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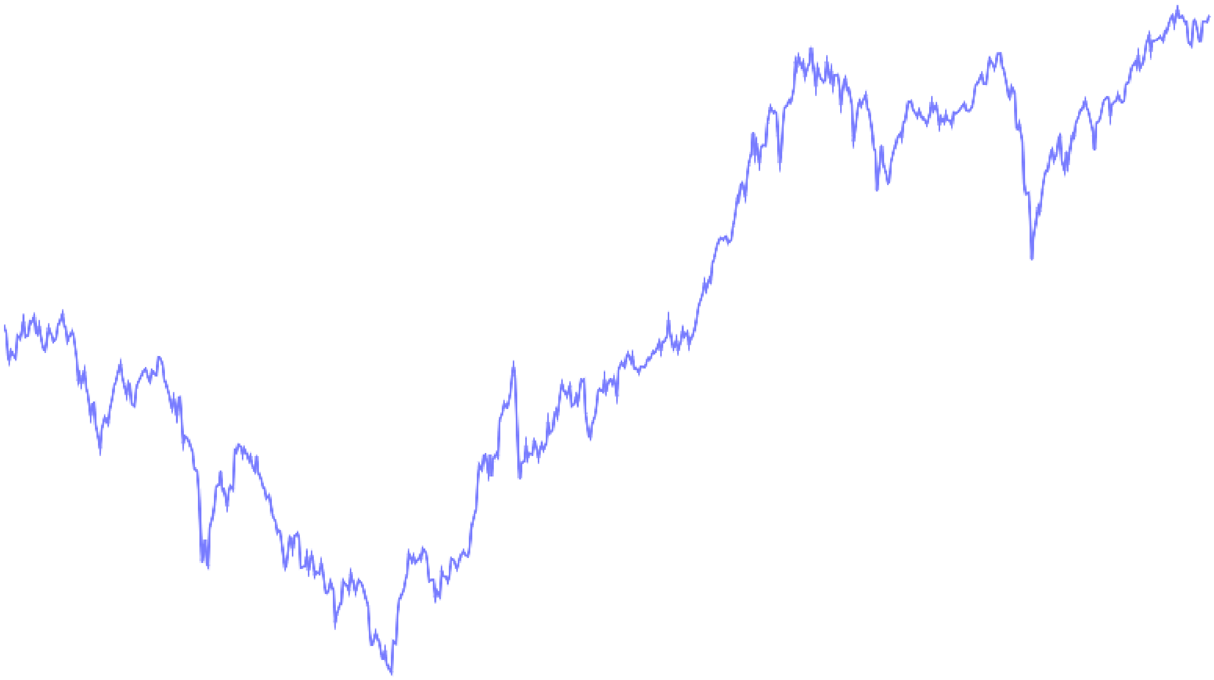
Modeling Capital Asset Returns on the Swedish Stock Market

An evaluation of Fama French's Five Factor Model against its predecessors



Kristoffer Bergram & Ludvig Göransson

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Abstract

This thesis compared the explanatory rate of three asset pricing models related to excess returns on the Swedish stock market. A more granular evaluation of each model's factors was also conducted. A random sample of 90 companies was drawn from the Stockholm Stock Exchange ($N = 371$) using a Blomberg terminal. From this sample, 22 value-weighted portfolios were constructed to create three asset pricing models known as the Fama French Three Factor model, Carhart Four Factor Model and the Fama French Five Factor model. Out of these 22 portfolios, 18 were evaluated using each of the three models. Specific model assumptions such as VIF-values, time dependence and the normality of the standardized residuals were assessed on the individual portfolios and variables of each model. The results concluded that the Fama French Five Factor model outperformed both the Fama French Three Factor model and the Carhart Four Factor model with a higher $\overline{R^2}$ on average. The most consistent factor of the models is the SMB of the Fama French Five Factor model.

Keywords: asset pricing modeling, time series regression, Fama French Five Factor model, Carhart Four Factor model, Fama French Three Factor model, Swedish stock market, portfolio theory, behavioral economics

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Contents

1 Introduction

All areas that can be illuminated with statistics and probability theory share the common feature of variability. In almost all branches of science, ranging from a technical application such as engineering or chemistry to economics and social science - explaining how and why phenomena vary is of major importance (Blom *et al.,* 2013). What paves the road to these explanations is usually approximations of reality in the form of abstract models. In the context of capital markets, understanding the factors of variation can potentially translate into substantial financial gains. In this context, the need for accurate models and precise predictions touches many actors, ranging from small private investors to international financial conglomerates.

