UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Momentum and Trend in Sweden:

Enhancing profits and limiting downside risk by using indicators from different time horizons

Alan Dari Lindahl

Jan Wiki

June 2020

Graduate School

A thesis submitted for the degree of Master of Science in Finance

Supervisor: Adam Farago

Abstract

Although being one of the most robust anomalies ever discovered, the momentum factor occasionally suffer big losses during market recessions periods. We apply and compare different factor models, and find that when sorting the momentum factor on prior 2-6 months it earns a higher average monthly return compared to the common sorting on prior 2-12 months. This difference however is not found to be significant, and this model still suffers from similar big downside risk. The trend factor on the other hand, by using moving averages of prices in various time horizons, earns an even higher return and significantly improves the downside risk. By examining the recession period following the 2008 financial crisis, this is evidently true. While the momentum factor along with its different sorting periods and the market all earn quite large negative monthly average returns, the trend factor has a corresponding positive return during this period. The performance of the trend factor is robust to various transaction costs, accounting for common risk factors, alternative portfolio formations and over additional stock markets.

Keywords: *momentum, momentum crash, echo, trend, moving averages, cross-section, downside risks, predictability, factor models, turnover, transaction costs*

Acknowledgement

First and foremost, we wish to thank Adam Farago for his insightful remarks and guidance throughout the process of writing this thesis. We would also like to thank our friends and families for their continuous support throughout our work with this thesis.

Contents

List of Figures

List of Tables

List of Abbreviations

CAPM capital asset pricing model.

HML high-minus-low.

IR intermediate horizon return factor.

LREV long-term reversal factor.

MA moving averages.

MDD Maximum Drawdown.

MOM momentum factor.

RR recent horizon return factor.

SMB small-minus-big.

SREV short-term reversal factor.

Trend trend factor.

WML winner-minus-loser.

1 Introduction

Factor-investing has been a highly researched topic where the aim is to trade on asset mispricings, so called anomalies. This is usually done through a long-short strategy, which is arguably the theoretically most suitable approach to capture the factor premia and earn an arbitrage-like profit. One such anomaly is the momentum anomaly with the fundamental idea that stocks that have performed well in the past, winner stocks, will continue to outperform and stocks that have performed bad in the past, loser stocks, will continue to underperform (Jegadeesh & Titman, 1993). Although momentum investing delivers high returns on average, it occasionally suffers crashes with a magnitude that scares of most risk avoiding investors (Barroso & Santa-Clara, 2015). Additionally, Mclean and Pontiff (2016), and Hou, Xue, and Zhang (2019) find that the potential profit for discovered anomalies generally drops after publication.

The concern that investors trade on the anomalies resulting in lost potential profits, however, appears to be specific to the US market (Jacobs & Müller, 2019). In fact, due its construction the momentum factor (MOM) is even benefiting from traders being active in the market (He & Li, 2015). Following their original publication on momentum investing Jegadeesh and Titman (2001) indeed found an increased post-publication relative return to high momentum stocks. The fact that more traders try to capture the momentum factor raises the question how to best time the momentum factor. This is also crucial to avoid the big momentum crashes. Novy-Marx (2012) approach this timing issue by simply altering the sorting period. It is found that portfolios sorted on prior 7-12 months (intermediate horizon return factor (IR)) outperform those sorted on prior 2-6 months (recent horizon return factor (RR)). This rather striking and surprising finding of an echo in returns, is robust over various US asset classes and does not fit the conventional view of momentum; winner stocks stay winners, and loser stocks stay losers. Since it is left without any economical explanation by the author it is instead attempted by Goyal and Wahal (2016) who found no robust evidence for an echo in any other market. Further, they argue that ”Any echo in the United States appears to be driven largely by a carryover of short-term reversals from month -2”(Goyal & Wahal, 2016, p. 1237). While the sorting period chosen appears to affect the returns, it does not address or solve the issue of momentum crashes.

The trend factor (Trend), developed by Han, Zhou, and Zhu (2016), does just that. The model takes its stand in the three major stock pattern that classical factor models fail to explain (Han et al., 2016): (1) short-term reversals documented by Jegadeesh (1990), Lehmann (1990) and (Lo & MacKinlay, 1990), (2) the momentum factor and (3) the long-term reversal effects (3–5 year reversals) documented by DeBondt and Thaler (1984). Han et al. (2016) then tries to exploit any economic gain by combining the three models and use price signals across all investment horizons. Instead of past returns, as commonly used by the momentum factor, the trend factor relies on the predictive power of moving averages (MA) (see e.g. (Treynor & Ferguson, 1985; Brown & Jennings, 1989; Cespa & Vives, 2012; Edmans, Goldstein, & Jiang, 2015)).The strategy to use price signals across various investment horizons proofs successful. Not only do Han et al. (2016) find that the trend factor outperform the momentum factor in the US, but also, arguably more importantly, it does not suffer the above mentioned periods of big crashes.

While both above mentioned strategies of the momentum echo and trend following render higher average return than the standard momentum factor, they also carry higher turnover rates. Since the high turnover of momentum investing already is a debated issue, this poses concern. This concern is met by both Novy-Marx (2012) and Han et al. (2016) by stating that the higher transaction cost induced by their strategies are more than offset by the higher average return generated. This is of course debatable since how to measure transaction cost is a subjective matter. In fact, the major part of research on momentum investing neglects important indicators of higher transaction cost (Lesmond, Schill, & Zhou, 2004).

Due to the limited research body of both the momentum echo and the trend factor relative to the well known momentum factor, we will in this thesis add a comprehensive analysis of both models in the Swedish market. Furthermore, we will provide a thorough comparison of both strategies which, to our knowledge, is not done before. Regarding transaction cost we do not aim to address the debate on how to calculate correct transaction cost directly. Rather, we will provide an in-depth picture of potential costs and how the different strategies and their relative performance will be affected. By mimicking the portfolio construction by Novy-Marx (2012) and Han et al. (2016) we sort quintile portfolios for both strategies. The echo factors are built much like the common momentum factor with the difference being the sorting horizon. Hence, we go long the Winner (Loser) portfolio containing stocks with the highest (lowest) return in previous 7 to 12 (intermediate) or 2 to 6 months (recent). The portfolios of the trend factor are instead sorted on the High (Low) expected return for month $t+1$, which in turn is found from cross-regressing moving averages of prices on previous individual stock returns in month t. We use the same lags for moving averages as Han et al. from 3-days up to 1,000 days resulting in a shorter effective sample period for the trend factor (January 1998 to January 2019) compared to the momentum and echo factors (January 1994 to January 2019.

We find, in contrast with Novy-Marx (2012) that momentum returns sorted on previous 2-6 months (RR) earns a higher average monthly return than returns sorted on previous 7-12 months (IR) in the Swedish stock market. The difference between the returns (1.50% and 0.82% for RR and IR respectively) is significant on a 10% level. The monthly average of RR is also higher than the common momentum factor that has a mean of 1.33%. Hence, we find no echo for momentum returns in the Swedish stock market. However, sorting months does affect returns, only in a different way compared to what Novy-Marx (2012) find. We also show that both IR and RR still suffers from negative skewness, which also is the case for momentum, indicating that altering the sorting period does not prevent the model from occasionally suffering large losses.

During our effective sample period the trend factor returns a 2.25% monthly average, compared to 1.36%, 0.82%, and 1.67% during the same period for MOM, IR, and RR respectively. The good relative performance of the trend factor to the other factors appears to be largely attributable to its superior ability to pick (and short) loser stocks. While all the momentum and echo factors still has positive but low returns of their Loser portfolio, the Low portfolio of the trend factor has a -0.3% monthly average return. Since the periods of crashes of the momentum factor are explained by the vast recovery of the short portfolio (Barroso & Santa-Clara, 2015) this is an important comparison. Indeed, by examining the recession period following the recent financial crisis the momentum has a monthly mean return of -1.75%, IR has slightly better -1.19% and RR a slightly worse -1.97%. Meanwhile, Trend earns a positive average of 0.75% during the same period. Furthermore, comparing single month losses bigger than 10% we find that MOM, IR and RR all records minimum twice as many such drops compared to Trend. The superior risk-return profile of the trend factor is summarized in a Sharpe ratio twice that of the momentum factor (0.39 versus 0.18) and also beating both IR and RR (0.12 and 0.23 respectively).

To make sure the profits earned by the different models is not due to loading on common systematic risk factors we run regressions against the well known capital asset pricing model (CAPM) and Fama-French three factor model. The return of both the echo factors and the trend factor is left unexplained by these factors. Further, we apply various transaction costs to our models to ensure that the costs imputed by the timing- and downside risk mitigating strategies does not eliminate the enhanced earnings. This is especially crucial for the trend factor, posing three times the turnover rate as the momentum strategy. However, the trend factor proves robust to transaction costs and endures even higher costs to compensate for stocks burdened with higher trading costs in the portfolio. Further, we find robust evidence of the trend factor in both the Danish and Finnish market.

The rest of the thesis is structured as follows: In section 2, we review literature on momentum and its possible echo, concerns regarding momentum crashes and high turnover, and the trend factor and its components. In section 3 and 4, we describe our sample data and the used methodologies. In section 5, we present results, starting with comparison of the momentum and echo factors which is followed by a detailed comparison with the trend factor. Finally, in section 6, we summarize main findings of our study and propose suggestions for further research.

2 Literature Review

2.1 Momentum factor

Momentum investing was originally introduced by Jegadeesh and Titman (1993), who found significant positive returns over holding periods of one through four quarters. The strategy consists of buying ”winners”, stocks that had performed good in the past, and selling ”losers”, stocks that had performed bad 1-4 quarters prior to the holding period. By back testing, the authors were able to show that the trading strategy of selecting stocks based on their past six-month returns and holding them for six months realized a compounded excess return of 12.01% per year on average over the period from 1965 to 1989. This momentum effect can be explained by conventional theories: on the one hand behavioural explanations suggesting that investors underreact to news so that new information is slowly incorporated in security prices yielding price momentum, on the other hand rational explanations point to the positive correlations of past performance and risk exposure which in turn leads to a similar expectation of price dynamics (Novy-Marx, 2012).

Since the Sharpe ratio of the momentum strategy exceeds that of the market as well as the size and value factors (Jegadeesh & Titman, 1993), and Israel and Moskowitz (2012) recognized the robustness of momentum strategies, momentum became ubiquitous: the research literature shows the effectiveness of momentum strategies over several periods of time, in many markets and in numerous asset classes. Moskowitz and Grinblatt (1999) find momentum in industrial portfolios, Rouwenhorst (1998) in developed and emerging equity markets. Okunev and White (2003) show that momentum exists in various currencies; Erb and Harvey (2006) in commodities, and Moskowitz, Ooi, and Pedersen (2012) in exchange-traded futures contracts. Asness, Moskowitz, and Pedersen (2013) have similar findings in eight different markets within and across different asset classes. As a result of these outcomes and its relative simplicity of application, a large number of investment fund managers incorporate a certain momentum into their investment decisions, so that strategies of relative strength are well established in practice (Barroso & Santa-Clara, 2015)

Besides the discussed testing of different asset classes, various authors have researched more on the sorting horizon. In doing so, Novy-Marx (2012), and Goyal and Wahal (2016) found that portfolios sorted on prior 7-12 month outperform portfolios sorted on prior 2-6 month, a so called echo. According to Goyal and Wahal (2016) this inconsistency with the traditional momentum view is mainly present in the US market whereas no robust evidence is found that the same is true for any of the other 37 tested countries. For instance, their analysis of the Swedish market over the period of 1982 - 2001 indicates that the average monthly return by sorting stocks into (value-weighted) quintiles based on prior recent months (1.14%) is higher than by sorting based on prior intermediate months (0.46%). However, Novy-Marx (2012) shows that sorting the momentum portfolio by intermediate past performance instead of recent past performance results in a larger momentum effect not only in the US equity market, but also in industries, international equity indices, commodities, and currencies. These findings contradict both previously mentioned theories, the behavior and rational explanations.

Though momentum investing seems highly profitable, it also comes with some drawbacks, where big "momentum crashes" is a major one. In just two months during 1932 the winner-minus-loser (WML) earned a negative 91.59% return and a negative 73.42% during a three-month period in 2009 (Barroso & Santa-Clara, 2015). These crashes wipe out big parts of the earnings made and hence might scare of investors who avoid negative skewness and kurtosis. The major part of these losses seems to stem from the Loser portfolio recovering following big market drawdowns (Daniel & Moskowitz, 2016). Following the 2008 financial crisis, the Loser portfolio rose 263% during March to May 2009 compared to only 8% for the Winner portfolio during the same three-month period. These momentum crashes, however, are predictable and numerous papers are able to manage the crash risk. For example, Barroso and Santa-Clara (2015) are able to manage the risk by scaling their exposure to the WML portfolio by its realized volatility, achieving nearly double Sharpe ratio of the unconditional momentum strategy. Daniel and Moskowitz (2016) introduces a dynamic momentum strategy, using bear market indicators and ex ante volatility estimators to forecast and weight the momentum portfolio. Unlike Barroso and Santa-Clara, Daniel and Moskowitz even put negative weights on the WML portfolio (i.e. buy the Loser portfolio and short sell the Winner portfolio) in 82 of their sampled months [1].

Other drawbacks of the traditional momentum strategy are possible difficulties with shorting stocks and trading costs. As maintaining short positions is generally more costly than maintaining long positions, and as some investors are prevented from taking short positions, Israel and Moskowitz (2012) observe that the contribution of short selling varies according to the size of the company. However, across all size classes, the authors cannot deny that the gain in momentum is generated equally by long and short positions. This is contradicting earlier papers (see Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004)), which find that small stocks are indeed contributing more to momentum profits. Israel and Moskowitz (2012) argues that "[...] the findings of Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004) that momentum is markedly stronger among small cap stocks and on the short side seems to be sample specific"(p.276). They point to the fact that similar results are obtained for shorter time periods used in the earlier papers [2] but for an entire 86-year US sample period (1926-2011) they found stronger momentum from small stocks to be inconsequential.

Regardless of the level of importance of small stocks, as discussed above, it is clear in Jegadeesh

[1] Daniel and Moskowitz (2016) uses 1927:06 to 2013:03 (1,029 months) as data sample set.

[2] 1980-1996 for Hong et al. (2000), and 1963-1999 for Grinblatt and Moskowitz (2004)

and Titman (1993) that the portfolios traded (i.e. Winner and Loser) have the lowest market cap on average. When estimating trading costs, however, Jegadeesh and Titman and many researchers following neglect this size issue. More specifically, they do not account for (1) firm size, (2) time-series variation in transaction cost, (3) bid-ask spread, short-sale costs, tax impacts and holding period risk and (4) liquidity of traded stocks (Lesmond et al., 2004). To disregard firm size and liquidity is especially concerning, argues Lesmond et al., since it is indeed small and iliquid stocks that generally are traded in the WML portfolio. Taking this into account the authors found momentum investing left unprofitable.

2.1.1 Momentum in Sweden

Studies on momentum are mainly conducted on US stock data and research on other stock markets is relatively limited, although a few papers have been written based on international market data. Most of these studies were compiled based on aggregated European, Scandinavian or developed market portfolios including Sweden. Fama and French (2012) show that their European winner-minus-loser portfolios have positive and significant excess returns from 1990-2011, confirmed by Asness et al. (2013), who find evidence of momentum excess returns in the European market. The Swedish market, however, is only included in their paper as a country equity index futures. In a sample period from 1926-2010, Novy-Marx (2012) observes that momentum strategies generate excess returns in developed markets. Bird and Casavecchia (2007) provides evidence of a momentum premium in portfolios combining the Scandinavian equity markets. They derived an average return of 1.84% for Scandinavia over the period from 1989 to 2004.

