76	-0.70	-1.32	-1.39	0.63	(2.04)
	FF3	-0.73	-0.70	-1.31	-1.36	0.63	(2.07)
	FF4	-0.81	-0.67	-1.28	-1.04	0.23	(0.73)
	FF5	-0.78	-0.82	-1.25	-1.23	0.46	(1.41)
	FF6	-0.84	-0.78	-1.23	-1.02	0.18	(0.56)
MOM 7-2	Raw	0.13	-0.26	-0.63	-0.59	0.72	(2.04)
	CAPM	-0.55	-0.87	-1.31	-1.40	0.85	(2.41)
	FF3	-0.55	-0.84	-1.31	-1.39	0.84	(2.36)
	FF4	-0.78	-1.00	-1.22	-0.93	0.15	(0.43)
	FF5	-0.69	-0.94	-1.20	-1.05	0.36	(0.97)
	FF6	-0.85	-1.04	-1.15	-0.78	-0.07	(-0.20)
MOM 12-7	Raw	0.43	-0.60	-0.93	-0.57	1.00	(2.43)
	CAPM	-0.31	-1.25	-1.58	-1.35	1.04	(2.51)
	FF3	-0.29	-1.21	-1.59	-1.33	1.04	(2.49)
	FF4	-0.67	-1.25	-1.49	-0.96	0.29	(0.70)
	FF5	-0.54	-1.21	-1.75	0.07	0.54	(1.24)
	FF6	-0.78	-1.24	-1.66	-0.86	0.07	(0.17)

5.5 Long-term performance of the DSI, short-term reversal and momentum

Following the study by Zhu et al. (2019) the long-term performance of the DSI strategy is also tested in this thesis. The long-term performance is evaluated by tracking the average monthly returns during the following 12-month period after the portfolio formation. As previous research have noted that the return-based anomalies typically diminish over time, this even time analysis delivers valuable insight of the longevity of the DSI returns. In table 10, there is reported the average monthly raw returns for long, short and long-short portfolios of DSI, short-term reversal and momentum strategy.

Table 10. DSI vs. short-term reversal vs. momentum in event time

This table reports the average monthly raw returns for long, short and long-short portfolios of DSI, short-term reversal and momentum strategy. Returns of the momentum portfolio are calculated as the cumulative 1-month lagged 11-month returns of the simple momentum strategy by Jegadeesh and Titman (1993). Returns of the short-term reversal portfolio are calculated as 1-month lagged monthly returns of a traditional short-term reversal strategy by Jegadeesh (1990). Newey and West (1987) t-statistics are reported in parentheses regarding long-short portfolios.

	DSI				Short-term reversal			
Month	Long	Short	L–S	t-Stat	Long	Short	L–S	t-Stat
1	-0.22	-1.80	1.58	(6.36)	-0.47	-1.11	0.63	(2.83)
2	-0.58	-1.27	0.68	(2.87)	-1.14	-0.52	-0.62	(-3.22)
3	-0.74	-1.17	0.43	(1.80)	-1.33	-0.47	-0.86	(-4.75)
4	-0.71	-1.24	0.52	(2.11)	-1.13	-0.92	-0.21	(-1.18)
5	-0.83	-1.08	0.26	(1.06)	-1.22	-0.68	-0.53	(-3.10)
6	-0.91	-1.09	0.18	(0.76)	-1.37	-0.65	-0.72	(-4.56)
7	-0.86	-1.09	0.23	(0.97)	-1.13	-0.84	-0.29	(-1.75)
8	-0.94	-1.03	0.09	(0.39)	-1.18	-0.84	-0.34	(-2.04)
9	-1.05	-0.88	-0.17	(-0.79)	-1.31	-0.74	-0.57	(-3.12)
10	-1.11	-0.96	-0.15	(-0.73)	-1.07	-0.90	-0.17	(-0.99)
11	-1.17	-0.93	-0.24	(-1.00)	-1.16	-0.88	-0.29	(-1.82)
12	-1.23	-0.50	-0.73	(-3.05)	-1.42	-0.57	-0.85	(-5.38)
	Momentum							
1	-0.32	-1.39	1.07	(4.14)				
2	-0.42	-1.34	0.92	(3.65)				
3	-0.59	-1.26	0.67	(2.78)				
4	-0.60	-1.19	0.58	(2.42)				
5	-0.74	-1.13	0.39	(1.59)				
6	-0.89	-1.10	0.21	(0.87)				
7	-0.89	-1.02	0.13	(0.55)				
8	-0.94	-1.03	0.08	(0.36)				
9	-1.02	-1.00	-0.02	(-0.10)				
10	-1.06	-0.94	-0.12	(-0.54)				
11	-1.10	-1.03	-0.07	(-0.30)				
12	-1.17	-0.84	-0.33	(-1.45)				