This thesis is focused on the ability of three asset pricing models to explain the variation of the Swedish stock market. These three particular models are extensions of what is known as the Capital Asset Pricing Model (CAPM). The general purpose of such models is to explain the excess financial returns of a group of assets in the best way possible. In this situation, "best" simply means accounting for as much variation as possible and this is typically quantified through the performance measure of a model. The factors or explanatory variables in these time series regression models are supposed to reflect different kinds of variation from an investors perspective. The asset pricing models that are inside the scope this thesis are The Fama French Three Factor Model (FF3), the Carhart Four Factor Model (CFFM) and the newly updated Fama French Five Factor Model (FF5). A brief background and context of these models will be further outlined in the next section.

1.1 Background

It will soon be apparent that the financial concepts of return and risk have their roots in the probabilistic notions of expectation and variance (Campbell & Viceira, 2005). Assets come in many shapes and forms but in the context of this thesis, an asset will always be in the form of a publicly listed stock. As mentioned above, the asset pricing models compared in this thesis are extensions from what is known as CAPM. The latter model originates from the findings during the early and mid-1960s of Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM is a linear model with the purpose of showing a potential investor how much return to expect given the risk of the asset or vice versa, the model can also illuminate how much risk the investor is willing to take - given the expected return of an asset (Bodie, *et al.,* 2001). A general point of criticism of the CAPM regards its simplicity and generalizing assumptions, i.e. the tendency of the model to not take enough of the variation in expected return into account. In Jensen, Black and Scholes (1972) they highlight that common investor's probably does not borrow or lend at the risk-free rate like treasury bills, which are commonly used in the CAPM. In summary, the CAPM has gotten further criticism as more extensions have been developed (Banz, 1981; Rosenberg *et al.,* 1985; Fama & French, 1993, 2015; Jegadeesh & Titman, 1993; Haugen & Baker, 1996; Carhart, 1997; Titman, Wei & Xie, 2004; Cooper *et al.,* 2008; Novy-Marx, 2013).

In Banz (1981), similarly as in Jensen *et al.,* (1972), it was pointed out that there is more to average stock returns than the expected excess return of the market (market risk premium). They argued that firms with small market capitalization performed on average better than big firms and called this the size effect. Rosenberg *et al.,* (1985) later published an investment strategy focusing on buying stocks with a high book-to-market ratio (B/M) and selling with low, i.e. buying value stock and selling growth stock. Later, Fama & French (1993) found evidence of the effects and strategies described by Banz (1981) and Rosenberg *et al.,* (1985) and created an extension of the CAPM called the Fama French Three Factor Model (FF3). In short, two variables were added to the CAPM and these variables will be thoroughly explained in Section 2.

Carhart (1997) made a subsequent extension of the FF3 with arguments based on the Jegadeesh and Titman's (1993) evidence of the effect of positive returns of an asset tends to last up to a year. This latter effect is known as momentum, (MOM). Fama & French also received criticism from Novy-Marx (2013) implying that their three-factor model did not take excess returns connected to the profitability of companies into account, calling this influence the profitability effect. Titman *et al.,* (2004) made the same statement with respect to stock investments. Building on these arguments, Fama & French (2015) extended the FF3 into a more complex model, now with five explanatory variables, called the Fama & French Five Factor Model (FF5).

Previous research focusing on an evaluation of the performance of asset pricing models has a wide array of debatable results. Van Dijk (2011) has investigated if the size factors are an outdated measurement or not. The conclusion is that the empirical evidence is too scarce to make reliable conclusions of sorts. Dimson and Marsh (2001) found no evidence for the size factor in the United Kingdom, in line with the results presented by Horowitz *et al.,* (2000). In opposite to Dimson and Marsh (2001), Bhatnagar and Ramlogan (2012) present a significant size effect in the UK markets.

