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Performance of Asset Pricing Models in the Nordic Stock Markets

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Abstract

This study aims to investigate the performance of four different asset pricing models, the Fama and French (1993) three factor model, the Carhart (1997) four factor model, the Fama and French (2015) five factor model, and the Hou et al. (2015) model, in the Nordic stock markets. I examine whether the Fama and French (2015) five factor model and the Hou et al. (2015) model outperform the other two models, in describing the variation in average stock returns. This is done by running time-series regressions and Gibbons, Ross, and Shanken (1989) tests for different combinations of portfolios, on these models. I also investigate whether there is a possibility to form a hybrid model that outperforms all the four models tested in this paper, by using a combination of the factors from the models. This is done by using Principal Component Analysis to pick the best factors to include in the hybrid model. I implement my analysis on a sample of all stocks traded on the four major Nordic stock markets (OMX Stockholm, OMX Copenhagen, OMX Helsinki, and Oslo Bors) in the period between July 1993 and June 2018. The main finding is that both the Carhart (1997) four factor model and the Hou et al. (2015) model outperform the two Fama and French (1993, 2015) models in explaining the variation in average stock returns on the Nordic stock markets. I also find evidence for two different seven factor hybrid models that outperform all the other four models in explaining the variation in average stock returns on the Nordic stock markets. These two seven factor models both include factors for market return, firm size, book-to-equity ratio, operating profitability, investment, return-on-equity, and momentum, all constructed based on Nordic stock data.

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Section 1

Introduction

The search for an accurate explanation of the variability in stock returns is an ever ongoing research topic and also an important one. Many empirical asset pricing models have been tested over the years. There are actually many models that prove to be good at making predictions of the variability in stock returns, but there is really no consensus on which the best one is, moreover these models are usually only tested on samples from the U.S. market. So how should an investor know which model to pick, to best describe the sources of stock returns? In this paper I investigate and compare the performance of four different asset pricing models for a sample of Nordic stocks. I create sample specific factors for Nordic firms and use the Gibbons, Ross, and Shanken (1989, GRS) test to compare the performance of these models. I also create and test three different hybrid models, using Principal Components (PCs) from Principal Component Analysis (PCA) on these sample specific factors.

An asset pricing model usually consists of several different factors that are believed to be driving asset returns. One usually performs a time-series regression and looks at the absolute value of the intercept, the so called alpha, to see how much of the variation in the stock returns that is described by the model. If the value is low it indicates that the return generated by other factors than the ones included in the model, is not significantly different from zero. Another important measure to take into consideration is the R^2-values of these time-series regressions, since these indicate how much of the variance in the dependent variable that is predicted by the independent variables, in the model. One of the first commonly used models was the Capital Asset Pricing Model (CAPM) proposed by Sharpe (1964), Lintner (1965), and Mossin (1966). In the CAPM the only source of risk is the market return.

Previous research has made it evident that there are a lot of potential factors that may contain additional information about the stock price. Some of the most common are the size of the firm (size factor), the value of the book-to-equity-ratio (value factor), and the momentum effect (All are defined later on in Section 3). The evidence of these effects inspired Fama and French (1993, FF3) to develop and investigate a three factor model were they add the aforementioned size and value factors to the CAPM and find evidence for it to explain over 90% of the variance in the returns of their sample from the U.S. stock market. Carhart (1997) extends this model into a four factor model by adding the Jegadeesh and Titman (1993) momentum factor and finds that it outperforms the CAPM as well as the FF3 model, in explaining stock returns.

More extensions have followed. Fama and French (2015, FF5) redefine their three factor model into a five factor model by adding factors that mimic profitability and investment. This builds on the theory that profitability and stock returns should be positively related and investment and stock returns should be negatively related. They find, for the U.S. sample, that this model outperforms the FF3 model in explaining stock returns. This finding is to some degree also confirmed in Fama and French (2017), where they test the FF5 model for different international regions. Hou et al. (2015, q4) develop a four factor model, that they call the q4 model. This model includes a market factor, a size factor, a profitability factor, and an investment factor, building on the same theories that size and investment should be negatively related with stock returns and that profitability should be positively related to stock returns. Their findings are that this model outperforms both the FF3 model and the Carhart model in describing stock returns.

In this study I compare the performance of these models (FF3, Carhart, FF5, and q4) in the Nordic stock markets, in order to test if these aforementioned results also holds for a sample of Nordic firms. I also elaborate on the question if it is possible to create a hybrid model that outperforms the aforementioned factor models, by using the factors from the aforementioned four different models. This in order to try to find the most optimal way of using these factors to explain the variation in stock returns on the Nordic stock markets.

Based on the previous findings in the literature and to answer my research questions I propose and test the following two hypotheses:

H1: *The FF5 model and the q4 model outperform the FF3 model and the Carhart model in describing stock returns on the Nordic stock market*

H2: *It is possible to create a hybrid model, using a combination of the factors from the four models tested, that outperforms these four models in describing stock returns on the Nordic stock market.*

To test these hypotheses and answer my research question I follow a similar methodology as Carhart (1997), Fama and French (2015, 2017), and Hou et al. (2015). I start by constructing the factors for the different models and calculate average returns for different types of stock portfolios. These factors are constructed by using the same methodology as Carhart (1997), Fama and French (2015), and Hou et al. (2015), but for a sample of Nordic stocks instead of

U.S. stocks, which is used in all of the aforementioned studies. This in order to test these models for another sample than the American market. In other words, I create sample specific factor returns for the Nordic market.

In order to answer the first hypothesis, I perform Gibbons, Ross, and Shanken (1989, GRS) tests to find if the intercept values for different regressions are jointly indistinguishable from zero. This is done in order to test how well these models explain the variation in expected returns. I compare the relative performance of my four models by looking at results of the GRS test. I also compare the size of the average value of intercepts, in absolute value, for tests on the four models. I also look at the size of the average value of t-statistics for the intercepts in absolute value, and the number of t-statistics for the intercepts that are lower than 1.96 in absolute value, which is the rejection level, on a 95% significance level, for the intercepts to be jointly indistinguishable from zero. Finally, I also look at the number of t-statistics for the intercepts that are lower/higher than 3 in absolute value, to account for the issue of multiple hypothesis testing. The reasoning behind looking at t-stats lower/higher than 3 in absolute value is that since I perform so many different tests on my models I would require a very high significance level to avoid false rejections of the hypothesis. A t-statistic above 3 in absolute value would indicate a very strong rejection of the hypothesis that the intercept value is indistinguishable from zero.

To answer the second hypothesis, I perform a Principal Component Analysis (PCA), to choose factors to include in potential hybrid models and then I test those models in the same manner as described above. I also perform an analysis for a model where the risk factors consist of rotated components from the PCA.

The first main finding of this paper is that the Carhart model and the q4 model are better at explaining the variation in average stock returns than the FF3 and FF5 models. This means that I reject my first hypothesis. Even though I find evidence for the q4 model to outperform the FF3 model, there is not enough evidence to say that the q4 model outperforms the Carhart model. For the FF5 model it is even more evident that I have to reject the first hypothesis, since there is no evidence for it to outperform either the FF3 model or the Carhart model.

The second main finding is that I can create two hybrid models that outperform the other four models in explaining the variation in stock returns. By using PCA, I develop two seven factor hybrid models, which use factors from the four models. I find evidence for these two hybrid models to outperform all the other four models. These two hybrid models both include factors for market return, size of the firm, book-to-market ratio, operating profitability, investment, return-on-equity, and momentum.

The remainder of this paper is structured as follows. In Section 2, I provide a literature review with a more detailed background of the models. In Section 3, I explain the models tested in the paper. In Section 4, I discuss the data used in the paper, the sources where I find it, and how I use it to construct the portfolios. In Section 5, I present my results and analyze them. In Section 6, I provide a discussion of the results and possible future research. Finally, in Section 7 I give the main conclusions of the paper.

Section 2

Literature Review

The first major asset pricing model in the history was the Capital Asset Pricing Model (CAPM), a model mainly developed by the works of Sharpe (1964), Lintner (1965), and Mossin (1966). The CAPM is easy to implement since the only explanatory factor in the model is the market excess return, where the coefficient, beta, is a measure of how a single stock is co-moving with the market. Due to this simplicity it has, over time, become a popular model to use, even though many empirical anomalies to the CAPM have been found.

Many suggest that the market return does not capture all the variation in stock returns and that more factors should be included when trying to explain the variation in stock returns. As an example, Banz (1981) investigates the relationship between the size of the firm and the stock return and finds a negative correlation. Another critique is that Fama and French (1992) show evidence of a value premium, studying the relationship between book-to-market ratio and stock returns. Even though empirical findings suggest that the CAPM is a pretty poor model it is still heavily used amongst practitioners. A study by Graham and Harvey (2001) shows that 75 percent out of 392 CFOs make use of the CAPM in their work.

Building on this critique of the CAPM, Fama and French (1992, FF3), study the effects of the market excess return, size, equity-to-price ratio, leverage, and book-to-market ratio on average stock returns. They find that all of these variables have significant explanatory power on the average stock returns, but more importantly, if they are used in combination the size and the book-to-market factors seem to absorb the effect of the leverage and the equity-to-price factors, making them redundant. This finding leads Fama and French (1993, FF3) to develop a three factor model, consisting of a market factor, a size factor, and a book-to-market value factor. Using the GRS test, they conclude that this model does not describe all of the variation in average stock returns, but that it outperforms the CAPM.

