Aalto-yliopisto
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Master's Programme in Finance

Is time over for momentum?

12-month Cross-sectional and Time-series momentum in Finland and Sweden

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Master's thesis
2025

Aalto-yliopisto
Aalto-universitetet
Aalto University

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Title of thesis Is time over for momentum?

Programme Master of Science in Economics and Business Administration

Major Finance

Thesis supervisor Peter Nyberg

Date 25.04.2025 **Number of pages** 45 **Language** English

Abstract

Momentum is one of the most explored topics in asset pricing theory. This thesis explores the performance of Time-Series Momentum (TSM) and Cross-Sectional Momentum (CSM) strategies in the Helsinki and Stockholm stock markets between 1993 and 2024. Utilizing historical return data, we construct momentum-based portfolios and analyse their returns. The TSM strategy capitalizes on the persistence of absolute asset returns over time, while the CSM approach ranks assets based on their past performance relative to each other. The study uses the Fama-French three-factor model to assess the explanatory power of market, size, and value factors on momentum returns.

Using a 12-month lookback period, one month lag and a holding period of one month, portfolios are formed by taking a long position on the top-performing securities and shorting the worst-performing ones. While momentum is present in the sample, the strenght of 12-month momentum has decreased over time and this can be attributed to the increased speed information is dispersed between investors.

A 120-month rolling window model is used to demonstrate how the robustness of the returns of a 12-month momentum portfolio has decreased. The returns that are not explained by the Fama-French three factor model have decreased to levels that are no longer statistically significant, while remaining statistically valid in regressions run on the entirety of the sample.

Literature has explained momentum by both under- and overreaction and this thesis supports the view that the speed at which these investor reactions are corrected for has increased, and further research should be conducted to better understand how the correction speed had developed to find the optimal time structure to capture the momentum anomaly.

Keywords Time-series momentum, cross-sectional momentum, asset pricing, anomaly

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Tekijä Henri Ailinpieti

Työn nimi Onko momentumin aika ohi?

Koulutusohjelma Kauppatieteiden maisteri

Pääaine Rahoitus

Työn ohjaaja Peter Nyberg

Päivämäärä 25.4.2025 **Sivumäärä** 45 **Kieli** Englanti

Tiivistelmä

Momentum on yksi tutkituimmista aiheista hinnoitteluteoriassa. Tämä pro gradu -tutkielma tarkastelee aikasarjamomentumin ja poikkileikkauksellisen momentumin strategioiden tuottoja Helsingin ja Tukholman pörsseissä vuosina 1993–2024. Historiallista kuukausittaista tuottoaineistoa hyödyntäen rakennan useita momentumportfolioita 12 kuukauden momentumin ympärille. Aikasarjamomentum hyödyntää absoluuttisten tuottojen jatkuvuutta, ja poikkileikkauksellinen momentum hyödyntää suhteellisen järjestyksen säilyvyyttä tuotoissa.

Tutkielmassa käytetään Fama-French kolmen faktorin (FF3) mallia arvioimaan markkina-, koko- ja arvofaktorien selitysvoimaa momentum-tuotoille. Momentum-strategiat perustuvat 12 kuukauden menneisiin tuottoihin, kuukauden odotuksella ja kuukauden pitoajalla, ostaen parhaiten tuottaneita osakkeita ja myymällä huonoiten tuottaneita osakkeita. Momentum-ilmiö on havaittavissa kaikilla strategioilla, mutta tuottojen tilastollinen merkityksellisyys on laskenut ajan kuluessa. Tämä vaikuttaa tukevan teoriaa momentumin perustuvan tiedon hitaaseen leviämiseen ja leviämisnopeuden kasvamiseen ajan myötä.

120 kuukauden liukuvan ikkunan malli osoittaa, että se osa momentumin tuotoista, jota ei voi selittää FF3-mallilla on vähentynyt ja eikä ole enää tilastollisesti merkitsevä, vaikka koko otoksessa momentum säilyy tilastollisesti merkitsevänä kaikilla strategioilla.

Kirjallisuudessa momentum on usein liitetty markkinan ali- ja ylireaktioihin, jotka korjaantuvat ajan myötä. Tutkielman tulokset antava tukea näkemykselle, jonka mukaan hinnoitteluvirheiden korjaantuminen on nopeutunut tiedonkulun nopeutumisen myötä. Lisää tutkimusta tarvitaan, jotta voimme paremmin ymmärtää momentum-tuottojen aikarakennetta, aikarakenteen muutosta ja kurssireaktioiden korjaantumista oikealle tasolle.

Avainsanat Aikasarjamomentum, poikkileikkauksellinen momentum, pääomamarkkinoiden hinnoittelumalli, anomalia

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Acknowledgements

I want to thank my thesis supervisor Prof. Peter Nyberg for support and directing me in this research.

I also want to thank my partner for their unwavering support and trusting the process.

Helsinki, 25 April 2025
Henri Ailinpieti

Abbreviations, Figures and Tables

List of Abbreviations

CAPM	Capital Asset Pricing Model
CMA	Conservative minus Aggressive
CSM	Cross-sectional momentum
CSMVW	Value-weighted cross-sectional momentum
FF3	Fama-French three factor model
HML	High minus low
RMW	Robust minus weak
SMB	Small minus big
TSM	Time-series momentum
TSMVW	Value-weighted time-series momentum

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1 Introduction

Momentum is one of the most researched anomalies in finance while being an anomaly that has been documented to span geographies, industries and asset classes (Asness, Moskowitz and Pedersen, 2013). Stock market momentum is a well-studied effect beginning from Jagedeesh and Titman identifying a persistence in returns (Jegadeesh and Titman, 1993) showing that in the stock market previous winners measured in return in outperform previous losers by a significant premium. Throughout three decades, empirical evidence has shown that the anomaly exists in other asset classes such as stocks, fixed income and currencies and others (Asness, Moskowitz and Pedersen, 2013).

Generating systematic excess returns compared to the market appears to contradict the efficient market hypothesis (Fama, 1970) according to which asset pricing reflects all the available current information on each equity. Fama synthesized on the findings of Sharpe (1964), Jensen (1968) and Lintner (1965), finding basis and coining the term “efficient capital markets”. Assuming efficient markets, prices immediately adjust to reflect all new information correctly. Building upon the Efficient Markets Hypothesis, prices are formed through a stochastic process where prior returns have no explanatory value for future returns. However, momentum suggests that returns have some level of autocorrelation and instead prices continue to drift generating returns.

Capital Asset Pricing Model (CAPM) has been one of the most widely known and adopted asset valuation models in finance, where expected returns are believed to be a function of excess return (Alpha), market risk exposure (Beta) and risk-free return. The basis on this theory was formed beginning in the 1950s, and several academics arrived at the same conclusions independently around the same period such as Sharpe (1964), Lintner (1965) and Black (1972). This is the basis of modern asset pricing theory that the theory is formed on. For the sake of clarity, this model is sometimes referred to as the Sharpe-Lintner-Black model in literature.

Since then, several theories have attempted to explain stock market returns based on market factors. The Fama-French three factor model used SMB and HML factors which respectively can be seen as size and value factors. This is one of the best-known asset pricing models today, capturing market risk, small firm effect and value effect. The Carhart four factor model (Carhart, 1997) incorporated momentum to explain stock market returns by adding a past performance measure first described by Jegadeesh and Titman (Jegadeesh and Titman, 1993) to the Fama-French 3-factor model.

The Fama-French five factor model (Fama and French, 2015) is a further iteration of the three-factor model including factors for profitability and investment (RMW and CMA) and notably omitting the momentum factor. It was later augmented further by including the cross-sectional momentum factor as used in the Carhart four factor model. The addition of the momentum factor to the asset pricing model gave the model the highest squared Sharpe ratio when compared to other models (Fama and French, 2018).

In this thesis I address momentum in the Helsinki and Stockholm stock exchanges, by building long-short portfolios using time-series and cross-sectional momentum strategies to capture the anomaly and compare it to literature based on CRSP data to better understand how momentum appears in these two Nordic stock exchanges.

Cross-sectional momentum (Jegadeesh and Titman, 1993) and time-series momentum (Moskowitz, Ooi and Pedersen, 2012) are two separate methods to capture a similar anomaly. Cross-sectional momentum uses zero-cost market neutral portfolios, in where a same sized long and short position form a portfolio that in theory is free to hold by ranking stocks on comparative returns in the past period and taking long position in the winners and short position in the losers.

Time-series momentum uses absolute stock return as the basis of portfolio formation. Winners are those stocks that have a return above a certain threshold, and losers are those stocks that have provided a return under another threshold. This causes the portfolio to not be zero-cost unless the positions are sized based on how many stocks in each period belong in the portfolio. Most previous literature uses an equal weighted approach for both anomalies, resulting in a varying net-long position.