However, these studies are not country-specific and due to the limited size of the Swedish market, Sweden generally receives a rather low weighting in the aggregated portfolios and the results are therefore not as representative. Regarding the Swedish stock market separately, there are only few, heterogeneous research results. Rouwenhorst (1998), for instance, examines in detail the Momentum strategy in 12 European markets and finds that Sweden is the only country where the return on the Momentum portfolio does not deviate significantly from zero. This is based on the performance of the previous six months and equally weighted deciles portfolios held for six months. For Sweden, an average monthly return of 0.16% results for the period from 1980 to 1995 is found. Contrary to this result, González and Parmler (2007) show that, following the method of portfolio formation used by Jegadeesh and Titman (1993) for different holding periods, momentum strategies in Sweden generate positive and statistically significant gains. They examine the excess return patterns of momentum using all stocks listed on the Stockholm Stock Exchange from 1981 - 2003 and present that the profit for a 12-month ranking and a 3-months holding is 2.32%, respectively 2.28% if 6 month are used for the ranking instead. Momentum gains only differ minimally if there is a one-month delay between the formation period and the ranking period. Additionally, Goyal and Wahal (2016) report in their paper on Echo an insignificant average monthly value-weighted return for the momentum factor in Sweden of 1.06% for the period from 1982 to 2001 (sorted into quintiles).

2.2 Trend factor

The goal of the trend factor by Han et al. (2016), the second factor we apply for the Swedish market, is to capture all three stock price trends – the short-, intermediate-, and long-term – simultaneously and to minimize one major drawback of the momentum factor, the big drops during recession periods. The already discussed momentum factor is regarded as an intermediate price trend, since in various studies sorting horizons up to one year prior sorting are applied.

In contradiction to Bayesian theorem[3], research in experimental psychology has found that the majority of people tend to overreact to unanticipated news events. DeBondt and Thaler (1984) examine, years before the Jegadeesh and Titman (1993) paper, whether such behavior impacts stock prices based on two hypotheses, both of which imply a violation of weak market efficiency: "(1) Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction. (2) The more extreme the initial price movement, the greater will be the subsequent adjustment" (p. 795). In line with their hypotheses, they presented evidence that portfolios with US stocks of prior "losers" outperform "winner portfolios" in the period from 1926 to 1982. Loser portfolios with a formation period and a holding period of three years each, for instance, have a cumulative average return that is almost 25% higher than that of the equally constructed winner portfolios. These findings – the so called long-term reversal effect – is the foundation for the researches in long-term stock price trends with sorting horizons up to five years prior portfolio construction and correspondingly long holding periods.

The momentum strategy has later changed regarding holding periods and the number of previous months for sorting. Common practise is to evaluate one-month returns based on previous 2-12 months, skipping the most recent, month $t-1$. The most recent month is skipped to avoid the short-term reversal following overreaction in stock returns – the short-term price trend. In contradiction to the random walk hypothesis,[4] Jegadeesh (1990) found significant negative first-order serial correlation in monthly stock returns, similar to the hypotheses of DeBondt and Thaler (1984). Further evidence for equity return predictability and short-term reversal is provided during the same time. Lehmann (1990) found that weekly returns follows the same negative serial correlation. Deviating from Jegadeesh usage of ten portfolios, the author constructed five portfolios sorted on previous weekly returns, varying number of sorting weeks and holding periods.

[3]In econometrics, it represents the probability of an event, using prior knowledge of conditions that might be associated with the event.

[4]The Random Walk Hypothesis states that previous stock returns can not help predict stock returns in the future (Fama, 1965).

By selling short the portfolio containing stocks with the highest previous week return and buying the bottom quintile portfolio it is possible to attain significant profits where the short portfolio has an average weekly return in percentage of -0.35 to -0.55 and the long portfolio has corresponding numbers of 0.86 to 1.24.

Negative autocorrelation for individual stock returns due to overreaction is not the sole explanation for contrarian profits. Lo and MacKinlay (1990) provide empirical evidence that positive cross autocorrelated stock returns account for the major part of such profits finding a lead-lag relationship between larger and smaller stocks. That is, if larger stocks has higher than market returns in period t, smaller stocks are expected to have higher returns in period $t+1$. Since the small stocks most likely will end up in the long portfolio of the contrarian investor (since it had lower return than the large stocks in the previous period) it will generate positive returns on average, not requiring negative autocorrelation due to overreaction. Additionally, Han et al. (2016) as well as Nagel (2012) found that short-term reversal strategies perform well during recession periods. During a financial crisis liquidity is likely to evaporate, which results in higher expected returns from liquidity provisions. Nagel concludes in his paper that the returns of short-term reversal strategies in stock markets can be seen as a proxy for these returns, and simultaneously shows the good performance of it in his three analysed crises: the Long-Term Capital Management Crisis in 1998, the Nasdaq decline in 2000-01, and the financial crisis starting in 2007.

The above mentioned articles and many other studies consider the price patterns – short-term reversal, intermediate momentum, and long-term reversal effects – all separately. Therefore, Han et al. (2016) combine all price information across the three investment horizons and develop the trend factor to determine if it is possible to generate profits and to better time the market. They construct the trend factor from cross-sectional regressions that allow several price signals to be included. The signals are based on moving averages (MA) of past prices from 3 days to 1,000 days (roughly four trading years) to obtain the forecast returns. As in most studies of price factor construction, Han et al. (2016) sort the stocks according to their forecasted returns, buy the stocks in the upper quintile with the highest expected returns, and short the ones with the lowest expected returns. The return of the trend factor is then equal to the difference between the equal-weighted returns of the two extreme quintiles. It is worth noting that the regressions are only made with information available at time t, making it an out-of-sample analysis.

When constructing the trend factor, Han et al. (2016) uses moving averages of past prices. Since this deviates from the common practice of momentum investing of using past returns, it is a motivated question why MA have the ability to predict future stock returns. The authors argue that MA is a popular tool among practitioners to time the market and allocate assets. Further, Brock, Lakonishok, and LeBaron (1992) used simple MA rules to predict and time the Dow Jones Index, providing strong evidence in favour of trend recognizing ability of moving averages. Their model provided buy (sell) signals when the short period MAs rose above (fell below) the long term MAs. While Brock et al. and other authors that apply MA strategies to market indices and individual stocks, Han, Yang, and Zhou (2013) provides the first study on cross-sectional profitability for trading based on past prices. The decile volatility portfolios of the American Stock Exchange (NYSE/AMEX) are used as investment assets. By investing in each portfolio if the current price is higher than the 10-day moving average and investing in the 30-day treasury bill otherwise, the authors are able to attain abnormal returns. Noteworthy is that for the high-volatility portfolios the MA returns outperforms those of the momentum strategy. Trading strategies based on MA are clearly dependent on future stock price predictability based on past prices. Many academics believe that stock markets are efficient enough to prevent such a strategy from achieving unusual profits. However, a number of papers provide strong contradicting findings to this fact. Among others, Treynor and Ferguson (1985), Brown and Jennings (1989), Cespa and Vives (2012), Hong and Stein (1999) and Edmans et al. (2015) provide findings indicating that past prices on their own or in combination with other information enable unusual profits, justifying the MA strategy. The above authors argue that these investment opportunities arise due to different timing for receiving non-public information about a security among investors, investors heterogeneity, behavior biases and asymmetrical trading and overinvestment from strategic speculators due to the feedback effect.

Han et al. (2016) show that the use of all price information over the entire investment horizon creates considerable economic profits. For this they use US stock prices from 1930 to 2014. The average return of the trend factor of 1.63% per month outperforms the returns of the short-term reversal, momentum and long-term reversal factors of 0.79%, 0.79% and 0.34% respectively, as well as the market portfolio, which generates an average return of 0.62% per month for the same period. A crucial advantage is that the trend factor works in both recession and expansion phases. This is illustrated by the monthly return of the trend factor of 0.75% during the recent financial crisis[5], while the market loses -2.03% and the momentum factor -3.88% per month. The worst monthly returns in the trend factor testing period were -19.96%, -89.70%, and -28.97% for the trend factor, the momentum factor, and the market, respectively. This illustrates the limited downside risk of the trend factor relative to the momentum factor. Overall, Han et al. (2016) show that the trend factor has far fewer negative outliers and a positive skewness, whereas the momentum factor has much more negative outliers and a negative skewness. The Sharpe ratio of the trend factor in monthly term is 0.47, which is more than twice that of the short-term reversal factor and more than four times the ratio of the momentum and market portfolio. In addition, the authors prove that cross-sectional regression based on moving averages is more efficient in reflecting short, medium and long-term price trends than any portfolio combination of the three individual factors short-term reversal, momentum and long-term reversal.

[5] Han et al. (2016) choose the period from December 2007 to June 2009 to test for the financial crisis.

3 Data

3.1 Data source

In this thesis, we will study the Swedish stock market. This is a developed market with 339 companies listed on the main Stockholm Stock Exchange (SSE) at a total market value of 6,707 billion SEK (Nasdaq, 2020a), and 373 companies listed on the smaller SSE First North (SSEFN) at an additional approximately 257 billion SEK[6] (Nasdaq, 2020b). The returns of these combined markets in our sample, both equal-, and value-weighted, are provided in Appendix A Figure 10.

In the existing literature on this topic, research is mostly based on the database of the Center for Research in Security Prices (CRSP). However, CRSP only provides limited data for individual Swedish companies. Hence, we collect the relevant data on Swedish stocks from FINBAS, the research data maintained by the Swedish House of Finance. FINBAS provides daily end-of-day stock price and market capitalization data for all listed firms in Sweden, adjusted for corporate actions (e.g., stock splits and dividend payments) in a similar way as the CRSP data. Even though the FINBAS database includes data from 1979, we decide to choose the companies listed on SSE and SSEFN from January 4, 1993 to January 30, 2019. The reason behind this decision is that FINBAS provides two lists of different time periods where one list has data from January 1979 to December 1992 and the other from January 1988 to December 2019. In the overlapping period from 1988 to 1992 certain companies are found in both lists with inconsistent prices. Since part of this study is to examine momentum crashes, at least one market crisis captured in our sample is essential, preferably the most recent financial crisis. Therefore we decided to work with the latest list, starting from January 1993.

The database covers prices for all companies, including both listed and delisted stocks during this period, which eliminates any survivorship bias. Note, that the list does not include companies that were listed on the stock exchange after 2017[7], as FINBAS has not updated the data accordingly. However, this is not relevant for our analysis, as we need the prices for at least four years previous to sorting in order to calculate the trend factor. Additionally, smaller Swedish stock exchanges, with the exception of SSEFN, are excluded in this study. Firstly, because the shares are not liquid enough, which also is argued by many studies on momentum[8], and secondly, because the available data on these lists does not meet the requirements of this study. To be able to derive the moving averages of the trend factor we collect price data on a daily frequency. For the other factors, we extract monthly prices from the same data and then construct monthly returns.

[6] Converted from 24.5 billion EUR at 10.517 exchange rate (Sveriges Riksbank, 2020b).

[7] For instance, Bygghemma Group First AB (newly listed on SSE at March 27, 2018) and Epiroc AB (June 18, 2018) (Nasdaq, Skatteverket).

[8] For example, Han et al. (2016) applies a price filter to remove stocks with a price under \$5.

3.2 Data filtering

Some companies have more than one stock class listed, for example A- and B-shares. As these usually have the same price development, our database should only contain one asset class per company, to avoid idiosyncratic risk through a possible double counting of a company in a portfolio. In these cases, we keep the stock class in the database based on the criteria of (1) which has prices for a longer time period and (2) is more liquid if the periods are the same length. We are also deleting all preferential shares.

Furthermore, the construction of the price trend factor requires data of approximately 4 years (1000 days) plus 12 months. For a given last trading day of a month, a price observation was necessary at least 999 days earlier, and each share must have at least 12 (consecutive) such months. As data is lacking for many stocks, the following adjustments are specified. If the last trading price of a day is missing, the average value of available ask and bid prices is taken as the missing price. In a further step, if a price is still missing, the most recent available price of the previous three days is chosen.

Finally, we determine the following condition. In order for all moving averages of a firm to be calculated and thus for one month to be included in a factor quintile portfolio, at least 75 percent of the data for each period length (3, 5, 10, 20, 50, 100, 200, 400, 600, 800 and 1000 days) must have a valid adjusted price observation. Hence, at least 750 observations were required for the 1000-day period, and all three observations for the three-day period. Applying these filters, our sample contains between 167 and 455 stocks for the Trend factor per month (see amount of stocks per long/short portfolio in Appendix B Figure 11).

4 Methodology

4.1 Momentum factor

To start the analysis, we divide the collected data of Swedish stocks into momentum portfolios. This is done by firstly compute the common measure of the past 12-month cumulative raw return on the assets, skipping the most recent month's return which is standard in the momentum literature to avoid the 1-month reversal in stock returns. To compute the cumulative return for each stock ($R_{t-12,t-2,i}$), we use the following formula:

$$R_{[t-12,t-2],i} = \left(\prod_{k=2}^{12} (1 + R_{t-k,i}) \right) - 1, \tag{1}$$

where $R_{t-k,i}$ is the return of stock i, k months prior the month of sorting t. The assets are then sorted by their respective cumulative return each month. Unlike Jegadeesh and Titman (1993), who divide the US assets into deciles, we divide the Swedish assets into quintiles so that each portfolio contains enough assets over the entire test period. Portfolio 1 then contains 20% of the assets with lowest cumulative returns during the sorting period, while portfolio 5, on the other side, comprises 20% of the assets, who have generated the highest cumulative returns. This procedure is repeated for each month t of the testing period. As such, we obtain, for each month, information about what asset belongs to which portfolio, and rebalance the portfolios accordingly.

After sorting the assets we will test if the momentum anomaly exists for the Swedish market by applying the method of Jegadeesh and Titman (1993), who only used the momentum portfolios without any other factors. As discussed before, we want to test the long-short approach, a zero-cost portfolio which is usually used in the literature. In this conventional approach we would go long the ”Winner” portfolio 5 with the highest cumulative returns and short the ”Loser” portfolio 1 with the lowest cumulative returns, to construct the winner-minus-loser (WML) factor. The return of these zero-cost portfolio looks like:

$$MOM_t = R_{W,t} - R_{L,t}, \tag{2}$$

where MOM_t is the return of the momentum factor in month t, which is in term the difference of the Winner portfolio's equal-weighted return ($R_{W,t}$) and the Loser portfolio's equal-weighted return ($R_{L,t}$), based on a 12-month sorting period and a 1-month holding period, as the momentum factor is constructed in the Kenneth French's data library (French, 2020). We use equal-weighted portfolios because this is how both the momentum and trend factor are constructed in the original papers (Jegadeesh & Titman, 1993; Han et al., 2016). Additionally, we construct value-weighted factors as a robustness check of our main results.

4.2 Echo factors

Goyal and Wahal (2016) showed that an echo in returns could only be proven with robust evidence in the United States. Even if they found the opposite for the Swedish market, we test this with the latest stock data, as their study only uses data from 1982 to 2001. To do so, we use the original momentum formula with small adjustments for time horizon to calculate the cumulative returns needed for the portfolio sorting:

- For the intermediate horizon returns for each stock ($R_{IR,i}$), prior 12 to 7 months:

$$R_{IR,i} = R_{[t-12,t-7],i} = \left(\prod_{k=7}^{12} (1 + R_{t-k,i}) \right) - 1 \tag{3}$$

- For the recent horizon returns for each stock ($R_{RR,i}$), prior 2 to 6 months:

$$R_{RR,i} = R_{[t-6,t-2],i} = \left(\prod_{k=2}^{6} (1 + R_{t-k,i}) \right) - 1 \tag{4}$$

After calculating the cumulative returns for both horizons, the portfolio construction looks exactly the same as for the "usual" momentum portfolio. Again, we divide the stocks in five equally sized portfolios and calculating the profit of the long-short portfolio. The returns of the zero-cost portfolios are computed the same way as for the momentum factor and are called IR_t and RR_t for the return of the intermediate horizon portfolio and the recent horizon portfolio, respectively. Note that we refer throughout this thesis to both IR and RR as the echo factors even though technically only IR would be a momentum echo.

4.3 Trend factor

Unlike the momentum- and echo factors that sort stocks based on previous returns, the trend factor sort stocks based on expected returns. Below we will provide a detailed explanation how the returns are predicted, and how the trend factor is constructed.