Jegadeesh and Titman (1993) investigate another pricing anomaly. They form zero cost portfolios, by investing in stocks with relatively high past return and short-selling stocks with relatively low past returns. By doing so they try to exploit the so called one-year momentum anomaly. They find that this investment strategy generates positive abnormal returns, which indicates that stocks which have experienced high past returns tend to keep experiencing high returns in the coming period. As an example, a portfolio based on the past six-month returns, on average generates a compounded excess return of 12.01% per year, on a sample of stocks for the time period 1965-1989. Using this finding Carhart (1997) develops a four factor model, where a momentum factor, based on Jegadeesh and Titman (1993), is added to the FF3 model. The main finding is that this four factor model explains a considerable amount of the variation in the cross-section of stock returns and substantially improves upon the CAPM and the FF3 model.

Even though the FF3 model seems to capture a lot of the variation in stock returns, it has become pretty evident in the recent years that there are other anomalies around that can explain variation in stock returns. Elaborating on this Hou et al. (2015, q4) propose a four factor model. The model consists of a market factor, a size factor, an investment factor, represented by the investment-to-assets ratio of the firm, and a profitability factor, represented by the return-to-equity ratio of the firm. By performing GRS tests, they conclude that this model is an improvement in comparison with both the Carhart model and the FF3 model.

In turn Fama and French (2015, FF5) extend their three factor model further into a five factor model where they add factors for operating profitability and investment. Novy-Marx (2013) show that gross profits-to-assets has the same power in predicting the cross-section of average stock returns as the book-to-market ratio. Fama and French (2015, FF5) use this as motivation for adding a factor for operating profitability to their model. Titman et al. (2004) show that firms which increase their capital investments experience negative abnormal returns, this is motivation for Fama and French (2015, FF5) to add a factor for investment to their model. Fama and French (2015, FF5) also motivate these factors by the dividend discount model, developed by Gordon and Shapiro (1956). This model connects the market value of the stock to the discounted value of expected future dividends. Using this model Gordon and Shapiro (1956) find that two differently priced firms with the same expected future dividends, cannot have the same expected return. Indicating that the future dividends are linked to higher risk. By combining these findings with the theory of Miller and Modigliani (1961), Fama and French (2015, FF5) come up with an expression for expected return, expected profit, expected investment, and book-to-market ratio. This expression comes with three important statements about expected stock returns. The first one is that higher book-to-market ratio implies higher expected return, a finding already shown by Fama and French (1993, FF3). The second statement is that higher expected earnings imply higher expected stock returns. This is also a relationship found by Novy-Marx (2013) and Titman et al. (2013). The third statement is that higher expected growth in book equity implies lower expected stock returns. This relationship is also supported by the findings of Aharoni et al. (2013), Sun et al. (2013), and Watanabe et al. (2013). Fama and French (2015, FF5) use these findings as a motivation for adding an operating profitability factor and an investment factor to their factor model.

Fama and French (2015, FF5) find that, by using the GRS test, the FF5 model does not describe all of the variation in average stock returns. But the conclusion is that, by looking at the GRS test statistics and absolute values of the regression intercepts, the FF5 model outperforms the FF3 model in explaining average stock returns.

Fama and French (2017) extend their research by also testing the FF5 model on four different regions (North America, Europe, Japan, and Asia Pacific). The study uses data from 1990-2015. In this study they find the same evidence for the effects of the different factors on the average stock returns for North America, Europe, and Asia Pacific, but for Japan the only evident effect is the value effect. They also test a global version of the model, but the conclusion is that this global version cannot explain differences in regional expected returns. But overall the FF5 model is outperforms the FF3 model.

Section 3

Models

In this section I present the four models that I perform tests on in this paper. First is the FF3 model which is among classic asset pricing models. It consists of a market factor, a size factor, and a value factor. The second one is the Carhart model, which adds a momentum factor to the FF3 model. The third one is the FF5 model, which adds an operating profitability factor and an investment factor to the FF3 model. Finally, the fourth one is the q4 model, which consists of a market factor, a size factor, a profitability factor, and an investment factor.

3.1 Fama and French (1993, FF3) Three Factor Model

The FF3 model is a classic asset pricing model. The model is using a market factor, a size factor, and a value factor in order to explain excess stock returns. The market factor is the market return in excess of the risk-free rate. The size factor is a zero-cost portfolio that invests in firms with relatively small market capitalization and goes short in firms with relatively high market capitalization, the so called small-minus-big (SMB) factor. The value factor is a zero-cost portfolio that invests in firms with relatively high book-to-equity ratio and goes short in firms with relatively low book-to-equity ratio, the so called high-minus-low (HML) factor. The model is expressed as:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}\left(R_{Mt} - R_{Ft}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + +\varepsilon_{it}, \qquad (1)$$

where R_{it} is the return on asset i for period t and R_{Ft} is the risk free return for time period t. On the right hand side are the three risk factors and the corresponding βs which represent the factor exposures to the excess stock returns. If the risk factors capture all of the variation in the excess stock returns the intercept α_i should be equal to zero for all the assets.

3.2 Carhart (1997) Four Factor Model

The Carhart model adds the Jegadeesh and Titman (1993) one year momentum factor to the FF3 model. The momentum factor (MOM) is a zero-cost portfolio that invests in firms with relatively high past return in the prior 11 months and goes short in firms with relatively low past return in the preceding 11 months. The model is expressed as:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}\left(R_{Mt} - R_{Ft}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \varepsilon_{it}\,, \qquad (2)$$

where the variables have the same meaning as in equation (1), with the corresponding βs representing the factor exposures to the excess stock return and if the risk factors capture all of the variation in the excess stock returns the intercept α_i should be equal to zero for all of the assets.

3.3 Fama and French (2015, FF5) Five Factor Model

The FF5 model is an extension of the FF3 model. It adds an operating profitability factor and an investment factor to the FF3 model. The operating profitability factor is a zero cost portfolio which invests in firms with relatively high operating profitability (OP) and goes short in firms with relatively low OP, the so called robust-minus-weak profitability factor (RMW). The investment factor is a zero-cost portfolio which invests in firms with relatively low yearly growth in assets and goes short in firms with relatively high yearly growth in total assets, the so called conservative-minus-aggressive investment factor (CMA). The model is expressed as:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}\left(R_{Mt} - R_{Ft}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \varepsilon_{it}, \qquad (3)$$

where, as before, the five different βs represent the corresponding risk factor exposure to the excess stock return and if the risk factors capture all of the variation in the excess stock returns the intercept α_i should be equal to zero for all the assets.

3.4 Hou et al. (2015, q4) Model

The q4 model, is a model that consist of four different risk factors. It is the market factor, a size factor (SIZE) that is created with another sorting than in the FF3- and FF5 model, a profitability factor (ROE), and an investment factor (INV), that is created with another sorting than in the FF5 model. SIZE is similarly SMB, a zero-cost portfolio investing in relatively small size firms and going short in relatively big size firms. ROE is a zero-cost portfolio that invest in firms with relatively high return-on-equity and goes short in firms with relatively low return-on-equity. INV is, similarly CMA in the FF5 model, a zero-cost portfolio investing in firms with relatively low yearly asset growth and going short in firms with relatively high yearly asset growth. The model is expressed as:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}\left(R_{Mt} - R_{Ft}\right) + \beta_{2i}SIZE_t + \beta_{3i}ROE_t + \beta_{4i}INV_t + \varepsilon_{it}, \qquad (4)$$

where as before the four different βs represent the corresponding risk factor exposures to the excess stock return and if the risk factors capture all of the variation in the excess stock returns the intercept α_i should be equal to zero for all the assets.

Section 4

Data

4.1 Data

The paper follows a similar methodology as earlier mentioned studies to test and compare the different models in my data sample. The data for the listed firms are obtained from Bloomberg, but the constituents for monthly indexes are only available back to 2002. Therefore, I use the Swedish House of Finance database, FINBAS, to get tickers for all listed firms all the way back to 1993. I include all firms that are listed on the four countries major stock exchanges (OMX Stockholm, OMX Copenhagen, OMX Helsinki, and Oslo Bors) and that have a ticker in Bloomberg. Firms that have data for less than 24 consecutive months are excluded, this follows the work of Fama and French (1993). After this, I end up with 1315 different stocks. The sample spans the period of July 1993 to June 2018, which means the study examines a period of 300 months.

4.2 Variable Definitions

The different variables used to form the factors in the models are computed independently for every stock and then combined to form portfolios and factors. All variables are collected annually at the end of the year, except for the Market Capitalization (MC) which is collected by the end of each month. The definition of variables follows here.

Market Capitalization (MC) is the closing share price multiplied by outstanding shares. It is computed at the end of each month and is used in calculating value weighted portfolios and for calculation of the book-to-market ratio. It is also used to form the SMB and SIZE factor in the FF3, FF5, and q4 models.

Book Equity (BE) is stockholders' equity plus deferred taxes and investment tax credit minus book value of preferred stocks, see Fama and French (1993, 2015, and 2017).

Book-to-Market ratio (BE/MC) is used to form portfolios at the end of each June and is the ratio of the book equity to the market capitalization (MC). It is computed as the BE in the previous year, divided by the MC in the previous year. It is used to form the HML factor in the FF3- and FF5 model.

Operating Profitability (OP) is used to form portfolios at the end of each June according to how profitable the operation of the firm is in relation to the value of the book equity. It is computed as operating profit minus interest expenses divided by BE, all from the year end of the previous year. This approach slightly differs from the approach of Fama and French (2015, 2017) who calculate the numerator of the ratio as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrational expenses. The reason for using a different approach is that for some firms in my dataset the variables that Fama and French (2015, 2017) use, are not available. However, their calculation of the numerator usually sums up to operating profit minus interest expenses, which is what I use. OP is used to form the RMW factor in the FF5 model.