Using a newer sample from 1993-2024 allows observing the most recent performance of the strategies in the Helsinki and Stockholm stock exchanges. This thesis focuses on the performance of momentum across time focusing on these two markets using a 12-month formation period which is followed by a month-long lag, and then a holding period of one month. Constructions similar are often found to present the strongest momentum profits.

The results show that the 12-month momentum anomaly have become less robust as time has passed, potential explanations to this could be that information dissipation has become faster and the markets have become faster at correcting under- and overreactions, which have been offered to be the most significant reasons for momentum. Studying a broader range of momentum at different time structures could show a shift towards faster reactions.

This thesis is structured as follows. To begin, we study the foundations of return momentum, both cross-sectional and time-series through efficient markets hypothesis and research carrier on factors explaining excess returns. Secondly, we build portfolios on Finnish and Swedish stock markets, based on time-series momentum and cross-sectional momentum with a 1 month holding period, following one month of lag and a 12-month formation period. After that we perform rolling window regressions to see how strongly the null-hypothesis can be rejected across 120-month windows. Finally, we will arrive at discussion and conclusion.

2 Literature review

In this chapter I go through key literature around the momentum anomaly, previous findings and the theoretical foundations for my hypothesis and methodology.

Firstly, I explain what efficient capital markets are, secondly, I look into the literature behind explaining the momentum anomaly and how it appears between different markets. Closely exploring the similarities and key differences between portfolio formation and theories on CSM and TSM concludes the part on literature on momentum. Finally, I conclude with presenting the contributions of the thesis and my hypothesis as well as research questions.

2.1 Efficient capital markets

The efficient capital markets (Fama, 1970) is a capital markets theory on research by Sharpe, Jensen and Lintner in the 1950s and 1960s. Efficient markets have been one of the hallmarks of finance research distinguishing three types of efficient markets. Fama categorised efficient markets into three forms: weak, semi-strong and strong form. Strong form efficiency appears in markets that have no transactions costs, all information is freely available to all participants and all participants agree on the implications for the current price and distributions of future prices.

Weak form efficiency assumes all the information is in the historical prices, in semi-strong form efficiency obvious data is included such as earnings reports and stock-splits and in strong form there is no part with monopolistic information. These assumptions have formed the basis on modern financial theory and "fully reflected" prices have been the basis of asset pricing theory. Expanding on the portfolio choice theory of Markowitz (1952), Sharpe (1964) and Lintner (1965) presented pricing models based on mean variance optimization, which later became established as the capital asset pricing model (CAPM), which has become one of the corner stones of modern asset pricing theory.

Building on CAPM, portfolio formation has focused on mean-variance optimization, in which investors select the variance (risk) they are willing to take in exchange for the level of expected return they wish to receive at $t-1$. The rational investor invests in an efficient portfolio based on the historical variance providing the most expected return for any risk. The realized return is the stochastic return at t. In total the investors in the market receive the joint return of the market portfolio. This model also expects a market portfolio to be mean-variance efficient. Assuming this model is correct and accurate, anomalies such as momentum should not provide excess returns.

2.2 Momentum

Literature on equity market momentum dates back three decades beginning with Jegadeesh and Titman (1993). The methodology used was sorting stocks into deciles based on past performance during varying length observation periods and then holding the portfolio for different periods of time. This allowed examining of the momentum of US equities in a similar cross-sectional fashion as Fama and French (1992) had used in their research. This formed the basis of momentum in financial academia, which for the purposes of this thesis is referred to as cross-sectional momentum.

As with other factors from previous research, momentum shows that returns are not completely stochastic but instead may offer investors excess returns by being predictable, with returns containing some level of autocorrelation.

Jegadeesh and Titman first documented the momentum anomaly, with Carhart adding it to a four-factor asset pricing model in building on the Fama and French's 3-factor model (Jegadeesh and Titman, 1993; Carhart, 1997) when assessing mutual fund returns. This was done by sorting funds based on past performance into deciles and creating a zero-cost portfolio holding the top a portfolio of assets showing positive momentum and shorting an equal size portfolio of assets with the least momentum. This was later adapted in different variations of return sorting, scaling and lags and usage expanded from mutual fund returns to other asset classes.

Momentum has been shown to also exist in markets outside of North America (Rouwenhorst, 1998; Walkshäusl, 2019) with some evidence for the anomaly being stronger in smaller markets. Momentum has also been tested in different asset classes such as commodities (Shen, Szakmary and Sharma, 2007).

Momentum studies are typically structured by using monthly returns with a formation period of 3-60 months and a holding period of 1-60 months. Several studies on momentum term-structures have shown 1 month holding period following a 12-month formation period to have the most significant excess returns (Jegadeesh and Titman, 1993; Novy-Marx, 2011). A cross-sectional momentum portfolio is based on a zero-cost portfolio with the short position being equal to the long position. Time-series momentum positions are on the contrary net long and thus have a cost associated with investing in risky assets. To increase comparability, one can deleverage the time-series momentum portfolio by sizing the positions so that the net-long position is zero at each rebalancing. Another possible way to address this is through holding a market portfolio in combination with the cross-sectional long-short portfolio sized so that it is equal to the size of the long leg of the time-series momentum long-short portfolio.

Research has shown momentum explaining a significant portion of stock market returns across geographies and asset classes. Asness, Moskwitz and Pedersen studied a large portion of possible asset classes, and both value and momentum explained a significant part of the returns (Asness, Moskowitz and Pedersen, 2013). In studies, time-series momentum has been shown to outperform cross-sectional momentum in stock markets. Some of this is attributed to time-series strategies taking a net long position in risky assets, but even when portfolio net long position has been scaled to have equal position between CSMOM and TSMOM, TSMOM strategies have outperformed across ranking and holding periods (Goyal and Jegadeesh, 2017).

Research into behavioural finance has argued that while prices are set by the markets, irrationalities and inefficiencies appear, which enables investors to generate significant excess returns. On a systematic level, if the markets were correctly reflecting all available information, generating excess return based solely on the information previous prices carry should not be possible.

The existence of momentum shows that returns exhibit some level of persistence over the medium-term. The reasoning for this has been rather varied, with literature showing that over longer terms reversals occur to bring long-term returns more in line with EMH. Momentum exploits autocorrelation in asset returns. Lewellen et al. (2002) argued that a behavioural explanation behind momentum could be excess covariance, not underreaction, but instead investors excessively taking news on one stock to represent information on other stocks or the market in general.

Momentum in the equity markets is one of the most studied phenomena in the recent decades. Commonly, momentum refers to cross-sectional momentum. However, the cause for the effect is still highly debated as can be seen in recent studies (Subrahmanyam, 2018). There are several hypotheses for momentum, and a single one has not been singled out and agreed upon as the reason for why momentum is apparent and why horizons such as 3-12 months are the period momentum appears and why the anomaly repeats across geographies and asset classes.

What has been consistent is that cross-sectional momentum has offered excess returns. The benefits of time-series momentum have been more differing and have been offering varying setups in portfolio formation. As the portfolio is not zero-cost, costs associated with the net position must be accounted for by deleveraging the position to achieve comparability between the two strategies and their returns. Recent research (Detzel, Novy-Marx and Velikov, 2023) finds many cross-sectional anomalies, such as using a five-factor model including momentum to be largely unexploitable due to high trading costs because of the associated high portfolio turnover.

High turnover has been a continuous issue among critics of momentum strategies. Literature has found times of increased trading volume to increase momentum (Connolly and Stivers, 2003). Equal weighted momentum strategies have been found to outperform value and liquidity weighted strategies without accounting for trading costs, while value weighted strategies offer more liquidity and capacity for trading and are more robust when accounting for trading costs (Korajczyk and Sadka, 2004). As value weighted strategies offer lower excess returns, trading costs present a limit to profiting from momentum strategies.

Momentum has in some studies been shown to be redundant with the HML (high-low) factor, but when a timelier value factor of Asness and Frazzini (Asness and Frazzini, 2013) is used, the momentum factor is not captured by other factors. Similarly, momentum or the high minus low factor were both not deemed redundant factors in a study comparing asset pricing models through Bayesian processing (Barillas and Shanken, 2018a). Barillas and Shanken discovered that six-factor model with market, momentum, size, value, investment, and profitability factors had the best probability of containing the relevant factors in a sample from January 1972 to December 2015.

Some potential explanations for momentum have been based on limited attention, for example through similar companies or companies in the same industry having the same analysts following them, other explanations are based on initial under-reactions to information (Moskowitz, Ooi and Pedersen, 2012). Studies such as Walkshäusl (2019) conclude that in markets where prices are less noisy and more driven by fundamentals, the momentum anomaly is stronger. This would suggest that markets with less liquidity and less trading would have a stronger momentum anomaly. This makes me believe that the anomaly might be interesting to explore between Finnish and Swedish markets since the markets are comparatively very similar, both being small regional markets with similar industrial compositions, but also offer a significant size and trading volume difference between the two.

