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Factor Effects in Nordic Equities

- A theoretical and practical study

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ABSTRACT

This thesis is concerned with uncovering whether return pattern effects from some of the most well-known factor models are present in a non-US sample. In a two-part analysis, taking both the theoretical academic perspective and the practical industry perspective, equity returns on the Nordic capital market (Sweden, Denmark, Norway and Finland) are scoured for evidence of factor patterns to size, value, momentum, profitability and investment.

Fama & French's methods for constructing the factor models are utilized when taking the academic perspective to factor effects, and investigating the ability of four factor models to price equity returns. The Fama & French (1993) three-factor model, Carhart (1997) four-factor model, Fama & French (2015) five-factor model, and a combinational six-factor model are estimated using ordinary least squares. Inference about the relevance of the factor models are made based on hypothesis tests on single models in the cross section of returns, and joint tests across the estimated models. While none of the factor models provide complete descriptions of variations in the cross section, an ability to explain between below 20-32% of the dependent portfolios, provides indication that factor effects are prevalent on the Nordic equity markets.

In the second part of the thesis' analysis, the thesis takes the industry perspective and evaluates the possible factor patterns as trade proposals instead. First, the simple, individual factor portfolios are evaluated on their performance during different market conditions in the 25 years from 1991-2015. Several of the long-short factor portfolios have provided attractive risk-return proposals, indicating factor return patterns in Nordic equities. From the individual portfolios, much inspired by the value-momentum findings of Asness, Moskowitz & Pedersen (2013), combinational factor portfolios are constructed in order to uncover diversification benefits between the factor effects. Simple portfolio combinations are constructed, as well as more complex mean variance optimized portfolios. The thesis is able to uncover a superior factor investment portfolio that has provided market-insensitive alpha the 25 years in which it would have been applied.

Overall, both the academic and industry perspective to factor patterns in returns presents compelling evidence towards the presence of factor effects on the Nordic markets.

CONTENTS

SECTION 1 INTRODUCTION

Factor models have become an important concept in modern finance. In academic financial research, factor models are econometric models that attempt to describe the return on a financial asset through its linear dependence on multiple factors. Following the seminal Fama-French three-factor model (Fama & French, 1993), a plethora of factors has been suggested to elaborate on cross sectional variations in returns over the recent two decades. In the industry, return patterns or factor effects documented in the models have proven to be attractive trade proposals, which can be exploited through exposure to the explanatory factors. Moreover, some factor patterns have been shown to correlate negatively with each other (value and momentum), offering diversification benefits. As such, investment managers have developed trading strategies on factor effects (for example AQR Capital). The research interest of this thesis lies at the intersection of the academic and industry use of factor models.

First, the majority of academic research papers on these models are based on the same data; CSRP market data and Compustat accounting data for NYSE, AMEX and NASDAQ listed stocks from around 1962. This comes from the fact that the US stock market is the most developed, with the largest and most complete sample globally. The problem is that new findings lose validity to data snooping at some point; if the same sample of data is under enough scrutiny, links between variables can be found, even if they do not make sense. Researchers have started looking at other markets for testing the robustness of US-found factor models, but non-US samples are far from exhausted. Thus, to investigate the robustness of previous, US-based findings, some of the more well-known factor models will be tested for their ability to elaborate on the Nordic (Sweden, Denmark, Norway and Finland) cross section of equity returns. Namely, the Fama & French (1993) three-factor, Carhart (1997) four-factor, and Fama & French (2015) five-factor models, along with a six-factor model combination of them all, will be tested.

Second, the industry perspective will be taken when the factors are viewed as trade proposals instead. This second part will exploit readily available academic research to acquire empirical returns, in an effort to see whether the same factors that are tested for their ability to price equities can provide returns based on the patterns instead. The starting point is the individual factor portfolios from the asset pricing models, to uncover whether academic factor research can provide empirical returns. From here, more complex portfolio construction is attempted to investigate possible synergy/diversification benefits between individual factor portfolios, inspired by Asness, Moskowitz & Pedersen's (2013) findings on value-momentum.

The asset pricing model tests and factor trading investigation will indicate whether the more prevalent factor effects from the academic literature is present on the out-of-sample Nordic equity market.

1.1 Thesis Statement

The objectives and limitations set out in the introduction is converted into the following over-arching thesis problem statement:

A complete investigation into the relevance of the three-, four-, five- and six-factor models on the Nordic equity markets, by 1) investigating the models' ability to price equity returns and 2) investigating the factor patterns' ability to capture return on both an individual and combinational basis.

To answer the overall research statement it has been operationalized into five sub-areas. The five sub-areas are equivalent to the outline of the thesis, highlighted in bold font.

1. **Factor literature review;** how were the factor effects discovered, and what are prevailing explanations for their presence?
2. **Methodology;** what methods and theories will the thesis rely on when 1) investigating the models' ability to explain return, and 2) constructing the factor trades and evaluating their performance?
3. **Data sample;** what data is needed to answer the overall thesis statement, and what procedures are undertaken to mitigate data quality issues?
4. **Analysis part 1: Factor model tests;** are there evidence of factor patterns in the cross section of equity returns in the Nordics, and are the factor models able to explain variations in these returns?
5. **Analysis part 2: Factor trading;** do the factor effect portfolios represent attractive trade proposals on the Nordic equity markets, and are there diversification benefits between them that allow for a combinational superior investment strategy?

The thesis will also include a final section that concludes and sets the stage for further research.

1.2 Thesis Delimitations

Beyond delimitations made towards the factors to focus on, and on which market, a few more overall delimitations are necessary to highlight early on.

First, whether to account for transaction is important. Especially for the factor trading analysis, as attractive gross results can be eliminated when accounting for real world transaction costs. For there to be a point in accounting for transaction costs, extensive amounts of data on historical trading costs in the Nordics should be at hand, to acquire reliable estimates on actual costs. As I do not have this, and because the intention of the thesis is to be a preliminary investigation of factor models and trading on a new market, I choose to not account for transaction costs.

Second, barriers to holding the long-short positions of factor trading should also have been accounted for. The ability to short stocks (especially the less liquid, small cap stocks) can be a problem for practical implementation. While shorting in the Nordics is not as frictionless as in the US (fewer facilitators of shorting), potential restrictions to shorting is not accommodated for in the trading analysis. Rather, as will be pointed out in the methodology and analysis of the trading, the thesis assumes the role of a sophisticated investor to lower the barriers of trading. Same as with transaction costs, accounting for frictions to shorting would add a layer of complexity beyond the intent of the thesis. Not accommodating for it might provide upward biased results and limited practical implementation of the results.

Lastly, the reader is assumed to have basic knowledge of modern financial theory such as efficient markets, portfolio theory, etc., and thus, there is no review section on these subjects.

Specific delimitations with regards to for example, but not limited to, choice of method for creating the factors, testing for significance, evaluating performance of a trade or choice of time window for the data, will be presented under the relevant sections of the thesis.

SECTION 2 FACTOR LITERATURE REVIEW

To contextualize the factor effects that are to be analyzed, a presentation of their history and reasons for their ability to explain and provide returns is important. Academics do not agree on the latter subject however, and one of two sides is often taken in the discussion; the rational or the behavioral explanation. While the rational or risk-based perspective to factor variations in returns attribute this to risk premia because of differences in systematic risk, the behavioral perspective coin the explanation to an inherent irrationality in the market place and its participants. This thesis does not take a stance on either perspective, and presents prevalent explanations from both 'schools'.

2.1 The History of Factor Models

From 1970 to 1990, the prevalent capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965a, 1965b), Mossin (1966) and others, was questioned. Researchers found that after controlling for the CAPM-postulated market beta, there were still significant variations in the empirical cross section of returns that could be explained by other economic phenomenon and ratios. Ross (1971), Jensen (1972) and Blume & Friend (1973) further questioned the equilibrium model framework on which the CAPM was based. Equilibrium models require some stringent assumptions concerning the distribution of returns, utility functions of agents, equilibrium state of the economy, and more that did not seem to hold empirically. From this criticism, Ross (1976) proposed the arbitrage pricing theory (APT) framework for modelling stock returns and systematic risk; a relatively more lenient framework for asset pricing models that allowed for an empirical approach to constructing the models. In other words, empirical patterns in the market could be modeled prior to developing a theoretically justified reason for the patterns.

At the intersection of the empirical CAPM anomalies and the more lenient APT framework for capital asset pricing, Eugene Fama and Kenneth French were first in developing a multifactor contender to the CAPM. They proposed an alternative, extended model to explain the cross-sectional variance of returns (Fama & French 1993), based on earlier results that the CAPM was flat after controlling for market values and book-to-market ratios in the returns (Fama & French, 1992a). The Fama-French three-factor model became the start of an academic race to investigate new factors and unveil the more "complete" capital asset pricing model. The factor model literature has figuratively exploded since, as several researchers have pointed out. McLean & Pontiff (2016) identifies 97 factors that previous literature have singled out as significant predictors of return, in their investigation of whether return predictability is being eliminated by paper publication. Harvey, Liu & Zhu (2016) questions the regular 2.0 t-stat hurdle rate for factor significance, based on the 316 significant predictors they find have been published historically.

This thesis is not an attempt to exhaust the possible factors effects in Nordic equity returns, but rather an investigation of the more relevant and known factor models. Size and value of the three-factor model (Fama-French, 1993), momentum of the four-factor model (Carhart, 1997) and the more recent profitability and investment of the five-factor model (Fama & French, 2015), are perhaps the most recurrent factors tested and debated in the published literature; hence the desire to test them on a new market. The origination and possible explanation of each of the five factors to be tested are discussed next.

2.2 Size Effect

Banz (1981) was first to use market values elaborate on the cross section of returns. He found that the CAPM was misspecified because small firms in his NYSE sample, on average, had significantly larger risk-adjusted returns than their large counterparts. The size anomaly was one of the two factors Fama and French used when they showed the empirical flatness of the CAPM (Fama & French, 1992a), and one of the two added factors in their three-factor model (Fama & French, 1993). Motivated by the observation that small firms earn higher risk-adjusted returns than larger firms, they form small-minus-big (SMB) size portfolios, in the spirit of the APT zero-investment framework.

Explanations

Neither Banz (1981) nor Fama & French (1992a, 1993) provide explicit explanations for why small stocks tend to earn higher risk-adjusted returns than large stocks. Banz conjecture towards the end of his paper that the size effect might be due to a theory of mergers – "*large firms are able to pay a premium for the stock of small firms since they will be able to discount the same cash flow at a smaller discount rate*" (Banz, 1981, page 17), but leaves it at that. Fama & French (1993) let both the size and book-to-market (B/M) effects remain unexplained towards the end of their three-factor model paper. Instead they reference earlier findings connecting size and B/M effects to systematic patterns in relative profitability and growth of stocks (Fama & French, 1992b). Two years later, they build on this and try to provide an economic foundation for the empirical relation between average return and size and book-to-market by relating the factors to profitability specifically (Fama & French, 1995). They do find a size effect in earnings that help explain the same effect in returns.

Specifically, there is a persistence in earnings for the firms investigated, where smaller (high B/M) firms with low or negative earnings continue to have low or negative earnings around earnings announcements, and vice versa for large (low B/M) firms. Hence, an argument for the size effect is a risk premium due to the "riskiness" of low earnings persistence. They remain cautious due to noisy data however.

Chan & Chen (1991) put the size effect in a perspective of risk and financial distress. They argue that small firms frequently are small due to prolonged bad performance, giving low efficiency and high leverage. Hence, the small firm premium should be due to a risk premium for holding the small, financially distressed firms that are more sensitive to economic downturns. Dichev (1998) builds on the financial distress motivation and investigates a possible link between bankruptcy risk and higher returns. He is not able to find a significant link. The financial distress risk premium has been rejected by the data in later papers, and as suggested by van Dijk (2011), even though not explored in direct relation with each other, size and liquidity risk could have a theoretically more solid connection to each other. Liew & Vassalou (2000) attempt to attribute Fama and French's SMB (and HML and momentum) to future growth in macroeconomic indicators such as GDP, consumption and investment, as a reason for the premium to small versus large stocks. Vassalou (2000) builds on her co-authored findings, and suggest that the size and book-to-market effects help explain both GDP growth and default premiums.

Behavioral explanations to the size effect are more often given jointly with the value effect. Hence, for some behavioral explanations to the size effect such as overreaction and investor preferences, I refer to the section discussing explanations for the value effect. As for explicit size effect explanation, one of these is a lack of information to the smaller cap stocks. Banz (1981) touches briefly upon this thought in the conclusion section to his paper as he references a model by Klein & Bawa (1977), and argues that investors are not willing to hold stock of smaller firms due to a lack of information on these stocks as opposed to the larger cap stocks. This irrationality causes an adverse information price pressure on the smaller stocks, giving a higher return than to be expected on these. Merton (1987) further investigates this issue in his analysis on the higher returns of smaller, less-known firms with smaller investor bases. Keim (1983) investigates the January effect's ability to absorb most of the size effect premium empirically. The January effect is rooted in behavioral finance of selling pressures due to realizations of tax gains to capital losses.

Following its early discovery and presumed trading exploitation, the size effect is recently considered to have died (Ang, 2014). Because of this, the literature on size in isolation is not extensive.

2.3 Value Effect

The principles of value investing essentially dates back to Graham & Dodd (1934) and postulate that investors should buy relatively undervalued "value" stocks and sell relatively overvalued "glamour" or "growth" stocks. There are numerous ratios uncovered that seem to proxy whether a stock is value or growth according to its fundamentals (see for example Hou, Xue & Zhang, 2015, Table 2 Panel B). The premise is that the price of a stock equals its expected future cash flow divided by the expected rate of return, so that flipping the equation, the expected return of a stock equals the expected cash flow divided by its price. Early work by Stattman (1980) and later by Rosenberg, Reid & Lanstein (1985) showed an ability of book-to-market (B/M) ratios to explain cross-sectional variations in returns beyond the CAPM. More specifically, high B/M ratio stocks seemed to outperform low B/M stocks. This result inspired Fama and French to include B/M ratios as an explanatory anomaly in the cross-section of return (Fama & French, 1992a) and as an APT inspired portfolio in the three-factor model they proposed. The factor mimicking portfolio of the B/M effect is long high B/M stocks, short low B/M stocks; a high-minus-low portfolio (HML).

Explanations

Earnings persistence (Fama & French, 1995), relative distress premia (Chan & Chen, 1991) and predictability of macroeconomic indicators (Liew & Vassalou, 2000), are all explanations listed under the previous size subsection that apply to the value effect as well. Thus, risk-based explanations for the value effect often relate to the robustness and relative expensiveness of large, low B/M firms, and vice versa for the smaller, high B/M firms. For example, Fama & French (1996) argue an embedded hedge against market downturns in large growth firms that investors pay for through lower returns. Petkova & Zhang (2005) elaborate on the hedge explanation when they show that the betas of value stocks covary positively with expected market risk premiums, while growth stock betas covary negatively. This indicates that as the market peaks or troughs, growth stocks are more resistant to the wide market movements than value stocks. They entrench their findings in the rationally motivated model by Zhang (2005), which links the higher risk of value firms with their costly reversibility relative to growth firms. In bad markets, value firms tend to be more restricted in scaling down production (capital-intensive, high book value firms), than their lower asset, growth counterparts, while in good markets, they have idle facilities that yet again can be put to use flexibly (contrary to the growth stocks' need for expansion). Hence, value firms are more adversely affected by downturns and can more easily ride upswings, making them follow economy-wide trends much more than their growth counterparts. Asness, Moskowitz & Pedersen (2013) find that value strategies across regions and asset classes tend to be positively correlated, which they believe could suggest a global systematic risk factor to the value effect.

As for behavioral explanations to the value effect, DeBondt & Thaler (1987) and Lakonishok, Shleifer & Vishny (1994) show the opposite of Petkova & Zhang (2005). Specifically, Lakonishok et al (1994) find that value betas are higher than growth betas in good times, but (absolute) lower in bad times, suggesting an inconsistency to the risk-based explanation. DeBondt & Thaler (1987) show a similar effect based on the reversal effect, which was an earlier version of the value effect where value equals low average return over the past five years. Instead, the authors of these papers attach an inherent under- and overreaction of investors to the value premium. Along with DeBondt & Thaler (1985) and Haugen (1995), they argue that the value premium arise from a contrarian investment strategy. Investors extrapolate good (bad) performance, of low (high) B/M stocks too long into the future, causing stocks to fall short of (exceed) expectations and earn lower (higher) returns than expected. Chan, Karceski & Lakonishok (2003) argue a similar result in their research of B/M ratios' disjointed ability to reflect past growth and future growth. Irrationality through extrapolation cause market participants to penalize past low growth, high B/M firms too much into subsequent years, while high growth, low B/M stocks are expected to maintain growth too long into the future. Thus, growth stocks are overvalued relative to value stocks, giving cause for a value premium effect.

Another popular behavioral explanation for the value effect is investors' preference for certain characteristics in their stock choices. Daniel & Titman (1997) argue that the B/M anomaly is due to high B/M firms being unattractive companies that investors do not want in their portfolios, while the glamorous, low B/M companies are the opposite. A related explanation is agency costs contended by Lakonishok, Shleifer & Vishny (1992). The authors argue that investment fund managers might be aware of an added return to value stocks, but nonetheless prefer the growth or glamour stocks, as they are easier to justify to clients. Bhushan (1989) and Jegadeesh, Kim, Krische & Lee (2004), back this growth stock attractiveness proposition, as they find that growth stocks more often are in exciting industries that draw media and analyst attention.

2.4 Momentum Effect

Jegadeesh & Titman's (1993) relative strength strategies is the classical reference on momentum. By constructing zero-cost (i.e. long-short) portfolios of winners and losers over the past J months and holding them over K months, they find that these strategies provide significant abnormal returns over different choices of J and K. Since then, the standard J period for calculating momentum has become 12 months, skipping the most recent due to microstructure or liquidity issues as discussed by Jegadeesh (1990), Lo & MacKinlay (1990), Asness (1994) and Moskowitz & Grinblatt (1999) among others. As the momentum effect was inspired by DeBondt & Thaler's (1985, 1987) work on irrationality in stock returns, the anomaly did not immediately figure as a factor elaborating on the cross-sectional variations in returns. Not until Carhart (1997) and his attempt to explain persistence in mutual fund performance, was the three-factor model of Fama & French (1993) extended by a momentum factor for the first time; winners-minus-losers (WML). The WML portfolio is long the top momentum stocks and short the bottom momentum stocks.

Explanations

Having been inspired by a behavioral concept, proponents of the risk-based view to factor models have had a hard time finding a suitable explanation for momentum. Jegadeesh & Titman (1993) provide evidence against a systematic market risk explanation already in the original momentum paper. After estimating market betas for the relative strength portfolios, they find that these evolve in different directions than what would be implied if momentum returns were compensated for beta risk. Rouwenhorst (1998) reaches the same conclusion in his investigation of international momentum effects; the winners outperform the losers by roughly one percent per month, but a WML strategy "*load negatively on conventional risk factors such as size and the market*" (Rouwenhorst, 1998 p. 283). Fama & French (1996) show that even though the longer term return reversal effect of DeBondt & Thaler (1985, 1987) can be consistent with their multifactor framework, they have a hard time justifying the medium term momentum effect.

Some researcher have entrenched the performance of momentum strategies to riskiness however. Berk, Green & Naik (1999) investigate the concept of persistent changes to systematic risk due to continual changes in a firm's growth options as a source to momentum returns premia. Chordia & Shivakumar (2002) build on the time-varying risk perspective of Berk et al (1999) when they show that momentum effects can be attributed to the predictability of a set of lagged macroeconomic variables. Controlling for these variables eliminate any significant momentum strategy profits, and apparently, momentum profits are only present in expansionary periods for the economy, suggesting a possible market risk perspective. Daniel & Moskowitz (2014) recently conducted an extension of this research by documenting the "crash risk" of momentum strategies. In high volatility markets following a long downturn, the short side of the momentum strategy experiences a significant upside that eliminates the long side gains. This could imply an option-like feature on momentum strategies, explaining their abnormal return premium in normal markets. Moskowitz & Grinblatt (1999) investigate momentum strategies at industry level, and find that momentum strategies are tilted towards a few industries, suggesting poorly diversified momentum portfolios and premia attributed to this risk. Avramov, Chordia, Jostova & Philipov (2007) explore the link between momentum strategies and firm credit ratings. Avramov et al finds that the extreme winner and loser portfolios are predominantly composed of high credit risk stocks, and excluding these from the analysis turn the statistically significant momentum returns insignificant.

Most behavioral proponents agree that momentum is due to DeBondt and Thaler's ideas of under-/overreaction to news about stocks (DeBondt & Thaler, 1985, 1987). Hence, behaviorists have rather sought to explain what causes the under- and overreaction. DeLong, Shleifer, Summers & Waldman (1990) blame noise traders. More specifically, positive feedback traders who jump onto the bandwagon lead the market from the rational fundamental focus to irrational speculation, giving prices momentum away from fundamentals. Daniel, Hirshleifer & Subrahmanyam (1998) contend a model describing overconfidence in private information relative to public information, and changes in this confidence as two main reasons for the under- and overreactions. The overconfidence leads to short-term positive autocorrelation in asset prices, which is equivalent to momentum. Barberis, Schleifer & Vishny (1998) propose a model based on two biases in the psychology literature, leading to under- and overreaction. First, a conservatism bias (Edwards, 1968) arises from skepticism towards new information and disregard of its full informational value, which causes momentum from an initial underreaction and subsequent slow incorporation of the news. Second, a representativeness bias (Tversky & Kahneman, 1974) in investor judgement make them think they see patterns historically that do not exist and attach a too significant probability and importance to these "patterns" into the future. This causes persistence in the drift of asset prices giving continued momentum, and eventually a corrective reversal over the longer term. Hong & Stein (1999) focus on different types of investors in the marketplace and the interaction between them. Specifically, "newswatchers" and "momentum traders", give rise to momentum as newswatchers incorporate news into the stock fundamental valuation slowly, while momentum traders trade on past price changes as a result of this slow incorporation (reaction) to news.

2.5 Profitability & Investment Effects

Lastly, the newly added factors of the five-factor model (Fama & French, 2015), profitability and investment are presented jointly under this section.

The motivation cited by Fama & French (2015) for adding the robust-minus-weak (RMW) profitability factor and conservative-minus-aggressive (CMA) investment factor to their three-factor model, is papers by Novy-Marx (2013) and Aharoni, Grundy & Zeng (2013), respectively. Fama and French find that the factors postulated by these papers does a good job in explaining much of the variation that the three-factor model has been criticized for leaving unexplained. Novy-Marx and Aharoni et al in turn cite inspiration from Fama & French (2006), and the intuitive explanation for B/M, profitability and investment effects in expected stock returns that can be realized from the Miller & Modigliani (1961) valuation formula. More specifically, Fama & French (2006) starts out with the theoretically sound dividend discount model (DDM) for the market value of a stock[1], and utilize Miller & Modigliani's (1961) approach to represent DDM through the clean surplus accounting framework. This ensures that expected future dividends at any point in time t can be represented by the expected equity earnings (Y) less the expected change in the book value of equity (dB). The valuation formula is divided by book value of equity to relate stock return (r) to B/M, profitability and investment.

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t} \tag{2.1}$$

First, holding all else constant and inverting the formula, a higher B/M ratio must be implied by a higher stock return r. This is the usual value B/M effect from the three-factor model. Second, holding all else constant, higher earnings must be offset by a higher return for the equation to hold. Hence, expected stock returns are positively related to profitability. Haugen & Baker (1996) had already documented this positive relation empirically, even after controlling for the prevailing B/M effect, using different measures of profitability such as profit margin, asset turnover, return on assets, and others. Third, again holding all else constant, an increase in investment (positive dB), must be offset by a lower return on the stock for the equation to hold. Thus, expected stock returns

[1] Market value = All expected future dividends / (1 + Expected return on equity)

are negatively related to investment. Titman, Wei & Xie (2004) had previously documented this negative relation between investment and stock returns empirically, using a capital investment measure based on capital expenditure in a given year divided by the average capital expenditure in the three preceding years.

For the profitability measure, Fama & French (2006) originally use current earnings on a per share basis. Novy-Marx (2013) criticizes this for being too far down the income statement, and thus polluted. Novy-Marx suggest closer to gross profit (Revenue – COGS) to be better proxies for a firms earnings. In their final five-factor model, Fama & French (2015) rely on Profitability = (Revenue – COGS – SGA – Interest Expense) / B. For the investment measure, Fama & French (2006) originally use asset growth on a per share basis, but is criticized by Aharoni et al (2013) because this representation cause the empirical relation between returns and investment to be positive, contradicting the valuation formula's intuitive rationale. By measuring the investment at firm level instead of per share level, Aharoni et al find that the intuitions from the valuations framework hold empirically. Fama & French (2015) end up relying on asset growth through total assets on a firm level in their five factor model, Investment = Total Assets_t – Total Asset_t-1) / Total Asset_t-1.

Explanations

Even though the profitability effect initially dates back to Haugen & Baker (1996), it is not until the mid-late 21st century that factor researchers have started paying much attention to it, and investment, as pure explanatory factors. This shorter time span for behavioral researchers to reply to the rationalists, might be part of the reason for less published research on the factors back and forth, resulting in fewer suggested explanations.

Wang & Yu (2013) suggest the profitability premium is due to an irrational mispricing, namely overpricing. They find the profitability premium to cluster around stocks with high limits to arbitrage and information uncertainty. This could suggest a behavioral explanation, as these frictions would eliminate the possibility of arbitraging away the mispricing, which is often a dismissive argument for a behavioral explanation if the effects persist. Further, Wang and Yu investigate patterns of profitability premiums across different holding periods and find that there is little evidence of a long-run reversal, supporting an underreaction hypothesis. They back the systematic underreaction story by the three behavioral models presented under the momentum section; overconfidence by Daniel et al (1998), conservatism by Barberis et al (1998) and limited attention by Hong & Stein

(1999). Sun, Wei & Xie (2014) contend Wang and Yu's findings and conclusions, when they investigate the profitability premium internationally. They find that the premium is stronger in countries with more lenient limits to arbitrage, and weaker in countries with stricter limits. Sun et al posit that this rather backs the rational, investment-based asset pricing Q-theory of Cochrane (1991, 1996), Zhang (2005), Liu, Whited & Zhang (2009) and Hou, Xue & Zhang (2015). Lam, Wang & Wei (2016) try to explain the profitability premium in both a macroeconomic risk perspective and an errors-in-expectations behavioral perspective. They find that the macroeconomic risk explanation, as measured through industry production and term premiums, at best complement another explanation as it accounts for only one third of the premium. Adding a mis-valuation factor based on the rationale that the premium is due to an expectation error explains a large portion of the premium however. Lam et al find that the premium is most persistent with firms that show good profitability, contrary to expectations, which have a low market valuation ex-ante.

Turning to the negative investment-return effect, the prevailing risk-based explanations relate to systematic risk through macroeconomic and business cyclicality. Mentioned under possible risk based explanation for the momentum effect, Berk, Green & Naik's (1999) paper on optimal investment and growth options can be put in an investment perspective also. Berk et al point out that as the availability of low risk projects increases, firms tend to increase their level of investments. As systematic risk is rewarded in returns, lowering the systematic risk by investing in low-risk projects should lower returns as well (giving lower returns to the aggressive growers). Real option perspectives to investing, as investigated by McDonald & Siegel (1986) and Carlson, Fisher & Giammarino (2004), also support this perspective of reducing systematic risk exposure to a firm by exercising the risky option of investing. In the more direct macroeconomic risk perspective, Cooper & Priestley (2011) show compelling evidence of relating the investment effect to factor loadings on the five macro factors presented by Chen, Roll & Ross (1986). Firms that invest heavily in macroeconomic expansions might be the more flexible growth firms that are able to scale back in economic downturns, while the more conservative asset growers are the larger behemoth firms sensitive to economic cyclicality that justifies a systematic premium. Behavioral explanations to the negative investment effect are often linked to investment being undertaken when stocks are overvalued, or so-called market timing. Stein (1996) points to managers undertaking investment projects when stocks are overvalued as a rational decision on irrational grounds. While the investment decision and stock price might not be directly related, a correction in the mispriced stock will then tend to follow an investment decision. Lamont & Stein (2006) argue managers will issue and dilute shares when their stock is overvalued, growing the company prior to the market value correcting the asset price. Another explanation to the investment effect is the recurrent slow reaction of investors. As discussed by Titman, Wei and Xie (2004), a slow reaction of investors to detect so-called empire building managers can cause the investment effect.

On a final note regarding the explanation of profitability and investment premiums in stock returns, the Miller-Modigliani rewritten valuation formula in equation (2.1) is a tautology, as emphasized by Fama & French (2006, 2015). Their ideas about profitability and investment hold because the formula holds, and vice versa. It does not say on which grounds the expectations are formed, they can be rational or irrational. As Aharoni et al (2013) note: "*It holds irrespective of whether investors are rational or suffer from cognitive biases. In other words, the relation between rational assessments of expected profitability and investment, current BM, and true expected returns should hold independently of the mechanism used by investors to form their expectations*" (Aharoni et al, 2013, p. 1). The effects have been grounded in economic theory through the valuation perspective, impervious of a rational or behavioral view.

SECTION 3 METHODOLOGY

Three methodological frameworks are utilized in this thesis; 1) handling of relevant data, 2) model estimation and inference, and 2) portfolio construction and evaluation. The two latter are the methodologies directly related to the overall research statement, and will thus be further elaborated in this section. The former, as it is a byproduct of the thesis' intention rather than a direct interest to explore, will be presented as it is walked through in section 4: 'Data Sample'.

3.1 Methodology for Model Tests

The methodology for construction of the models is inspired by the Fama and French methodology from their several research papers on factor models (Fama & French 1993, 2012, 2015). The statistical framework of ordinary least squares regressions and inference from hypothesis testing form the basis for model estimation and significance tests, respectively.

3.1.1 The Models

Four asset pricing models will be tested on their ability to elaborate on the Nordic equity returns. Across the models, this constitutes five factors beyond the market factor. The first model is the original three-factor model from Fama & French (1993)

$$\mathrm{R_{it}} - \mathrm{R_{Ft}} = \mathrm{a_i} + \mathrm{b_i}(\mathrm{R_{Mt}} - \mathrm{R_{Ft}}) + \mathrm{s_i SMB_t} + \mathrm{h_i HML_t} + \mathrm{e_{it}} \tag{3.1}$$

The first factor is the regular CAPM postulate of stock returns' sensitivity to the market (R_M) excess of the risk free rate (R_F). Excess returns are from here on denoted as lower case r, while gross returns are denoted upper case R. The second factor is the small-minus-big portfolio (SMB), or size factor. The third is the high-minus-low (HML), value factor.

The second model is the first extension of the three-factor model, as presented by Carhart (1997). The added winners-minus-losers (WML) factor is based on the momentum effect of stock returns

$$r_{it} = \mathrm{a_i} + \mathrm{b_i r_{Mt}} + \mathrm{s_i SMB_t} + \mathrm{h_i HML_t} + \mathrm{w_i WML_t} + \mathrm{e_{it}} \tag{3.2}$$

The third model is the more recent response of Fama & French (2015) to critics claiming their original model is insufficient, as discussed in section 2. The robust-minus-weak (RMW) profitability factor and conservative-minus-aggressive (CMA) investment factor is added to the original three-factor model (*not* the Carhart four-factor model)

$$r_{it} = \mathrm{a_i} + \mathrm{b_i r_{Mt}} + \mathrm{s_i SMB_t} + \mathrm{h_i HML_t} + \mathrm{r_i RMW_t} + \mathrm{c_i CMA_t} + \mathrm{e_{it}} \tag{3.3}$$

The fourth and final model is the fully extended six-factor model, motivated by a desire to test all of the most acclaimed Fama and French models and extensions at the same time. To the best of my knowledge, no published papers have so far used this full model to explain the cross-section of returns.

$$r_{it} = \mathrm{a_i} + \mathrm{b_i r_{Mt}} + \mathrm{s_i SMB_t} + \mathrm{h_i HML_t} + \mathrm{w_i WML_t} + \mathrm{r_i RMW_t} + \mathrm{c_i CMA_t} + \mathrm{e_{it}} \tag{3.4}$$

For all models, the lower case coefficients of the factors represents a stock or portfolio i's exposure to the factor, the intercepts a_i represent what is left to be explained by the model on the cross section of returns, while the e_{it} terms are the zero-mean residual of the models or shocks to the returns not predicted by the model.