Investment is used to form portfolios every June according to how high or low the firm's growth in assets are. It is measured as change in total assets between the ends of the preceding years, divided by total assets at the end of the year prior to the previous year, $\left(\frac{Total\ assets_{t-2} - Total\ assets_{t-1}}{Total\ assets_{t-2}}\right)$. It is used to form the CMA factor in the FF5 model and the INV factor in the q4 model.

Return on equity (ROE) is used to form portfolios at the end of each June according to how profitable the firms are. It is measured as income before extraordinary items at the end of the previous year divided by total equity from the end of the previous year, and is used for forming the ROE factor in the q4 model.

4.3 Construction of Portfolios

The variables described above are used to sort firms into three different sets of portfolios. These portfolios are summarized in Table 1.

The first set of portfolios are used to construct factors based on size, book-to-market value, operating profitability, investment, and momentum. These portfolios are used to form the factors in the FF3, FF5 and Carhart models. The portfolios are formed based on 2 x 3 intersections of size and one of the other variables, respectively. The firms are divided into two groups based on size using the median as a breakpoint. The firms are also divided into three groups respectively based on book-to-market value, momentum, profitability, and investment, using the 30th and 70th percentile as breakpoints. The intersections of each size group with each one of the other variables, respectively, form a set of 24 different portfolios.

Table 1
Construction of portfolios

Stocks are assigned to portfolios based on Size, book-to-market value ratio (BE/MC), operating profitability (OP), Investment (INV), Return-on-Equity (ROE), and Momentum (MOM). The portfolios are formed in June of year t based on these sorts. The intersection of either 2 or 3 sorts gives a number of different portfolios of stocks. Monthly value weighted excess returns are calculated for each portfolio. Median breakpoint means that stocks are divided into 2 groups. Quintile breakpoint means that stocks are divided into 5 groups.

Set	Sort	Breakpoints
2 x 3 sorts	6 portfolios on Size and BE/MC	Size: median
	6 portfolios on Size and OP	BE/MC: 30th and 70th percentiles
	6 portfolios on Size and INV	OP: 30th and 70th percentiles
	6 portfolios on Size and MOM	INV: 30th and 70th percentiles
		MOM: 30th and 70th percentiles
2 x 3 x 3 sorts	18 portfolios on Size, ROE, and INV	Size: median
		ROE: 30th and 70th percentiles
		INV: 30th and 70th percentiles
5 x 5 sorts	25 portfolios on Size and BE/MC	Size: quintiles
	25 portfolios on Size and OP	BE/MC: quintiles
	25 portfolios on Size and INV	OP: quintiles
	25 portfolios on Size and ROE	INV: quintiles
	25 portfolios on Size and MOM	ROE: quintiles
		MOM: quintiles

The second set of portfolios are used to construct factors based on size, return on equity, and investment. These portfolios are used to form the factors in the q4 model. The portfolios are formed as 2 x 3 x 3 intersections of size with both return-on-equity and investment. The firms are, as before, divided into two groups based on size. The firms are also divided into three groups respectively based on return-on-equity and investment, using the 30th and 70th percentiles as breakpoints. The 2 x 3 x 3 intersections of each size group with each return-on equity-group and each investment group, form a set of 18 different portfolios.

The third set of portfolios are used to compute value weighted portfolio excess returns which are used as test assets in the regressions. There are five subsets of portfolios each consisting of 25 portfolios. They are formed as 5 x 5 sorts on size and one of: book-to-market ratio, operating profitability, investment, return on equity, or momentum. This is done by using the 20th, 40th, 60th, and 80th percentiles as breakpoints.

The firms are assigned to a corresponding portfolio at the end of each June. As an example, the 2 x 3 portfolio based on size and book-to-market is constructed after sorting all firms for year t in order of size, finding a median firm. Firms above this median level are labelled as big stocks. All firms below that level are considered as small stocks. In the same way all firms are sorted based on their book-to-market value. Firms in the top 30th percentile are considered as high value stocks. Firms between the 30th and the 70th percentile are considered as neutral value stocks. Firms in the bottom 30th percentile are considered as low value stocks. The intersections of these sorts on size and book-to-market value produce six different portfolios for year t.

After these portfolios are defined, I calculate value weighted monthly excess return for these portfolios from the start of July in year t to the end of June in the next year and portfolios are then rebalanced. Returns are weighted with respect to the market capitalization of the firm each month. The excess return of these weighted portfolios are calculated by subtracting the rate of the one month Swedish Treasury bill. This follows the approach of Fama and French (2015) who use the one month U.S. Treasury bill rate.

4.4 Construction of Factors

4.4.1 Fama and French (1993, 2015) Models and Carhart (1997) Four Factor Model

The construction of factors for the FF3, FF5 and Carhart models are based on the 2 x 3 portfolio sorts, where size is split into two groups and one of the other factors into three groups. The excess returns of the portfolios from the first set, in Table 1, are used when constructing the returns of the factors. The SMB factor is the average return of the small stock portfolios minus the average return of the big stock portfolios. The HML factor is the average return of the high book-to-market ratio stock portfolios minus the average return of the low book-to-market ratio stock portfolios. The RMW factor is the average return of the high operating profitability stock portfolios minus the average return of the low operating profitability stock portfolios. The CMA factor is the average return of the low investment stock portfolios minus the average return of the high investment stock portfolios. The MOM factor is the average return of the high momentum stock portfolios minus the average return of the low momentum stock portfolios.

4.4.2 Q4 Model

The factors used in the q4 model are the SIZE-, the ROE-, and the INV factors. The second set of portfolios, in Table 1, are used to form these factors. The SIZE factor is the difference between the average return of the small size stock portfolios and the average return of the big stock portfolios. The ROE factor is the difference between the average return of the high return-on-equity stock portfolios and the average return of the low return-on-equity stock portfolios. The INV factor is the difference between the average return of the low investment stock portfolios and the average return of the high investment stock portfolios.

4.4.3 Market (Mrkt) Factor

The Mrkt factor, which is used in all the models, is calculated as a value weighted return of all the stocks in the sample minus the rate of the Swedish Treasury bill with one month maturity. Since most of the firms in the sample are Swedish, the Swedish Treasury bill is used as a proxy of the risk free rate. The rate is collected from Sveriges Riksbank and the monthly rate is calculated as an average of all daily observations during the given month.

Section 5

Results

5.1 Average Returns

In the first part of the analysis I take a look at the average returns of the 125 portfolios, which are my test assets, from the third set of portfolios in Table 1. For my sample, of Nordic stocks, the findings on average returns are pretty similar to those of Fama and French (1993, 2015). The average returns for my sample are presented in Table 2. The pattern for Size over all the panels is that the small stock portfolios generate higher average returns than the big stock portfolios do. This pattern indicates that the size effect found by Fama and French (1993) is evident in my dataset. Having stated this I take a look at the other variables.

Panel A shows the returns of the 25 portfolios sorted on Size and BE/MC. There is one outlier amongst these portfolios, and that is the portfolio in the third column and fourth row which generates the highest average excess return (3.25%), after further investigation of the returns in my dataset I find that this portfolio return, and three other portfolio returns amongst my 125 portfolios, experience these high returns as a result of one single firm exhibiting a huge return in one single month. This is not something that has an effect on my main results and therefore due to the limited time span of my work on this paper I will not elaborate further on this, but I provide results of some robustness tests, excluding this return from my dataset, in the appendix. Looking at the value effect, increasing BE/MC and holding Size constant, I find that the average portfolio returns are increasing in all of the five rows, indicating a pattern towards a positive value effect. This pattern is though not evident from the third quantile to the fourth quantile, where average returns are dropping to then increase again for the firms with the highest BE/MC ratios, but overall there is a pattern of average returns to increase with the BE/MC ratio.

Table 2

Average monthly excess returns of test portfolios

Average monthly excess returns for portfolios formed on Size and BE/MC, Size and OP, Size and INV, Size and ROE, and Size and MOM. Firms are assigned to five Size groups at the end of each June based on the market capitalization. In a similar way firms are also assigned to five groups of BE/MC, OP, INV, ROE, and MOM. Value weighted portfolios are formed based on intersections of these groups and average monthly returns in excess of the 1 month Swedish treasury bill rate are presented in the table below.