Since both are comparatively small markets with similar industrial composition, the prevalence of momentum would be expected to be similar or closely following one another.

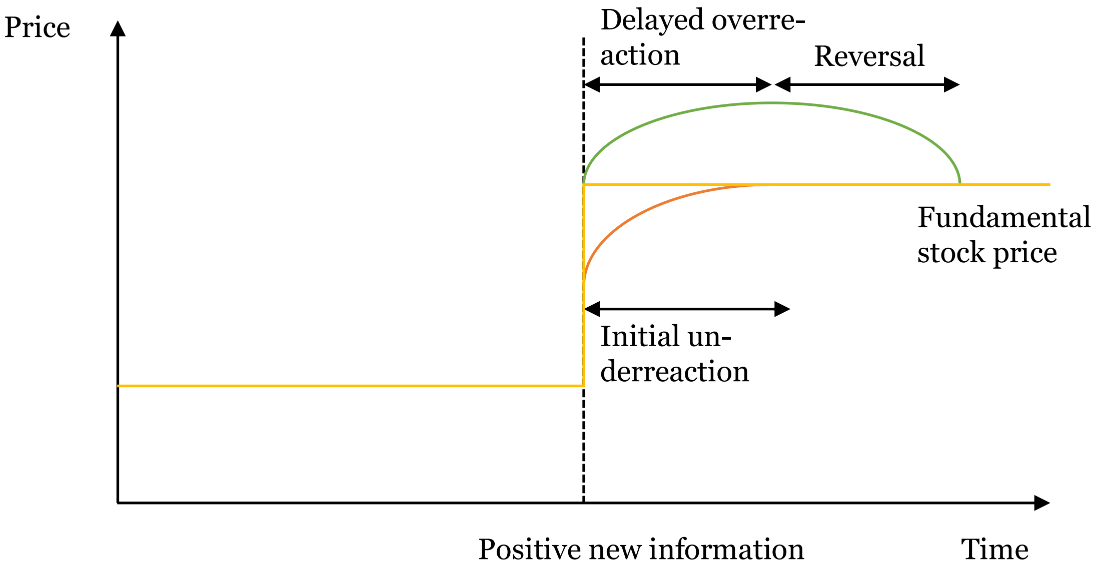


Figure 1 Investor over and underreaction (Wiest, 2023)

Some research has suggested that some of the momentum could be explained by investor underreaction, especially considering returns individual stocks (Lewellen *et al.*, 2002) and the phenomena is also present in industry, size and B/M portfolios. Figure 1 provides a visual representation on how underreaction causes a delay in the market adjusting to the new information.

Another possible behavioural hypothesis is delayed investor overreaction, where the price change continues to climb past a fundamental value as a reaction to new information, where momentum continues as a lagged increase in value, which is the corrected further on in time over a long-term reversal. This reaction is also visually represented in figure 1. Both reactions have been found to play a role in momentum (Hur and Singh, 2016) where overreactions have been found to occur less in recent times and the anomaly being primarily driven by underreaction. However, research has not been able to explain why investors underreact and overreact on different sets of firm-specific information.

It is a possibility that the momentum anomaly captures changes in investor appetite, which could be connected to what is called herding in behavioural finance. This means that investors follow other investors, and drive prices through focused interest in certain value chains, industries or even specific companies. Herding playing a role in the momentum effect has been confirmed in literature such as Lin, Wu and Zhang (2023). This has been more popular in the recent years, for example when talking about “meme stocks”, as information flow has increased in speed, but market participants trading on sentiment has existed for long.

The concept of information diffusion having a limited rate is further corroborated by shared analyst coverage capturing momentum spillover (Ali and Hirshleifer, 2020). Assuming analysts focus on industries or value chains, information from one company is applied to other companies, but with a limited rate. Ali and Hirshleifer found returns to have predictability when the companies shared analysts, as any lead-lag effect with the returns would be too high frequency to be captured by monthly or even weekly return data. This effect of cross-predictability could be linked to by information on one stock slowly also being incorporated in other stocks or erroneously having the reaction leak within the industry or supply chain to other stocks.

Time series momentum has been studied with a wide range of formation periods, holding periods and lags and this looks to be largely at the discretion of the study. In these studies, a lagged formation period of 12 months and a holding period of 1 month has often yielded the most significant excess returns (Moskowitz, Ooi and Pedersen, 2012), but the effect has often diminished with longer formation periods. This however depends on the chosen market and differs somewhat between them, but the consensus is that the most significant effect appears in portfolios where returns are ranked based on 12-month performance and then held for 1 month.

Combining research in time-series momentum with research in cross-sectional momentum allows us to see how these two phenomena interact and if they have variance between the two markets. The markets themselves are similar with companies often having comparable valuations, have similar market dynamics and industrial composition, but have a significant difference in size between the two markets, albeit both being on the smaller side.

These strategies share the goal of identifying winners and losers, and as such results should be similar. The selection between individual assets is different, but there will be major overlap in selection. The largest differences happen at times of strong bull and bear markets, when the CSMOM strategy is limited to the best and worse ranks, and TSMOM benefits from variation in the amount of assets each leg of the strategy holds.

Momentum portfolios exhibit short-term reversals, which is consistent with what we know about mean reversion in the markets. When the single month performance is lagged over 1 month (Novy-Marx, 2011) the performance of the strategy drops significantly compared no other alternatives.

2.3 Time Series Momentum and Cross-Sectional Momentum

Most studies have focused on cross sectional momentum studying the returns of market neutral zero-cost portfolios. This strategy can be explained as holding a short position half of the market while taking a long position in the other half, and the position are sized equally at each rebalancing, typically between each period. In time series momentum or TSM studies, positions are typically net-long, meaning they have a cost of capital. This inherently makes the results of a study less universal, as investors would need to account for their own cost of capital before being able to assess if a particular strategy is profitable.

Even though the theory behind time-series momentum is more recent, it has been at times dismissed, and studies have been more focused on cross-sectional momentum as cross-sectional momentum allows for zero-cost portfolios. Time-series momentum analyses asset returns at an individual level, every asset has either positive or negative momentum, whereas cross-sectional momentum divides assets into a portfolio of winners and losers based on the deciles they rank into when looking at the entire market.

Time-series momentum has been typically associated with more significant excess returns compared to the more traditional cross-sectional momentum. Cross-sectional momentum portfolios maintain a set percentage of the market in both portfolios, and as a result likely hold too few winners in bull markets, and too many losers in bear markets (Bird, Gao and Yeung, 2017).

As time-series momentum is defined separately for each asset, it can be possible that all the assets could either be long or short at each single point in time. As the stock market tends to grow overall in value, typical time-series momentum portfolios are net long as previously said.

This excess return has been partially explained by differences in the portfolio formation and that a time series momentum strategy is not zero-cost, which would require the short and long legs to have the same value directly after each rebalancing. However, as time-series momentum uses individual stock returns instead of return deciles like the CSMOM strategy, balancing TSMOM legs would require significant varying in the positions to allow zero-cost portfolio formation.

To account for these differences, we need to include a cost of capital for the long or short leg of the strategy. This allows for the returns between the two strategies to be comparable. This is done by a sensitivity analysis, adding a spread above the risk-free rate.

The most important distinction between the two types of momentum is that cross sectional momentum assigns the assets into winners and losers based on relative performance and time series momentum uses absolute performance as the measure. CSMOM portfolios are assigned based on ranking all of the returns during the formation period and assigning the best performing portion (for example 10%) into the winner portfolio, and conversely the worst performing portion into the loser's portfolio. TSMOM portfolios are formed by placing a certain hurdle where assets where returns are in excess for the formation period are placed in the winner's portfolio, and another hurdle, where the assets where returns are below this threshold are placed in the loser's portfolio. This can be a set return such as over 2% and under -2%, 0 return or the mean return of all of the assets in question.

Returns for CSMOM are calculated by assuming a short position in the loser's portfolio, and a long position in the winner's portfolio. Portfolio returns can hence be calculated by subtracting the loser's return from the winner's portfolio. TSMOM handles returns in the same way, where two portfolios are formed, and a long-short portfolio is formed out of the difference between these portfolios.

Combining these two strategies allows us to analyse whether the market is more strongly favouring positive returns in contrast to betting on past winners. To account for a variance in cost of capital, the TSM strategy would need to yield higher returns before taking the cost of capital into account and therefore an analysis on the effects of a cost of capital based on LIBOR and a sensitivity analysis based on a variable spread above that might result in interesting analysis. To address this, we will scale the CSM returns by adding a market portfolio position equal to the net long position in the TSM portfolio. This results in both of the portfolios having a similarly sized net-position.

