A Comparison of Asset Pricing Models on Nordic Markets

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Abstract:

This paper applies the Fama and French five-factor model to Nordic stock markets, comparing its performance to the Fama and French three-factor model and CAPM. The five-factor model is not found to outperform the three-factor model or CAPM. While the five-factor model performs well in GRS tests, the model exhibits high values of average absolute alpha as compared to the three-factor model, suggesting that the three-factor model may be more reliable for analysis on Nordic stock markets. Furthermore, the size-factor, value-factor and profitability factor are found to be redundant for describing average returns in the sample. The paper concludes that the five-factor model is not well-suited for analysis on the Nordic stock markets.

Keywords:

Asset pricing model, five-factor model, three-factor model, market-premium, size-premium

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1 Introduction

Reducing “alpha”, the intercept from regressions of asset returns on a selection of factors, is an objective of many investors. In many asset pricing models, alpha represents an estimate of the idiosyncratic risk of an asset, and pricing models are frequently judged on the basis of how much variation in returns is left unaccounted for by estimation error and explanatory variables. As such, there is a plethora of asset pricing models attempting to explain the cross-section of returns. However, much of the literature focuses on US stock markets, and should there be discrepancies in the performance of asset pricing models on different markets, then investors who are not primarily exposed to US stocks may be disadvantaged. This study compares the performance of three popular and prominent asset pricing models on Nordic markets by creating factors from a sample of Nordic stocks and conducting Gibbons, Ross and Shanken (GRS) (1989) tests.

One of the seminal contributions to the asset pricing literature was made by Sharpe (1964), Lintner (1965) and Mossin (1966) who developed the Capital Asset Pricing Model (CAPM). CAPM relates the returns of an asset in excess of the risk-free rate, to the returns of a market-portfolio, where beta, the exposure to the market portfolio, explains variation in stock returns. CAPM was an early iteration of an approach to asset pricing which is still widely taken - namely to regress asset returns on a selection of factors, and to analyse the values of alpha in order to judge the performance of the model in explaining the cross-section of average returns.

Since the advent of CAPM, studies have tested and expanded on its core tenets, introducing multiple factors to explain returns on assets. Fama and French (1993) developed a three-factor model, arguing that the addition of size (market cap) and value (book-to-market ratio) as factors improves on CAPM, better explaining returns. Subsequent studies confirm that the three-factor model performs well in explaining the cross-section of stock returns, such as Fama and French (1996, 1998) and Liew and Vassalou (2000).

However, recent studies have suggested that additional factors to size and value may exhibit strong relationships with stock returns. Novy-Marx (2013) found that a proxy for expected profitability co-moves with average returns, and Aharoni et al (2013) identify a relationship between investment and average returns. In response to these revelations, Fama and French (2015) present an expanded model to explain average returns, the five-factor model, adding profitability and investment as factors in the three-factor model.

Fama and French (2015) found that the five-factor model better explains a cross-section of stock-returns than CAPM or the three-factor model. Fama and French (2017) confirm this finding in international tests.

The purpose of this study is to assess the findings in Fama and French (2015) on out-of-sample data on Nordic equities, and to compare the performance of the five-factor model to that of the Fama and French (1993) three-factor model and CAPM. In doing so, the study investigates whether market-premium, size, value, profitability and investment explains average returns on Nordic markets, and whether these factors perform better than the three-factor model using market-premium, size, and value, and CAPM using only market-premium as the explanatory variable. This study contributes to the existing literature through applying three prevalent asset pricing models to new data, the Nordic markets, evaluating both their isolated and relative performance.

The following hypotheses are tested in this study:

H1: When applied to the Nordic markets, the Fama French (2015) five-factor model explains average portfolio returns.

H2: When applied to the Nordic markets, the Fama French five-factor model performs better in explaining average portfolio returns than;

H2A: The Fama French three-factor model

H2B: The CAPM model

H3: When applied to the Nordic markets, the HML factor in the Fama French five-factor model is not made redundant by other factors in the model.

The hypotheses are tested using the same methodology as Fama and French (2015). Sample specific factors and test portfolios are constructed for the three tested models in the same way as presented in Fama and French (2015). In order to test the first hypothesis, GRS tests are conducted to test whether the alpha values for regressions of test portfolio returns on the models are indistinguishable from zero. The second hypothesis is then tested through comparing the results from the GRS tests, particularly focusing on the average absolute values of alpha, and the frequency with which their t-statistics exhibit significance on a 5% level. Finally, H3 is tested through analysing multiple regressions of each of the five factors on the other four factors, and through comparing GRS results between the five-factor model and a four-factor model which excludes HML.

The study rejects the first hypothesis, that the five-factor model explains average stock returns on the Nordic markets, on a 5% significance level. Furthermore, the study rejects both H2A and H2B. The five-factor model is found to perform better than CAPM with respect to GRS statistics and the number of alpha values significantly different from zero, but does not exhibit lower average absolute alpha values in all three sets of portfolio regressions. The five-factor model does not produce lower GRS-statistics than the three-factor model in all tests, and the three-factor model produces, on average, lower absolute alpha values than the five factor model. Furthermore, the three-factor model exhibits fewer significant alpha values than both the five-factor model and CAPM. Finally, the third hypothesis is rejected, due to the fact that HML exhibits insignificant alpha values in the factor regressions. However, the conclusions that can be drawn from the third test are somewhat ambiguous due to results from the GRS tests.

1.3 Sequence

Section 2 contains a review of relevant literature, and outlines their findings and the application of relevant models. Section 3 presents the theoretical framework. Section 4 comprises an overview of the process of data collection and filtering. Section 5 describes the methodology used to test the performance of CAPM, the three-factor model, and the five-factor model on Nordic markets. The choice of variables is explained as well as the process of factor and portfolio construction.

Section 6 first presents results and summary statistics for the factors and regression portfolios, and discusses their implications for the five-factor models' performance on Nordic markets. Second, this section conducts GRS-tests on CAPM, the three-factor model, a four-factor model which excludes HML, and the five-factor model. Third, section 6 presents factor regressions which test whether each factor's returns can be explained by the other factors, and tests H3. Finally, section 6 presents statistics for alpha values for 48 regressions. Section 7 discusses the results of the study. Section 8 concludes the study.

2 Previous Research

Research by Sharpe (1964), Lintner (1965) and Mossin (1966) contributed to the development of the first major equilibrium asset pricing model, known as the Capital Asset Pricing Model (CAPM). CAPM relates the expected return of an asset to the risk-free rate, and the exposure of the asset to the market (the market-risk premium). The model's simplicity allows for the easy comparison of different investment alternatives, which is partly why it remains in wide use today. However, a number of anomalies have been found in the model since its conception and adoption. The major issue was that the CAPM left some variation in returns to be explained, leading to the development of more complex models implementing a variety of explanatory variables in addition to the market premium.

One of the first notable critiques of CAPM was delivered by Banz (1981) who found that there was a significant relationship between the size risk of assets, and expected returns, contradicting CAPM, which uses market risk as the only explanatory value. He found that small stocks exhibited higher returns than could be explained solely by market risk, and that asset size explained more cross-sectional variation in returns than beta. Fama and French (1993) conducted a similar study, adding value (book value of equity divided by market value) as an explanatory variable. In all of their tests, they found that the market beta in CAPM was not significantly different from zero, stating that the relationship between beta and average return diminished in the period 1963-1990, and that value explained more cross-sectional variation in average returns than the size factor.

This rejection of CAPM moved Fama and French (1993) to suggest a new model for predicting average returns, a three-factor model which regresses excess returns on the market-premium, asset size, and asset value. Through conducting GRS-tests (explained at greater length in section 5.3), Fama and French concluded that the three-factor model outperformed CAPM, but also left some return variation to be explained.

Hence, the 3-factor model has also been expanded upon in attempts to explain remaining anomalies. Aharoni et al (2013) find that investment, measured as the growth in total assets, B/M value and profitability, all have significant relationships with average returns. Novy-Marx (2013) find that profitability, measured as gross profit-to-asset ratios, correlates significantly with average returns, and holds the same explanatory power as the B/M-ratio. Fama and French (2015) expand their model in response to the findings in Aharoni et al (2013) and Novy-Marx (2013), adding proxies for profitability and investment to the three-factor model. Fama and French use a GRS-test to test their model, and reject the hypothesis that the five-factor model explains variation in expected returns. However, an analysis of absolute alpha values and GRS-test statistics leads them to conclude that the five-factor model outperforms the three-factor model. These findings are confirmed in international tests in Fama and French (2017), conducted on North American, European, Japanese and Pacific markets.

3 Theoretical Framework

In order to better understand the mathematical intuition of the asset pricing models tested in this study, this section describes the valuation model, which Fama and French (2015) use to derive their five-factor model. Furthermore, this section presents the regression equations for the three tested models.

3.1 The Valuation Model

The main reason for the addition of proxies for profitability and investment as factors in the five-factor model proposed by Fama and French (2015), is provided in the authors' derivation of a dividend discount model that illustrates how changes to the terms in the model affect average expected long term portfolio returns.

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

In equation (1), M_t denotes the market capitalization, B_t the book value of equity, r the long-term average expected stock return, $Y_{t+\tau}$ the total equity earning for period $t + \tau$, $dB_{t+\tau}$ the change in total book equity, and $E(Y_{t+\tau} - dB_{t+\tau})$ the expected dividend per share for period $t + \tau$.

If M_t decreases, B_t/M_t effectively increases. Holding all else constant, r must increase in order for the equation to balance. This implies that value stocks (stocks with high B_t/M_t-ratios) are associated with higher expected long-term returns than growth stocks (stocks with low B_t/M_t). Likewise, if $Y_{t+\tau}$ increases and all else is held constant, r must increase for the equation to balance. On this basis, stocks with higher equity earnings are also associated with higher expected long-term returns. Finally, in the event of asset growth, represented in the model as a positive change in $dB_{t+\tau}$, r must decrease if all else is held constant. In this case, Fama and French (2015) argue that stocks with lower asset growth are associated with lower expected long-term returns than those with higher asset growth.