The trend factor, introduced by Han et al. (2016), is designed to capture and combine price information over short-, intermediate- and long-term horizons. For this, it relies on the predictive power of moving averages. More specifically, we use the same eleven lag lengths as Han et al. (2016) for the MAs: 3-, 5-, 10-, 20-, 50-, 100-, 200-, 400-, 600-, 800-, and 1000-days. These MA signals indicate the daily, weekly, monthly, quarterly, one-year, two-year, three-year, and four-year price trends of the underlying stock. These lags are then used to calculate the MA prices on the last trading day of each month. The definition of the MA on the last trading day d of month t of lag L is

$$A_{jt,L} = \frac{P^t_{j,d-L+1} + P^t_{j,d-L+2} + ... + P^t_{j,d-1} + P^t_{j,d}}{L}, \tag{5}$$

where P^t_{jd} is the closing price for asset j on the last trading day of the month. To make the moving averages comparable over differently priced stocks, Han et al. (2016) suggest that the MAs are normalized by the closing price on the last trading day of the month,

$$\widetilde{A}_{jt,L} = \frac{A_{jt,L}}{P^t_{jd}}. \tag{6}$$

Not only will this normalization mitigate the problem with high priced stocks possibly having an unwarranted high MA signal compared to low priced stocks, but it will also make the MA signals econometrically stationary (Han et al., 2016).

Next, we estimate a cross-sectional regression of stock returns on observed normalized MA signals. This is the first step in a two-step procedure to predict the monthly expected stock returns. The time-series of the coefficients on the signals is obtained in each month t:

$$R_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t}\widetilde{A}_{jt-1,L_i} + \varepsilon_{j,t}, \qquad j = 1,...,N, \tag{7}$$

where $R_{j,t}$ is the return on stock j in month t, $\widetilde{A}_{jt-1,L_i}$ is trend signal at the end of month $t-1$ on stock j with lag L_i, $\beta_{i,t}$ is coefficient of the trend signal with lag L_i in month t, $\beta_{0,t}$ is the intercept in month t, and N is the number of stocks. Note that only information prior to month t is needed to forecast returns in month t, making this study an out-of-sample analysis.

In step two of our two-step procedure, the coefficients from the above regression are used to estimate the expected return for month $t+1$:

$$E_t[R_{j,t+1}] = \sum_i E_t[\beta_{i,t+1}]\widetilde{A}_{jt,L_i}, \tag{8}$$

where $E_t[R_{j,t+1}]$ is the forecasted expected return on stock j for month $t+1$, and $E_t[\beta_{i,t+1}]$ is the estimated expected coefficient of the trend signal with lag L_i, and is given by

$$E_t[\beta_{i,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \beta_{i,t+1-m}, \tag{9}$$

which is the average of the estimated loadings on the trend signals over the past 12 months. Note that the intercept, $\beta_{0,t}$, is excluded in the equation above. The intercept is the same for all stocks at time t, and hence irrelevant for purposes of ranking the stock returns.

Now, in each time t we have a return vector with expected returns for time $t+1$ and can finally construct the trend factor. We first rank the stocks from highest to lowest expected return. It is worth noting that, since the betas can be negative, a stock that has a low comparable normalized MA can actually rank high. Since the betas change in each time t, different time horizons can have different impacts on the predicted returns. Based on this ranking we then form five equal-weighted and monthly rebalanced portfolios. To create a zero-cost portfolio for the trend factor simply buy the top ranked quintile, stocks that are expected to yield the highest returns, and sell short the bottom quintile, stocks that are expected to yield the lowest returns. The return of the trend factor is then defined as the difference between these quintile portfolios.

4.4 Reversal factors

The trend factor captures price information over various time horizons. While the common momentum factor represents the intermediate time horizon, we will in this section introduce the short-term (SREV) and long-term (LREV) reversal factors. As the names indicate, these factors differ from the momentum factor in two ways: the sorting horizons (short and long) and the zero-cost portfolio constructions (reversals). As the sorting horizons can alter in different papers, we follow the Kenneth French Library when calculate the (cumulative) returns for the corresponding period.

- The sorting for SREV is based on the returns of the prior month $t-1$ ($R_{SREV,i}$), which is the month the momentum factor skips:

$$R_{SREV,i} = R_{t-1,i} \tag{10}$$

- For LREV, cumulative returns for each stock ($R_{LREV,i}$) are based on a five year horizon, skipping the most recent year prior sorting:

$$R_{LREV,i} = R_{[t-60,t-13],i} = \left(\prod_{k=13}^{60} (1 + R_{t-k,i}) \right) - 1 \tag{11}$$

After calculating the (cumulative) returns for both factors, the portfolio construction differs from the momentum factor. Again, we divide the stocks in five equally sized portfolios. However, since these are reversal factors, we buy the Loser portfolio and sell short the Winner portfolio. The returns of the zero-cost portfolios are the differences between these portfolios, so called loser-minus-winner portfolios.

4.5 Performance measures

To evaluate the overall performance of all the above-mentioned factors, we use some key performance measures, namely the Sharpe ratio, the Maximum Drawdown (MDD), and the Calmar Ratio.

4.5.1 Sharpe ratio

According to Sharpe (2007) the Sharpe ratio measures the return of a portfolio compared to its risk. If investors are only interested in the mean and variance of the portfolio return and it is possible to borrow or lend at a risk-free interest rate, the investment decision of an investor can be evaluated by calculating the Sharpe ratio of its portfolio:

$$Sharpe\ ratio = \frac{E[R_p - R_f]}{\sigma_p}, \tag{12}$$

where R_p, R_f denote the portfolio returns and the risk-free rate[9] respectively, and σ_p is the standard deviation of the portfolio excess return. By subtracting the risk-free interest rate from the portfolio return, it is possible to better isolate the profits associated with risk-bearing activities. In general, the higher the value of the Sharpe ratio, the more attractive the risk-adjusted return compared to similar portfolios (same or lower returns). However, this is connected to mean-variance preferences, while investors may have preferences particularly for downside risk.

4.5.2 Maximum Drawdown

Han et al. (2016) define the Maximum Drawdown as the largest percentage drop in portfolio value from a peak to a trough over a specified time. The MDD measures the maximum loss incurred by an investor investing in the portfolio at the worst possible time, and is therefore an indicator of downside risk:

$$MDD = max(Drawdown_t) \tag{13}$$

$$Drawdown_t = \frac{(max_{s \leq t} V_s) - V_t}{(max_{s \leq t} V_s)}, \tag{14}$$

with $(max_{s \leq t} V_s)$ indicating the highest portfolio value (cumulative return) up until month t and commonly known as the portfolio's high-water mark. While the MDD measures the largest loss, it does not take into consideration the frequency of losses, nor the volume of profits.

4.5.3 Calmar ratio

An other metric Han et al. (2016) and investors are using to measure the performance of a portfolio is the Calmar ratio. It is a comparison of the annualized rate of return and the downside risk, and is calculated as follows:

$$Calmar\ ratio = \frac{(\prod_{t=1}^{T} R_t)^{\frac{1}{T}}}{MDD}, \tag{15}$$

[9]We use the one-month Swedish treasury bill provided by Sveriges Riksbank (2020a) as our risk-free rate .

where $(\prod_{t=1}^{T} R_t)^{\frac{1}{T}}$ is the annualized rate of return of a portfolio. The higher the Calmar ratio, the better the portfolio performed on a risk-adjusted basis over a fixed time, hence, the better the downside risk-return tradeoff.

4.6 Cost indicators

The differences in opinion if momentum or trend strategies are profitable or not after taking transaction cost into account largely depends on the models used and assumptions which they rely on. Although some papers (see eg. Lesmond et al. (2004)) criticise previous research for not taking important indicators of higher transaction cost into account, we do not intend to address this debate directly. Rather, we aim to highlight the potential weaknesses of the trend factor versus the momentum factor. For this we will use popular models for transaction cost in line with Barroso and Santa-Clara (2015) and Han et al. (2016). The portfolio return including transaction costs ($\tilde{R}_{pt}$) according to the models is given by

$$\tilde{R}_{pt} = \sum_{i=1}^{N} w_{it} R_{it} - c\left|w_{it} - \tilde{w}_{it}\right|, \tag{16}$$

where N is the total number of stocks in a portfolio, c the one-way proportional transaction costs, and R_{it} and w_{it} are the return and weight of stock i in month t. $\tilde{w}$ denotes the change in stock weights, including stock rebalancing due to previous month relative returns (losses) and is found by

$$\tilde{w}_{it} = w_{it-1} \frac{1 + R_{it-1}}{1 + R_{pt-1}}. \tag{17}$$

An important indicator of transaction cost is the turnover ratio. This measures the change of stocks as a percentage of the portfolio, and is given by

$$Turnoverratio_{pt} = 0.5 \sum_{i=1}^{N} \left|w_{it} - w_{it-1}\right|. \tag{18}$$

Note that we use w_{it-1} instead of $\tilde{w}_{it}$, neglecting any stock rebalancing. This is because we only want to compare new companies in the portfolio induced by the different strategies.

4.7 Factor regressions

Time-series tests of the CAPM, the Fama-French three-factor model, and the momentum and echo factors will be done on the zero-cost factors Trend, MOM, IR and RR through the following regressions:

$$R^e_{it} = \alpha_i + \beta_{i,mkt} R^e_{mkt,t} + \varepsilon_{it}\ , \quad t = 1, ..., T, \tag{19}$$

$$R^e_{it} = \alpha_i + \beta_{i,mkt} R^e_{mkt,t} + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{it} \ , \quad t = 1, ..., T, \tag{20}$$

$$R^e_{it} = \alpha_i + \beta_{i,mkt} R^e_{mkt,t} + \beta_{i,MOM} MOM^e_t + \beta_{i,IR} IR^e_t + \beta_{i,RR} RR^e_t + \varepsilon_{it} \ , \quad t = 1, ..., T, \tag{21}$$

where R^e_{it} denotes the excess return over the risk free rate of factor i at month t. $R^e_{mkt,t}$, SMB_t and HML_t are the excess returns of the market and Fama-French factors small-minus-big (SMB) and high-minus-low (HML), respectively. In addition we have added MOM^e_t, IR^e_t, and RR^e_t in equation (21), which along with $R^e_{mkt,t}$ are the excess return at time t of the factors obtained in section 5.1. The Fama-French factors for the Swedish market are obtained from the AQR website[10]. Unlike our portfolios, the factors are constructed by using value-weighted portfolios (AQR, 2020). However, considering the different portfolio construction of the factors we do not expect it to have a big impact on the result and still find them to be useful for our regressions.

4.8 Value-weighted portfolios

So far we have computed all our portfolio returns equal-weighted, i.e.:

$$R_{pt} = \sum_{i=1}^{N} R_{it} * w_{it}, \tag{22}$$

where R_{pt} is the return of quintile portfolio p in month t, and w_{it} is constructed equally-weighted, i.e:

$$w_{it} = \frac{1}{N_t}, \tag{23}$$

where N_t is the number of stocks in the portfolio at time t.

As for the value-weighted we will recalculate the w_{it} as:

$$w_{it} = \frac{MV_{it}}{MV_{pt}}, \tag{24}$$

where MV_{it} is the market value of stock i at month t and MV_{pt} is the total market value of all the stocks in portfolio p.

Over our sample period, the short (long) portfolios contain between 28 and 93 stocks (see Figure 11 in Appendix B). This is a relative low number of stocks, imputing a risk that few companies gain a too big weight in the portfolio. As an example, the largest stock in the Loser portfolio

[10] https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly; the factors are gathered from the date set ”Quality minus junk”, which includes SMB and HML.

of the momentum factor exceeds 50% portfolio weight several times (further discussed in section 5.3.2). Too avoid this problem that a few companies gain too big of weight in the portfolio, we put restrictions on the maximum weight of a single stock, s.t.

$$w_{it,restricted} = min(w_{it}, 0.2), \tag{25}$$

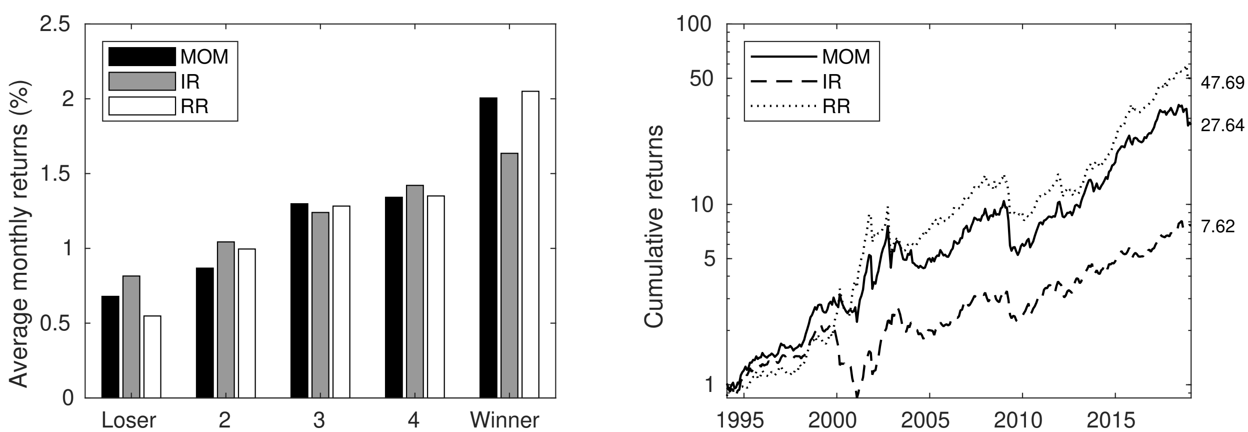
where w_{it} is the weight from equation (24) and 0.2 is the 20% maximum weight restriction. The difference between $w_{i,restricted}$ and w_i is then distributed equally over the remaining stocks in the portfolio s.t. $w_1 + w_2 ... + w_N = 1$. We then check so that the 20% restriction still holds and, if necessary, recalculate equation (25).

5 Results and analysis

5.1 Momentum

5.1.1 General results

As described in the methodology, we construct the momentum factor sorted on previous 12 months, skipping the most recent, to evaluate return for 1-month holding period. Due to the one-year sorting horizon the effective sample period of the momentum factor is from January 1994 through January 2019. As seen in Figure 1a, the average monthly return is higher for the Winner portfolio (2.01%), containing stocks with the highest previous cumulative return, compared to the Loser portfolio (0.68%) containing the stocks with the lowest previous return. The zero-cost portfolio, investing 1$ in the Winner portfolio and shorting 1$ in the Loser portfolio, gains a significant cumulative return of approximately 28 during our sample period, as presented in Figure 1b. This result is in line with González and Parmler (2007) who found significant gains by using momentum strategies in the Swedish stock market. However, the results contradicts Rouwenhorst (1998) who found Sweden to be the only market examined with gains from the momentum portfolio not being significant. Note that the author used an entirely different sample period and constructed the momentum slightly differently, which are possible reasons behind the different result.



(a) Average returns of momentum & echo portfolios

(b) Cumulative returns of the zero-cost portfolios

Figure 1: Momentum and echo factors: average and cumulative returns.
The bar plot in figure (a) shows the average monthly returns of the equally weighted quintile portfolios of the momentum factor, including both echo factors, the intermediate horizon (IR) and recent horizon (RR), respectively. The returns are in percentage. Portfolio 1 is called "Loser", whereas Portfolio 5 is called "Winner". The (logarithmic scaled) line graph in figure (b) demonstrates the cumulative return of the zero-cost momentum and echo portfolios. The cumulative return is in absolute numbers and is constructed by investing 1$ in the Winner portfolio, and shorting 1$ in the Loser portfolio. The effective sample period is from January 1994 through January 2019.

As seen in Figure 1a the Loser portfolio has less than half the average monthly return of the Winner portfolio, but has still a positive average return. Hence, the zero-cost (WML) portfolio has a lower average monthly return than the Winner portfolio (see Table 1 Panel A and Figure 1a). Furthermore, the skewness of MOM is negative. In combination with the large kurtosis this means that the momentum factor has a fat tail on the left side – i.e. negative outliers are more likely than positive ones. The market, in contrast, has a skewness of approximately 0 (0.0033). Additionally, MOM is performing only slightly better than the market with the difference being insignificant (see Table 1 Panel B) and is associated with more risk showed by the higher standard deviation, 6.44% monthly compared to 5.34% for the market. Note, that the market is constructed as one long portfolio, whereas the momentum factor contains a long and a short portfolio. Thus, the direct comparison of MOM and Market is not entirely suitable. While it is common for a private individual investor to hold stocks only long in its portfolio (similar to the market), this is not zero-cost due to the lack of short stocks.

Table 1: Momentum and echo factors: summary statistics.
Panel A reports the summary statistics of the long-short portfolios (WML) for the momentum factor (MOM), the echo factor for the intermediate horizon (IR), the echo factor for the recent horizon (RR), and the market (Market). Panel B presents the differences in monthly means between the four factors (MOM-IR / MOM-RR / MOM-Market / IR-Market / IR-RR / RR-Market). We report monthly sample mean in percentage, sample standard deviation in percentage, skewness, and kurtosis. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by ***, **, and *, respectively. The effective sample period is from January 1994 through January 2019.