The findings of Bird, Gao and Yeung (2017) show that time-series momentum yields positive return in a broader spectrum of markets than cross-sectional momentum. They studied TSM and CSM in up and down market states and found that CSM generally performs weaker in down states. They suggest this is due to CSM portfolios holding a higher number of weak performance stock in its long portfolio during reversals and downturns.

Portfolio turnover is often higher in momentum strategies than in other factor strategies resulting in higher trading costs. This requires the strategy to present a higher alpha than other trading strategies. If there is significantly more turnover, an estimate of trading costs would need to be included to show robustness of the results to a degree, where the anomaly is exploitable.

Additional phenomena often discussed around momentum are called momentum crashes, causing turndowns to be more severe, as equities that have had high momentum for a longer period often result in high valuations, where the risk for significant price movements is elevated. Studies have found that momentum crashes are predictable and happen when individuals start focusing on losses against probabilities (Daniel and Moskowitz, 2016). As such momentum crashes are highly predictable, a modified version of the strategy can largely avoid the risks from realizing (Barroso and Santa-Clara, 2014) and they don't present as a serious issue as is possible. For the purposes of this thesis, we will be using un-managed momentum, but a possibility to expand this study would be to also include the results with varying weights to manage risk exposure to momentum.

Cross-sectional momentum has been studied by many researchers over the years with varying results, and many attributing the excess return in a zero-cost portfolio to be attributable to other factors. However, while finding proof of the phenomena across markets and geographies, little research has been published between smaller European markets instead of treating the European stock markets as one whole. The whole universe of European stocks is more closely sized to the New York Stock Exchange, but the European market is more heterogenous as companies, valuations and investors who tend to overweight stocks in their own country, having a home bias. I hypothesis this causes differences in the way investors act and as momentum is believed to be a largely behavioural anomaly of either under-reacting or over-reacting, looking into differences between European stock markets could be of interest.

Explanation for momentum have largely been two-fold. Research offers explanations based on behavioural and risk-based explanation. I will largely focus on behavioural explanations in this thesis. Behavioural explanations such as limits to available arbitrage capital have been studied (Wang, Yan and Zheng, 2021) and empirical evidence has supported momentum being possibly a behavioural anomaly and a risk-based anomaly. Summarising 30 years of momentum literature (Wiest, 2023) concludes risk-based and behavioural-based explanations having reasonable arguments, but more recent developments in industry momentum and factor momentum are still lacking theoretical foundation.

One of the potential explanations of momentum being caused by the "frog-in-the-pan" phenomena of investors not paying enough attention to information coming continuously in small amounts (Da, Gurun and Warachka, 2014). However, the amount of information of a smaller market is less in quantity and if a significant portion of investors pay increased attention to their home market, I believe this effect should be less pronounced. There is a counterargument to be made of less following causing larger mispricing, but generally many analysts tend to give similar predictions and are mostly not too far off from aggregate numbers.

Momentum is often presented as being related to information dispersion. At times momentum has been presented as a byproduct of overreaction, underreaction, industry reaction, common analyst following and so on. Many of these theories have shown null, where the hypothesis doesn't follow a reaction that would be expected.

Overreaction theories stem on the idea that reactions would be too pronounced, with mean reversion following.

One of the key reasonings for reaction sizing is information diffusion. Diffusion has been tested in literature (Hong, Lim and Stein, 2000) finding that especially negative information takes time to diffuse among the investing public and the effect is especially pronounced in smaller firms. Goyal, Jegadeesh and Subrahmanyam (2024) find investors to typically underreact to new information arriving in small chunks, supporting the frog in the pan theory (Da, Gurun and Warachka, 2014).

In latest literature factor momentum has been shown to capture the momentum anomaly, including industry momentum and intermediate momentum (Ehsani and Linnainmaa, 2019), but for thesis we will focus on momentum of Jegadeesh and Titman (1993) and time-series momentum of Moskowitz, Ooi and Pedersen (2012).

A study (Bird, Gao and Yeung, 2017) found Finnish and Swedish stocks to outperform US equity markets using value weighted returns. It is possible this has been the effect of a few stocks making up most of the market capitalization of the stock market at times. To decrease the effect of numerically few stocks having too much of an effect in the overall, studies have used equally weighted portfolios, but similarly to other markets this leads to microcap stocks having a disproportional allocation and a market capitalization weighted portfolio replicated more closely a portfolio that an investor would be available to hold and trade on.

The same study found Sweden to exhibit a larger difference between TSM and CSM than Finland, with portfolio formation being approximately the same as the methodology I plan on using. This in interesting, since it could be explained by differences in investor reactions or sentiment. I expect the market microstructures to be comparable.

For decades, outperformance was tested on running a regression on the entire period that was being looked at, which may have been selected as the result of cherry picking or p-hacking. More recently, out of sample (OOS) testing become more commonplace, as a phenomenon should be considered valid only if it exists also outside of the selected sample, making cherry picking and p-hacking less likely to occur as phenomena that only appear in a certain set sample could not be exploited in the real world. Using sample data that cannot be replicated in other datasets would be sign of over-rejection of the null hypothesis. Some research argues that cross-sectional momentum does not appear robust out of sample (Choi and Zhao, 2020) and time-series momentum (Huang *et al.*, 2020) might be explained by differences in mean returns instead of predictability. Using data from post 1993 will allow for avoiding biases from data that is known to produce the wanted result, known as cherry-picking.

Building on the findings of literature, I hypothesize that the strength of momentum strategies has decayed over time as information dispersion rates have increased.

2.4 Contributions of this thesis

This thesis seeks to contribute to better understanding how momentum appears in Finnish and Swedish stock markets. Research into smaller markets is necessary, to better understand how the phenomena propagate into different markets with possible different structures. Empirical evidence of these two markets is lacking, and I aim to show how closely related the market movements between the markets are.

Most behavioural explanations are universal, and as such, it is expected that market participants act similarly across markets, and as time has gone by, with increased international market access, and the increase velocity of information, we should expect many of the anomalies uncovered in previous literature to be exploited by global investors with limited liquidity constraints.

Overall, this thesis will increase the understanding of cross-sectional and time-series momentum in the context of these two markets. The research could be broadened to other markets in the future to gather a more universally applicable understanding of the momentum anomaly.

2.5 Research questions and hypothesis

This thesis aims to address questions on how time-series and cross-sectional momentum appear in the Helsinki and Stockholm stock exchanges and is it a stronger or weaker effect than in more typical North American data available from CRSP.

Comparing both CSM and TSM allows us to see if the anomaly presents itself differently between the two stock exchanges. 12-month momentum is chosen since in most research, it has presented the strongest momentum anomaly out of the time periods that have been studied.

Out of the two different momentum definitions, time-series momentum typically outperforms, as it is not market-neutral.

Based on the literature review I expect time-series momentum to be more significant in the Helsinki stock exchange, as it has less companies for information diffusion, analysts typically cover companies in a broader range of industries, and industry coverage by analysts is not as focused as on Stockholm or especially in New York.

I split the time-series into 60 month rolling window regressions to test if the anomaly is consistent over time, or if the anomaly returns change over time and how robust the returns are at different points in time. Due to increased rates of information penetration and dispersion over time, I expect the anomalies to have less robustness over time.

3 Data and Methodology

This chapter describes the data and methodology used for in this thesis. First, I introduce the sourcing of the data used in this thesis. Secondly, I explain how returns are calculated and how the portfolios used in this thesis are formed.

To analyse this effect on the stock market returns I looked to the monthly market returns between 1993 and 2024 of companies listed in the Helsinki and Stockholm stock exchanges. The data composed of using the closing price for the first day of the month or the most recent closing price if the first day is not a trading day.

The data was sourced from Datastream. After filtering stocks with no valid data on the ISIN, total return index, price, price-to-book or market capitalization data on Datastream, we have a set of returns that that can be used to calculate the used factors. This resulted in 80 570 monthly observations on 324 securities in the Helsinki Stock Exchange and 265 826 monthly observations on 1 296 securities listed in the Stockholm Stock Exchange.

The total return index consists of an index assuming dividends are reinvested and as such is the best number to reflect continuous growth, and unlike raw price data, does not need to be fixed for splits, reverse splits, dividends and other changes that would be affect the price, but not the return experienced by the investors.

Price-to-book data is acquired from Datastream using the mnemonic price-to-book-value (PTBV). This is calculated based on the most recent closing price and the most recent reported book-value. As such it is a trailing value, and the reporting on non-US book-value is based on annual reports unlike US data, where quarterly reports provide a higher resolution of data. Annual reports are typically released during February and accessible markets in March. The book value is lagged by three months to account for this. The book to market value is calculated by dividing the book value by the market value.

The market value is the previous closing price of the stocks in the company multiplied by outstanding shares. This represents the market value of the equity stakes the investors hold in the company.

