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An Evaluation of Asset Pricing Models in the Swedish Context

Is Carhart's Four-Factor Model more suitable than its predecessors for explaining the Swedish stock exchange?

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Abstract

This thesis investigates the explanatory power of the Capital Asset Pricing Model, the Fama French Three-Factor Model and the Carhart Four-Factor Model on the Stockholm Stock Exchange over the period 2012-2016. The purpose is to examine whether or not the Carhart Four-Factor Model explains excess return variability better than the Capital Asset Pricing Model and the Fama French Three-Factor Model. The results conclude that the Carhart Four-Factor Model has significantly better explanatory power than the Capital Asset Pricing Model, but not significantly better than the Fama French Three-Factor Model.

JEL Classification: G10, G12.

Keywords: Capital Asset Pricing Model, Fama French Three-Factor Model, Carhart Four-Factor Model, Swedish stock exchange, r-square-adjusted.

Abbreviations

CAPM – Capital Asset Pricing Model

CFFM – Carhart Four-Factor Model

FF3 – Fama French Three-Factor Model

B/M – Book-to-market ratio

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1 Introduction

1.1 Background

Estimating returns, as well known, is an essential part of investing in the stock market and the investors have a number of models at their disposal when it comes to pricing assets. Three of these models are CAPM, FF3 and CFFM, all of them having been widely used. Studies testing the models have mostly been conducted on US-data, leading to critique regarding the applicability of the models in other contexts than the American. Research has during the last decade been conducted on European data, often focusing on specific European countries. A Swedish study by Encontro, Hjalmarson & Pantzar (2012) sets out to compare the CAPM with the FF3. From their results they conclude that the FF3 exhibits significantly greater explanatory power than the CAPM. Research in other European countries has put forward mounting evidence of the need for modifying the models depending on the region subject to analysis (Artmann, Finter and Kempf, 2012; Fama and French, 2010). Size-premiums have appeared to be vanishing in many countries, and therefore there is a search for other explanatory factors. The country-specific studies have shown that alternative multiple-factor models of the CAPM are more suitable to explain stock market excess return variability. (Christidis, Gregory and Tharyan, 2013; Griffin, 2002). This thesis follows the previous research by testing the CAPM, FF3 and CFFM in the Swedish context.

1.2 Research questions and purpose

The purpose of this thesis is to investigate if the CFFM is the most suitable asset pricing model compared to the CAPM and the FF3 in Sweden, using contemporary data. We examine this through two null hypothesis:

- *The Carhart Four Factor-model explains the excess return of the Swedish market significantly better than the Capital Asset Pricing Model*
- *The Carhart Four Factor-model explains the excess return of the Swedish market significantly better than the Fama French Three Factor-model*

1.3 Contributions

The contribution of the thesis is threefold. First, we use non-US data which previous research emphasize is scarce. Second, we investigate whether or not the size-premium is justifiable since it has been questioned in previous research. Third, we use contemporary data reaching from January 2011 to December 2016.

1.4 Delimitations

A number of delimitations are made in this thesis. Firstly, the sample size is limited to 60 stock, a smaller sample than in most previous research. Secondly, the sampling period is limited to six years. Third, only size and book-to-market sorted portfolios are used to test the models.

1.5 Results

We find a significant difference in explanatory power between CAPM and CFFM. The CFFM can explain more of the excess return variability in each portfolio tested than the CAPM. The CFFM does not exhibit better explanatory power than the FF3. Moreover, size-factors are significant, contradicting previous research pointing to disappearing size-premiums (Dijk, 2011).

1.6 Thesis organization

The thesis is organized as follows: the next section contains a literature review of previous research done on capital assets pricing models in Europe. The literature review is followed by a theory section explaining the models we use to test our hypotheses. Following is the data and methodology sections describing sampling and portfolio construction procedures. Our findings are presented in the empirical results sections followed by a conclusion.

2 Literature review

The CAPM was introduced by Treynor (1961), Litner (1965), Moussin (1966) and Sharpe (1964) and has ever since been one of the most known asset pricing models in the world. The CAPM is a linear equation with the intercept being the risk-free rate of return. An investor can weigh the portfolio between risky and risk-free assets in order to achieve the preferred risk-return combinations based on the investors risk aversion. The CAPM has during the last decades lost ground because of the growing insight that the market-factor does not adequately explain the cross-sectional differences in average returns. There has been numerous propositions of new variables to be included, e.g. size, book-to-market ratio and earnings-to-price ratio (Artmann et al., 2012).

One of the most famous extensions of the CAPM was presented by Fama & French (1991, 1992, 1993) where they critique the CAPM on the grounds of it having only one independent variable explaining the expected return. They presented an extension of the CAPM with two extra explanatory variables, *Small Minus Big (SMB)* and *High Minus Low (HML)*. This extended version of the CAPM is called the FF3. The FF3 asserts that the size and book-to-market ratio of firms (B/M, book equity divided by market equity) has an effect on their stock-return.

During the same year as Fama and French found strong arguments for their discovery, Jegadeesh and Titman (1993) detected another factor further explaining stock-return; winners tend to win and losers tend to lose. They called it the momentum factor, *MOM*. Carhart (1995) used this factor in addition to the FF3, creating the CFFM which was officially published in 1997 (Carhart, 1997). The CFFM has become industry standard for modelling stock return (Artmann et al, 2012).

Since this thesis is aimed at testing the explanatory power of the CAPM, FF3 and CFFM in a Swedish context, we review previous research made on European markets below.