Factor	Mean (%)	Std dev (%)	Skewness	Kurtosis	MOM	IR	RR	Market
	Panel A: long-short portfolios (WML)				Panel B: differences in means (%)			
MOM	1.33***	6.44	-1.09	8.52	-	0.51**	-0.18	0.07
	(3.57)					(2.04)	(-0.7)	(0.12)
IR	0.82***	5.30	-0.72	6.38		-	-0.68*	-0.44
	(2.69)						(-1.72)	(-0.88)
RR	1.50***	6.35	-0.92	8.93			-	0.24
	(4.1)							(0.43)
Market	1.26***	5.34	0.00	5.01				-
	(4.09)							

5.1.2 Comparison with echo factors

In accordance with Novy-Marx (2012) and Goyal and Wahal (2016) we compare results by altering the horizon for sorting periods, constructing portfolios sorted on prior 7-12 (intermediate) and 2-6 (recent) months. Recent horizon returns are outperforming intermediate horizon and momentum returns, as presented in Table 1 and Figure 1b. The monthly average returns for the winner-minus-loser portfolios are 1.5%, 0.82% and 1.33% for RR, IR, and MOM, respectively. This result might seem to contradict previous findings, as Novy-Marx (2012) found that the opposite was true, i.e. that IR outperformed RR. Their research, however, were conducted on US stocks only. When Goyal and Wahal (2016) tried to replicate this study for other markets, they found no significant results. In fact, in their data set RR and IR returned an average of 1.14% and 0.46% respectively in the Swedish stock market. This points in the direction of our results and in addition, unlike the previous authors, the outperformance of RR is significant in our sample on a 10% level (see Table 1 Panel B).

As stated before, the recent horizon return factor performs better than the momentum factor. This can be understood by looking at Figure 1a in which the Winner (long) portfolio of RR performs marginally better and additionally, the Loser (short) portfolio worse compared to MOM. This leads to the higher winner-minus-loser return. However, this difference is small and not significant. The cumulative returns of these two factors tend to move in similar ways as seen in Figure 1b. One explanation may be that the RR factor is similar constructed to the MOM factor, distinguished only by the shorter sorting period of 6 months instead of 12 months. In contrast to the IR factor, both factors only omit the last month before sorting, and not six. Thus, the shrinking of the sorting period has a positive impact on the momentum factor in our sample period, compared to the negative impact of skipping more months prior sorting. As for the momentum factor, both IR and RR do not significantly differ from the market. RR, however, performs better than the market, while IR is the only so far discussed factor which performs worse than the market.

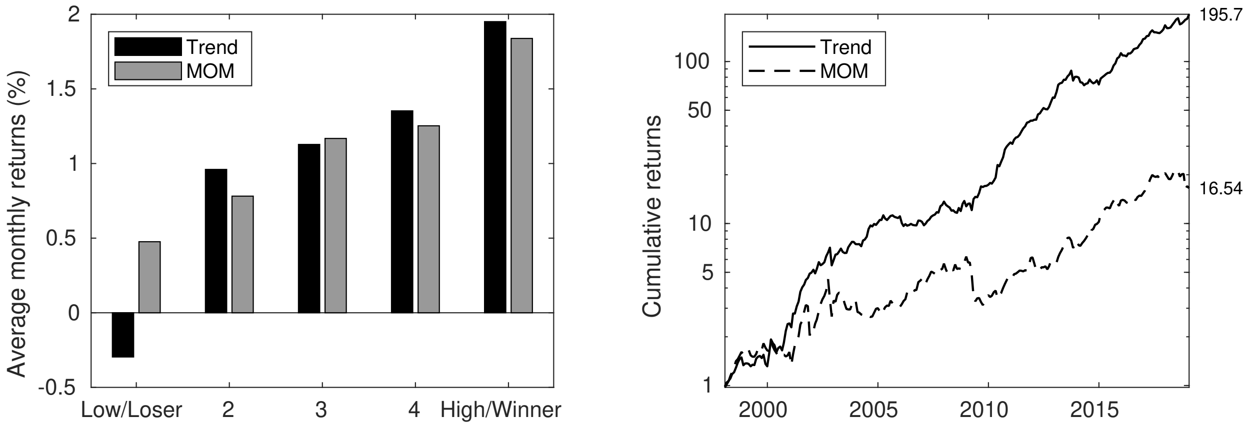
As RR performs slightly better than the MOM, it is still part of the further study. However, the difference is not significant, RR and MOM show similar patterns , and the factors are, except of the sorting period, constructed the same. Thus, we mainly focus on the comparison of Trend and the ”original” MOM in section 5.2. Although IR performs significantly worse than both MOM and RR, the factor remains a part of the comparisons for the sake of completeness.

5.2 Trend factor

5.2.1 General results

In this section we will present general results and report summary statistics for the trend factor (Trend) along with the short-term reversal factor (SREV), momentum factor (MOM) and the long-term reversal factor (LREV). Additionally, we will add the echo factors (IR and RR) from the previous section. Since the trend factor need 1,000 days to compute the trend signals and 12 subsequent months to smooth the betas, our effective sample period shortens to January 1998 through January 2019. Note that we have adjusted the momentum- and echo factors as well to replicate the same effective sample period for comparison measures. Hence, some numbers for MOM, IR and RR will differ under part 5.2 compared to 5.1.

Figure 2 shows the average monthly return in percentage for the quintile portfolios and the cumulative return during the effective sample period for the zero-cost (Trend and MOM) portfolios. The



(a) Average returns of the trend & momentum portfolios

(b) Cumulative returns of the zero-cost portfolios

Figure 2: Trend and momentum factor: average and cumulative returns.
Figure (a) shows the average monthly returns of the equally weighted quintile portfolios of the trend and momentum factor. The returns are in percentage. Portfolio 1 of Trend (MOM) with the lowest expected return (prior returns) is called ”Low”(Loser), whereas Portfolio 5 with the highest expected return (prior returns) is called ”High”(Winner). Figure (b) demonstrates the cumulative returns of the zero-cost trend and momentum portfolios. The cumulative returns are in absolute numbers and are constructed by investing 1$ in the High(Winner) portfolio, and shorting 1$ in the Low(Loser) portfolio. The effective (displayed) sample period is from January 1998 through January 2019.

portfolios sorted on low expected return to high expected return have an average monthly return in the same respective order, meaning the Low portfolio has the lowest average return and the High portfolio has the highest average return. Noteworthy here is that the Low portfolio is not only the worst performing portfolio but, unlike the momentum portfolios, it has a negative (-0.3%) return. In addition, the High portfolio has a higher average return than the Winner portfolio for momentum. This increases the return of the High-Low portfolio resulting in a high cumulative return, as shown in Figure 2b.

Summary statistics for the trend factor along with MOM, IR, RR, Market and the reversal factors are presented in Table 2. During the effective sample period (January 1998 - January 2019) the trend factor earns 2.25% a month, or 27% annualized return, 65% higher than the MOM and more than doubling the market return. Despite the higher return, the standard deviation is kept low in comparison. It is slightly lower than the market and 20% lower than MOM. The combination of higher return and lower standard deviation results in a Sharpe ratio that doubles that of both the momentum factor and the market (0.18 for both). The outperformance of the trend factor compared to the momentum factor in the Swedish stock market is consistent with what Han et al. (2016) find in the US market. This is also the case for the skewness and kurtosis. As momentum suffers from big momentum crashes, as shown by Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015), it increases the probability for large negative return, implying a fat left tail. Consistent with this MOM has a skewness of -1.09 and 7.90 kurtosis in our sample. In contrast, returns from

Table 2: The trend factor and other factors: summary statistics.
This table reports the summary statistics, including the financial crisis as a recession period, for the trend factor (Trend), the short-term reversal factor (SREV), the momentum factor (MOM), the long-term reversal factor (LREV), the intermediate horizon return factor (IR), the recent horizon return factor (RR), and the market portfolio (Market). For each factor, we report monthly sample mean in percentage, sample standard deviation in percentage, Sharpe ratio, skewness, and kurtosis. All variables are calculated for the zero-cost portfolios. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by ***, **, and *, respectively. The sample period (Panel A) is from January 1998 through January 2019 and the recession period (Panel B) from December 2007 through June 2009.

Factor	Mean (%)	Std dev (%)	Sharpe ratio	Skewness	Kurtosis	Mean (%)	Std dev (%)	Sharpe ratio	Skewness	Kurtosis
	Panel A: sample period (01/1998 - 01/2019)					Panel B: Financial crisis (12/2007 - 06/2009)				
Trend	2.25***	5.35	0.39	0.19	6.41	0.75	6.32	0.08	0.87	3.63
	(6.68)					(0.52)				
SREV	0.30	5.35	0.03	0.55	6.40	2.63*	6.86	0.36	-0.11	3.66
	(0.89)					(1.67)				
MOM	1.36***	6.85	0.18	-1.09	7.90	-1.75	9.11	-0.21	-1.11	4.15
	(3.16)					(-0.84)				
LREV	-0.07	5.20	-0.04	1.36	10.70	-0.12	5.17	-0.05	0.03	2.11
	(-0.21)					(-0.1)				
IR	0.82**	5.57	0.12	-0.73	6.08	-1.19	6.28	-0.21	-0.89	3.24
	(2.34)					(-0.83)				
RR	1.67***	6.68	0.23	-0.95	8.66	-1.97	7.96	-0.27	-1.19	4.69
	(3.97)					(-1.08)				
Market	1.11***	5.39	0.18	-0.14	4.43	-1.06	8.89	-0.14	0.37	3.88
	(3.29)					(-0.52)				

the trend factor are positively skewed with a kurtosis, meaning it has higher probability for large gains instead. IR and RR performs as described in the previous section, however a few remarks are worth mentioning. While we observed that RR had a higher average return than the momentum factor (1.67% during the shorter sample period), it still does not get close to the trend factor. Both IR and RR suffer from a similar fat left tail as does MOM.

Panel A of Table 2 illustrates that both reversal factors SREV and LREV perform relatively poorly throughout the period considered. SREV generates an average monthly return of only 0.30%, while, surprisingly, LREV has even a minimal negative return (-0.07%). These low returns indicate that a combination of the three factors – SREV, MOM, and LREV respectively – is not worthwhile to beat the performance of the trend factor. This is supported by the performance measurements, which are considerably worse than those of the trend factor. Not only the Sharpe ratios, but also the maximum drawdowns and Calmar ratios in Table 3 underline this. Note, that SREV clearly outperforms all factors in the financial crisis (see Panel B in Table 2), including Trend. This finding is not consistent with the results of Han et al. (2016) for the US market, where SREV has a negative average during the financial crisis. In contradistinction, Nagel (2012) shows that SREV has performed remarkably well during recent crises, especially during the financial crisis, which is true for Han et al. (2016) over all recessions analyzed together between 1930 and 2014. Both papers report that the SREV factor performs better during recessions than over their full sample periods, which is in line with our results. However, not to the extent that SREV outperforms the trend factor, as in our case. It is worth emphasizing, that Trend is still second best in crises and beats all other factors. The poor overall performance of SREV and LREV lead to our decision to discuss the two factors only marginally in the following chapters.

5.2.2 MA coefficients over time

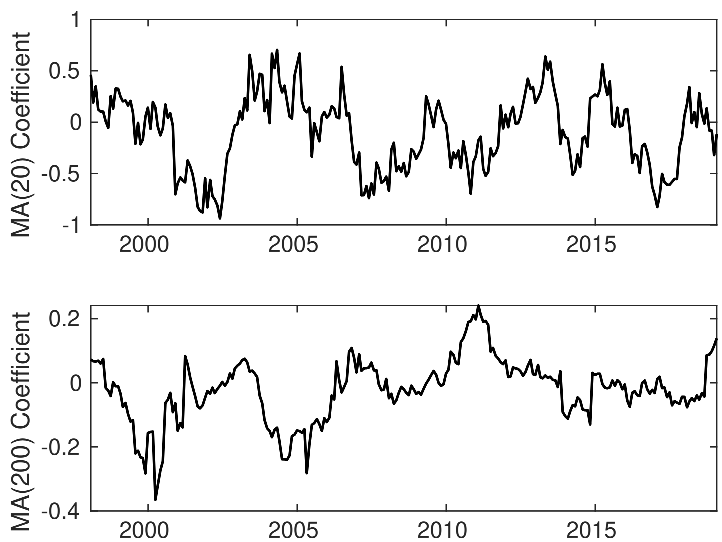


Figure 3: Trend factor: selected MA Coefficients.
This figure represents the smoothed coefficients of two selected moving averages, MA(20) and MA(200) respectively, estimated from equation (9). The sample period is from January 1998 through January 2019.

To maintain the out-of-sample performance of the trend factor, we calculate the betas from equation (7) for each sample month. Han et al. (2016) argues that the betas obtained are dependent on the portion of technical traders in the market and hence are expected to change through time. The time-series of the smoothed betas, defined in equation (9), for all moving averages are represented in Figure 12 in the Appendix C. Two selected smoothed betas in Figure 7 illustrate the short-term horizon of approximately one trading month (MA(20)) and the intermediate-term horizon of approximately one trading year (MA(200)). The betas indeed vary substantially over time, where coefficient for MA(20) has a much higher variance than the MA(200) coefficient. The longer time period used for MA, the more stable the coefficient get, where the MA(1,000) coefficient are volatile around market turbulent times, year 2000 and 2009 in our sample, and stable otherwise. Further, as seen in Figure 7 the coefficient can be both positive and negative. To understand the impact of negative betas, the sorting method of Trend portfolios has to be considered. When the coefficient is negative, the MA has an inverse impact on the expected return for $t+1$ in equation

(8). This result in lower MA having a better (less negative) expected return, and since the ranking of stocks is relative, it is more likely to end up in the High portfolio.

To further understand the dynamics of the trend factor, we consider the relative importance of the different MA lags in two different ways. Firstly, it appears that the magnitude of coefficients from shorter time periods are greater than those from longer ones on average, meaning that the former has a bigger impact on expected return. Hence, the trend factor relies more on shorter time lags. Secondly, the magnitude of different lags change over time, which alters the relative order of importance. This fact, combined with the occasional change of sign of the various coefficients highlights the difference in dynamics between the trend factor and the other factors considered, where the impact and reliance of historical information remains constant.

5.2.3 Tail risk

In this section we will evaluate some performance measures, explained in Section 4.5, to compare the results of the trend factor to MOM, IR and RR. Since we find that the return distribution of the momentum factor has a fat left tail in Sweden, which is already shown to be true for various other markets (Daniel & Moskowitz, 2016; Barroso & Santa-Clara, 2015), we expect the maximum drawdown (MDD) to be large for MOM. This is found to be accurate (see Table 3) as MDD for MOM is 48.78%. The corresponding figure for trend is half the size (22.24%). Hence, an investor that invests in the MOM portfolio at the worst possible time will suffer twice the loss as an equally bad timing for the trend factor. To put the downside risk in relation to the return we use the Calmar ratio. A higher Calmar ratio indicates that the investment has a better expected risk-return tradeoff. Unsurprisingly, considering the MDD and average monthly return, the trend factor outperforms on this metric as well. It has a Calmar ratio of 75.90% which is more than eight times that of MOM (9.09%). Note though that the MOM has more than 50% higher Calmar ratio versus the market (5.83%). By listing big monthly drops, see Table 3, another way of expressing downside risk, we again see MOM suffering almost twice the number of larger than 5% drops (28) compared to Trend (15). Furthermore, it has 9 and 4 drops larger than -10%, and -20%, respectively, whereas the trend factor only records 4 and 1 drops.

Regarding the echo factors, RR performs similarly as MOM in all measurements except the Calmar ratio. This difference in Calmar ration is mainly due to the higher return of RR. These two factors are both suffering the most extreme monthly decline in returns, and are the only ones in the sample to experience a drop of over 30%. IR on the other hand, shows worse MDD (60.8%) and Calmar (3.26) figures than both MOM and RR. However, it suffers less from large drops over 20% (2).