To summarize, the valuation model relates differences in expected long-term return to changes in the model's variables. Building on this model, portfolios can be formed and used as risk-factors in asset pricing models, as is done in the Fama French five-factor model (and the Fama French three-factor model).

3.2 CAPM and Fama French Models

The three models that are compared in this study are the Capital Asset Pricing Model (CAPM), the Fama French 3-factor model, and the Fama French 5-factor model. CAPM relates average returns to the market premium. The 3-factor model adds size and value risk as factors. The 5-factor model further adds investment and operating profitability as factors.

The models are defined as follows;

CAPM: $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + e_{it}$ (2)

where R_{it} is defined as as the portfolio return, R_{Ft} the risk free return, a_i the intercept, b_i the portfolio beta, R_{Mt} the market return, and e_{it} the error term;

FF-3F: $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it}$ (3)

where SMB_t is the return of a portfolio with long exposure to small stocks and short exposure to big stocks, and HML_t the return of a portfolio with long exposure to high B/M stocks and short exposure to a portfolio of low B/M stocks;

FF-5F: $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$ (4)

where RMW_t is the return of a portfolio with long exposure to robust profitability stocks and short exposure to weak profitability stocks, and CMA_t the return of a portfolio with long exposure to conservative investment stocks and short exposure to aggressive investment stocks.

4 Data

4.1 Data Collection

All data is downloaded from the TDS database. The time-frame of the study ranges from July 1999 until June 2019 to match available data for the MSCI Nordic Countries Index (MSCINCI), the benchmark index. The downloaded MSCINCI is a value-weighted index with return data on the Swedish, Norwegian, Danish and Finnish stock markets. Data on all equities listed on the major stock exchanges in these countries is retrieved from 1997/12/31 until 2019/06/30. The data is downloaded starting December 1997 in order to compute lagging variables as factor construction inputs. The data sample consists of monthly data on stock prices and returns adjusted for dividends and yearly data on total assets, total liabilities, common shares outstanding, and operating profit, where operating profit is defined as the difference between sales and total operating expenses.

Moreover, only equities listed in the respective country's currencies are downloaded. The monthly exchange rates between the respective domestic currencies and euros is also downloaded for each country (the exchange rate is later used to convert all prices to euros, except for the Finnish stocks whose prices are already denominated in euros). Finally, the Swedish one-month treasury bill is downloaded for the sample period.

A total of 5,488 equities are retrieved, where 2,994 were Swedish, 1,150 Norwegian, 826 Danish, and 518 Finnish.

4.2 Data Filtering

Some of the stock data contain errors or missing values. Several stocks' data have not been updated since 1997-12-31 or earlier. Through sorting on the "DATE/TIME"-variable (a static variable retrieved from TDS), these stocks are deleted. Stocks with no accounting or pricing data are also removed. Furthermore, some stocks have static data for the entire period. These are removed accordingly. These three filters removed 2,979 equities. Other stocks lack data for a specific time period (as a consequence of either having become listed or delisted during the sample period). In these cases, only the available time period is considered.

Sorting the sample by ticker symbol and name, several companies are found to have multiple share classes listed. In order to avoid duplicates and overlapping data, these are filtered so that the share class with the most data is kept and the other one removed. This step removed an additional 319 equities from the sample.

As in Fama and French (1993), stocks with less than 24 months of consecutive pricing data are removed. This filter removes an additional 289 stocks.

After the filtering process, the total amount of equites is reduced to 1,908, where 902 are Swedish, 472 Norwegian, 308 Danish, and 226 Finnish.

4.3 Limitations

This study analyses size, book-to-market ratio, profitability and investment and their relationship to stock returns. The data used in the study comes from Thomson Data Stream (TDS). The raw sample contains all available stock data for the relevant countries. However, because the chosen benchmark index is not available before 1999, the study's timeframe is July 1999 until June 2019. Companies included in the sample are equities, and must have data for price, return, total assets, total liabilities, operating income and shares outstanding. The study focuses on the four largest Nordic countries, Sweden, Norway, Denmark and Finland. Only companies listed on the four countries' respective main markets (Nasdaq Stockholm, Oslo Børs, Nasdaq Copenhagen, Nasdaq Helsinki) are included in the sample.

5 Method

5.1 Fama French Factor Construction

The factors used in this study are constructed in the same way as in Fama and French (2015), but relies on 2x3 sorts for factor construction, rather than exploring alternative sorting methods. This is because Fama and French found no notable differences in performance based on the choice of construction method. Furthermore, 2x3 sorts are the most common method in creating Fama and French factors.

5.1.1 Variables

The following variables are used to construct the five Fama French factors:

Market Capitalization (Market cap): Market value of equity at a specific date, calculated by multiplying common shares outstanding with the share price;

Book equity: Yearly total assets minus yearly total liabilities;

Book-to-Market Ratio (B/M): Calculated by dividing book equity by the year-end market cap;

Operating profitability: Calculated by dividing operating income by book equity. Operating income is defined as the difference between sales and total operating expense;

Investment: Defined as the difference between total assets at time *t-1* and total assets at *t-2* divided by total assets at *t-2*. Investment is used as a measure of how much of the company's earnings are reinvested into the company, as opposed to being paid out as dividends;

$$Investment = \frac{Total\ Assets_{t-1} - Total\ Assets_{t-2}}{Total\ Assets_{t-2}} \qquad (4)$$

Market premium: The arithmetic returns for each stock's total return index (RI).

The Swedish one-month treasury bill is used as a proxy for the risk-free rate due to the fact that Sweden has, by far, the most stocks in the data sample.

5.1.2 Portfolio Sorting

After filtering the data and converting prices to euros, sorted portfolios are created, using accounting data starting at 1997-12-31, since the investment variable uses data lagging two years. Portfolios are sorted at the end of June of each year, to ascertain that the accounting data from the previous year would have been available to investors at the time of sorting, as is done in Fama and French (2015). Since portfolios are sorted at the end of each June, the first available return observation is at the end of July 1999, and the final return observation is at the end of June 2019, making the de-facto time period for the analysis 20 years.

The process of creating 2x3 sorts starts with defining the yearly break-points for size (market cap), value (B/M ratio), profitability (operating income divided by book equity) and investment (the previous year's percent change in total assets). The market cap median for the yearly sample is used as the breakpoint for size, as in Fama and French (2015). For value, profitability and investment, the 30th and 70th percentiles from the sample are used as breakpoints.

The intersections of the yearly breakpoints are used to independently sort stocks into six size-B/M portfolios, six Size-OP portfolios and six Size-Inv portfolios. Having done this, the portfolios are value-weighted (VW) by market cap, and monthly returns are calculated for each of the 48 portfolios. When the portfolio returns have been calculated, the factors can be constructed.

Each factor portfolio is annotated with two letters, the first representing the size, big or small (B or S), and the second representing the B/M ratio, OP, or Inv. For B/M ratios, H represents high ratios and L represents low ratios. For OP, R represents robust profitability and W represents weak profitability. For Inv, C represents conservative (low) investment and A represents aggressive investment.

HML is created by subtracting the two portfolios with low B/M-ratios, SL and BL, from the two portfolios with high B/M-ratios, SH and BH. RMW is created by subtracting the two portfolios with weak profitability, SW and BW, from the portfolios with robust (high) profitability (SR and BR). CMA is created by subtracting the two portfolios with aggressive investment figures, SA and BA, from the portfolios with conservative investment figures, SC and BC. The neutral portfolios (the middle 40% between the 30th and 70th percentile) are excluded in the construction of HML, RMW, and CMA as per Fama and French (2015).

The Size factor, SMB, is calculated by taking the mean of the 2x3 sorts. The big portfolio returns in the Size-B/M sort are subtracted from the small portfolio returns. The same is done for the Size-OP and Size-Inv portfolios. The mean of the three size factors is then taken to construct SMB. Table 1 presents the breakpoints and the calculations for the factor creation process.

Table 1: Portfolio Sorting
2x3 portfolio sorts where the market cap median is used as a breakpoint for size, and the 30th and 70th percentiles are used as breakpoints for value, profitability and investment. Each factor portfolio is annotated with two letters, the first representing the size, big or small (B or S), and the second representing the B/M ratio, OP, or Inv. H represents high value, L represents low value, R represents robust profitability, W represents Weak profitability, C represents conservative (low) investment, and A represents aggressive (high) investment. N stands for "neutral", interval between 30th and 70th percentiles.

			B/M	
		High	Neutral	Low
Size	Big	BH	BN	BL
	Small	SH	SN	SL
			OP	
		Robust	Neutral	Weak
Size	Big	BR	BN	BW
	Small	SR	SN	SW
			Inv	
		Conservative	Neutral	Aggressive
Size	Big	BC	BN	BA
	Small	SC	SN	SA

Table 2: Construction of Factors
Construction of Size, B/M, profitability, and investment factors. Using independent sorts, stocks are assigned to two Size groups, and three B/M, operating profitability (OP) and investment groups. The intersection of the groups represents the VW portfolios used to create the risk factors. The portfolios are labelled with two letters. The first letter denotes size, small or big, and the second letter denotes either B/M, OP, or Inv, in accordance with the description in table 1.

Breakpoints	Factors and their components
Size: Sample median	$SMB_{B/M} = (SH + SN + SL)/3 - (BH + BN + BL)/3$
	$SMB_{OP} = (SR + SN + SW)/3 - (BR + BN + BW)/3$
	$SMB_{Inv} = (SC + SN + SA)/3 - (BC + BN + BA)/3$
	$SMB = (SMB_{B/M} + SMB_{OP} + SMB_{Inv})/3$
B/M: 30th and 70th percentiles	$HML = (SH + BH)/2 - (SL + BL)/2$
OP: 30th and 70th percentiles	$RMW = (SR + BR)/2 - (SW + BW)/2$
Inv: 30th and 70th percentiles	$CMA = (SC + BC)/2 - (SA + BA)/2$

5.1.3 Regression Portfolios

In order to test the performance of CAPM as well as the three-factor and five-factor models, 48 VW Left-hand-side (LHS) regression portfolios are constructed from the sample data, and regressed on the factors. The regression portfolios are created in much the same way as in Fama and French (2015) with the exception that Fama and French construct Size-B/M, Size-OP and Size-Inv regression portfolios using 5x5 sorts, whereas this study uses 4x4 sorts to maintain a sufficient level of diversification in the portfolios, since the data sample used in this study is smaller than that used in Fama and French (2015).