Our inspiration for this thesis comes from Encontro et al. (2012) conducting research comparing the CAPM and FF3 explanatory rate on the Swedish stock exchange where they found statistical significance in favor of the FF3. In previous research we have found that the FF3 and CFFM show mixed results explaining returns of local markets (Artmann, 2012;

Fama French, 2010; Trimech & Kortas, 2009). Some research emphasize the fact that factors specific for that market are preferable (Artmann, 2012; Griffin, 2002; Trimech & Kortas, 2009).

Fama and French (2010) illuminate the fact that regional versions of asset pricing models give good explanations of the regional stock returns. Models using portfolios formed on size and value sorts have greater explanatory power in Europe than global models, i.e. asset pricing is not integrated across regions. The reasons for this can be various, e.g. differences in accounting practices across countries and a varying amount of macroeconomic risk exposure in smaller countries. Griffin (2002) argues that the best asset pricing models can only be constructed using country-specific data.

Artmann et al. (2012) conduct a large sample investigation in the determinants of expected returns on the German stock market. They argue three points which cast doubt on the possibilities of the Fama French model to explain stock return. First, the results from testing the models are heavily dependent on the underlying assets being tested, even a small change in the underlying assets can lead to vastly different validities of the models. Fama and French (2010) conclude that their three-factor model has good explanatory power when analyzing portfolios created according to size and book-to-market ratio. However, the model does a poor job explaining returns in portfolios created according to momentum. Second, most of the tests made on the FF3 and CFFM have been done on US-data. Hence, the evidence of the models working in other countries is wanting. Third, the inclusion of the size-variable is questioned due to it seemingly having disappeared in many countries.

Artmann et al. (2012) conclude that the market- and size-factors do not exhibit any significant premiums, the size-factor even shows a negative (although insignificant) effect. B/M and momentum, among others, have positive effects on average stock returns. However, only B/M shows a significant cross-sectional effect on stock returns. The conclusion is that the FF3 does a poor job explaining cross-section of average stock returns in Germany. The CFFM or an alternative four-factor model exhibits greater explanatory power for the German stock market.

Kortas and Trimech (2009) analyze the CFFM over various time horizons (time-scales) on the French stock market. The size-factor is, similar to Artmann et al.'s (2012) study, negative.

The difference in the French case is that the effect is significant for portfolios consistent of small-cap stock. The size *risk* is found to be negative for big portfolios over large time-scales. Trimech and Kortas conclude that the CFFM does a good job explaining the return on the French stock market for the medium- and long-run time-scales. They also conclude that the effects of market-, size-, value- and momentum-factors are scale-sensitive, meaning that they are heavily influenced by the length of the specific time period examined.

Christidis, Gregory and Tharyan (2013) construct and test alternative versions of the FF3 and CFFM on the UK stock market. They form risk factors using value-weighted factor components as proposed by Cremers, Petajisto and Zitzewitz (2010). Christidis et al. (2013) find that the alternative CFFM performs relatively well when testing portfolios formed on size and value sorts, but it gives an even better cross-sectional explanation of the UK stock returns when excluding smaller firms.

Dijk (2011) discusses if the size of a firm no longer is relevant, using US stock returns. He emphasizes the gap between empirical and theoretical research and concludes that the size premiums cannot be justified since the size effect is no longer relevant.

3 Theory

3.1 Capital Asset Pricing Model

The CAPM explains the excess return of the portfolio by market premium and the systematic risk of the asset.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (1)$$

The first term of the CAPM is called *Jensen's Alpha* and reflects the risk-adjusted expected return. The sign of the alpha gives us an indication about whether or not the portfolio under- or outperforms the market. A negative sign indicates an underperforming asset, and vice versa for a positive alpha (Bodie, 2014).

The second term contains $\beta_{1,i}$ and the risk premium. $\beta_{1,i}$ is the sensitivity of portfolio-to-market returns, meaning the amount of systematic risk the portfolio is exposed to. A $\beta_{1,i} > 1$

indicates that market fluctuations are amplified in the portfolio and a $\beta_{1,i} < 1$ indicates that market fluctuations are mitigated (Bodie, 2014).

The last term is the error term. The error term represents the asset-specific non-diversifiable risk. This term should be uncorrelated to the rest of the variables under the exogeneity assumption¹ (Fama French 1993).

3.2 Fama French Three-Factor Model

Fama and French (1992, 1993) expand the CAPM by adding two factors, *SMB* and *HML*, claiming that the additional size premium and B/M-ratio explains the excess return better than just the market risk premium and the volatility of the asset.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i}r_{SMB,t} + \beta_{3,i}r_{HML,t} + \varepsilon_{i,t} \quad (2)$$

The first term in the model, or intercept, is called the *Three factor-alpha* (Fama French, 1993) and is interpreted the same way as the Jensen's alpha in CAPM, explaining the risk-adjusted return. The second term together with the first is the original CAPM.

The second variable, *SMB*, explains the negative correlation between the size and return of a stock. This implies that the systematic risk of larger firms is less compared with the systematic risk of smaller ones (Fama & French, 1992, 1993). *SMB* represents the difference in return between big and small firms. The sign of the coefficient₂ gives an indication of the investor's strategy. A positive sign indicates a portfolio heavily weighted towards small firm stock, a negative sign indicates a portfolio comprised of mostly big firm stock.

The third variable is the last variable from the FF3, *HML*. This variable suggest positive correlation between the B/M-ratio and average return. Which means that companies with higher B/M-ratio tend to have higher earnings on assets than smaller companies. Higher B/M should also include a higher risk, if we follow Fama and French's (1993) arguing about rational pricing.

¹ This assumption states that by observing the variability of the regressors it should not be possible to learn anything about the variability in the error term.

The last term is the error term and should be interpreted the same way as in the CAPM.