From table 10, we can see that the average monthly raw returns of the DSI strategy turn negative after 8 months following the portfolio formation and the statistically significant positive returns after 3 to 4 months following the portfolio formation. The returns of the long leg decrease over time and the returns of the long leg decrease over time. However, the highest average monthly raw return of 1.58% is recorded during the first month after portfolio formation.

The short-term reversal strategy reports statistically significant and positive average monthly raw returns only during the first month after the portfolio formation. Short-term reversal effect seems to diminish during months 2 to 12, as the long leg’s returns are smaller than the short leg’s returns during that time. Similarly to the DSI strategy, the long leg’s returns of the momentum strategy decrease linearly over time, and the returns of the short leg increase over time. Thus, the momentum strategy also records statistically significant positive returns during the first 4 months after the portfolio formation. All in all, it is evident that the DSI strategy behaves much similar to the momentum strategy rather than to the short-term reversal strategy. Interestingly, for all strategies, the average monthly raw returns seem to be driven by the short leg of the portfolio as the long legs do not produce positive returns at all.

Studying the DSI strategy with the US stocks, Zhu et al. (2019) report in their study that the DSI strategy produces the highest statistically significant average monthly returns during the first 6 months after the portfolio formation. Their DSI strategy also beats the momentum and short term-reversal strategies’ returns during the first 5 months after the portfolio formation. In the Nordic setting, the DSI strategy beats the momentum and short-term reversal strategies during the first month only.

5.6 Performance evaluation of DSI and momentum strategies

In this section there is presented the performance statistics of the DSI strategy and the momentum strategy as well as compared the top 20 worst monthly performances.

Following Zhu et al. (2019), we have compared two kinds of relative strength strategies with differing holding periods, 1-month and 2-month, to the momentum strategy.

The performance statistics of the strategies are reported in table 11. Out of the three strategies, the DSI strategy with a 2-month holding period generates the highest average monthly raw returns of 2.02% (t-stat 3.98) compared to the 1-month holding period DSI strategy's returns of 1.02 (t-stat 2.78) and momentum strategy's returns of 0.69% (t-stat 1.76). Both of the relative strength strategies have also higher Sharpe ratios than the momentum strategy. Interestingly, the kurtosis values of both the DSI atregies are remarkably low, in fact both of them being under 3, implying that is very low tail risk. However, only the DSI strategy with a 1-month holding period has lower volatility than the momentum strategy. These findings suggest that the DSI strategy with a 1-month holding period performs significantly better than the momentum strategy.

Table 11. Performance statistics of DSI and momentum strategies

This table reports performance statistics of DSI strategy with a 1-month holding period, denoted as DSI (1), DSI strategy with a 2-month holding period, denoted as DSI (2) and 1-month lagged 11-month returns of the simple cross-sectional momentum strategy by Jegadeesh and Titman (1993). Specifically, monthly average raw returns, standard deviations, skewness, kurtosis and Sharpe ratios for each strategy are reported. Newey and West (1987) t-statistics are reported in parentheses.

Strategy	**Mean return**	**Std.dev**	**t-Stat**	**Skewness**	**Kurtosis**	**Sharpe ratio**
DSI (1)	1.02	6.84	(2.78)	-0.15	2.40	0.15
DSI (2)	2.02	9.45	(3.98)	0.00	2.09	0.21
Momentum	0.69	7.25	(1.76)	-0.74	4.98	0.09

Table 12. Top 20 worst performances of DSI and momentum strategies

This table reports the top 20 worst performances for the DSI strategy with a 1-month holding period, denoted as DSI (1), DSI strategy with a 2-month holding period, denoted as DSI (2) and 1-month lagged 11-month returns of the simple cross-sectional momentum strategy by Jegadeesh and Titman (1993). Each strategies' monthly raw returns are reported for the long-leg, short-leg and zero-cost strategy, L-S, respectively.