Whereas the factor components relied on 2x3 sorts to create portfolios from the intersections of the breakpoints, the regression portfolios use independent 4x4 sorts, arranging stocks into sixteen Size-B/M, Size-OP, and Size-Inv groups. Thus, 25th percentile, median, and 75th percentile breakpoints are used for all four variables, sorting stocks into groups ranging from one to four, creating a total of 48 regression portfolios.

Monthly returns for the regression portfolios are calculated in the same way as the returns for the factor components, and the stocks are sorted into Size-B/M, Size-OP and Size-Inv portfolios. The created portfolios are denoted in the same way as in the factor creation process, but use s1, s2, s3 and s4 instead of B and S, to signify the Size group, so that s1 corresponds to the smallest quartile, and s4 represents the highest quartile. The same is true of B/M ratio (v1, v2, v3, v4), OP (p1, p2, p3, p4) and Inv (i1, i2, i3, i4), where i1 represents the lowest (most conservative) investment level, and i4 represents the highest (most aggressive) investment level.

Table 3: Construction of 48 Regression Portfolios
Construction of 16 Size-B/M portfolios, 16 Size-OP portfolios, and 16 Size-Inv portfolios. Using independent sorts, stocks are assigned to four Size, B/M, Operating profitability (OP), and Investment groups. The intersection of the Size groups with the other three allows for the construction of 48 regression portfolios.

		B/M			
		High	3	2	Low
Size	Big	s4v4	s4v3	s4v2	s4v1
	3	s3v4	s3v3	s3v2	s3v1
	2	s2v4	s2v3	s2v2	s2v1
	Small	s1v4	s1v3	s1v2	s1v1

		Operating Profit			
		Robust	3	2	Weak
Size	Big	s4p4	s4p3	s4p2	s4p1
	3	s3p4	s3p3	s3p2	s3p1
	2	s2p4	s2p3	s2p2	s2p1
	Small	s1p4	s1p3	s1p2	s1p1

		Investment			
		Aggressive	3	2	Conservative
Size	Big	s4i4	s4i3	s4i2	s4i1
	3	s3i4	s3i3	s3i2	s3i1
	2	s2i4	s2i3	s2i2	s2i1
	Small	s1i4	s1i3	s1i2	s1i1

5.2 Hypothesis Testing

H1 is tested using a GRS-test at the 5% significance level, as is done in Fama and French (2015).

H2A and H2B are tested through comparison of three different parameters, which feature heavily in the Fama and French (2015) evaluation of model performance. GRS statistics are generated and compared for three sets of regression portfolios and the three tested models (the five-factor model, three-factor model and CAPM). Furthermore, the average absolute values of alpha for the three tested models are generated for regressions of all 48 regression portfolios. Finally, the number of t-statistics of alpha which are significant at the 5% level are counted for the regressions of 48 regression portfolios on each of the three tested models. In order for H2A and H2B not to be rejected, the 5-factor model must exhibit lower GRS statistics than the three-factor model and CAPM, respectively, for each of the three sets of regressions (16 Size-B/M, Size-OP, and Size-Inv portfolios). In addition to this, the five-factor model must exhibit a lower average absolute value of alpha than the three-factor model and CAPM, respectively. Finally, the five-factor model must also exhibit a lower total number of alpha values significantly different from zero at the 5% significance level.

H3 is tested using the same methodology as Fama and French (2015). Factor regressions are run for each of the five Fama and French (2015) factors, and the alpha value and its level of significance is analyzed. In order for H3 to be rejected, HML must exhibit an insignificant alpha value on the 5% level.

5.3 GRS Test

First presented by Gibbons, Ross, and Shanken (1989), the GRS statistic aims at testing the mean variance efficiency between an LHS set of assets and a RHS set of assets.

The GRS test statistic is constructed as follows:

$$\left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \sim F(N, T-N-L) \qquad (5)$$

where $\hat{\propto}$ is an Nx1 vector of estimated alphas, $\hat{\sum}$ is an unbiased estimate of the residual covariance matrix, $\bar{\mu}$ is an Lx1 vector of the regression portfolios' sample means, $\hat{\Omega}$ is an unbiased estimate of the regression portfolios' covariance matrix. If $\propto_i = 0\ \forall_i$ then the GRS statistic is equal to zero. The higher the value of $|\propto_i|$, the greater the GRS statistic.

6 Results

6.1 Average excess returns for regression portfolios

Table 4: Average returns for 48 Regression Portfolios
Average monthly percent returns for 16 Size-B/M portfolios, 16 Size-OP portfolios, and 16 Size-Inv portfolios between July 1999-June 2019, 240 months. The numbers are a scale from one through four representing the lowest S, V, P, and I groups (1) and the highest (4). See **Table 3** for a full description of the sorting.

	Low	2	3	High
	Panel A: Size-B/M portfolios			
Small	0.69	0.61	1.00	1.02
2	0.77	0.44	0.49	0.81
3	0.34	0.67	0.79	0.58
Big	0.43	0.75	0.86	1.03
	Panel B: Size-OP portfolios			
Small	0.71	0.70	1.16	1.09
2	0.25	0.50	0.97	1.00
3	- 0.56	0.44	0.89	0.95
Big	1.00	0.67	0.49	0.62
	Panel C: Size-Inv portfolios			
Small	1.24	0.88	1.72	0.42
2	0.77	0.76	0.50	0.13
3	0.82	1.00	0.54	0.06
Big	1.09	0.63	0.34	0.47

Table 4 displays three panels with monthly excess returns for 16 VW portfolios. In most cases, small and big companies (size 1 and 4) seem to produce higher returns than medium sized companies (size 2 and 3). This somewhat contradicts the findings by Fama and French (2015), where smaller companies tend to outperform bigger ones.

Analyzing Panel A, no consistent pattern can be identified for the B/M factor. S1v1 and s2v1, for instance, exhibit higher average returns than s1v2 and s2v2. Furthermore, s3v3 is seen produce higher returns than s3v4. However, focusing on the two extremes (Low B/M and High B/M), there is a clear tendency for assets with a high B/M ratio to outperform assets with low B/M. Moreover, the assets on the second-highest B/M level (3) always outperform the level 2 B/M assets.

In Panel B, as in panel A, no pattern can be observed that is equally concistent to that in Fama and French (2015) for corresponding portfolios. There is, however, a tendency for companies with a high OP-ratio to outperform those with a low OP. The exception is the big companies (s4), where there appears to be a negative relationship between OP and returns, an observation which is antithetical to that found in Fama and French (2015).

Panel C displays the relationship between Size and Inv and their corresponding asset returns. The table seems to indicate negative correlation between Inv and returns. Medium sized stocks exhibit a stronger negative relationship with returns than bigger stocks. Regarding small stocks, no consistent pattern can be identified. In a comparison of the two extremes (Low Inv and High Inv), the relationship is negative.

6.2 Summary Statistics for Factor Returns

Table 5: Factor Summary Statistics

Summary statistics for monthly factor percent returns; July 1999-June 2019, 240 months. In Panel A, HML(s) denotes the average return of big, high B/M portfolios minus the average return of big, low B/M portfolios. HML(b) is likewise the average return of small, high B/M portfolios minus the average return of small, low B/M portfolios, making HML the average of HML(s) and HML(b), and HML(s-b) the difference between HML(s) and HML(b). RMW(s), RMW(B), RMW, RMW(s-b), CMA(s), CMA(b), CMA, CMA(s-b) are defined using the same principle but with high and low OP and Inv instead of high and low B/M, respectively. Standard deviation and t-statistics are displayed next to each factor. In Panel B, the correlations of the factors from the factor models are displayed.

Panel A: Averages, standard deviations, and t-statistics for monthly returns

	Mean	Std dev.	t-statistic
RM-Rf	0.55	6.21	1.38
SMB	- 0.07	2.62	- 0.39
HML	0.32	4.29	1.14

RMW	0.42	5.59	1.17
CMA	0.57	3.29	2.69
HML(s)	0.05	2.30	0.31
HML(b)	0.27	2.80	1.49
HML(s-b)	-0.23	2.82	-1.24
RMW(s)	0.37	3.42	1.67
RMW(b)	0.05	4.17	0.20
RMW(s-b)	0.31	5.19	0.94
CMA(s)	0.33	1.90	2.69
CMA(b)	0.24	2.41	1.54
CMA(s-b)	0.09	2.84	0.50

Panel B: Correlations between factors

	RM-Rf	SMB	HML	RMW	CMA
RM-Rf	1.00	-0.54	-0.52	-0.02	-0.37
SMB	-0.54	1.00	0.24	-0.24	0.24
HML	-0.52	0.24	1.00	-0.16	0.44
RMW	-0.02	-0.24	-0.16	1.00	-0.02
CMA	-0.37	0.24	0.44	-0.02	1.00

In Panel A of Table 5, the average monthly return for RM-Rf is 0.55, which is a slightly higher than was seen in Fama and French (2015) on the US market (0.50). This comes as no surprise as the time series are different and different markets are studied. It could also have to do with the Nordic sample being smaller or due to different exchange rates that have affected the equities in the sample.

The average monthly SMB-return is -0.07 in the Nordic sample and 0.29 in the US sample, the HML-return 0.32 in the Nordic sample and 0.37 in the US sample, the RMW-return 0.42 in the Nordic sample and 0.25 in the US sample, and the CMA-return 0.57 in the Nordic sample and 0.33 in the US sample. The figures indicate that there is a negative size-premium for Nordic stocks and positive premiums for HML, RMW, and CMA, growing in that order. This suggests that the theory behind equation (1) holds on the Nordic Market, except for the relationship between M_t and r (where a lower M_t should generate a higher r), where average returns indicate the opposite relationship. The reason for the discrepancy between this study and Fama and French (2015) may be due to the different time periods, different geographies, different sample sizes, and/or differences in exchange rates.