3.1.2 Model Component Construction

For all the models, two sets of portfolios must be constructed based on the sample. First, the explanatory, right-hand-side (RHS) portfolios that are to explain the cross section of returns. Second, the dependent, left-hand-side (LHS) portfolios that are to represent the cross section of returns to be explained. All portfolio returns in the construction of both RHS and LHS portfolios will be value-weighted. Value weighting is chosen because most factor model research papers rely on this as opposed to equally weighting the returns, and as shall be discussed in the data sample section; value weighting mitigates some of the influence from extreme return observations of small cap stocks. As for the choice of sort-timing concerning the accounting variables for construction of HML, RMW and CMA portfolios, the conventional end of June timing is adhered to. Fama & French (1992a) chose to sort their stock sample for construction of the HML factor at the end of June in any given year to ensure that the accounting variables on which to sort were known at the time of the sort, to avoid look-ahead bias in their analysis. As fiscal years run over different periods for different firms, a six-month lag-period between the end of a calendar year and the point in time where the accounting information is assumed known should be sufficient to avoid this bias. Even though it is a conservatively long lag period (at the most extreme, relying on 17 month old data for stocks that have January-end fiscal years), it is necessary to avoid bias in the data. Most Nordic firms rely on calendar year equivalent fiscal years, so that the outdating of the information is assumed minimal.

For the construction of the different percentile portfolios discussed below, it is common for research papers on the US markets to use NYSE stocks as breakpoints when designating stocks to the different 'categories'. This is done to avoid a skewed distribution towards small stocks, from the small cap AMEX and NASDAQ exchanges. When Fama & French (2012) evaluate their models on the global markets, they try to replicate the NYSE breakpoints for construction of the RHS and LHS factors. This is not accommodated for in the sorts of this thesis, and breakpoints are rather constructed on the full sample. This because 1) an even distribution of small and large cap firms is assumed on the Nordic exchanges and 2) influence from US stock markets is not desirable from the intent of the thesis statement (to investigate well-known US factor models on a new market). This might introduce a small cap bias into my analysis.

Right-Hand Side Portfolios (RHS)

The excess market portfolio is one of the commonalities in all of the four models above. For construction of the market portfolio, convention is followed and it is calculated as the value weighted return of all equities, excess of the risk free rate

$$r_{Mt} = \sum_{i=1}^{N} \frac{MV_{it} * (R_{it} - R_{Ft})}{\sum_{i=1}^{N} MV_{it}} \quad \forall\, i = \text{Stock } 1, \dots, \text{Stock } N \text{ and } t = \text{time } 1, \dots, \text{time } T \tag{3.5}$$

Note that time is defined differently for returns and market values above. For returns, time is an interval from t to t+1, while for market values time is at the start of the interval t. To avoid over-dimensionalizing simple formulas, I treat time as a single dimension, but rather note this fact.

As for the remaining RHS factors in (3.1), (3.2), (3.3) and (3.4), construction of these is not as conventional as the market proxy in order to best explain what one would like to explain. In the original three-factor model, Fama & French (1993) construct the HML at the intersection of independent sorts on size and book-to-market ratios, so-called 2x3 sorts. Specifically, at the end of June of a year t they sort their sample independently based on 1) the size or market value, and split this sort at the median, and 2) B/M ratios and split this sort in three; the top 30%, the middle 40% and the bottom 30%. This creates six sub-samples on which to construct the SMB and HML portfolios

$$r_t^{SMB} = SMB_t = \frac{R_t^{Small/High} + R_t^{Small/Medium} + R_t^{Small/Low}}{3} - \frac{R_t^{Big/High} + R_t^{Big/Medium} + R_t^{Big/Low}}{3} \tag{3.6}$$

$$r_t^{HML} = HML_t = \frac{R_t^{Small/High} + R_t^{Big/High}}{2} - \frac{R_t^{Small/Low} + R_t^{Big/Low}}{2} \tag{3.7}$$

This procedure should deal with joint size and value effects in the two different RHS portfolios of SMB and HML. A similar 2x3 construction can be done for WML, RMW and CMA, using the respective "signal" and size as sorts. The problem arises when more than two factors (beyond the market) are introduced in a model, as several joint effects need to be controlled for in each of the RHS portfolios. Take the six-factor model (3.4) as an example; how to jointly control for the size, value, momentum, profitability and investment effects in each of the RHS portfolios? Alternatives are 2x2x2x2x2, 2x3x3x3x3, or some other variant, but eventually, next to no stocks would be left at the intersections of the sorts. Fama & French (2015) try the 2x3 sorts described above, 2x2 sorts for a more diversified sample and 2x2x2x2 sorts on size, value, profitability and investment to ensure joint controls. They find that the models perform similar no matter what type of RHS factors are used as explanatory, and they conclude: "*In the end, precedent, flexibility in accommodating more or fewer factors, and the fact that they perform as well as the 2x2 and 2x2x2x2 factors in our tests of asset pricing models lead us back to the factors from the 2x3 sorts.*" (Fama & French, 2015 page 19). As such, the more common 2x3 sorts will be relied on for construction of the RHS factors.

Hence, the high-minus-low (HML) value factor will be constructed as presented above (eq. 3.7). Book-to-market (B/M) ratios are constructed from the preceding year's book values (which are required to be positive, negative ones are set to missing) and end-of-December market values. B/M ratios are static from June year t up to June year t+1 when new book and year-end market values are acquired. Size sorts on the other hand are updated monthly, in accordance with varying market values, so that there might be some changes to the HML portfolio composition throughout the year.

The winners-minus-losers (WML) momentum portfolio is constructed the same way as above, only the B/M ratio value signal is replaced by the momentum signal (MOM). MOM is calculated as the average of the preceding twelve months returns, excluding the most recent month (in line with conventional momentum calculation as discussed in section 2.4). "Winners" are the top 30% MOM stocks and "losers" are the 30% bottom stocks. The momentum portfolios are updated monthly on both size and momentum sorts.

The robust-minus-weak (RMW) profitability portfolios will rely on the Fama & French (2015) definition of operating profitability, inspired by Novy-Marx (2013). The operating profitability signal is defined as $OP_t = (Revenue_t – COGS_t – Depreciation_t – SGA_t – InterestExpense_t) / Book\ Value_t$.

A stock is required to have at least revenue, COGS and a positive book value to get an OP ratio. "Robust" stocks are the top 30% OP stocks, while "weak" stocks are the bottom 30% OP stocks. The portfolios are updated monthly on the size sort, and annually on the OP-sorts, same as the HML portfolios.

The conservative-minus-aggressive (CMA) investment portfolios are constructed from fiscal year asset growth. Specifically, the investment signal is defined INV_t = (Total $Assets_t$ – Total $Assets_{t-1}$)/Total $Assets_t$. "Conservative" stocks are the 30% *bottom* INV stocks, while "aggressive" stocks are the 30% *top* INV stocks. Same as HML and RMW, CMA portfolios are updated monthly on size, annually on the INV "signal".

The size portfolios, SMB, are formed as the average of the value weighted returns of the different small halves from the construction of the preceding portfolios, minus the average of the value weighted returns of the big halves from the preceding portfolios. See Appendix 1.1 for detailed formulae on the factor portfolios.

Left-Hand Side Portfolios (LHS)

For the LHS portfolios, the goal is to get a representative sample of the cross section of equity returns in the Nordic market. At the same time, the portfolios have to be well-diversified, as implied by the APT framework (systematic risk is priced, and if portfolios are not well-diversified, idiosyncratic risk will remain that cannot be priced by the systematic factors). Carhart (1997) rely on fund returns sorted into momentum deciles for his LHS portfolios to be explained. Fama & French (2012) form 5x5 size-B/M and -momentum LHS portfolio when testing the Carhart four-factor model in a global setting. Fama & French (2015) create 5x5 and 2x4x4 LHS portfolios when testing their five-factor model. For the cross section of equity returns used in this thesis, 5x5 sorts on size and all the other factors one by one (value, momentum, profitability and investment) are chosen. This provides four different sets of 25 subsets of LHS portfolios and thus a total of 100 portfolio return time series, which should provide satisfyingly diversified portfolios, and an adequate variation in the portfolio cross section for the models to elaborate on.

The common size sorting on all the LHS portfolios is performed to avoid poor diversification from the choice to value weighting portfolio returns. Value weighting portfolios returns could lead to poorly diversified portfolios if a larger cap stock figures in a portfolio with several smaller cap stocks for some sort. Thus, by sorting on size for each signal of the LHS portfolios (as opposed to for example 5x5 value-profitability sorts), I mitigate the problem of having poorly diversified portfolios by ensuring that each quintile considered to match up with for example a value quintile, is based on a sample of same-size stocks.

Contrary to the RHS portfolios, the LHS are not self-financing in the sense that one goes long the advantageous signal of a percentile sort and short the other, but rather goes long all the different percentiles of a sort and finance the long by going "short" the risk free rate instead. Hence, a 5x5 sort gives 25 different portfolios of returns made excess of the risk free, rather than one long-short portfolio. Specifically, the LHS portfolios are formed by sorting the sample at each relevant month into size quintiles, and BM/MOM/OP/INV quintiles, independently. Then, 25 LHS portfolios for each type of sort are formed at the intersection of the five size quintiles and the BM/momentum/OP/INV quintiles. The returns of the stocks within a given size-signal quintile are value weighted and made excess of the risk free. Hence, the cross section on which to test each model is represented by 100 LHS portfolios (25 size-BM/MOM/OP/INV portfolios).

3.1.3 Model Estimation and Inference

The model estimation will rely on ordinary least squares (OLS) based on multivariate statistical regressions. OLS estimate sets of coefficients for multivariate regressions by the objective to minimize the dependent variable's residual from the fitted model. The methodology for using the OLS framework in an asset pricing setting is inspired by Skovmand (2013), Cuthbertson & Nitzsche (2004) and Campbell, Lo & MacKinlay (1997). The closed-form OLS coefficient estimator is derived on single-dimension data, which is a problem for my TxN (294 months x 100 LHS portfolios) panel data. As shown by Mittelhammer, Judge & Miller (2000) however; when the same matrix of explanatory X variables (the RHS factor sets of each model) appear in all the N dimension regressions, the N system of regressions can be estimated one equation 'i' at a time

$$\widehat{\boldsymbol{\theta}}_{\mathbf{i}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}_{\mathrm{i}}, \ \forall \mathrm{i} = 1, \dots, \mathrm{N} \tag{3.8}$$

The theta vector is the coefficient estimates of each LHS regression, the X matrix is the sets of explanatory factor return time series (different size for each model, but same for each dependent LHS portfolio, i.e. no subscript), while the Y vector is the time series of return for each LHS portfolio.

While panel data is not a problem for the model estimation, it is a problem when testing coefficient estimates for model significance across regression, so-called joint testing. The reason for this is that it is hard to figure out the distribution of the vectors of coefficient estimates (theta hat). Calculating variance and covariance between the elements in the theta vectors would move the statistical method over to the realm of generalized least squares or maximum likelihood (Skovmand, 2013 section 3.5), which I would like to avoid for the purpose of scope and delimitation of this thesis' methodology. The rescue comes from testing the models in the APT framework, as the interest only revolves around the estimates of the intercepts and not all the coefficient estimates, which is possible within the OLS methodology. The reason for the sole interest in intercepts from the APT implication is quickly motivated below. For a more thorough walk-through of the concept, I refer to Cuthbertson & Nitzsche (2004, Chapter 7) and Campbell, Lo & MacKinlay (1997, Chapter 6).

What to Test for: Factor Models and the APT Framework

Intuitively, if the factor mimicking RHS portfolios are well-specified and extensive proxies for systematic risk in the cross section of equity returns (LHS portfolios), the individual alpha terms should individually and jointly not be significantly different from zero. If they are, something is left to be explained in the dependent return not captured by the model. This would imply either that arbitrage opportunities exist or that the model is misspecified (i.e. the chosen RHS factors are not explaining the LHS assets, or the model leaves out RHS factors that help explain the dependent LHS asset even more, which is captured in the significant intercept). The former would scrap the APT framework, as well as the efficient market hypothesis (arbitrage opportunities should not exist in efficient markets). Hence, significant intercepts are rather assumed to be due to the latter, implying that a given model is an insufficient one to elaborate on the cross section of stock returns if its intercept is significant.

Thus, when evaluating the performance of the four models the estimated intercepts will be tested for significance, both single alphas from each LHS regression (to say something about the rejection rate of the models across time) and joint alphas from each set of LHS regressions (to say general explanatory power of the model). Rejection of the null hypothesis will be synonymous with model rejection.

Hypothesis Testing and Inference

For the model testing on the individual regression intercepts, or **single tests on alphas** (intercept and alpha are from here used interchangeably), the null that the alpha is insignificant will be tested against the two-sided alternative that it is not. Specifically

$$\mathrm{H_{oi}}: \alpha_\mathrm{i} = 0, \mathrm{H_{Ai}}: \alpha_\mathrm{i} \neq 0,\ \forall\, \mathrm{i} = 1, \dots, \mathrm{N} \tag{3.9}$$

Each test involves testing one parameter from K+1 parameters estimated in each OLS regression (K explanatory variable coefficients and 1 intercept), and since each OLS estimator can be shown to follow the distribution (Skovmand, 2013, 3.3.6)

$$\widehat{\boldsymbol{\theta}} \sim \mathrm{N}(\boldsymbol{\theta}, \widehat{\sigma}^2(\mathbf{X'X})^{-1}) \tag{3.10}$$

The test-statistic for each alpha can be shown to be

$$\frac{\widehat{\alpha}}{\widehat{\sigma}\sqrt{\mathbf{R}(\mathbf{X'X})^{-1}\mathbf{R'}}} \sim \mathrm{t}(\mathrm{df} = \mathrm{T} - \mathrm{K}) \tag{3.11}$$

The **R** vector is the restriction vector that is serving the purpose of extracting relevant moments from matrices and vectors to test a desired coefficient. The alphas are the first estimated coefficients of the theta hat vectors, and as such **R**' = [1 0 0 0] for the four coefficient estimated in the three-factor model, as an example. An absolute t-stat above 1.96 (since T is sufficiently high, the t distribution is asymptotically normal), implies a significant alpha and thus model rejection.

For model testing on intercepts across the individual regressions, or the **joint tests on alphas**, the null and alternative hypotheses are equivalent to (3.9). The difference is that the hypotheses are based on vectors of alphas for each set of 25 LHS regressions instead. Specifically,

$$\mathrm{H_o}: \boldsymbol{\alpha} = 0, \mathrm{H_A}: \boldsymbol{\alpha} \neq 0 \tag{3.12}$$

Where an $\boldsymbol{\alpha}' = [\alpha_{\text{LHS Size1-Value1}},\dots,\alpha_{\text{LHS Size5-Value5}}]$ for each the four signal sorts of the LHS portfolios. The distribution and test statistic of these tests are more mathematically involved, but refined tests for joint vectors do exist. The Wald test is one of these, where a vector of multiple parameters can be tested against a single true parameter or vector of true parameters. The Wald statistic (W) for the null is (Skovmand, 2013, 3.5)

$$\mathrm{W} = \mathrm{T}[1 + \widehat{\boldsymbol{\mu}}_\mathrm{K}'\widehat{\boldsymbol{\Omega}}_\mathrm{K}^{-1}\widehat{\boldsymbol{\mu}}_\mathrm{K}]^{-1}\widehat{\boldsymbol{\alpha}}\widehat{\boldsymbol{\Sigma}}^{-1}\widehat{\boldsymbol{\alpha}} \sim \lim_{\mathrm{T}\to\infty} \mathrm{X}^2(\mathrm{df} = \mathrm{N}) \tag{3.13}$$

$\widehat{\boldsymbol{\mu}}$ is a vector of averages for the K dependent RHS factors, $\widehat{\boldsymbol{\Omega}}$ is the variance-covariance matrix of the K dependent RHS factors, $\widehat{\boldsymbol{\alpha}}$ is the vector of alpha estimates from each set of LHS regressions, while $\widehat{\boldsymbol{\Sigma}}$ is the variance-covariance matrix of the set of residuals from each LHS regression. The issue with the Wald statistic is that it only follows an approximate chi-square distribution in finite samples. Jobson & Korkie (1985) (referenced by Campbell, Lo and MaKinlay (1997, chapter 6)), derives a modified Wald (J_1) that follows an exact F-distribution in finite samples however

$$J_1 = \frac{T-N-K}{TN} * W \sim F(df = N, T-N-K) \tag{3.14}$$

The J_1 statistic will form the basis for the joint intercept testing of significance across the panel data. The significance levels of the F-distributed modified Wald depend on N and T-N-K degrees of freedom. Thus across the three- (K=3), four- (K=4), five- (K=5) and six-factor (K=6) models, the critical value quantiles (CV) at the 95% confidence level (for T=294 months and N=25 LHS portfolios in each set) is given in table 3.1.

Table 3.1 – Critical values / significance levels for J_1 test of joint significance, by model

	Three-factor	Four-factor	Five-factor	Six-factor
CV_F (df1=N, df2=T-N-K)	1.5475	1.5477	1.5479	1.5480

The adjusted R^2 of each regression of each model will be calculated as well. The R^2 say something about how much of the variability in the returns of the different portfolios that the models are able to explain. The adjusted R^2 is used to avoid the phenomenon that the clean R^2 automatically and spuriously increase when extra explanatory variables are added to the model. The adjusted R^2 is given by

$$\text{adj } R^2 = 1 - \frac{(1-R^2)(T-1)}{T-K-1}, \tag{3.15}$$

Where the clean R^2 is calculated

$$R^2 = 1 - \frac{\hat{\sigma}^2_{\varepsilon i}}{\hat{\sigma}^2_i}, \ \forall\, i = 1, \dots, N \tag{3.16}$$

The nominator in (3.16) is the variance of the residuals to each regression, while the denominator represents the full variance of the dependent LHS portfolio of a particular regression.

Implications and Assumptions of the Tools

On an ending note for the statistical methodology of the model testing, it is necessary to review some of the more important assumptions and implications underlying the methodology.

First, **multicollinearity** is important to avoid. This is evident from the closed formula of the OLS estimators, which rely on inverses of the independent variable matrix. Inverse matrices imply non-singularity, which makes the model break down in case of linear dependence in the explanatory factors. Multicollinearity across the RHS factors investigated here is assumed not to be an issue, based on previous extensive literature on the factors.

Second, many of the tools used above rely on the **normality** assumption of statistical analysis. Most of the inference and hypothesis testing for example make explicit assumptions with regards to the distribution of the sample data in the limit. Even though returns rarely have behaved normal historically, this is an assumption that is necessary to make in order to rely on all the useful tools of statistical analysis and one that is frequently made in academic research.

Third, when running OLS regressions, **stationary data** is important. If data is not stationary, i.e. there is autocorrelation across points in time, and all bets are off with regards to the estimators and hypothesis testing. In case of non-stationarity, the distributions of the estimators will not be asymptotically normal, and the earlier described hypothesis testing cannot be utilized. Stationarity in the data will not be tested for, as autocorrelation in equity returns would imply rejection of the efficient market hypothesis in its weakest form; an assumption assumed to hold.

3.2 Methodology for Trading

The methodology for the trading analysis on factor effects consists of two parts; 1) portfolio construction and back testing, and 2) evaluation of the strategies. Pedersen (2015) chapters three, four and five mainly inspire the methodology, but in general, it is less reliant on a rigorous theoretical framework than the model testing.

The inspiration for the factor trading analysis is Asness, Moskowitz & Pedersen (2013) and their findings on the diversified value-momentum combo effect. The goal of the analysis is to figure out if factor patterns have delivered returns on the Nordic market historically, and if they have, is combinations of them can enhance portfolio performance through diversification benefits. Obtaining a factor portfolio combination that is relatively impervious to general market movements is the ultimate goal. This is in line with sophisticated investment managers such as hedge funds, which chase so-called 'alpha' or market-insensitive returns. By assuming the role of a sophisticated investor, more confidence is placed in the ability to implement the trades, particularly concerning the short side.

3.2.1 Portfolio Construction and Back Testing

The baseline case for the portfolio construction is the individual factor portfolios (the RHS portfolios discussed in 3.1.2) and equally weighted combinations of these. The simple combos are called the 'static portfolios' and their construction is in line with Asness, Moskowitz & Pedersen's (2013) value-momentum methodology. In a response to the simpler static strategies, more complex and optimized portfolio positions are constructed. These are called the 'dynamic portfolios'.

Static Portfolios

A static portfolio combination of for example the WML momentum portfolio and the CMA investment portfolio, is constructed

$$\mathbf{r}_{\mathrm{WML-CMA}} = \frac{\mathbf{r}_{\mathrm{WML}} + \mathbf{r}_{\mathrm{CMA}}}{2} \quad (3.17)$$

Where **r** is a vector of returns from 1991-2015. Based on patterns of counter-cyclicality or differences in risk-return properties, it is interesting to see if the combo portfolios can enhance the performance of the individual portfolios.

Pedersen (2015, page 55) lists six principles that characterize successful portfolio construction. Of these, only two are directly adhered to by the simple, static strategies. First, the second principle concerning diversification is believed to be fulfilled. The portfolios are after all based on the diversified 2x3 RHS portfolios. Second, the sixth principle concerning the importance of correlation, especially between longs and shorts, is essentially what this analysis aims to investigate. The combo portfolios are supposed to account for correlation diversification benefits among the individual factor portfolios. In total, seventeen static combo portfolios will be constructed to investigate correlation benefits among factors; fifteen pairs of the individual factor portfolios, one equally weighted combo of all the six factors (market, SMB, HML, WML, RMW, CMA), and a three-factor combo portfolio based on the most desirable three individual factor portfolios.

Based on the return history of the static portfolios (both individual and combos), total return index (TRI), high water mark (HWM) and drawdown (DD) series will be created and illustrated through plots, to document each portfolio's developments and cyclicality. The TRI for a portfolio is calculated

$$\mathrm{TRI}_t = \mathrm{TRI}_{t-1} * (1 + \mathrm{R}_{t-1>t}) \quad (3.18)$$

Where the subscript 't-1>t' denotes the return from month t-1 to t, and the TRI will be indexed at 100 in June 1991. The high water mark in any given month depend on the past TRI developments

$$\mathrm{HWM}_t = \max_{s \le t} \mathrm{TRI}_s \quad (3.19)$$

In other words, the high water mark represents the highest past TRI from the beginning (June 1991) and up to point t. This will indicate a portfolio's ability to continually perform, and together with the TRI make up the drawdowns to a portfolio

$$\mathrm{DD_t} = \frac{\mathrm{HWM_t} - \mathrm{TRI_t}}{\mathrm{HWM_t}} \tag{3.20}$$

The drawdown represents a portfolio's prevailing loss for months in-between high water marks. End-TRI, maximum HWM and maximum DD are presented as performance evaluation metrics to show holding period return and riskiness of the portfolios.

Dynamic Strategies

Since the static portfolios adhere to only two of Pedersen's (2015) six principles for successful portfolio construction, a more complex method of designing the factor combo portfolios is desirable. To fulfill this, the mean-variance optimization theory of Markowitz (1952, 1959) will be utilized. Specifically, the minimum variance portfolio (MV), maximum slope portfolio (MS) and equally weighted combination portfolios of these (V-S) will be constructed. Presented in the linear algebra notation of Munk (2015, chapter 7), the MV and MS portfolios are calculated

$$\boldsymbol{\pi}_{\mathrm{MV}} = \frac{1}{\mathbf{1}' * \boldsymbol{\Sigma}^{-1} * \mathbf{1}} \boldsymbol{\Sigma}^{-1} * \mathbf{1} \tag{3.21}$$

$$\boldsymbol{\pi}_{\mathrm{MS}} = \frac{1}{\mathbf{1}' * \boldsymbol{\Sigma}^{-1} * \boldsymbol{\mu}} \boldsymbol{\Sigma}^{-1} * \boldsymbol{\mu} \tag{3.22}$$

Where the outputs, $\boldsymbol{\pi}_{\mathrm{MV}}$ and $\boldsymbol{\pi}_{\mathrm{MS}}$, are vectors of weights (for this thesis, 6x1 vectors of weights in the six factors). The **1** vectors act as sum-operators, the $\boldsymbol{\mu}$s are vectors of return for the six factors, while the $\boldsymbol{\Sigma}$ is the estimated variance-covariance matrix of the six factor portfolios. The equally weighted V-S portfolio is constructed same as the static combos in (3.17)

$$\boldsymbol{\pi}_{\mathrm{V-S}} = \frac{\boldsymbol{\pi}_{\mathrm{MV}} + \boldsymbol{\pi}_{\mathrm{MS}}}{2} \tag{3.23}$$

The mean variance efficient portfolios adhere more to the portfolio construction principles of Pedersen (2015). Specifically, the weights will be sized according to the algorithm's estimated conviction and risk (principle three and four) based on return, variance and covariance between the factor portfolios. Further, instead of applying the mean variance optimization at the end of the sample, the algorithm will be applied over a rolling, 'dynamic' time window of past data on the six factor portfolios. This ensures that the sixth principle, the continual resizing of positions according to risk and conviction, is upheld as well.

As for the choice of a rolling time window, the MV and MS portfolios will be constructed over a rolling horizon of four and five years of past data. A longer horizon is not viable due to a short sample, and a shorter horizon is not viable due to excessive correlation among the factors over shorter time spans. As a consequence of the latter fact, extreme weightings in the different factor portfolios can occur. The four-year rolling window will lose return observations from 1991-1994, while the five-year window from 1991-1995.

Same as with the static portfolios, TRI, HWM and DD plots will be created for the dynamic strategies. Further, charts containing the portfolio composition over time (i.e. evolution of the optimal weights) will be created to investigate the turnover of the strategies. A stable portfolio composition is desired, to minimize unaccounted-for transaction costs.

3.2.2 Evaluation: Performance Measures & Risk Management

To evaluate the performance of the factor portfolios and combinations hereof, performance metrics will be calculated. The performance metrics are chosen to evaluate a portfolio's performance directly (performance measures) as well as performance through risk (risk management measures).

Performance: Expected Return, Volatility and Sharpe Ratios

Estimates of expected return (E[R]) and volatility (σ[R]) for a given portfolio X, will be made on the portfolio's history of returns from 1991-2015 (1995-2015 and 1996-2015 for the four- and five-year mean variance optimized portfolios)

$$E[R_X^m] = \left(\sum_{t=1}^{T} R_t\right)\frac{1}{T},\ \forall\, t = 1, \dots, T \tag{3.24}$$

$$\sigma[R_X^m] = \sqrt{\left(\sum_{t=1}^{T} (R_t - E[R_X^m])^2\right)\frac{1}{T-1}},\ \forall\, t = 1, \dots, T \tag{3.25}$$

Since the data will be on a monthly basis, the estimates will be monthly as well. As such, since it is more common to present estimates of risk and return annually, the estimates will be annualized (return is compounded, variance is not and so standard deviation scales with the square root of time)

$$E\left[R_X^y\right] = (1 + E[R_X^m])^n - 1 \tag{3.26}$$

$$\sigma\left[R_X^y\right] = \sigma[R_X^m] * \sqrt{n} \tag{3.27}$$

Thus, estimates of annual expected return and volatility, (3.26) and (3.27), are the first two performance measures considered. While these two are good metrics to look at for evaluating the performance of a single portfolio, they are less informative for comparing the performance across portfolios. A portfolio might have a lot higher return than another portfolio simply because it is riskier. Hence, to adjust for differences in risk across portfolios, risk-reward ratios are calculated. The relevant risk-reward ratio for the "total return" estimates of (3.26) and (3.27) are the Sharpe ratio (SR), which measures the investment reward per unit cost of risk

$$SR = \frac{E[R_X^y]}{\sigma[R_X^y]} \tag{3.28}$$

Performance: Alpha, Beta, Tracking Error and Information Ratios

In assuming the role as a sophisticated investor such as a hedge fund, it is important to account for the fact that these investors are evaluated by their ability to supply alpha or absolute returns. As such, a fund's performance can frequently be benchmarked to the market. Thus, to supplement the 'zero-benchmark' performance measures above, the same measures benchmarked against the return on the value weighted market of Nordic equities from 1991-2015 will be calculated as well. Portfolio X's return is segmented into the CAPM's security market line

$$R_t = \alpha_t + \beta_X r_{M,t} + \varepsilon_t, \ \forall\, t = 1, \dots, T \tag{3.29}$$

The α measure the abnormal return beyond what is rewarded from market exposure, $\beta^* r_M$ constitutes the part of a portfolio's return that is rewarded from its market exposure or systematic risk, while ε are idiosyncratic shocks to the return due to unsystematic risk. For each portfolio constructed in 3.2.1, an OLS regression will be run to estimate the portfolio's beta. This beta estimate will figure under the risk management metric category and show each portfolio's exposure to the market. The estimate will further be used to adjust each portfolio's return to the market, so that only the alpha and idiosyncratic 'shock' to the portfolios' return is left

$$\alpha_t + \varepsilon_t = R_t - \beta_X r_{M,t} \tag{3.30}$$

Based on this market-adjusted return history for each portfolio, the expected annual alpha are calculated as in (3.24) and (3.26), while the annual volatility or tracking error to the market is calculated as in (3.25) and (3.27). A portfolio's risk-reward ratio, here called information ratio (IR), is calculated from the alpha and tracking error estimates

$$\mathrm{IR} = \frac{\mathrm{E}[\alpha_X^y]}{\sigma[\varepsilon_X^y]} \tag{3.31}$$

In comparison with the SR, the IR show how much of each portfolio's return is attributable to passive market exposure and what is attributable to desirable abnormal return.

Risk Management: Value at Risk and Expected Shortfall

While the volatility and tracking error estimates technically say something about the risk of a portfolio, they are more useful as components to calculate risk-reward ratios than comparing riskiness across portfolios (for the same reason returns have little comparative information value). Thus, to evaluate riskiness across portfolios, value at risk (VaR) and expected shortfall (ES) are calculated.

VaR is a measure of how much a portfolio can lose during the worst z% of times. It is based on historical information and assumes that the variable it describes is normally distributed. The VaR used in this thesis will be at the 95% confidence level, or equivalently during the worst 5% of times, and will be calculated in two ways. First, based on the *monthly* estimates of expected return and volatility for a portfolio's total return (eq. 3.24 and 3.25), the 95% theoretical VaR will be found as the quantile corresponding to the fifth percentile (z=5%) of a normal distribution with the given mean (μ) and standard deviation (σ). In other words, a normal cumulative distribution (ϕ) will be inverted to find the theoretical 95% VaR

$$95\%\ \mathrm{VaR}_{\mathrm{Theoretical}} = \phi^{-1}(z, \mu, \sigma) \tag{3.32}$$

Second, to account for non-normality in the return distributions, a sample 95% VaR will be extracted from historical portfolio returns. In other words, the sample 95% VaR will be found as the fifth percentile of the actual sample distribution of each portfolio's return from 1991-2015.