	DSI (1)				DSI (2)				Momentum		
Date	**Long**	**Short**	**L–S**	**Date**	**Long**	**Short**	**L–S**	**Date**	**Long**	**Short**	**L–S**
Apr-2001	2.20	29.91	-27.72	Apr-2009	-2.36	39.57	-41.93	Oct-2002	3.99	46.78	-42.79
Nov-2020	12.30	39.65	-27.35	Nov-2001	9.98	37.17	-27.19	Apr-2001	1.80	27.37	-25.57
Apr-2009	1.20	26.24	-25.04	Dec-2020	25.67	50.92	-25.25	Apr-2009	11.07	36.55	-25.48
Jan-2012	-0.21	14.25	-14.47	Nov-2020	10.25	28.61	-18.36	Apr-2003	7.84	33.21	-25.38
Jul-2014	-4.53	9.87	-14.40	Oct-2004	6.58	23.67	-17.09	Oct-2001	6.70	25.81	-19.10
Oct-2001	7.02	21.35	-14.33	Aug-2003	0.72	17.50	-16.78	Apr-2015	1.76	17.83	-16.07
Mar-2009	-3.52	10.56	-14.08	Dec-2001	1.58	17.45	-15.88	Mar-2009	3.32	18.53	-15.21
Apr-2003	9.57	22.61	-13.04	Apr-1999	-2.95	12.83	-15.78	Jan-2003	-2.60	11.74	-14.34
Apr-2015	2.11	15.02	-12.91	Jul-2003	-2.89	12.89	-15.77	Nov-2020	14.16	28.08	-13.93
Jul-2003	-4.02	8.81	-12.84	Aug-2017	2.03	17.74	-15.71	Nov-2001	0.90	14.71	-13.82
Jan-2003	-3.35	8.54	-11.89	Apr-2001	-9.20	6.33	-15.53	Mar-1999	0.02	13.14	-13.12
May-2000	-13.43	-2.28	-11.14	Dec-2017	-2.71	12.03	-14.75	Nov-2018	-8.74	4.33	-13.08
Jul-2017	0.99	11.87	-10.88	Jun-2000	-19.76	-5.18	-14.59	May-2009	9.27	22.15	-12.88
Nov-1996	0.97	11.77	-10.79	Nov-2002	9.57	23.91	-14.34	Jan-2012	1.57	14.22	-12.65
Jul-1993	1.76	12.46	-10.70	Nov-2013	7.80	22.11	-14.31	Jan-2001	-0.65	11.55	-12.20
Nov-2013	2.03	12.45	-10.42	May-1999	-11.05	3.20	-14.25	Nov-1993	-16.14	-5.25	-10.90
Mar-2000	-6.26	4.15	-10.41	Aug-2014	-4.61	9.46	-14.06	Nov-2002	6.03	16.56	-10.53
Apr-1999	-2.85	7.43	-10.28	Feb-2012	12.12	25.68	-13.56	May-2000	-13.74	-3.26	-10.48
Nov-2001	2.77	13.04	-10.27	Dec-1996	-2.01	10.13	-12.14	Aug-2011	-9.54	0.83	-10.36
Oct-2004	-1.20	8.57	-9.77	Apr-2003	11.18	22.70	-11.52	Aug-2008	-8.05	2.16	-10.21

Table 13. Correlation between the top 20 worst performances

This table reports the same top 20 worst monthly performances of the strategies presented in table 12 but here the returns are only reported for the long-short portfolios, L-S. The corresponding returns of the DSI (1), DSI (2) and the momentum strategy are reported and the correlation between the strategies are denoted by COR. Newey and West (1987) t-statistics are reported in parentheses.