	Low	2	3	4	High
Panel A: Size - BE/MC portfolios					
Small	0.89%	0.85%	0.96%	0.58%	1.14%
2	0.29%	0.53%	0.37%	0.46%	0.69%
3	0.24%	0.40%	0.70%	0.43%	0.62%
4	0.07%	0.66%	3.25%[1]	0.54%	0.90%
Big	0.48%	0.53%	0.51%	0.68%	0.70%
Panel B: Size - OP portfolios					
Small	1.06%	0.99%	0.59%	1.19%	1.53%
2	0.47%	0.49%	0.42%	0.63%	0.79%
3	0.15%	0.35%	0.43%	0.72%	0.78%
4	0.25%	0.43%	3.04%[1]	0.48%	0.71%
Big	0.41%	0.30%	0.57%	0.55%	0.61%
Panel C: Size - INV portfolios					
Small	1.17%	1.17%	0.68%	0.95%	0.80%
2	0.51%	0.85%	0.42%	0.58%	0.34%
3	0.50%	0.44%	0.50%	0.70%	0.36%
4	0.55%	0.68%	0.51%	0.65%	0.24%
Big	0.56%	0.55%	0.64%	0.51%	0.43%
Panel D: Size - ROE portfolios					
Small	0.95%	0.73%	0.84%	1.24%	1.57%
2	0.52%	0.31%	0.51%	0.60%	0.84%
3	0.26%	0.30%	0.56%	0.72%	0.54%
4	0.37%	2.65%[1]	0.47%	0.55%	0.58%
Big	0.43%	0.25%	0.58%	0.67%	0.55%
Panel E: Size - MOM portfolios					
Small	0.81%	0.83%	0.83%	0.82%	1.01%
2	0.52%	0.39%	0.54%	0.56%	0.50%
3	0.09%	0.30%	0.58%	0.58%	0.63%
4	0.60%	0.46%	0.53%	2.99%[1]	0.62%
Big	0.43%	0.55%	0.55%	0.58%	0.51%

[1] These returns fall in line with the overall pattern once the single extreme outlier return is removed from my dataset, see table A1 in appendix.

In panel B, I find once again that the portfolio in the third column and fourth row is producing the highest average return (3.04%). Looking at the OP across the Size rows, I find that average returns are increasing with OP in every row, indicating a positive relationship between OP and returns.

In Panel C, looking at investment while holding Size constant I find that as investment increases the returns decrease in all 5 columns. This is a pattern that indicates that the low investment portfolios generate a higher average return than the high investment portfolios do.

In Panel D, holding Size constant and looking at the return-on-equity, I find that in all rows the average returns are increasing with return-on-equity. This indicates a positive relationship between returns and return-on-equity.

In Panel E, holding Size constant and looking at the momentum, I can observe that the average returns are increasing in 4 of the rows, even though only slightly in the fourth row. This indicates a pattern of average returns increasing with momentum. This pattern is though not evident from the fourth to the fifth quantile, since I can observe that the returns are higher in the fourth quantile than in the fifth quantile in four of the cases, but overall there is a pattern of the average returns to increase with momentum.

5.2 Descriptive Statistics of Factor Returns

Table 3

Descriptive statistics for monthly factor returns

The market portfolio factor (Mrkt) is calculated as a value weighted monthly return of all stock in my sample, in excess of the 1 month Swedish Treasury bill rate. Firms are assigned to 2 size groups at the end of each June, based on the market capitalization. In a similar way firms are assigned to 3 groups of BE/MC, OP, INV, ROE, and MOM using 30^{th} and 70^{th} percentiles as breakpoints. Intersections of the Size groups with different combinations of the other variables form the factor portfolios.

	Mrkt-Rf	SMB	HML	RMW	CMA	MOM	SIZE	ROE	INV
Mean (%)	0.99	0.12	0.33	0.32	0.20	0.47	0.21	0.46	0.33
Std. dev. (%)	3.69	2.57	3.03	2.87	2.92	6.09	1.60	2.54	2.95
t-Statistic	4.65	0.80	1.91	1.94	1.19	1.33	2.28	3.15	1.96
p-Value	0.00	0.43	0.06	0.05	0.24	0.18	0.02	0.00	0.05

In Table 3, I present descriptive statistics for the factor returns used in the models. The average monthly value weighted return for my sample of Nordic stocks is 0.99%. It is almost twice as large as the estimated return for the U.S. sample in Fama and French (2015), where the average value weighted return is estimated at 0.50%. This might be an effect of the exchange rate being different or maybe one should consider the Nordic stock market to be riskier than the U.S. market? It might also be an effect of my sample being smaller than in Fama and French (2015). All the average returns for the factors, except for Mrkt used in the FF3, FF5 and Carhart models are relatively small. Looking at the t-statistics, the returns of these factors are not indistinguishable from zero at a 95% significance level, since the t-statistics are all lower than 1.96. The average returns for the factors used in the q4 model are all significantly different from zero at a 95% significance level. On average all of the factor returns are though positive, which gives me some more indication that the different investment strategies on average generate positive returns.

In Table 4, I find that most of the factor returns are not highly correlated. Two factors that though are highly correlated is the CMA and the INV factor which shows to be highly positively correlated (0.88), this is to be expected since they are both formed from the investment variable, explained in Section 3. The RMW and the ROE factor, shows to be highly positively correlated (0.83), this is also to be expected since they both incorporate a measure of profitability. I also find that the SMB and the MOM factor are pretty highly negatively correlated (-0.62). This is interesting since that would indicate that small stocks would tend to more often be so called loser stocks. It is also interesting since the other factor formed based MC, SIZE, does not show a significant correlation with MOM (0.03). I also find that HML is pretty highly positively correlated with the CMA and the INV factor (0.55 & 0.53). This indicates that stocks with high book-to-market ratio tends to more often experience high yearly growth in assets. Another interesting finding from the correlation matrix, is that the Mrkt factor is significantly correlated, on a 95% significance level, with all factors except the MOM factor. This is an indication that almost all of my factors show some sort of correlation with the market return generated for my sample of stocks.

Table 4

Correlations of factor returns

Correlations between the nine different factor returns used in the four different factor models. * indicates that the correlations is significantly different from zero at a 95% significance level.

	Mrkt-Rf	SMB	HML	RMW	CMA	MOM	SIZE	ROE	INV
Panel A: Correlations									
Mrkt-Rf	1.00								
SMB	-0.27*	1.00							
HML	-0.41*	-0.05	1.00						
RMW	-0.21*	-0.17*	0.13*	1.00					
CMA	-0.19*	0.17*	0.55*	-0.24*	1.00				
MOM	0.02	-0.62*	-0.05	0.19*	-0.12*	1.00			
SIZE	-0.31*	0.67*	0.04	0.03	0.16*	-0.03	1.00		
ROE	-0.29*	0.10*	0.17*	0.83*	-0.03	0.07	0.25*	1.00	
INV	-0.32*	0.29*	0.53*	-0.05	0.88*	-0.09	0.31*	0.26*	1.00

5.3 Performance of Asset Pricing Models

Here I present the results from the regressions of average portfolio returns on the four models. The main goal is to see if the intercept values are indistinguishable from zero for the four different models and to investigate how well the models are capturing the variance in average returns. The results are presented in Table 5. The GRS test is used in order to find out if the estimated intercepts from multiple regressions, on the models, are jointly indistinguishable from zero. 25 regressions are run for the four models, using my test assets. The results of these regression are presented in Panels A-E. In Panel F, 125 regression are run on the four different models, using all of my test assets. The theory predicts that a correctly specified model has an intercept equal to zero. A p-value of 0.05 or smaller means that I can reject the hypothesis that the intercepts are jointly indistinguishable from zero at a 95% significance level. I also look at the average of absolute value intercepts, average R-square values, mean absolute value t-statistics for the intercepts, the amount of absolute value t-statistics, for the intercepts, smaller than 1.96, and the amount of absolute value t-statistics, for the intercepts that are smaller than 3. This in order to be able to compare the relative performance of the models.

Table 5

Results for tests of asset pricing models

Tests on how well factors describe monthly excess returns on 25 Size – BE/MC portfolios (Panel A), 25 Size – OP portfolios (Panel B), 25 Size – INV portfolios (Panel C), 25 Size – ROE portfolios (Panel D), 25 Size – MOM portfolios (Panel E), and all 125 portfolios (Panel F). Tests are run for all of the four models. GRS-statistics tests whether the intercepts for 25 or 125 regressions are zero, the p-value shows the significance of the test. Avg|α| is the average absolute intercept value, in basis points, of 25 or 125 regressions, Avg(R^2) is the average R-square value of 25 or 125 regressions, Avg |t-stat| is the average of absolute t-statistic values for intercepts from 25 or 125 regression, t-stat <|1.96| is the amount of absolute t-statistic values lower than 1.96 for intercepts from 25 or 125 regressions, t-stat <|3| is the amount of absolute t-statistic values lower than 3 for intercepts from 25 or 125 regressions, and t-stat>|3| is the amount of absolute t-statistic values higher than 3 for intercepts from 25 or 125 regressions.

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	GRS	p-Value	Avg|α|	Avg(R^2)	Avg|t-stat|	t-stat<|1.96|	t-stat<|3|	t-stat>|3|
Panel A: 25 Size - BE/MC portfolios								
FF3	1.37	0.12	0.53	0.49	1.64	16	21	4
Carhart	0.93	0.56	0.22	0.52	1.14	24	25	0
FF5	1.67	0.03	0.54	0.52	1.42	17	24	1
q4	1.92	0.01	0.28	0.44	0.96	23	25	0
Panel B: 25 Size - OP portfolios								
FF3	2.30	0.00	0.59	0.46	1.86	13	20	5
Carhart	1.58	0.04	0.28	0.49	1.30	20	24	1
FF5	1.86	0.01	0.54	0.52	1.53	18	22	3
q4	1.80	0.01	0.25	0.48	0.87	23	24	1
Panel C: 25 Size - INV portfolios								
FF3	1.52	0.06	0.30	0.47	1.60	18	22	3
Carhart	1.02	0.44	0.20	0.48	1.01	22	25	0
FF5	1.66	0.03	0.23	0.53	1.28	21	25	0
q4	1.36	0.12	0.17	0.50	0.85	25	25	0
Panel D: 25 Size - ROE portfolios								
FF3	2.17	0.00	0.53	0.46	1.78	15	24	1
Carhart	1.56	0.04	0.23	0.49	1.11	19	25	0
FF5	1.78	0.01	0.46	0.51	1.40	19	23	2
q4	1.65	0.03	0.23	0.48	0.85	22	24	1
Panel E: 25 Size - MOM portfolios								
FF3	1.57	0.05	0.54	0.40	1.51	16	22	3
Carhart	0.87	0.64	0.21	0.45	0.95	23	25	0
FF5	1.65	0.03	0.51	0.43	1.27	19	23	2
q4	1.32	0.15	0.27	0.40	0.86	24	25	0
Panel F: 125 portfolios								
FF3	1.05	0.38	0.50	0.46	1.68	78	109	16
Carhart	0.92	0.71	0.23	0.49	1.10	109	124	1
FF5	0.99	0.53	0.46	0.50	1.38	94	117	8
q4	0.99	0.51	0.24	0.46	0.88	117	123	2