A criticism of the VaR metric is that is does not account the tail risk of losses on a portfolio. VaR is a cut off point for a loss that can happen with z% probability, but if the z% of adverse outcomes do happen, how much a portfolio stand to lose is often more interesting. Losses do not often occur in isolation, but can be followed by more losses because market conditions postulate it. ES deals with the tail risk as it concerns itself with the distribution's z% tail, and answers the question; what is the expected loss given that the worst z% of cases does happen? Specifically,

$$\mathrm{ES}_{\mathrm{z}} = \mathrm{E}[\mathrm{Loss}|\mathrm{Loss} > \mathrm{VaR}_{\mathrm{z}}] \tag{3.33}$$

ES will only be based on the portfolios' sample distribution. All months with losses more severe than the sample 95% VaR will be averaged to form an estimate of the expected shortfall in the 5% tail of each portfolio distribution.

Because the data is monthly to begin with, the VaR and ES metrics will monthly as well. It does not make sense to annualize "occurrence-numbers" for the VaR and ES metrics based on the sample, and as such they are left as they are.

Risk Management: Kurtosis and Skewness

To give an indication of severe deviations from normality in the portfolio return distributions, seeing as the VaR and ES rely on the normality assumption, the kurtosis and skewness of the distributions will be calculated and discussed under the risk management metrics as well.

The kurtosis of a distribution relate to the peakedness of the distribution relative to a normal one. Kurtosis will be calculated excess of normal, and so a positive kurtosis implies a more peaked distribution than a normal one, having more observations in the "risky" tails. Vice versa for a negative kurtosis. Hence, a portfolio with a lower VaR but higher kurtosis than another can be more risky because it has more extreme, low return observations not accounted for by the VaR cut off.

The skewness of a distribution deals with asymmetry to the tail risk of a distribution. A positive skew to a portfolio's return distribution means that the distribution of returns has a long tail towards the positive, high returns. Vice versa for a negative skew. Hence, a portfolio with a comparatively low VaR, but with a negative skew, often has more adverse losses than a higher VaR portfolio, and can thus be more risky even though it does not seem so from the VaR metric.

3.2.3 Results Quality

On an ending note to the trading analysis methodology, it is important to underline the quality of the results and possible shortcomings. For both the construction of portfolios (static and dynamic) and evaluation of them, the output is only as good as the input. In other words, faulty estimates of return, risk, correlation, etc. can cause the analysis to reach wrong conclusions. This result quality issue is especially the case for the more "black box" mean variance optimization algorithm applied. A proposition to deal with this, mentioned by Pedersen (2015), is to make estimates more conservative; adjusting return estimates down and risk estimates up. As this is a preliminary investigation into factor trading on the Nordic markets, I have chosen not to go any deeper into these issues or adjusting the data to make it more conservative. This is a possibility for future research.

SECTION 4 DATA SAMPLE

The data for the analysis constitute market and accounting data for Nordic stocks. For data on non-US stocks, a reliable source is Thomson Reuters Datastream (TDS) database, where Datastream provides market data and Worldscope provides fundamental data. TDS data is often 'too raw' to be applied directly for analysis however, as pointed out by Ince & Porter (2006), who propose a filtering process to increase the data quality of raw TDS data. Schmidt, Schrimpf, Wagner, Ziegler & von Arx (2011) have built further upon Ince and Porter's work, but for global data and with the intention of using the data for analysis of the Fama-French three-factor model. Since this thesis is not an investigation of data quality issues in the TDS database, these two papers will be relied on extensively for treating the data. All data can be found in spreadsheets on the attached USB appendix, in the folder 'Data'.

4.1 Data Gathering

Before presenting the treatment process performed on the raw data, it is useful to present the data gathered and considerations concerning this.

4.1.1 Constituent Lists

Constituent lists refer to the sample to be extracted from TDS, and for this thesis the constituent list optimally contains a complete sample of Nordic common stocks. While the TDS interface can be used to construct a constituent list of the Nordic equity markets (DS lists), already in-place research lists can be used as well, in line with both Ince & Porter (2006, page 465) and Schmidt et al (2011, page A-5) – IP lists. Having constructed both lists and compared them (list descriptions can be found in appendix 2.1), the DS constituent list provides the more complete sample on which to begin screening (4,921 versus 4,481 unique listings), and will thus be used for extracting the sample data.

4.1.2 Time Window

For the choice of time window, the aim is to have as large a sample as possible to get robust and reliable results. Factor papers on US data usually start in the 1960s. The availability of TDS data is however limited compared to historical availability of US data through CSRP and Compustat. As noted by Ince & Porter (2006, page 470), the amount of matches from their TDS sample to their CSRP sample is very low (less than 10% match rate) before the 1980s, from when TDS entries start matching up more frequently against CSRP. Schmidt et al (2011, page 4) note that a representative sample of firms with both Datastream and Worldscope data is available from 1986 for US data, while for most other countries data is too limited before 1989. To adhere to the findings of these papers, and due to the fact that asset data from t-2 years before the start of the analysis time window is needed (for the investment factor), the sample time window will start in 1991. As will be shown later, an earlier start could impair the availability of the data. The sample window will continue up to, and including, December 2015. Market data will be gathered monthly, and accounting data will be gathered annually.

4.1.3 Currency

As the data is pan-Nordic, with different currencies across the four countries, all currency-denoted data have to be extracted through a common currency. This allows for the use of one risk free rate, by assuming the interest rate parity holds fairly well when units of one currency is converted to another. The common currency is set as the Swedish Krona (SEK), because the Stockholm stock exchange is by far the largest market of the four considered (+2,000 unique listings in the raw sample compared to +800 for Denmark and Norway, and +500 for Finland). Hence, the risk free rate will have to be based on a Swedish proxy.

4.1.4 Data Series

Time Series

For calculation of stock returns, total return indices (**datatype 'RI'**) on the sample stocks will be utilized. Simple, discrete returns over a month, R_t, will be calculated from a listing's return index at the start of the month, RI_t, and the end of the month, RI_{t+1}

$$R_t = \frac{RI_{t+1}}{RI_t} - 1 \tag{4.1}$$

For the risk free returns, the 90-day (or 3 month) rate (**datatype 'SDTB90D'**) is chosen. The 30-day rate is an often chosen alternative, but the 90-day is chosen because the two behave almost identically, only that the 90-day has less significant deviations or "spikes" (see appendix 2.2). The T-Bill rate provided by TDS (RF_t^Y) is forward-looking, in percent and on an annual basis. Hence, the raw TDS rate is adjusted to its monthly equivalent (RF_t^M) by

$$RF_t^M = \left(1 + \frac{RF_t^Y}{100}\right)^{\frac{1}{12}} - 1 \tag{4.2}$$

For the size portfolios and value weighting of returns, the market capitalization (**datatype 'MV'**) of the sample's stocks will be used. In the few cases where there are lacking MV-observations, but available observations on the number of shares outstanding (**datatype 'NOSH'**) and un-adjusted stock prices (**datatype 'UP'**), the MV TDS data has been supplemented by

$$\mathrm{MV_{it}} = \mathrm{NOSH_{it}} * \mathrm{UP_{it}}, \quad \forall\, \mathrm{i} = 1, \dots, \mathrm{N}; \;\; \mathrm{t} = 1, \dots, \mathrm{T} \tag{4.3}$$

For the HML portfolios, book-to-market ratios are needed. For book values, an issue is that several datatypes can correspond to these. In line with Schmidt et al (2011, page A-8) and other sources[2], 'Common Equity' (**datatype 'WC03501'**) are used. For the RMW portfolios, in addition to book values, revenue (**'WC01001'**), COGS excl. depreciation (**'WC01051'**), depreciation (**'WC04049'**), SGA (**'WC01101'**) and interest expenses (**'WC01075'**) are gathered. Lastly, for the investment factor and CMA portfolios, total assets (**'WC02999'**) are extracted.

Static Series

As discussed further in the static screening below, several static variables are needed to filter out non-relevant listings such as non-common equity and foreign stocks. Specifics on these are found there, and the full list of both static and time series variables gathered is found in appendix 2.3.

4.2 Data Treatment

Having extracted the data above, a raw sample of 4,921 unique listings (2,676 from Stockholm, 811 from Copenhagen, 862 from Oslo and 572 from Helsinki) will be reduced to 2,333 unique listings through the two-stage screening process proposed by Schmidt et al (2011), inspired by the two-level screens of Ince & Porter (2006).

4.2.1 Static Screens

The largest part of the screening process involves the cross-sectional, static screening. The static screen is applied through seven steps to eliminate duplicate listings, other-than-common equity, lacking observations, etc. See appendix 2.4 for a detailed overview on the number of listings, and what types of data, deleted at each step.

Step 1 involves sorting the sample on the security type (**datatype 'TYPE'**), and delete entries other than the TDS definition of common equity; 'EQ'.

[2] See for example https://bizlib247.wordpress.com/2013/04/17/datastream-searching-for-book-to-market/

Step 2 sorts the sample on another static for what type of traded instrument each listing is (**datatype 'TRAD'**). Listings defined as 'Ordinary Shares' are kept, while other listings are deleted.

Step 3 involves the default 'Name' static that is provided automatically when a time series is extracted. When constructing the constituent list for the Nordic sample, stocks that do not have observations in the later chosen time window will be included in this list. These will read '#ERROR' in the name static, and consequently deleted from the sample as they do not contain data.

Step 4 deals with dual or multiple stock listings of a company, and concerns a static that indicates whether a particular listing is the firm's major listing based on liquidity and other TDS info (**datatype 'MAJOR'**). Non-major listings 'N' are filtered out.

Step 5 involves the static variable that indicates the home country of a listing (**datatype 'GEOGN'**). While both Ince & Porter (2006) and Schmidt et al (2011) delete all non-domestic listings, only non-domestic equities that are domestic in one of the other sample countries are deleted from my sample. This is done to keep the sample as large as possible. In other words, a Norwegian stock listed on OMX Copenhagen is deleted. A Swiss stock listed on OMX Copenhagen (which has endured the filtering thus far, indicating it is common equity 'EQ', 'Ordinary Share' and a major listing) is kept.

Step 6 relies on the extended name static of TDS (**datatype 'ENAME'**). The extended name often contains information on what type a particular listing is, if it is not ordinary or common shares. As such, a non-common equity phrase in the extended name is cause for manual deletion. The list of phrases that give cause for deletion, inspired by Ince & Porter (2006, page 471), Schmidt et al (2011, page A-18), Campbell, Cowan & Salotti (2010, page 3089), and Lee (2011, page 140 footnote 5), can be found in appendix 2.5.

Step 7 also relies on the extended name static of the preceding step. It is the most involved step thus far, performed in three sub-steps. First, all listings are sorted alphabetically and marked if the first three letters match with the first three letters of adjacent listings. A lot of companies that are completely different, but with similar names, are consequently marked together with actual duplicate listings. Second, all marked matches are gone through manually to see if they are matched by chance (by similarities in the company name) or by actually being dual, or multiple, listing on the same company. Third, listings that are duplicates or multiples of another, more frequently traded stock, are deleted. This concludes the static screening, having reduced the raw sample by 2,532 non-equity, -common, -major, and/or –domestic listings, being left with 2,389 unique listings across the four markets.

4.2.2 Dynamic Screens

On the static screened sample, the dynamic screens, inspired by Schmidt et al (2011, Table A.2, page A-19) and the level 1 and 2 screens of Ince and Porter, are performed. The dynamic screens are considerably less eliminative than the static ones, and mostly deals with extreme return observations. The screening of penny and extreme value stocks (see DS03 and DS04 of Schmidt et al (2011, page A-19) and Ince & Porter (2006, section 'IV. TDS Data Issues')) have not been done, and there are three reasons for this. First, Ince and Porter motivate these screens by errors in the TDS data, and it is assumed that the data provider has been able to correct some of this in the ten years that have passed since the release of the Ince & Porter paper. Second, a lot of the adjustments to penny and extreme value stocks seem a bit arbitrary, as the authors point out themselves. Too much tampering with the raw data is desirable to avoid, in order to keep data quality and not introduce biases such as survivorship and selection. Third, the data sample should remain as close to reality or practical application as possible. Quantitative trading on equities in the Nordic markets would include low-price and high-price stocks, and as such, they should be included in the final sample. What is more, the portfolios will be value weighted, which ought to even out some of the influence by the most extreme return observations of the smallest stocks. Some extreme returns are removed in the latter steps of the dynamic screening, but these are few and related to non-plausible returns (i.e. continued errors in the TDS data). The dynamic screening process consists of three steps.

Step 1 exclude listings that only have one observation for the return index over the time window. With only one return index observation, it is not possible to construct a return. 56 listings are excluded from the sample.

Step 2 involves the returns created from the return index. As inspired by the DS09 screen of Schmidt et al (2011), all monthly returns above 990% are set to missing. It seems unlikely that a stock has a return above 990% over a month, and observations of this magnitude might be due to decimal errors or similar. This is the case for 10 observations of monthly returns.

Step 3, inspired by Ince & Porter (2006, page 473 and 474) and the DS10 screen of Schmidt et al (2011), extreme returns one month that are reversed over the course of the next month, are set to missing. As Ince & Porter and Schmidt et al argue, a return above 300% in one month that is reversed over the next month seems more due to a decimal error or other database error than an actual occurrence. Thus, observations where the following hold are set to missing

$$\textbf{If } \mathrm{R_t} \textbf{ or } \mathrm{R_{t-1}} > 300\% \textbf{ and } (1+\mathrm{R_t})(1+\mathrm{R_{t-1}}) - 1 < 50\% \tag{4.4}$$

This concludes both the dynamic and overall screening on the full sample, and 2,333 unique listings on which to form factor portfolios remain.

4.2.3 Portfolio Screens

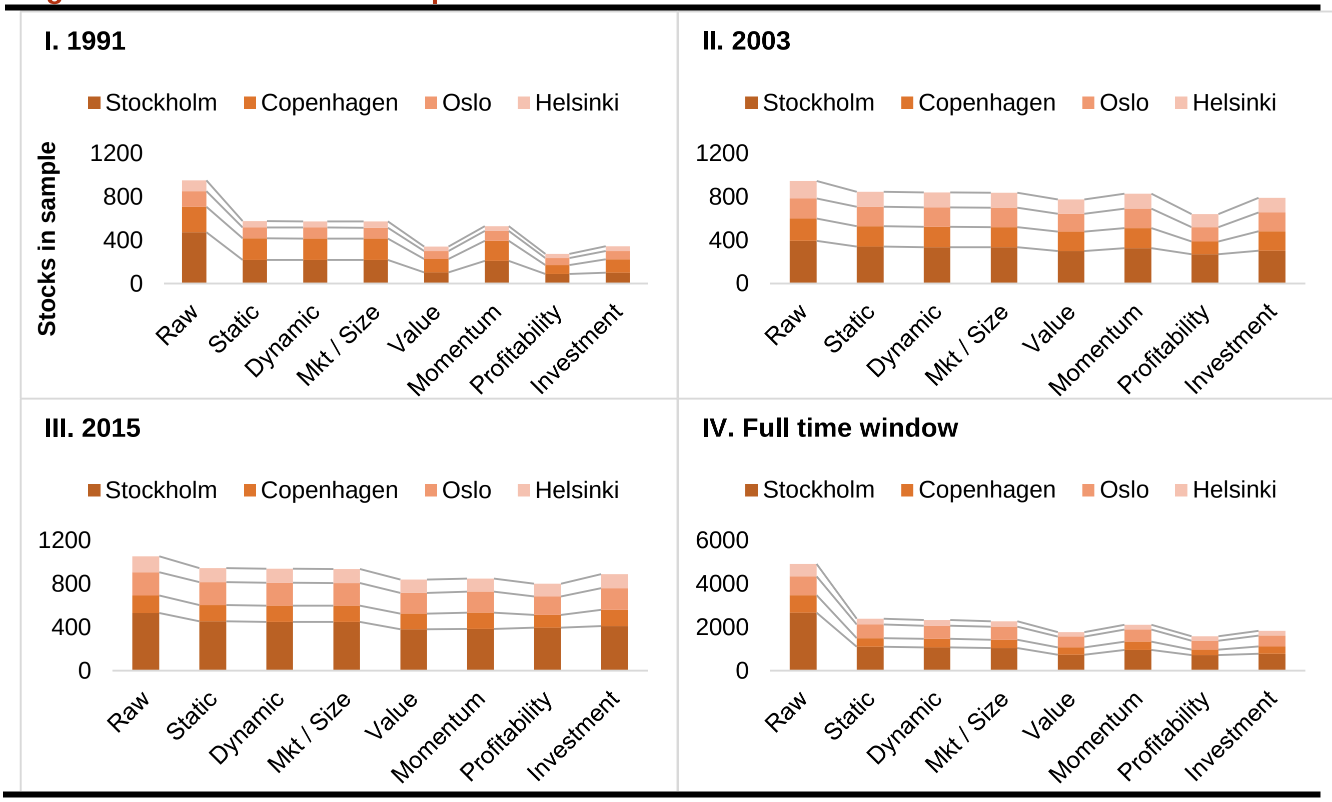
Out of the final screened sample, not all of the 2,333 unique listings contain all of the necessary data for construction of the different portfolios. As outlined in the RHS portfolio construction of section 3.1.2, the different portfolios rely on different accounting and market information, and a lack of this leads to a forced exclusion from the portfolios.

For the size-sorts and calculation of the market portfolio in a given month, a listing is required to have its market value at the beginning of the month and a return observation over the following month. 55 listings do not fulfill this requirement over the full time window. For the value-sorts, a listing further needs a book-to-market ratio that is constructed from the preceding year's *positive* book value of equity and preceding year-end December market value. 552 listings are not able to fulfill these requirements over the full time window. For the momentum-sorts in a given month, beyond primo-month market values and return over the month, returns over the preceding twelve months (excluding the most recent) is required. Over the full time window, 211 stocks do not satisfy these requirements to data availability. The profitability-sorts are the strictest in requirement of available data. Beyond market values and a return (same as all other sorts), the preceding fiscal year's revenues, COGS and *positive* book values are required to be available (depreciation, SGA and interest expenses will be subtracted *if* available). 746 listings do not satisfy the data availability requirements. Lastly, for the investment portfolios, the investment measure will be constructed from the two past fiscal years' total assets. 496 listings do not have these observations available throughout the time window.

4.2.4 Sample Evolution

In Figure 4.1 below, four graphs that show the sample size according to the different stages of the filtering process at different points in time, in total and for each country, is presented (each year's number of observations are recorded at the end of June). As is evident from the graphs, the sample gets considerably more stable to the different screens as time progresses. This provides a justification to the choice of time window. In 1991, going from raw data to HML portfolios eliminates over 50 % the sample, while it is a lot more stable in 2015. Any earlier choice of time window could introduce impairments to data availability. In appendix 2.6, detailed, numerical tables of the four graphs below, along with all the other years, are given.

Figure 4.1 – Evolution of Sample over Screens



4.3 Data Quality Issues

Even though the data sample has been subjected to a thorough screening, not all data quality issue can be expected to have been mitigated.

4.3.1 Source Data

TDS do not provide the highest quality for direct use of its raw data. The mentioned research papers trying to deal with this issue point out this fact. Given the extensive screening that have been performed to deal with erroneous data entries such as duplicates and other non-common equity listings, the final sample should be of higher quality than the raw however. From the lack of a better source than TDS for the extensive amount of data needed, the quality issues related to the source cannot be handled better than the screens above.

4.3.2 Screened Data

The raw data extracted should not have any significant biases beyond the quality issues discussed in the previous subsection, as it is the broadest possible sample of equity-like securities in the Nordics from 1991-2015. Over the course of the several screens however, the possibility of having deleted too extensively from strict filters and chosen methodology stands out as a minor worry for introducing biases such as survivorship, look-ahead and selection. As an example, the Fama & French (1993) methodology for constructing the value-tilted portfolios and the delisted common equity of Swedish company Connecta is highlighted.

Following the Fama-French methodology, the book-to-market ratios (B/M) on which the value sorts are performed are constructed from the preceding fiscal year's book values of equity and corresponding market values from the end of December. This yields static B/M ratios. For Connecta B, which delisted in June 2000, this choice of methodology means that even though TDS have provided data on book values for the company for 1998 and 1999, and return and market value data from October 1999 to June 2000, the stock cannot be considered in the value portfolios. If B/M ratios had instead been constructed on rolling market values, the stock could have been included in the analysis from October 1999 (based on book values from 1998 and prevailing market values in any given month) up to its delist in June 2000. A general fear from this choice of methodology is that many of the shorter-lived stocks are excluded in the portfolios that rely on the "static" accounting information.

While this strictness in filters and methodology might introduce both survivorship bias (by deleting the shorter-lived stocks) and selection bias (lowering the representativeness of my sample), it is a necessary strictness due to the low quality of the raw TDS data and for delimitation of this study. The intention of the thesis is to reproduce Fama and French's methodology closely to try and generalize their US results in the Nordics as well. As such, the static B/M ratios are chosen instead of the rolling ones. Other deletions might have occurred due to strict filters, but generally, the sample is broad, with both dead and active stocks included, and the survivorship bias should be miniscule.

4.3.3 Lack of Screens

While the case can be argued that too strict deletion procedures from the raw sample can introduce a selection bias in my sample (as above), the coin can be flipped to argue that too lenient deletion may introduce the same bias.

As mentioned in the dynamic screen section, a few of the screens performed by Ince & Porter and Schmidt et al were ignored. Particularly, the deletion of stocks from the two ends of the price spectrum (penny stocks and extreme price stocks). The choice was made from a feeling of arbitrary cut off points for deletion and by a desire to maintain a practical realness in the data (with respect to trading on these stocks). Having kept the extreme return observations might hurt the representativeness of my sample and introduce a selection bias. Once again however, I point to the intention of value weighting the portfolios as a valid reason for ignoring these screens. As Ince & Porter (2006, Table 3, page 468) show, their value weighted comparison of TDS data to CSRP data hold up better than the equally weighted counterpart did. Hence, while *some* erroneous extreme observations might influence the data, the value weighting procedure should ensure little weight on these (frequently) low market value stocks.

4.3.4 Time Window

Another source of a selection bias in the sample can be a non-representative choice of time window. While most US research on factor models are done on data stretching back to 1962, this is not possible on TDS data. As shown in the sample evolution, the stability of the sample size is impaired at the start of the time window, and any further back could introduce survivorship bias from lacking data on smaller and dead stocks as opposed to the larger and more successful ones. As for the end of the sample, there have been some extreme market movements in the wake of the financial crisis in 2007-2008, which could distort the results. A pre-2007 or -2008 cutoff eliminates nearly half my sample however. Further, extreme market movements are a part of the dynamics of the capital markets, and not occurrences that should be facilitated in a data sample. Hence, the 25 years from 1991 to 2016 is assumed representative for the analysis. Moreover, several years are out-of-sample with respect to some of the factors (namely, size, value and momentum), which is implying a robustness to the final results.

SECTION 5 ANALYSIS PART 1: FACTOR MODEL TESTS

5.1 Summary Statistics

As an initial check into the possible presence of the factor effects on the Nordic markets, this subsection (5.1) presents the summary statistics for the 2x3 RHS factor portfolios and the 5x5 LHS dependent portfolios, and discussion of these. The subsequent section (5.2) contains the specific model tests, while the final section (5.3) summarizes and concludes the first part of the analysis. Portfolio calculations are value weighted, and all numbers in table 5.1 are monthly.

5.1.1 Explanatory Factor Portfolios, RHS

Starting out in panel A of table 5.1 below, the equity premium for stocks in the Nordics from 1991 to 2015, this is estimated at an average monthly return of 0.69% (approx. 8.6% annually). The premium estimate is subject to high uncertainty, with a standard deviation of 5.22% monthly (approx. 18% annually), but nonetheless, having been estimated on a sample of 294 months the premium estimate along with its standard deviation yields a t-stat of 2.28. In other words, the equity premium estimate is significantly different from zero based on the 95% confidence 1.96 hurdle-rate. The statistical evidence for the equity premium on the value weighted market for Nordic common stocks is consistent with the notion that investing in equities yields a higher, albeit riskier return than holding risk free assets. This is an important implication for backing the fact that there should be some systematic risk factor exposures underlying differences in returns across assets.

Moving over to panel B and C, the size and value premia, the results from the factor mimicking SMB and HML portfolios are dismissive of their respective effects. At t-stats of 0.89 and 1.04 for SMB and HML respectively, the estimates of the size and value premia cannot be statistically proven to be significant at a satisfying level of confidence. What is more, the SMB size effect premium is estimated to be negative in the Nordic region from 1991-2015. In other words, having gone long the small cap and short the big cap Nordic common stocks from 1991-2015 would have yielded a monthly average return -0.18% (approx. -2% annually). In fact, none of the sub-components of the SMB strategy (from the individual sorts on value, momentum, profitability and investment) yield a positive size premium. As noted by Ang (2014, page 457), the size effect is believed to have disappeared following its discovery in the early 1980s and exploitation thereafter, which seem to be the case for the Nordics as well, based on this sample. Contrary to size, the value factor does yield a positive monthly premium of 0.26% (~3% annually), but again, with a sample standard deviation of 4.23% monthly, the resulting t-statistic of 1.04 gives little confidence in the estimate and it might as well be negative or zero, in truth. Since the book-to-market representation of the value-effect is the factor with perhaps the most traction in the literature historically, this lack of significance for the value premium is a bit surprising.

Table 5.1 –2x3 RHS Portfolios, descriptive statistics (monthly)

Panel A: Market premium

	RM - RF	RM	RF
Mean (in %)	0.69	1.00	0.31
Standard deviation (in %)	5.22	5.20	0.26
t-statistic	**2.28***	**3.30***	**20.34***

Panel B: Size premium

	SMB	SMB[B/M]	SMB[MOM]	SMB[OP]	SMB[INV]
Mean (in %)	-0.18	-0.23	-0.04	-0.12	-0.32
Standard deviation (in %)	3.40	3.40	3.46	3.73	3.64
t-statistic	0.89	1.15	0.19	0.54	1.52

Panel C: Value premium

	HML	HML[Small]	HML[Big]
Mean (in %)	0.26	0.30	0.21
Standard deviation (in %)	4.23	4.82	5.04
t-statistic	1.04	1.08	0.71

Panel D: Momentum premium

	WML	WML[Small]	WML [Big]
Mean (in %)	1.56	1.89	1.23
Standard deviation (in %)	5.09	4.90	6.59
t-statistic	**5.26***	**6.61***	**3.21***

Panel E: Profitability premium

	RMW	RMW [Small]	RMW [Big]
Mean (in %)	0.44	0.71	0.18
Standard deviation (in %)	3.66	3.91	5.75
t-statistic	**2.07***	**3.10***	0.52

Panel F: Investment premium

	CMA	CMA [Small]	CMA [Big]
Mean (in %)	0.57	0.53	0.62
Standard deviation (in %)	3.59	3.57	5.11
t-statistic	**2.74***	**2.55***	**2.08***

** Significant t-stat*

Turning to panel D and the WML factor, the momentum effect provide the most promising results thus far. Going long the top 30% performing stocks over the past 12 months excluding the most recent month, while shorting the bottom 30% counterparts, would have yielded an average monthly return of 1.56% (~20% annually) from 1991 to 2015. Given a factor volatility of 5.09% monthly, lower than the broad market of 5.22%, the WML factor premium is clearly significant, with a t-statistic of 5.26. These results are promising for both factor models involving WML and trades on the momentum proposition, but the WML factor returns are also more prone to transaction costs (due to higher turnover), as is discussed more in section 6. Decomposing WML into its small and big cap components provides some redemption to the size effect, as the small cap part of WML clearly is the higher performer (with the most significant t-stat) compared to its big cap counterpart.

For panel E and F of the RMW profitability factor and CMA investment factor, respectively, further significant results are obtained. For RMW, even though the estimated premium ends at only 0.44% month (~5% annually), the relatively low riskiness of the factor (standard deviation of 3.66% per month), gives the RMW premium estimate a statistically significant t-statistic of 2.07. The t-stat is undoubtedly close to the 1.96 hurdle rate of 95% confidence, and the sample of 294 month-observations is not extremely broad, but significance is nonetheless significance and the profitability factor has provided significant risk-adjusted returns from 1991 to 2015. The CMA factor yields the second most significant premium, next to momentum. A relatively solid average monthly return of 0.57% (~7% annually) and a low sample standard deviation of 3.59% monthly, gives a statistically significant t-statistic of 2.74. This result, along with the significant profitability premium, gives traction to Fama & French's (2015) notion that the profitability and investment factors might out-explain the value premium, leaving the book-to-market value effect redundant in their framework. This is an interesting set up for the model tests. Decomposing the RMW and CMA factors into their small and big cap components further redeems the size effect; at least for RMW, where only the small cap part of the factor provides a significant factor premium estimate. For CMA, both small and big cap components of the factor yield significance and the small cap component more so (even though the big cap component has a higher factor premium estimate.

5.1.2 Dependent Portfolios, LHS

By having documented which of the proposed systematic factors that have yielded significant factor premia in the Nordics historically, it is interesting to observe how well the factor effects hold up in the cross section of the 5x5 portfolios. For example, if the notion of a value effect in the Nordic markets has any traction to it, there should be a clear relation between average returns and the book-to-market ratio quintiles of the 5x5 size-value portfolios. All portfolio returns are value weighted, and all numbers are monthly (except for the Sharpe ratios, which are annualized without compounding).

Size-Value Portfolios

Table 5.2 – 5x5 Size-Value LHS Portfolios, descriptive statistics (monthly)

Panel A: Average returns (R), in %

	Growth	2	3	4	Value
Small	2.07	0.86	0.48	0.31	0.92
2	0.61	0.06	0.12	0.11	0.72
3	-0.38	0.12	0.07	0.33	0.31
4	0.05	0.38	0.29	0.51	0.54
Big	0.41	0.41	0.52	0.46	0.62

Panel C: Annualized Sharpe ratios

	Growth	2	3	4	Value
Small	0.41	0.38	0.25	0.20	0.54
2	0.31	0.05	0.09	0.08	0.49
3	-0.27	0.10	0.06	0.25	0.24
4	0.04	0.38	0.29	0.44	0.40
Big	0.47	0.48	0.60	0.43	0.53

Panel B: Standard deviation (σ), in %

	Growth	2	3	4	Value
Small	17.41	7.88	6.65	5.53	5.82
2	6.89	4.70	4.54	4.58	5.09
3	4.92	4.16	4.07	4.50	4.44
4	3.87	3.49	3.48	4.05	4.67
Big	2.99	2.98	3.01	3.66	4.01

Panel D: Average numbers of stocks in portfolios

	Growth	2	3	4	Value
Small	17	16	18	23	36
2	21	25	28	32	34
3	29	27	30	30	29
4	33	35	31	28	22
Big	41	37	32	27	18

Tracing out the return patterns for the 25 portfolios on the horizontal in panel A (equivalent to average portfolio returns for different B/M quintiles), shows that the return-B/M relation is difficult to pinpoint. Given a row (equivalent to size quintiles), moving from left to right in the average return-matrix does not yield monotonically increasing average returns. Rather, the average return behaves completely arbitrary, turning higher in one B/M quintile compared to the preceding, but lower in the next quintile, and so on. The most redeeming features of the average return-matrix in panel A, is perhaps the biggest cap quintile (last row), and the extreme value quintile (rightmost column). The former portfolios demonstrate a better-behaved return-relation to the increasing B/M ratios, with the exception being the second highest B/M quintile, where average return declines. The latter portfolios (almost) consistently provide the highest average returns, where the exception is for the mid cap quintile (row 3), and the smallest cap quintile (row 1). The smallest cap quintile also contain the most erroneous observation of the matrix, as the portfolio with the highest average return of them all is found in the extreme growth quintile of the book-to-market columns, with a monthly return of 2.07%. The reason for the portfolio's extreme return relates to the low number of stocks in the portfolio in the years from 1991 to approximately 2000. Even though the portfolio over the whole time window averages 17 stocks (panel D), it averages only about 3.5 stocks from 1991 to 2000. Because of this, the returns of a few stocks matters a lot in the portfolio, and since it is the smallest cap portfolio, the return on these few stocks will sometimes be extreme (by the fact that movements in these stocks' small magnitude of monetary value, will cause large returns in either direction). From 1991-2000 solely, the average monthly return of the small-growth portfolio is 5.68%, while the average monthly return from 2001-2015 is -0.21%. This problem have been caused by the decision to not adjust for penny stocks in the data sample, which may cause the smaller cap quintile portfolios to be less representative of portfolios with systematic risk only (as mentioned earlier, a necessary criteria for relying on the APT in the asset pricing models).