In Fama & French (2012) they evaluate the FF3 and the CFFM on an International scale and find that the value effect, companies with high B/M to outperform companies with low B/M, is present in Europe while again finding little to no evidence for the size factor. Assessing the momentum factor, they find evidence of significance but that the contribution is small. Foye *et al.* (2013) also evaluates the FF3 and does not find any evidence of a present size premium on European data from 2004. Although, there is a presented significant value premium present in Foye *et al.* (2013). Based on the findings in Fama & French (2012) and Foye *et al.* (2013), Foye (2016) compares the overall presence of the factors in the total European market in relation to specific countries (the study is based on 12 countries). They find that the momentum and value factor is present on a European scale and that the size factor's present country-specific significance. Other scholars such as Gregory, Tharyan, and Christidis (2013) also evaluated the FF3 and the CFFM in the United Kingdom market. They make similar operations as Horowitz *et al.,* (2000) but in the momentum factor. They remove small firms and, in opposition to Horowitz *et al.,* (2000), they get a more significant momentum factor. Their finding is in line with the assessment of Fama & French (2012), where they imply difficulty explaining excess returns of small stock with the momentum factor. Racicot and Rentz (2017) recently evaluated the FF5 against a six factor model, FF5 plus a liquidity factor. They use the data set used in the Fama & French (2015) and find that the only present factor of the models is the market premium.

In Fama & French (2017) the FF5 model is evaluated on international markets, finding that the FF5 outperforms the FF3 on the European market but that the Investment factor is more or less redundant. The Investment factor has problems to capture the variation in small stocks, specifically sorted on Operational Profitability. Further, Sundqvist (2017) makes an evaluation of the FF5 on the Scandinavian markets on contemporary data and finds that the FF5 has trouble explaining the variation in small stocks as well.

It is worth noting that there are sensible arguments for many other variables explaining variation in excess returns on assets that are not included in the three models highlighted in this particular thesis. Basu (1977) has argued for a price-earnings ratio, Roll (1977) saying that it is impossible to create a market portfolio since an investor cannot observe all investments' possible return and the arguments rage on. Although, recent research made by Levy and Roll (2010) contradicts the initial statement of an inefficient market proxy. In summary, many of the explanatory variables in these linear models can be descriptively correct while being mechanistically wrong, i.e. even though we can sometimes account for a lot of variation in a given dependent variable - that does not mean that we preserve an accurate explanation of the cause and effect patterns of complex phenomenon such as financial markets.

A more general point of criticism echoing this sentiment comes from the perspective of behavioral economics. According to Barberis and Thaler (2003), the traditional financial paradigm seeks to understand financial markets using models in which actors are assumed to be "rational". Assumptions include that when financial actors such as investors receive new information, they update their beliefs accordingly in a Bayesian fashion, make choices that are consistent with maximizing their own utility while they also have a preference for risk aversion and so on. Barberis and Thaler (2003) highlight that this traditional financial paradigm is appealingly simple but not necessarily that well aligned with the empirical data, i.e. several financial market phenomena can be better understood using models in which some of the actors are not assumed to be fully rational. After decades of gathering evidence that supports this latter point, Richard Thaler was awarded the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2017 (The Nobel Prize, 2018). While financial models have been thoroughly discussed in previous literature it can still be hard to grasp what many of these concepts mean in a statistical or mathematical context. Before the asset pricing models under investigation are further clarified, the purpose of this thesis will be stated.

1.2 Purpose and Contribution

The contribution of this thesis is mainly focused on external validity i.e. testing whether a prior finding can be replicated in a new setting or context. As previously mentioned, Fama & French (2015) recently developed the FF5 that is used to predict excess returns in stock portfolios.

Research on the Swedish market or more exactly on the Stockholm Stock Exchange (SSE) measuring the performance of the FF5 is scarce. Specifically, the purpose of this thesis is to compare the performance measure of the FF5 to two other models known as FF3 and CFFM over a specific time period. The performance measures of these models will be compared on non-US data, in this case, the SSE. Apart from the standard comparison using an $\overline{R^2}$, a more granular investigation of the significance of each model's factors will also be conducted. What this distinction means will be covered in the next section.

1.3 Research Questions

As mentioned earlier, the purpose of this thesis is to measure the performance of the FF5 in relation to the FF3 and CFFM on the Swedish stock exchange. In line with this, data will be collected to investigate the following two research questions:

RQ 1. How much of the variance in excess returns on the Swedish stock market can be explained by the FF3, CFFM and FF5 models?

RQ 2. Which of the factors in the FF3, CFFM and FF5 models will be the best predictors of excess returns on the Swedish stock market?

These two questions will be investigated over the time period 2012 to 2018. Setting the aspects of model validity aside for the moment, the first research question will be answered in terms of the individual $\overline{R^2}$ value of each model. The second question is more granular and will be answered in terms of the magnitude and significance of the regression coefficients related to each of the individual portfolios. How these concepts relate to one another will become more apparent in the subsequent chapter, which will give a deeper explanation of these models, their constituent properties and their context from the standpoint of statistics and portfolio theory.