In Panels A-E, I find that there is only one model for which I can reject that the intercepts are jointly indistinguishable from zero, in all of the panels. That is the FF5 model, which for the test produces a p-value below 0.05, for all tests. The FF3 model and the q4 model are rejected in three of the panels. The model that performs best, looking at the GRS-tests in panel A-E, is the Carhart model, which I am only able to reject in two of the panels. Further looking at the average of the absolute value intercepts for Panel A-E, I find that the Carhart model and the q4 model always produce the lowest values, indicating that those two models are better in capturing variation in average returns than the FF3 and FF5 models are. I also find that the q4 model always generates the lowest average value of absolute value t-statistics for the intercepts of the 25 individual regressions. Looking at the number of absolute value t-statistics smaller than 1.96, it is evident that the Carhart model and the q4 model produce the highest number. For the number of absolute value t-statistics smaller than 3, the same pattern is evident.

In Panel A, where regressions are made for Size - BE/MC portfolios, the hypothesis of the intercepts being jointly indistinguishable from zero are rejected for two of the models, the FF5 model and the q4 model. I also find that the Carhart model and the q4 model generate lower average values of absolute value intercepts than the FF3 and FF5 models do. The average R-square value is around 50% for all of the models. Continuing with taking a look at the intercept values of the 25 individual regressions, I find that the average value of the absolute value t-statistics for the Carhart model and the q4 model are lowest, comparing the four models, the q4 model performing the lowest value (0.96). I also find that the Carhart model and the q4 model do not produce a single absolute value t-statistic higher than 3, for the 25 regressions.

In panel B, where the regressions are made for Size - OP portfolios, I can reject that the intercepts are jointly indistinguishable from zero for all of the models. The pattern for the average of absolute value intercepts is the same as in Panel A, with the Carhart model and the q4 model showing the lowest values. For the average of the absolute value t-statistics the Carhart model and the q4 model produce the lowest values. The q4 model is also the model that produce the highest number of absolute value t-statistics that are smaller than 1.96.

In panel C, where the regressions are made for Size - INV portfolios, I can reject that the intercepts are jointly indistinguishable from zero for the FF5 model. The lowest values of the absolute value intercepts are once again found for the Carhart model and the q4 model. Those models are also producing the lowest values for the average of the absolute value t-statistics. Looking further on the absolute value t-statistics, there is not a single one higher than 3 for the Carhart model, the FF5 model and the q4 model. The q4 model performs best in this measure, producing no absolute value t-statistic above 1.96.

In Panel D, where regressions are made for Size - ROE portfolios, I find the same result as in Panel B for the GRS test. I can reject that the intercepts are jointly indistinguishable from zero for all of the models. This is no surprise since the correlation matrix showed us that the RMW- (formed on OP) and the ROE factor were strongly correlated to each other. For the average value of the absolute value intercepts I once again find that the Carhart model and the q4 model produce the lowest values, the same goes for the average value of the absolute value t-statistics. Another finding is that all of the models produce at least 23 absolute value t-statistics that are smaller than 3. The q4 model once again produces the highest number of absolute value t-statistics smaller than 1.96 (22).

In panel E, where regressions are made for Size - MOM portfolios, I can reject that the intercepts are jointly indistinguishable from zero for the FF3- and FF5 model. Once again the average absolute value intercepts for the Carhart model and the q4 model are lower than for the FF3- and FF5 model. In this panel average values of the absolute value t-statistics are below 1 for both the Carhart model and the q4 model. Both of these models also produce no absolute value t-statistic above 3 and the q4 model produces the highest number of t-statistics smaller than 1.96 (24).

In Panel F, I run the GRS test using all of the 125 portfolios as test assets. The finding here is that I cannot reject that the intercepts are jointly indistinguishable from zero for any of the models. The pattern for the average of the absolute value intercepts is the same as for the other panels. The Carhart model and the q4 model produce the lowest values. Looking at the 125 individual intercepts, the average value of the absolute value t-statistics is lowest for the q4 model (0.88). I also find that the Carhart model generates the highest number of absolute value t-statistics smaller than 3 (124). But for absolute value t-statistics smaller than 1.96, the q4 model generates the highest number (117).

To sum up, the evidence of these tests favours the Carhart model and the q4 model to perform best in explaining stock returns in my dataset. These two models always produce the lowest average values of the absolute value intercepts. Using the absolute value t-statistics to look at the significance of these intercepts, it is also clear that these two models perform best. It is obvious that these two models produce the lowest number of intercept values of which I can reject to be indistinguishable from zero.[2]

[2] Results for tests on the four models using the portfolio returns where the single extreme outlier return is removed from my dataset, are provided in table A2 in the appendix

5.4 Hybrid Model

5.4.1 Choosing the Number of Factors

In this part of the analysis, I investigate my second hypothesis: Is it possible to choose factors to create a hybrid model that outperforms the four models tested in the paper? There are many possible approaches to pursue. In this paper, I choose factors based on Principal Component Analysis (PCA). PCA is a statistical method that converts a set of observed and possibly correlated variables into Principal Components (PCs), which is a set of uncorrelated variables (Li and Wang, 2014). The first PC accounts for the maximal variance in the data, and then the following PCs give the maximal variance given that it is uncorrelated to all the previous variables. I use a screeplot of the PCs in order to decide how many factors to include in my model and then I use factor weights in the PCs to decide which factors to include in the model. It is important to note that even though PCA makes the PCs uncorrelated, removing second-order dependencies, it does not remove higher-order dependencies. So the PCA factors may still exhibit higher-order dependence (Shlens, 2014).

Table 6

PCA for the factor returns

Results of PCA on the nine factor returns used in the four different models. Showing the components that explains most of the variance in the dataset as component 1 and then showing components in falling order based on how much of the variance in the dataset it explains expecting that it is uncorrelated to the other variables. Cumulative showing the accumulated correlation described by components adding up to 1 for all nine components. Explained variance shows how much of the variance that is explained by the component.

Component	Cumulative	Explained Variance
1	0.32	0.32
2	0.55	0.23
3	0.74	0.19
4	0.84	0.10
5	0.92	0.08
6	0.97	0.05
7	0.99	0.01
8	0.99	0.00
9	1.00	0.01

In Table 6, I present the results of the PCA. The first principal component explains around 32% of the joint variation in the dataset. Then for every component the cumulative explanation of the variation in the dataset gets higher until it slows off at the 7th component. For the 7th component I find a cumulative explanation of the variation in the dataset of around 99% and for the 8th component I also find a cumulative explanation of the variation in the dataset to be around 99%. Building on these results I choose to include seven factors in my hybrid model.

5.4.2 Choosing Factors

To choose which of the original factors to use in the hybrid model, I first rotate the PCs so that the sum over columns of the within-column variances are maximized. Any rotation of the PCs spans the same space as the original PCs. The intuition behind rotating the PCs is to seek an easier way to interpret the PCs. After rotating the PCs, I look at which of the nine original factors have the highest weights in the rotated PCs. The results are presented in Table 8. The seven components are created by weighting the factors. For example, the first principal component is obtained by calculating the weighted sum of the nine factors using the weights in the column for COMP1.

The chosen factors for the hybrid model are highlighted in Table 7, and are, respectively, CMA, MOM, SIZE, ROE, RMW, Mrkt, and HML. One thing to note is that since I do not standardize the factors before PCA, it might be that the reason for the weight being high, is that the weight compensates for the scale within them. This is a problem if for example one of the variables exhibits much higher variation than the other variables. Then it is obvious that PCA, in trying to maximize the variance of the dataset, would pick a high weight on this specific variable, instead of picking the variable that is more useful in explaining the variation in the dataset (The Pennsylvania State University, 2018). But if we take a look back at Table 3 we see that the only variable that exhibits a somewhat higher variance than the other ones is the MOM factor, so this should not be a huge problem in this case.

Table 7

Results of predicting seven components by the nine factor returns

Showing the predicted weights of explanation assigned to each one of the nine factor returns for each of the seven rotated components used based on the PCA. The highest number for every component is displayed in bold type.