Positions in the TSM strategy are tested both scaled to volatility and without scaling to ensure that the strategy does not exploit the high volatility of some assets. Scaling to the selected factor has also been used in other literature (Baltas and Kosowski, 2012; Moskowitz, Ooi and Pedersen, 2012). Since some literature explains TSM by volatility such as Goyal and Jegadeesh (2018), we test TSM also without scaling. By having two TSM portfolios with different volatility, we can test if the adjustment in volatility has a significant effect on the returns. The scaling will also size of the long leg of the strategy and thus increase exposure to the market risk factor.

Both country portfolios are calculated on the mean of these returns. Cross-sectional momentum is calculated by ranking all the returns in each preceding 12-month period and taking a long position in the top three deciles and a short position in the bottom three deciles. The transaction costs are not considered, which could effect the results.

3.1 Portfolio Formation

The portfolios are created separately for both Helsinki and Stockholm exchanges. The stocks are classified into either long or short positions based on their 12-month past performance, with a long position in the stocks that have a positive 12-month return, and a short position in stocks that have a negative-12-month return, with a 1-month lag. This is similar to what has been done in previous literature on time-series momentum, other variations in literature being a 30-40-30 split long-short: going long on best performing 30 % of past stocks that have provided a positive return and shorting stocks where the past return has been negative. In cross-sectional momentum, most literature uses quintiles or deciles to rank returns and uses the best decile or quintile to form the long portfolio, and the worst performing decile or quintile to form the short portfolio to form a zero-cost portfolio.

The portfolios are tested both value-weighted and equal-weighted to account for market microstructure. This is a significant effect, since many of the stocks listed in either of the two exchanges are small and have limited liquidity to use in strategies requiring constant trading. In practice many of the stocks in question are not shortable for many investors, as no market participant is interested in the stock as large parts of the stock market are held by pension funds or the state.

Cross-sectional momentum portfolios are formed by ranking 12-month returns across the exchanges, forming a long position on the best performing 30% of companies, and an equally sized short position on the worst performing 30% and then holding the stock for the following 1-month period following a 1-month lag. The 12-month formation period, 1-month lag and 1-month holding period will henceforth be called a 12/1/1 portfolio.

By scaling each position in the time-series momentum portfolio to 40% ex-ante volatility we can achieve comparability to other studies. Using a 1 month holding period lagged by 1 month following a 12-month lookback period is one of the most common time-series momentum portfolios in academic literature used in Moskowitz, Ooi and Pedersen (2012) and many other since then, but has been refuted by claims of volatility being the reason for time-series returns.

The returns of the portfolios are benchmarked to the Fama-French three-factor model and the Carhart four-factor model. The three-factor model enhances CAPM explaining the returns by adding size and value premium as regression factors.

The small minus big (SMB) factor is calculated by sorting the returns into deciles by market capitalization and forming long-short portfolios on the top and quantile measured by market value and the high minus low (HML) factor is calculated by similarly ranking returns based on the book-to-market ratio forming long-short portfolios on the bottom and top 30%. The market capitalization and price-to-book ratios were obtained through Datastream, and to calculate the HML factor, the required book-to-market value was obtained by calculating the inverse of the price-to-book which was provided by Datastream.

Data was sourced with a period from January 1993 to December 2024. As data is very sparse in the period preceding the 1990s and compared to US equities data where studies often use a sample beginning in 1960s, Nordic stock markets have used samples starting in the 1990s, as this was a period when the Finnish stock market started to be more accessible to trading (Grobys and Huhta-Halkola, 2019). The period used in this study reflects periods that have been chosen in other studies due to data availability.

Using data in the Nordic countries does not provide as a robust dataset as North American data. The stock markets have developed only in the 1980s as access to the financial markets was opened for foreign capital and investments increased. However, having 31 years of data provides a robust sample size, and avoids time periods in which many of these factors were originally studied, the 1950s and 1960s, which also adds robustness to the results.

For TSM the portfolio was constructed by having a 12-month formation period and a 1 month holding period with skipping one month in between to isolate the anomaly from short-term reversal. If the stock returns were positive for the past 12-month period, the stock was then held for one month, and conversely if the returns were negative for the 12-month period, a short position was taken on that security for the following month.

The CSM portfolio was constructed based on a similar 12-month lookback period, with holding the better holding the best performing 30% of the stock market and shorting the bottom three deciles. This was done to have the groups be large enough, since with deciles, or even quantiles, the group sizes would become at times smaller than what would be optimal.

Companies that merged or were delisted, were held towards their final value, but excluded from portfolio formation at later date when no more returns were calculated based on the total return index that was used to calculate returns.

The high minus low (HML) and small minus big (SMB) were calculated by creating portfolios for the top 30% and the bottom 30% in a similar methodology that was originally documented by Fama and French (1992). High meaning high valuation based on the highest 30% book-to-market (BM) ratio and low the bottom 30% based on book-to-market (BM) ratio, the 40% in the middle are sorted as neutral. The SMB factor is calculated based on market capitalization, with using the top decile of companies as the big companies, and the bottom decile as small companies. With these a 2x3 sort of companies is formed based on their size and value, for which factor returns can be calculated to capture these effects. The book-to-market ratio is a monthly value, that differs from the one Fama and French use but compared to having an annually lagged book-to-market, a monthly number derived from the latest filing should be more accurately reflected in pricing.

Volatility is calculated ex-post from returns, considering the last 12 observations of returns, which is then scaled to annual volatility:

$$\sigma_{annual} = \sigma_{monthly} * \sqrt{12}$$

Test for TSM benefitting from the long equity position holding, the CSM portfolio will be leveraged to a similar level, through holding a long equity portfolio. This will make the results more comparable between the strategies.

The scaled return for each stock in the time-series momentum portfolio is calculated followingly:

$$r_{i,t} = sign\left(r_{i,t} - r_{i,t-12}\right)\frac{40\%}{\sigma_t}r_{i,t}$$

r is the monthly return on each individual stock, the lower indices are the time index. The scaling factor is the same as Moskowitz, Ooi and Pedersen (2012) used to increase comparability between the results, but we could use a volatility number that is derived from the data, to more closely match the annual volatility of the stocks in the selected markets.

For unscaled TSM returns, I omit the scaling factor but otherwise calculate the returns in the same way to calculate returns without volatility scaling.

Cross-sectional momentum is tested unscaled and by scaling the returns to better match TSM, through calculating the net-long position of TSM and adding a long market portfolio to match the long position, and to adjust away from a zero-cost portfolio. This will make the two portfolios more comparable.

CSM is also tested scaled, with adding a market portfolio component. The scaled CSMVW portfolio is scaled by the net-long position of the TSM portfolio by holding a market portfolio that is sized to the net-long position of the TSM portfolio. This results in the TSM and scaled CSMVW portfolios having the same market position. This makes the portfolios equally costly to hold and increases the comparability between the two portfolios.

Table 1 Descriptive statistics on data

This table reports descriptive statistics of the data used in the sample between Helsinki and Stockholm stock exchanges. The sample period is from January 1993 to December 2024. The observations are monthly, with the returns using the closing price of the first day of the month.

		N	**Min**	**Max**	**Mean**	**SD**
Helsinki	Return	80570	-86.1%	1000.4%	0.7%	11.1%
	Price to Book ratio	80570	-651.85	1038.96	0.6822	32.08
Stockholm	Return	265826	-99.0%	10678.9%	0.7%	26.3%
	Price to Book ratio	265826	-5000.01	6828.50	3.618	49.96

Table 1 presents the statistics on the return and price to book ratio data before forming the portfolios. As evident in the table, the size of the Stockholm stock exchange is approximately four times the size of the Helsinki stock exchange by the amount of price observations in the data set, while resulting in similar, but more risky returns at higher valuations.

3.2 Comparing TSM and CSM

I evaluate the CSM and TSM strategies if either one is advantageous over one another by regressing over the benchmark of market return. The dependant variable is the strategy return and independent variables are the market return and the FF3 factors: High minus low and small minus big.

$$r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + \epsilon_{i,t}$$
$$r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + \epsilon_{i,t}$$

The intercept α represents the excess return that is not captured by the linear regression. The coefficients β, s and h represent the factor loadings, meaning how sensitive the return is to changes in the corresponding regression factor.

I also run spanning test between the strategies to see if any of the strategies spans one another.

$$r_t = \alpha_t + \beta_t RMRF_t + h_t HML_t + s_t SMB_t + b_t BM_t$$

The added factor in this regression is a benchmark factor, which in the case of time-series is the cross-sectional momentum factor and vice versa to see if the factors are spanned by each other. If this decreases the alpha of the model, we can consider the dependent factor to be spanned by the model.