3.3 Carhart Four-Factor Model

Carhart (1997) gives an intuitive explanation of the model as a model tracking performance through four different strategies: high versus low beta, large versus small market capitalization, high versus low B/M and one-year momentum against contrarian stocks. Since the large versus small stock, *SMB*, and high versus low stock, *HML*, were explained in the previous section and we will mainly focus on the momentum factor.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i}r_{SMB,t} + \beta_{3,i}r_{HML,t} + \beta_{4,i}r_{MOM,t} + \varepsilon_{i,t} \quad (3)$$

The first term in the model is called the *Four factor-alpha* (Carhart, 1997) and is interpreted the same way as the FF3 and CAPM alpha.

The fourth term of the CFFM is the momentum factor. There is a simple theory behind the inclusion of this variable; winners tend to win and losers tend to lose. Stocks that tend to produce profitable return show a tendency to continue doing so, conversely for stocks showing negative return. $\beta_{4,i} < 0$ indicates that the portfolio is heavily invested in losing stock, and vice versa for a $\beta_{4,i} > 0$.

Rearmost is the error term which should be interpreted the same way as in the CAPM and FF3.

4 Data

4.1 Sampling

The data used ranges from January 1, 2011 to December 31, 2016 and was sourced from the Bloomberg terminal². The population consists of all 362 company stock listed on the Stockholm Stock Exchange. Stock selection starts with arranging the population into three groups; *Large Cap*, *Mid Cap* and *Small Cap*. A random sampling process *without* replacement is used to pick 20 stock from each group in order to avoid having doublets in the sample. Furthermore, the requirements for stock being included in the sample are that they all

² This sample period is in the middle of a boom period and therefore the results from analyzing the data may only be indicative of the different model's boom period-performance.

have historical data spanning the sampling period and that they do not show negative book equity (Fama & French 1993). The resulting sample consists of 60 assets with the following four types of data for each asset:

- *Closing price*
- *Amount of outstanding shares*
- *Total return index gross dividends*
- *Book value per share*

All data are collected at the last trading day of each week (usually Fridays) included in the sample period. The total number of observations for each type of data is 313. The *Closing price* refers to the last price at which the stock trades during the trading day. The number of outstanding shares of a specific type of stock (e.g. A-, B- or preferred stock) is referred to as *Amount of outstanding shares*. *Total return index gross dividends* is the return from each asset *including* dividends and capital gains being reinvested in the particular asset. This measurement of return is frequently used in academic research (Andreasson & Kronborg 2017; Boamah 2015). The *book value per share* is the latest reported common equity divided by number of shares outstanding. All prices are denominated in Swedish Krona (SEK).

We use the Swedish 1-month Treasury bill as the proxy for the risk-free rate, compared to Encontro et al (2012) who use the overnight rate, since the overnight rate is the rate at which depository institutions lend or borrow funds with other depository institutions (Riksbank, (1) 2017). Banks are usually the only ones that can access this rate. Most of the previous research, except Encontro et al (2012), use treasury bills (Jegadeesh & Titman, 1993; Fama & French, 1993; Fama & MacBeth, 1973) as the risk-free rate proxy. With that said, it is noteworthy that the overnight rate *could have* been used without having a significant impact on the results due to it having an almost identical numerical value and development to the 1-month T-bill during the period 2011-2016 (Riksbank, (2) 2017).

The OMX Stockholm 30 Index (OMXS30) is used as the market proxy. Picking this index has three reasons. First, the Index is value-weighted which the portfolios used for return estimation also are. Second, this index already is widely used as a general measurement instrument for the Stockholm Stock Exchange. Third, value weighted indices are used as market proxies in several previous studies (Titman, 1993).

SMB is the simple average difference between the *Small* and *Big* portfolios with approximately the same B/M-ratio, see equation (5). This difference is calculated on a weekly basis following the weekly return data. The factor is meant to reflect the risk related to stock size and should therefore be free of influence from B/M (Fama & French, 1993).

$$SMB = \frac{Small\ Low + Small\ Neutral + Small\ High}{3} - \frac{Big\ Low + Big\ Neutral + Big\ High}{3} \quad (4)$$

HML should reflect the risk related to B/M. This factor is the difference in simple average returns between the two high B/M portfolios and the two low B/M portfolios, see equation (6). Similar to *SMB*, *HML* is calculated on a weekly basis. Since *HML* is supposed to focus on differences in return behaviors of high B/M and low B/M stock, it should be free of stock size influence (Fama & French, 1993).

$$HML = \frac{Small\ High + Big\ High}{2} - \frac{Small\ Low + Big\ Low}{2} \quad (5)$$

The momentum variable should mimic the momentum effect of the assets previous performance, which can last up to 12 months (Jegadeesh & Titman, 1997). *MOM* is the difference in simple average returns between the winner- and loser-stock, see equation (7). In other words, the winners tend to win and losers tend to lose with a lagged effect. This is defined by companies change in market capitalization. Companies with high return have a bigger impact on market capitalization than companies with low return (Goetzmann & Jorion, 1993).

$$MOM = \frac{Small\ Winners + Big\ Winners}{2} - \frac{Small\ Losers + Big\ Losers}{2} \quad (6)$$

4.2 Anomalies

The data shows a few outliers but it is negligible, since the data set is big enough. Further, the data set may suffer from survivorship bias due to the requirements implemented in the stock selection process. This means that the results might not give the best prediction, since the stock that survived during the test period might not be representative for the market as a whole. (Stock & Watson, 2015).

5 Methodology

5.1 Creating portfolios

We construct portfolios on a yearly basis replicating the method used by Carhart (1997) and introduced by Fama & French (1995).