The analysed performance measures prove that the trend is more robust against severe downturns

Table 3: The trend factor and other factors: Extreme values.
This table reports the maximum drawdown (MDD) in percentage, Calmar ratio in percentage, and number of big losses of the trend factor (Trend), the short-term reversal (SREV), the momentum factor (MOM), the long-term reversal (LREV), the intermediate horizon return factor (IR), the recent horizon return factor (RR), and the market portfolio (Market). The last two columns represents the returns of the two worst months of each factor in percentage. The sample period is from January 1998 through January 2019.

Factor	Performance measures		Big losses				Worst sample months	
	MDD (%)	Calmar (%)	n(R <-5%)	n(R <-10%)	n(R <-20%)	n(R <-30%)	worst (%)	2^{nd} worst (%)
Trend	22.24	75.90	15	4	1	0	-22.24	-13.20
SREV	38.79	3.95	28	6	0	0	-19.61	-18.45
MOM	49.78	9.09	28	9	4	1	-34.11	-26.84
LREV	62.93	1.34	28	3	0	0	-17.86	-15.63
IR	60.80	3.26	32	11	2	0	-24.38	-20.97
RR	47.37	16.36	26	10	4	1	-31.73	-28.86
Market	56.63	5.83	28	7	0	0	-18.06	-15.27

in returns and should therefore experience less likely big crashes, but nevertheless generates high returns. The two worst sampled months further strengthen the picture of a lower downside risk of the trend factor. Trend has -22.24% and -13.20% as the two worst months while MOM has -34.11% and -26.84%, as seen in Table 3.

5.2.4 Financial crisis

Note that the recession period selected as sample period for the financial crisis is the same as in Han et al. (2016), even though we examine different markets. This is for three main reasons: (1) To compare results obtained from the same time period facilitates the comparison, (2) while the crisis started in the US[11] it was eventually arguably a global crisis and (3) these dates correspond well with the market return from our data.

As shown earlier, the momentum factor occasionally suffers big crashes. Barroso and Santa-Clara (2015) argues that this is the case due to the vast recovery of the Loser portfolio following a crisis. In Figure 4 which displays Trend, MOM and Market during the recession period following the financial crisis, we look for two things: (1) is the momentum crash present in the Swedish market as well and (2) does the trend factor stand more robust during the crash. For the recession following the financial crisis, both (1) and (2) is evidently true. Furthermore, the crash of MOM seems, just as Barroso and Santa-Clara (2015) argues, to happen as the market recovers. Actually, up until the market recovery around December 2008/January 2009 MOM performs above Trend and returns a non-negative 20% cumulative profit during the selected period. The trend factor however seems quite robust to the vast recovery of the market. Initially the returns stays relatively

[11]The Business Cycle Dating Committee of the National Bureau of Economic Research (NBRE) determined that business activity in the US economy bottomed out in June 2009. This trough marks the end of the recession that began in December 2007 (NBRE, 2010).

flat and then follows the market recovery upwards, ending with a 10% profit for the recession period. This is especially impressing considering the negative 25% return of the market and over 30% loss of the momentum factor. Furthermore, during the financial crisis Trend has a higher skewness (0.87) compared to MOM (-0.21), and a standard deviation that is lower than the entire sample corresponding number for the momentum factor (6.32 versus 6.85). The reason why MOM performs badly during the market recovery is the out of the ordinary good return of the Loser (short) portfolio relative to the Winner (long) portfolio (Barroso & Santa-Clara, 2015). In our sample, during the five market recovery months January through May 2009, the Loser (Winner) portfolio returns a monthly average of 16% (4.6%) and total cumulative profit of 103% (24.25%). In turn, the corresponding numbers for the trend factor is an average return of 8.28% (11.35%) and cumulative profit of 48% (66.86%) for the Low (High) portfolio. The outperformance of the trend factor relative to the momentum factor following the financial crisis is hence due to both the limited loss in the short portfolio and higher return of the long portfolio.

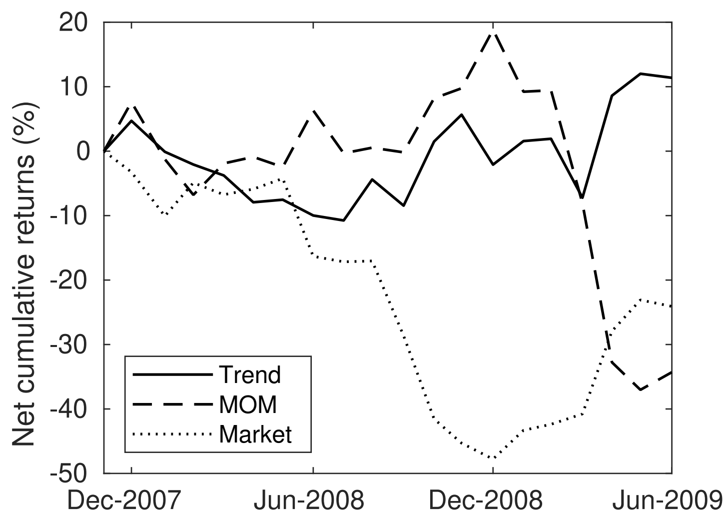


Figure 4: Financial crisis: comparison of trend and momentum factor.
This figure demonstrates the net cumulative return of the zero-cost portfolios of both the trend factor (Trend) and the momentum factor (MOM), and the market index, constructed by all available companies in our data sample, during the financial crisis. The net cumulative return is presented in percentage. The effective (displayed) sample period is from December 2007 through June 2019.

The trend factor uses market indicator from various different time horizons, including a number of short ones. In contrast MOM still relies on previous 2-12 months returns. Hence, Trend is better at capturing the market trend (Han et al., 2016), likely being the reason for this quick adaption and following the market up during the recovery. This adaption is also a reason for the remarkable return of the short-term reversal factor, which relies only on the returns one month prior sorting and additionally goes long with the prior Loser portfolio. Therefore SREV benefits from the high returns on these Loser portfolios during the period of market recovery. As previously discussed in 5.2.3, the downside risk of RR is equivalent to that of MOM. That RR is not a solution to the drawback of MOM, high losses during crises, is supported by the return during the financial crisis (see Table 2, Panel B). During the financial crisis, the order between IR and RR is actually reversed, i.e. IR is performing better than RR (-1.19% versus -1.97%), however again, neither of them are close to the trend factor.

5.2.5 Further comparison with the momentum factor

In this section we further compare the trend with the momentum by their correlation and the analysis of their five sorted portfolios. Due to not significantly higher/different results, this section does not include a comparison with IR and RR. Table 4 shows the correlation matrix of the trend factor with the momentum factor and the market. Over the whole sample period the correlation of the trend factor is positive with the momentum factor (24%), but negative with the market index (-11%). The explanation for the low but positive correlation of Trend and MOM is that the cumulative returns of the factors tend to move in the same direction over the entire period. However, the trend factor shows a significantly higher return (see Table 2, panel A) with a simultaneous lower volatility, i.e. it is more stable.

Table 4: The trend and momentum factor: correlation matrix.
This tables shows the correlation between the trend factor (Trend), momentum factor (MOM), and the market portfolio (Market) for the whole sample period (Panel A) and the correlation of these factors during the financial crisis. The effective sample period is from January 1998 through January 2019 and the period for the financial crisis from December 2007 through June 2009.

Factor	Trend	MOM	Market	Trend	MOM	Market
	Panel A: sample period			Panel B: financial crisis		
Trend	1.00	0.24	-0.11	1.00	-0.24	0.32
MOM		1.00	-0.45		1.00	-0.74
Market			1.00			1.00

A closer look at the quintile portfolios in Table 5 and Figure 2 further confirms the low correlation. Since the overall trend is the same, the long (short) portfolios of both factors are indeed positively correlated, and the correlation is actually as high as 86% (79%). Nevertheless, the trend factor captures the trend much better, so that the trend has a higher average monthly return for the long leg (P5) than the momentum factor, namely 1.95% versus 1.84%, and a much smaller, even negative, average monthly return for the short leg (P1) of -0.30% versus 0.48%. This implies that both the Low and High portfolios of the trend factor have a better performance than the Loser and Winner portfolios of the momentum factor. Consequently, the trend factor, as the spread portfolio, must outperform the momentum factor. The main driver for the significant difference of the trend and momentum factors is hence the trend factors ability to predict (and short) future loser stocks. This difference in the Loser/Low portfolio is statistically significant on a 1% level, whereas there is no significance in the difference of the long portfolios.

Table 5: The trend and momentum factor: comparison of quintile portfolio.
This table reports the average monthly return and standard deviation of the five quintile portfolios, and the average market capitalization of the companies within these portfolios for the trend factor (Panel A) and the momentum factor (Panel B), respectively. P1 is the Low or Loser portfolio, and P5 the High or Winner portfolio for the trend, respectively the momentum factor. The mean and standard deviation are in percentage, whereas the average market capitalization is in million SEK. The two last columns show the correlation (in percentage) between the qunitiles portfolios of the trend factor and momentum factor ($\rho_{Trend,MOM}$), and the differences of P1, P5, respectively P5-P1 and the corresponding t-test with a significance at the 1%, 5%, and 10% level given by ***, **, and *, respectively. The sample period is from January 1997 through January 2019.

Portfolio	Mean (%)	Std dev (%)	Avg. Market Cap. (SEKm)	Mean (%)	Std dev (%)	Avg. Market Cap. (SEKm)	Correlation (%)	Differences (%)
	Panel A: the trend factor			Panel B: the momentum factor			(Trend,MOM)	Trend-MOM
P1	-0.30	7.20	9'121	0.48	8.78	7'141	86.96	-0.77***(-2.82)
P2	0.96	5.00	19'656	0.78	5.69	18'402	87.90	
P3	1.13	4.94	22'281	1.17	4.85	24'254	90.67	
P4	1.35	5.28	23'495	1.25	4.68	23'028	90.50	
P5	1.95	6.57	15'194	1.84	5.38	16'903	78.93	0.11 (0.44)
P5-P1	2.25	5.35		1.36	6.85		24.39	0.88*(1.85)

But why does the correlation of the trend and momentum factor turns to negative -24% during the financial crisis? This follows our previous observations. Due to the drawback of the momentum factor of not generating a profit in recessions, the two factors move in opposite directions, especially in the recovery period of the crisis. In addition, the volatility of the momentum factor increases by about 33% during the financial crisis, while the standard deviation of the trend factor grows by only 18%. Even though the correlation of the factors turned negative, the correlation of the short and long portfolios of them are higher than over our whole sample period. The correlation amounts to 91% and 89% for the short, respectively the long portfolios. Again, the Low and High portfolios of Trend outperform the Loser and Winner portfolios of MOM. The difference between the corresponding portfolios is even higher, and thus, a further reason for the negative correlation of the trend and momentum factors during these times. The long leg of the trend factor has a less negative average monthly return than the one of the momentum factor, -0.46% versus -1.66%, and simultaneously the low leg has a negative return of -1.21% contrary to the slightly positive return of 0.09% of the momentum's Loser portfolio. This leads to the non-negative monthly return of the trend factor (0.75%), respectively to the negative return of the momentum factor (-1.75%) as it is stated in Panel B of Table 2.

In Table 5 we can additionally see, that the short portfolio of both the trend factor and the momentum factor has the highest volatility of all quintile portfolios, and simultaneously contains the smallest companies, measured by their market capitalization. This is consistent with Jegadeesh and Titman (1993) and could impose difficulties on trading in general, and transaction costs in particular. This will be further discussed in section 5.3.1.

5.2.6 Factor regressions

In this section we check if the trend, momentum, and echo factors earn a significant positive return after controlling for different common factors. The results are presented in Table 6. Panel A reports the CAPM alpha along with market beta (see equation (19)). The market beta is a risk measure where higher beta indicates higher risk of the portfolio but also higher potential return. Trend along with momentum and the echo factors all have negative betas and positive significant alphas (2.19%, 1.76%, 1.04% and 1.96% for Trend, MOM, IR and RR, respectively). Higher risk according to CAPM is not an explanation to the positive return of the factors.

In Panel B the two well known Fama-French factors, SMB and HML, are added to the regression (see equation (20)). The alphas of the factors are slightly lower compared to the CAPM regression, but still significantly positive at a 1% level. Further, all factors have negative SMB beta, indicating that they contain less (or are short) small companies, and positive HML beta, indicating that it contains value stocks, as opposed to growth stocks. The negative beta for Trend, significant on a 10% level, is not that surprising considering the low market cap for the short portfolio shown in Table 5.

Table 6: Factor regressions.
This table reports alphas and risk loadings with respect to the CAPM in Panel A and Fama-French three-factor model in Panel B, respectively, for the trend factor (Trend), the momentum factor (MOM), the intermediate horizon return factor (IR). Panel C reports the alphas and betas with respect to a model including the momentum and echo factors (MOM, IR, & RR) for the trend factor. The intercepts (α) are reported in percentage. The t-statistics are in parentheses and a significance at the 1%, 5%, and 10% level given by ***, **, and *, respectively.

Rank	Panel A: CAPM		Panel B: Fama-French				Panel C: Momentum factors				
	$\alpha(\%)$	β_{mkt}	$\alpha(\%)$	β_{mkt}	β_{smb}	β_{hml}	$\alpha(\%)$	β_{mkt}	β_{MOM}	β_{IR}	β_{RR}
Trend	2.19***	-0.1*	2.08***	-0.05	-0.19*	0.06	1.58***	0.02	-0.04	-0.06	0.36***
	(6.46)	(-1.65)	(6.05)	(-0.69)	(-1.88)	(0.9)	(4.66)	(0.32)	(-0.3)	(-0.57)	(3.88)
MOM	1.76***	-0.57***	1.54***	-0.47***	-0.24**	0.19**					
	(4.51)	(-8.03)	(3.96)	(-6.09)	(-2.1)	(2.48)					
IR	1.04***	-0.39***	0.84***	-0.29***	-0.13	0.25***					
	(3.16)	(-6.51)	(2.58)	(-4.57)	(-1.32)	(3.8)					
RR	1.96***	-0.46***	1.78***	-0.38***	-0.24**	0.15*					
	(4.97)	(-6.47)	(4.48)	(-4.82)	(-2.02)	(1.83)					

In Panel C we regress Trend on the market return along with MOM, IR and RR (see equation (21)). Trend has the lowest alpha when accounting for these factors (1.58%) but it is still positive and significant at a 1% level. Noteworthy is that the trend factor has close to zero beta for Market, MOM and IR (0.02, -0.04 and -0.06 respectively) but the highest beta in all three regressions towards RR (0.36). This is the only beta for Trend that is significant at a 1% level. In general, we see that the betas are low (and not highly significant) for the trend factor and higher (and significant) for all the other factors.

5.3 Robustness

In this section we test whether the superior performance of the trend factor is robust to various adjustments of the model. This is done through adding transaction costs, value-weighted instead of equal-weighted portfolios, and altering the smoothing horizon of the trend betas. Lastly, we also compare results of the trend and momentum factors in additional markets.

5.3.1 Transaction costs

Whether the gains from the common momentum factor is still exploitable after taking transaction cost into account is a debated issue. One concern is that the monthly rebalancing of the portfolio will encounter a high turnover. Additionally, the trend factor gather moving average prices of various time lengths making it likely to adapt quickly to market trends and therefore have an even higher turnover of stocks traded in the portfolio. Hence, the issue of transaction costs becomes highly relevant for the trend factor as well. Table 7 compares turnover rate, average return including different transaction costs and break even costs for Trend, MOM, IR, and RR. Trend has a monthly turnover rate (58%) which is almost three times that of the momentum factor (20%), and approximately twice that of both the echo factors IR (29%) and RR (32%). While the higher turnover is expected and consistent with Han et al. (2016), the relative difference between the factors is higher than previous mentioned authors findings, since MOM is found to have a lower turnover in our sample.

Table 7: Indicators of possible transaction costs.
This table shows the Turnover rate of the trend factor, MOM, IR, and RR and the corresponding break-even transaction costs, which would completely offset the returns. Additionally, the table reports the average monthly returns of the four factors if three possible transaction costs were taken into account. The turnover rate, average returns, and zero return rates are presented in percentage. The effective sample period is from January 1998 through January 2019.