3.3 Rolling window regression

To test for model applicability as a function of time, I regress the model to a 120-month rolling window regression. Calculating the T-test on these results will show if the null-hypothesis of the regression coefficients being other than 0 can be rejected. The choice of 120 months is purely coincidental, being equal to 10 years. This provides a sample size, that allows some robustness, and provides 21 years of submodels, providing a time series with 252 observations.

The strategies are regressed on a FF3-model, with a window of 120 observations. The regression is the same as the FF3 on the entire sample but covers the past 120 observations. Plotting the t-test of the regression alpha on the time axis allows us to visualize how the robustness of the excess returns has changed over time.

3.4 Portfolio performance

The Sharpe ratio (Sharpe, 1966) is one of the most used metrics measuring the risk-adjusted return of portfolios. Sharpe ratio can be used ex-post or ex-ante to measure the risk-adjusted portfolio performance over the risk-free asset.

$$SR = \frac{R_P - R_f}{\sigma_P}$$

R_p is the mean portfolio return, R_f is the mean risk-free return, in this case the government bonds, and σ_P is the volatility of the portfolio. The Sharpe ratio is not a perfect measure, as the portfolios have varying net long positions, but it allows for some comparison of the returns to the risk taken. However, the risk-free rate could be adapted to use a risk-free rate that accounts for the net long position as a portion of the portfolio.

I also use model alpha as a measure of performance not captured by other factors. This shows if the strategy generates returns that are not explained by the independent variables. Jensen's alpha is a similar performance measure, but I do not regress risk-free return in the regressions as the portfolios have a varying net-long position, with CSM strategies being zero-cost, and TSM having a varying net-long position.

4 Results

The purpose of this chapter is to present the results. I present the performance of the selected momentum portfolios in the Helsinki and Stockholm stock exchanges and regress them on the FF3 portfolio as well as regress a spanning test on the cross-sectional and time-series momentum portfolios by adding the other momentum portfolio as a regression factor. I test the portfolios on a 120-month rolling window model to plot statistical robustness of the excess return of the model over a FF3-model.

4.1 Descriptive statistics of the results

Table 2 Descriptive statistics on strategy returns

The values are monthly observations. Portfolios are formed over a 12-month period, followed by a month of lag and a one month holding period. The TSM portfolio is formed by splitting the stocks into losers and winners based on the median return in the formation period. Scaled TSM scales each position to 40% annual volatility. Value-weighted TSM uses the market value of each company to weight the position. CSM ranks the returns during the past 12 months and shorts the bottom 30% while holding a long position the top 30%. Value-weighted CSM takes a value-weighted position in each stock. Scaled CSMVW scales the value-weighted position to match the net-long position f the TSM-portfolio. This table reports the summary on the returns. The sample period is from January 1993 to December 2024. All of the returns are significant at a level of 5%. The returns are expressed as percent.

Helsinki	**TSM**	**Scaled TSM**	**TSMVW**	**CSM**	**CSMVW**	**Scaled CSMVW**
Mean	0.53	1.24	0.78	0.22	0.51	0.90
Median	0.56	1.11	0.36	0.31	0.32	0.55
StdDev	2.73	4.15	4.46	1.33	3.77	5.42
Skewness	1.53	0.42	0.64	-0.99	0.73	-0.03
Kurtosis	15.24	3.82	7.56	5.72	13.6	9.95
Minimum	-11.9	-16.5	-21.5	-8.43	-21.1	-31.9
Maximum	23.3	22.8	29.2	4.85	29.1	33.0
T-test	3.71	5.77	3.44	3.17	2.58	5.42
Stockholm						
Mean	0.44	1.05	0.64	0.20	0.48	0.87
Median	0.46	0.97	0.71	0.30	0.44	0.78
StdDev	2.58	3.29	3.63	1.57	2.47	4.35
Skewness	-0.28	0.09	0.06	-2.10	1.13	0.61
Kurtosis	8.89	3.19	2.59	11.59	8.50	4.13
Minimum	-12.4	-13.3	-13.6	-9.43	-8.09	-17.2
Maximum	17.2	16.7	18.1	4.59	17.7	21.7
T-test	3.30	6.16	3.39	2.50	3.73	3.85

Table 2 shows scaled time-series momentum to have a significant edge over other portfolios, which is explained by the extreme leverage that getting enough volatility requires in a monthly rebalanced portfolio. This could be decreased by introducing cap on the scaling factor, often numbers between 1 and 1.5 are often used to not over lever, but this factor was omitted in this study. This likely however means that the leverage-ratio on the strategy is high. Scaling the CSMVW portfolio to the net-long position of the TSM portfolio increases the volatility of the portfolio, but increases the return more than the additional risk.

All of the strategies being studied offer positive and have a significant unequalness to zero, meaning that at a 5% confidence level, the null hypothesis can be rejected. This means that the strategies all provide a return that is statistically different from zero.

4.2 Regression analysis

In this subchapter I regress the resulting portfolio returns on the Fama and French 3-factor regression model as well as regress the returns on a four-factor model, where the FF3-model is expanded with a benchmark factor where the other momentum base portfolio is used to study if the anomalies are spanned by each other. I then compare the findings to other research.

Table 3 Stockholm FF3 regression results

This table presents the results of the Stockholm TSM, TSMVW, CSM, CSMVW FF3 regression. The portfolios are long-short portfolios. The monthly portfolio returns are regressed on monthly factors and the monthly market return. The bracketed number below the value of each coefficient is the standard error. The sample period is 1993-2024. The values are expressed in decimal format.

	Dependent variable:			
	TSM	TSMVW	CSM	CSMVW
	(1)	(2)	(3)	(4)
mkt	-0.059**	0.228***	-0.124***	0.176***
	(0.030)	(0.040)	(0.016)	(0.026)
HML	-0.135***	-0.160***	-0.097***	-0.165***
	(0.031)	(0.042)	(0.017)	(0.027)
SMB	-0.070***	0.019	-0.114***	-0.042*
	(0.025)	(0.034)	(0.014)	(0.022)

Constant	0.002	0.003	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	371	371	371	371
R^2	0.052	0.139	0.209	0.220
Adjusted R^2	0.044	0.132	0.202	0.214
Residual Std. Error (df = 367)	0.025	0.034	0.014	0.022
F Statistic (df = 3; 367)	6.709***	19.741***	32.312***	34.499***
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 3 shows the FF3 regression on the equal weighted and value weighted momentum portfolios in the Stockholm stock exchange. The R-squared is weak on all models, providing that the returns are only slightly explained by the FF3-model. The negative HML factor coefficients suggest that returns are driven by companies with higher valuations, and the negative SMB coefficients suggest that larger companies are selected in the TSM portfolio.

Table 4 Helsinki FF3 regression results

This table presents the results of the Helsinki TSM, TSMVW, CSM, CSMVW FF3 regression. The portfolios are long-short portfolios. The monthly portfolio returns are regressed on monthly factors and the monthly market return. The bracketed number below the value of each coefficient is the standard error. The sample period is 1993-2024. The values are expressed in decimal format.

	Dependent variable:			
	TSM	TSMVW	CSM	CSMVW
	(1)	(2)	(3)	(4)
mkt	0.053*	0.143***	-0.074***	0.030
	(0.029)	(0.048)	(0.014)	(0.040)
HML	0.030	-0.084**	-0.027**	-0.134***
	(0.024)	(0.040)	(0.012)	(0.033)
SMB	0.044	-0.069	-0.047***	-0.119***
	(0.027)	(0.045)	(0.013)	(0.038)
Constant	0.006***	0.005*	0.002***	0.002
	(0.002)	(0.002)	(0.001)	(0.002)
Observations	359	359	359	359
R^2	0.013	0.061	0.084	0.066
Adjusted R^2	0.005	0.053	0.076	0.059

Residual Std. Error (df = 355)	0.027	0.044	0.013	0.037
F Statistic (df = 3; 355)	1.552	7.688***	10.832***	8.426***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4 provides the results for the FF3 regression on the equal weighted and value weighted momentum portfolios in the Helsinki stock exchange. The results are similar but with an even lower R-squared. The model does not explain the momentum portfolios in Helsinki. The estimates on the coefficient hare the findings, with broadly speaking larger companies with higher valuations explaining the returns. The excess return, the constant or alpha, are stronger in the Helsinki stock exchange than the Stockholm exchange. The constants are mostly statistically different from zero in Helsinki, but not in Stockholm, after accounting for the FF3 factors.