We begin by ranking all the sampled assets after their market equity (ME) in ascending order. This is done in December of year $t-1$. The assets are then divided into two prime groups, the dividing line between the groups is the median of all assets. The two prime groups are called *Small* and *Big*, the assets put in *Small* are the ones with a low ME and the ones put in *Big* are the ones with a high ME. Each prime group is then broken into three B/M groups. The B/M is the book common equity reported in December of year $t-1$ divided by the market equity in December $t-1$. This is done by ranking the prime group assets after their B/M in ascending order and then forming three groups corresponding to the 30- and 70-percent breaking points (Boamah, 2015; Fama & French, 1995). The B/M groups are called *Low*, *Neutral* and *High*; with *Low* containing the bottom 30 percent, *High* containing the top 30 percent and *Neutral* containing the middle 40 percent. This process of dividing the prime groups creates a total of six subgroups. These subgroups are also our six value-weighted portfolios:

- *B/L = The 30 percent of the big firms with the lowest B/M*
- *B/N = The 40 percent of the big firms with neutral B/M*
- *B/H = The 30 percent of the big firms with the highest B/M*
- *S/L = The 30 percent of the small firms with the lowest B/M*
- *S/N = The 40 percent of the small firms with neutral B/M*
- *S/H = The 30 percent of the small firms with the highest B/M*

MOM is calculated by ranking the assets in the two prime groups in ascending order according to return year $t-1$. Each prime group is broken into two equally-weighted subgroups called *Winners* and *Losers*. *Winners* contain the upper 30 percent of the prime group, *Losers* contain the bottom 30 percent.

The weekly value-weighted portfolio returns are calculated for the B/M-portfolios for the period January of year t to December of year t and the portfolios are reconstructed in

December of year t (Fama & French, 1995; Carhart, 1997). The weekly equally-weighted portfolio returns are calculated for the *MOM*-portfolios (Carhart, 1997; Cremer's et al, 2010).

It is assumed that all prices follow a log-normal distribution and all returns are normally distributed. Therefore, the return can be calculated with the following equation (Fama French, 1995):

$$R_{i(t)} = \ln \left(\frac{S_{i(t)}}{S_{i(t-1)}} \right) \quad (7)$$

5.2 Statistical tests and \bar{R}^2

We will measure the goodness of fit of the different models by R^2 and adjusted R^2 , \bar{R}^2 (Gujatari & Porter, 2009). To make sure our results are reliable we test our data set for heteroscedasticity, autocorrelation, multicollinearity and seasonality. This is done by performing *Breusch-Pagan test* for homoscedasticity, *White's General Heteroscedasticity*, *Breusch-Godfrey test* for autocorrelation, calculating the *Variance inflation factor*, *VIF*, and testing if time has an impact on the variables.

Our measurement of explanation rate when comparing the different models is \bar{R}^2 . We use \bar{R}^2 since it takes the number of independent variables into account and penalizes for every extra variable in comparison to R^2 (Gujatari & Porter, 2009), see equation (7) and (8).

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS} \quad (8)$$

$$\bar{R}^2 = 1 - \left(1 - R^2 \right) \frac{n-1}{n-k} \quad (9)$$

One way to test for multicollinearity is to make a collinearity matrix and see if the independent variables have a strong correlation to one another. This is made by Carhart (1997) where he also includes the market proxy in the matrix. Another is to create *VIF*. *VIF* is created by running regressions between the different independent variables with respect to one of the independent variables, one at the time (Gujatari & Porter, 2009).

$$VIF(X_h) = \frac{1}{1-r_{23}^2} \quad (10)$$

X_h = Independent variable in the main model

$r_{23}^2 = R^2$ from the regressing one independent variable on another

Shown in equation (10) above, the *VIF* increases as the R^2 increases. Which makes perfect sense, testing if the independent variables are highly correlated to one another or not. *VIF* shows how the presence of multicollinearity inflates the variance of an estimator (Gujatari & Porter, 2009). If $VIF > 5$ then we should suspect collinearity (Encontro et al, 2012).

One of the two test used for testing heteroscedasticity is, as mentioned, *Breusch-Pagan test* for heteroscedasticity, the other one is *White's General Heteroscedasticity*. *White's* test runs a regression, saves the residuals and then runs an auxiliary regression which is a regression on the squared residuals with the original independent variables as squared independent variables. The R^2 from this regression is multiplied with the number of observations in the sample, n . The product follows the chi-squared, χ^2 , distribution and therefore χ^2 is used as the critical value. If the χ^2 obtained from the test exceeds the critical χ^2 , we reject the null hypothesis of homoscedasticity (Gujatari & Porter, 2009). This method has been criticized, which is why we also use the *Breusch-Pagan test* for heteroscedasticity (Gujatari & Porter, 2009).

Testing for serial correlation we use the *Breusch-Godfrey test*. The test permits non-stochastic variables (i.e. lagged dependent variables), higher orders of autoregressive models and moving averages of the white noise error term. The null hypothesis of the test is that there is no correlation between the variables and it assumes that the error terms are homoscedastic (Gujatari & Porter, 2009; Wooldridge 2009).

Due to having cross-sectional time series data, we conduct tests for trends and seasonality. Testing for trends is performed by running regressions with each portfolios excess return as the dependent variable and time, t , as the independent variable. If t has a statistically significant effect there is a trend in the data (Wooldridge, 2009).

Testing for seasonality is performed by running regressions with each of our variables as the dependent variable and week-dummies as the independent variables. If statistically

significant, we reject the null hypothesis of no seasonality and adjust by predicting the residuals and use them as the new variable (Gujatari & Porter, 2009).