Factor weights	COMP1	COMP2	COMP3	COMP4	COMP5	COMP6	COMP7
Mrkt-Rf	0.0026	-0.0156	0.0165	0.0156	-0.0179	**0.9932**	-0.0071
SMB	-0.0416	-0.4428	0.4133	0.2079	-0.2519	-0.0947	-0.1175
HML	-0.0029	-0.0207	0.0211	0.0106	-0.0147	-0.0072	**0.9909**
RMW	0.0380	-0.0442	0.0500	0.0896	**0.9110**	-0.0257	-0.0206
CMA	**0.8077**	-0.0391	0.0238	-0.1919	0.1347	0.0154	-0.0093
SIZE	0.0133	0.1002	**0.9003**	-0.0519	0.0681	0.0309	0.0387
ROE	-0.0875	0.0286	-0.0388	**0.8595**	0.1242	0.0285	0.0161
INV	0.5799	0.0567	-0.0296	0.4090	-0.2506	-0.0284	0.0110
MOM	-0.0190	**0.8864**	0.1121	0.0523	-0.0708	-0.0332	-0.0427

In Table 7 I also find that the INV factor perform a pretty high weight (0.5799) in COMP1, where CMA perform the highest weight, which is not a surprise since these two factors are highly correlated, and SMB perform high weights (-0.4428 & 0.4133) in both COMP2 and COMP3, where MOM and SIZE perform high weights, which is not a surprise since these two factors are highly correlated with the SMB factor, SIZE and SMB are also created based on the MC of the firm. Therefore I decide to also test a seven factor hybrid model that include the INV and SMB factors instead of the CMA and SIZE factors.

These results makes me end up testing two seven factor hybrid models:

Hybrid model 1:

$$R_{it} - \mathrm{R}_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - \mathrm{R}_{Ft}) + \beta_{2i}\mathrm{SIZE}_t + \beta_{3i}\mathrm{HML}_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \beta_{6i}ROE_t + \beta_{7i}MOM_t + \varepsilon_{it}, \quad (5)$$

Hybrid model 2:

$$R_{it} - \mathrm{R}_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - \mathrm{R}_{Ft}) + \beta_{2i}SMB + \beta_{3i}\mathrm{HML}_t + \beta_{4i}RMW_t + \beta_{5i}INV_t + \beta_{6i}ROE_t + \beta_{7i}MOM_t + \varepsilon_{it}, \quad (6)$$

Another model I decide to test, is a model where I use the PCs as risk factors. The PCs are portfolios that can be created by calculating the weighted sum of the factors, using the weights in Table 9. Therefore I will also test a model, called the PC model, looking like this:

$$R_{it} - \mathrm{R}_{Ft} = \alpha_i + \beta_{1i}PC1_t + \beta_{2i}PC2_t + \beta_{3i}\mathrm{PC3}_t + \beta_{4i}PC4_t + \beta_{5i}PC5_t + \beta_{6i}PC6_t + \beta_{7i}PC7_t + \varepsilon_{it}, \quad (7)$$

5.4.3 Performance of Hybrid Models

In Table 8 I present the results of the regressions made for average portfolio returns on the two hybrid models and the PC model. Starting off with Panel A-E, I find that for the PC model I cannot reject that the intercepts are jointly indistinguishable from zero for any of the GRS tests performed on this model, which is better than for any of the four models tested earlier. For hybrid model 1 (HM1), I can reject this for tests in Panel B and Panel D , which is a similar result to that of the Carhart model, in Table 5. For hybrid model 2 (HM2) I cannot reject that the intercepts are jointly indistinguishable from zero in any of the panels.

For the average of absolute value intercepts it is clear that the PC model produce the lowest values on overall. I also find that my two hybrid models, overall, produce lower values than all of the four models in Table 5. Looking at the absolute value t-statistics I find that all the three models tested in Table 8, overall, produce lower averages than the four models in Table 5. The PC model produce the lowest average in all of the panels. Neither of these three models produce a higher number than two absolute value t-statistics higher than 1.96. The PC model and HM2 produce no absolute value t-statistic higher than 3 in any of the panels.

In Panel F, where all the 125 portfolios are used as test assets, I find that I cannot reject that the intercepts are jointly indistinguishable from zero for any of the models. That is the same case as for the four models in Table 5. Looking at the average of absolute value intercepts I find that all these three models produce lower values than all of the four models in Table 5. It is also evident, looking at average value t-statistics, that these three models produce fewer intercepts that can be rejected to be different from zero on a 95 % significance level.

Table 8

Results for tests of seven factor asset pricing models

Tests on how well factors describe monthly excess returns on 25 Size – BE/MC portfolios (Panel A), 25 Size – OP portfolios (Panel B), 25 Size – INV portfolios (Panel C), 25 Size – ROE portfolios (Panel D), 25 Size – MOM portfolios (Panel E), and all 125 portfolios (Panel F). Tests are run for my three models. The first model is hybrid model 1 (HM1), the second model is hybrid model 2 (HM2) and the third one is the PC model (PC). GRS-statistics tests whether the intercepts for 25 or 125 regressions are zero, the p-value shows the significance of the test. Avg|α| is the average absolute intercept value of 25 or 125 regressions, Avg(R^2) is the average adjusted R-square value of 25 or 125 regressions, Avg|t-stat| is the average of absolute t-statistic values for intercepts from 25 or 125 regression, t-stat <|1.96| is the amount of absolute t-statistic values lower than 2 for intercepts from 25 or 125 regressions, t-stat <|3| is the amount of absolute t-statistics values lower than 3 for intercepts from 25 or 125 regressions.

	GRS	p-Value	Avg|α|	Avg(R^2)	Avg|t-stat|	t-stat<|1.96|	t-stat<|3|	t-stat>|3|
Panel A: 25 Size - BE/MC portfolios								
HM1	1.42	0.09	0.20	0.55	0.84	25	25	0
HM2	1.17	0.27	0.22	0.55	0.87	24	25	0
PC	1.24	0.21	0.15	0.56	0.75	25	25	0
Panel B: 25 Size – OP portfolios								
HM1	1.64	0.03	0.17	0.56	0.78	23	24	1
HM2	1.25	0.20	0.22	0.56	0.87	23	25	0
PC	1.42	0.09	0.14	0.56	0.75	23	25	0
Panel C: 25 Size – INV portfolios								
HM1	1.31	0.16	0.15	0.56	0.79	25	25	0
HM2	0.93	0.57	0.12	0.55	0.68	25	25	0
PC	1.00	0.46	0.13	0.56	0.69	25	25	0
Panel D: 25 Size – ROE portfolios								
HM1	1.72	0.02	0.18	0.55	0.81	23	25	0
HM2	1.32	0.15	0.21	0.55	0.87	24	25	0
PC	1.46	0.08	0.15	0.55	0.77	24	25	0
Panel E: 25 Size – MOM portfolios								
HM1	1.28	0.17	0.23	0.48	0.91	25	25	0
HM2	1.14	0.30	0.23	0.49	0.80	23	25	0
PC	1.18	0.26	0.18	0.48	0.78	25	25	0
Panel F: 125 portfolios								
HM1	0.92	0.68	0.19	0.54	0.83	121	124	1
HM2	0.83	0.86	0.20	0.54	0.82	119	125	0
PC	0.86	0.82	0.15	0.54	0.75	122	125	0

The evidence from tests on these three models favours all of them to outperform the four models tested in Table 5, in explaining the variation in average stock returns. I find that the models in Table 8 on average produce lower absolute value intercepts than any of the four models in Table 5. Further looking at absolute value t-statistics for the intercepts, it is evident that my two hybrid models and the PC model produce fewer intercepts that are indistinguishable from zero than all the four models in Table 5 do. Another finding is that the results for my two hybrid models differ for the GRS test statistics, which favours HM2 to be better at predicting the variation in average returns for my test assets. But for the other measures investigated, the two hybrid models perform very similar results. This finding leads me to investigate these two models a bit further.

5.4.4 SIZE vs SMB and CMA VS INV

The PCA analysis favours to include the SIZE factor (from the q4 mode) and the CMA factor (from the FF5 model), instead of the SMB factor, from the FF3- and FF5 model, and the INV factor, from the q4 model. In order to further investigate which of these factors performs best in a hybrid model I take a deeper look into the results from the 25 regressions on the Size – INV test assets. In Table 9, I present results of these 25 regressions for HM1 and for a seven factor model where I switch SIZE, in HM1, for SMB. Looking at alpha values (intercepts) for the two models in Panel A, I cannot find any clear cut evidence that speaks in favour for using any of the factors over the other one. The intercepts are pretty similar across the portfolios, except for the small Size portfolios were the model using SMB produce lower absolute values than HM1 does.

Further looking at the factor loadings (βs) of SIZE and SMB, in panel B, I find that there is an overall pattern for the SIZE factor to produce higher absolute values than the SMB factor. This pattern is evident both over rows and columns. This is also to be expected, to some degree, since the SIZE factor has a lower standard deviation then the SMB factor has, looking at the descriptive statistics in Table 3. So this might just be an effect of the factor loadings of SIZE being compensated for this. For the factor loadings on CMA, in Panel C, I find that they are very similar for both models, indicating that the factor loadings on CMA is not affected by switching out the SIZE factor for the SMB factor. Finally, looking at R^2-values, in Panel D, for the two models, I also find that the results are pretty similar for both of the models, the only exception is for the small-low portfolio, where the model including SIZE produces a much higher R^2-value.

Table 9

SIZE/SMB

Results from 25 regressions, on two seven factor models, using Size-INV sorted portfolios as test assets. SIZE is the original hybrid model 1 (HM1) and SMB is the same seven factor model, except for including the SMB factor instead of the SIZE factor. Panel A shows the 25 intercepts, in basis points, from the individual regressions. Panel B shows the factor loadings (βs) for the SIZE/SMB-factor from the individual regressions. Panel C shows the factor loadings (βs) for the CMA-factor from the individual regressions. Panel D shows the R^2 values from the individual regressions.