Further on, I regress the strategies to modified four factor model. The factors are as discussed in the previous chapter, with using the other factor as a benchmarking momentum to see if the anomaly is spanned by the other. The CSM and TSM strategies are equal weighted, and the TSMVW and CSMVW strategies are value weighted.

$$r_{i,t} = \alpha_i + \beta_i MKT + h_t HML + s_t SMB + b_t BM$$

Table 5 Monthly alphas with spanning

The monthly alphas for the tested portfolios in percentages. The number under the alpha in parenthesis is the t-test result of the alpha. The added benchmark factor is in the second row of the table. The bolded numbers are statistically significant at a 5% level. The sample period for the returns is from January 1993 to December 2024 and with a 12-month long formation period combined with a 1-month lag, the portfolios are formed starting from February 1994.

DV	**TSM**	**Scaled TSM**	**TSMVW**	**CSM**	**CSMVW**	**Scaled CSMVW**
Bench-mark	*CSM*	*CSM*	*CSM*	*TSM*	*TSM*	*TSM*
Hel-sinki	**0.25%** **(2.43)**	**0.68%** **(4.64)**	0.03% (0.17)	0.10% (0.20)	-0.12% (-0.58)	-0.24% (-1.02)
Stock-holm	**0.34%** **(3.98)**	**0.91%** **(6.50)**	**0.45%** **(2.63)**	**-0.20%** **(-4.09)**	-0.11% (-0.82)	0.31% (1.48)

The results of the regression in table 5 show that TSM present an alpha in Helsinki not captured by HML, SMB or CSM factors and the effect is similar in Stockholm. As to be expected, scaling TSM increases the alpha, as these result in increasing the net long position by increasing the volatility of the individual positions. Value-weighted TSM offers alpha in Stockholm, but curiously it the returns are captured by the other factors in Helsinki.

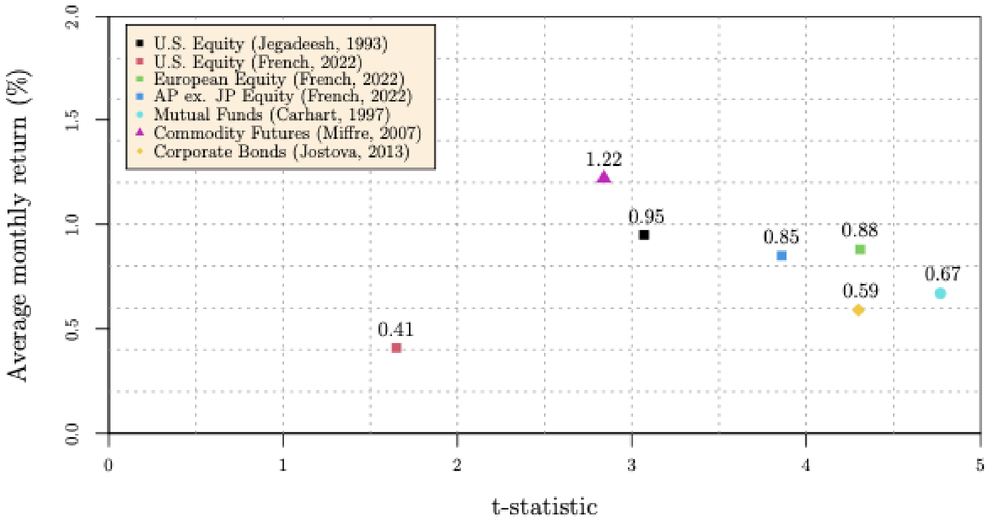


Figure 2 Average monthly returns and their t-statistics in several cross-momentum studies (Wiest, 2023)

Comparing results to Wiest's summary of cross-sectional momentum returns in figure 2, I document a mean monthly return of 0.22 % in the Helsinki stock exchange with a t-statistic of 3.17 and 0.20 % mean monthly return with a t-statistic of 2.50 in the Stockholm stock exchange. This shows that the effect is observable in both markets being studied, but the momentum anomaly is less pronounced. in the Stockholm stock exchange. This could be due to having more market activity and liquidity in the market. Showing weaker returns could be due to the sample being more recent than many other studies with information diffusion rates increasing and leading to weakening the anomaly.

The TSM portfolio holds a mean net-long position of 16% in the Helsinki portfolio and 13% in the Stockholm portfolio. The scaled CSMVW portfolio holds the same size market portfolio, so the portfolio should perform similarly. Between the TSM portfolio and the scaled CSMVW we can notice that scaling CSMVW shows stronger returns. This hints at the long volatility being a source of the returns, but also that the returns of the strategies are comparatively weak compared to the market portfolio, however scaled CSMVW and TSM have the same cost associated with holding the portfolio.

4.3 Rolling window regression

In this subchapter I run a rolling window regression on the portfolios using a 120-month FF3-model. By plotting the t-test of the alpha as a function of time we can visualize how robust the excess returns are for the portfolio, controlling for the three factors used in the model.

The regression in the rolling window model is a Fama-French 3-factor model.

$$r_{i,t} = \alpha_{i,t} + \beta_i \cdot MKT + s_i \cdot SMB_t + h_i \cdot HML_t$$

The model is the same as previously used, but the key difference in these regressions is using a rolling model and forming approximately 240 linear regressions that can then be used to estimate the residuals, standard errors and run a t-test individually in all of the regressions which can then be plotted as a time-series. This results in a plot where peaks form areas where a 120 month sample could be picked and claim that the sample shows the anomaly is statistically different from the null hypothesis.

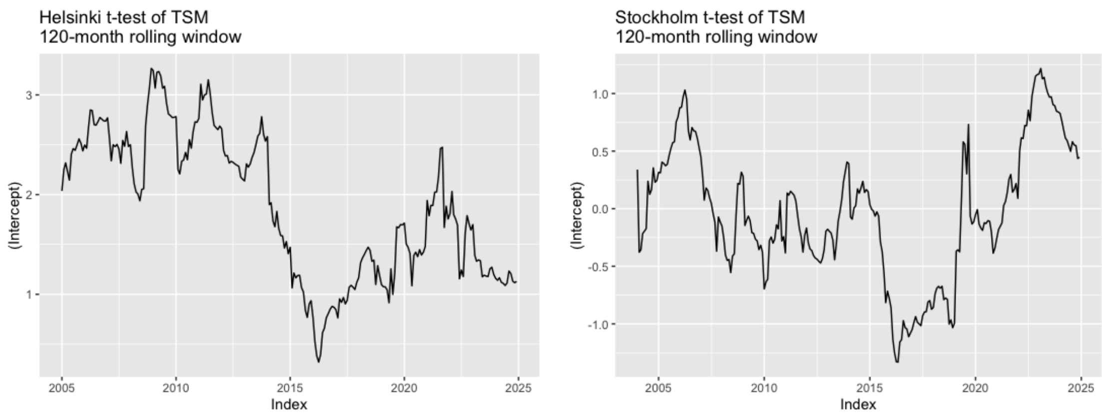
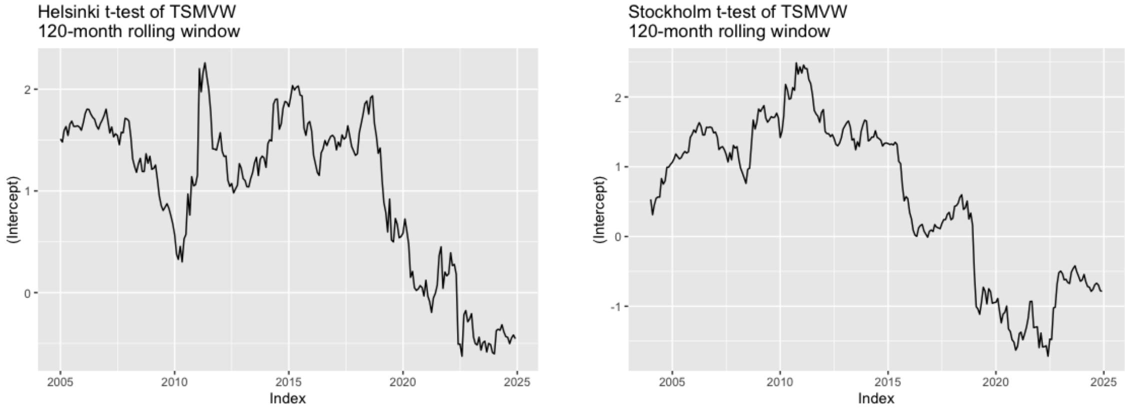


Figure 3 T-test on TSM FF3 regression alpha

As can be seen in figure 3, the robustness of time-series momentum with a 12/1/1 portfolio in these markets has diminished, and is not statistically different from zero. In the Swedish market there is no time period where I could conclude time-series momentum to be present, and in the Finnish market it has largely dissipated, and has not been observed at 5% significance in the past 10 years. With a sample size of 120, a two-tailed t-test would need a score of more than 1.980 to reject the null hypothesis at 5% significance.



Similar rolling window regressions on value-weighted TSM in figure 4 show

Figure 4 T-test on TSMVW FF3 regression alpha

weak t-tests for alpha on the 120-month rolling window regression. What we can notice is that the results have become closer to 0 and limit the ability to reject the null-hypothesis.