Attempting to document the value effect by looking at risk-adjusted returns or Sharpe ratios instead (panel C), does little to help the effect. High and low average returns have correspondingly high and low standard deviations, making the observations of moving from left to right in the average return matrix much the same for the Sharpe ratio matrix. Worth noting is that the smallest cap, extreme growth-portfolio issue is adjusted a lot however, due to its highly volatile standard deviation of 17.41% monthly.

Moving to the vertical of the return matrix to document a size effect instead, is as with value difficult. For all book-to-market quintiles, moving from the small cap to big cap quintiles provide a non-linear, u-shaped return curve. For three of the B/M quintiles, the smallest average, and risk-adjusted, return can be found in the mid cap size-quintile, while the remaining two B/M quintiles have the lowest return in second smallest cap quintile.

It is difficult to say something about the cause for the lack of size and value effects on the Nordic markets. One observation that is important to reiterate is the low average number of stocks in the size-value portfolios (panel D), relative to some of the other 5x5 portfolios below. The less stocks in the portfolios, the less diversified it is, and the more sensitive to idiosyncratic shocks the portfolio will be. This can quite possibly distort an underlying linear, systematic relation between B/M ratios and returns. It is hard to do anything about this without tampering too much with the data, something I would like to avoid. In the Nordic equity markets from 1991 to 2015, there simply seems to have been few small cap growth stocks with my chosen breakpoints. The lack of a linear relation between market values and returns, and book-to-market ratios and returns, can perhaps be problematic for the three-factor model's ability to explain the cross section of stock returns.

Size-Momentum Portfolios

Table 5.3 – 5x5 Size-Momentum LHS Portfolios, descriptive statistics (monthly)

Panel A: Average returns (R), in %

	Loser	2	3	4	Winner
Small	-0.07	0.24	0.79	0.90	1.16
2	-0.70	-0.29	0.34	0.59	1.24
3	-1.66	-0.53	0.37	0.74	1.11
4	-0.75	-0.27	0.35	0.53	1.08
Big	-0.50	0.03	0.07	0.38	1.21

Panel C: Annualized Sharpe ratios

	Losers	2	3	4	Winner
Small	-0.04	0.14	0.48	0.48	0.47
2	-0.40	-0.23	0.28	0.48	0.81
3	-0.97	-0.45	0.32	0.63	0.82
4	-0.45	-0.24	0.35	0.51	0.96
Big	-0.24	0.02	0.09	0.47	1.07

Panel B: Standard deviation (σ), in %

	Losers	2	3	4	Winners
Small	7.01	5.91	5.64	6.51	8.64
2	6.06	4.37	4.28	4.26	5.34
3	5.96	4.08	3.94	4.06	4.70
4	5.72	3.78	3.42	3.57	3.93
Big	7.22	3.91	2.96	2.77	3.92

Panel D: Average numbers of stocks in portfolio

	Losers	2	3	4	Winner
Small	53	30	23	19	25
2	38	33	28	26	28
3	29	32	31	30	31
4	22	30	33	35	35
Big	13	30	40	44	34

For the momentum portfolios, in all of the size quintiles, there is a clear linear relation between a portfolio's reward and its position on the momentum scale. Moving from the extreme loser portfolios towards the extreme winners provide consistently higher average (panel A), and risk-adjusted (panel C), returns for each step to the right. What is more, looking at the average number of stocks contained in each portfolio (panel D), the portfolios seem to be stock abundant and thus diversified, which is a good sign for the APT implication of asset pricing models.

As for the size-effect on the vertical of the matrices, it is as for the value portfolios difficult to pinpoint a clear gain in moving from the big quintile towards the smaller ones. For the two leftmost momentum columns, the bottom average and risk-adjusted return is found in the mid cap size quintile, from where it monotonically increases in both size directions. The most promising momentum portfolios with regards to a size effect is the third and fourth columns, where the top average return is earned in the smallest cap portfolios and the lowest average return is earned in the largest cap portfolios. Looking at risk-adjusted returns instead, the fourth quintile momentum portfolio lose its size-effect, but the third persevere. Lastly, the extreme winner portfolios of the rightmost column present a reverse size-effect for the risk-adjusted returns.

In summary, even though the size-effect is less pronounced in the momentum-sorted portfolios, the momentum effect is clear. This can prove a good sign towards explaining the cross-section of returns through the momentum-extended Fama-French models.

Size-Profitability Portfolios

Table 5.4 – 5x5 Size-Profitability LHS Portfolios, descriptive statistics (monthly)

Panel A: Average returns (R), in %

	Weak	2	3	4	Robust
Small	0.91	1.35	0.91	0.77	0.78
2	-0.02	0.14	0.40	0.62	0.57
3	-1.12	0.08	0.70	0.73	0.19
4	-0.19	0.41	0.52	0.62	0.54
Big	0.37	0.32	0.19	0.56	0.55

Panel C: Annualized Sharpe ratios

	Weak	2	3	4	Robust
Small	0.35	0.41	0.37	0.35	0.38
2	-0.01	0.10	0.28	0.40	0.38
3	-0.70	0.06	0.60	0.65	0.13
4	-0.11	0.36	0.47	0.60	0.48
Big	0.16	0.29	0.23	0.80	0.46

Panel B: Standard deviation (σ), in %

	Weak	2	3	4	Robust
Small	9.12	11.31	8.51	7.67	7.14
2	5.84	5.01	4.97	5.28	5.14
3	5.59	4.33	4.02	3.94	4.86
4	5.70	4.01	3.82	3.59	3.92
Big	8.22	3.85	2.87	2.44	4.13

Panel D: Average numbers of stocks in portfolio

	Weak	2	3	4	Robust
Small	36	17	9	9	14
2	30	24	18	14	20
3	23	26	23	22	22
4	16	25	30	31	26
Big	8	23	35	39	30

The presence of a profitability effect in returns is less clear than momentum, but more clear than value. Excluding the smallest and largest cap size quintiles (row 1 and 5), as well as the most robust profitability quintile (column 5), the average returns (panel A) increase when moving from weak profitability towards the more robust. Looking at the Sharpe ratios of panel C, the profitability effect remains evident, even when including the largest cap size quintile.

Studying the exceptions to a well-behaved profitability effect instead, the smallest cap quintile has average returns drop by moving towards the more profitable columns, while the Shape ratios remain rather flat across the profitability columns. The robust profitability quintile has average returns and Sharpe ratios drop relative to the preceding profitability quintile. In other words, the most profitable companies on the Nordic markets from 1991-2015 have on average delivered less equity returns than their marginally less profitable adjacencies. A subjective conjecture for this is that it can be related to market expectations or consensus. Even though not consistent with a rational explanation, market expectations to the most profitable firms can often be unsustainably high, meaning too high profitability is priced into the stocks. Thus, even though these firms might deliver solid profitability (actually the most solid), it is not solid enough to satisfy the market consensus, which will damage returns.

As for the size-effect on the vertical, it is no more pronounced in the profitability-sorts than in either of the two preceding sorts. The behavior of average return when moving from small cap to big cap across the profitability quintiles is similar to the size-momentum portfolios.

On an ending note, the profitability portfolios have together with the value portfolios the lowest number of average stocks. The profitability sorts rely on revenues, COGS and book values of equity to be provided by Worldscope for a listing to be included in the sort, which narrows in the sample a lot (see sample overview in appendix 2.6). The smallest cap, second and third most robust portfolios contain an average of only 9 stocks over the whole time window, while the largest cap, weakest profitability portfolio have only 8 stocks on average. Again, this quite possibly presents some problematic diversification issues concerning the systematic asset pricing.

Size-Investment Portfolios

Table 5.5 – 5x5 Size-Investment LHS Portfolios, descriptive statistics (monthly)

Panel A: Average returns (R), in %

	Cons	2	3	4	Aggr
Small	0.98	1.26	0.74	0.45	0.17
2	0.31	0.54	0.35	0.07	-0.20
3	0.13	0.51	0.21	0.24	-0.56
4	0.55	0.57	0.52	0.43	0.02
Big	0.71	0.51	0.28	0.24	0.55

Panel C: Annualized Sharpe ratios

	Cons	2	3	4	Aggr
Small	0.52	0.68	0.32	0.22	0.07
2	0.21	0.42	0.27	0.05	-0.14
3	0.10	0.43	0.19	0.20	-0.41
4	0.41	0.53	0.50	0.43	0.01
Big	0.59	0.55	0.38	0.29	0.46

Panel B: Standard deviation (σ), in %

	Cons	2	3	4	Aggr
Small	6.48	6.40	8.00	6.97	8.49
2	5.21	4.46	4.48	4.71	5.00
3	4.63	4.10	3.78	4.15	4.74
4	4.64	3.72	3.56	3.49	4.14
Big	4.22	3.22	2.56	2.88	4.13

Panel D: Average numbers of stocks in portfolios

	Cons	2	3	4	Aggr
Small	39	22	16	16	20
2	34	29	26	25	27
3	28	28	29	30	32
4	21	30	33	34	35
Big	18	35	40	40	30

Lastly, the investment effect (which is an inversion of the other effects, in the sense that returns should monotonically decrease from leftmost conservative to rightmost aggressive investment firms) has similarities to the profitability effect. Discarding the most conservative column and the biggest cap row (opposite of profitability's small cap row), the investment effect is showing a well-behaved, monotonically decreasing return-growth relationship for both average returns and Sharpe ratios. Similar to the profitability effect, the most conservative growers have lower returns than their marginally higher-growth adjacencies. The exception is the biggest cap portfolios, where the investment effect is present from the most conservative column until the second most aggressive column, upon where the average return increases a lot into the most aggressive investment quintile. Overall, the case can be made for an investment effect in stocks on the Nordic markets. The investment portfolios are also relatively abundant in stocks on average throughout the time window, similar to the momentum portfolios, which is good for pricing the portfolios' systematic risk.

For the size effect, the u-shaped return curve that has been observed for all the other sorts can be observed for the investment-tilted portfolios as well.

5.2 Asset Pricing Model Tests

This section presents the results from the 100 regressions run on the four models, in line with the methods described in section 3.1. Across the models, this has resulted in 400 OLS regressions, with all the statistics and hypotheses tests each entails. Due to space limitations and relevance, only the aggregated summary statistics are presented and discussed in here. The relevant results to each regression have been placed in appendix 3, and will be referenced where appropriate. For estimating the models and acquiring the inference statistics, the statistical programming language R has been utilized, and the model scripts along with the underlying data can be found on the USB appendix stick attached to the thesis, in the folder "Analysis I".

5.2.1 Individual Model Performance

Table 5.6 – Summary on significance tests and adjusted R^2s of individual regressions

		Three-Factor	Four-Factor	Five-Factor	Six-Factor
# significant intercepts	Size-Value	16	21	20	22
	Size-Momentum	18	17	16	17
	Size-Profitability	17	18	17	20
	Size-Investment	17	17	17	21
	Rejection frequency, total	68%	73%	70%	80%
	Average adjusted R^2	0.398	0.428	0.430	0.459

In table 5.6, the first four rows (size-value, -momentum, -profitability and -investment) represents the number of the single intercepts that was found to be significantly different from zero statistically, in line with the single intercept hypothesis testing described in section 3. A significant intercept implies model rejection since the model fails to capture the whole variation in the dependent variable. Thus, each of the four rows represent the number of individual models rejected for each of the four sets of 25 LHS portfolios across the four overall factor models tested. The fifth row gives the rejection frequency of a particular model (the sum of rejections divided by the total models estimated), while the sixth row gives the average adjusted R^2 across the sets of

LHS portfolios for each model. The full estimates of each regression's intercept, t-stat, p-values to the hypotheses and individual adjusted R^2s can be found in appendix 3.1.

Overall, the individual tests of the four asset pricing models on the Nordic markets are predominantly rejected by the data. The rejection rate of the 100 OLS regressions from the set of LHS portfolios across the four models ranges from a low 68% for the three-factor model and a high 80% for the fully extended six-factor model. In other words, more than half of the cross sectional portfolios have significant variations left to be explained in the intercept, across the models. Nonetheless, the results are not all that bad. Even the most frequently rejected six-factor model is able to explain up to 20% of the cross sectional portfolio returns, leaving the intercept non-significant statistically. For the 4x1 size-profitability portfolio for example, the six-factor model estimates an intercept with a t-stat of a mere 0.40, giving a p-value of 69.1%. As for the less frequently rejected three-factor model, a full 32% of the LHS portfolios can statistically be explained, and the "least significant" intercept (OLS of the 4x5 size-investment portfolio) has a t-stat of only -0.01, equivalent to a p-value of 99.2%. In other words, the intercept is not statistically different from zero even at the 1% confidence level. The average adjusted R-squares continue the story of the rejection frequency; a bit less than half (ranging from ~0.40 to ~0.46) of the variation in the LHS portfolios can be explained by the fitted factor models, on average. To highlight some of the more successful regressions, the 2x4 size-value portfolio has an adjusted R-square of 0.72 in the five-factor model, meaning about 72% of the portfolio's variance can be explained by common variation with the five explanatory factors of the model. In the size-momentum sorts, the 2x2 portfolio has an adjusted R-square of 0.68. In summary, on an overall basis for the individual regressions tests and statistics, even though the models are predominantly rejected, the fact that a substantial amount of the LHS portfolios can be explained is an interesting result for the Fama-French models on the Nordic markets. It hints to the fact that some of the factors help explain cross sectional differences in equity returns.

Turning to the comparison of the models, the significance tests on the intercepts (rejection rate of the models) and the average variance explained (average adjusted R^2s) provide contradictive conclusions as to the preferred model. The three-factor model has the least number of significant intercepts, at a significance rate or model rejection rate of 68%. The five-factor model is a close second with a model rejection frequency of 70%. The latter in fact performs better in explaining the size-momentum portfolios, and just as well for size-profitability and –investment, but lacks the ability to explain size-value portfolios as well as the former. The four-factor model comes in third with respect to the rejection frequency, landing at a rejection rate of 73%. As expected, the model does a better job in explaining the cross section of momentum-sorted portfolios, but perhaps more surprising does worse in explaining value- and profitability-sorted portfolios than its less expanded three-factor counterpart. In the four-factor model, 21 out of 25 intercepts for the size-value portfolios are significantly different from zero. Lastly, 80% of the OLS estimated six-factor models are rejected with significant intercepts. This is a surprising result as this model is the most elaborated and was expected to take care of sorting-differences in the LHS cross-section.

Over to the other side of the story and the average adjusted R^2 of each model; with an ability to explain roughly 46% of the average variance in the LHS portfolios, the six-factor model is the preferred choice. In this setting, the three-factor model performs relatively the worst, at an average adjusted R^2 of approximately 40% of the total variance. Because of this conflicting result, it is hard to say anything clever about a preferred model from the initial simple tests, and hopefully, the joint tests will complement the single tests towards a preferred model.

5.2.2 Joint Model Performance

Table 5.7 – Joint tests on intercept

		Three-Factor	Four-Factor	Five-Factor	Six-Factor
J_1 test stat	Size-Value	4.69	5.20	4.65	5.29
	Size-Momentum	6.65	4.83	6.15	4.83
	Size-Profitability	6.71	5.96	5.73	5.32
	Size-Investment	5.57	5.50	4.98	5.30
p-value	Size-Value	4.02E-11	1.19E-12	5.45E-11	6.29E-13
	Size-Momentum	0.00E+00	1.46E-11	1.78E-15	1.57E-11
	Size-Profitability	0.00E+00	6.33E-15	3.08E-14	5.26E-13
	Size-Investment	8.90E-14	1.40E-13	5.30E-12	5.86E-13

Comparing the modified Wald (J_1) test statistics above with the 95% critical values for the stats (see table 3.1 in section 3.1.3), it quickly becomes that the four factor models are rejected by the data on the joint tests. Observing the p-values for the test statistics confirms the story for the level of confidence at which H0 can be rejected. In this case, the very high J_1 test statistics suggest that the joint intercepts of the models are significantly different from zero, and the null can be rejected at high levels of confidence. Still, acquiring non-significant intercepts in the joint tests of the models was not expected, as it would be relatively groundbreaking to fit a factor model that well to the Nordic cross section of returns. The results from the joint tests here are similar to the joint tests performed by Fama & French (2015); the models obtain high joint test statistics and low p-values ("*the p-values for all models round to zero to at least three decimals"* as reported by Fama & French, 2015 page 10), resulting in rejection of the joint model tests. This indicates that the models are incomplete descriptions of expected returns, but not wrong descriptions. Hence, even though the models are rejected by the tests, it is interesting to salvage something from them. This is done by comparing the joint test results across models instead of concluding on their own.

Contrary to its slight superiority in the individual intercept tests, the three-factor model has a harder time in the joint tests of intercept significance, similarly to the three-factor model more recently by Fama & French (2015). With J_1 test statistics of 6.65 and 6.71 for the size-momentum and size-profitability LHS portfolios, it gets the highest "rejection-confidence" of the models, with a p-value so close to zero that R and Excel does not have enough decimal accuracy. The size-value sorted portfolios provide a lower confidence level for null hypothesis rejection of the three-factor model, while the investment-sorted portfolios end up somewhere in between. The four-factor model is, similar to its individual intercept tests in the mid-range of the four models; not most severely rejected by the data, nor the least. Lastly, the five- and six-factor models take turns in being rejected "the least". The five-factor model appears to do a better job in explaining the value- and investment-sorted LHS portfolios across the models, while the six-factor model appears to do better on the momentum- and profitability-sorted portfolios. Couple the ambiguity between the five- and six-factor models in the joint tests with the relatively high performance of the five-factor model in the individual tests, and I deem the five-factor model as the most appropriate factor model to explain the cross section of returns on the Nordic equity market.

5.3 Section Conclusions

In line with what has been suggested by earlier literature on factor models, there seems to be traction to some of the factor effects in the data for Nordic equities in the time span from 1991-2015. The summary statistics for the RHS factor portfolios showed significant effect-premiums for the equity market in total, as well as momentum, profitability and investment. Significant factor premiums were harder to document for the size- and value-effect. Looking at the summary statistics on the four different sets of LHS portfolios, the size effect was hard to pinpoint in the data there as well, same as with a consistency to the value effect. Momentum demonstrated the clearest linear presence in the data, while the profitability and investment effects were less clear but nonetheless with some presence.

As for the specific statistical tests of the models, with strongly significant joint intercepts across the four different LHS-portfolio sorts, none of the factor models provide a complete description on the cross section of Nordic equity returns. This was not the goal, nor expected however, and relative to the aim of investigating the *possibility* of a factor presence on the Nordic markets, the factor models tested did deliver elaboration on equity returns. The three-factor model worked (relative to the other models) well in explaining single portfolios, with the lowest number of significant intercepts. It had a harder time in the joint explanation however, presumably because of its inability to explain the size-momentum portfolios. The six-factor model held up better in the joint tests, doing best in explaining the joint LHS sets of size-momentum and size-profitability. The model fell a bit short in the individual LHS tests however, where it ranked last for all the LHS-sorts (rejection frequency of 80% in total), except for momentum-tilts, where it came in second to the five-factor model. The five-factor model in the end seems like the most elaborate choice of an asset pricing model for equity returns on the Nordic markets from 1991-2015. With an individual portfolio rejection frequency at the same level as the three-factor model (less ability to explain value-tilted portfolios, but equivalent on profitability- and investment-tilted, and a lot better on momentum-tilted) and the second highest average adjusted R^2, it does a good job in the single tests of model significance. In the joint tests, it holds up best of the models, and so emerges as the model of choice. Lastly, on a cautionary note, it should be said that the results here might be due to either poorly specified LHS portfolios (i.e. a bad cross section) or a poor choice of breakpoints for the sorts (poorly diversified LHS and/or RHS portfolios). These issues are left for further research.

The investigation into the presence of factor effects and models of this section bodes well for the possibility of obtaining trading gains from exposure to the factors tested. Especially for momentum, profitability and investment, the results are promising, with significant factor premiums and a positive return-relation to the factors. It might be that the arbitrary patterns of size and value behave counter-cyclical to the three aforementioned factors however, and as such, can figure as good combinational factor strategies.

SECTION 6 ANALYSIS PART 2: FACTOR TRADING

Having taken the academic perspective to investigating the presence of factor effects in the Nordic equity market, this section turns to the industry perspective and seeks to analyze factor effects as trading strategies. The aim is analyze whether having factor effect exposure can act as attractive trade proposals, both by individual factor exposure and by combining them for possible diversification benefits. All data presented can be found in the spreadsheet 'Portfolios.xlsm' in the folder 'Analysis II', attached on the USB appendix.

6.1 Portfolio Trade Performance

Considering the portfolios whose constructions were presented in 3.2, this subsection discusses the performance of these. These discussions constitute the main findings of the trading analysis, and revolve around performance metrics of the portfolios and portfolio evolution over time for optimal combination of the factors. The individual factor portfolios are presented first, followed by the static combinations of these, and lastly the dynamic mean variance optimized portfolios. In all performance measure tables (table 6.1, 6.2 and 6.3) the 'Performance' metrics are annualized, while the 'Risk' metrics are given monthly (the reason for this is discussed in the methodology of section 3.2.2). In all the figures (figure 6.1-6.12) of the Total Return Index (TRI), High Water Mark (HWM) and Draw Down (DD) plots for the strategies, the left-hand side plot has a normal primary axis, while the right-hand side plot has a logarithmic scaled primary axis (to handle exponential magnitudes in the index of some strategies). The primary axis in both plots corresponds to the TRI and HWM, while the secondary axis in both plots corresponds to the DD.

6.1.1 Individual Portfolios

In table 6.1 below, the performance and risk measures (as discussed in 3.2.2) for evaluation of individual factor portfolio performance can be found. Given the significant premia estimated on the WML, RMW, and CMA portfolios in 5.1.1, it is interesting to see how the individual portfolios have fared by the more advanced performance measures. A correlation matrix for the six factors can be found in appendix 4.1.

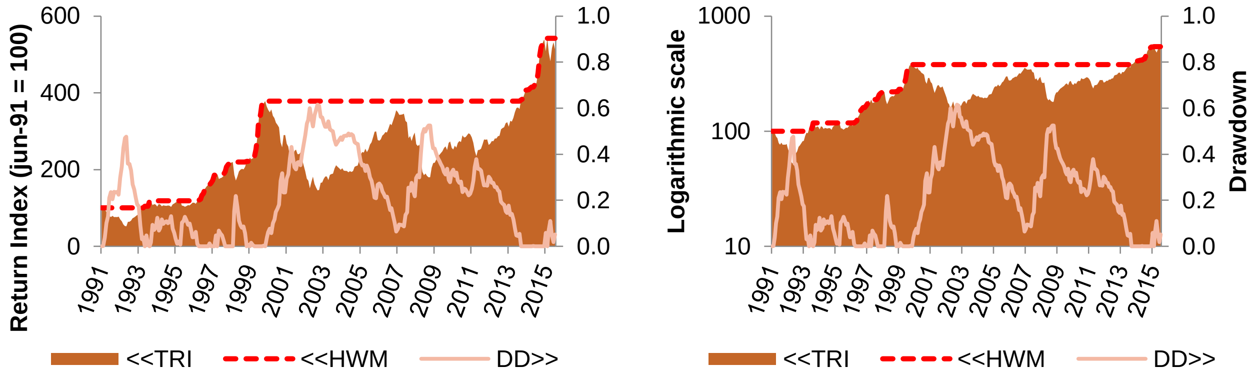
Comparing Sharpe and information ratios (SR and IR) across the portfolios, the WML momentum portfolio clearly outperforms the other. By delivering a return above its volatility and an alpha above its tracking error (SR = 1.16 and IR = 1.06), the portfolio's total return index lands at 6,568 points by the end of 2015 (corresponding to its high water mark). High returns often correspond to high risk however. With a relatively high counter-cyclical market exposure (beta = -0.20) and total volatility estimate of 17.63% annually, the WML portfolio is subject to periods of large drawdowns over the shorter term. Having the second lowest maximum drawdown, it might not initially seem like a comparatively risky portfolio, but some of the more advanced risk metrics show it. The return distribution of WML has a very negative skew compared to the other portfolios, implying it has a long tail of (possibly extreme) negative returns. Further, WML's VaR measures indicate a relative riskiness to the other factor portfolios. In five percent of the months the portfolio is held, the WML should experience a loss of 6.8% based on estimated mean and standard deviation, or 6.9% based on the sample data. In the worst five percent of the months, the WML portfolio is expected to experience a loss or shortfall of 10.9%, the second highest expected shortfall behind the market. Hence, for investment managers and other investors that often do not have the most risk seeking clients or preferences, the WML strategy might not be the best choice from its high riskiness, even though it delivers solid returns (and risk-adjusted returns).

Table 6.1 – Individual factor portfolio performance
('Performance' numbers annualized, 'Risk Mgmt' numbers monthly)

		Market	SMB	HML	WML	RMW	CMA
Performance	Expected return (%)	8.65	-2.10	3.13	20.45	5.43	7.12
	Volatility (%)	18.09	11.76	14.65	17.63	12.68	12.45
	Sharpe ratio (SR)	0.48	-0.18	0.21	1.16	0.43	0.57
	Jensen's alpha (%)	0.00	0.35	5.04	22.47	6.81	7.68
	Tracking error volatility (%)	0.00	15.25	17.88	21.22	14.66	13.24
	Information ratio (IR)	NA	0.02	0.28	1.06	0.46	0.58
	Max high water mark	542	129	271	6,568	343	480
	End-2015 return index (TRI)	514	50	164	6,568	300	447
Risk Mgmt	Market Beta	1	-0.30	-0.22	-0.20	-0.16	-0.06
	Max drawdown (%)	61.5	65.0	67.6	42.0	59.5	38.5
	Skewness	-0.04	0.03	0.04	-0.23	-0.44	0.37
	Excess kurtosis	1.6	2.3	3.6	2.2	3.0	2.5
	95% VaR (%), theoretical	-7.9	-5.8	-6.7	-6.8	-5.6	-5.3
	95% VaR (%), sample	-8.1	-5.2	-6.3	-6.9	-6.4	-4.9
	Expected shortfall (%), sample	-11.3	-7.4	-9.6	-10.9	-9.1	-7.3

Thus, for risk management purposes, evaluating the portfolios from the bottom and up in table 6.1 is a good alternative. In doing this, the CMA portfolio emerges as a preferred choice. At a low expected shortfall, theoretical and sample VaR, CMA delivers lower, but more stable returns. This translates to an SR of 0.56 and IR of 0.58. The portfolio has been relatively impervious to market movements from 1991-2015 (beta = -0.06), and an investment in 1991 would have quadrupled by the end of 2015. Overall, the three rightmost factor portfolios (WML, RMW and CMA) seem like preferred choices in a performance and risk perspective. Hence, combinations of these, especially the risky WML and the less risky RMW and CMA, are the most interesting combos to test later on. The market (even though more risky) has delivered performance as well, and given that all of the factor portfolios have a negative market beta, diversification benefits might be obtained from a stake in the market as well. The remainder of this subsection presents the factor portfolios' return index plots over time. This ought to give an impression of how the portfolios have fared during turbulent market periods, both individually and compared to each other (with an emphasis on 'compared to the market', as mitigation of market risk and deliverance of 'alpha' is a desire when combining the factors).

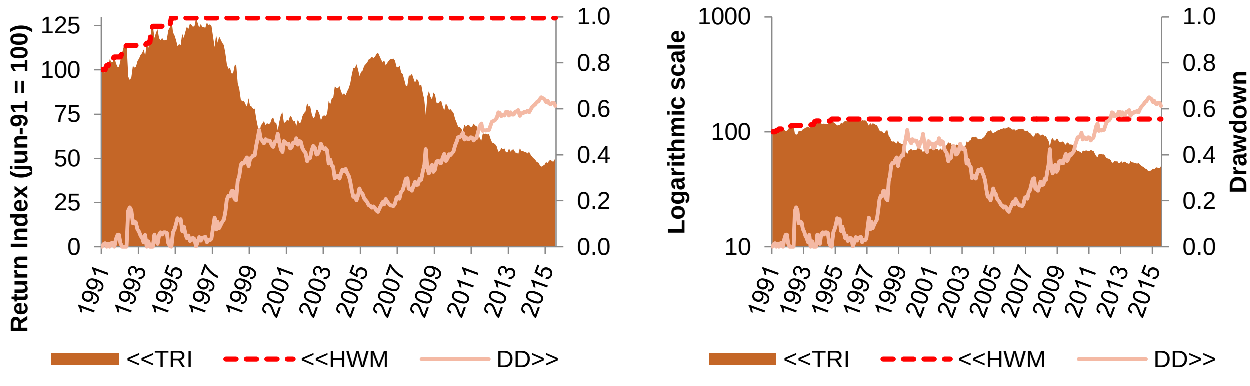
Figure 6.1 –TRI, HWM and DD for the Market Portfolio (excess of the risk free rate)



The return index and drawdowns for the market portfolio follow the pattern that could have been expected beforehand. Nonetheless, the pattern is important to observe for understanding the mechanics and market risk of the other factor portfolios.

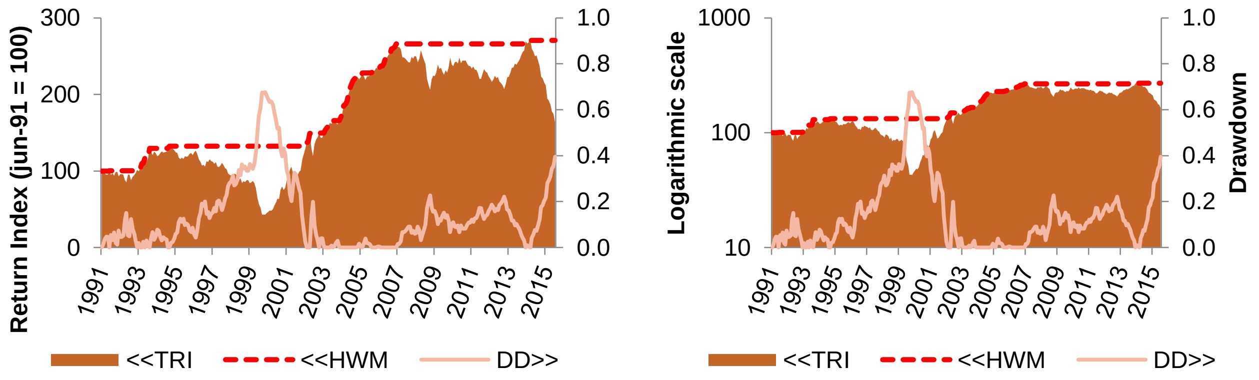
From the onset of the sample, the Nordic equity market succumb to immediate drawdowns, supposedly due to a nervous market from a series of events during these years (Iraqi invasion of Kuwait, Japan asset price bubble bursting, and attacks to the European currency pegs). From this initial drawdown and towards the burst of the dotcom bubble, the market portfolio performs well. Starting at the turn of the millennium however (presumably with the irrational asset pricing bubble building in the preceding years), a long period of decreasing TRI makes the portfolio reach its maximum drawdown of >60% in the second half of 2002. From the max DD and until the financial crisis of 2007-2008, the market portfolio yet again regains some of its lost ground, but from a height in 2007 (still not at a new HWM), the market return index drops and the drawdown increases. The loss is not as severe as during the dotcom bubble, suggesting that the Nordic equity markets were more resistant to the aftershocks of the US credit bubble. Since then, the market has steadily increased, with a more recent decline due to the oil price drop of late 2014 and market correction of late 2015.