It is notable that the t-statistics for the factors in the Nordic sample are all lower than 1.96 and hence not indistinguishable from zero at the 5% significance level, except for the CMA-factor, whose t-statistic is 2.69. In Fama and French's paper (2015), all t-statistics were above 1.96. The difference is noteworthy, but it should still be mentioned that the HML-, the RMW-, and the CMA-returns are positive, which could be viewed as a slight indication that the investment strategies work. Although all factors except SMB seem to exhibit the same signs as in Fama and French (2015), the fact that all factors but one are insignificant, indicates that the various factor-premiums hypothesized in equation (1) are markedly weaker for the Nordic markets.

Moreover, HML(s) stands at 0.05 and HML(b) at 0.27, making HML(s-b) -0.23, indicating a negative value premium for small companies. As for RMW and CMA, small companies experience a premium of 0.31 and 0.09 percentage points, respectively. These findings are somewhat in line with Fama and French (2015). Their numbers indicate positive RMW- and CMA-premiums for small companies. However, their HML-premium for small companies is also positive, which indicates a difference between the US market and the Nordic market. It should be mentioned that apart from CMA(s-b), the t-statistics for HML(s-b) and RMW(s-b) are insignificant on the Nordic market. This limits any conclusions that can be drawn from their mean values.

With regard to the correlations in Panel B, it is notable that the market premium has a negative correlation with all other factors. Also, with the SMB-factor having a -0.54 correlation with the market premium, it seems as if small stocks have smaller market betas than big stocks. This seems counterintuitive, not only because Fama and French (2015) found a positive correlation (0.28), but also because small stocks, in general, tend to move more with the market than big stocks. Another interesting correlation is the one between RMW and CMA, -0.02. Even though Fama and French (2015) observed -0.11, one could claim that these two factors should be correlated since the amount of money a company can invest (or pay out as dividends) is dependent on the profitability of the company.

6.3 GRS Results

Table 6: GRS Tests on Factor Models

GRS tests run on CAPM, the three factor model, and the five factor model using average monthly percent returns of 16 Size-B/M portfolios, 16 Size-OP portfolios, and 16 Size-Inv portfolios between July 1999-June 2019, 240 months. The GRS statistic (denoted as GRS in the table) tests the mean variance efficiency between an LHS set of assets and a RHS set of assets. pGRS is the p-value of the GRS statistic the factor models, Avg abs alpha the average absolute interecept for the factor models, and Avg R2 the average R-squared value. In the third row of each panel, data on a four-factor model is presented.

	GRS	pGRS	Avg abs alpha	Avg R2
Panel A: 16 Size-B/M portfolios				
RM-Rf	1.90	0.02	0.40	0.48
RM-Rf SMB HML	1.71	0.05	0.25	0.70
RM-Rf SMB RMW CMA	1.97	0.02	0.42	0.66
RM-Rf SMB HML RMW CMA	1.81	0.03	0.37	0.73
Panel B: 16 Size-OP portfolios				
RM-Rf	5.26	0.00	0.48	0.48
RM-Rf SMB HML	4.97	0.00	0.42	0.66
RM-Rf SMB RMW CMA	4.92	0.00	0.51	0.67
RM-Rf SMB HML RMW CMA	4.78	0.00	0.49	0.69
Panel C: 16 Size-Inv portfolios				
RM-Rf	2.55	0.00	0.47	0.45
RM-Rf SMB HML	2.30	0.00	0.36	0.60
RM-Rf SMB RMW CMA	2.08	0.01	0.45	0.63
RM-Rf SMB HML RMW CMA	1.88	0.02	0.40	0.64

The results of the GRS tests presented in the table show that the hypothesis that all intercepts from regressions on the five-factor model are indistinguishable from zero, is rejected on a 5%

significance level for all sets of regressions. Thus, the first hypothesis, that the five-factor model describes average returns on the Nordic markets, is rejected.

In panel A, where regressions are run for 16 Size-B/M portfolios, CAPM exhibits the highest GRS-statistic, followed by the five-factor model. The three-factor model exhibits the lowest GRS statistic and the hypothesis that all intercepts are jointly indistinguishable from zero cannot be rejected on a 5% significance level. Furthermore, the average absolute value of the intercepts are markedly higher for CAPM and the five-factor model, at 0.40 and 0.37 respectively, than for the three-factor model, which exhibits an average absolute alpha value of 0.25.

In panel B, presenting the results from regressions for 16 Size-OP portfolios, the results are more similar between models, where the hypothesis of intercepts being jointly indistinguishable from zero is rejected for all models. The five-factor model exhibits the lowest GRS statistic, whereas the three-factor model, again, outperforms the other models when looking to the average absolute value of the intercept. The three-factor model exhibits an average absolute alpha value of 0.42, as compared to 0.48 and 0.49 for the five-factor model and CAPM respectively, suggesting that the three-factor model better captures the cross-section of excess returns than the other models.

Panel C, presenting the results from regressions for 16 Size-Inv portfolios, exhibits GRS statistics that allow for the rejection of the hypothesis that the regression intercepts are jointly indistinguishable from zero, for all models, as in panel B. Notably, a greater dispersion in GRS statistics can be observed, with the five-factor model exhibiting a GRS statistic of 1.88 as compared to the three-factor model, with a GRS statistic of 2.3, and CAPM, with a GRS statistic of 2.55. However, the three-factor model appears once again to outperform the other models with regard to the average absolute value of alpha.

Seeing as the five-factor model does not outperform the three-factor model in all of the three conducted GRS tests, and furthermore is clearly outperformed by the three-factor model with regard to the average absolute value of alpha in all three sets of regressions, the hypothesis H2A, that the five-factor model outperforms the three-factor model in explaining average returns on

Nordic stock markets, is rejected. Furthermore, since the five-factor model exhibits a higher average absolute value of alpha than CAPM in panel B, regressions of 16 Size-OP portfolios, H2B, that the five-factor model outperforms CAPM, is also rejected.

Fama and French (2015) found in conducting GRS tests that a four-factor model comprising RM-Rf, SMB, RMW, and CMA, does not exhibit notably different results from GRS tests of their five-factor model. In Fama and French (2015), the GRS-statistics for the four-factor model stood at 2.84, 1.87, and 3.33 for tests on Size-BM, Size-OP, and Size-Inv portfolios respectively. This compared to the GRS-statistics exhibited by their five-factor model for the three sets of portfolios, at 2.84, 1.87, and 3.32 respectively. Thus, they observed virtually identical results in comparing the four-factor and the five-factor models. In this study, the GRS-statistics are markedly lower for the five-factor model than for the four-factor model in all three sets of regressions. This tentatively suggests that HML is not a redundant factor, or at least that it should be deemed *less* redundant when applied to Nordic markets than to US markets. However, it is the factor regressions in the following section that inform whether to reject H3 or not, as in Fama and French (2015).

To summarize, the five-factor model exhibits lower GRS-statistics than CAPM in all three panels, and lower statistics than the three-factor model in two out of three panels. Furthermore, the five-factor model does not exhibit lower average absolute alpha values than either CAPM or the three-factor model in *all* three panels. Thus, H2A and H2B are rejected. However, the fact that the GRS tests appear to favor the five-factor model while average absolute alpha values do not, invites the further analysis of the intercept terms and their significance. This is discussed in section 6.5.

6.4 Factor regressions

In this section, factor regressions are performed in which each factor features as a regressand, with the remaining factors featuring as regressors in order to test whether factor returns are explained by the other factors in the model.

Table 7: Factor Regressions

Factor regressions using each single risk-factor and regressing it on the remaining risk-factors using average monthly percentage returns between July 1999-June 2019, 240 months. $R_m - R_f$ is the dependent variable in the first row, then SMB in the second row and so on. α denotes the intercept for each factor regression.

	α	RM-Rf	SMB	HML	RMW	CMA	R2
RM-Rf							
Coef	0.85		-1.13	-0.58	-0.22	-0.16	0.50
t-Statistic	2.90		-9.64	-7.62	-4.15	-1.62	
SMB							
Coef	0.12	-0.25		-0.09	-0.13	0.07	0.38
t-Statistic	0.85	-9.64		-2.30	-5.24	1.42	
HML							
Coef	0.34	-0.34	-0.24		-0.15	0.37	0.38
t-Statistic	1.51	-7.62	-2.30		-3.72	5.11	
RMW							
Coef	0.59	-0.31	-0.81	-0.36		0.11	0.14
t-Statistic	1.70	-4.15	-5.24	-3.72		0.94	
CMA							
Coef	0.52	-0.07	0.13	0.27	0.03		0.23
t-Statistic	2.69	-1.62	1.42	5.11	0.94		

Starting with the $R_m - R_f$ regressions, the intercept is positive at 0.85 and with a t-statistic of 2.90. Surprisingly, after regressing the SMB-factor on all other risk factors, the intercept is 0.12 and has a t-statistic of 0.85. It therefore seems that there is barely any size premium once controlling for the other risk-factors. The same goes for the HML- and the RMW-factor, as these also generate insignificant intercepts, at 0.34 intercept with a t-statistic of 1.51 and at 0.59 t with a t-statistic of 1.70 respectively.

These observations allow for the rejection of H3. Although the GRS statistic decreased when adding HML to a 4-factor model, the factor regressions produced an insignificant alpha value for HML. This indicates that HML scarcely contributes to explaining returns, as a large part of its explanatory value is already accounted for by the other factors. Thus, HML is redundant by definition.

Moreover, unlike Fama and French (2015), who found that only the HML-factor was redundant, this test tells also shows that that SMB and RMW have insignificant intercepts. This certainly raises the question as to how well the 5-factor model actually performs on the Nordic market. In the following sections, this will be discussed further.

6.5 OLS Regressions

Table 8: OLS Regression on 16 Size-B/M portfolios

Regressions run on average monthly percentage returns on 16 Size-B/M portfolios between July 1999-June 2019, 240 months. α is the intercept and t(α) the t-statistic of the intercept, where a bolded t-statistic indicate significance on the 5% level.