	L-S sorted by DSI (1)			**L-S sorted by DSI (2)**			**L-S sorted by Momentum**		
Date	**DSI (1)**	**MOM**	**Date**	**DSI (2)**	**MOM**	**Date**	**MOM**	**DSI (1)**	**DSI (2)**
Apr-2001	-27.72	-25.57	Apr-2009	-41.93	-25.48	Oct-2002	-42.79	-6.76	-7.81
Nov-2020	-27.35	-13.93	Nov-2001	-27.19	-13.82	Apr-2001	-25.57	-27.72	-15.53
Apr-2009	-25.04	-25.48	Dec-2020	-25.25	1.64	Apr-2009	-25.48	-25.04	-41.93
Jan-2012	-14.47	-12.65	Nov-2020	-18.36	-13.93	Apr-2003	-25.38	-13.04	-11.52
Jul-2014	-14.40	0.27	Oct-2004	-17.09	-4.62	Oct-2001	-19.10	-14.33	-0.30
Oct-2001	-14.33	-19.10	Aug-2003	-16.78	3.47	Apr-2015	-16.07	-12.91	-10.53
Mar-2009	-14.08	-15.21	Dec-2001	-15.88	-4.48	Mar-2009	-15.21	-14.08	-9.69
Apr-2003	-13.04	-25.38	Apr-1999	-15.78	-7.07	Jan-2003	-14.34	-11.89	7.06
Apr-2015	-12.91	-16.07	Jul-2003	-15.77	-8.67	Nov-2020	-13.93	-27.35	-18.36
Jul-2003	-12.84	-8.67	Aug-2017	-15.71	-5.26	Nov-2001	-13.82	-10.27	-27.19
Jan-2003	-11.89	-14.34	Apr-2001	-15.53	-25.57	Mar-1999	-13.12	-5.13	-5.58
May-2000	-11.14	-10.48	Dec-2017	-14.75	2.90	Nov-2018	-13.08	-8.01	-7.91
Jul-2017	-10.88	-1.06	Jun-2000	-14.59	-3.93	May-2009	-12.88	23.51	-4.65
Nov-1996	-10.79	-2.89	Nov-2002	-14.34	-10.53	Jan-2012	-12.65	-14.47	-9.20
Jul-1993	-10.70	-6.62	Nov-2013	-14.31	5.02	Jan-2001	-12.20	-5.55	0.63
Nov-2013	-10.42	5.02	May-1999	-14.25	-7.41	Nov-1993	-10.90	-9.48	-7.73
Mar-2000	-10.41	-6.42	Aug-2014	-14.06	1.94	Nov-2002	-10.53	-6.51	-14.34
Apr-1999	-10.28	-7.07	Feb-2012	-13.56	5.37	May-2000	-10.48	-11.14	-3.02
Nov-2001	-10.27	-13.82	Dec-1996	-12.14	-2.36	Aug-2011	-10.36	-2.35	1.57
Oct-2004	-9.77	-4.62	Apr-2003	-11.52	-25.38	Aug-2008	-10.21	-7.57	-7.81
COR		0.59			0.38			0.26	0.27
t-Stat		(3.14)			(1.74)			(1.14)	(1.19)
P-value		0.01			0.10			0.27	0.25

Table 12 reports the 20 worst performances of the two DSI strategies and the momentum strategy. We can see that, on average, the relative strength strategies' worst monthly performances are better than the momentum strategy's worst performances but in general of all strategies suffer from major drawdowns during the observation period. The DSI strategy with a 2-month holding period records nearly identical worst performances as the momentum strategy. All strategies worst monthly performances are generally due to the momentum crash effect, where the short leg of the portfolio generates high generates high positive returns. Again, the 1-month holding period DSI strategy performs the best when compared to the other two strategies as the performances during crash periods are less severe. This suggests that the DSI strategy also takes into account the short-term information.

Table 13 reports the correlations between the top 20 worst performances of the DSI with a 1-month and 2-month holding periods, and the momentum strategy. We can see that during the 20 worst months of the 1-month DSI strategy, momentum returns during the corresponding months correlate positively, with a correlation of 0.59. This explains that the DSI strategy behaves rather similarly to the momentum strategy during its worst months. However, when looking at the 20 worst months of the 2-month DSI strategy, the correlation between the 2-month DSI and the momentum strategy is statistically insignificant. Similar results are also received during the 20 worst months of the momentum strategy implying that the correlation diminishes over time, and the great losses of momentum during its worst months do not directly imply as great losses for DSI strategies.