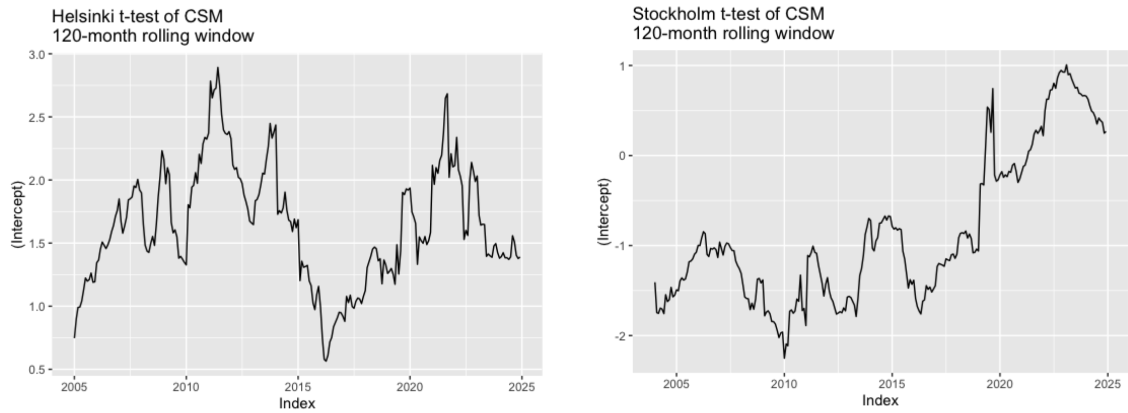


Figure 5 T-test of CSM FF3 regression alpha

Running the same rolling window model on the CSM and CSMVW regression alpha t-test yield similar results shown in figure 5 and 6, with timeframes where CSMVW has offered statistically significant alpha in the FF3 regression, but through most of the history, the absolute value of the t-test is not high enough to reject the null hypothesis.

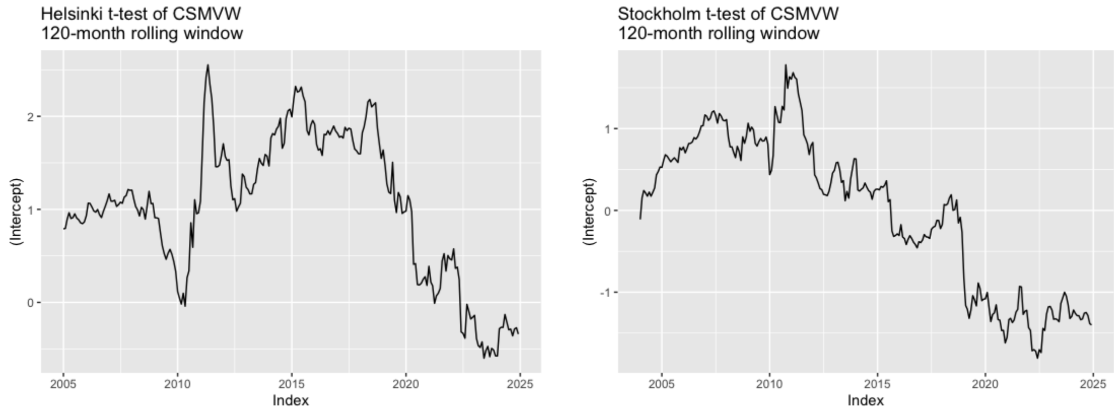


Figure 6 T-test of CSMVW regression alpha

4.4 Portfolio performance and riskiness

In this subchapter I analyse how well momentum portfolios perform and how risky the portfolios are compared to a market portfolio; we look at several factors. These factors are calculated on the monthly data of the static models.

4.4.1 Volatility

Volatility, measured by the standard deviation is a measure of the riskiness of returns. The measure is backwards looking and based on the historical distribution of the returns. The results show that all the portfolios tested are less volatile than market returns.

Table 6 Standard deviations
The standard monthly standard deviations of the portfolios.

	Helsinki	**Stockholm**
TSM	2.74%	2.58%
TSM scaled	4.15%	3.29%
CSM	1.33%	1.54%
CSMVW	3.77%	2.43%
CSMVW scaled	5.42%	4.36%
Market portfolio	5.55%	4.70%

The standard deviations in table 6 show that the unadjusted momentum portfolios (TSM and CSM) are less risky to hold than the market portfolio. The CSM scaled portfolio, which holds a market portfolio in addition to the

CSM portfolio, which matches the size of the TSM portfolio, provides less risk than the market portfolio, while also providing a more significant return than the TSM portfolio at the same cost of holding the portfolio.

4.4.2 Annualized Sharpe Ratio

The Sharpe ratio (Sharpe, 1966) is a commonly used metric to compare the performance of investing into risky assets compared to investing in risk-free assets. Comparing the Sharpe ratios of these strategies allow some increased understanding of the differences in performance between the two markets.

Table 7 Annualized Sharpe

The annualized Sharpe ratios of the portfolios are calculated based on the local risk-free rate. The Sharpe ratio is calculated to understand the risk-reward ratio compared to the risk-free asset, in this case the 10-year treasuries. The risk-free rate is calculated as the monthly return from holding a portfolio of 10-year benchmark bonds. These are adjusted from monthly Sharpe ratios to annual to present more comparable results.

	Helsinki	**Stockholm**
TSM	0.063	-0.0416
TSMVW	0.2078	0.1264
TSM scaled	0.6222	0.6065
CSM	-0.5873	-0.5514
CSMVW	-0.0049	0.0045
CSMVW scaled	0.2052	0.2732
Market portfolio	0.4374	0.6768

According to Sharpe ratios in table 7, equal weighted cross-sectional momentum returns in both markets lose money compared to holding a risk-free portfolio. However, this is the one portfolio with a completely market neutral position, and the return in table 2 and table 3 should not be impaired by the cost of holding the portfolio, as there is no cost associated.

To have more meaningful results, the Sharpe should consider the net long position. Since the CSM strategies are zero-cost and TSM strategies have a varying net-long position, they are not directly comparable to a Sharpe ratio of a net-long portfolio. However, the ratios are included for comparison.

5 Conclusions

In this chapter I present my conclusions based on the results of the regressions and how the empirical evidence fits in with the theory addressed in the literature review.

The results in tables 3, 4 and 5 support my hypothesis of momentum being a stronger anomaly in the Helsinki stock exchange. I find this to support the hypothesis that momentum is more pronounced in markets that are smaller and driven more strongly by fundamentals. This is consistent over cross-sectional and time-series momentum. However, in samples of the US markets, the anomaly has been stronger than I find in the sample. The finding here is inconsistent and would looking into how the anomaly acts under different timeframes and using US equity data to test the anomaly with the same time frame and methodology to account for small differences in portfolio formation. This could be explained by a mismatch in formation or time period.

CSM performance does not provide returns as expected and is largely captured by the HML factor in the Stockholm stock exchange. This is consistent with the findings of Ehsani and Linnainmaa (2025), but having the HML based on the monthly stock price and the annual book value, I expected there to be a less significant connection as had happened when a timelier factor was used (Asness and Frazzini, 2013).

The rolling window regressions show that for 10-year periods, the anomalies are not as pronounced and robust as could be expected from the literature. However, periods can be identified when a sample could be selected that would offer a robust sample. I find the rolling window models interesting, as it offers an opportunity to add a view into the anomaly, that would have been computationally hard to run 252 linear regressions when Jegadeesh and Titman (1993) when originally documented the anomaly.

I find the rolling window regressions to show that the anomaly is not very robust, and as a trend, the anomaly has been weakening in all variants in the more recent time periods of the sample. This is consistent with findings such as Bhattacharya, Li and Sonaer (2017). This supports my hypothesis of anomalies weakening as information is faster to distribute to investors and analysts.

In addition,, the Swedish stock market appears to conform more strictly to the EMH. This could hint towards the Helsinki stock market having some microstructures that limit the effectiveness of asset pricing. Having investors with less liquidity limits might allow for more efficient markets, and research into whether limited liquidity is a limiting factor would be interesting.

The results could be further expanded on by using a variety of formation periods and holding periods. A significant part of recent studies combine momentum signals with variable per asset holding periods, which decreases portfolio turnover and manages risk of momentum crashes as well as volatility. Factor-momentum has been shown to span momentum, and I expect the same weakening to also appear there.

Many topics are reasons for further research. A wider variety of formation and holding periods could be used to examine the anomaly and strategies at different time horizons. The use of higher frequency data could still show that the anomaly is there, however the results of the thesis show that 12/1/1 might not offer the momentum profits that have previously been documented. This does not mean momentum does not occur, but only that the anomaly might have become more short-lived as information speed has increased over the years.

6 References

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