B/M:	Low	2	3	High	Low	2	3	High
Panel A: One-factor intercepts: RM-Rf								
	α				t(α)			
Small	0.27	0.29	0.75	0.79	0.57	0.88	**2.08**	**3.14**
2	0.31	0.15	0.26	0.58	0.96	0.68	1.36	**2.36**
3	- 0.12	0.34	0.50	0.27	- 0.52	1.61	**2.25**	1.00
Big	- 0.17	0.39	0.50	0.64	- 0.96	**2.23**	**2.27**	**2.40**
Panel B: Three-factor intercepts: RM-Rf, SMB, HML								
	α				t(α)			
Small	0.54	0.23	0.54	0.60	1.49	0.84	1.68	**3.04**
2	0.46	0.03	0.12	0.27	**2.10**	0.18	0.81	1.56
3	- 0.14	0.15	0.26	- 0.06	- 0.69	0.91	1.59	- 0.31
Big	0.10	0.20	0.17	0.19	0.81	1.30	1.04	1.06
Panel C: Five-factor intercepts: RM-Rf, SMB, HML, RMW, CMA								
	α				t(α)			
Small	0.77	0.44	0.66	0.69	**2.20**	1.71	**2.02**	**3.49**
2	0.61	0.20	0.26	0.31	**2.91**	1.31	1.82	1.72
3	0.12	0.30	0.41	0.13	0.65	1.95	**2.53**	0.68
Big	0.08	0.25	0.36	0.27	0.63	1.56	**2.28**	1.50

Regressions of 16 Size-B/M portfolios on CAPM, the three-factor model and the five factor model respectively show that the three-factor model exhibits by far the fewest alpha values significantly different from zero at the 5% significance level. 2 out of 16 regressions on the three-factor model exhibit significant alpha values, as compared to 7 out of 16 for CAPM and 6 out of 16 for the five-factor model. This may partly explain the markedly superior performance of the three-factor model in the GRS test on the Size-B/M portfolios, with the only p-value that precludes the rejection of the hypothesis that all intercepts are jointly indistinguishable from 0. It appears that the three-factor model much better captures the cross-section of excess returns for Size-B/M sorted portfolios.

Table 9: OLS Regression on 16 Size-OP portfolios
Regressions run on average monthly percentage returns on 16 Size-OP portfolios between July 1999-June 2019, 240 months. α is the intercept and t(α) the t-statistic of the intercept, where a bolded t-statistic indicate significance on the 5% level.

OP:	Low	2	3	High	Low	2	3	High
Panel A: One-factor intercepts: RM-Rf								
		α				t(α)		
Small	0.34	0.49	0.99	0.88	0.87	**2.04**	**4.63**	**2.64**
2	- 0.18	0.26	0.76	0.73	- 0.56	1.20	**3.75**	**3.41**
3	- 1.10	0.06	0.60	0.62	**- 3.06**	0.28	**2.93**	**3.02**
Big	0.35	0.24	0.03	0.07	0.61	1.05	0.19	0.47
Panel B: Three-factor intercepts: RM-Rf, SMB, HML								
		α				t(α)		
Small	0.26	0.38	0.85	0.75	0.86	**2.06**	**4.44**	**2.57**
2	- 0.16	0.07	0.56	0.61	- 0.70	0.42	**3.79**	**3.38**
3	- 1.20	- 0.08	0.36	0.41	**- 4.02**	- 0.43	**2.33**	**2.45**
Big	0.54	0.12	- 0.14	0.25	0.96	0.55	- 0.91	1.86
Panel C: Five-factor intercepts: RM-Rf, SMB, HML, RMW, CMA								
		α				t(α)		
Small	0.42	0.47	0.94	0.94	1.43	**2.56**	**4.84**	**3.23**
2	0.06	0.18	0.61	0.70	0.30	1.14	**4.13**	**3.85**
3	- 0.87	0.14	0.50	0.57	**- 3.28**	0.81	**3.23**	**3.42**

Big	0.85	0.36	-0.00	0.23	1.65	1.64	-0.03	1.82

Regressions of 16 Size-OP portfolios on CAPM, the three-factor model and the five-factor model respectively, exhibit more ambiguous results with regard to values of alpha and their t-statistics. Notably, all three models exhibit a high fraction of significant alpha values, with 8 out of 16 alphas significantly different from 0 at the 5% level, for all three models. Furthermore, it is notable that all three models exhibit significant alpha values for the same specific portfolios. Thus, it would seem that neither of the three asset pricing models perform particularly well in regressions for Size-OP portfolios.

Table 10: OLS Regression on 16 Size-Inv portfolios
Regressions run on average monthly percentage returns on 16 Size-Inv portfolios between July 1999-June 2019, 240 months. α is the intercept and t(α) the t-statistic of the intercept, where a bolded t-statistic indicate significance on the 5% level.

Inv:	Low	2	3	High	Low	2	3	High
Panel A: One-factor intercepts: RM-Rf								
		α				t(α)		
Small	1.05	0.68	1.42	0.08	**3.18**	**2.57**	1.47	0.19
2	0.54	0.53	0.18	-0.20	**2.39**	**2.38**	0.73	-0.66
3	0.54	0.70	0.16	-0.37	**2.63**	**3.15**	0.65	-1.27
Big	0.65	0.16	-0.20	-0.04	**3.09**	0.68	-1.03	-0.16
Panel B: Three-factor intercepts: RM-Rf, SMB, HML								
		α				t(α)		
Small	0.88	0,57	1.16	-0,01	**3.08**	**2.59**	1.20	-0.04
2	0.34	0.36	0.07	-0.24	1.87	**2.09**	0.37	-1.04
3	0.33	0.45	0.00	-0.46	**1.97**	**2.71**	0.01	-1.81
Big	0.59	0.07	-0.12	-0.08	**2.77**	0.30	-0.64	-0.28
Panel C: Five-factor intercepts: RM-Rf, SMB, HML, RMW, CMA								
		α				t(α)		
Small	0.93	0.70	1.31	0.24	**3.17**	**3.29**	1.33	0.68
2	0.25	0.38	0.26	0.19	1.40	**2.21**	1.40	1.00

3	0.41	0.55	0.21	- 0.08	**2.45**	**3.33**	1.02	- 0.35
Big	0.25	0.22	0.08	0.29	1.41	0.91	0.47	1.15

Regressions of 16 Size-Inv portfolios tentatively suggest a superior performance from the five-factor model, with 5 significant alpha values out of 16 regressions, as compared to 6 significant alpha values for the three-factor model, and 7 significant alpha values for CAPM.

The three tables show that the three-factor model is superior to CAPM and the five-factor model with regard to number of significant values of alpha. The three-factor model exhibits a total of 16 alpha values significantly different from 0, out of 48 regressions, whereas the five-factor model exhibits a total of 19 significant alpha values out of 48. CAPM performs poorest, exhibiting a total of 22 significant alpha values out of 48.

7 Discussion

This study does not find evidence that the Fama and French five-factor model describes average returns on the Nordic stock markets. Furthermore, little evidence is found to suggest that the five-factor model outperforms the Fama and French three-factor model in explaining average returns on the Nordic Stock markets, for the tested time period. Nor does evidence support the hypothesis that the five-factor model outperforms CAPM. Finally, evidence does not support the hypothesis that HML is *not* a redundant factor.

The hypothesis that the alpha values for the five-factor model are jointly indistinguishable from zero is rejected for all three of the conducted GRS tests, whereas the hypothesis that the alpha values for the three-factor model are jointly indistinguishable from zero is rejected for only two of the three GRS tests conducted. This allows the study to reject both the first hypothesis and H2A. These results contrast the findings of Fama and French (2015) as well as Fama and French (2017) who find evidence that the five-factor model outperforms the three-factor model in US markets and internationally.

The five-factor model is outperformed by the three-factor model in the GRS-test for regressions with 16 LHS Size-B/M portfolios. For all three groups of 16 portfolios, regressions on the three models exhibit lower average absolute alpha values for the three-factor model. Furthermore, the three-factor model exhibits a lower number of alpha values significantly different from zero for two out of three sets of regressions. The total number of significant alpha values for the three-factor model is 16, whereas the five-factor model exhibits 19 significant alpha values, and CAPM exhibits 22 significant alpha values. H2B is rejected due to the five-factor model exhibiting a higher average absolute alpha value than CAPM for regressions of Size-OP portfolios.

However, it should be noted that, while the results quite clearly preclude the conclusion that the five-factor model outperforms the three-factor model, since the three-factor model performed better in many respects, the conclusions that can be drawn from the rejection of H2B are less clear. For example, there is little support in the results for the claim that CAPM outperforms the five-factor model, since the five-factor model exhibits better results in the overwhelming majority of tests. These results do, however, cast further doubt on the possible application of the five-factor model on the Nordic markets.

Factor regressions indicate that the HML factor is redundant. However, the results in this study are somewhat ambiguous as compared to Fama and French (2015). Fama and French found that HML was the sole redundant factor in their factor regressions, and GRS tests corroborated this, exhibiting negligibly different GRS-statistics in a comparison of their five-factor model, and a four-factor model excluding HML. However, this study, as opposed to Fama and French (2015), finds that three out of five factors appear to be redundant. While this allows the third hypothesis to be rejected, the conclusions that can be drawn from these findings are more limited, for several reasons. In Fama and French (2015), the alpha value for HML in the factor regressions stood at -0.04% and its t-statistic stood at -0.47. However, in this study, where three factors are found to be redundant, the alpha value of HML in factor regressions stands at 0.34% and its t-statistic stands at 1.51. This would explain the fact that, in this study, a four-factor model excluding HML generates markedly higher GRS-statistics than the five-factor model, indicating that, while HML appears to be redundant, this finding is not as obvious as in Fama and French (2015). Furthermore, since Fama and French (2015) only observe redundancy in HML, there would, perhaps, be stronger support for excluding the factor from their model. However, in *this* study, the redundancy of three out of five factors would rather suggest that the model as a whole performs poorly on Nordic markets.

The improvements of the five-factor model on the three-factor model witnessed by Fama and French (2015) do not appear to hold for the Nordic markets in the studied time period, where the results are largely inverse. Whereas Fama and French (2015) found that the average absolute values of alpha where lower for the five-factor model than for the three-factor model in all three sets of regressions with 16 LHS portfolios, the findings in this study show the opposite, with lower average absolute alpha values from the three-factor model in all three sets of regressions.