2 Modeling Capital Asset Returns

This chapter highlights four models, the first one is mainly used as pedagogical aid while the latter three are central to the purpose of this thesis. In a statistical sense, these latter models can be categorized as time series regression models. However, it is important to note that the formal statistical definitions of these models have been adopted from the field of portfolio theory. The notations can sometimes sacrifice descriptive accuracy for formal algebraic accuracy e.g. subscripts are sometimes used ambiguously indicating an index or a linguistic descriptor for a variable in some of this literature. Yet, for the sake of consistency we have still chosen to adopt the notation seen in portfolio theory while minimizing mathematical ambiguity.

Since the FF3, CFFM and FF5 models are all extensions of the basic CAPM, the latter model serves as a solid benchmark from a theoretical and pedagogical perspective. The CAPM is also one of the most well-known models in investment contexts and marks the birth of asset pricing theory (Bodie *et al.,* 2001; Fama & French, 2004).

2.1 The Capital Asset Pricing Model

As mentioned earlier, the model can be colloquially interpreted as answering the question: Is the risk of investing in a given asset worth taking, given that asset's expected return? More formally, the model evaluates the amount of systematic risk of the asset or portfolio (the latter being a cluster of assets or stocks) given a certain expected return (Fama & French, 2004). Systematic risk refers to the risk of the market, also called undiversifiable risk inherited from the market. The model can also be interpreted as if a stock gives a reasonable expected return in relation to the risk associated with that stock, or vice versa if the risk of investing is worth taking given the expected return, Bodie *et al.,* (2001). Fama & French (2004) formulate CAPM according to the equation below:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \epsilon_{it} \tag{1}$$

r_{it}: Return of the i:th portfolio at time t

r_{ft}: Risk free rate at time t

α_i: Intercept of the i:th portfolio

β_i: Coefficient of the excess return and shows the volatility of an asset in relation to the market for each of the i:th portfolios: $\text{Cov}(r_{it}, r_{mt})/\sigma_m^2$

r_{mt}: Return of the market portfolio at time t

ϵ_{it}: Systematic risk for the i:th portfolio at time t

The dependent variable in the above model is the result of a subtraction and its difference constitutes the excess return of a portfolio's expected return. The time variable t of this excess return is measured at monthly intervals. The intercept of the model is called *Jensens alpha* and determines if the portfolio gives a high enough return given its risk. A positive alpha means that the portfolio outperforms the market and a negative means that it does not, given its risk, Bodie *et al.,* (2001). The independent variable multiplied by the regression coefficient consists of the market index portfolio and the risk-free rate. This difference $(r_{mt} - r_{ft})$ gives a measurement of the excess market returns. The market index portfolio is meant to mimic the fluctuations of the market as a whole, Bodie *et al.,* (2001). A market index can be seen as a sample of a population, the sample is meant to represent the variation of the population. In the same way, the market index is meant to represent the variation of the market as a whole.

The regression coefficient in this model is referred to as *beta* and measures the relative variation of an asset to the variation of the market. If an asset has a $\beta_i < 1$, then the expectation is that the asset decreases the risk of the portfolio since the asset has a lower risk than the market and the opposite if we instead have a beta above one. If a $\beta_i < 0$ it would mean that the portfolio has a negative relation to the market, which is very unlikely. Now that CAPM and its essential properties have been explained we can dig deeper into the models that will be used in this thesis.

2.2 The Fama French Three Factor Model

The FF3 adds the explanatory variables *Small Minus Big (SMB)* and *High Minus Low (HML)* to the CAPM, see equation 2 below. Fama & French (1993) underscore that the intercept of the model is called the *Fama French Three Factor alpha* but is interpreted the same way as the *Jensen's alpha* that was explained earlier. All the terms that lack a specified description have the same interpretation as the model in the former section. The $\beta_{1,i}$ plays the role of β_i, from the previous model. Fama & French (1993) formally define their FF3 model as:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i}(r_{mt} - r_{ft}) + \beta_{2,i}(SMB_t) + \beta_{3,i}(HML_t) + \epsilon_t \quad (2)$$

r_{it}: Return of the i:th portfolio at time t

r_{ft}: Risk free rate at time t

$\beta_{2,i}$: Coefficient of SMB and an indication in which way the portfolio tilts according to size for the i:th portfolio.

$\beta_{3,i}$: Coefficient of HML and an indication in which way the portfolio tilt according to value for the i:th portfolio.