	Low	2	3	4	High	Low	2	3	4	High
			SIZE					SMB		
Panel A:			α					α		
Small	0.09	0.28	0.13	0.38	0.37	-0.06	0.10	0.04	0.22	0.17
2	-0.12	0.12	-0.03	0.10	-0.12	-0.20	0.05	-0.08	0.06	-0.14
3	0.09	-0.14	-0.10	0.10	-0.09	0.06	-0.17	-0.12	0.09	-0.12
4	0.12	0.13	-0.13	0.04	-0.12	0.12	0.10	-0.10	0.02	-0.01
Big	-0.24	-0.21	0.04	-0.20	-0.20	-0.20	-0.25	0.00	-0.16	-0.17
Panel B:			β SIZE					β SMB		
Small	2.05	1.66	1.11	0.85	1.26	1.19	1.45	0.90	0.92	1.25
2	0.84	0.78	0.25	0.60	0.68	0.74	0.65	0.43	0.47	0.49
3	0.36	0.23	0.31	0.56	0.71	0.31	0.23	0.27	0.37	0.52
4	-0.20	0.06	0.15	0.22	0.12	-0.12	0.11	0.11	0.17	-0.16
Big	-0.20	-0.31	-0.40	-0.26	0.10	-0.03	-0.10	-0.17	-0.24	0.01
Panel C:			β CMA					β CMA		
Small	0.81	0.15	-0.31	-1.04	-0.90	0.87	0.13	-0.32	-1.07	-0.93
2	0.36	0.03	-0.03	-0.26	-0.70	0.35	0.02	-0.03	-0.26	-0.70
3	0.29	0.09	-0.09	-0.38	-0.58	0.28	0.08	-0.10	-0.38	-0.58
4	0.35	0.11	-0.02	-0.22	-0.66	0.35	0.10	-0.02	-0.22	-0.64
Big	0.24	0.16	0.05	-0.16	-0.38	0.23	0.15	0.04	-0.15	-0.37
Panel D:			R^2					R^2		
Small	0.69	0.52	0.43	0.34	0.55	0.59	0.53	0.41	0.36	0.58
2	0.56	0.46	0.40	0.42	0.63	0.57	0.46	0.40	0.42	0.62
3	0.56	0.48	0.48	0.59	0.69	0.56	0.48	0.48	0.57	0.68
4	0.47	0.51	0.54	0.58	0.68	0.47	0.52	0.54	0.58	0.68
Big	0.65	0.67	0.71	0.77	0.75	0.64	0.65	0.70	0.77	0.75

In Table 10 I present the same results as in Table 9 but for HM1 and a seven factor model where I switch the CMA factor, in HM1, for the INV factor. Looking at intercepts for the two models, in Panel A, I cannot find any clear cut evidence that speaks in favour for using any of the factors over the other one. The intercepts are very similar across the portfolios. The pattern for the small Size portfolios to perform lower intercept values that was evident in Table 9 is not evident here, indicating that this was an effect of switching the SIZE factor for the SMB factor.

Table 10

CMA/INV

Results from 25 regressions, on two seven factor models, using Size-INV sorted portfolios as test assets. CMA is the original hybrid model 1 (HM1) and INV is the same seven factor model, except for including the INV factor instead of the CMA factor. Panel A shows the 25 intercepts, in basis points, from the individual regressions. Panel B shows the factor loadings (βs) for the SIZE factor from the individual regressions. Panel C shows the factor loadings (βs) for the CMA/INV-factor from the individual regressions. Panel D shows the R^2 values from the individual regressions.

	Low	2	3	4	High	Low	2	3	4	High
			CMA					INV		
Panel A:			α					α		
Small	0.09	0.28	0.13	0.38	0.37	-0.13	0.27	0.14	0.43	0.41
2	-0.12	0.12	-0.03	0.10	-0.12	-0.13	0.12	-0.04	0.12	-0.09
3	0.09	-0.14	-0.10	0.10	-0.09	0.09	-0.14	-0.09	0.11	-0.07
4	0.12	0.13	-0.13	0.04	-0.12	0.11	0.13	-0.13	0.05	-0.09
Big	-0.24	-0.21	0.04	-0.20	-0.20	-0.25	-0.21	0.03	-0.20	-0.18
Panel B:			β SIZE					β SIZE		
Small	2.05	1.66	1.11	0.85	1.26	2.00	1.66	1.12	0.84	1.26
2	0.84	0.78	0.25	0.60	0.68	0.82	0.78	0.50	0.60	0.70
3	0.36	0.23	0.31	0.56	0.71	0.34	0.22	0.32	0.58	0.74
4	-0.20	0.06	0.15	0.22	0.12	-0.24	0.05	0.17	0.24	0.20
Big	-0.20	-0.31	-0.40	-0.26	0.10	-0.20	-0.31	-0.39	-0.24	0.15
Panel C:			β CMA					β INV		
Small	0.81	0.15	-0.31	-1.04	-0.90	0.85	0.09	-0.28	-0.67	-0.64
2	0.36	0.03	-0.03	-0.26	-0.70	0.33	0.04	-0.02	-0.16	-0.58
3	0.29	0.09	-0.09	-0.38	-0.58	0.29	0.09	-0.14	-0.34	-0.57
4	0.35	0.11	-0.02	-0.22	-0.66	0.46	0.10	-0.11	-0.25	-0.87
Big	0.24	0.16	0.05	-0.16	-0.38	0.19	0.11	0.00	-0.23	-0.51
Panel D:			R^2					R^2		
Small	0.69	0.52	0.43	0.34	0.55	0.69	0.51	0.42	0.22	0.50
2	0.56	0.46	0.40	0.42	0.63	0.56	0.46	0.40	0.41	0.60
3	0.56	0.48	0.48	0.59	0.69	0.56	0.48	0.48	0.58	0.68
4	0.47	0.51	0.54	0.58	0.68	0.48	0.51	0.54	0.58	0.71
Big	0.65	0.67	0.71	0.77	0.75	0.64	0.66	0.71	0.77	0.77

Further looking at the factor loadings (βs) of the SIZE factor, in panel B, I find that the result are very similar for the two models, indicating that the factor loadings on SIZE is not effected by switching the CMA factor for the INV factor. Comparing the factor loadings of the CMA factor with the factor loadings of the INV factor, in Panel C, I find that they are pretty similar for both models and there is no overall pattern for one of the factors to perform either higher or lower coefficients than the other model does. Finally, looking at R^2- values, in Panel D, for the two models, I also find that the results are very similar for both of my models, except for the small portfolios where there is pattern towards the model including CMA producing higher R^2-values.

Section 6

Discussion

In this paper, I find evidence that the Carhart model and the q4 model outperform the FF3 model and the FF5 model in explaining the variation in stock returns on the Nordic stock market for the tested time period.

The Carhart model performs better than the FF3- and the FF5 model in all the measures I have investigated, the most evident being that it in all cases generates a lower average value of absolute value intercepts and also a lower average value of absolute value t-statistics for these intercepts.

There is also evidence suggesting that the q4 model outperforms the FF3- and the FF5 model, in explaining the variation of stock returns. Overall the q4 model performs better than either of these two models for the measures I have investigated. The clearest example being that it generates lower averages of absolute value intercepts and also lower averages of absolute value t-statistics for these intercepts.

There is no evidence suggesting that the FF5 model outperforms the FF3 model, in describing the variation in stock returns on the Nordic market for the tested time period. The FF5 model is rejected by the GRS test for five of the six different sets of test assets and the FF3 model is only rejected for three of them. This does not go along with the findings of Fama and French (2015, 2017), who actually find evidence for the FF5 model to outperform the FF3 model for both the U.S. market and in international markets.

These findings do not go along with my first hypothesis, especially that the Carhart model outperforms the FF5 model and also seems to perform at least equally as well as the q4 model, in describing the variation in average stock returns. This is also something that becomes evident looking at the PCs from the PCA, where all of the factors from the Carhart model ends up with relatively high predicted weights of explanation in at least one of the PCs. Indicating that all of the factors in the Carhart model adds to the explanation of the variation in the dataset.

Adding to these findings, my results also show evidence for size, value, profitability, investment, and momentum effects for Nordic stocks. Looking at patterns of the average returns I find that there is a pattern for small stock portfolios to generate higher average returns than big stock portfolios. There is also a tendency for high value stock portfolios to generate higher average return than the low value stock portfolios. I also find that there is a tendency of high OP stock portfolios to generate higher average returns than low OP stock portfolios. There is also evidence of a pattern for low investment stock portfolios to generate higher average returns than high investment stock portfolios. I also find evidence for high return-on-equity stock portfolios to generate higher average returns than low return-on-equity stock portfolios. There is also a small pattern of high past return stock portfolios to generate higher average returns than low past return stock portfolios. Looking at the descriptive statistics of the factors I also find that all of the factor portfolios generate positive returns on average for the whole time period, even though only marginal for some of the factors.

In this paper, I also develop two different hybrid models consisting of the Mrkt, SIZE/SMB, HML, RMW, CMA/INV, ROE, and MOM factors. These models are formed based on findings from the rotated PCs. For HM1, intercepts are only rejected to be jointly indistinguishable from zero for two of the six different sets of test assets, which is as good as for the Carhart model. For HM2 I cannot reject that the intercepts are significantly different from zero for any of tests performed. There is even evidence suggesting that these two models perform better than all of the other tested models, in describing the variation in average stock returns. The two models generate lower average values of absolute value intercepts. They also generate lower averages of absolute value t-statistics for these intercepts. Investigating the absolute value t-statistics on the intercepts for the individual regressions further, I find that these hybrid models also perform very well in comparison with the other four models. Especially looking at the test made on all the 125 test assets. For HM1 only 4 out of 125 intercepts are rejected to be indistinguishable from zero on a 95% significance level and for HM2 the number of intercepts that are rejected to be indistinguishably different from zero are 6.