The reasons for the discrepancies in the findings of this study and Fama and French (2015) may have several explanations. It is possible that the minimum market cap for listing on NYSE, 50 million dollars (NYSE 2020), causes the companies examined in Fama and French (2015) to behave much differently from the stocks examined in this study, since the minimum market caps for listings on Swedish, Norwegian, Danish and Finish main markets amounts to 1 million euros (NASDAQ 2020). For this reason, a suggested area of further research on the Nordic stock market is to change the size breakpoints for factor construction and regression portfolios, excluding stocks with a market cap lower than the equivalent of 50 million dollars.

8 Conclusion

The aim of this study is to test the performance of the Fama and French (2015) five-factor asset pricing model on Nordic markets, and to compare its performance to the Fama and French (1993) three-factor model and CAPM.

Factor returns for the Nordic stock markets are constructed in accordance with the methodology of Fama and French (2015). Six sets of value-weighted (VW) diversified factor portfolios are created through making yearly sorts of the sample of stocks into two Size-groups, with median market cap as the breakpoint. The stocks are also sorted into groups of three based on breakpoints for B/M, Operating Profit divided by book equity (OP) and yearly percent change in total assets (Inv). The breakpoints for B/M, OP, and Inv are the 30th and 70th percentiles for the yearly samples. This process results in the creation of the following factors: SMB, HML, RMW, CMA. Furthermore, the market-premium factor is created by subtracting the one-month Swedish treasury bill rate (the risk-free return proxy) from the MSCI Nordics total return index (the market benchmark).

The same method is used to create three sets of 16 regression portfolios, but here Size, B/M, OP, and Inv are divided into quartiles, and the intersections of the 4 Size groups with the 4 B/M, OP and Inv groups create a total of 48 regression portfolios.

Regressions are run for all 48 regression portfolios on the Fama and French (2015) five-factor model, the Fama and French (1993) three-factor model and CAPM. Thereafter, the hypotheses are tested.

The hypotheses that are tested in this study are:

> H1: When applied to the Nordic markets, the Fama French (2015) five-factor model explains average portfolio returns.
>
> H2: When applied to the Nordic market, the Fama French five-factor model performs better in explaining average portfolio returns than;

H2A: The Fama French three-factor model

H2B: The CAPM model

H3: When applied to the Nordic market, the HML factor in the Fama French five-factor model is not made redundant by other factors in the model.

In this study, H1, H2A, H2B and H3 are rejected. The five-factor model does not capture all average returns on the Nordic stock markets, as shown in the GRS tests conducted on three sets of 16 regression portfolios. Furthermore, the five-factor model does not outperform the three-factor model in describing average returns, seeing as the three-factor model performs better in GRS tests for Size-B/M portfolios, exhibits lower average absolute alpha values for all three sets of 16 regressions, and exhibits fewer alpha values significantly different from zero. In addition to this, the five-factor model is not found to consistently outperform CAPM, as it exhibits a higher value of average absolute alpha in regressions for 16 Size-OP portfolios. Finally, HML is found to be redundant, in factor regressions, in addition to SMB and RMW.

The findings of this study suggest that there is no benefit to using the five-factor model in analysis of Nordic stock returns over the three-factor model, and that the three-factor model may in fact better capture average returns, due to the observed lower average absolute alpha values and fewer significant alpha values.

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Appendix

Table A1: Regression Table
48 regressions on the five-factor model

		a	RM-Rf	SMB	HML	RMW	CMA	Rsquared
s4v4	coeff	0,27	1,04	0,23	0,85	-0,07	-0,07	0,81
	t-stat	1,50	26,50	2,75	16,78	-2,04	-1,14	
s4v3	coeff	0,36	0,87	0,24	0,60	-0,14	-0,18	0,80
	t-stat	2,28	25,04	3,29	13,36	-4,70	-3,45	
s4v2	coeff	0,25	0,80	0,18	0,32	-0,07	0,00	0,76
	t-stat	1,56	22,82	2,48	6,97	-2,43	0,08	
s4v1	coeff	0,08	0,85	-0,24	-0,49	0,03	0,01	0,93
	t-stat	0,63	29,72	-4,01	-13,17	1,11	0,13	
s3v4	coeff	0,13	0,91	0,88	0,47	-0,21	-0,09	0,74
	t-stat	0,68	22,34	10,11	8,90	-6,10	-1,49	
s3v3	coeff	0,41	0,82	0,86	0,37	-0,11	-0,15	0,75
	t-stat	2,53	23,07	11,40	7,88	-3,51	-2,73	
s3v2	coeff	0,30	0,83	0,69	0,22	-0,18	-0,06	0,78
	t-stat	1,95	24,18	9,46	4,95	-6,28	-1,23	
s3v1	coeff	0,12	0,93	0,72	-0,09	-0,23	-0,21	0,81
	t-stat	0,65	22,75	8,29	-1,76	-6,55	-3,35	
s2v4	coeff	0,31	0,79	0,87	0,42	-0,10	0,06	0,67
	t-stat	1,72	20,15	10,49	8,38	-3,04	1,08	
s2v3	coeff	0,26	0,63	0,81	0,19	-0,10	-0,14	0,71
	t-stat	1,82	20,18	12,28	4,59	-3,65	-3,06	
s2v2	coeff	0,20	0,76	0,96	0,09	-0,14	-0,14	0,78
	t-stat	1,31	23,21	13,84	2,17	-5,06	-2,78	
s2v1	coeff	0,61	0,94	1,36	-0,51	-0,21	-0,04	0,81
	t-stat	2,91	20,31	13,89	-8,57	-5,31	-0,52	
s1v4	coeff	0,69	0,71	0,99	0,22	-0,11	-0,04	0,61
	t-stat	3,49	16,38	10,82	3,98	-3,06	-0,54	
s1v3	coeff	0,66	0,77	1,05	0,26	-0,11	-0,10	0,40
	t-stat	2,02	10,74	6,86	2,81	-1,74	-0,93	
s1v2	coeff	0,44	0,78	1,12	-0,10	-0,26	-0,08	0,61
	t-stat	1,71	13,59	9,19	-1,37	-5,46	-0,96	
s1v1	coeff	0,77	0,81	1,65	-0,84	-0,34	-0,02	0,66
	t-stat	2,20	10,60	10,11	-8,45	-5,23	-0,16	
s4p4	coeff	0,23	0,83	-0,24	-0,22	0,13	-0,13	0,92
	t-stat	1,82	29,75	-4,10	-6,02	5,70	-3,06	
s4p3	coeff	-0,00	0,95	0,11	0,33	-0,07	-0,16	0,85
	t-stat	-0,03	28,50	1,58	7,73	-2,57	-3,22	
s4p2	coeff	0,36	0,83	0,08	0,18	-0,21	-0,18	0,72

	t-stat	1,64	17,31	0,77	2,92	-5,10	-2,54	
s4p1	coeff	0,85	0,98	0,13	-0,78	-0,73	0,30	0,56
	t-stat	1,65	8,69	0,55	-5,29	-7,63	1,77	
s3p4	coeff	0,57	0,83	0,66	0,35	-0,08	-0,19	0,75
	t-stat	3,42	22,81	8,51	7,40	-2,70	-3,36	
s3p3	coeff	0,50	0,79	0,70	0,38	-0,09	-0,14	0,75
	t-stat	3,23	23,17	9,77	8,64	-3,28	-2,62	
s3p2	coeff	0,14	0,88	0,83	0,11	-0,23	-0,11	0,80
	t-stat	0,81	23,93	10,58	2,39	-7,55	-2,05	
s3p1	coeff	-0,87	1,17	1,09	-0,09	-0,44	-0,09	0,77
	t-stat	-3,28	20,09	8,84	-1,20	-9,02	-1,03	
s2p4	coeff	0,70	0,71	0,78	0,15	-0,05	-0,11	0,65
	t-stat	3,85	17,82	9,23	2,90	-1,57	-1,85	
s2p3	coeff	0,61	0,68	0,84	0,26	-0,07	-0,02	0,69
	t-stat	4,13	20,71	12,08	6,16	-2,60	-0,38	
s2p2	coeff	0,18	0,71	0,84	0,23	-0,12	-0,06	0,70
	t-stat	1,14	20,33	11,43	5,15	-4,10	-1,22	
s2p1	coeff	0,06	0,99	1,43	-0,29	-0,24	-0,12	0,80
	t-stat	0,30	21,01	14,35	-4,84	-6,13	-1,64	
s1p4	coeff	0,94	0,61	1,04	0,07	-0,20	-0,11	0,42
	t-stat	3,23	9,61	7,65	0,89	-3,68	-1,10	
s1p3	coeff	0,94	0,50	0,59	0,19	-0,08	-0,06	0,44
	t-stat	4,84	11,76	6,56	3,50	-2,33	-1,00	
s1p2	coeff	0,47	0,62	1,00	0,05	-0,12	-0,03	0,62
	t-stat	2,56	15,48	11,72	0,98	-3,54	-0,42	
s1p1	coeff	0,42	0,97	1,50	-0,15	-0,27	0,03	0,64
	t-stat	1,43	14,91	10,91	-1,80	-5,00	0,31	
s4i4	coeff	0,29	0,87	-0,02	0,15	-0,13	-0,53	0,72
	t-stat	1,15	15,70	-0,15	2,14	-2,69	-6,22	
s4i3	coeff	0,08	0,85	-0,22	0,04	0,09	-0,48	0,87
	t-stat	0,47	22,99	-2,76	0,83	2,90	-8,55	
s4i2	coeff	0,22	0,91	0,14	0,17	-0,08	-0,18	0,70
	t-stat	0,91	17,41	1,30	2,54	-1,76	-2,25	
s4i1	coeff	0,25	0,93	0,14	-0,06	-0,01	0,63	0,80
	t-stat	1,41	23,66	1,70	-1,15	-0,22	10,56	
s3i4	coeff	-0,08	0,92	0,84	0,11	-0,22	-0,44	0,72
	t-stat	-0,35	17,81	7,65	1,71	-5,10	-5,61	
s3i3	coeff	0,21	0,89	0,72	0,19	-0,17	-0,17	0,72
	t-stat	1,02	19,72	7,57	3,22	-4,49	-2,55	
s3i2	coeff	0,55	0,85	0,80	0,37	-0,11	-0,06	0,74
	t-stat	3,33	23,34	10,42	7,95	-3,58	-1,01	
s3i1	coeff	0,41	0,76	0,64	0,31	-0,10	-0,04	0,70
	t-stat	2,45	20,86	8,29	6,57	-3,11	-0,66	