SMB_t: Average returns of small minus big firms according to market equity at time t.

HML_t: Average returns of high minus low firms according to book to market equity at time t.

ϵ_{it}: Systematic risk for the i:th portfolio at time t.

The second and third explanatory variables in the above model require some additional elaboration. The variable SMB_t is included with the purpose of captureing the risk in returns attributable to market capitalization, i.e. the size of a given company. Theoretically, small firms, companies with small market capitalization tend to outperform large firms – size effect, Banz (1981), Fama & French (2015). This parameter is interpreted as follows, if $\beta_{2,i} > 0$, then the portfolio is heavily invested in small stock and the opposite if $\beta_{2,i} < 0$ (Fama & French, 1993). The third explanatory variable: HML_t is included to mimic the risk in returns belonging to book-to-market equity (B/M). This, as previously mentioned, is called value effect and the expectation is that stocks with high B/M known as value stocks will outperform stocks with low B/M (growth stocks). We interpret the parameter in the following way, $\beta_{3,i} > 0$ indicates that the portfolio is heavily invested in value stock and vice versa if the $\beta_{3,i} < 0$ (Fama & French, 1993).

2.3 The Carhart Four Factor Model

As previously mentioned, Carhart (1997) made an extension of the FF3 with arguments based on the Jegadeesh and Titmans (1993) discovery, building on DeBondt and Thalers (1985) findings of violation of Bayes rule. Carhart showed that the effect of positive returns of an asset tends to last up to 12 months and called this effect momentum, (MOM). Again, all the variables that are not described have the same interpretation as the model in the former section. The CFFM is formulated as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i}(r_{mt} - r_{ft}) + \beta_{2,i}(SMB_t) + \beta_{3,i}(HML_t) + \beta_{4,i}(MOM_t) + \epsilon_{it} \quad (3)$$

r_{it}: Return of the i:th portfolio at time t

r_{ft}: Risk free rate at time t

$\beta_{4,i}$: Coefficient of MOM and an indication in which way the portfolio tilt according to momentum for the i:th portfolio.

MOM_t: Average returns of winning minus losing stock according to total return index at time t.

ϵ_{it}: Systematic risk for the i:th portfolio at time t.

The momentum is simply included to take the momentum effect in portfolios excess returns into account. A $\beta_{4,i} > 0$ indicates that the portfolio is mainly invested in winning stock and contrary if $\beta_{4,i} < 0$.

2.4 The Fama French Five Factor Model

The last model, important to this thesis, is the FF5. This is a recently updated extension of the FF3, with two additional factors. In this model Fama & French (2015) divide firms into groups with regards to earnings before taxes and call this variable Robust Minus Weak profitability (RWM_i), taking operational profitability in excess return into account. Furthermore, they do the same with respect to total asset growth creating Conservative Minus Aggressive investments (CMA_i), taking variation in excess return from total growth in assets into account. As in prior sections, only the additional explanatory variables will be described in the model. The FF5 model is defined in the following way:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i}(r_{mt} - r_{ft}) + \beta_{2,i}(SMB_t) + \beta_{3,i}(HML_t) + \beta_{4,i}(RMW_t) + \beta_{5,i}(CMA_t) + \epsilon_{it} \tag{4}$$

r_{it}: Return of the i:th portfolio at time t

r_{ft}: Risk free rate at time t

$\beta_{4,i}$: Coefficient of RMW and an indication in which way the portfolio tilts according to operational profitability for the i:th portfolio.

$\beta_{5,i}$: Coefficient of CMA and an indication in which way the portfolio tilts according to investments for the i:th portfolio.

RMW_t: Average returns of robust minus weak firms according to earnings before tax at time t.

CMA_t: Average returns of conservative minus aggressive firms according to growth in total assets at time t.

ϵ_{it}: Systematic risk for the i:th portfolio at time t.

The two new variables and their coefficients will now be further defined. A company's profitability effect (RMW_t), simply means operating profitability minus interest expense divided by book value (Novy-Marx, 2013). Fama & French (2015) outline that the regression coefficients are interpreted with the same intuition as SMB and HML. A $\beta_{4,i} > 0$ suggest a preponderance of robust stocks in the portfolio and vice versa if the $\beta_{4,i} < 0$. The guiding theory behind including CMA_t is that this variable lets the model take the risk in excess returns into an account belonging to an asset's total growth. Again, a $\beta_{5,i} > 0$ indicates that the portfolio has a majority of conservative stocks and a $\beta_i < 0$ indicates a majority of aggressive stocks according to Fama & French (2015). The theoretical aspects of these time series regression models have now been covered, the next chapter will delve deeper into how the empirical data of this thesis was collected and processed.