6 Conclusions

In this thesis the relative strength strategy, originally introduced by Zhu et al. (2019), is studied in the Nordic stock markets during 1993–2021. This thesis aims to carefully replicate the research methodology of the Zhu et al. (2019) study. They propose a simple measure of relative strength over short-and intermediate horizons, which they call as the DSI measure. DSI is calculated by comparing the short and intermediate term performance of a stock. The strategy is based purely on the DSI measure, as the zero-cost portfolio is formed by buying the stocks with the lowest DSI and shorting the stocks with the highest DSI values. DSI strategy is a unique and simple combination of the traditional cross-sectional momentum strategy and the short-term reversal strategy, thus capturing both the short and intermediate term returns.

Cross-sectional momentum (Jegadeesh and Titman, 1993) and short-term reversal anomaly (Jegadeesh, 1990) anomalies are one of the most studied market phenomena. The previous research regarding both strategies focus mainly on the US and European stock markets. Only a few studies have studied the strategies in the Nordic stock markets during the last decade (see e.g., Grobys and Huhta-Halkola, 2019). Similarly, the DSI strategy is only being studied in the US stock markets (Zhu et al., 2019). Therefore, this thesis contributes valuable insight, not only to the academic research of the DSI strategy, but also to academic research of momentum and short-term reversal anomalies in the Nordic stock markets.

The main empirical finding of this thesis is that the DSI strategy does produce positive and statistically significant average monthly abnormal returns of 1.02% in the Nordic stock markets exceeding the average monthly abnormal returns of both the short-term reversal strategy (0.26%) and the 12-1-1 momentum strategy (0.69%). This suggests that greater returns and thus greater information is captured by synthesizing the short- and intermediate-term information.

The superior performance of the DSI strategy is robust to various factor models, except the Carhart's (1997) four-factor model and Fama-French (2018) six-factor model. Both of the models were able to predict the value-weighted returns of the DSI strategy, suggesting that the DSI strategy records very similar returns to the momentum strategy. While the DSI strategy is also robust to different market conditions, January effect and alternative measures of past performance, the returns and effectiveness of the strategy diminish during the post-2000 period similarly to the short-term reversal and momentum strategy.

As a comparison to the previous research regarding DSI strategy, Zhu et al. (2019) record rather similar but more robust findings. The DSI strategy performs even better in the US stock markets and records positive average monthly returns even during the recent decade. Therefore, we can conclude that even though the DSI strategy is profitable in the Nordic stock markets over the observation period, the lack of performance during the post-2000 period affects the significance of the DSI strategy negatively. However, DSI seems like an interesting measure, and it should definitely be researched further. It is a good evidence of investor conservatism, as it demonstrates how investors benefit from trading for the longer-term price trend but against the short-term price trend, which is consistent with the idea that investors typically undervalue short-term information.

Even though this thesis utilizes a variety of robustness test there is still lots of potential aspects to research in the future as well. For example, as evidenced in this thesis both the traditional cross-sectional momentum strategy and DSI strategy are vulnerable to crashes, therefore a risk-managed DSI strategy could generate larger returns. Also, DSI strategy should be researched in other market settings as well, for example in the European, Asia-Pacific and emerging markets. Lastly, this thesis does not take into account trading costs and therefore including them into the methodology would provide important insight into the robustness of the DSI strategy.

References

Aharoni, G., Grundy, B., & Zeng, Q. (2013). Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis. *Journal of financial economics*, 110(2), 347-357. https://doi.org/10.1016/j.jfineco.2013.08.003

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets (Amsterdam, Netherlands)*, 5(1), 31-56. https://doi.org/10.1016/S1386-4181(01)00024-6

Asness, C. S., Liew, J. M., & Stevens, R. L. (1997). Parallels between the cross-sectional predictability of stock and country returns: Striking similarities in the predictive power of value, momentum, and size. *Journal of Portfolio Management*, 23(3), 79–87. https://doi.org/10.3905/jpm.1997.409606

Asness, C. S., Moskowitz, T. J. & Pedersen, L. H. (2013). Value and Momentum Everywhere. *Journal of Finance*, 68(3), 929-985. https://doi.org/10.1111/jofi.12021