Factor	Turnover rate (%)	Average return incl. transaction costs (%)			Break even costs (bps)
	Mean	(1) 8.36 bps	(2) 42.49 bps	(3) 117.14 bps	Zero return rate
Trend	58.86	2.15	1.73	0.82	173
MOM	20.59	1.29	1.12	0.75	226
IR	29.08	0.77	0.55	0.06	104
RR	32.28	1.44	1.19	0.63	205

Due to the high turnover of all the factors, we apply different transaction costs to test the robustness of the returns. The transaction costs are then used as c in equation (16). To our knowledge there are no recent papers providing substantiated numbers for transaction cost in the Swedish stock market, so we use numbers from 2010 Q2 to 2019 Q1 documented by Virtu Financial (2019) for Europe excluding UK, which Sweden is a part of. The first cost (1) is average market commission cost.

The returns are barely affected. Trend returns a monthly 2.15% compared to 1.29% for MOM, 0.77% for IR and 1.44% for RR. However, commissions are only a part of the total transaction cost.

Lesmond et al. (2004) argues that it is particularly concerning that bid-ask spread and market size is not taken into account when accounting for transaction cost. We therefore first add implementation shortfall (IS) cost, which is defined as ”The difference, or slippage between the arrival price and the execution price for a trade” (Virtu Financial, 2019, p.33) to cost (2). It is, however, reasonable to assume that the second concern, market size, will affect both commission- and IS cost. As seen in Table 5, according with the remark of Lesmond et al., the portfolios traded for both MOM and Trend are clearly the ones with lowest average market cap. Neither Han et al. (2016) nor Barroso and Santa-Clara (2015) account for this in their calculations. IS cost for small cap is not listed by Virtu Financial (2019) for the European market, so for cost (3) we therefore try to adress the market size concern by constructing a proxy for comparison. We do this by calculating the difference between small cap costs and average costs listed for the US market, and apply the same premium to the average European costs from (2). Trend withstand both transaction cost (2) and (3), performing slightly higher average return than MOM and RR while the return for IR is close to zero. Note here that since MOM has a lower turnover rate than RR the return of the momentum factor has surpassed that of RR when the highest transaction cost (3) is considered.

Following Grundy and Martin (2001) we calculate break even costs for the trend- and momentum factor along with IR and RR, presented in Table 7. The transaction costs when the respective factors are yielding a zero return are 173 bps for Trend, 226 bps for MOM, 104 bps for IR and 205 bps for RR. We have seen that gathering indicators of various time lengths, as Trend does, both results in higher monthly return and higher turnover rate. Therefore it is not that surprising that Trend can not withstand higher transaction cost than MOM. This result differs from that of Han et al. (2016) who finds higher break-even transaction cost for the trend factor than the momentum factor. Possible reasons are the lower turnover rate and higher average return of MOM in our sample relative to that of Han et al.

Since we now know that MOM will eventually surpass Trend as the more profitable strategy when taking transaction costs into account, and that the costs are investor dependent, we construct Figure 5 which shows the average return yield in percentage at various different transaction costs. In addition we can see at what level of cost that the higher turnover induced by the trend strategy exceeds the benefits compared to the momentum strategies. The excess return of the trend factor relative to the momentum factor is offset at 137 bps and relative to RR at 130 bps. The corresponding number when the excess return of RR relative to MOM is in turn offset at 154 bps. IR remains the worst strategy throughout all possible costs in Figure 5. Note that all the crossover costs are higher than

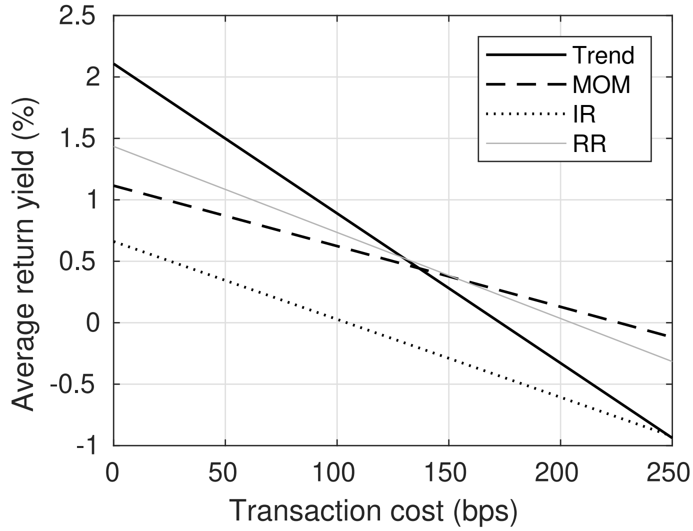


Figure 5: Average yield and transaction cost.
This figure shows the average monthly return yields adjusted for various different transaction costs for the trend factor (Trend), the momentum factor (MOM), the intermediate horizon factor (IR), and the recent horizon factor (RR). The yields and the costs are presented in percentage. The effective sample period is from January 1994 through January 2019.

50 bps which in some studies is used as an upper bound for possible transaction costs (Balduzzi & Lynch, 1999) and also higher than our proxy for small cap transaction cost. Therefore, trend seems to be the best performing factor taking into account currently ”realistic” transaction costs, represented in the left part of the Figure 5.

5.3.2 Value-weighted portfolios

So far throughout the thesis, all factors have been constructed through equal-weighted portfolios. This is mainly because the factors are equal-weighted in the original paper of Han et al. (2016) on Trend, and the original paper on MOM from Jegadeesh and Titman (1993). It follows then that the other factors should be equal-weighted as well for comparison. In this section, however, we compare the results if value-weighted portfolios were used. We hold over time between 28 and 93 stocks in our portfolios and hence a single large company stock can gain big weight in the portfolio. To illustrate this, Figure 6 shows the time variation of the highest weight of a single company in the short portfolio of the momentum factor in each month throughout our sample period[12]. We can see that the highest weighted company accounts for a large stake of the Loser portfolio. Out of 253 sample months, the highest weight exceeds 50% of the portfolio in 106 months, and even rise above 80% in more than a tenth of the months (28). This is around the same amount of months with a highest weight below 20% (26).

[12]The highest weight in the short momentum portfolio is 94.7% reached by Telefonaktiebolaget L M Ericsson sorted end of September 2001.

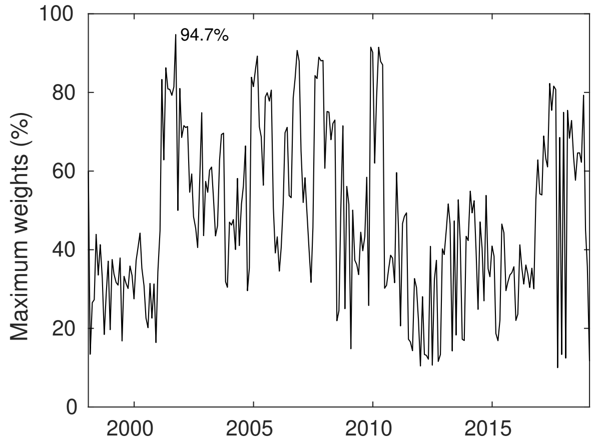


Figure 6: Maximum weights of the short momentum portfolio.
This figure shows the maximum weights of a stock in the short (Loser) portfolio of the momentum for each month during the effective sample period from January 1998 to January 2019. Additionally, the highest weight of the sample is pointed out. The weights are reported in percentage.

The fact that the return from the momentum factor may be tilted toward smaller stocks, depending on the sample period used (Hong et al., 2000; Grinblatt & Moskowitz, 2004; Israel & Moskowitz, 2012) and the higher idiosyncratic risk that follows from single stocks accounting for big parts of the portfolios, is a possible reason why MOM loses all gains to a 0.03% average monthly return when value-weighting is applied (see Appendix D Table 11). To avoid the problem with too big of idiosyncratic risk in our portfolios from single stocks, we put a restriction on 20% portfolio weight per stock. The restricted value-weighted results for the whole effective sample period and during the financial crisis are presented in Table 8. Both Trend (2.25% to 1.66%) and MOM (1.36% to 0.69%) has slight drops in monthly average return. This is somewhat expected, considering the lower weight from small stocks and larger idiosyncratic risk, as stated above. During the financial crisis Trend actually has a higher mean (1.37% versus 0.75%) and doubling the Sharpe ratio while MOM is kept around the same numbers. SREV has somewhat higher mean during the whole sample (0.37% versus 0.30%) but lower number during the financial crisis (1.48% versus 2.63%) while returns in the same periods for LREV change from -0.07% to 0.02% and from -0.12% to 0.46%. The market average return is actually increasing (1.11% to 1.38%) which is partly attributable to the improved mean during the financial crisis (-1.06% to -0.05%).

Regarding the momentum and echo factors, we find same order in returns among the factors if value-weighted portfolios are used. IR has a monthly average of 0.35% compared to 0.82% for the equal-weighted portfolio. RR has corresponding numbers of 0.93% compared to 1.67%. Furthermore, as for the equal-weighted factors, RR is the worst performing of all discussed factors during the financial crisis. The already poor return turns to be even worse (-1.97% equal-weighted versus -3.02% value-weighted).

Table 8: Value-weighted portfolios: summary statistics for 20%-cap.
This table reports the summary statistics, including the financial crisis as a recession period, for the trend factor (Trend), the short-term reversal factor (SREV), the momentum factor (MOM), the long-term reversal factor (LREV), the intermediate horizon return factor (IR), the recent horizon return factor (RR), and the market portfolio (Market). For each factor, we report monthly sample mean in percentage, sample standard deviation in percentage, Sharpe ratio, skewness, and kurtosis. All variables are calculated for the zero-cost portfolios, whereas the Loser and Winner, respectively Low and High portfolios are value-weighted according to their market capitalization. A company has a maximum stake of 20% in a portfolio. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by ***, **, and *, respectively. The sample period (Panel A) is from January 1997 through January 2019 and the recession period (Panel B) from December 2007 through June 2009.

Factor	Mean (%)	Std dev (%)	Sharpe ratio	Skewness	Kurtosis	Mean (%)	Std dev (%)	Sharpe ratio	Skewness	Kurtosis
	Panel A: sample period (01/1998 - 01/2019)					Panel B: Financial crisis (12/2007 - 06/2009)				
Trend	1.66***	6.17	0.24	-0.72	12.99	1.37	8.18	0.14	0.80	5.15
	(4.27)					(0.73)				
SREV	0.37	5.66	0.04	0.32	5.87	1.48	7.82	0.16	-0.74	3.36
	(1.04)					(0.82)				
MOM	0.69	8.29	0.07	-1.44	10.31	-2.41	12.39	-0.21	-2.08	7.64
	(1.33)					(-0.85)				
LREV	0.02	5.95	-0.02	0.72	8.43	0.46	7.75	0.03	0.36	2.66
	(0.05)					(0.26)				
IR	0.35	6.92	0.03	-0.94	6.04	-0.87	9.29	-0.12	-1.58	5.46
	(0.8)					(-0.41)				
RR	0.93*	7.71	0.10	-1.42	12.38	-3.02	10.28	-0.32	-1.37	5.10
	(1.92)					(-1.28)				
Market	1.38***	4.93	0.25	-0.08	4.22	-0.05	7.67	-0.04	0.24	3.71
	(4.45)					(-0.03)				

5.3.3 Smoothing betas

In the trend factor, in accordance with Han et al. (2016) we smooth the betas over 12 months (see equation (9)). By altering the number of smoothing-months we find that the lower return follows lower number of months to average the betas. The cumulative returns are shown in Figure 7. Already by reducing the months from 12 to 9, over 50% of the total return is gone (195.7 versus 86.99). 6-month smoothing returns about 10% of the original return (20.09). If the betas were not smoothed at all i.e. the beta obtained through regression in time t were used to estimate return for month $t+1$, the return would drop by over 95% resulting in a cumulative return of only 6.44.

It is clear in our sample that for the betas to maintain a predictive power, some smoothing is necessary. This is consistent with similar test run by Han et al. (2016), who argues that the beta is required to be smoothed over a time series to provide a consistent estimator. The argument stated above, along with the clear diminishing return following lower number of months for time series average of the beta makes it look like higher number for smoothing the beta will give a better estimate, and hence, improve the performance of the trend factor. We therefore, unlike Han et al. (2016) try a 15-month average for the beta. The result is 94.17, close to the one for 9-month

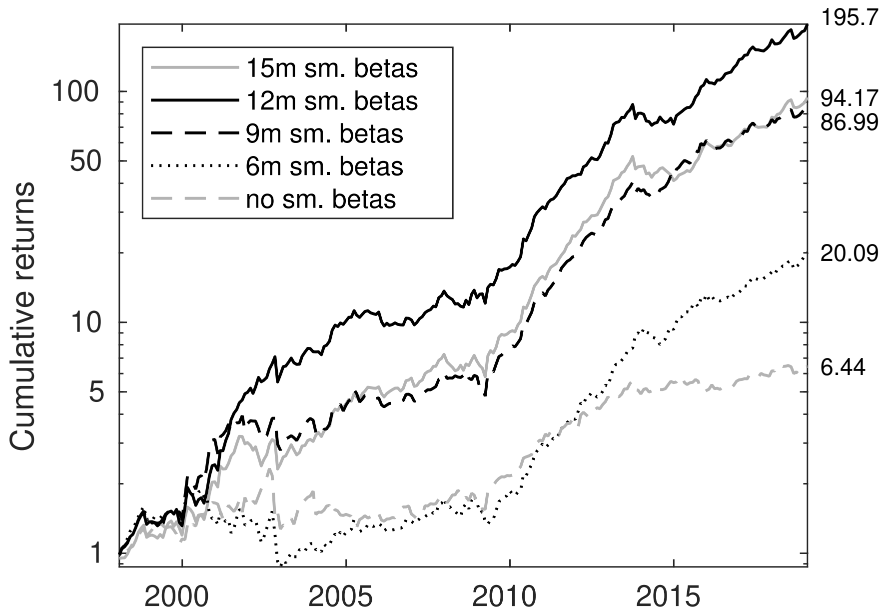


Figure 7: Trend factor: smoothed betas.
This figure shows the cumulative returns of the trend factor using different smoothing horizons for the betas. The five plots are based on betas that range between 15 months of smoothing and no smoothing. The original trend factor is smoothed by 12 months. The cumulative returns are in absolute numbers and are constructed by investing 1$ in the High(Winner) portfolio, and shorting 1$ in the Low(Loser) portfolio. The effective sample period is from January 1998 through January 2019.

smoothing, namely around 50% of the original return[13]. Why 12 months is so clearly superior is beyond the scope of this thesis, but it is also in line with for instance the momentum factor that uses cumulative return over previous 12 months (skipping the most recent).

5.3.4 Comparison of Nordic countries

In this section we will consider the three momentum and echo factors along with the trend factor in two additional Nordic countries: Finland and Denmark. Following the structure throughout the results in this thesis, the first part of this section will contain a more comprehensive comparison of MOM, IR and RR. The second part will highlight the difference between Trend and MOM, and some additional comparison between Trend and IR, RR and Market.

For the comparison of Sweden with its neighbour countries we conducted the same three factors, the momentum factor, the intermediate horizon return factor, and the recent horizon return factor respectively, for Finland and Denmark. Note that due to lack of Finnish and Danish data the sample

[13]Since 15-month smoothing lowers the effective sample by 3-months, the original return is calculated during the same period for comparison. The result is 183.12.

period is a little shorter, and therefore the Swedish results deviate marginally from the previous calculations. Table 9 presents similar results, were all countries have positive and significant zero-cost and Winner portfolios, which adds to the robustness of the momentum factor.