5.3 Econometric analysis

In this thesis we run OLS regressions using the CAPM, FF3 and CFFM formulas found in equations (2), (3) and (4) respectively. The regressions are run over the period Jan 2012 - Dec 2016.

6 Empirical results

6.1 Statistical tests.

We received low values throughout the VIF-test which means that the predicted variation of our model is close to the real one of the regressions. This is good and we do not need to worry about multicollinearity, see table 1 in appendix.

The seasonality tests show that almost all of our portfolios show strong signs of seasonality for all variables. We detrend the seasonal effect then, run regressions using Newey West standard error with at lag of 52 adjusting for seasonality. The results are presented in table 3 in appendix.

The Breusch-Pagan test and White's test for heteroscedasticity show statistically significant for the exact same portfolios using the models FF3 and CFFM. CAPM show significance for S/M and S/H which FF3 and CFFM does not. The Breusch-Godfrey test for autocorrelation show no significance for any of the models, see table 2 in appendix.

6.2 Results from OLS Regressions

Testing CAPM on our six portfolios yields unexpected results. The market-coefficient is smaller in the Small portfolios than in the Big, contradicting the size-premium assumption that small-cap stock is more sensitive towards market fluctuations than large-cap (Fama & French, 1992, 1993). The reasons for this can be various, one of them being our market proxy (OMXS30) which mimics the performance of the 30 largest stock on the Stockholm Stock Exchange. The Big portfolios can be composed of one or more stock that also make up the index composition, hence the higher correlation. The $\overline{R^2}$ of the CAPM leaves us wanting, the model can only explain 42,94 percent of excess return variation on average. This poor

explanatory power of the CAPM is expected, previous studies have rigorously critiqued the model on the grounds of only including one explanatory variable (Artmann et al., 2012). FF3 does a considerably better job explaining portfolio excess return. There is no longer an obvious contradiction to the size-premium assumption, and the span of market-beta values has shrunk. The size-factor, *SMB*, is significant in five of six portfolios, inconclusive with Dijk's (2011) study. The coefficient assumes a negative sign or is insignificant for all Big portfolios, this follows the logic behind the portfolio construction; Big portfolios are long in Large stock and short in Small, an increase in size-premium *decreases* Big portfolio excess return. The size-factor coefficient has a positive sign in Small portfolios, a clear difference compared to Trimech and Kortas (2009) and Artmann et al's (2012) results showing *negative* size-factors in small-cap portfolios.

HML is significant in five out of six portfolios. Only the high B/M portfolios have positive *and* significant value-factor coefficients, this is expected as value-portfolios perform better when value-premium increases, similar to the results in Artmann et al. (2012). The \bar{R}^2 of the FF3 portfolio tests is a significant improvement from CAPM. The model explains on an average 69,52 percent of the variation in portfolio excess return.

When comparing CFFM with CAPM and FF3, it is obvious that CFFM has a greater explanatory power than CAPM. However, the results are extremely similar to the FF3 tests. The market-, size- and value-factor coefficients have the same signs and assume similar values. The momentum-factor, *MOM*, is significant in four out of six portfolios and indicates whether the portfolios are long in last year's winners or losers. One would expect the significance of the momentum-factor to increase the explanatory power of the model, but the \bar{R}^2 remains the same as the FF3's, only improving by 0,5 percentage units, contrary to the results of Trimech and Kortas (2009).

Table 1

	CAPM			FF3			CFFM			$\overline{R^2}$
	$\beta_{1,i}$	$\beta_{2,i}$	$\beta_{3,i}$	$\beta_{1,i}$	$\beta_{2,i}$	$\beta_{3,i}$	$\beta_{1,i}$	$\beta_{2,i}$	$\beta_{3,i}$	
B/L	0,6701** (16,25)	0,6219** (12,79)	-0,2546** (-7,46)	-0,3325* (-7,09)	0,6224** (13,69)	-0,2617** (-9,15)	-0,3455** (-8,58)	-0,0885** (-8,58)	0,6100	
B/N	1,0201** (25,89)	0,9479** (23,36)	-0,3075** (-3,81)	-0,1948** (-3,68)	0,94876** (20,76)	-0,3175** (-3,85)	-0,2131** (-3,92)	-0,1244** (-3,02)	0,7189	
B/H	0,9949** (21,65)	0,9826** (31,60)	0,0016 (0,05)	0,1899** (7,00)	0,9820** (27,50)	0,0092 (0,24)	0,2037** (7,49)	0,0947** (3,15)	0,7697	
S/L	0,7017** (4,95)	1,0620** (37,18)	1,0781** (19,05)	-0,9205** (-16,12)	1,0619** (37,06)	1,0793** (18,19)	-0,9182** (-15,99)	0,0153 (0,30)	0,8972	
S/N	0,6414** (14,60)	0,7891** (24,68)	0,5394** (8,44)	0,0258 (0,37)	0,7889** (23,69)	0,5422** (8,49)	0,0309 (0,45)	0,0345 (0,48)	0,4997	
S/H	0,5108** (6,38)	0,7013** (17,99)	0,8220** (13,23)	0,5572** (10,35)	0,7023** (18,42)	0,8084** (13,69)	0,5325** (11,51)	-0,1679** (-2,79)	0,7041	
Average									0,6999	

Table 1 reports the CAPM, FF3 and CFFM excess return over the time period Jan 2012 - Dec 2016. Dependent variables are the excess returns of the six portfolios B/L, B/N, B/H, S/L, S/N, and S/H. The independent variables are the seasonally adjusted factors of the model, shown is the coefficients of the variables. Also shown, is the and $\overline{R^2}$ its average. The parentheses show the t-value of the coefficients, corrected with Newey West standard errors. The intercepts and the R^2 is shown in appendix, table 4. All regression had 260 observations present.