3 Portfolios based on the Stockholm Stock Exchange Data

This chapter outlines the methodology of this thesis in four sections. The first covers how the empirical data was extracted. The second describes the construction process of the portfolios. The third explains how the independent variables of the models were constructed from the portfolios and the last section highlights the statistical tests that were used to validate the models and their respective assumptions.

3.1 Data extraction

It is important to untangle two of the steps that were performed during the data collection procedure. First, a random sample of companies was drawn from the Stockholm Stock Exchange (SSE) using a Bloomberg terminal. The second and much more complex step was to sort and create portfolios on these randomly selected companies. This latter step will be explained in the next section.

The data collection procedure and subsequent creation of the portfolios follow strict procedures (Fama & French, 1993; Carhart, 1997). While the procedures from the latter two articles have been followed, measures were also constructed based on Fama & French (2017) for the FF5. These measures will be described in a later section. The currently 372 publicly listed companies on the SSE were randomly sampled over the time period of 2011 - 2018. The time period is selected with respect to the long-lasting recessions of financial crises 2008 (Welfens, 2011). By taking a simple random sample (without replacement) as outlined by Scheaffer *et al.,* (1971). Here, the units of analysis are publicly listed companies, each with a vast collection of key performance indicators (KPI:s) when displayed in the Bloomberg terminal. The following data points were collected on each randomly selected company on a monthly basis over the specified time period:

- Closing price of the OMX Stockholm 30 Index (OMXS30)
- Total number of outstanding shares
- Operating income
- Net provisions (interest expense)
- Closing price of the stock
- Book value per share
- Total return index
- Total assets

The above data points are financial KPI:s and their exact meaning and underlying theory are outside the scope of this thesis. Their importance lies in the fact that they are essential components for constructing the asset pricing models under investigation in this thesis.

Along with this financial KPI:s, 1 month Swedish Treasury bills were collected from the website of the central bank of Sweden (Sveriges Riksbank, 2018). These Treasury Bills along with the above data points were then used to create 22 clusters of companies, the portfolios. The portfolios are sampled over the time period 2012 to 2018. The reason for this is because we use a yearly lag to create some of the measurements needed for the models. Choices such as these are not arbitrary, they follow the model specification of Fama & French (1993) for the FF3 portfolios, Carhart (1997) for the CFFM and Fama & French (2015) for the FF5 portfolios. These portfolios and their construction will be further described in the next section.

The OMXS30 is meant to represent the market index portfolio as previously mentioned. The OMXS30 is a value weighted index of the 30 most traded companies on the SSE, recreated every 6:th month. The choice of the OMXS30 is twofold. Value-weighted indexes are used as market proxies in previous research and the returns of the portfolios are also value-weighted (Bodie *et al.,* 2001; Fama & French, 2015).

The 1 month Swedish Treasury bill is used as the risk-free rate. Risk-free rate indicates the return on investment an investor can get without taking any risk. Treasury bills are used in previous research as an instrument for the risk-free rate, (Fama & French, 1993, 2012, 2015, 2017; Carhart, 1997; Jegadeesh & Titman, 1993).