Avramov, D., Chordia, T. & Goyal, A. (2006). Liquidity and Autocorrelations in Individual Stock Returns. *The Journal of Finance (New York)*, 61(5), 2365-2394. https://doi.org/10.1111/j.1540-6261.2006.01060.x

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance (New York)*, 61(4), 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bali, T. G., Cakici, N. & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2), 427-446. https://doi.org/10.1016/j.jfineco.2010.08.014

Ball, R. (2009). The Global Financial Crisis and the Efficient Market Hypothesis: What Have We Learned? *Journal of Applied Corporate Finance*, 21(4), pp. 8-16. doi:10.1111/j.1745-6622.2009.00246.x

Baltas, A. N., Kosowski, R. (2013). Momentum strategies in futures markets and trend-following funds. *SSRN Electronic Journal*. 10.2139/ssrn.1968996.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307-343. https://doi.org/10.1016/S0304-405X(98)00027-0

Bodie, Z., Kane, A. & Marcus, A. J. (2014). Investments (10th global ed.). *New York: McGraw Hill Education.*

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance (New York)*, 52(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chan, K., Hameed, A., & Tong, W. (2000). Profitability of Momentum Strategies in the International Equity Markets. *The Journal of Financial and Quantitative Analysis,* 35(2), 153. https://doi.org/10.2307/2676188

Cheng, S., Hameed, A., Subrahmanyam, A. & Titman, S. (2017). Short-Term Reversals: The Effects of Past Returns and Institutional Exits. *Journal of Financial and Quantitative Analysis*, 52(1), 143-173. https://doi.org/10.1017/S0022109016000958

Chiang, I. E., Kirby, C. & Nie, Z. Z. (2021). Short-term reversals, short-term momentum, and news-driven trading activity. *Journal of Banking and Finance*, 125, 106068. https://doi.org/10.1016/j.jbankfin.2021.106068

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? *Journal of Accounting & Economics*, 58(1), 41-58. https://doi.org/10.1016/j.jacceco.2014.06.001

Cooper, M. J., Gutierrez JR, R. C. & Hameed, A. (2004). Market States and Momentum. *The Journal of Finance (New York)*, 59(3), 1345-1365. https://doi.org/10.1111/j.1540-6261.2004.00665.x

Daniel, K., Hirshleifer, D. & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of finance (New York)*, 53(6), 1839-1885. https://doi.org/10.1111/0022-1082.00077

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122(2), 221-247. https://doi.org/10.1016/j.jfineco.2015.12.002

De Bondt, W. F. M. & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance*, 40(3), 793-805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F. M. & Thaler, R. (1987). Further Evidence On Investor Overreaction and Stock Market Seasonality. *The Journal of finance*, 42(3), 557-581. https://doi.org/10.1111/j.1540-6261.1987.tb04569.x

Edwards, W. (1982). Conservatism in human information processing. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), Judgment under Uncertainty: Heuristics and Biases (pp. 359-369). *Cambridge University Press*. doi:10.1017/CBO9780511809477.026

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance*, 46(5), 1575-1617. https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fama, E. F. & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance,* 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of financial economics,* 82(3), 491-518. https://doi.org/10.1016/j.jfineco.2005.09.009

Fama, E. F. & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, 116(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F. & French, K. R. (2018). Choosing factors. *Journal of financial economics*, 128(2), 234-252. https://doi.org/10.1016/j.jfineco.2018.02.012

French, K. (2023). Data library. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

Geczy, C. C., & Samonov, M. (2016). Two Centuries of Price-Return Momentum. *Financial Analysts Journal*, 72(5), 32–56.

Grobys, K. (2021). What do we know about the second moment of financial markets? *International review of financial analysis*, 78, 101891. https://doi.org/10.1016/j.irfa.2021.101891

Grobys, K., & Huhta-Halkola, T. (2019). Combining value and momentum: Evidence from the Nordic equity market. *Applied economics*, 51(26), 2872-2884. https://doi.org/10.1080/00036846.2018.1558364

Grossman, S. J. & Miller, M. H. (1988). Liquidity and Market Structure. *The Journal of finance (New York)*, 43(3), 617-633. https://doi.org/10.1111/j.1540-6261.1988.tb04594.x

Han, Y., Zhou, G. & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? *Journal of financial economics*, 122(2), 352-375. https://doi.org/10.1016/j.jfineco.2016.01.029