*= significance level of 5%

**= significance level of 1%

The CAPM systematic risk in our portfolios varies substantially depending on the underlying assets, only once exceeding 1. The CAPM market-coefficient of the B/L portfolio is 0,67, showing that any fluctuations in the market will be mitigated in the portfolio. The CAPM $\overline{R^2}$ is 0,4746. The CAPM market-coefficient of the B/N-portfolio is 1,02, showing that, even though the market-coefficient is very close to 1, market fluctuations in this portfolio are amplified, contrary to the B/L-portfolio. The B/N $\overline{R^2}$ is 0,6671, meaning CAPM explains more of the excess return variability in this portfolio than in B/L. The B/H-portfolio has a CAPM market-coefficient of 0,995, showing that market fluctuations are almost *replicated* in the portfolio. The B/H-portfolio $\overline{R^2}$ is 0,7350, being the highest CAPM $\overline{R^2}$ -value amongst our six portfolios. The S/L-portfolio has a CAPM market-coefficient of 0,70, showing that the systematic risk in the portfolio is similar to the B/L-portfolio. The similarities in systematic risk and both portfolios consisting of low B/M-stock can create the illusion of a correlation between book-to-market ratio and systematic risk. The CAPM $\overline{R^2}$ is 0,1443, the lowest $\overline{R^2}$ -value amongst our six portfolios. The S/N-portfolio with a CAPM market-coefficient of 0,64 quickly dissolves the idea of correlation between B/M and systematic risk. This portfolio has a *smaller* systematic risk than S/L, contrary to B/N which has a substantially larger systematic risk than B/L. The S/N-portfolio $\overline{R^2}$ is 0,3390, representing the small stock portfolio variability best explained by the CAPM. The CAPM market-coefficient of the S/H-portfolio is 0,51, representing the smallest systematic risk amongst our six portfolios. The S/H $\overline{R^2}$ is 0,2196, a smaller value than in S/N. The lower $\overline{R^2}$ indicates that there are important explanatory factors excluded in the model, the systematic risk cannot by itself explain portfolio variability in a satisfactory manner. This seems to hold true for all CAPM tests on small-stock portfolio, they all exhibit lower $\overline{R^2}$ -values than big-stock portfolios.

The market-coefficient of the CFFM B/L-test is 0,61. This is smaller than the portfolio market-coefficient in the CAPM-test. The portfolio systematic risk is *smaller* than previously. The inclusion of the size-, value- and momentum-factors seems to influence the market-coefficient, suggesting that the additional independent variables increase the models power to explain variability in portfolio excess return. The size-coefficient is -0,26. The negative sign is expected since this particular portfolio is heavily invested in large firm-stock and a significant size-premium indicates that small-stock return is higher than big-stock return. Further, the statistically significant size-factor goes against the results from previous research by Artmann et al. (2012) and Kortas and Trimech (2009), but is conclusive with the study

done by Encontro et al. (2012). The value-coefficient is -0,35. The sign of this coefficient is also expected; this portfolio contains growth-stocks and a value-premium indicates lower returns for low-B/M stock than for high-B/M stock. The significant value-coefficient is conclusive with previous research (Atmann et al, 2012; Kortas & Trimech, 2009; Encontro et al, 2012). The momentum-coefficient is -0,09 in B/L, showing a small but statistically significant momentum-effect. Interpreting the momentum-coefficient demonstrates that this portfolio is invested in stock with poor past performance. \bar{R}^2 is 0,61, a significant improvement in explanatory power compared to the CAPM B/L-portfolio test.

The market-coefficient is smaller in the CFFM B/N-portfolio test than in the CAPM-test, assuming a value of 0,95. The B/N size-coefficient is -0,32 and the value-coefficient is -0,21. Both factors are significant and therefore further strengthening the results in the B/L-test; size- and value-effects are present on the Stockholm Stock Exchange. The B/N momentum-coefficient is -0,12 and statistically significant, indicating that the B/N-portfolio contains previous losers. \bar{R}^2 is 0,7189 which does not show a significantly better explanatory power than the CAPM B/N-portfolio test where the \bar{R}^2 is 0,6671.

Comparing the market-coefficient of the CAPM and CFFM B/H-portfolio tests one sees that the values are very similar, changing only by approximately 0,0128. The B/H size- and value-coefficients are 0,01 and 0,20 respectively. However, the size-factor is *not* statistically significant and even if it would have been, its coefficient would have a value very close to zero. This confirms (if only in testing this particular portfolio) the results of Artmann et al's (2012) showing insignificant size-factors. B/H momentum-coefficient is 0,09 and significant. The explanatory power is little improved compared to the CAPM B/H-test, increasing from 0,7350 to 0,7697. Common to all big-stock portfolios seems to be a significant momentum-factor, indicating that large firm stock could be more sensitive to momentum than small.

The market-coefficient is substantially larger in the CFFM S/L test than in the CAPM-test, exhibiting a value of 1,06. The size-coefficient is 1,08 and the value-coefficient is -0,92, again implicating that size- and value-effects *are* present. The momentum-coefficient is, however, statistically insignificant. This could indicate that the momentum-effect may only be present among large firm-stock, since they are more frequently traded and their performance may be subject to more influence from past performance than small firm-stock.

CFFM regression output shows that the portfolio is subject to a significantly higher systematic risk than seen in the CAPM-test and is very sensitive to both size- and value-factors. The $\overline{R^2}$ is also very high, 0,8972, substantially higher than in the CAPM S/L-test. Actually this is the portfolio whose variability the CAPM explains the worst and CFFM explains the best, an increase from 0,1443 to 0,8972. This indicates that size- and value-factors are very important when estimating the return of small stock with low B/M.