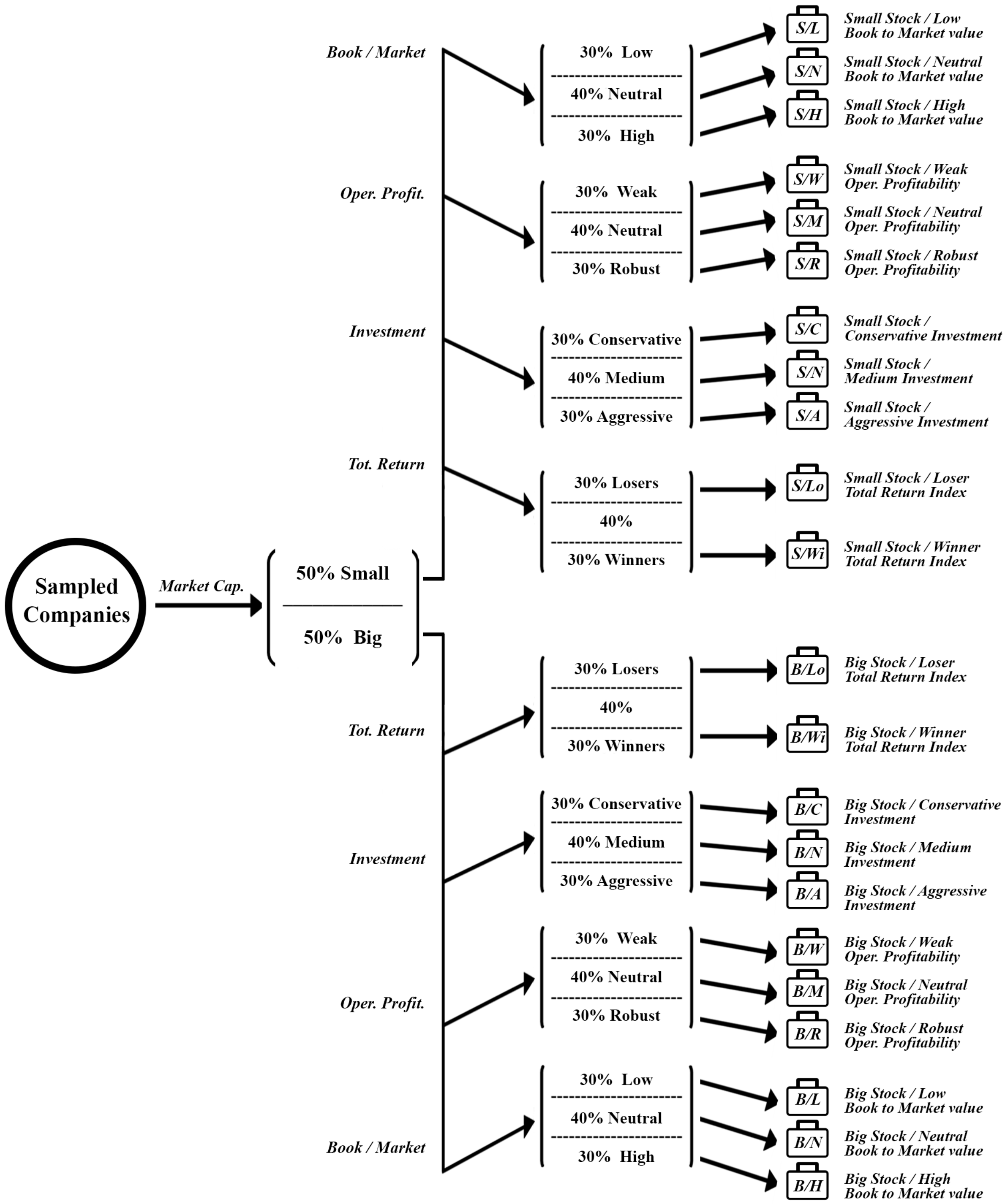

Figure 1: *Flowchart illustrating the stratification of the sampled companies into 22 portfolios*

3.2 Portfolio Construction

A portfolio refers to a cluster of assets or companies in this particular case. As mentioned earlier, 22 portfolios were constructed at the end of each fiscal year, specifically at the end of June of each year. These portfolios were then used from the first of July year T to the end of June year $T + 1$ in a calendar year, in accordance with Fama & French (1993; 2015). The fiscal year will from now on just be referred to as "year". Figure 1 on the next page highlights how these portfolios were constructed from the original sample of companies.

It should be noted that when these portfolios are constructed, a particular company can end up in several portfolios. The dependencies created by this fact could also be investigated but this topic is not studied here as we analyze only one dimensional models for each response variable r_{it}, $i = 1, 2, \ldots, 22$. The multivariate models for $\mathbf{r}_t = (r_{1t}, r_{2t}, \ldots, r_{22t})$ has not been developed yet.

The portfolios in Figure 1. were used as dependent variables and as parts of the independent variables in the models. The momentum portfolios created are only used in the momentum factor of the CFFM, see equation 3. Fama & French (2017) do not evaluate the momentum portfolios which is why they will be excluded here as well. The momentum portfolios were S/Lo, S/Wi, B/Lo and B/Wi, see Figure 1. Due to the scope of this thesis regressions will be performed on 2x3x3 portfolios, evaluating a total of 18 portfolios. In other words, 4 of the 22 constructed portfolios were outside the scope of the analysis and were therefore not evaluated.