Figure 6.2 – TRI, HWM and DD for SMB (Size)



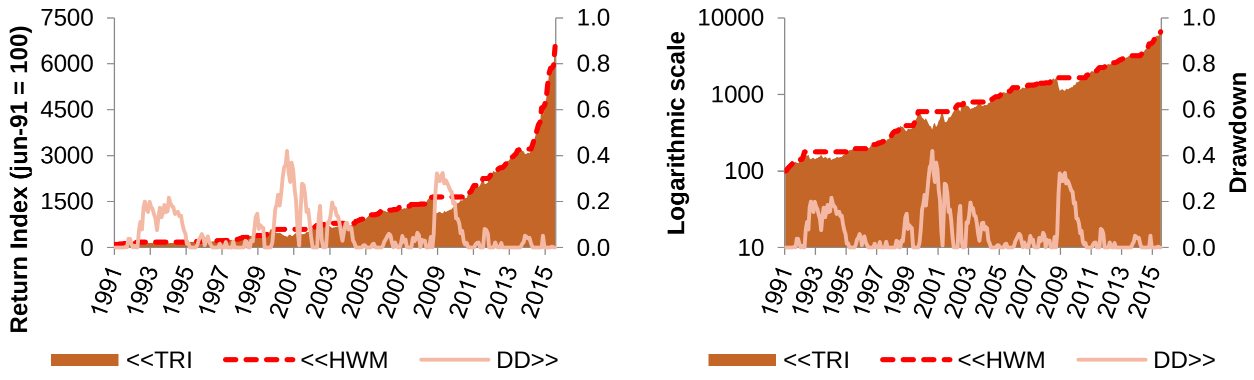
The return index and drawdown plots for the size-inspired SMB portfolio is a bleak view, but expected following the estimated negative size premium in table 5.1. The portfolio did have periods of HWMs at the onset of the sample period (1991-1995), among a general positive trend in these years. At the end of the 1990s however, the portfolio experienced several periods of negative returns, causing the return index to fall sharply and the drawdown to increase. Following an SMB strategy during the irrational investor behavior of the dotcom bubble build-up would have been devastating; completely contrary to the market of the previous figure. From the early years of the 2000s, the portfolio's return index flattens out and even increases some up until the start of the financial crisis. From mid-2006, the SMB portfolio has steadily declined, and as of the end of the sample, the portfolio has never returned to its HWM of April 1995. In other words, a period of 20 years that would have resulted in a negative holding period return if the investment had been made at the 1995 high. The portfolio does correlate with a relatively high counter-cyclicality to the market however (appendix 4.1), which can make it act as a hedge to market exposure.

Figure 6.3 – TRI, HWM and DD for HML (Value)



The HML portfolio has not performed that bad, as perhaps expected from the insignificant value premium in table 5.1, and the lacking B/M-return relation in table 5.2. The first half of the sample is a very bad period for the HML portfolio however. The underlying reason for the dotcom bubble was the hype of low book-to-market growth companies, and irrational bandwagon valuation contrary to fundamental analysis. In other words, value investing was not a popular concept during these years. After the correction of the irrational dotcom bubble on the other hand, the HML strategy did very well. From around 2000 and in the years leading up to the financial crisis, the return index saw a sharp increase from around 50 points to just shy of 300, with little to no drawdown after regaining the lost grounds in late 2002. The portfolio did suffer from the market turbulence of 2007-2009, but clearly less severe than the market (and both the WML and RMW, as shall be seen below) did. Hence, the portfolio was less sensitive to the market during this period. More recently, the HML portfolio has been volatile, with increasing drawdowns in the latter parts of the sample. Overall, the HML portfolio have not done extremely well on its own (with an end-TRI of 164 points and volatile nature), but it might seem counter-cyclical to market movements (and WML as will be seen next). Hence, in conjunction to these, HML can work in providing diversification.

Figure 6.4 – TRI, HWM and DD for WML (Momentum)

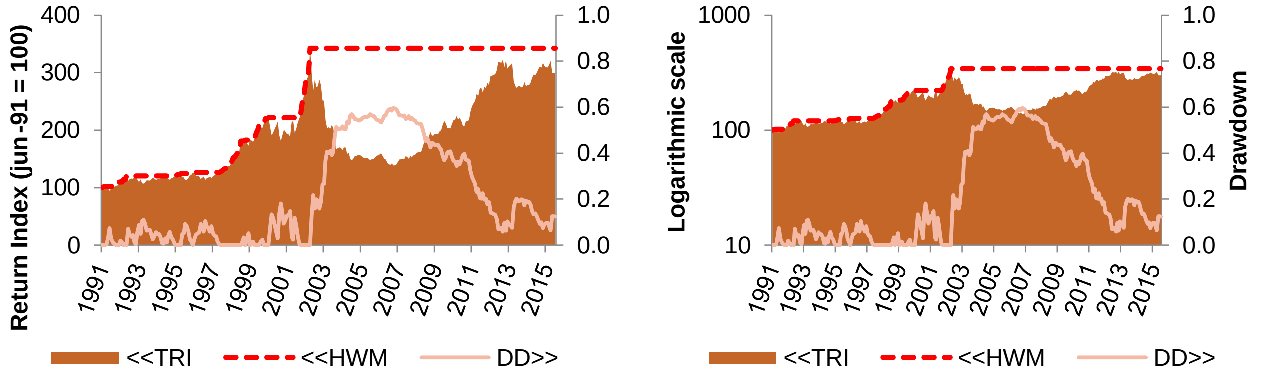


The return index of the WML portfolio is as expected given that it ends up at just shy of 6,600 points at the end of 2015. This corresponds to a holding period return[3] of 6,468% or compound annual growth rate[4] of 19.05%; unparalleled to the other factor portfolios. Still, the strategy is very volatile (as seen best through the DD line). Attempts to time the portfolio or a lack of the ability to keep cool during turbulent markets could have resulted in substantial drawdowns. The WML portfolio has peak drawdowns in the early 1990s market turbulence, dotcom crisis and the financial crisis, and as such, it demonstrates sensitivity to market cyclicality (though more often in the wake of the market drawdown periods, thus the negative market beta). Hence, even though the payoff to the portfolio has been high historically, a momentum-investor has to stomach bad periods from time to time, and contrary to for example the CMA portfolio (below), the strategy is in more danger of bad market timing.

Another point that must be made is that the strategy is prone to higher transaction costs than the other portfolios. This could eat into the apparent solid profits. The monthly update of the momentum signal leads to more frequent changes to the portfolio composition than the annual report signals of the other portfolios, and higher stock turnover means higher transaction costs. Only gross returns are considered in this thesis, and as such, the problem proposition will have to be left for future research.

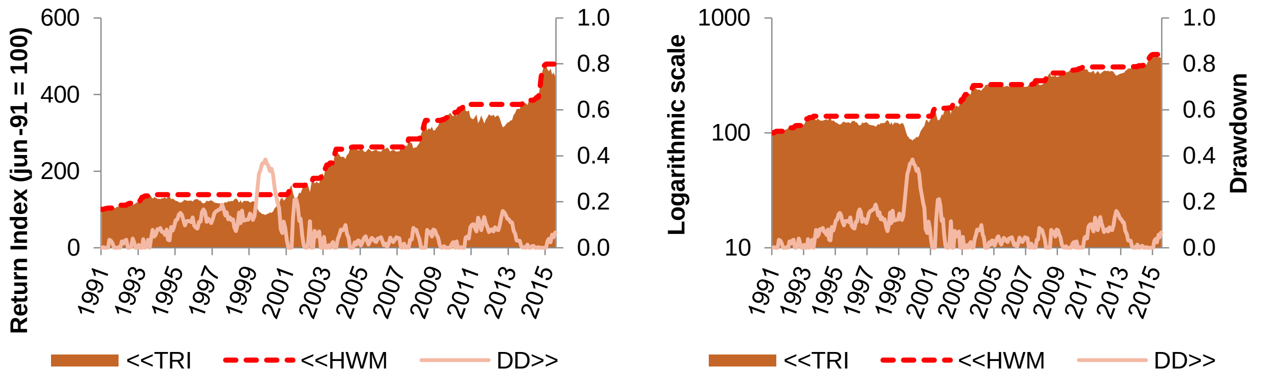
[3] HPR = (End Value / Start Value) - 1
[4] CAGR = (End Value / Start Value)^(1/Holding period years) - 1

Figure 6.5 – TRI, HWM and DD for RMW (Profitability)



For profitability investing and the RMW portfolio, an interesting pattern emerges from the plots; the RMW seems to be behaving counter-cyclical to general market movements. RMW's TRI peaks in the early 2000s, a time in which the preceding portfolios are in retraction, followed by a decline during the time where the other portfolios are on the rise (in the aftermath of the dotcom burst of 2002-2006), and lastly a peaking DD at the onset of the financial crisis. The rationale behind this market counter-cyclicality might be that the portfolio keeps focus on what is important during periods of irrational valuation build-up; underlying profitability. This focus leaves the portfolio well positioned for periods in which the markets experience corrections and volatility. As such, the RMW portfolio might figure as a good hedge to market exposure from the other factors. Other than some very significant drawdowns during the mid-2000s, the portfolio has been stable in the other parts of the window. In the end, the portfolio has tripled the value of an investment made in 1991.

Figure 6.6 – TRI, HWM and DD for CMA (Investment)



Lastly, the investment effect portfolio CMA is proving a solid trade on the Nordic markets from 1991-2015. Not only does the portfolio provide an attractive return, with the TRI ending up just shy of 450 points at the end of 2015, but also the portfolio's road there is the least volatile of them all.

The drawdowns for the portfolio are most severe in the years leading up to the dotcom bubble, implying that the aggressive growers were rewarded more than the conservative was in this period. Other than this, the portfolio sees comparatively small drawdowns over the rest of the time window. Rather, CMA sees a steady increase in its TRI; notice in particular the strong performance during the severely turbulent market of 2007-2009. An investor that positioned her portfolio long in the conservative asset growers and short the aggressive ones during this time, would emerge from the financial crisis with a profit. In other words, the CMA portfolio proves relatively robust to general market movements, which is also reflected in its very low market beta, and similar to the RMW, the CMA portfolio can thus provide a good hedge towards general market movements, acting as a catalyst in lowering portfolio volatility.

6.1.2 Static Portfolios

Given space limitations and for keeping an overview, only four combo portfolios are presented here in the thesis' main body text. These are the three most successful combo portfolios (Mkt-WML, WML-RMW-CMA and equally weighted all six [EW6]), and Asness, Moskowitz & Pedersen's (2013) HML-WML portfolio, due to it being the motivation for investigating factor synergies. The table containing performance measures for the remaining thirteen combo portfolios, as well as their TRI plots can be found in appendix 4.2.

Table 6.2 – Static factor combination portfolio performance
('Performance' numbers annualized, 'Risk Mgmt' numbers monthly)

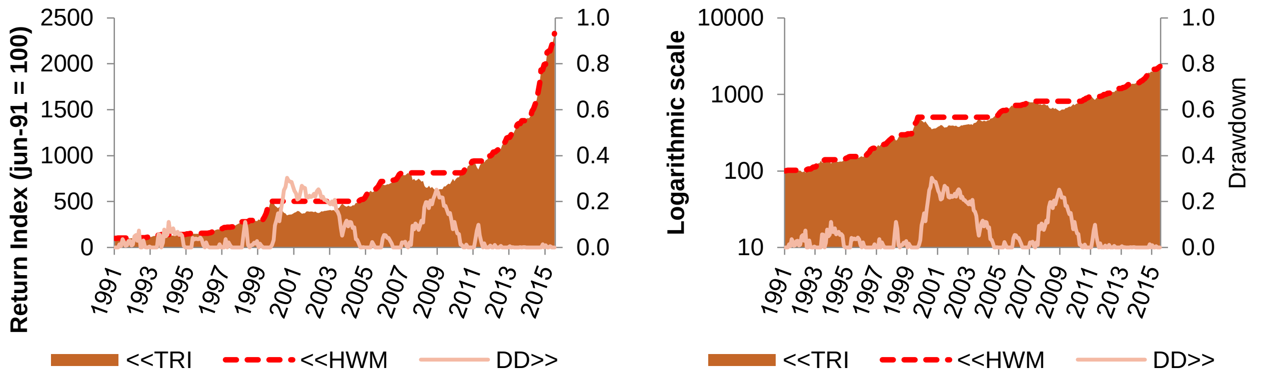
		Mkt-WML	HML-WML	WML-RMW-CMA	EW6
Performance	Expected return (%)	14.41	11.48	10.82	6.92
	Volatility (%)	11.23	11.72	8.41	4.94
	Sharpe ratio (SR)	1.28	0.98	1.29	1.40
	Jensen's alpha (%)	10.71	13.45	12.11	6.83
	Tracking error volatility (%)	6.67	14.21	9.60	4.89
	Information ratio (IR)	1.58	0.95	1.26	1.40
	Max high water mark	2,330	1,223	1,137	502
	End-2015 return index (TRI)	2,330	1,216	1,137	500
Risk Mgmt	Market Beta	0.40	-0.21	-0.14	0.01
	Max drawdown (%)	30.4	21.5	19.1	10.4
	Skewness	0.32	0.30	-0.27	0.41
	Excess kurtosis	1.7	5.8	3.7	4.0
	95% VaR (%), theoretical	-4.2	-4.7	-3.1	-1.8
	95% VaR (%), sample	-4.1	-4.6	-2.9	-1.5
	Expected shortfall (%), sample	-5.8	-7.4	-4.9	-2.6

Comparing table 6.2 to table 6.1, the combinational portfolios' relative outperformance of the individual factor portfolios is evident. This result bodes well for the proposition of diversification benefits to combining different factor portfolios. Not considering the individual WML portflio, the combinational portfolios presented in table 6.2 outperform their simpler counterparts on basically all performance measures (first eight rows of the tables). Except for the HML-WML combination, all the combo portfolios above deliver a total return above its total risk (SR > 1) and a market-risk adjusted return, or 'alpha', above its tracking errror volatility (IR > 1).

As for the risk measures of the portfolio performance (last seven rows of the table), all four combinational portfolios in table 6.2 outperform all the individual portfolios in table 6.1. The largest maximum drawdown among the portfolios comes from the Mkt-WML combo, at 30.4% (during the dotcom crisis, as can be seen in figure 6.7 below), which is well below the smallest maximum drawdown of the individual CMA portfolio in table 6.1 (at 38.5%). The smallest maximum drawdown of the combo portfolios comes from the equally weighted portfolio of all the factor strategies (EW6), at a peak drawdown of only 10.4% over the 25 year period from 1991-2015. Several of the combo portfolios do have a high excess kurtosis (for example HML-WML at an excess kurtosis of 5.8), which indicates a fatter tail to the return distribution of the portfolios compared to a normal distribution. Fatter tails indicate a higher probability of more extreme return outcomes, but given that the combo portfolios have a relatively low estimate of standard deviation to begin with, the value at risk (both theoretical and based on the sample) and expected shortfall measures are on average well below what was seen on the individual portfolios. In summary, the combination factor portfolios outperform the individual factor portfolios in a risk-return perspective.

Turning to how the combo portfolios have performed on their own during more turbulent, as well as booming, market conditions, the TRI, HWM and DD plots are presented for each of the four portfolios of table 6.2 below.

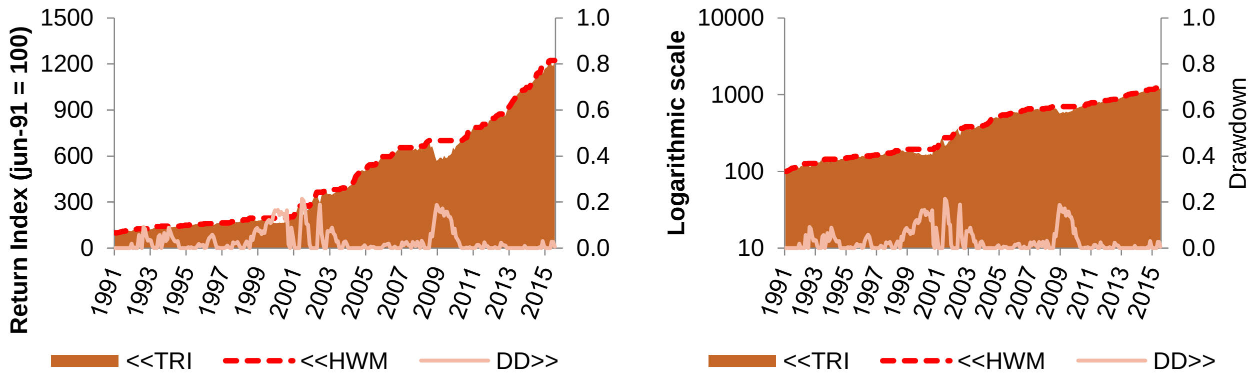
Figure 6.7 – TRI, HWM and DD for Mkt-WML (50/50 Market-Momentum)



An immediate observation from the return index of the Mkt-WML strategy is that much of the portfolio's high return has come from recent performance. During the 'bullish' recovery period in the wake of the financial crisis, i.e. from a bottom in 2009 and onwards, a portfolio consisting of a 50% stake in the broad Nordic equity market and a 50% stake in WML portfolio, has delivered very good returns. With little to no drawdowns over the period, the Mkt-WML portfolio has climbed from a low-point of around 600 points to 2,330 at the end of 2015. This roughly 290% HPR from 2009-2015 is mainly driven by the sharp increase of the WML portfolio's return index during the same period. Including the broad market porfolio to the equation has rather raised the return in periods prior to 2009, lowering the drawdown volatility of the clean WML portfolio during these years somewhat.

In other words, combining the risky momentum portfolio with a stake in the broad market, has diversified the portfolio, lowering its risk. The combo portfolio still has a lot volatility left in it however. Had the analysis been done on the 2009-2015 sub-period, the 50/50 market-momentum strategy might have been the top performing portfolio of all the evaluated ones, at low risk and high return. But this is not the case for the whole time window. With a relatively flat return index in the 1990s, and significant drawdowns during both the dotcom turbulence and the financial crisis, a high return to the market-momentum portfolio can suddenly be more due to good market timing than a low-risk, continually performing portfolio. Significant drawdowns during tubulent markets can cause investors to abandon a market-momentum position on their own, or forcibly by margin calls. Thus, even though the Mkt-WML portfolio has provided a good indication of synergy effects to combining factor portfolios, other combinations might provide a more market impervious portfolio.

Figure 6.8 – TRI, HWM and DD for HML-WML (50/50 Value-Momentum)

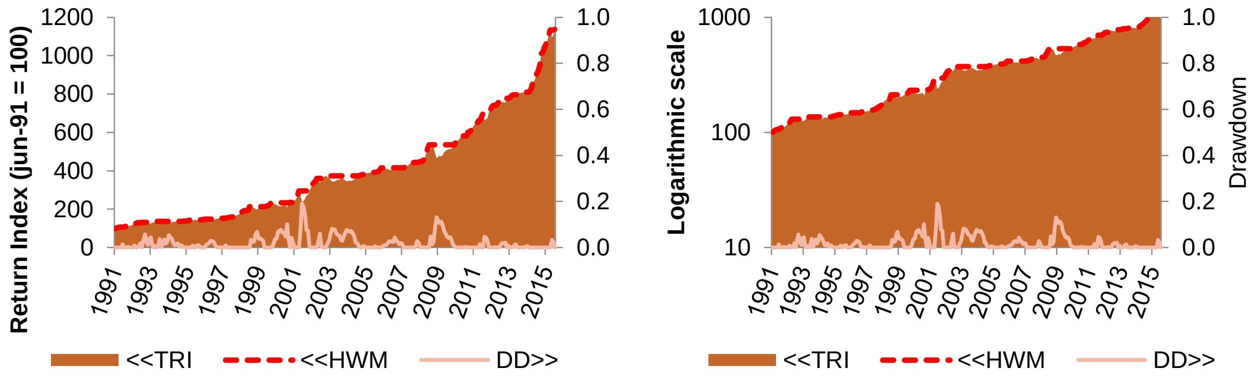


Turning to Asness, Moskowitz & Pedersen's (2013) value-momentum portfolio, the risk-reward proposition seems a lot better over the whole time period than for the market-momentum combo. Even though the portfolio does not end up at the high return index levels of the Mkt-WML portfolio (TRI at the end of 2015 is slightly above 1,200 points for HML-WML), the path is a lot smoother concerning volatility and drawdowns.

During the value-turbulent latter parts of the 1990s, the HML and WML acted as offsetting strategies, which dampens some of the large drawdowns to the HML portfolio on its own (seen in figure 6.3). Value investing had a hard time during these years, and for a lot of the reasons value investing had a hard time (ref. hysteria and bandwagon), momentum investing worked during these years. At the burst of the bubble, the tables turned and momentum investing hurt, while value acted as the offsetting catalyst instead. Since value is not sufficiently offsetting the momentum losses, the HML-WML portfolio does take drawdowns during this period, but clearly less severe than for the WML on its own. What is more, the value-momentum portfolio regains its dotcom drawdown relatively fast, and sees increases to its high water mark already from around 2003. This offsetting concept of the two investment strategies is also evident during the financial crisis of 2007-2008. While earlier portfolios investigated experienced severe drawdowns over longer periods of time, the HML-WML combo sees a sharp, but quick, drawdown during the latter parts of 2008 that is regained over the course of 2009.

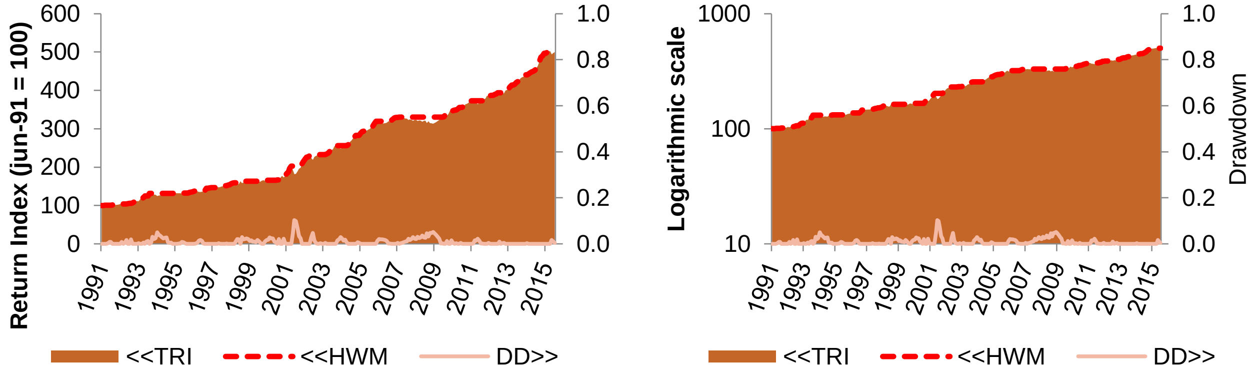
All in all, the results for a value-momentum portfolio on the Nordic equity markets, is very similar to the global results found by Asness, Moskowitz & Pedersen (2013). The two concepts seem like complementing strategies, working when the other fails and vice versa. This ensures a more steady portfolio return, with less volatility (although volatility and drawdowns are still very much present). Although the value-momentum does not look as attractive as market-momentum from the performance numbers in table 6.2 (Mkt-WML outperform on all metrics but the maximum drawdown), I believe several of these numbers to be distorted by the extreme performance of the Mkt-WML portfolio in the more recent years. Thus, as mentioned earlier, market-momentum is more dependent on good market timing than value-momentum, and the HML-WML presents a better diversification proposition towards systematic risk.

Figure 6.9 – TRI, HWM and DD for WML-RMW-CMA (33/33/33 Momentum-Profitability-Investment)



For the momentum-profitability-investment portfolio that was motivated by the seeming counter-cyclicality of the individual factors, the diversification benefit is realized. By delivering an average annual return of 10.82% at a standard deviation of only 8.41%, the portfolio increases more than tenfold from 1991-2015, with the return index ending up at 1,137 at the end of 2015. The maximum drawdown over the period only amounts to 19.1%. From combining the counter-cyclical RMW portfolio, the high return and volatile WML portfolio, and the steady CMA portfolio, an equity portfolio that is relatively impervious to general movements in the market for Nordic common stocks during 1991-2015 has been constructed. While the portfolio does experience drawdowns during both the dotcom bubble (peaking at 19.1%) and the financial crisis (at 13% in mid-2009), the cyclical pattern of the market portfolio in figure 6.1 is hard to trace in the TRI plot of the WML-RMW-CMA strategy above. The concept of reaping diversification benefits by combining factor effect portfolios seem to have traction in the Nordics.

Figure 6.10 – TRI, HWM and DD for 6-factor combo portfolio (Equally weighted Mkt-SMB-HML-WML-RMW-CMA)



The equally weighted portfolio combination of all the factors provides the most market-insensitive portfolio thus far. The total return index ends up at 500 at the end of 2015, meaning the strategy has delivered a comparatively unimpressive annual return of 6.92% from 1991-2015. The end result for the portfolio's return is not what is interesting however, but rather its minimally volatile TRI in getting there. In the end, low returns in a low risk strategy can be magnified by further leverage, as will be discussed later. With an estimated total volatility of 4.94% annually, the strategy has delivered the highest Sharpe ratio thus far, at 1.40. Given the minimal market exposure of the portfolio (beta = 0.01), the information ratio remains the same as the Sharpe, meaning most returns are due to alpha rather than market exposure. The drawdown over the 25 years considered peaks at only 10.4% in November 2001, which was regained by April 2002. Based on the estimates of the mean and standard deviation for the return distribution, the 95% theoretical value at risk amounts to only 1.8%. The sample 95% value at risk ends up even lower, at 1.5%. With an excess kurtosis of 4.0. the tail risk is higher than for a normal distribution, but this is somewhat offset by the positive skew of the return distribution, resulting in an expected shortfall of only 2.6% in the worst five percent of months.

These metrics have resulted in perhaps the most well-behaved TRI and DD graphs so far. Given the little market exposure of the portfolio, a lack of any significant market patterns in the TRI of the EW6 portfolio is perhaps expected, but the near total lack of abrupt drawdowns during the known turbulent market periods is nonetheless surprising. Hence, an investor that would have equally weighted her portfolio exposure to the six factors considered, would have a portfolio that would have been positioned so that it behaved resistant to the most adverse market movements during

1991-2015. This result is an interesting setup for the mean variance optimization of the weight exposure in the six factors, that follows.

6.1.3 Dynamic Portfolios

Lastly, the performance of the six mean variance optimized portfolios (three different portfolios; minimum variance [MV], maximum slope [MS] and variance-slope combo [V-S], based on two different time windows; four and five year) are summarized in table 6.3 below.

Table 6.3 – Dynamic factor combo-portfolio performance
('Performance' numbers annualized, 'Risk Mgmt' numbers monthly)

		MV 4yr	MV 5yr	MS 4yr	MS 5yr	V-S 4yr	V-S 5yr
Performance	Expected return (%)	5.51	5.97	8.79	7.87	7.14	6.92
	Volatility (%)	3.52	3.64	6.78	6.54	4.59	4.64
	Sharpe ratio (SR)	1.57	1.64	1.30	1.20	1.56	1.49
	Jensen's alpha (%)	5.22	5.72	8.14	7.00	6.67	6.36
	Tracking error volatility (%)	3.41	3.54	6.32	5.96	4.36	4.38
	Information ratio (IR)	1.53	1.61	1.29	1.17	1.53	1.45
	Max high water mark	298	309	537	421	403	361
	End-2015 return index (TRI)	297	306	537	421	403	361
Risk Mgmt	Market Beta	0.03	0.03	0.07	0.09	0.05	0.06
	Max drawdown (%)	7.3	6.4	16.3	16.7	8.5	6.3
	Skewness	0.23	0.22	-0.81	-0.38	-0.45	-0.14
	Excess kurtosis	1.0	1.2	2.7	3.9	1.9	2.6
	95% VaR (%), theoretical	-1.2	-1.2	-2.5	-2.5	-1.6	-1.6
	95% VaR (%), sample	-1.3	-1.4	-2.4	-2.3	-1.6	-1.5
	Expected shortfall (%), sample	-1.7	-1.8	-4.6	-3.9	-2.7	-2.4

Compared to the individual portfolios of table 6.1, the dynamic portfolios are superior mainly due to their low risk. All six portfolios in table 6.3 have very low risk, which translates to very good risk-adjusted ratios (SR and IR) even though the dynamic portfolios' return are a lot lower than for some of the individual factor portfolios. Compared to the static combo portfolios of table 6.2, the dynamic portfolios also deliver better risk-return proposals, except for the Mkt-WML, WML-RMW-CMA and EW6, who outcompete some of the MS portfolios through SR and IR ratios. In general, the more complex weighting scheme on the different factors does seem to outperform the equal weighting of section 6.1.2 however, given that some of the dynamic portfolios deliver very good performance numbers (namely the MV 4yr and 5yr, and the V-S 4yr).

Among the dynamic portfolios, the MV portfolios perform very well, particlarly with regards to risk control. By definition of an MV portfolio, the weights on the factors are decided on a desire to minimize risk and take advantage of negative or lacking correlations among assets to achieve this.

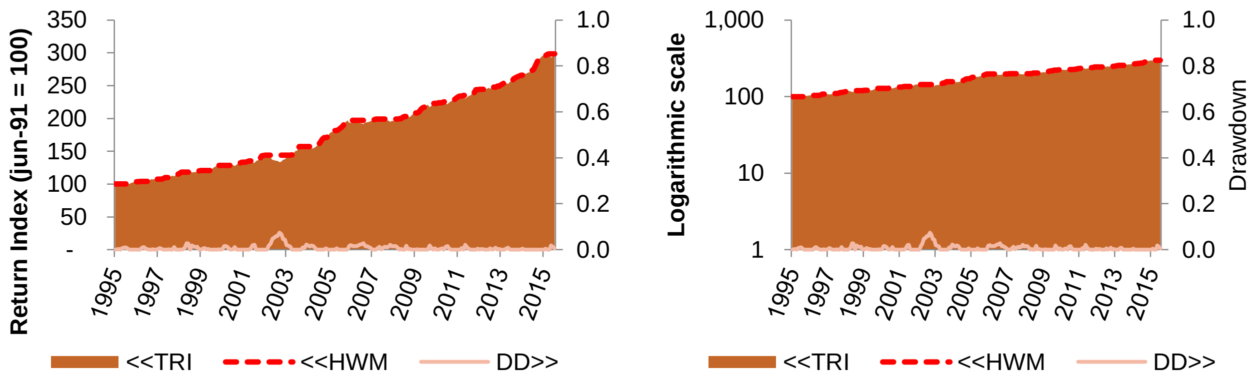
Hence, based on both a four- and five-year window of rolling data, even though the MV portfolios do not deliver the highest returns (5.51% and 5.97%, respectively), they do so at a very low risk ’cost’, resulting in high Sharpe ratios. As the portfolios have little market exposure (beta = 0.03 for both rolling windows), the IRs are correspondingly high as well. The MS portfolios deliver a higher average annual return than their MV counterparts, but naturally at a higher risk. This lowers the MS portfolios’ SRs, and since they are more exposed to the market, the IRs are further lowered. The optimal risk of the MV and optimal return of the MS portfolios, consequently leaves the 50/50 combo portfolios of these somewhere in the middle. The risk-return tradeoff leaves the V-S portfolios outperforming the MS portfolios, but not the MV portfolios. Specifically, both MV portfolios have higher SRs and IRs, as well as lower theoretical and sample value at risk and expected shortfall than the V-S combos.