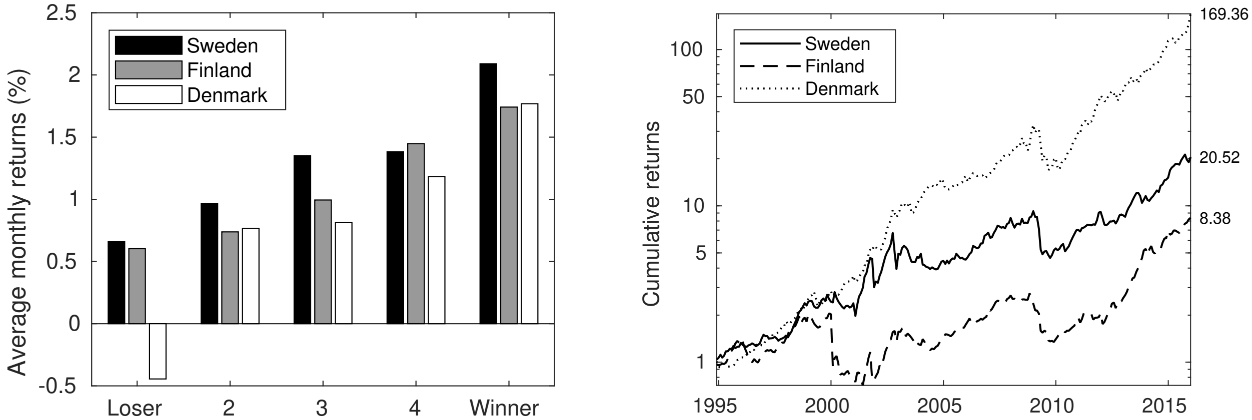
Table 9: Nordic countries: the momentum and echo factors.
This table compares the monthly sample means of Sweden, Finland, and Denmark. The returns are reported for the MOM factor (Panel A), the IR factor (Panel B), and the RR factor (Panel C), respectively. We report the returns for the Winner (portfolio 5), Loser (portfolio 1), and Winner-Loser (WML portfolio). In addition, the return differences of IR and RR (IR-RR), respectively MOM and RR (MOM-RR) WML-factors (Panel D) are displayed. The Returns are in percentage. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by ***, **, and *, respectively. The sample period is from November 1994 through December 2015.

Country	Winner (%)	Loser (%)	WML (%)	Winner (%)	Loser (%)	WML (%)	Winner (%)	Loser (%)	WML (%)	IR-RR (%)	MOM-RR (%)
	Panel A: MOM factor			Panel B: IR factor			Panel C: RR factor			Panel D: Differences	
Sweden	2.09***	0.66	1.43***	1.74***	0.94*	0.79**	2.21***	0.56	1.65***	-0.85*	-0.22
	(6.18)	(1.21)	(3.41)	(4.99)	(1.92)	(2.3)	(6.02)	(1.07)	(3.98)	(-1.94)	(-0.78)
Finland	1.74***	0.60	1.14***	1.58***	0.44	1.14***	1.83***	0.66	1.17***	-0.03	-0.03
	(4.73)	(1.1)	(2.54)	(4.3)	(0.98)	(3.41)	(4.79)	(1.23)	(2.68)	(-0.06)	(-0.13)
Denmark	1.77***	-0.44	2.21***	1.41***	0.11	1.29***	1.66***	-0.03	1.69***	-0.40	0.52**
	(6.28)	(-0.99)	(6.05)	(4.81)	(0.28)	(3.87)	(5.6)	(-0.08)	(5.22)	(-1.19)	(2.35)

Even though the returns for each country tend to move in similar directions it can be seen in Figure 8b that the Danish momentum factor outperforms both the Swedish and Finnish factor with an average monthly return for the WML portfolio of 2.21% compared to 1.43% and 1.14% for Sweden and Finland respectively. This is mainly due to the fact that Denmark is the only country with a negative average return for the Loser portfolio (-0.44%) as seen in Figure 8a, which contributes positively to the highest long-short return, in spite of the fact that the Swedish Winner portfolio performs better than the corresponding Danish portfolio. The results of Goyal and Wahal (2016) show the same tendencies, although their Swedish and Finnish result are not significant, with average monthly returns of 1.41%, 1.06% and 0.97% for Denmark, Sweden and Finland respectively[14].

The comparison of the echo factors shows that the recent horizon returns performs better than the intermediate horizon return for each country. Unlike Sweden however, the difference between IR and RR in our sample is not found statistically significant for neither Denmark nor Finland. For the sample period used by Goyal and Wahal (2016), the Finnish IR performs slightly, but also insignificantly, better than its RR factor. Taking these results into consideration, it is not surprising that the difference in the IR-RR for Finland in our sample, which is presented in Panel D of Table 9, is close to zero. Denmark however, is the only country in our sample for which the momentum factor outperforms the recent horizon return factor. This difference, which is indeed significant on a 5% level, is primarily due to the difference in the short portfolio. The Loser portfolio of RR performs slightly negative, which has in turn a positive effect on the WML return, but not as bad

[14] Note that the authors calculated the returns of value-weighted quintiles, using different time periods for each country, starting earliest 2000 for Denmark and ending for all countries in 2001.



(a) Average returns of MOM portfolios per country

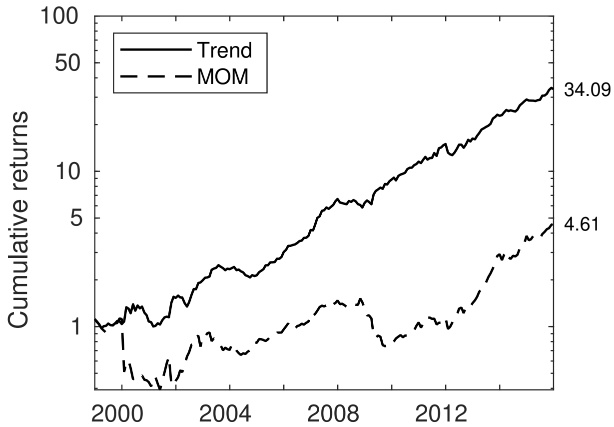
(b) Cumulative returns of MOM per country

Figure 8: Nordic countries: average and cumulative returns of the momentum factor.
Figure (a) shows the average monthly returns of the five momentum portfolios for the analysed Nordic countries Sweden, Finland, and Denmark, respectively. The returns are in percentage. Figure (b) reports the development of the cumulative returns for these three countries. The cumulative returns are in absolute numbers and are constructed by investing 1$ in the Winner portfolio, and shorting 1$ in the Loser portfolio. To display and compare the development of the curves nicely, the axis of the cumulative returns is log scaled. The sample period is from November 1994 through December 2015.

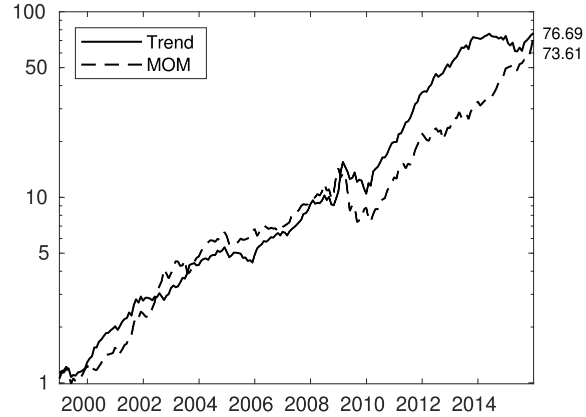
as the Loser portfolio of MOM. The Danish momentum factor has in addition a higher return for the Winner portfolio which increases the difference even more.

Just as for the comparison with MOM, RR and IR, we add to the comparison of Trend and MOM by looking at the two additional markets. The average returns for all three markets along with performance measures used throughout the thesis are presented in Table 10. We find that Trend has a significant average monthly return close to 2% for both additional markets. While the trend factor beats the momentum factor regarding the cumulative returns in both Finland and Denmark (see Figure 9), it actually has a slightly lower average return than MOM in the latter (2.26% versus 2.32%; see Table 10). This is likely a result of a very good performing momentum factor in the Danish market, which in turn, as discussed above, is enabled through Denmark being the only market observed in our sample where the Loser portfolio has a negative return. Remember from earlier results that the short portfolio is the cause of momentum crashes and that a large reason for the outperformance of the trend factor against the momentum factor in the Swedish market was due to the clear lower return of P1 (Low/Loser).

Looking at the performance measures presented in Table 10 we find that all of them are in favour of the trend factor. MOM, IR and RR have negative skewness (positive for Trend) and larger MDD than the trend factor in both Finland and Denmark. This further strengthens the lower downside risk profile of Trend and are summarized in the return-downside risk performance measure Calmar



(a) Cumulative returns for Finland



(b) Cumulative returns for Denmark

Figure 9: Nordic countries: cumulative returns of the trend and momentum factor.
These figures present the cumulative returns of the trend and momentum factor for (a) Finland and (b) Denmark, respectively. The cumulative returns are in absolute numbers and are constructed by investing 1$ in the Winner portfolio, and shorting 1$ in the Loser portfolio. The axes of the cumulative returns are log scaled.The sample period is from November 1994 through December 2015.

ratio. In Finland the Calmar ratio is 10 times as high for Trend than MOM and in Denmark, where the momentum factor actually had a higher average return, the Calmar ratio is almost twice as high for Trend (28.48 versus 18.80).

Table 10: Nordic countries: performance measures for the trend and other factors.
This table reports the performance measures for Trend, MOM, IR, RR, and Market. For each factor, we report monthly sample mean in percentage, sample standard deviation in percentage, skewness, kurtosis, maximal drawdown (MDD) in percentage, and the Calmar ratio in percentage. The last column presents the differences of the trend factor to the other factors (Diff Trend/Factor) in percentage. All variables are calculated for the zero-cost portfolios. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by ***,**, and *, respectively. The sample period is from January 1998 through January 2019.

Factor	Mean (%)	Std dev (%)	Skewness	Kurtosis	MDD (%)	Calmar (%)	Diff Trend/Factor (%)
				Sweden			
Trend	2.27***	5.75	0.21	5.83	22.24	39.97	-
	(5.64)						
MOM	1.35***	7.25	-1.03	7.44	49.78	5.29	0.91
	(2.66)						(1.46)
IR	0.65	5.97	-0.65	5.51	60.80	2.16	1.61***
	(1.57)						(2.75)
RR	1.73***	7.13	-0.90	8.03	47.37	10.72	0.53
	(3.48)						(0.88)
Market	1.23***	5.62	-0.09	4.21	56.63	5.06	1.04*
	(3.12)						(1.75)
				Finland			
Trend	1.84***	4.77	0.93	6.73	28.04	18.21	-
	(5.52)						
MOM	1.09**	7.58	-2.47	17.77	65.32	1.80	0.75
	(2.06)						(1.21)
IR	1.09***	5.56	-1.21	9.50	48.72	3.70	0.75
	(2.8)						(1.46)
RR	1.29**	7.21	-1.40	10.67	53.25	5.20	0.56
	(2.55)						(0.92)
Market	1.02***	5.24	0.55	5.26	51.47	1.97	0.82*
	(2.78)						(1.80)
				Denmark			
Trend	2.26***	5.09	0.55	6.09	32.64	28.48	-
	(6.36)						
MOM	2.32***	6.24	-0.77	4.84	48.70	16.80	-0.05
	(5.31)						(-0.11)
IR	1.26***	5.63	-0.67	4.49	55.30	5.34	1.00**
	(3.21)						(2.24)
RR	1.66***	5.54	-0.32	4.06	38.28	12.96	0.61
	(4.28)						(1.36)
Market	0.87***	4.54	-0.67	5.15	64.73	3.64	1.39***
	(2.74)						(2.81)

6 Conclusion

Our paper examines the momentum anomaly in the Swedish stock market along with two additional strategies, as the momentum factor suffers from large collapses during recessions. The echo strategy, developed by Novy-Marx (2012) and further investigated by Goyal and Wahal (2016), divides the momentum sorting period into two horizons: the intermediate horizon return (IR) and the recent horizon return (RR). IR has a significantly lower average monthly return than the momentum factor, whereas RR, on the other hand, performs slightly better than MOM. However, the difference is insignificant and, more importantly, RR does not tackle the problem of big losses.

The Trend factor introduced by Han et al. (2016) address this issue by using price signals through MA of past prices over various time horizons. The difference of the highest expected return quintile, which we buy, and the lowest expected return quintile, which we sell to construct a zero-cost portfolios earns an average monthly return of 2.25% per month, and thus, more than RR, MOM, and IR with returns over the same period of 1.67%, 1.36%, and 0.82%, respectively. Our results show in addition that the trend factor is more stable than MOM and withstands the market disruptions with an positive average monthly return of 0.75% during the recession period of the most recent financial crisis. Furthermore, the trend factor outperforms the other factors with a higher Sharpe ratio, a lower maximum drawdown, less extreme monthly losses, and a Calmar ratio which is close to five times as high as the next best one of RR. This ratio indicates a better expected downside risk-return tradeoff of the trend factor.

Since concerns has been raised regarding high stock turnover imposed by the momentum factor, our findings of a three times higher turnover ratio of the trend factors is a concerning fact. However, we find that the superior return of Trend is robust to the application of various potential transaction costs. Further, the positive return of the trend factor stays significant when regressing against the well known CAPM and Fama-French three factor models. Finally, the robustness of the trend factor in Sweden is underlined by the findings in the comparison with its neighbours, Finland and Denmark.

For further research we suggest two directions. The smoothing horizons of the trend betas seem to have a large impact on the returns. However, our findings do not economically explain why the 12-months smoothing is superior both to the shorter and longer smoothing horizons. Therefore, a deeper analysis of the smoothed betas of the trend factor would be a topic that could be investigated further. Secondly, considering the current market situation caused by the COVID-19 pandemic of which the long-term economic consequences and useful data are not yet known or available, it would be interesting to test the robustness of the trend factor. This is a motivated addition to previous test since, although Trend performed well during the recent financial crisis, this crisis has had an exceptional vast market downturn and recovery so far.

References

AQR. (2020). *Quality minus junk: Factors, monthly.* Retrieved 2020-05-06, from https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum every-where. *Journal of Finance*, *3*(68), 929–985.

Balduzzi, P., & Lynch, A. W. (1999). Transaction costs and predictability: some utility cost calculations. *Journal of Financial Economics*, *52*(1), 47–78.

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, *1*(116), 111–120.

Bird, R., & Casavecchia, L. (2007). Value enhancement using momentum indicators: the european experience. *International Journal of Managerial Finance*, *3*(3), 229–262.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*, *47*(5), 1731–1764.

Brown, D. P., & Jennings, R. H. (1989). On technical analysis. *The Review of Financial Studies*, *2*(4), 527–551.

Cespa, G., & Vives, X. (2012). Dynamic trading and asset prices: Keynes vs. hayek. *The Review of Economic Studies*, *79*(2), 539–580.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, *122*(2), 221–247.

DeBondt, W. F. M., & Thaler, R. (1984). Does the stock market overreact? *The Journal of Finance*, *40*(3), 793–805.

Edmans, A., Goldstein, I., & Jiang, W. (2015). Feedback effects, asymmetric trading, and the limits to arbitrage. *The American Economic Review*, *105*(12), 3766–3797.

Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal*, *62*(2), 69–97.

Fama, E. F. (1965). Random walks in stock market prices. *Financial Analysts Journal*, *21*(5), 55–59.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457–472.

French, K. R. (2020). *Detail for 10 portfolios formed monthly on momentum.* Retrieved 2020-04-09, from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_port_form_pr_12_2.html

González, A., & Parmler, J. (2007). Is momentum due to data-snooping? *European Journal of Finance*, *13*(4), 301–318.

Goyal, A., & Wahal, S. (2016). Is momentum an echo? *Journal of Finance and Quantitative Analysis*, *6*(50), 1237–1267.

Grinblatt, M., & Moskowitz, T. J. (2004). Predicting stock price movements from past returns: the role of consistency and tax-loss selling. *Journal of Financial Economics*, *71*(3), 541—579.

Grundy, B. D., & Martin, J. S. (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *The Review of Financial Studies*, *14*(1), 29–78.

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, *48*(5), 1433–1461.

Han, Y., Zhou, G., & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? *Journal of Financial Economics*(122), 352–375.

He, X.-Z., & Li, K. (2015). Profitability of time series momentum. *Journal of Banking and Finance*, *C*(53), 140–157.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, *55*(1), 265–295.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance,*, *54*(6), 2143–2184.

Hou, K., Xue, C., & Zhang, L. (2019). Replicating anomalies. *The Review of Financial Studies*(forthcoming).

Israel, R., & Moskowitz, T. (2012). The role of shorting, firm size, and time on market anomalies. *Journal of Financial Economics*, *2*(108), 275–301.

Jacobs, H., & Müller, S. (2019). Anomalies across the globe: Once public, no longer existent? *Journal of Financial Economics*, *135*(1), 213–230.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance*, *45*(3), 881–898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *1*(48), 65–91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, *56*(2), 699–720.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, *105*(1), 1–28.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. *Journal of Financial Economics*, *2*(71), 349-–380.

Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction? *The Review of Financial Studies*, *3*(2), 175–205.

Mclean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *The Journal of Finance*, *1*(71), 5–32.

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum? *The Journal of Finance*, *54*(4), 1249–1290.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, *104*(2), 228–250.