s2i4	coeff	0,19	0,79	1,32	0,07	-0,11	-0,68	0,76
	t-stat	1,00	18,36	14,54	1,27	-2,98	-10,54	
s2i3	coeff	0,26	0,81	1,05	0,11	-0,09	-0,25	0,72
	t-stat	1,40	19,88	12,18	2,16	-2,54	-3,98	
s2i2	coeff	0,38	0,71	0,93	0,20	-0,06	0,02	0,64
	t-stat	2,21	18,47	11,43	4,04	-1,78	0,30	
s2i1	coeff	0,25	0,71	0,80	0,20	-0,09	0,28	0,64
	t-stat	1,40	18,45	9,77	3,91	-2,67	4,73	
s1i4	coeff	0,24	0,90	1,46	0,01	-0,17	-0,26	0,52
	t-stat	0,68	11,81	9,02	0,06	-2,57	-2,27	
s1i3	coeff	1,31	0,95	1,38	0,44	0,03	-0,31	0,09
	t-stat	1,33	4,36	2,99	1,58	0,15	-0,95	
s1i2	coeff	0,70	0,58	0,88	0,02	-0,20	-0,00	0,54
	t-stat	3,29	12,28	8,80	0,27	-5,10	-0,06	
s1i1	coeff	0,93	0,64	1,09	0,15	-0,08	0,01	0,38
	t-stat	3,17	9,98	7,96	1,84	-1,48	0,10	

Table A2: Regression Table
48 regressions on the four-factor model

		a	RM-Rf	SMB	RMW	CMA	Rsquared
s4v4	coeff	0,56	0,75	0,02	-0,20	0,25	0,57
	t-stat	2,14	14,35	0,18	-4,16	2,96	
s4v3	coeff	0,57	0,67	0,10	-0,23	0,04	0,65
	t-stat	2,72	16,10	1,00	-6,10	0,62	
s4v2	coeff	0,36	0,69	0,11	-0,12	0,12	0,72
	t-stat	2,06	20,08	1,33	-3,82	2,19	
s4v1	coeff	-0,09	1,02	-0,13	0,10	-0,18	0,88
	t-stat	-0,51	30,17	-1,58	3,29	-3,23	
s3v4	coeff	0,29	0,75	0,76	-0,28	0,08	0,66
	t-stat	1,35	17,79	7,70	-7,31	1,21	
s3v3	coeff	0,54	0,70	0,78	-0,16	-0,01	0,68
	t-stat	2,96	19,45	9,22	-4,92	-0,22	
s3v2	coeff	0,38	0,75	0,63	-0,22	0,02	0,76
	t-stat	2,33	23,40	8,41	-7,31	0,34	
s3v1	coeff	0,09	0,96	0,74	-0,21	-0,24	0,81
	t-stat	0,47	26,16	8,60	-6,28	-4,10	
s2v4	coeff	0,45	0,64	0,77	-0,17	0,22	0,58
	t-stat	2,25	16,11	8,22	-4,54	3,46	
s2v3	coeff	0,32	0,56	0,77	-0,12	-0,08	0,69
	t-stat	2,19	19,44	11,26	-4,67	-1,63	

s2v2	coeff	0,23	0,73	0,94	-0,16	-0,10	0,78
	t-stat	1,52	24,65	13,56	-5,69	-2,19	
s2v1	coeff	0,43	1,12	1,49	-0,13	-0,23	0,75
	t-stat	1,81	23,55	13,40	-2,96	-2,98	
s1v4	coeff	0,76	0,63	0,94	-0,15	0,05	0,58
	t-stat	3,79	15,83	10,03	-3,99	0,73	
s1v3	coeff	0,75	0,68	0,98	-0,15	-0,00	0,38
	t-stat	2,28	10,44	6,42	-2,43	-0,04	
s1v2	coeff	0,41	0,81	1,14	-0,25	-0,12	0,61
	t-stat	1,58	15,83	9,48	-5,28	-1,47	
s1v1	coeff	0,48	1,10	1,85	-0,21	-0,33	0,55
	t-stat	1,21	14,07	10,08	-2,92	-2,62	
s4p4	coeff	0,16	0,91	-0,19	0,17	-0,21	0,91
	t-stat	1,15	33,76	-3,03	6,83	-4,88	
s4p3	coeff	0,11	0,83	0,03	-0,12	-0,04	0,81
	t-stat	0,66	25,03	0,39	-4,04	-0,73	
s4p2	coeff	0,42	0,77	0,03	-0,23	-0,12	0,71
	t-stat	1,91	17,60	0,34	-5,86	-1,68	
s4p1	coeff	0,58	1,25	0,32	-0,61	0,02	0,51
	t-stat	1,08	11,68	1,27	-6,22	0,10	
s3p4	coeff	0,69	0,71	0,57	-0,14	-0,06	0,69
	t-stat	3,76	19,66	6,76	-4,12	-0,97	
s3p3	coeff	0,63	0,66	0,61	-0,15	0,01	0,66
	t-stat	3,57	18,83	7,49	-4,77	0,10	
s3p2	coeff	0,17	0,84	0,80	-0,25	-0,07	0,79
	t-stat	1,04	25,28	10,24	-8,26	-1,35	
s3p1	coeff	-0,90	1,20	1,11	-0,43	-0,12	0,77
	t-stat	-3,41	23,01	9,11	-8,98	-1,49	
s2p4	coeff	0,75	0,66	0,75	-0,08	-0,06	0,64
	t-stat	4,09	18,18	8,76	-2,29	-0,97	
s2p3	coeff	0,70	0,59	0,78	-0,11	0,08	0,64
	t-stat	4,43	18,65	10,50	-3,88	1,53	
s2p2	coeff	0,26	0,63	0,79	-0,16	0,02	0,67
	t-stat	1,57	19,13	10,24	-5,20	0,41	
s2p1	coeff	-0,04	1,09	1,50	-0,20	-0,23	0,78
	t-stat	-0,17	24,71	14,55	-4,90	-3,19	
s1p4	coeff	0,96	0,59	1,02	-0,21	-0,08	0,42
	t-stat	3,34	10,29	7,61	-4,00	-0,87	
s1p3	coeff	1,00	0,43	0,55	-0,11	0,01	0,41
	t-stat	5,09	11,13	5,96	-3,18	0,11	
s1p2	coeff	0,49	0,60	0,99	-0,13	-0,01	0,62
	t-stat	2,67	16,80	11,71	-3,88	-0,11	
s1p1	coeff	0,37	1,02	1,54	-0,25	-0,03	0,64

	t-stat	1,26	17,47	11,24	-4,69	-0,27	
s4i4	coeff	0,34	0,82	-0,06	-0,15	-0,47	0,72
	t-stat	1,35	16,35	-0,47	-3,26	-5,80	
s4i3	coeff	0,09	0,83	-0,22	0,08	-0,46	0,87
	t-stat	0,55	25,28	-2,91	2,79	-8,75	
s4i2	coeff	0,28	0,85	0,10	-0,10	-0,11	0,69
	t-stat	1,15	17,97	0,92	-2,40	-1,50	
s4i1	coeff	0,23	0,95	0,16	0,00	0,61	0,80
	t-stat	1,30	26,98	1,89	0,05	10,74	
s3i4	coeff	-0,04	0,88	0,81	-0,24	-0,40	0,72
	t-stat	-0,18	18,96	7,45	-5,64	-5,32	
s3i3	coeff	0,27	0,82	0,68	-0,20	-0,10	0,71
	t-stat	1,32	20,03	7,03	-5,30	-1,58	
s3i2	coeff	0,68	0,72	0,71	-0,17	0,08	0,67
	t-stat	3,67	19,67	8,31	-4,99	1,41	
s3i1	coeff	0,52	0,66	0,57	-0,14	0,08	0,65
	t-stat	2,87	18,44	6,81	-4,41	1,38	
s2i4	coeff	0,22	0,76	1,30	-0,12	-0,66	0,76
	t-stat	1,13	19,85	14,50	-3,37	-10,68	
s2i3	coeff	0,30	0,77	1,03	-0,11	-0,20	0,72
	t-stat	1,61	20,96	11,90	-3,11	-3,45	
s2i2	coeff	0,45	0,64	0,88	-0,09	0,09	0,62
	t-stat	2,54	18,04	10,61	-2,72	1,62	
s2i1	coeff	0,31	0,64	0,75	-0,12	0,35	0,62
	t-stat	1,74	18,11	9,02	-3,59	6,11	
s1i4	coeff	0,24	0,90	1,46	-0,17	-0,26	0,52
	t-stat	0,69	13,19	9,13	-2,67	-2,38	
s1i3	coeff	1,46	0,79	1,27	-0,04	-0,15	0,08
	t-stat	1,48	4,07	2,78	-0,23	-0,47	
s1i2	coeff	0,71	0,57	0,88	-0,21	0,00	0,54
	t-stat	3,34	13,61	8,88	-5,33	0,03	
s1i1	coeff	0,98	0,59	1,05	-0,11	0,07	0,37
	t-stat	3,35	10,17	7,73	-1,96	0,72	