Given this, the MV portfolios will be the center of attention for the remainder of this section. The TRI, HWM and DD plots of the max slope and variance-slope portfolios (found in appendix 4.3) further show that these portfolios are much more sensitive to market movements, experiencing sharp drawdowns during tubulent market periods. What is more, the MS and V-S portfolios demonstrate much more frequent changes to the portfolio composition, indicating they are more prone to market frictions that are unaccounted for in this thesis (also appendix 4.3). For these two reasons, a focus on the MV portfolios and rather concluding on an appropritate rolling time window for optimizing these portfolios, are justified.

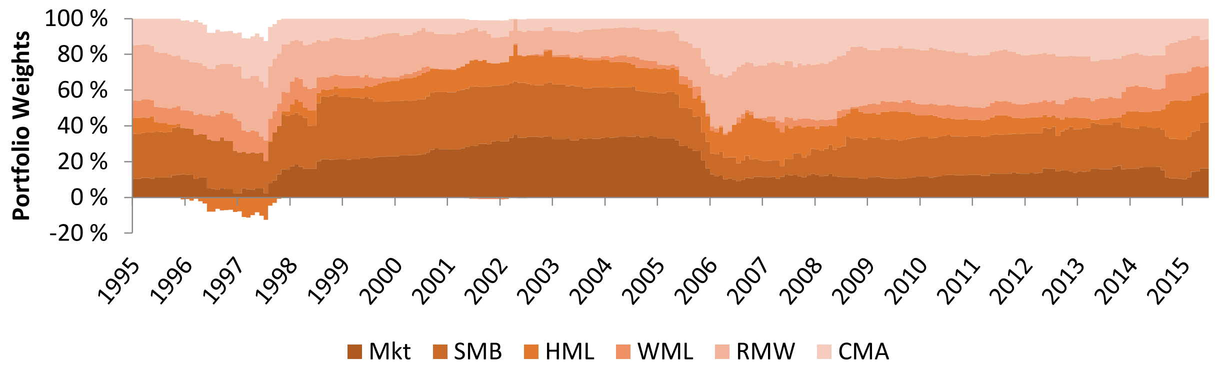
Starting out in panel A of figure 6.11 below, the return index of the four-year MV portfolio is very well-behaved. Starting in June 1995, an investor that would have monthly updated her portfolio to a minimum variance weighting exposure in the six factors, would have earned just shy of 200% on her initial investment by end 2015. While this return is not particularly impressive (compared to for example the approximate 6,500% return on the WML strategy), the resistance to general market volatility while acquiring the return is. Except for the strategy’s peak drawdown at only 7.3% in the wake of the dotcom bubble (building from November 2002 through March 2003), little of the market movements that was seen in figure 6.1 can be traced in the figure above. Consequently, the investor would have to worry little about adverse market movements; her portfolio would run steady through both the dotcom bubble and the financial crisis almost without drawdowns at all.

Figure 6.11 – Minimum Variance Portfolio, 4-year time window

Panel A: TRI, HWM and DD graphs



Panel B: Evolution of portfolio composition

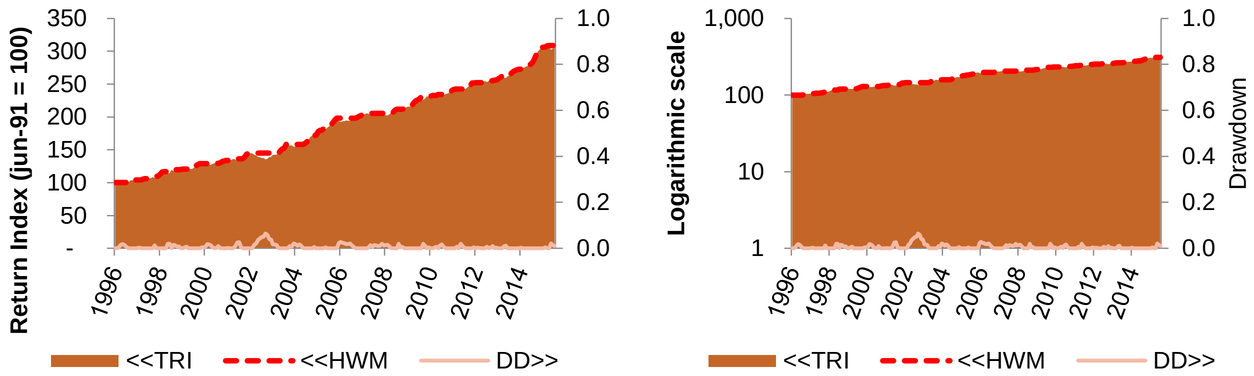


Because of this minimal risk proposition to the strategy, there is quite the possibility of levering up further, to magnify returns. The point is that the safety of the strategy will mitigate portfolio problems in levering up such as margin calls and investor aversion to keeping a risky position during adverse market periods. The portfolio will already be levered through the short positions, but sophisticated investors such as a hedge fund should be able to lever up a lot more. Take for example Long-Term Capital Management, which was levered 25:1 prior to its demise in 1998. As for the specifics of levering up (how to put on extra leverage in the zero-cost long/short positions through for example derivatives, more stringent risk management of the portfolio through stress testing, etc.), this is a topic in itself and beyond the scope of this thesis.

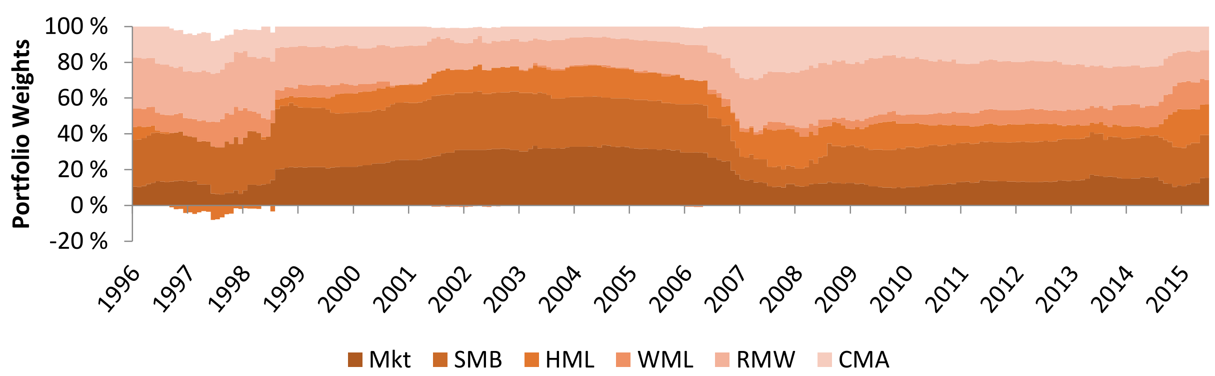
Turning to panel B of figure 6.11, which plots the portfolio weight composition in the different factors over time, and comparing it to the known market movements during the 20 years from 1995-2015 (figure 6.1) provides an interesting read. The behavior of the MV weights in the different factors over time almost seem predictive of changes to the market environment. The largest changes to the portfolio composition happens in expectation of the most adverse market movements during the time span (prior to the dotcom bubble and the financial crisis), while the weights are more stable in the recovery periods of 2003-2006 and 2009-2013/14. The portfolio for example shorts the value-strategy during the irrational build-up of the dotcom bubble and consequently turns long value in anticipation of the bubble bursting. Further, the portfolio loads up on the robust RMW and CMA portfolios in anticipation of the financial crisis, such that the MV optimization of the portfolio ensures that the strategy remain impervious to these market movements. At the same time, the large changes to the portfolio composition towards the end of the 1990s and the mid 2000s is a bit of a worry with regards to transaction costs eating into already small returns. As such, it is desriable to achieve a more stable portfolio composition.

Figure 6.12 – Minimum Variance Portfolio, 5-year time window

Panel A: TRI, HWM and DD graphs



Panel B: Evolution of portfolio composition



The total return index of panel A in figure 6.12 is basically equivalent to that of figure 6.11. This is expected; given the same optimizing algorithm and data (only extending the historical data a year) there cannot be radical changes to the portfolio performance, neither with respect to return nor risk.

Other than noting that the TRI of the MV 5yr portfolio is able to earn a marginally higher return, landing at 306 points contrary to MV 4yr's 297 points, I am therefore not commenting beyond what was said for panel A of figure 6.11.

Turning to panel B of figure 6.12, and comparing it to the same chart in figure 6.11, the portfolio weights for the long horizon rolling window are considerably more stable. Same as with the four-year window, the weights on the five-year portfolios are changing in lockstep with relevant market movements and in anticipation of more adverse market movements (value-short in dotcom build up, value-long close to bubble bursting; weighing up on RMW and CMA prior to financial crisis), but the changes are much less abrupt. This presumably lowers transaction costs for the portfolio as a whole, and make the portfolio's return more robust. Hence, the minimum variance portfolios on the six factors based on a five-year rolling window of historical information is preferred to the four year window. The return distributions behave pretty much the same, but the changes to the portfolio are much more stable for the five year window. It is likely that even longer time interval windows would increase the performance further, but due to a limited amount of data sample, longer windows are not tested. All in all, having gone from showing return-attractive individual factor portfolios, to diversification benefits of static factor combinations, the final MV optimized portfolios have combined attractive factor trades to a market-insensitive portfolio that delivers alpha at low risk.

6.2 Portfolio Trade Implementation Issues

The results above are based on theoretical positions on gross returns. As such, a section discussing implications to real-world trading is important, for perspective.

6.2.1 Information Issues

The information issue for the considered portfolios in section 6.1 is two-fold. First, a well-known issue in the capital markets is that the past is rarely an indicator of the future, and since the analysis and its results are based on past information, it is hard to say how these portfolios will hold up during the next 25 years. That said, 25 years of equity data should be indicative of a general trend in the performance of these factors. The portfolios have performed well in not one, but two relatively turbulent market environments, indicating robustness to adverse and shifting market conditions.

The second issue regarding information is that some of the factors can be argued to not being known upon periods where they are put to trade. Particularly, the important counter-cyclical profitability factor (RMW) and risk-attractive investment factor (CMA) were not included in the Fama-French framework until 2015 (Fama & French, 2015), making it pioneering to trade on them from 1995. Consequently, after the factors have become known in the later parts of the sample, buying pressures on the strategies can have eliminated profits from them. Still, as mentioned in the review of the factors in section 2, Haugen & Baker (1996) and Berk, Green & Naik (1999) were among the first to discuss profitability and investment effects, respectively. These early papers should have made it possible for sophisticated investors to notice possible patterns and trade on the ideas underlying the factor before 2015. After all, hedge funds traded on ideas such as value (Alfred Winslow Jones) and momentum (Paul Tudor Jones) years before they gained real academic traction (Mallaby, 2010).

6.2.2 Trade Friction Issues

Another issue concerning the trades revolves around trade frictions, some of which have been mentioned already. First, the inability to short particular stocks is a huge issue for the trades considered in this section. As shorting is a big part of eliminating market and position risk, as well as giving added returns to some of the factors, the inability to take the short side of the trade might erase the return, or magnify the risk. Synthetic shorts can be achieved by derivatives trading (long at-the-money put and short at-the-money call, for example), but this can raise the cost of the trades, which brings me over to the second trade friction issue. Transaction costs are not considered, and these could potentially be a huge blow for the strategies. Particularly the smaller cap parts of the trades that involve less liquid stocks (shown to be the more attractive parts of the factors, in section 5.1), can be attached to large transaction costs that eliminate documented gross trade returns. Third, while periods of market turbulence are shown and discussed for the factor portfolios, trade frictions arising from these periods have not been accounted for. With large position drawdowns, drawdown controls can kick in, such as margin calls on short positions. In other words, even though most trades overcame drawdowns during turbulent periods and delivered returns over longer-term horizons, it might not always be that an investor is allowed to hold her positions throughout the adverse periods. Further, it might not be that the investor can stomach holding her positions during adverse periods. These are frictions not accounted for in this trading analysis. It is not possible to account for all eventualities in such an analysis, and the results here are a start for further research.

6.3 Section Conclusions

To summarize, there definitely seem like there is some traction to the notion of factor investing in the Nordics. Having gone from investigating the individual factor portfolios, and found that some of them have very high return performance (WML), while another yields a much safer investment proposal (CMA), and yet a third delivers counter-cyclical traits (RMW and HML), combo portfolios were constructed to reap diversification benefits in differences between the individual portfolios.

The Asness, Moskowitz and Pedersen's (2013) motivated HML-WML portfolio and the self-motivated WML-RMW-CMA portfolio performed well compared to the individual factor portfolios. Among the static combos, the EW6 portfolios seemed to perform the best however, especially in the risk perspective.

This finding set the stage for investigating the best possible combination of weights in the six factor strategies, using the mean variance optimization algorithm on a rolling past window of information. Among the minimum variance, maximum slope and slope-variance portfolios, constructed on four- and five-year rolling windows, the MV portfolios seemed superior in the performance on a risk-adjusted basis. The MV portfolios delivered an unlevered (beyond inherent short positions) return of 200% over the years 1991-2015, at next to no risk and market sensitivity. Between the four- and five-year MV portfolios, even though they had very similar return distributions, the MV portfolio based on the five-year rolling window gave a more stable portfolio composition. This stability justified a preference toward the MV five-year portfolio due to lower portfolio turnover and thus transaction costs.

On an ending note, implications to the implementation of the trading strategies such as information issues and trade frictions cautioned some of the results of the section.

SECTION 7 CONCLUSIONS AND FURTHER RESEARCH

7.1 Conclusions

Compelling evidence towards the presence of factor effects on the Nordic equity markets has been found.

Statistically significant estimates of risk premia on the 2x3 portfolios for the momentum, profitability and investment factors were found. This result, along with a linear return pattern in the respective factors' 5x5 sorted portfolios, these three has demonstrated the most pronounced presence in the Nordics from 1991-2015. Size and value premia have proved insignificantly different from zero over the sample period, and it was more difficult to pinpoint an accurate return pattern to these effects in the 5x5 portfolios.

As for the factors' ability to systematically explain equity returns, all four asset pricing models were clearly rejected as complete descriptions of the cross section; as implied by the highly significant joint tests of the modified Wald statistics. The hypothesis that any of the four models tested would be complete description of cross sectional variations in returns was not expected however. The rejection of the joint tests is line with earlier results by Fama and French. On a more positive note, some elaboration on Nordic equity returns by the models has been documented. Across the four models, 40-46% of the variance in the cross section was explained by the factor portfolios, on average. 20-32% of the models tested gave insignificant intercepts, indicating the models' explanatory factors were sufficient predictors of a return time series. Among the models, the five-factor model seemed like the preferred model to predict a stock's return, as it performed comparatively well in both the single tests of model significance and the joint. The three-factor model did well in the single tests of model significance, but performed the worst in the joint tests. Vice versa for the six-factor model.

As for the industry perspective to factor effects, and the second part of the analysis, several of the factor patterns have substantiated attractive trades over the past 25 years. Momentum investing has yielded significant returns at high risk, while profitability and asset growth investing have provided lower returns but on comparatively more market-insensitive terms. These fundamental differences in risk and reward among the factor portfolios resulted in enhanced risk-reward portfolios by combining the individual ones, in extension of Asness, Moskowitz and Pedersen's (2013) findings on value and momentum. Both the HML-WML portfolio and the WML-RMW-CMA portfolio motivated by the data did comparatively well to the individual ones. The the best risk-reward proposition was obtained by combining all six factors equally (EW6) however, as the diversification from market movements was significant. By applying mean-variance optimizing algorithms to this six-factor combo portfolio, over a dynamic window of past data on the factors, the factor synergy proposition was further exploited. In the end, a minimum-variance portfolio algorithm applied over the past five years of data proved the most attractive alternative, providing almost exclusively alpha returns, at low risk. The relatively longer time window of past data resulted in a more stable portfolio composition, minimizing turnover and thus transaction costs.

The academic and industry perspective to investigating factor models have provided deep insight to the presence of prevalent factor effects on the Nordic equity markets from 1991-2015. Based on the relative advantage of trading on the factors as opposed to using them to price returns, it might seem as though the five (six with the market) factors tested are more due to anomalies that remain to price than a description of equity returns, and the data has yet to find a model it likes.

7.2 Further Research

As for further research, a deeper look at the factor investigation performed here seem likely to do either for the first part of the analysis (model testing) or the second part (trading).

7.2.1 Model Testing

For the factor model testing, three extensions of the methodology utilized in this thesis are of interest.

First, attempts at other methods for the construction of the model components, RHS and LHS portfolios, could be of interest to see if they increase (or decrease) model performance. As discussed earlier, the construction of 2x3 sorted and 5x5 sorted RHS and LHS portfolios was chosen to adhere to the original Fama-French methodology, but several alternatives to these sorts are possible. 2x4x4 size-signal-signal sorts, 2x2x2x2x2 size-all signals sorts, or other combinations can prove better at explaining equity returns by controlling for more effects in the factors, or represent a better cross section on which to explain returns.

Second, given the sample of Nordic stocks, more can be done to replicate the breakpoints constructed by Fama and French on the NYSE sample. The way breakpoints have been constructed in this thesis (on the full sample), might make the sample skewed towards the smaller cap stocks, as there are more of these than the large cap stocks. Because of this skew, small cap stocks extend too far into the larger cap percentiles of the sorts. Small cap stocks often have extreme return volatility due to them being less frequently traded and block transactions in small cap stocks can move the stock price a lot. Earlier factor research papers have shown the smaller cap parts of their factors to demonstrate less of a return pattern than their large counterparts (for example Fama & French, 2015). As such, they are more difficult to price in a systematic risk perspective, and more representative breakpoints to get an even sample could mitigate this issue.

Third, the Fama-MacBeth regressions are a natural extension to the significance tests performed here (Fama & MacBeth, 1973). The Fama-MacBeth regressions estimate the risk premia on the factors based on estimated coefficients. In other words, the FM regressions take the model testing one step farther than the model tests performed in this thesis, and investigate whether the factors have provided significant risk premia historically, based on the pricing of the equity cross section.

7.2.2 Trading

For the factor portfolio trading analysis, three extensions are relevant for future research here as well.

First, allowing for the delimitations that were made early on is a natural. Accounting for transaction costs and possible barriers to the portfolio trades will investigate the robustness of the gross results presented here.

Second, making the data more conservative is another way of increasing the robustness of the results presented here. As discussed in the results quality subsection (3.2.3) of the trading methodology, Pedersen (2015) suggests adjusting return estimates down and risk estimates up to account for the garbage-in garbage-out fallacy of bad estimates in portfolio analysis. Further, as was done by Asness, Moskowitz & Pedersen (2013) in their analysis of the value-momentum combo, the less liquid and often return-influential small cap part of the sample could have been excluded from the analysis, to make the data and its result more conservative.

Third, in line with the leverage proposal for magnifying low and safe portfolio returns of the minimum variance portfolios, a deeper look into how this could have been done practically seems like a natural extension. Issues such as how to acquire the leverage in the positions (synthetic positions, etc.), rigorous stress testing of portfolio positions, accommodating for margin calls during turbulent market periods, and such, are interesting perspectives to accommodate in a more practically grounded trading analysis.

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APPENDIX

Appendix 1 – Methodology

Appendix 1.1 – RHS Portfolio Calculation

Independent sorts are used to assign stocks to two Size groups and three B/M, MOM, OP and INV groups. The value-weighted portfolios at the intersection of the 2x3 groups form the factors. S and B denotes small or big size, H and L denotes high or low B/M, Wi and Lo denotes winners or losers w.r.t momentum, R and W denotes robust or weak profitability, C and A denotes conservative or aggressive investment / asset growth.

Sort	**Breakpoints**	**Factors and components**
No sort	None	Market = Value weighted return on all stocks excess of risk free
2x3 sort on MVxBM	Size=Median BM = 30/70	HML = (SH+BH)/2 – (SL+BL)/2
2x3 sort on MVxMOM	Size=Median MOM = 30/70	WML = (SWi+BWi)/2 – (SLo+BLo)/2
2x3 sort on MVxOP	Size=Median OP = 30/70	RMW = (SR+BR)/2 – (SW+BW)/2
2x3 sort on MVxINV	Size=Median INV = 30/70	CMA = (SC+BC)/2 – (SA+BA)/2
See above…	See above…	SMB[BM] = (SH+SM+SL)/3 – (BH+BM+BL)/3 SMB[MOM] = (SWi+SN+SLo)/3 – (BWi+BN+BLo)/3 SMB[OP] = (SR+SN+SW)/3 – (BR+BN+BW)/3 SMB[INV] = (SC+SN+SA)/3 – (BC+BN+BA)/3 SMB = (SMB[BM]+SMB[MOM]+SMB[OP]+SMB[INV])/4

Appendix 2 – Data

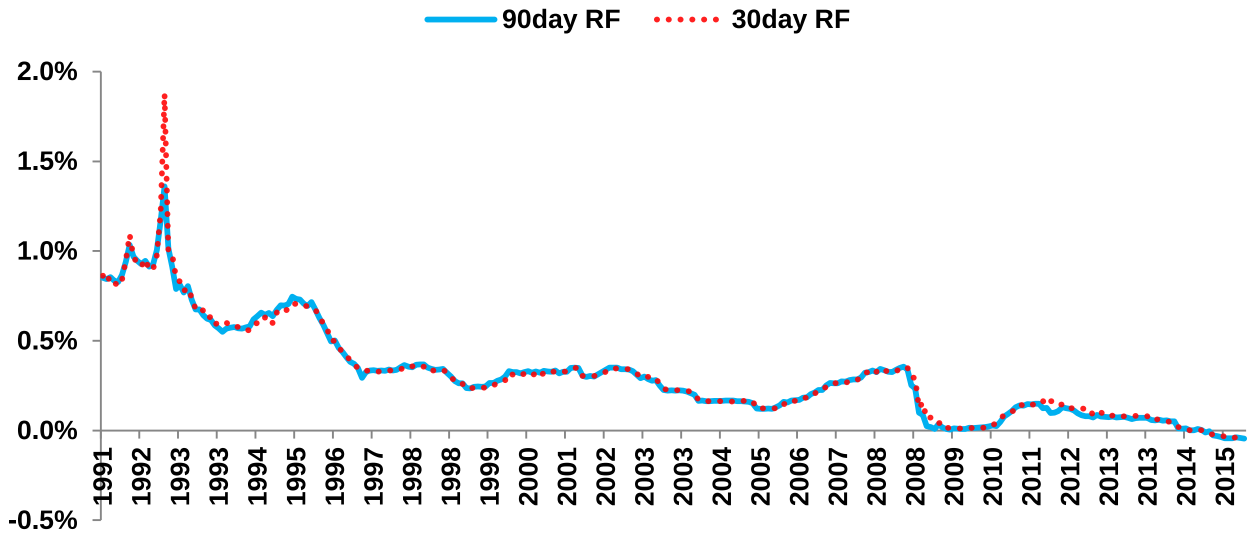
Appendix 2.1 – Constituent Lists

	DS-list	**IP-list**
Sweden	Category: Equities ➔ Market: Sweden ➔ Exchange: Stockholm (2856 listings) ➔ Type: Equity (2676 listings) Excluded from TDS filter: - 85 ETFs - 52 Preference Shares - 30 Closed-End Funds - 13 Warrants **Total = 2676 constituents**	WSCOPESD (978 constituents) FSWD (759 constituents) DEADSD (1404 constituents) **Total = 2311 constituents***
Denmark	Market: Equities ➔ Country: Denmark ➔ Exchange: OMX Nordic Exchange Copenhagen (847 listings) ➔ Type: Equity (811 listings) Excluded from TDS filter: - 2 ADRs - 7 Preference Shares - 27 Closed-End Funds **Total = 811 constituents**	WSCOPEDK (591 constituents) FDEN (165 constituents) DEADDK (387 constituents) **Total = 800 constituents***
Norway	Category: Equities ➔ Market: Norway ➔ Exchange: Oslo Bors (927 listings) ➔ Type: Equity (862 listings) Excluded from TDS filter: - 58 ETFs - 3 Preference Shares - 4 Closed-End Funds **Total = 862 constituents**	WSCOPENW (545 constituents) FNOR (246 constituents) DEADNW (574 constituents) **Total = 898 constituents***

Finland	Category: Equities ➔ Market: Finland ➔ Exchange: Helsinki (589 listings) ➔ Type: Equity (572 listings) Excluded from TDS filter: - 6 ETFs - 7 Preference Shares - 4 Closed-End Funds **Total = 572 constituents**	WSCOPEFN (269 constituents) FFIN (154 constituents) DEADFN (272 constituents) **Total = 472 constituents***
Risk Free	Category: Interest Rates ➔ Market: Sweden Name: Sweden Treasury Bill 90 Day Symbol: SDTB90D	

*The reason why the numbers of each list do not add up is that there are overlapping observations in each constituent lists, meaning adding the third list to a selection of the other two really does not add that many, generally.

Appendix 2.2 – Monthly Swedish 1M vs 3M T-Bill



Appendix 2.3 – Datatype List

Series Type	Series Code	Augmentation (Non-Padded*+Currency)	Frequency	Series Description
Dynamic	UP	(UP#T)~SK	Monthly	Share close-price, unadjusted. Currency-converted and stopped upon delist.
	RI	(RI#T)~SK	Monthly	Return index, theoretical growth in value of a share over a period, assuming re-investment of payouts. Currency-converted and stopped upon delist.
	MV	(MV#T)~SK	Monthly	Market value of a listing, raw share price multiplied by number of ordinary shares in issue. Currency-converted and stopped upon delist.
	NOSH	-	Monthly	Number of ordinary shares outstanding.
	WC03501	(WC03501)~SK	Yearly	Common equity, book value of equity. Currency-converted.
	WC02999	(WC02999)~SK	Yearly	Total assets. Currency-converted.
	WC01001	(WC01001)~SK	Yearly	Net sales or revenue. Currency-converted.
	WC01051	(WC01051)~SK	Yearly	Cost of goods sold (COGS) ex. depreciation and amortization. Currency-converted.
	WC04049	(WC04049)~SK	Yearly	Depreciation and depletion. Currency-converted.
	WC01075	(WC01075)~SK	Yearly	Interest Expense, total. Currency-converted.
	WC01101	(WC01101)~SK	Yearly	Selling, General and Administrative Expenses (SGA). Currency-converted.
	SDTB90D		Monthly	3 month Swedish T-Bill rate
Static	TYPE	-	-	Type of instrument requested.
	TRAD	-	-	Description of each security type.
	MAJOR	-	-	Binary indication of whether the security is the most significant among multiple listings, in terms of market value and liquidity.
	GEOGN	-	-	Geographical classification of a company, specifying home or listing country of a company security.
	ENAME	-	-	Expanded, unabbreviated name of a quote.
	EXMNEM	-	-	Datastream exchange code of a listing. OME = Stockholm, CSE = Copenhagen, OSL = Oslo, HEL = Helsinki.

* The TDS default handling of delisted stocks is to display the last observed closing value of the particular variable from delist up to the end of the time window; the time series is padded with the last known value. Since the Danish, Norwegian and Finnish stocks are converted to SEK during the extraction, the floating exchange rate will make padded, delisted observations vary. It is consequently hard to pinpoint the time when a particular stock was delisted. The default padding can be adjusted by adding the term #T to the datatypes that are to be extracted, which will make delisted securities' observations unpadded.

Appendix 2.4 – Static Screen: Detailed Deletion at Each Step

	Static Filter	Deletion Details			
		Stockholm	**Copenhagen**	**Oslo**	**Helsinki**
Step 1	TYPE - Keep 'EQ'	1 ADR 11 0-entries **12 Total**	1 0-entry **1 Total**	1 ETN 1 0-entry **2 Total**	**0 Total**
Step 2	TRAD - Keep 'Ordinary Shares'	31 Rights 25 Subs Rights 20 Paid Subsc Rights 15 SDRs 8 Red. Pref. Shares 2 DRs 1 ADR 1 Pref Share **103 Total**	4 Subsc Rights 3 OE Funds **7 Total**	1 Subsc Right **1 Total**	3 Opt Rights 1 Pref Share 1 Right **5 Total**
Step 3	Name - Keep those with a name (other than #ERROR)	**918 Total**	**329 Total**	**136 Total**	**207 Total**
Step 4	MAJOR - Keep 'Y'	**399 Total**	**72 Total**	**86 Total**	**86 Total**
Step 5	GEOGN - Delete listings geographically located in one of the other three Nordic countries than the one investigated	4 Danish 101 Norwegian 7 Finnish **112 Total**	5 Swedish 2 Norwegian 0 Finnish **7 Total**	9 Swedish 5 Danish 0 Finnish **14 Total**	7 Swedish 0 Danish 0 Norwegian **7 Total**
Step 6	ENAME I - Delete according to list in Appendix 1.5	8 Redemp Shares 3 SDRs 2 Rights **13 Total**	**0 Total**	**0 Total**	**0 Total**
Step 7	ENAME II - Delete dual/duplicate listings	**10 Total**	**1 Total**	**0 Total**	**4 Total**
	Total Deleted	**1567 listings**	**417 listings**	**239 listings**	**309 listings**

Appendix 2.5 – Static Screen: List of Non-Common Share Phrases / Abbreviations

CV, CONV, CVT, FD, OPVCM, PREF, PF, PFD, PFC, PFCL, RIGHT, RTS, UNIT, UNITS, WTS, WT, WARR, WARRANT, WARRANTS, REDEMP, NIL, SDR, NDR, DDR, FDR, ADR, GDR.

Appendix 2.6 – Full Sample Overview

Each year's count is the number of listings with observations for the different categories at the end of June that same year. For Raw and Static, the count is performed on available price observations, for Market/Size the count is performed on available return and market value, while for the other the count is done on available return and whatever signal that is used to sort on. The 'All' count is the total number of listings figuring in the sample at any point in time.