Hou, K., Xue, C., & Zhang, L. (2020). Replicating Anomalies. *The Review of financial studies*, 33(5), 2019-2133. https://doi.org/10.1093/rfs/hhy131

Hong, H., & Stein, J. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *The Journal of Finance (New York)*, 54(6), 2143-2184. https://doi.org/10.1111/0022-1082.00184

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *The Journal of Finance*, 45(3), 881-898. https://doi.org/10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N. & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1), 65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jegadeesh, N. & Titman, S. (1995a). Overreaction, Delayed Reaction, and Contrarian Profits. *The Review of financial studies*, 8(4), 973-993. https://doi.org/10.1093/rfs/8.4.973

Jegadeesh, N. & Titman, S. (1995b). Short-Horizon Return Reversals and the Bid-Ask Spread. *Journal of Financial Intermediation*, 4(2), 116-132. https://doi.org/10.1006/jfin.1995.1006

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance (New York)*, 56(2), 699-720. https://doi.org/10.1111/0022-1082.00342

Kuhn, T. (1970). The Structure of Scientific Revolutions. *The University of Chicago Press.*

Lehmann, B. N. (1990). Fads, Martingales, and Market Efficiency. *The Quarterly Journal of Economics*, 105(1), 1-28. https://doi.org/10.2307/2937816

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1), 13-37. https://doi.org/10.2307/1924119

Liu, Y., & Tsyvinski, A. (2018). Risks and Returns of Cryptocurrency. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3226952

Lord, C. G., Ross, L. & Lepper, M. R. (1979). Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *Journal of personality and social psychology*, 37(11), 2098-2109. https://doi.org/10.1037//0022-3514.37.11.2098

Malkiel, B. G. (1973). A random walk down Wall Street. *New York: Norton*

McLean, R. D., & Pontiff, J. (2016). Does Academic Research Destroy Stock Return Predictability? The Journal of Finance (New York), 71(1), 5-32. https://doi.org/10.1111/jofi.12365

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012). Currency momentum strategies. *Journal of Financial Economics*, 106(3), 660–684. https://doi.org/10.1016/j.jfineco.2012.06.009

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum? *Journal of Finance*, 54(4), 1249–1290. https://doi.org/10.1111/0022-1082.00146

Moskowitz, T. J., Ooi, Y. H. & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2), 228-250. https://doi.org/10.1016/j.jfineco.2011.11.003

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, 34(4), 768-783. https://doi.org/10.2307/1910098

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3), 703-708. https://doi.org/10.2307/1913610

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of financial economics,* 103(3), 429-453. https://doi.org/10.1016/j.jfineco.2011.05.003

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1), 1-28. https://doi.org/10.1016/j.jfineco.2013.01.003

Pastor, L. & Stambaugh, R. (2003). Liquidity Risk and Expected Stock Returns. *The Journal of political economy*, 111(3), 642-685. https://doi.org/10.1086/374184

Pitkäjärvi, A., Suominen, M. & Vaittinen, L. (2020). Cross-asset signals and time series momentum. *Journal of Financial Economics*, 136(1), 63. https://doi.org/10.1016/j.jfineco.2019.02.011

Rouwenhorst, K. G. (1998). International Momentum Strategies. *The Journal of Finance*, 53(1), 267–284. https://doi.org/10.1111/0022-1082.95722

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 19(3), 425. https://doi.org/10.2307/2977928

Subrahmanyam, A. (2005). Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns. *The Financial review (Buffalo, N.Y.)*, 40(1), 11-35. https://doi.org/10.1111/j.0732-8516.2005.00091.x

Titman, S., Wei, K. C. J. & Xie, F. (2004). Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis*, 39(4), 677-700. https://doi.org/10.1017/S0022109000003173

Zhu, Z. & Yung, K. (2016). The interaction of short-term reversal and momentum strategies. *Journal of Portfolio Management*, 42(4), 96-107. https://doi.org/10.3905/jpm.2016.42.4.096

Zhu, Z., Duan, X. & Tu, J. (2019). Relative strength over investment horizons and stock returns. *Journal of Portfolio Management*, 46(1), 91-105. https://doi.org/10.3905/jpm.2019.1.111