Comparing these two seven factor hybrid models against each other the evidence does not really speak in favour of any of them over the other one. HM2 perform better looking at the GRS statistics, since I cannot reject that the intercepts are jointly indistinguishable from zero for any of the tests performed on this model. But on the other hand HM1 perform lower averages for absolute value intercepts, even though only slightly, than HM2 does. HM1 also performs fewer intercepts than can be rejected to be indistinguishably different from zero, on a 95% significance level.

One finding that might be the reason for HM2 to perform better for the GRS tests, is that when looking at the intercept values for the 25 test assets sorted on SIZE-INV, in Table 9, I find that the values for the small size portfolios are lower for a model including the SMB factor instead of the SIZE factor. This pattern is though not evident for any of the other portfolios, suggesting that HM2 only performs better than HM1 for the small size portfolios. More investigation is needed to find exactly which factors to include in this seven factor hybrid model, but it is still evident that both of these models outperform the other four tested models in this paper, in describing the variation in average stock returns, for my sample.

There are many subjects on this topic that have not been investigated in this paper, and remain interesting for further research. This paper is only a study of Nordic markets, it would be interesting to investigate these models, especially my suggested hybrid models, in other markets to see if these findings are sample specific or not. It would also be interesting to add other models in further studies and compare their performance to the four models, and my hybrid models, tested in this study. One model that I would suggest to add to the investigation is the q5 model, introduced by Hou et al. (2018), adding an expected growth factor to the q4 model.

Section 7

Conclusion

The aim of this paper is to investigate the performance of four different asset pricing models in the Nordic stock market. To investigate this question, I construct factor returns for the Nordic stock market following the methodology of Carhart (1997), Fama and French (2015), and Hou et al. (2015). The data consists of 1315 Nordic stocks for the time period July 1993-June 2018. I form five sets each of 25 value weighted diversified portfolios respectively, which are used as test assets in the regression analysis. 2 x 3 sorted or 2 x 3 x 3 sorted portfolios are also constructed to form the different factor portfolios: SMB, HML, RMW, CMA, SIZE, ROE, INV, and MOM. A market factor (Mrkt) is also constructed, as a value weighted average of the market excess return.

The following two hypotheses are stated and investigated in the paper:

H1: *The FF5 model and the q4 model outperform the FF3 model and the Carhart model in describing stock returns on the Nordic stock market*

H2: *It is possible to create a hybrid model, using a combination of the factors from the four models tested, that outperforms these four models in describing stock returns on the Nordic stock market.*

In this paper I find evidence for the second hypothesis, but I cannot prove the first hypothesis. I can conclude that both the Carhart model and the q4 model are better in describing the variation in average stock returns than the FF3 model and the FF5 model are, on the Nordic stock market for the tested time period. This goes against my first hypothesis. This conclusion is mainly a result of average values of absolute value intercepts being lower for regressions made on these two models than for regressions made on the FF3- and FF5 model. Therefore I suggest that practitioners working with Nordic stocks should choose to work with either of these two models, if they choose among the four models that I have investigated in this paper. I also present two different seven factor hybrid models, which I conclude to outperform all the four models tested in this paper. This is proof of my second hypothesis, that it is possible to create a hybrid model by using a combination of the factors from the four different factor models, which outperform the other four models tested in this paper. These two hybrid models both include factors for market return, size of the firm, book-to-market ratio, operating profitability, investment, return-on-equity, and momentum.

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Appendix

Table A1

Average monthly excess returns of test assets (extreme outlier return removed)

Average monthly excess returns for portfolios formed on Size and BE/MC, Size and OP, Size and INV, Size and ROE, and Size and MOM, where the single extreme outlier return is removed from my dataset. Firms are assigned to five Size groups at the end of each June based on the market capitalization. In a similar way firms are also assigned to five groups of BE/MC, OP, INV, ROE, and MOM. Value weighted portfolios are formed based on intersections of these groups and average monthly returns in excess of the 1 month Swedish treasury bill rate are presented in the table below. The average returns that are different in comparison to Table 2 are displayed in bold.

	Low	2	3	4	High
Panel A: Size - BE/MC portfolios					
Small	0.89%	0.85%	0.96%	0.58%	1.14%
2	0.29%	0.53%	0.37%	0.46%	0.69%
3	0.24%	0.40%	0.70%	0.43%	0.62%
4	0.07%	0.66%	**0.55%**	0.54%	0.90%
Big	0.48%	0.53%	0.51%	0.68%	0.70%
Panel B: Size - OP portfolios					
Small	1.06%	0.99%	0.59%	1.19%	1.53%
2	0.47%	0.49%	0.42%	0.63%	0.79%
3	0.15%	0.35%	0.43%	0.72%	0.78%
4	0.25%	0.43%	**0.56%**	0.48%	0.71%
Big	0.41%	0.30%	0.57%	0.55%	0.61%
Panel C: Size - INV portfolios					
Small	1.17%	1.17%	0.68%	0.95%	0.80%
2	0.51%	0.85%	0.42%	0.58%	0.34%
3	0.50%	0.44%	0.50%	0.70%	0.36%
4	0.55%	0.68%	0.51%	0.65%	0.24%
Big	0.56%	0.55%	0.64%	0.51%	0.43%
Panel D: Size - ROE portfolios					
Small	0.95%	0.73%	0.84%	1.24%	1.57%
2	0.52%	0.31%	0.51%	0.60%	0.84%
3	0.26%	0.30%	0.56%	0.72%	0.54%
4	0.37%	**0.49%**	0.47%	0.55%	0.58%
Big	0.43%	0.25%	0.58%	0.67%	0.55%
Panel E: Size - MOM portfolios					
Small	0.81%	0.83%	0.83%	0.82%	1.01%
2	0.52%	0.39%	0.54%	0.56%	0.50%
3	0.09%	0.30%	0.58%	0.58%	0.63%
4	0.60%	0.46%	0.53%	**0.51%**	0.62%
Big	0.43%	0.55%	0.55%	0.58%	0.51%

Table A2
Results for tests of asset pricing models (extreme outlier return removed)

Tests on how well factors describe monthly excess returns on 25 Size – BE/MC portfolios (Panel A), 25 Size – OP portfolios (Panel B), 25 Size – INV portfolios (Panel C), 25 Size – ROE portfolios (Panel D), 25 Size – MOM portfolios (Panel E), and all 125 portfolios (Panel F), where the single extreme outlier return is removed from the dataset. Tests are run for all of the four models. GRS-statistics tests whether the intercepts for 25 or 125 regressions are zero, the p-value shows the significance of the test. Avg|α| is the average absolute intercept value, in basis points, of 25 or 125 regressions, Avg(R^2) is the average R-square value of 25 or 125 regressions, Avg |t-stat| is the average of absolute t-statistic values for intercepts from 25 or 125 regression, t-stat <|1.96| is the amount of absolute t-statistic values lower than 1.96 for intercepts from 25 or 125 regressions, t-stat <|3| is the amount of absolute t-statistic values lower than 3 for intercepts from 25 or 125 regressions, and t-stat>|3| is the amount of absolute t-statistic values higher than 3 for intercepts from 25 or 125 regressions.

	GRS	p-Value	Avg|α|	A(R^2)	Avg|t-stat|	t-stat<|1.96|	t-stat<|3|	t-stat>|3|
Panel A: 25 Size - BE/MC portfolios								
FF3	1.30	0.16	0.27	0.49	1.57	16	22	3
Carhart	0.96	0.53	0.21	0.51	1.15	25	25	0
FF5	1.68	0.02	0.24	0.52	1.30	18	25	0
q4	1.93	0.01	0.19	0.46	0.94	23	25	0
Panel B: 25 Size - OP portfolios								
FF3	2.53	0.00	0.35	0.46	1.77	14	21	4
Carhart	1.82	0.01	0.26	0.48	1.29	20	24	1
FF5	2.11	0.00	0.25	0.52	1.39	19	23	2
q4	2.00	0.00	0.17	0.50	0.88	23	24	1
Panel C: 25 Size - INV portfolios								
FF3	1.52	0.06	0.30	0.47	1.60	18	22	3
Carhart	1.02	0.44	0.20	0.48	1.01	22	25	0
FF5	1.66	0.03	0.23	0.53	1.28	21	25	0
q4	1.36	0.12	0.17	0.50	0.85	25	25	0
Panel D: 25 Size - ROE portfolios								
FF3	2.20	0.00	0.35	0.46	1.74	14	24	1
Carhart	1.61	0.04	0.23	0.48	1.16	18	25	0
FF5	1.85	0.01	0.23	0.52	1.30	20	24	1
q4	1.79	0.01	0.16	0.50	0.83	22	24	1
Panel E: 25 Size - MOM portfolios								
FF3	1.41	0.10	0.30	0.40	1.41	17	23	2
Carhart	0.87	0.65	0.21	0.44	0.97	23	25	0
FF5	1.51	0.06	0.23	0.43	1.16	19	24	1
q4	1.30	0.16	0.19	0.42	0.84	24	25	0
Panel F: 125 portfolios								
FF3	1.07	0.35	0.31	0.46	1.62	79	112	13
Carhart	0.93	0.66	0.22	0.48	1.11	108	124	1
FF5	0.99	0.51	0.24	0.50	1.29	97	121	4
q4	0.99	0.52	0.18	0.47	0.87	117	123	2