Table A3: Regression Table
48 regressions on the three-factor model

		a	RM-Rf	SMB	HML	Rsquared
s4v4	coeff	0,19	1,07	0,28	0,86	0,80
	t-stat	1,06	28,17	3,49	18,13	
s4v3	coeff	0,17	0,93	0,34	0,60	0,77
	t-stat	1,04	26,09	4,50	13,50	
s4v2	coeff	0,20	0,82	0,24	0,34	0,76
	t-stat	1,30	24,30	3,43	8,08	
s4v1	coeff	0,10	0,84	-0,26	-0,50	0,93
	t-stat	0,81	30,76	-4,62	-14,50	
s3v4	coeff	-0,06	0,99	1,04	0,52	0,70
	t-stat	-0,31	23,39	11,74	9,81	
s3v3	coeff	0,26	0,87	0,93	0,36	0,72
	t-stat	1,59	24,45	12,57	8,15	
s3v2	coeff	0,15	0,89	0,83	0,26	0,75
	t-stat	0,91	25,12	11,15	5,95	
s3v1	coeff	-0,14	1,02	0,88	-0,07	0,77
	t-stat	-0,69	23,43	9,67	-1,32	
s2v4	coeff	0,27	0,81	0,96	0,47	0,66
	t-stat	1,56	21,40	12,03	9,98	
s2v3	coeff	0,12	0,67	0,87	0,18	0,68
	t-stat	0,81	21,50	13,40	4,61	
s2v2	coeff	0,03	0,82	1,06	0,10	0,75
	t-stat	0,18	24,35	15,13	2,46	
s2v1	coeff	0,46	1,01	1,53	-0,46	0,79
	t-stat	2,10	21,57	15,61	-7,77	
s1v4	coeff	0,60	0,75	1,08	0,25	0,59
	t-stat	3,04	17,74	12,26	4,77	
s1v3	coeff	0,54	0,81	1,12	0,27	0,39
	t-stat	1,68	11,77	7,75	3,13	
s1v2	coeff	0,23	0,87	1,32	-0,04	0,56
	t-stat	0,84	14,94	10,86	-0,48	
s1v1	coeff	0,54	0,92	1,92	-0,73	0,62
	t-stat	1,49	11,93	11,85	-7,57	
s4p4	coeff	0,25	0,80	-0,36	-0,30	0,91
	t-stat	1,86	27,71	-6,05	-8,23	
s4p3	coeff	-0,14	0,98	0,15	0,32	0,84
	t-stat	-0,91	29,89	2,22	7,67	
s4p2	coeff	0,12	0,91	0,22	0,20	0,67
	t-stat	0,55	18,60	2,20	3,31	
s4p1	coeff	0,54	1,19	0,75	-0,45	0,45

	t-stat	0,96	9,85	2,95	-3,00	
s3p4	coeff	0,41	0,87	0,71	0,33	0,73
	t-stat	2,45	24,11	9,32	7,28	
s3p3	coeff	0,36	0,83	0,77	0,38	0,72
	t-stat	2,33	24,59	10,89	8,95	
s3p2	coeff	-0,08	0,96	1,00	0,16	0,75
	t-stat	-0,43	24,38	12,13	3,29	
s3p1	coeff	-1,20	1,31	1,44	0,03	0,69
	t-stat	-4,02	20,37	10,64	0,41	
s2p4	coeff	0,61	0,74	0,82	0,14	0,64
	t-stat	3,38	19,11	10,08	2,87	
s2p3	coeff	0,56	0,70	0,89	0,28	0,68
	t-stat	3,79	22,16	13,51	7,08	
s2p2	coeff	0,07	0,75	0,93	0,26	0,68
	t-stat	0,42	21,77	12,95	5,93	
s2p1	coeff	-0,16	1,07	1,61	-0,24	0,76
	t-stat	-0,70	22,09	15,87	-4,01	
s1p4	coeff	0,75	0,69	1,19	0,11	0,38
	t-stat	2,57	10,90	9,02	1,42	
s1p3	coeff	0,85	0,53	0,65	0,20	0,42
	t-stat	4,44	12,93	7,59	3,97	
s1p2	coeff	0,38	0,66	1,09	0,08	0,60
	t-stat	2,06	16,82	13,29	1,72	
s1p1	coeff	0,26	1,05	1,72	-0,05	0,60
	t-stat	0,86	16,17	12,67	-0,64	
s4i4	coeff	-0,08	0,96	0,03	0,06	0,66
	t-stat	-0,28	16,41	0,25	0,83	
s4i3	coeff	-0,12	0,85	-0,34	-0,11	0,82
	t-stat	-0,64	21,09	-3,96	-2,25	
s4i2	coeff	0,07	0,95	0,19	0,15	0,69
	t-stat	0,30	18,70	1,78	2,40	
s4i1	coeff	0,59	0,88	0,21	0,11	0,71
	t-stat	2,77	19,36	2,22	1,87	
s3i4	coeff	-0,46	1,03	0,97	0,07	0,65
	t-stat	-1,81	18,55	8,41	1,08	
s3i3	coeff	0,00	0,96	0,84	0,20	0,68
	t-stat	0,01	21,04	8,87	3,52	
s3i2	coeff	0,45	0,89	0,88	0,40	0,73
	t-stat	2,71	24,87	11,87	8,88	
s3i1	coeff	0,33	0,80	0,72	0,33	0,69
	t-stat	1,97	22,35	9,62	7,50	
s2i4	coeff	-0,24	0,87	1,34	-0,07	0,64
	t-stat	-1,04	17,33	12,67	-1,13	

s2i3	coeff	0,07	0,86	1,10	0,08	0,69
	t-stat	0,37	21,03	12,88	1,56	
s2i2	coeff	0,36	0,72	0,97	0,22	0,64
	t-stat	2,09	19,70	12,71	4,88	
s2i1	coeff	0,34	0,72	0,90	0,30	0,60
	t-stat	1,87	18,42	11,03	6,09	
s1i4	coeff	- 0,01	0,98	1,57	- 0,01	0,49
	t-stat	- 0,04	13,06	10,03	- 0,07	
s1i3	coeff	1,16	0,96	1,33	0,35	0,09
	t-stat	1,20	4,64	3,05	1,37	
s1i2	coeff	0,57	0,64	1,04	0,08	0,49
	t-stat	2,59	13,59	10,52	1,40	
s1i1	coeff	0,88	0,67	1,16	0,18	0,37
	t-stat	3,08	10,81	8,94	2,38	

Table A4: Regression Table
48 regressions on CAPM

		a	RM-Rf	Rsquared
s4v4	coeff	0,64	0,70	0,52
	t-stat	2,40	16,08	
s4v3	coeff	0,50	0,64	0,58
	t-stat	2,27	17,99	
s4v2	coeff	0,39	0,64	0,68
	t-stat	2,23	22,60	
s4v1	coeff	- 0,17	1,08	0,86
	t-stat	- 0,96	38,43	
s3v4	coeff	0,27	0,56	0,42
	t-stat	1,00	13,06	
s3v3	coeff	0,50	0,53	0,47
	t-stat	2,25	14,57	
s3v2	coeff	0,34	0,61	0,58
	t-stat	1,61	18,14	
s3v1	coeff	- 0,12	0,84	0,67
	t-stat	- 0,52	22,19	
s2v4	coeff	0,58	0,42	0,33
	t-stat	2,36	10,79	
s2v3	coeff	0,26	0,40	0,42

	t-stat	1,36	13,10	
s2v2	coeff	0,15	0,54	0,50
	t-stat	0,68	15,46	
s2v1	coeff	0,31	0,82	0,50
	t-stat	0,96	15,57	
s1v4	coeff	0,79	0,41	0,30
	t-stat	3,14	10,13	
s1v3	coeff	0,75	0,46	0,21
	t-stat	2,08	7,98	
s1v2	coeff	0,29	0,58	0,34
	t-stat	0,88	11,03	
s1v1	coeff	0,27	0,75	0,28
	t-stat	0,57	9,54	
s4p4	coeff	0,07	0,99	0,87
	t-stat	0,47	39,17	
s4p3	coeff	0,03	0,83	0,80
	t-stat	0,19	30,75	
s4p2	coeff	0,24	0,78	0,65
	t-stat	1,05	21,20	
s4p1	coeff	0,35	1,18	0,41
	t-stat	0,61	12,80	
s3p4	coeff	0,62	0,59	0,57
	t-stat	3,02	17,83	
s3p3	coeff	0,60	0,52	0,51
	t-stat	2,93	15,59	
s3p2	coeff	0,06	0,67	0,58
	t-stat	0,28	18,09	
s3p1	coeff	- 1,10	0,97	0,54
	t-stat	- 3,06	16,87	
s2p4	coeff	0,73	0,50	0,47
	t-stat	3,41	14,66	
s2p3	coeff	0,76	0,40	0,39
	t-stat	3,75	12,21	
s2p2	coeff	0,26	0,44	0,41
	t-stat	1,20	12,99	
s2p1	coeff	- 0,18	0,79	0,49
	t-stat	- 0,56	15,02	
s1p4	coeff	0,88	0,37	0,17
	t-stat	2,64	6,95	
s1p3	coeff	0,99	0,31	0,25
	t-stat	4,63	8,97	
s1p2	coeff	0,49	0,38	0,29
	t-stat	2,04	9,95	

s1p1	coeff	0,34	0,67	0,33
	t-stat	0,87	10,86	
s4i4	coeff	- 0,04	0,93	0,66
	t-stat	- 0,16	21,63	
s4i3	coeff	- 0,20	0,97	0,81
	t-stat	- 1,03	31,36	
s4i2	coeff	0,16	0,85	0,68
	t-stat	0,68	22,42	
s4i1	coeff	0,65	0,80	0,70
	t-stat	3,09	23,36	
s3i4	coeff	- 0,37	0,78	0,54
	t-stat	- 1,27	16,73	
s3i3	coeff	0,16	0,69	0,57
	t-stat	0,65	17,68	
s3i2	coeff	0,70	0,54	0,49
	t-stat	3,15	15,06	
s3i1	coeff	0,54	0,51	0,50
	t-stat	2,63	15,47	
s2i4	coeff	- 0,20	0,59	0,39
	t-stat	- 0,66	12,28	
s2i3	coeff	0,18	0,58	0,48
	t-stat	0,73	14,74	
s2i2	coeff	0,53	0,42	0,37
	t-stat	2,38	11,71	
s2i1	coeff	0,54	0,40	0,34
	t-stat	2,39	11,05	
s1i4	coeff	0,08	0,62	0,27
	t-stat	0,19	9,42	
s1i3	coeff	1,42	0,53	0,05
	t-stat	1,47	3,41	
s1i2	coeff	0,68	0,37	0,25
	t-stat	2,57	8,87	
s1i1	coeff	1,05	0,34	0,15
	t-stat	3,18	6,38	