Nagel, S. (2012). Evaporating liquidity. *The Society for Financial Studies*, *25*(7), 2005–2039.

Nasdaq. (n.d.). *Main market listings 2018.* Retrieved 2020-04-06, from http://www

.nasdaqomxnordic.com/news/listings/main-market/2018

Nasdaq. (2020a). *Monthly report - total equity trading april 2020.* Retrieved 2020-05-30, from https://newsclient.omxgroup.com/cdsPublic/viewDisclosure.action?disclosureId=939584&lang=en

Nasdaq. (2020b). *Total equity trading first north april 2020.* Retrieved 2020-05-30, from https://newsclient.omxgroup.com/cdsPublic/viewDisclosure.action?disclosureId=942166&lang=en

NBRE. (2010). *The national bureau of economic research: Announcement of june 2009 business cycle through/end of last recession.* Retrieved 2020-04-23, from https://www.nber.org/cycles/sept2010.html

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, *3*(103), 429–453.

Okunev, J., & White, D. (2003). Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis*, *38*(2), 425–447.

Rouwenhorst, K. G. (1998). International momentum strategies. *The Journal of Finance*, *53*(1), 267–284.

Sharpe, W. F. (2007). *Investor and markets: portfolio choices, asset prices, and investment advice*. Princeton and Oxford: Princeton University Press.

Skatteverket. (n.d.). *Aktiehistorik.* Retrieved 2020-04-06, from https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik.4.dfe345a107ebcc9baf80009051.html

Sveriges Riksbank. (2020a). *Statistics: Search interest exchange rates.* Retrieved 2020-04-12, from https://www.riksbank.se/en-gb/statistics/search-interest--exchange-rates/

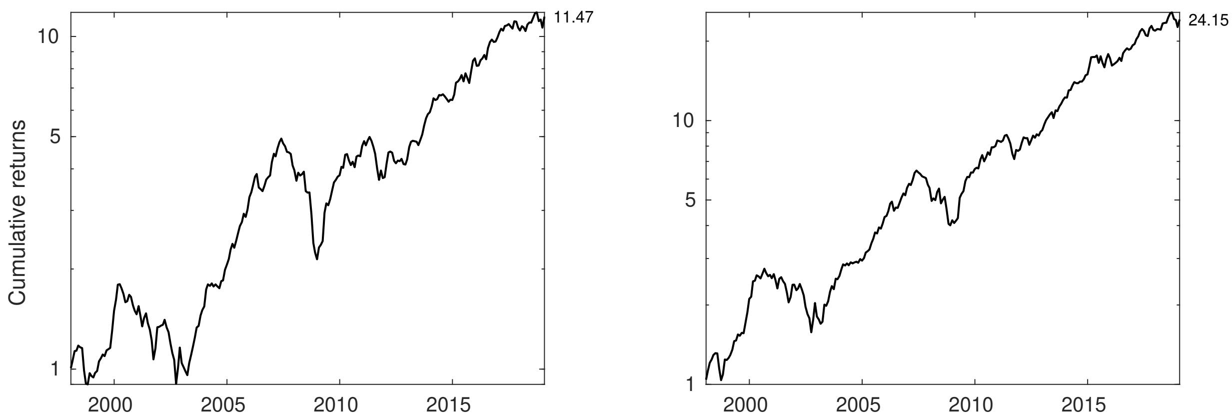
Sveriges Riksbank. (2020b). *Statistik.* Retrieved 2020-05-31, from https://www.riksbank.se/sv/statistik/

Treynor, J. L., & Ferguson, R. (1985). In defense of technical analysis. *The Journal of Finance*, *40*(3), 757–773.

Virtu Financial. (2019). *Global cost review q2 2019.* Retrieved 2020-04-28, from https://www.virtu.com/uploads/documents/Virtu-Global-Cost-Review-2019Q2.pdf

Appendix

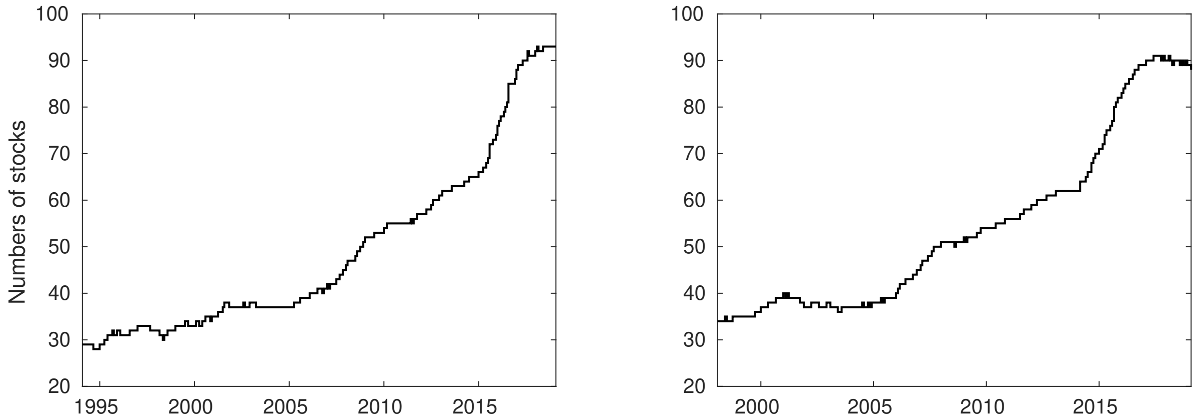
A.



(a) Equal-weighted market　　**(b)** Value-weighted market

Figure 10: Swedish market.
The figure shows the cumulative returns of the Swedish market applied on the available stock date with different stock-weighting. The sample period is from January 1998 through January 2019.

B.

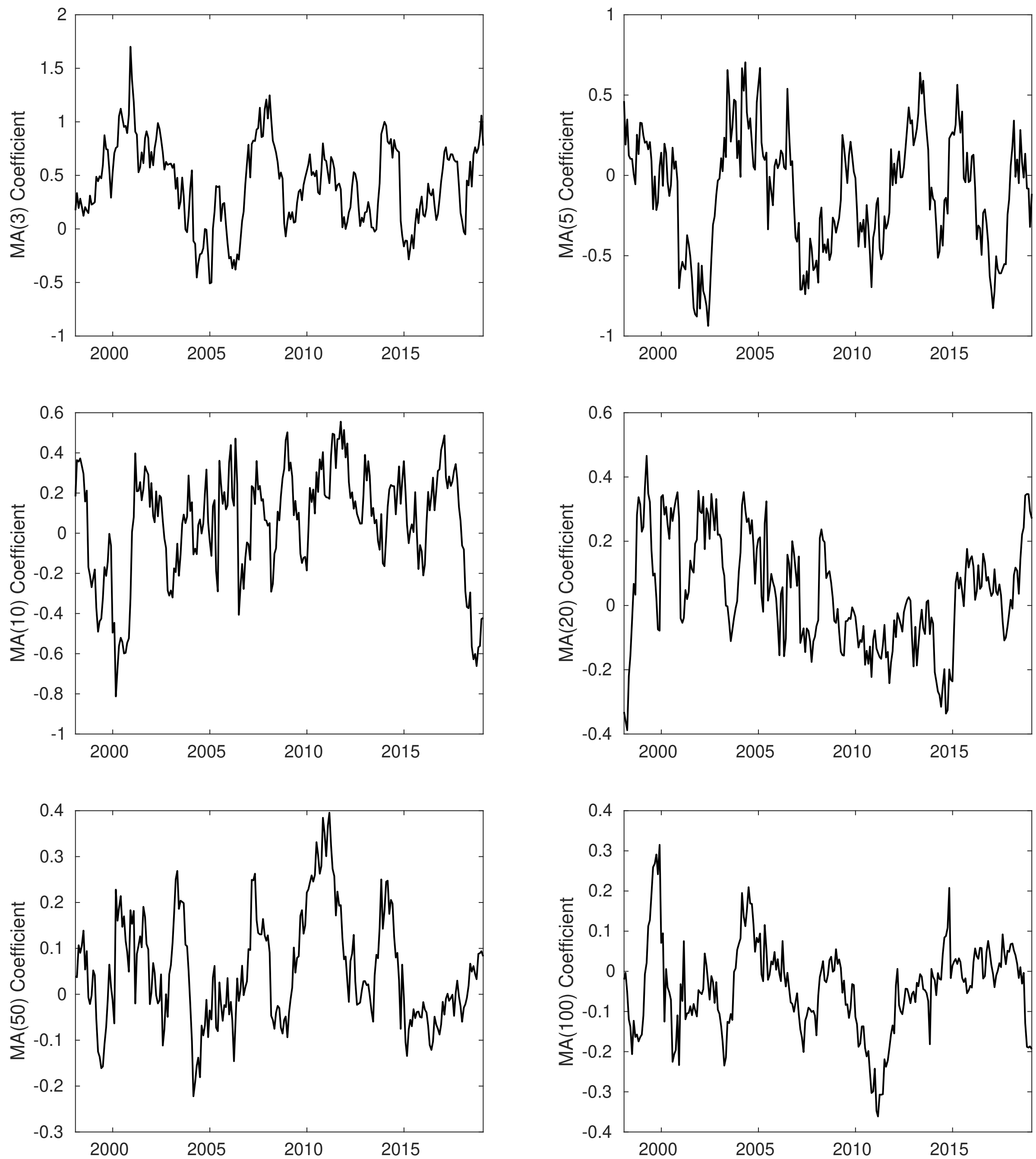


(a) Momentum factor (01/1994 - 01/2019)

(b) Trend factor (01/1998 - 01/2019)

Figure 11: Numbers of stocks per short/long portfolio over the sample period.
The figure shows the numbers of stocks which the short/long portfolios of the momentum, respectively trend factor are containing at the end of each month (rebalance/sorting frequency). The numbers of stocks for the momentum factor differs between 28 & 93, whereas they differs between 34 & 91 for the trend factor. Note, that the sample periods are not the same due to the longer sorting horizon of the trend factor. The sample periods are from January 1994 for the momentum factor, respectively from January 1998 for the trend factor, through January 2019.

C.


MA(3) Coefficient
MA(5) Coefficient
MA(10) Coefficient
MA(20) Coefficient
MA(50) Coefficient
MA(100) Coefficient
2000
2005
2010
2015

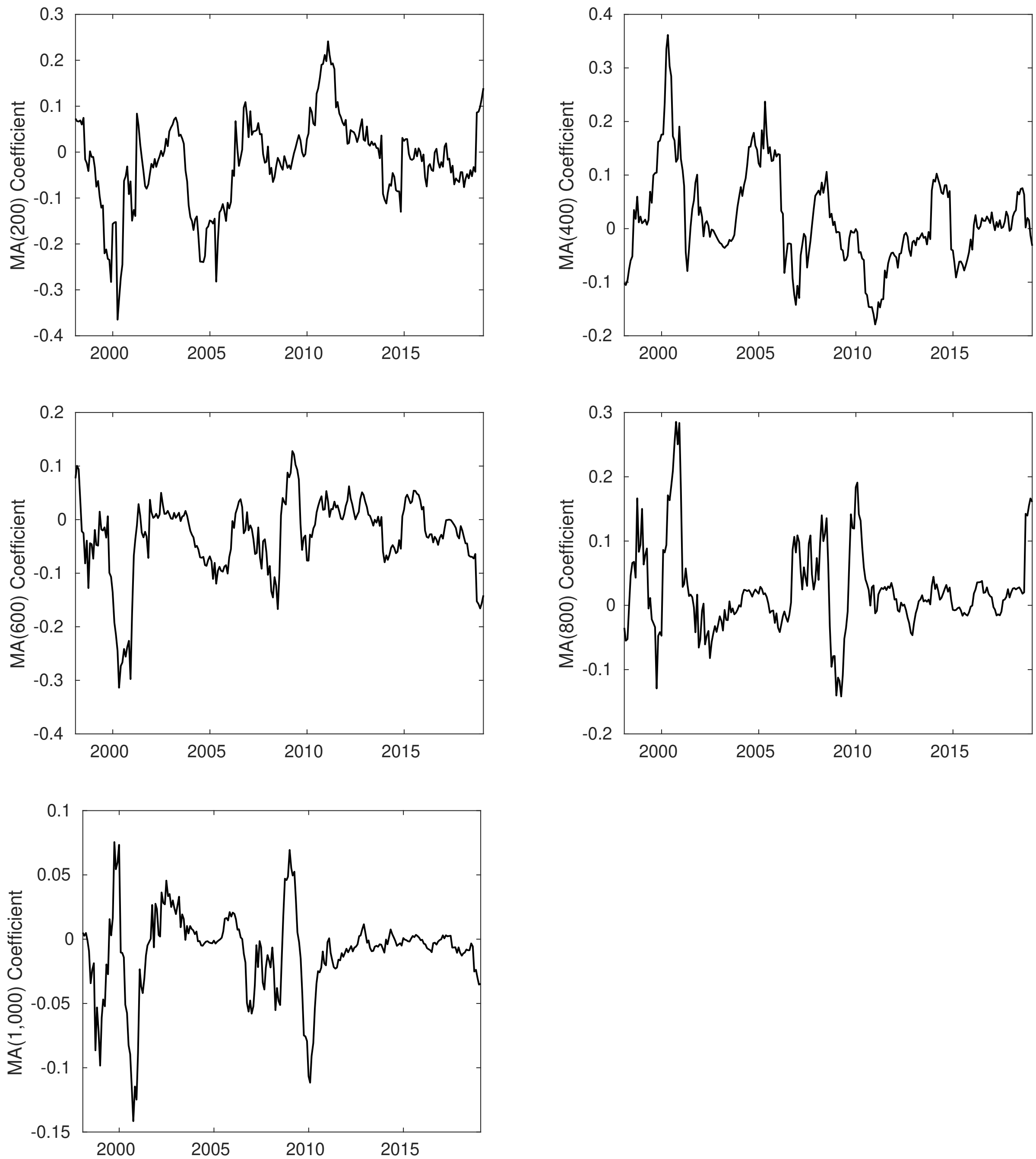


Figure 12: Trend factor: applied MA Coefficients.
This figure represents the smoothed coefficients of the 11 applied moving averages, MA(3) to MA(1000), estimated from equation (9). The sample period is from January 1998 through January 2019.

D.

Table 11: Value-weighted portfolios: summary statistics without cap.
This table reports the summary statistics, including the financial crisis as a recession period, for the trend factor (Trend), the short-term reversal factor (SREV), the momentum factor (MOM), the long-term reversal factor (LREV), the intermediate horizon return factor (IR), the recent horizon return factor (RR), and the market portfolio (Market). For each factor, we report monthly sample mean in percentage, sample standard deviation in percentage, Sharpe ratio, skewness, and kurtosis. All variables are calculated for the zero-cost portfolios, whereas the Loser and Winner, respectively Low and High portfolios are value-weighted according to their market capitalization without cap. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by ***, **, and *, respectively. The sample period (Panel A) is from January 1997 through January 2019 and the recession period (Panel B) from December 2007 through June 2009.

Factor	Mean (%)	Std dev (%)	Sharpe ratio	Skewness	Kurtosis	Mean (%)	Std dev (%)	Sharpe ratio	Skewness	Kurtosis
	Panel A: sample period (01/1998 - 01/2019)					Panel B: Financial crisis (12/2007 - 06/2009)				
Trend	1.23	8.87	0.12	-1.46	19.47	1.03	9.90	0.08	0.71	4.45
	(2.20)					(0.45)				
SREV	0.12	9.58	0.00	2.76	34.25	-0.51	10.62	-0.07	-0.64	4.04
	(0.19)					(-0.21)				
MOM	0.03	10.40	-0.01	-1.34	10.10	-3.02	13.83	-0.24	-1.28	5.09
	(0.04)					(-0.95)				
LREV	0.18	8.16	0.00	0.27	6.08	1.85	11.36	0.14	0.58	2.52
	(0.35)					(0.71)				
IR	0.02	9.09	-0.01	-0.66	5.20	-1.05	11.73	-0.11	-1.70	6.49
	(0.04)					(-0.39)				
RR	0.71	9.89	0.06	-1.85	18.41	-3.75	13.20	-0.30	-1.03	4.23
	(1.14)					(-1.24)				
Market	1.39	4.95	0.25	-0.02	4.21	-0.03	7.59	-0.04	0.28	3.73
	(4.46)					(-0.02)				