The CFFM S/N-test also yields interesting results. The market- and size-coefficients are as expected, 0,79 and 0,54 respectively, but the value-factor *and* the momentum-factor are insignificant and their coefficients are very small. The fact that this portfolio contains neutral-B/M stock could help explain the insignificant value-factor; the portfolio is equally invested in lower-B/M stock as in higher-B/M stock, hence the value-effect is neutralized. These results appear inconclusive with some previous research (Artmann et al, 2012; Kortas & Trimech, 2009). Nonetheless, the insignificant value-factor confirms the results from Encontro et al. (2012) demonstrating no value-effect on neutral-B/M stock portfolios and the insignificant momentum-factor supports the evidence from Christidis et al. (2013) that implies a better CFFM-performance when excluding smaller firms. The $\overline{R^2}$ is significantly higher, 0,4997, than in the CAPM S/N-test, showing that the inclusion of the size-factor makes model estimation better.

The CFFM S/H market-, size- and value-coefficients are 0,70, 0,81 and 0,53 respectively. S/H momentum-factor *is* significant and the coefficient is -0,17. This is the only significant momentum-factor amongst the small-stock portfolios and shows that S/H has the highest momentum-sensitivity of all portfolios, indicating that this particular portfolio is heavily invested in previous losers. The $\overline{R^2}$ is 0,7041, significantly higher than the CAPM S/H- $\overline{R^2}$.

The FF3 B/L $\overline{R^2}$ is 0,6055, very similar to the CFFM B/L $\overline{R^2}$ of 0,61. FF3 B/N $\overline{R^2}$ is 0,7129 compared to a CFFM B/N $\overline{R^2}$ of 0,7189 and FF3 B/H $\overline{R^2}$ is 0,7659 whilst CFFM B/H $\overline{R^2}$ is 0,7697. As seen, the market-, size- and value-factors for all portfolios in the FF3-tests are extremely similar to the ones in the CFFM-tests, showing if not anything else that there is little to none augmentation in explanatory power when including momentum. CFFM S/L $\overline{R^2}$ is 0,8972 and FF3 $\overline{R^2}$ is 0,8975. CFFM S/N $\overline{R^2}$ is 0,4997 and FF3 $\overline{R^2}$ is 0,5009.

Obviously, the $\overline{R^2}$'s in the CFFM-tests are *lower* than the FF3-tests when the momentum-factor shows no statistical significance, we can see this in the S/L and S/N portfolio tests. CFFM S/H $\overline{R^2}$ is 0,7041 and FF3 S/H $\overline{R^2}$ is 0,6882.

7 Conclusion

Our results show that the CFFM does a significantly better job explaining portfolio excess return variabilities than the CAPM. The CFFM does not perform significantly better than the FF3. The size-factors are often significant, contradicting the study of Artmann et al. (2012) and Dijk (2011), and positive for small-stock portfolios, inconsistent with the research of Kortas and Trimech (2009). The value-factors are often significant and show positive premiums for high-B/M stock, similar to Artmann et al. (2012). The momentum-factors are significant but their inclusion in the CFFM is not increasing explanatory power compared to the FF3, inconclusive with the studies of Artmann et al (2012), Kortas and Trimech (2009) and Christidis et al. (2013). The reasons to the differing results can be that all the mentioned authors used large samples ranging over longer time-periods than we did in this thesis. We did not test the models on momentum-sorted portfolios, something that Artmann et al. (2012) and Christidis et al. (2013) did. CFFM exhibiting little to no improvement in explanatory power may be due to the portfolios only being sorted on size and value, if the portfolios also would have been momentum-sorted, the results may have differed. Our tests do however show similarities with the results of Encontro et al (2012), that a multiple factor model (in their case the FF3, in our case the CFFM) does exhibit significantly better explanatory power than the basic CAPM.

As a general conclusion regarding investors/portfolio managers decisions it can, by interpreting the results in this thesis, be said that some areas of focus seem to be more worthwhile than others. The size-effect being present on the Stockholm Stock Exchange indicates that investors/portfolio managers have some fruitful information to analyze in terms of small firm-stock's performance in relation to large firm-stock. The presence of the value-effect is in its turn indicative of important information to be gathered regarding firms book-to-market ratio. The combination of fundamentally analyzing size- and value-factors can possibly produce effective placement strategies where small value-stock is the focal point. Regarding the momentum-effect, it seems to be somewhat present on the Stockholm Stock Exchange. However, this effect appears to only influence large firm-stock and value-stock

performance. Having this in mind, a portfolio manager may perhaps limit the technical analysis comprised of gathering historical performance-data to large firm-stock and small value-stock. Incorporating this knowledge, in the before mentioned strategies, would result in studying all three effects (size, value and momentum) when investing in small value-stock.

Further research is needed on the subject of Swedish stock returns, especially using larger samples and longer time-periods. There is also a need for testing momentum-sorted portfolios and possibly including other factors such as earnings-to-price mimicking Artmann et al. (2012) and Christidis et al. (2013) in order to find the model most suitable for the Swedish context. Further, size-premiums in Sweden is a topic worthy of investigation.