	Full Sample (Nordics)							
	Raw	Static	Dynamic	Market / Size	Value	Momentum	Profitability	Investment
1991	952	575	574	572	342	530	272	345
1992	918	591	585	584	373	515	305	379
1993	765	557	555	554	390	517	318	394
1994	807	598	595	593	406	529	332	403
1995	846	660	657	655	449	562	364	438
1996	878	686	682	680	464	614	386	460
1997	963	771	768	766	584	644	398	474
1998	1,054	873	870	868	699	731	429	685
1999	1,095	923	920	918	757	820	434	769
2000	1,097	950	943	941	777	826	408	775
2001	1,079	944	941	939	828	867	497	809
2002	1,005	890	888	886	810	859	513	814
2003	945	845	840	838	775	827	639	789
2004	929	835	832	830	741	783	642	769
2005	943	854	851	849	756	788	649	763
2006	988	900	898	896	811	800	676	792
2007	1,101	1,010	1,007	1,004	878	855	786	908
2008	1,141	1,054	1,051	1,048	976	961	850	978
2009	1,098	997	993	990	945	961	846	960
2010	1,095	992	987	984	921	939	847	958
2011	1,076	974	968	965	913	923	819	938
2012	1,033	937	932	929	885	904	794	906
2013	1,002	901	897	894	838	869	765	870
2014	996	899	894	890	815	833	768	860
2015	1,055	946	940	938	839	849	803	890
All	4,921	2,389	2,333	2,278	1,781	2,122	1,587	1,837

Stockholm								
	Raw	Static	Dynamic	Market / Size	Value	Momentum	Profitability	Investment
1991	473	219	218	217	103	208	89	101
1992	385	186	180	179	104	170	96	106
1993	260	155	153	152	108	141	99	109
1994	286	181	178	177	117	143	106	115
1995	289	198	195	194	132	164	112	122
1996	300	207	203	202	140	180	126	137
1997	345	250	247	246	166	184	128	136
1998	390	301	298	297	218	231	136	201
1999	429	340	337	336	235	280	138	246
2000	449	378	372	371	268	304	131	255
2001	450	380	377	376	308	346	184	294
2002	416	356	354	353	307	335	202	304
2003	394	342	336	335	301	327	270	302
2004	397	348	345	344	289	314	277	299
2005	398	352	349	348	301	326	271	292
2006	432	384	382	381	333	333	289	312
2007	481	433	430	429	367	360	352	377
2008	504	454	451	450	409	409	384	409
2009	509	440	436	435	402	416	393	414
2010	513	442	437	436	397	409	391	416
2011	506	434	429	428	393	403	382	409
2012	480	413	408	407	382	393	367	391
2013	467	397	393	392	365	376	352	375
2014	476	407	402	401	363	371	365	380
2015	533	455	449	449	382	386	397	412
All	2,676	1,109	1,078	1,047	742	958	720	777

Copenhagen								
	Raw	Static	Dynamic	Market / Size	Value	Momentum	Profitability	Investment
1991	236	197	197	196	123	187	83	122
1992	296	244	244	244	150	196	105	145
1993	286	238	238	238	150	232	109	150
1994	280	233	233	233	151	229	110	151
1995	275	231	231	231	155	224	113	154
1996	282	233	233	233	157	224	115	156
1997	273	227	227	227	194	223	115	156
1998	275	235	235	235	203	222	121	202
1999	270	234	234	234	216	225	123	209
2000	253	221	220	220	205	214	111	202
2001	235	208	208	208	200	201	109	194
2002	213	192	192	192	185	191	100	186
2003	204	186	186	186	177	185	117	181
2004	193	177	177	177	168	176	116	171
2005	186	172	172	172	162	167	113	164
2006	186	173	173	173	162	165	109	162
2007	211	197	197	197	176	171	124	180
2008	221	208	208	208	197	193	133	196
2009	208	196	196	196	192	193	138	192
2010	206	194	194	194	188	190	144	191
2011	194	184	183	183	179	181	137	183
2012	188	178	178	178	171	176	132	178
2013	179	168	168	168	160	167	126	167
2014	165	157	157	157	147	153	120	154
2015	159	151	151	151	144	149	118	149
All	811	394	389	386	333	379	255	335

Oslo								
	Raw	Static	Dynamic	Market / Size	Value	Momentum	Profitability	Investment
1991	144	101	101	101	73	91	64	77
1992	139	103	103	103	74	93	67	83
1993	137	104	104	104	86	91	69	87
1994	154	120	120	119	92	99	75	87
1995	159	136	136	135	98	114	82	93
1996	173	151	151	150	99	121	85	97
1997	203	180	180	179	137	143	86	101
1998	239	214	214	213	177	168	97	178
1999	235	214	214	213	192	198	97	190
2000	223	205	205	204	177	185	89	184
2001	221	208	208	207	182	181	101	186
2002	209	196	196	195	180	189	103	184
2003	187	179	180	179	166	177	133	173
2004	186	180	180	179	158	163	133	172
2005	203	197	197	196	169	168	146	178
2006	218	211	211	210	191	173	159	189
2007	255	249	249	247	209	197	189	222
2008	272	265	265	263	246	234	214	248
2009	240	235	235	233	227	228	195	229
2010	238	232	232	230	215	218	193	228
2011	238	232	232	230	220	215	183	222
2012	230	225	225	223	212	215	183	217
2013	221	216	216	214	198	209	174	209
2014	215	210	210	207	188	191	167	201
2015	216	210	210	208	192	193	168	200
All	862	623	607	594	499	558	413	505

Helsinki								
	Raw	Static	Dynamic	Market / Size	Value	Momentum	Profitability	Investment
1991	99	58	58	58	43	44	36	45
1992	98	58	58	58	45	56	37	45
1993	82	60	60	60	46	53	41	48
1994	87	64	64	64	46	58	41	50
1995	123	95	95	95	64	60	57	69
1996	123	95	95	95	68	89	60	70
1997	142	114	114	114	87	94	69	81
1998	150	123	123	123	101	110	75	104
1999	161	135	135	135	114	117	76	124
2000	172	146	146	146	127	123	77	134
2001	173	148	148	148	138	139	103	135
2002	167	146	146	146	138	144	108	140
2003	160	138	138	138	131	138	119	133
2004	153	130	130	130	126	130	116	127
2005	156	133	133	133	124	127	119	129
2006	152	132	132	132	125	129	119	129
2007	154	131	131	131	126	127	121	129
2008	144	127	127	127	124	125	119	125
2009	141	126	126	126	124	124	120	125
2010	138	124	124	124	121	122	119	123
2011	138	124	124	124	121	124	117	124
2012	135	121	121	121	120	120	112	120
2013	135	120	120	120	115	117	113	119
2014	140	125	125	125	117	118	116	125
2015	147	130	130	130	121	121	120	129
All	572	263	259	251	207	227	199	220

Appendix 3 – Asset Pricing Model Tests (Analysis Part 1)

Appendix 3.1 – Alphas, Alpha t-stats, R squared per model per regression

Three-Factor Model

Alpha estimate in % (Size-Value)

	Growth	2	3	4	Value
Small	2.39	1.19	0.83	0.59	1.05
2	0.80	0.30	0.40	0.23	0.74
3	-0.20	0.25	0.21	0.42	0.30
4	0.10	0.40	0.30	0.56	0.32
Big	0.51	0.41	0.52	0.26	0.33

Regression adj R^2 (Size-Value)

	Growth	2	3	4	Value
Small	0.12	0.30	0.41	0.52	0.51
2	0.48	0.46	0.62	0.72	0.68
3	0.52	0.50	0.62	0.63	0.71
4	0.32	0.46	0.43	0.55	0.54
Big	0.45	0.20	0.25	0.46	0.49

Alpha estimate in % (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.09	0.46	1.05	1.23	1.36
2	-0.65	-0.07	0.48	0.86	1.45
3	-1.74	-0.41	0.54	0.94	1.25
4	-0.95	-0.31	0.40	0.63	1.15
Big	-0.75	-0.04	0.06	0.40	1.18

Regression adj R^2 (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.42	0.50	0.48	0.44	0.29
2	0.45	0.66	0.62	0.62	0.51
3	0.36	0.54	0.69	0.66	0.33
4	0.18	0.40	0.52	0.53	0.29
Big	0.04	0.00	0.04	0.21	-0.02

Alpha estimate in % (Size-Profitability)

	Weak	2	3	4	Robust
Small	1.07	1.64	1.21	1.10	0.96
2	0.06	0.29	0.56	0.81	0.67
3	-1.16	0.16	0.80	0.81	0.31
4	-0.31	0.39	0.59	0.60	0.54
Big	0.16	0.19	0.19	0.63	0.61

Regression adj R^2 (Size-Profitability)

	Weak	2	3	4	Robust
Small	0.44	0.20	0.24	0.36	0.23
2	0.52	0.57	0.46	0.54	0.43
3	0.49	0.50	0.47	0.51	0.38
4	0.17	0.41	0.48	0.38	0.27
Big	0.04	0.04	0.08	0.02	0.07

Alpha estimate in % (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	1.16	1.42	1.02	0.75	0.47
2	0.37	0.73	0.54	0.25	0.02
3	0.17	0.60	0.32	0.36	-0.42
4	0.48	0.54	0.55	0.45	-0.00
Big	0.61	0.46	0.25	0.22	0.61

Regression adj R^2 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.42	0.47	0.32	0.40	0.26
2	0.54	0.58	0.63	0.56	0.47
3	0.52	0.61	0.58	0.49	0.49
4	0.29	0.51	0.59	0.34	0.27
Big	0.15	0.14	0.03	0.05	0.07

Alpha t-stat (H0: true alpha = 0) (Size-Value)

	Growth	2	3	4	Value
Small	**2.49***	**3.05***	**2.74***	**2.61***	**4.39***
2	**2.74***	1.50	**2.41***	1.63	**4.39***
3	-1.01	1.43	1.42	**2.63***	**2.11***
4	0.54	**2.65***	**1.97***	**3.49***	1.70
Big	**3.95***	**2.61***	**3.36***	1.63	1.94

P-value alpha H0 (Size-Value)

	Growth	2	3	4	Value
Small	1.3%	0.3%	0.7%	0.9%	0.0%
2	0.6%	13.6%	1.6%	10.5%	0.0%
3	31.2%	15.3%	15.7%	0.9%	3.5%
4	59.3%	0.9%	5.0%	0.1%	9.0%
Big	0.0%	1.0%	0.1%	10.4%	5.3%

Alpha t-stat (H0: true alpha = 0) (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.28	1.88	**4.42***	**4.31***	**3.18***
2	**-2.46***	-0.47	**3.13***	**5.60***	**6.62***
3	**-6.22***	**-2.55***	**4.13***	**6.71***	**5.52***
4	**-3.10***	-1.77	**2.85***	**4.38***	**5.87***
Big	-1.80	-0.16	0.34	**2.76***	**5.08***

P-value alpha H0 (Size-Momentum)

	Loser	2	3	4	Winner
Small	77.9%	6.1%	0.0%	0.0%	0.2%
2	1.5%	63.7%	0.2%	0.0%	0.0%
3	0.0%	1.1%	0.0%	0.0%	0.0%
4	0.2%	7.7%	0.5%	0.0%	0.0%
Big	7.3%	87.3%	73.6%	0.6%	0.0%

Alpha t-stat (H0: true alpha = 0) (Size-Profitability)

	Weak	2	3	4	Robust
Small	**2.66***	**2.75***	**2.76***	**3.05***	**2.60***
2	0.27	1.49	**2.64***	**3.86***	**2.94***
3	**-4.97***	0.89	**4.67***	**5.01***	1.38
4	-1.00	**2.15***	**3.68***	**3.57***	**2.76***
Big	0.34	0.84	1.19	**4.45***	**2.61***

P-value alpha H0 (Size-Profitability

	Weak	2	3	4	Robust
Small	0.8%	0.6%	0.6%	0.2%	1.0%
2	78.9%	13.7%	0.9%	0.0%	0.4%
3	0.0%	37.6%	0.0%	0.0%	17.0%
4	31.8%	3.2%	0.0%	0.0%	0.6%
Big	73.1%	40.0%	23.7%	0.0%	1.0%

Alpha t-stat (H0: true alpha = 0) (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	**4.00***	**5.17***	**2.64***	**2.37***	1.08
2	1.78	**4.30***	**3.34***	1.36	0.07
3	0.92	**3.99***	**2.20***	**2.05***	**-2.13***
4	**2.08***	**3.51***	**4.08***	**2.67***	-0.01
Big	**2.67***	**2.64***	1.71	1.36	**2.61***

* = significantly different from zero (i.e. model rejection)

P-value alpha H0 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.0%	0.0%	0.9%	1.9%	28.0%
2	7.7%	0.0%	0.1%	17.4%	94.2%
3	35.8%	0.0%	2.8%	4.1%	3.4%
4	3.8%	0.1%	0.0%	0.8%	99.2%
Big	0.8%	0.9%	8.8%	17.6%	1.0%

Four-Factor Model

Alpha estimate in % (Size-Value)

	Growth	2	3	4	Value
Small	3.09	1.37	1.14	0.77	1.24
2	0.94	0.44	0.44	0.32	0.78
3	-0.03	0.36	0.35	0.45	0.29
4	0.17	0.43	0.36	0.61	0.42
Big	0.42	0.49	0.64	0.39	0.32

Regression adj R^2 (Size-Value)

	Growth	2	3	4	Value
Small	0.13	0.30	0.42	0.53	0.51
2	0.48	0.46	0.62	0.72	0.68
3	0.53	0.51	0.63	0.63	0.71
4	0.32	0.46	0.43	0.54	0.54
Big	0.46	0.20	0.26	0.46	0.48

Alpha estimate in % (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.84	0.86	0.99	1.06	0.88
2	0.28	0.15	0.41	0.63	0.81
3	-0.69	-0.06	0.51	0.73	0.61
4	0.05	0.06	0.34	0.39	0.65
Big	0.87	0.80	0.17	0.13	0.34

Regression adj R^2 (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.52	0.53	0.48	0.44	0.31
2	0.65	0.68	0.62	0.64	0.63
3	0.62	0.61	0.68	0.68	0.49
4	0.43	0.47	0.52	0.57	0.42
Big	0.47	0.39	0.05	0.29	0.38

Alpha estimate in % (Size-Profitability)

	Weak	2	3	4	Robust
Small	1.29	2.23	1.26	1.22	1.04
2	0.28	0.36	0.65	0.86	0.87
3	-0.91	0.36	0.79	1.00	0.52
4	-0.08	0.47	0.70	0.64	0.61
Big	0.53	0.27	0.24	0.50	0.55

Regression adj R^2 (Size-Profitability)

	Weak	2	3	4	Robust
Small	0.44	0.21	0.23	0.36	0.23
2	0.53	0.57	0.46	0.54	0.43
3	0.51	0.52	0.47	0.53	0.39
4	0.18	0.41	0.48	0.37	0.27
Big	0.05	0.03	0.08	0.03	0.06

Alpha estimate in % (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	1.40	1.55	1.16	1.01	0.70
2	0.56	0.75	0.48	0.37	0.21
3	0.29	0.51	0.31	0.55	-0.27
4	0.56	0.62	0.46	0.45	0.16
Big	0.48	0.57	0.29	0.32	0.55

Regression adj R^2 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.43	0.47	0.32	0.41	0.26
2	0.55	0.58	0.63	0.57	0.48
3	0.52	0.61	0.58	0.51	0.50
4	0.28	0.51	0.59	0.33	0.28
Big	0.15	0.14	0.02	0.06	0.06

Alpha t-stat (H0: true alpha = 0) (Size-Value)

	Growth	2	3	4	Value
Small	**3.07***	**3.35***	**3.62***	**3.29***	**4.90***
2	**3.03***	**2.07***	**2.54***	**2.16***	**4.35***
3	-0.15	**1.99***	**2.30***	**2.65***	1.92
4	0.84	**2.71***	**2.20***	**3.62***	**2.15***
Big	**3.09***	**2.95***	**3.94***	**2.36***	1.79

P-value alpha H0 (Size-Value)

	Growth	2	3	4	Value
Small	0.2%	0.1%	0.0%	0.1%	0.0%
2	0.3%	3.9%	1.2%	3.2%	0.0%
3	88.0%	4.8%	2.2%	0.9%	5.6%
4	39.9%	0.7%	2.8%	0.0%	3.2%
Big	0.2%	0.3%	0.0%	1.9%	7.4%

Alpha t-stat (H0: true alpha = 0) (Size-Momentum)

	Loser	2	3	4	Winner
Small	**2.79***	**3.44***	**3.94***	**3.51***	**1.98***
2	1.24	0.98	**2.48***	**3.98***	**4.03***
3	**-3.05***	-0.37	**3.72***	**5.09***	**2.93***
4	0.19	0.33	**2.33***	**2.67***	**3.49***
Big	**2.66***	**4.26***	0.97	0.91	1.75

P-value alpha H0 (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.6%	0.1%	0.0%	0.1%	4.9%
2	21.5%	32.7%	1.4%	0.0%	0.0%
3	0.2%	71.5%	0.0%	0.0%	0.4%
4	85.0%	74.2%	2.0%	0.8%	0.1%
Big	0.8%	0.0%	33.5%	36.2%	8.1%

Alpha t-stat (H0: true alpha = 0) (Size-Profitability)

	Weak	2	3	4	Robust
Small	**3.05***	**3.58***	**2.73***	**3.22***	**2.67***
2	1.11	1.78	**2.85***	**3.84***	**3.64***
3	**-3.75***	1.90	**4.37***	**6.02***	**2.23***
4	-0.25	**2.47***	**4.10***	**3.64***	**2.91***
Big	1.07	1.15	1.41	**3.37***	**2.22***

P-value alpha H0 (Size-Profitability

	Weak	2	3	4	Robust
Small	0.3%	0.0%	0.7%	0.1%	0.8%
2	26.6%	7.6%	0.5%	0.0%	0.0%
3	0.0%	5.8%	0.0%	0.0%	2.7%
4	80.3%	1.4%	0.0%	0.0%	0.4%
Big	28.4%	25.3%	15.9%	0.1%	2.7%

Alpha t-stat (H0: true alpha = 0) (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	**4.64***	**5.34***	**2.84***	**3.04***	1.55
2	**2.56***	**4.17***	**2.82***	1.94	0.92
3	1.44	**3.18***	**2.00***	**3.03***	-1.29
4	**2.30***	**3.87***	**3.29***	**2.55***	0.73
Big	**2.00***	**3.10***	1.83	1.85	**2.22***

* = significantly different from zero (i.e. model rejection)

P-value alpha H0 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.0%	0.0%	0.5%	0.3%	12.3%
2	1.1%	0.0%	0.5%	5.3%	35.7%
3	15.0%	0.2%	4.6%	0.3%	19.7%
4	2.2%	0.0%	0.1%	1.1%	46.9%
Big	4.7%	0.2%	6.8%	6.6%	2.7%

Five-Factor Model

Alpha estimate in % (Size-Value)

	Growth	2	3	4	Value
Small	2.37	1.35	0.87	0.71	0.91
2	0.82	0.47	0.36	0.24	0.67
3	-0.01	0.33	0.34	0.51	0.31
4	0.35	0.51	0.39	0.57	0.35
Big	0.43	0.44	0.60	0.34	0.41

Regression adj R^2 (Size-Value)

	Growth	2	3	4	Value
Small	0.11	0.31	0.41	0.53	0.51
2	0.51	0.49	0.63	0.72	0.68
3	0.55	0.52	0.63	0.63	0.71
4	0.37	0.49	0.43	0.54	0.54
Big	0.48	0.24	0.28	0.47	0.52

Alpha estimate in % (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.35	0.43	1.02	1.19	1.22
2	-0.49	-0.03	0.43	0.91	1.34
3	-1.42	-0.19	0.65	0.96	1.23
4	-0.64	-0.12	0.46	0.71	1.13
Big	-0.65	0.02	0.10	0.43	1.23

Regression adj R^2 (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.44	0.51	0.48	0.44	0.28
2	0.46	0.66	0.62	0.62	0.52
3	0.40	0.58	0.69	0.65	0.33
4	0.22	0.42	0.52	0.53	0.29
Big	0.07	-0.01	0.03	0.20	-0.03

Alpha estimate in % (Size-Profitability)

	Weak	2	3	4	Robust
Small	1.18	1.67	1.17	0.96	0.95
2	0.27	0.38	0.59	0.77	0.46
3	-0.84	0.28	0.81	0.83	0.26
4	-0.01	0.53	0.67	0.65	0.61
Big	0.42	0.60	0.23	0.54	0.51

Regression adj R^2 (Size-Profitability)

	Weak	2	3	4	Robust
Small	0.45	0.19	0.23	0.36	0.22
2	0.60	0.59	0.46	0.53	0.44
3	0.58	0.54	0.47	0.51	0.38
4	0.26	0.47	0.48	0.37	0.27
Big	0.44	0.28	0.08	0.07	0.31

Alpha estimate in % (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	1.00	1.22	1.06	0.90	0.85
2	0.24	0.56	0.56	0.37	0.35
3	0.09	0.57	0.32	0.47	-0.06
4	0.43	0.56	0.53	0.63	0.37
Big	0.56	0.28	0.38	0.34	0.51

Regression adj R^2 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.48	0.48	0.31	0.40	0.27
2	0.67	0.64	0.62	0.58	0.52
3	0.58	0.62	0.59	0.51	0.56
4	0.38	0.53	0.59	0.36	0.36
Big	0.28	0.40	0.05	0.11	0.31

Alpha t-stat (H0: true alpha = 0) (Size-Value)

	Growth	2	3	4	Value
Small	**2.37***	**3.40***	**2.77***	**3.09***	**3.67***
2	**2.82***	**2.32***	**2.12***	1.59	**3.81***
3	-0.04	1.85	**2.24***	**3.09***	**2.14***
4	1.85	**3.35***	**2.42***	**3.42***	1.82
Big	**3.30***	**2.77***	**3.84***	**2.10***	**2.41***

P-value alpha H0 (Size-Value)

	Growth	2	3	4	Value
Small	1.9%	0.1%	0.6%	0.2%	0.0%
2	0.5%	2.1%	3.5%	11.3%	0.0%
3	96.9%	6.6%	2.6%	0.2%	3.3%
4	6.6%	0.1%	1.6%	0.1%	7.1%
Big	0.1%	0.6%	0.0%	3.7%	1.6%

Alpha t-stat (H0: true alpha = 0) (Size-Momentum)

	Loser	2	3	4	Winner
Small	1.09	1.73	**4.10***	**3.99***	**2.74***
2	-1.80	-0.20	**2.65***	**5.63***	**5.97***
3	**-5.03***	-1.17	**4.85***	**6.60***	**5.25***
4	**-2.09***	-0.71	**3.19***	**4.74***	**5.59***
Big	-1.53	0.08	0.56	**2.83***	**5.08***

P-value alpha H0 (Size-Momentum)

	Loser	2	3	4	Winner
Small	27.8%	8.5%	0.0%	0.0%	0.7%
2	7.3%	84.2%	0.9%	0.0%	0.0%
3	0.0%	24.2%	0.0%	0.0%	0.0%
4	3.8%	47.9%	0.2%	0.0%	0.0%
Big	12.6%	94.0%	57.6%	0.5%	0.0%

Alpha t-stat (H0: true alpha = 0) (Size-Profitability)

	Weak	2	3	4	Robust
Small	**2.85***	**2.69***	**2.57***	**2.55***	**2.47***
2	1.20	1.93	**2.64***	**3.48***	1.94
3	**-3.80***	1.54	**4.56***	**4.95***	1.10
4	-0.03	**2.97***	**4.03***	**3.71***	**2.97***
Big	1.11	**3.01***	1.37	**3.72***	**2.42***

P-value alpha H0 (Size-Profitability

	Weak	2	3	4	Robust
Small	0.5%	0.7%	1.1%	1.1%	1.4%
2	23.2%	5.4%	0.9%	0.1%	5.3%
3	0.0%	12.4%	0.0%	0.0%	27.3%
4	97.6%	0.3%	0.0%	0.0%	0.3%
Big	26.8%	0.3%	17.3%	0.0%	1.6%

Alpha t-stat (H0: true alpha = 0) (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	**3.53***	**4.34***	**2.61***	**2.74***	1.92
2	1.32	**3.46***	**3.36***	**2.00***	1.64
3	0.50	**3.70***	**2.14***	**2.65***	-0.30
4	1.94	**3.56***	**3.84***	**3.71***	1.82
Big	**2.57***	1.87	**2.49***	**2.07***	**2.42***

* = significantly different from zero (i.e. model rejection)

P-value alpha H0 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.0%	0.0%	1.0%	0.6%	5.6%
2	18.9%	0.1%	0.1%	4.7%	10.3%
3	61.5%	0.0%	3.3%	0.9%	76.7%
4	5.4%	0.0%	0.0%	0.0%	7.0%
Big	1.1%	6.3%	1.3%	3.9%	1.6%

Six-Factor Model

Alpha estimate in % (Size-Value)

	Growth	2	3	4	Value
Small	3.00	1.48	1.13	0.86	1.09
2	0.92	0.56	0.40	0.32	0.71
3	0.11	0.41	0.45	0.52	0.30
4	0.36	0.52	0.42	0.62	0.43
Big	0.37	0.49	0.68	0.44	0.38

Regression adj R^2 (Size-Value)

	Growth	2	3	4	Value
Small	0.12	0.31	0.42	0.53	0.52
2	0.51	0.49	0.63	0.72	0.68
3	0.55	0.52	0.63	0.63	0.71
4	0.36	0.48	0.43	0.54	0.54
Big	0.48	0.24	0.29	0.48	0.52

Alpha estimate in % (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.97	0.78	0.97	1.03	0.81
2	0.31	0.16	0.36	0.69	0.77
3	-0.53	0.09	0.61	0.77	0.65
4	0.19	0.17	0.40	0.48	0.68
Big	0.77	0.76	0.19	0.18	0.46

Regression adj R^2 (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.53	0.55	0.47	0.44	0.30
2	0.65	0.68	0.62	0.64	0.65
3	0.64	0.63	0.69	0.68	0.50
4	0.45	0.48	0.52	0.57	0.43
Big	0.49	0.39	0.04	0.29	0.39

Alpha estimate in % (Size-Profitability)

	Weak	2	3	4	Robust
Small	1.34	2.20	1.21	1.09	1.02
2	0.41	0.42	0.66	0.81	0.67
3	-0.69	0.42	0.80	1.00	0.46
4	0.12	0.56	0.75	0.68	0.66
Big	0.63	0.59	0.26	0.42	0.50

Regression adj R^2 (Size-Profitability)

	Weak	2	3	4	Robust
Small	0.45	0.20	0.23	0.36	0.22
2	0.60	0.59	0.46	0.53	0.46
3	0.58	0.55	0.47	0.53	0.39
4	0.26	0.47	0.48	0.37	0.26
Big	0.44	0.27	0.08	0.08	0.31

Alpha estimate in % (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	1.23	1.35	1.18	1.11	1.00
2	0.40	0.59	0.50	0.47	0.47
3	0.19	0.48	0.30	0.63	0.03
4	0.49	0.62	0.46	0.61	0.46
Big	0.43	0.39	0.39	0.42	0.50

Regression adj R^2 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.49	0.48	0.31	0.41	0.27
2	0.68	0.64	0.62	0.58	0.52
3	0.58	0.62	0.58	0.53	0.56
4	0.38	0.53	0.59	0.36	0.36
Big	0.28	0.41	0.04	0.11	0.31

Alpha t-stat (H0: true alpha = 0) (Size-Value)

	Growth	2	3	4	Value
Small	**2.90***	**3.56***	**3.51***	**3.58***	**4.26***
2	**3.01***	**2.64***	**2.26***	**2.08***	**3.88***
3	0.51	**2.22***	**2.87***	**3.01***	1.95
4	1.85	**3.24***	**2.53***	**3.54***	**2.16***
Big	**2.72***	**3.00***	**4.23***	**2.62***	**2.14***

P-value alpha H0 (Size-Value)

	Growth	2	3	4	Value
Small	0.4%	0.0%	0.1%	0.0%	0.0%
2	0.3%	0.9%	2.5%	3.8%	0.0%
3	61.0%	2.7%	0.4%	0.3%	5.3%
4	6.5%	0.1%	1.2%	0.0%	3.2%
Big	0.7%	0.3%	0.0%	0.9%	3.3%

Alpha t-stat (H0: true alpha = 0) (Size-Momentum)

	Loser	2	3	4	Winner
Small	**3.18***	**3.11***	**3.74***	**3.34***	1.76
2	1.37	1.00	**2.16***	**4.25***	**3.83***
3	**-2.35***	0.57	**4.37***	**5.24***	**3.08***
4	0.71	0.99	**2.66***	**3.22***	**3.60***
Big	**2.33***	**3.94***	1.06	1.22	**2.38***

P-value alpha H0 (Size-Momentum)

	Loser	2	3	4	Winner
Small	0.2%	0.2%	0.0%	0.1%	7.9%
2	17.0%	32.0%	3.1%	0.0%	0.0%
3	1.9%	56.7%	0.0%	0.0%	0.2%
4	47.9%	32.4%	0.8%	0.1%	0.0%
Big	2.0%	0.0%	29.0%	22.2%	1.8%

Alpha t-stat (H0: true alpha = 0) (Size-Profitability)

	Weak	2	3	4	Robust
Small	**3.13***	**3.44***	**2.55***	**2.79***	**2.54***
2	1.73	**2.06***	**2.82***	**3.54***	**2.79***
3	**-3.01***	**2.29***	**4.30***	**5.83***	1.93
4	0.40	**3.05***	**4.31***	**3.75***	**3.08***
Big	1.61	**2.83***	1.51	**2.86***	**2.29***

P-value alpha H0 (Size-Profitability

	Weak	2	3	4	Robust
Small	0.2%	0.1%	1.1%	0.6%	1.2%
2	8.4%	4.1%	0.5%	0.0%	0.6%
3	0.3%	2.3%	0.0%	0.0%	5.4%
4	69.1%	0.2%	0.0%	0.0%	0.2%
Big	10.8%	0.5%	13.3%	0.5%	2.3%

Alpha t-stat (H0: true alpha = 0) (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	**4.18***	**4.65***	**2.81***	**3.26***	**2.17***
2	**2.13***	**3.48***	**2.90***	**2.44***	**2.14***
3	0.99	**3.00***	1.94	**3.48***	0.14
4	**2.10***	**3.84***	**3.17***	**3.43***	**2.17***
Big	1.90	**2.46***	**2.44***	**2.45***	**2.29***

* = significantly different from zero (i.e. model rejection)

P-value alpha H0 (Size-Investment)

	Conservative	2	3	4	Aggressive
Small	0.0%	0.0%	0.5%	0.1%	3.1%
2	3.4%	0.1%	0.4%	1.5%	3.3%
3	32.2%	0.3%	5.4%	0.1%	89.2%
4	3.6%	0.0%	0.2%	0.1%	3.1%
Big	5.9%	1.4%	1.5%	1.5%	2.3%

Appendix 4 – Factor Trading (Analysis Part 2)

Appendix 4.1 – Correlation Matrix Factor Portfolios

	Market	SMB	HML	WML	RMW	CMA
Market	1					
SMB	-0.46	1				
HML	-0.27	0.16	1			
WML	-0.21	0.01	0.05	1		
RMW	-0.22	-0.21	0.03	0.19	1	
CMA	-0.09	0.01	0.39	0.05	-0.31	1

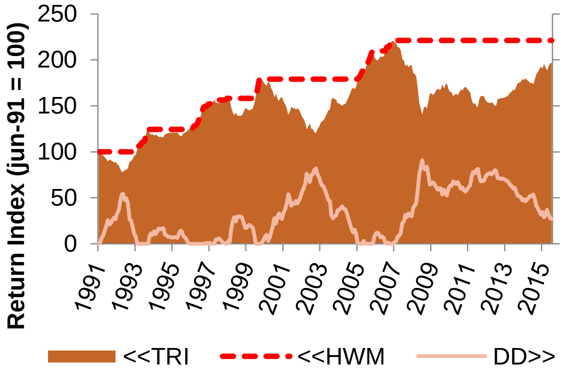
Appendix 4.2 – Static Combo Data

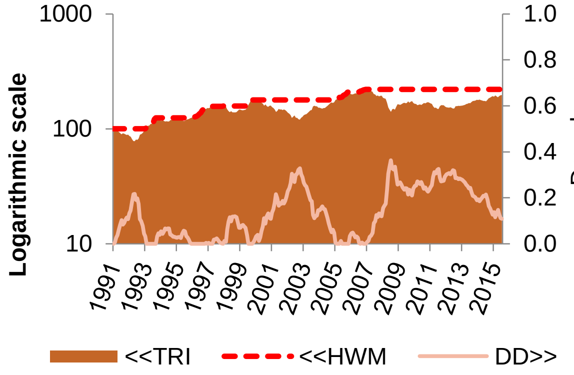
A4.2.1 – Performance Measures (all remaining static combos)