8 Appendix

8.1 Statistical test

Table 1. VIF

<i>Dependent</i>	<i>Independent</i>	<i>VIF</i>
$(r_{m,t} - r_{f,t})$	$r_{SMB,t}$ $r_{HML,t}$ $r_{MOM,t}$	1,12
$r_{SMB,t}$	$r_{HML,t}$ $r_{MOM,t}$ $(r_{m,t} - r_{f,t})$	1,03
$r_{HML,t}$	$r_{MOM,t}$ $(r_{m,t} - r_{f,t})$ $r_{SMB,t}$	1,08
$r_{MOM,t}$	$(r_{m,t} - r_{f,t})$ $r_{SMB,t}$ $r_{HML,t}$	1,18

Table 1 shows the result of regressions on each of the independent variables as the dependent variable and the *VIF* for each of the independent variables as the dependent variable. A $VIF > 5$ indicates that multicollinearity is present.

Table 2. Statistical tests

	CAPM			FF3			CFFM		
	<i>Breusch – Pagan</i>	<i>White's test</i>	<i>Breusch – Godfrey</i>	<i>Breusch – Pagan</i>	<i>White's test</i>	<i>Breusch – Godfrey</i>	<i>Breusch – Pagan</i>	<i>White's test</i>	<i>Breusch – Godfrey</i>
B/L	4,86*	3,48	1,610	10,59**	25,67**	0,402	10,89**	31,55**	0,429
B/M	0,48	1,44	2,815	0,47	38,85**	2,080	0,78	47,93**	1,458
B/H	11,06**	8,73**	0,062	6,84**	38,83**	0,223	7,35**	46,41**	0,258
S/L	3,78	0,37	0,042	50,71**	59,40**	1,549	54,68**	62,80**	2,442
S/M	3,82	7,40*	3,011	1,34	5,29	0,598	1,35	13,34	0,827
S/H	0,00	5,92	0,056	1,94	16,04	0,080	1,32	9,17	0,331

Table 2 shows the results from testing heteroscedasticity and autocorrelation. Represented are the χ^2 values. * = significance level of 5%. ** = significance of 1%.

Table 3. Testing for seasonality

	<i>B/L</i>	<i>B/M</i>	<i>B/H</i>	<i>S/L</i>	<i>S/M</i>	<i>S/H</i>
Time	0,709	0,460	0,399	0,737	0,726	0,924
Season_{CAPM}	0,0043**	0,0000**	0,0000**	0,1501	0,0001**	0,0000**
Season_{FF3}	0,0057**	0,0000**	0,0009**	0,0000**	0,0000**	0,0000**
Season_{CFFM}	0,0087**	0,0000**	0,0015**	0,0000**	0,0000**	0,0000**

Table 3 show results from testing the weeks for seasonality and results from testing the dependent variables, B/L, B/M, B/H, S/L, S/M, S/H, for time trends, for each of the three models. * = significance level of 5%. ** = significance of 1%.

8.2 Results from OLS Regressions

Table 4

	CAPM			FF3			CFFM					
	α_{CAPM}	$\beta_{A,I}$	$\overline{R^2}$	α_{FF3}	$\beta_{A,I}$	$\beta_{S,I}$	$\overline{R^2}$	α_{CFFM}	$\beta_{A,I}$	$\beta_{S,I}$	$\overline{R^2}$	
B/L	-1,10e-11 (-0,00)	0,6701** (16,25)	0,4746	-1,12e-12 (-0,00)	0,6219** (12,79)	-0,2546** (-7,46)	-0,3325* (-7,09)	-2,16e-12 (-0,00)	0,6224* (13,69)	-0,2617** (-9,15)	-0,3455** (-8,58)	0,6100
B/N	-2,30e-11 (-0,00)	1,0201** (25,89)	0,6671	-1,52e-11 (-0,00)	0,9479** (23,36)	-0,3075** (-3,81)	-0,1948** (-3,68)	-1,67e-11 (-0,00)	0,94876 (20,76)	-0,3175** (-3,85)	-0,2131** (-3,92)	0,7189
B/H	1,55e-11 (0,00)	0,9949** (21,65)	0,7350	1,17e-11 (0,00)	0,9826** (31,60)	0,0016 (0,05)	0,1899** (7,00)	1,29e-11 (0,00)	0,9820* (27,50)	0,0092 (0,24)	0,2037** (7,49)	0,7697
S/L	2,99e-12 (0,00)	0,7017** (4,95)	0,1443	7,04e-12 (0,00)	1,0620** (37,18)	1,0781** (19,05)	-0,9205** (-16,12)	7,22e-12 (0,00)	1,0619* (37,06)	1,0793** (18,19)	-0,9182** (-15,99)	0,8972
S/N	-6,39e-12 (-0,00)	0,6414** (14,60)	0,3390	-1,39e-11 (-0,00)	0,7891** (24,68)	0,5394** (8,44)	0,0258 (0,37)	-1,35e-11 (-0,00)	0,7889* (23,69)	0,5422** (8,49)	0,0309 (0,45)	0,4997
S/H	-1,02e-11 (-0,00)	0,5108** (6,38)	0,2166	-3,19e-11 (-0,00)	0,7013** (17,99)	0,8220** (13,23)	0,5572** (10,35)	-3,39e-11 (-0,00)	0,7023* (18,42)	0,8084** (13,69)	0,5325** (11,51)	0,7041
<i>Average</i>			0,4294									0,6999

Table 4 reports the CAPM, FF3 and CFFM excess return over the time period Jan 2012 - Dec 2016. Dependent variables are the excess returns of the six portfolios B/L, B/N, B/H, S/L, S/N, and S/H. The independent variables are the seasonally adjusted factors of the model, shown is the coefficients of the variables. The intercepts are the Jensen's alpha. Three factor alpha and Four factor alpha. Also shown, is the $\overline{R^2}$ its average. The parentheses show the t-value of the coefficients, corrected with Newey West standard errors. All regression had 260 observations present.

*= significance level of 5%
 **= significance level of 1%

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