		Mkt-SMB	Mkt-HML	Mkt-RMW	Mkt-CMA	SMB-HML	SMB-WML	SMB-RMW	SMB-CMA	HML-RMW	HML-CMA	WML-RMW	WML-CMA	RMW-CMA
Performance	Expected return (%)	3.15	5.86	7.03	7.88	0.49	8.64	1.60	2.42	4.28	5.11	12.71	13.60	6.27
	Volatility (%)	8.24	9.97	9.82	10.50	10.11	10.65	7.70	8.61	9.82	11.29	11.81	11.03	7.40
	Sharpe ratio (SR)	0.38	0.59	0.72	0.75	0.05	0.81	0.21	0.28	0.44	0.45	1.08	1.23	0.85
	Jensen's alpha (%)	0.18	2.49	3.35	3.77	2.67	10.91	3.53	3.96	5.92	6.35	14.39	14.86	7.24
	Tracking error volatility (%)	5.34	6.09	5.68	5.58	12.72	13.32	9.44	10.16	11.67	12.90	13.93	12.50	8.21
	Information ratio (IR)	0.03	0.41	0.59	0.68	0.21	0.82	0.37	0.39	0.51	0.49	1.03	1.19	0.88
	Max high water mark	221	421	489	593	178	664	175	179	308	344	1,584	1,965	439
	End-2015 return index (TRI)	197	358	470	563	99	664	137	164	248	290	1,584	1,965	415
Risk Mgmt	Market Beta	0.35	0.39	0.42	0.47	-0.26	-0.25	-0.23	-0.18	-0.19	-0.14	-0.18	-0.13	-0.11
	Max drawdown (%)	36.4	36.5	36.9	24.5	57.2	22.7	27.4	39.8	26.5	54.5	29.7	24.1	14.8
	Skewness	-0.02	0.72	-0.20	0.66	-0.00	-0.20	-0.49	0.08	-0.11	0.09	-0.42	-0.19	0.17
	Excess kurtosis	1.5	4.7	1.2	3.6	2.2	2.2	3.9	1.7	4.1	3.6	2.9	3.7	3.1
	95% VaR (%), theoretical	-3.7	-4.3	-4.1	-4.3	-4.8	-4.4	-3.5	-3.9	-4.3	-4.9	-4.6	-4.2	-3.0
	95% VaR (%), sample	-3.6	-4.1	-4.2	-4.0	-4.2	-3.9	-3.1	-3.7	-4.3	-4.3	-4.6	-4.0	-2.3
	Expected shortfall (%), sample	-5.0	-5.5	-6.1	-5.7	-6.6	-6.7	-5.1	-5.5	-6.6	-7.4	-7.7	-6.5	-4.1

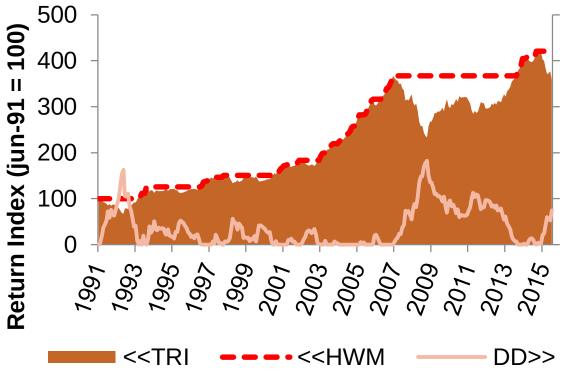
A4.2.2 – TRI, HWM and DD plots (all static combos)

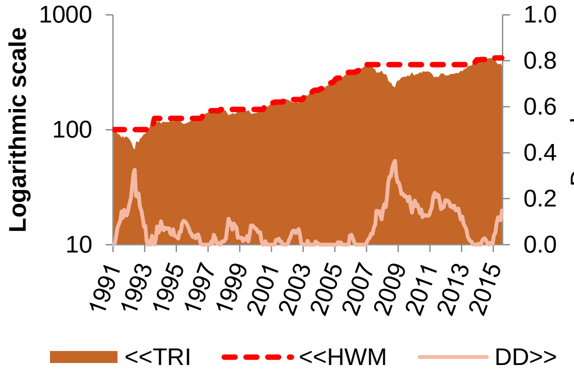
Panel A: Mkt-SMB



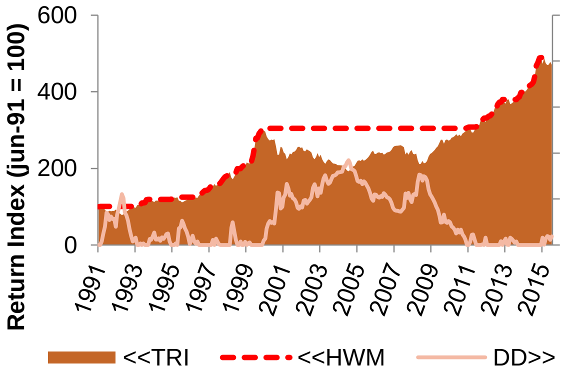


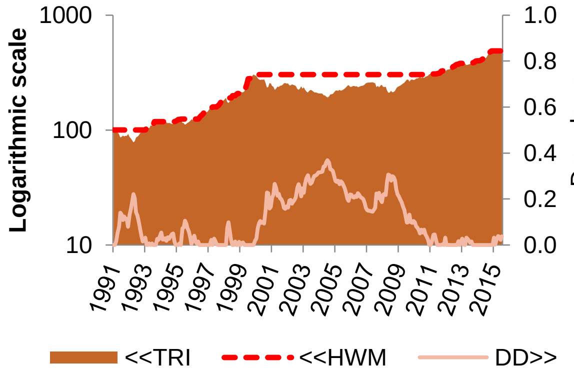
Panel B: Mkt-HML



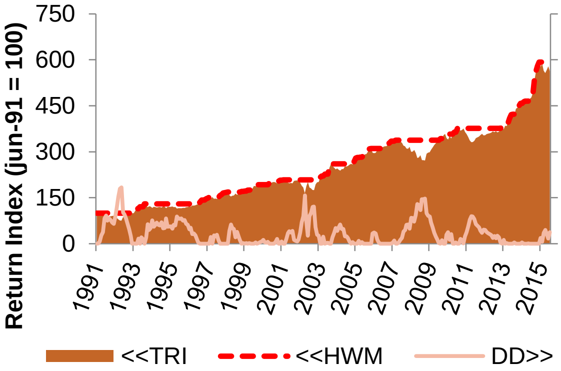


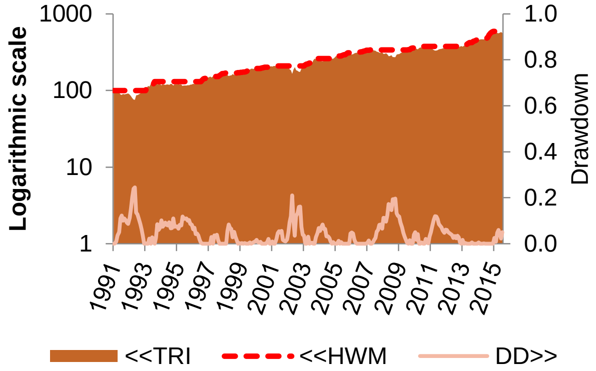
Panel C: Mkt-RMW



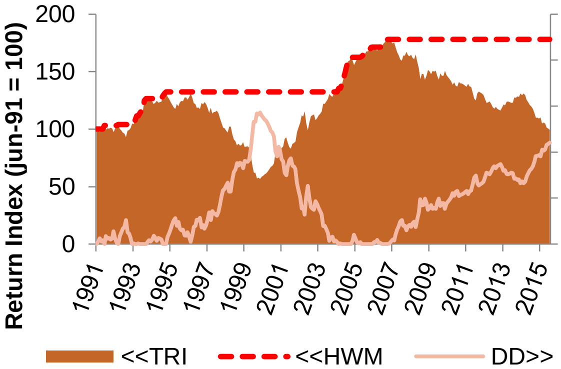


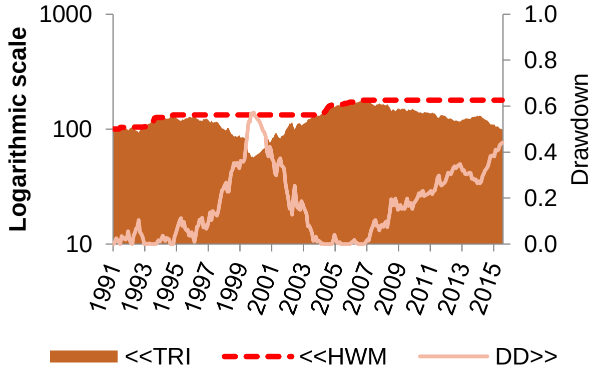
Panel D: Mkt-CMA



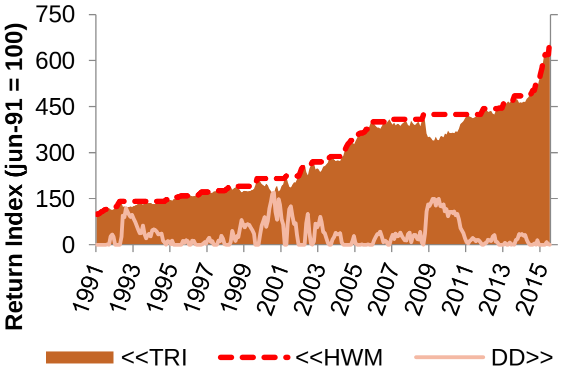


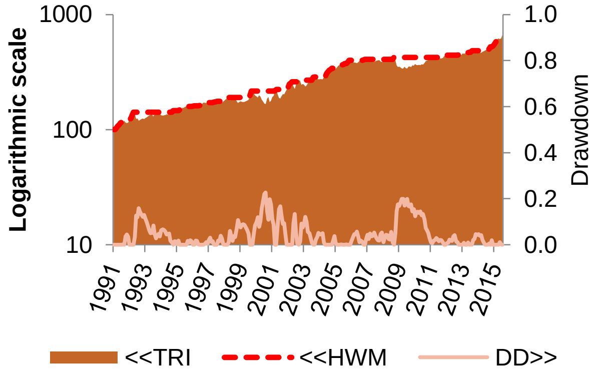
Panel E: SMB-HML



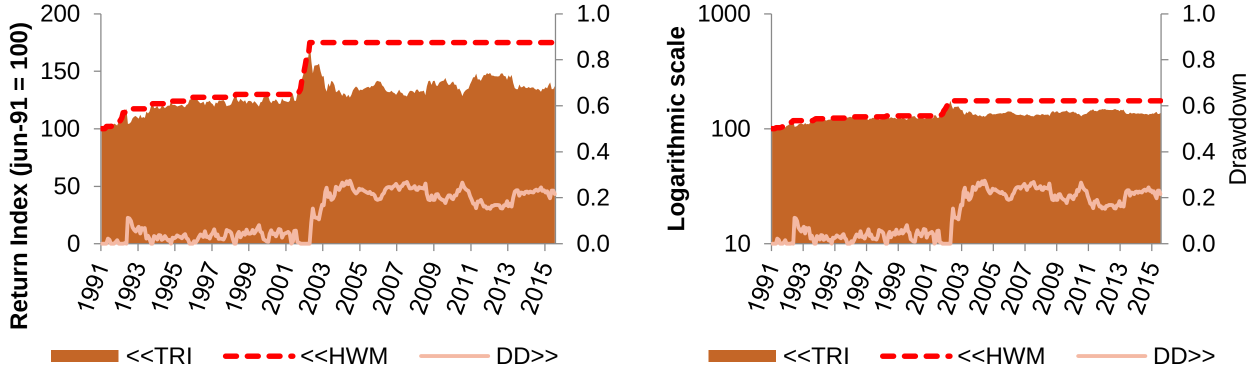


Panel F: SMB-WML

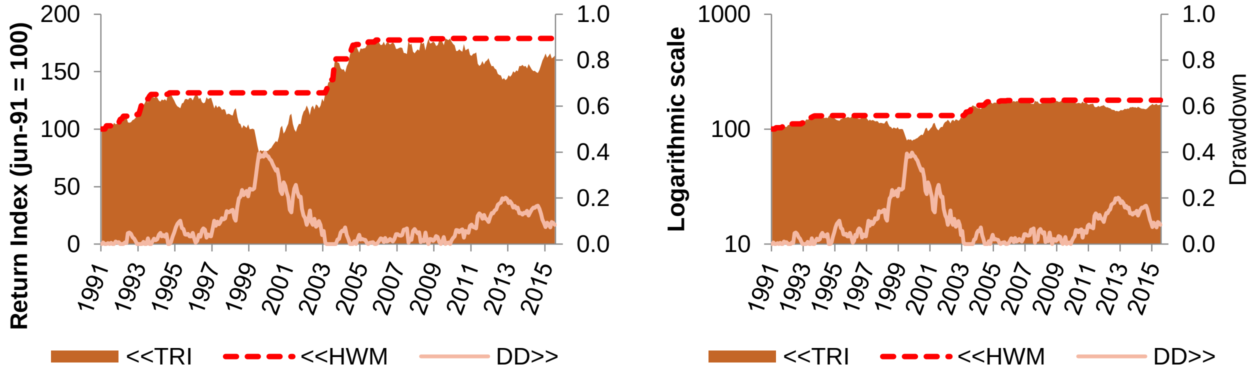




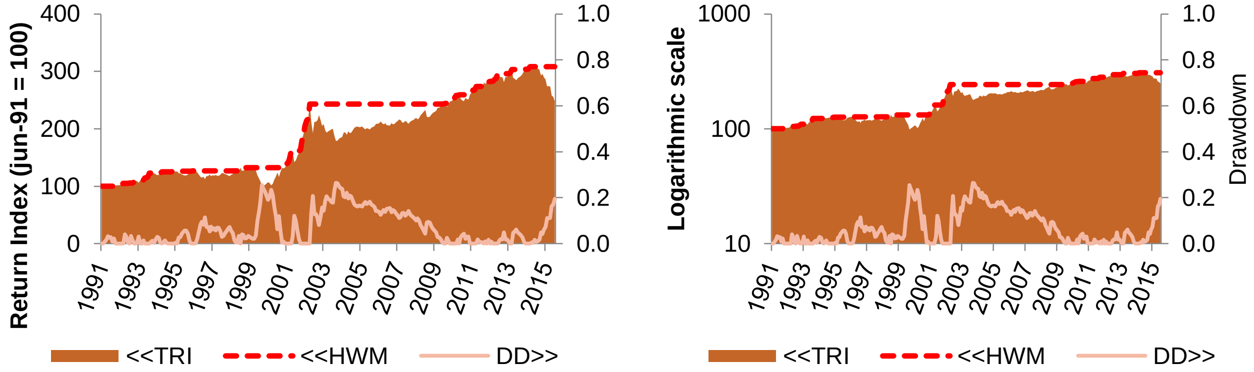
Panel G: SMB-RMW



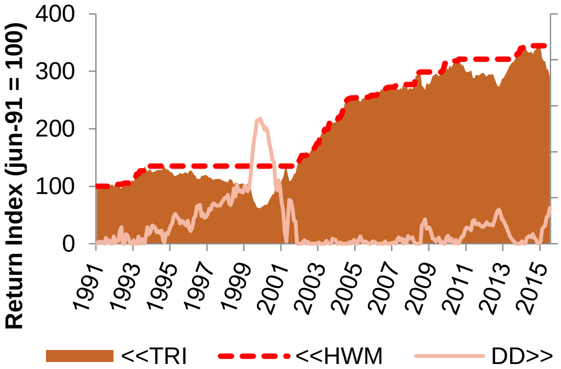
Panel H: SMB-CMA

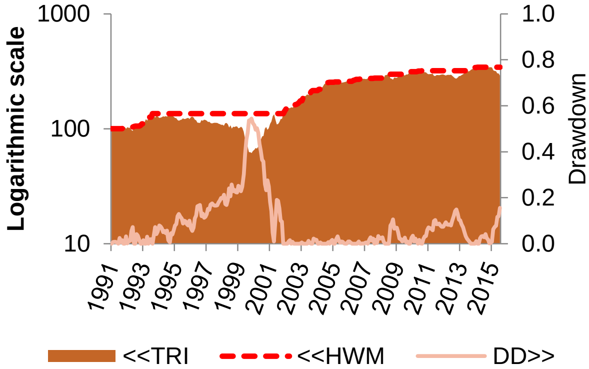


Panel I: HML-RMW

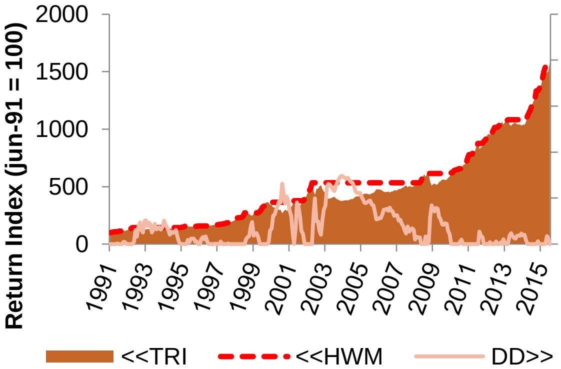


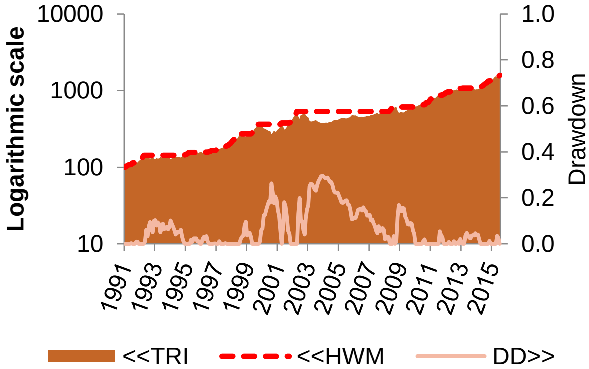
Panel J: HML-CMA



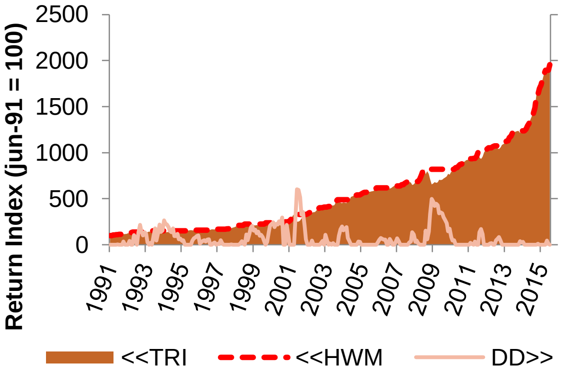


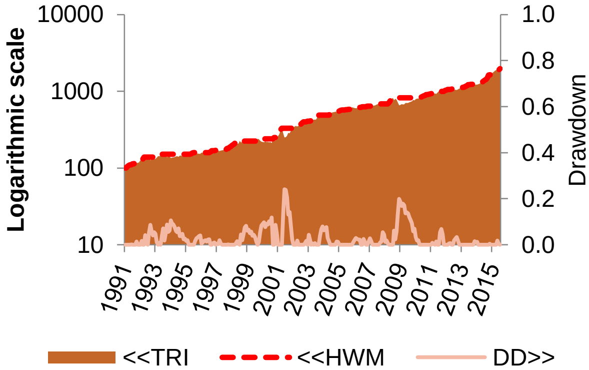
Panel K: WML-RMW



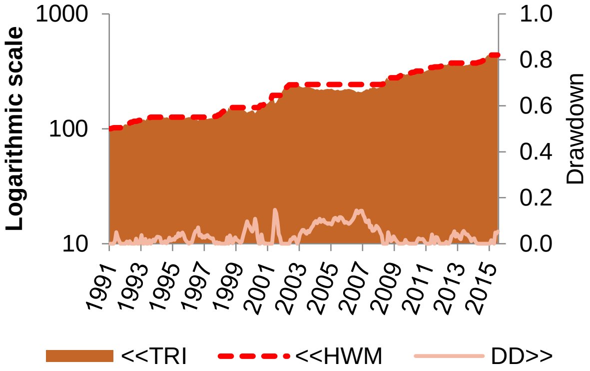


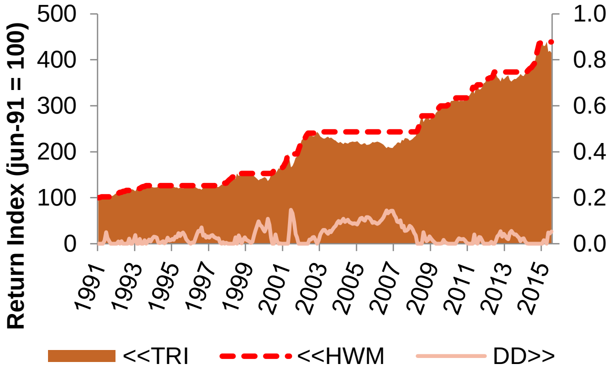
Panel L: WML-CMA





Panel M: RMW-CMA

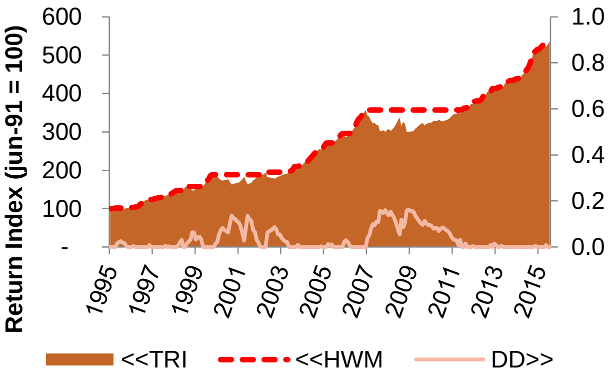


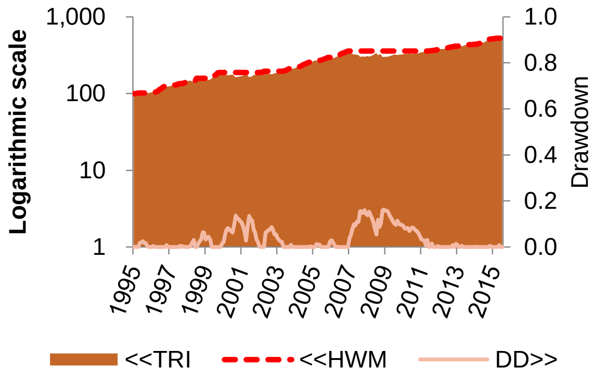


Appendix 4.3 – Dynamic Combo Figures

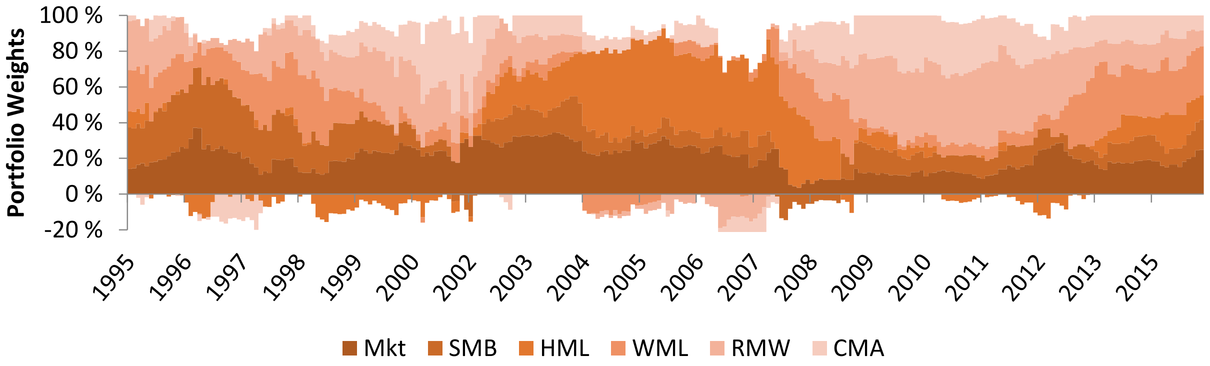
A4.3.1 – TRI, HWM & DD plots, and weighting composition ('MS 4yr' portfolio)

Panel A: TRI, HWM and DD graphs



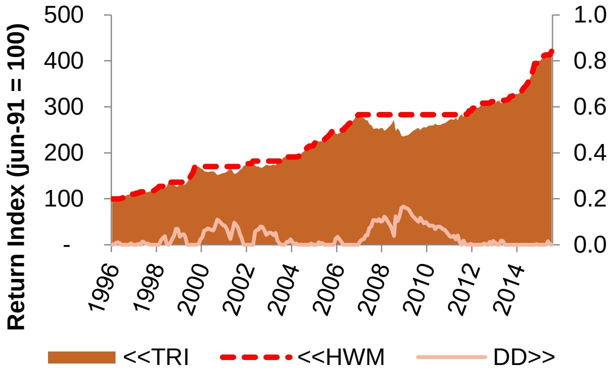


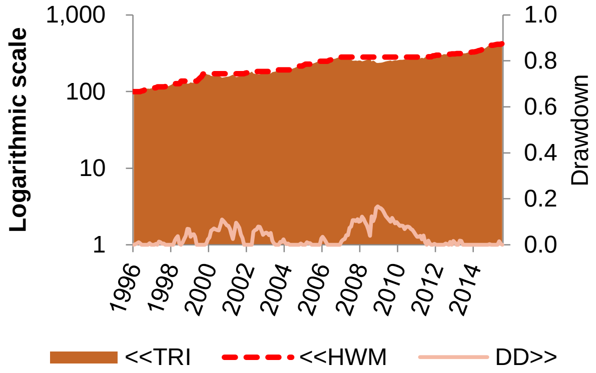
Panel B: Evolution of portfolio composition



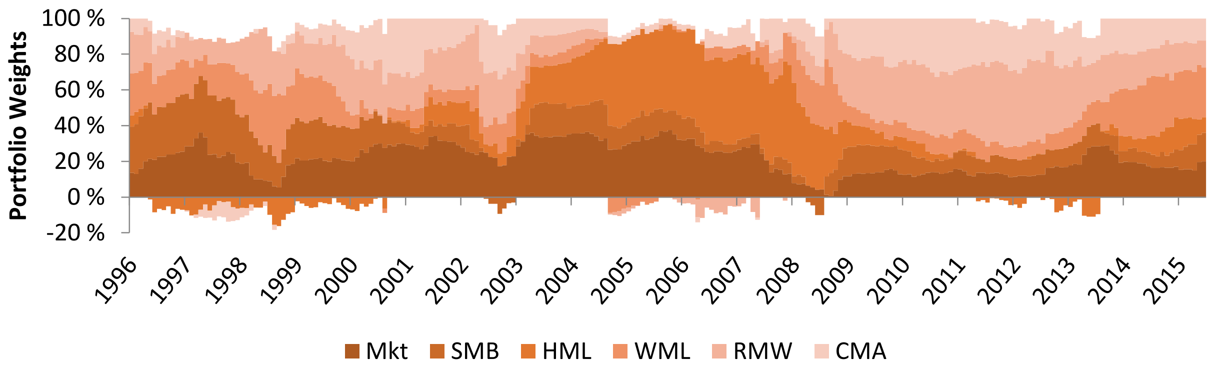
A4.3.2 – TRI, HWM & DD plots, and weighting composition ('MS 5yr' portfolio)

Panel A: TRI, HWM and DD graphs



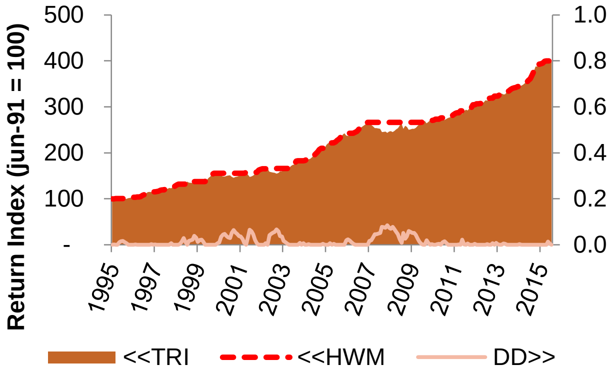


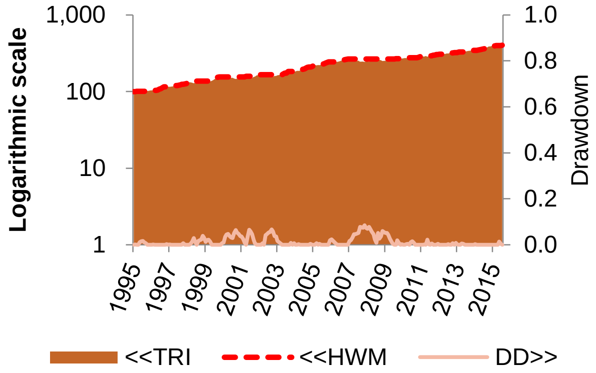
Panel B: Evolution of portfolio composition



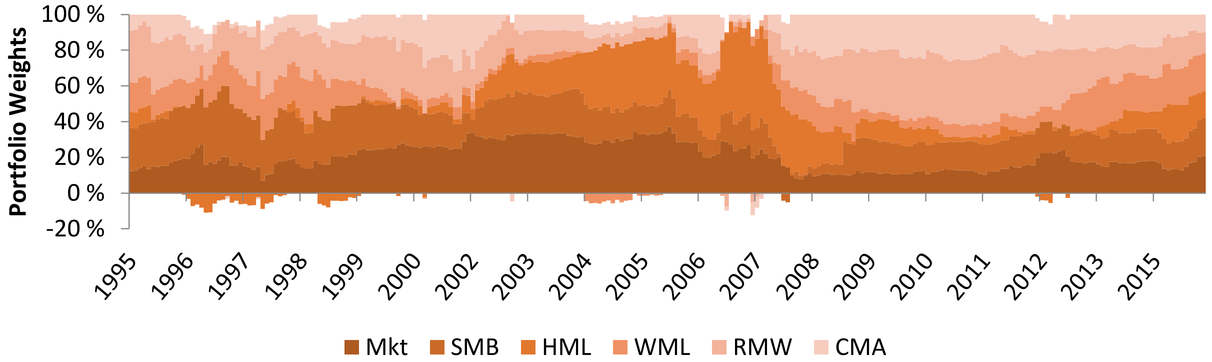
A4.3.3 – TRI, HWM & DD plots, and weighting composition ('V-S 4yr' portfolio)

Panel A: TRI, HWM and DD graphs



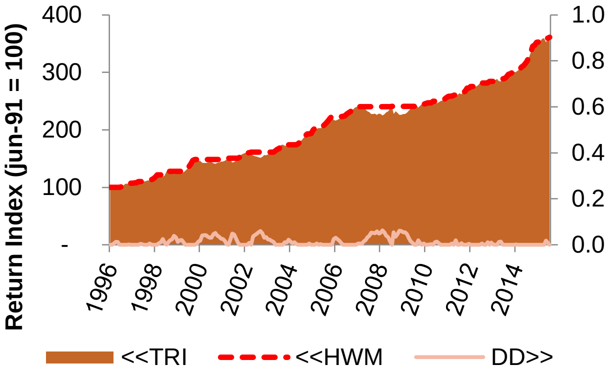


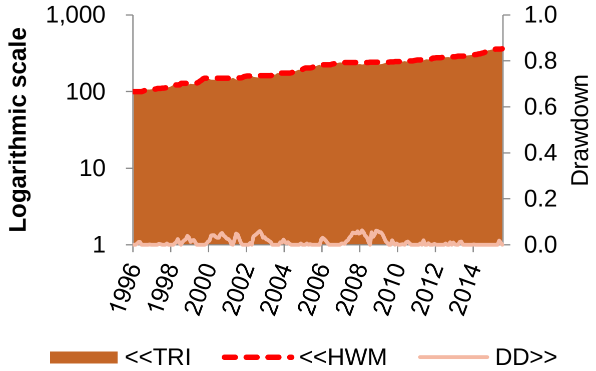
Panel B: Evolution of portfolio composition



A4.3.4 – TRI, HWM & DD plots, and weighting composition ('V-S 5yr' portfolio)

Panel A: TRI, HWM and DD graphs





Panel B: Evolution of portfolio composition