As Figure 1 shows, all portfolios were first sorted in ascending order on market capitalization and then divided by the median into; small (median > market capitalization) and big stock (median < market capitalization). To calculate market capitalization for each company at year T, the number of outstanding shares were taken in June year $T-1$ and then multiplied with the closing price at the last trading day in June $T-1$. The two primary groups, Small and Big, are then sorted on different measures; the book to market ratio (B/M), total return index, operational profitability and growth of total assets. Our choice of measurements or KPI:s follows Fama & French (1993; 2015) and Carhart (1997). However, in line with Fama & French (2017), only portfolios sorted on B/M, total return index and operational profitability will be evaluated.

B/M at year T was calculated by first multiplying book value per share and then multiplying the number of outstanding shares at the end of June year $T-1$, which creates a financial KPI known as book value. The book value of June year $T-1$ is then divided by the market capitalization of June year $T-1$, which is the same as explained in the previous section. This results in B/M. The stocks first sorted on market equity is now sorted on B/M as well. The lower 30% of the B/M constitutes low B/M, the top 30% constitutes the high B/M and the middle 40% include the neutral B/M stocks. This creates a total of 6 portfolios, S/L, S/N, S/H, B/L, B/N, B/H, sorted on market equity and B/M. The S/L in Figure 1, on the previous page is the small capitalization stock with low B/M.

Total return index is an index tracking the price of an asset, in this case, a stock, where all dividends are reinvested and it is commonly used to calculate the momentum for an asset (Jegadeesh & Titman, 1993; Carhart, 1997). This index is used to evaluate winners and losers which is, as earlier mentioned, what momentum represent. We calculate the average returns for the stocks during year $T-1$, from July $T-1$ to June $T-1$, for portfolios run from year T. Then, we divide the small and big stock into three subgroups separately according to average returns. The low 30% of the returns are losers and the top 40% is the winners, the middle 40% is excluded. This creates a total of 4 portfolios each year, S/Lo, S/Wi, B/Lo, B/Wi. S/Lo is small market equity stock with a low total return index, see Figure 1.

The next six portfolios are sorted on Size and Operational profitability. Due to scarce data on interest expense, operating income was divided by book equity in accordance with Novy-Marx's (2013). The same approach was used for creating the portfolios for growth and value stocks, data from June $T-1$ creates portfolios for July year T which is run and reevaluated at June year T. The low 30% sorted on operational profitability creates the small and big portfolios called Robust, the top 30% are called Weak and the mid 40% is the Neutral stock. The portfolios in short S/R, S/N, S/W, B/R, B/N, B/W where S/R would be small stocks sorted on low operational profitability in Figure 1.

The last portfolios created are sorted on size and growth in total assets during a year. Total assets are taken at year $T-1$ minus total assets year $T-2$ divided by total assets year $T-2$, which shows yearly growth for a firm (Titman *et al.,* 2004). The growth rate is then sorted in ascending order and divided into 6 portfolios total, following the same pattern as portfolios sorted on B/M and operational profitability. The portfolios are as follows; S/C, S/M, S/A, B/C, B/M, B/A. In Figure 1 S/C is small stock that with low growth. The portfolios sorted on different measures (B/M, Momentum etc.) are now measured in returns by the closing price. The returns for each portfolio are then evaluated and recalculated each month in value-weighted returns. As a definition, value-weighted returns indicate that the returns of each asset in the portfolio is weighted by a ratio of market equity of the i:th stock in the portfolio to the total market equity of the portfolio (Campbell, Lo & MacKinlay, 1997).

In closing, the standard procedure when creating these portfolios is to omit companies with negative book value. This is due to the fact that one cannot interpret a negative book value since it is the value of the company, held by shareholders (Fama & French, 1993). All stocks from the sample were included in the portfolios, even though they might not be listed at the SSE at a certain point in time. This latter choice was made in order to avoid bias due to missing values.

3.3 Variables and Measurements

The following section describes how the portfolios on the right hand side in Figure 1 was used when creating the explanatory variables of the three time series regression models. These variables are featured in equation 1 - 4 in the previous chapter. To reiterate, the variable SMB in the FF3 model with the following notation $SMB_{B/M}$ would be the difference in simple average returns between firms with small and big market equity, taking risk of size in excess returns of a portfolio into account (Fama & French, 1993).

$$SMB_{B/M} = \frac{S/L + S/M + S/H}{3} - \frac{B/L + B/M + B/H}{3}$$

The variable HML is constituted of two main groups, companies with high and low B/M, called value and growth stock respectively. The simple averages of these two components are calculated and together they create the factor HML. The high B/M portfolios are S/H and B/H and the low B/M portfolios are S/L and B/L. The portfolios are the same as used in $SMB_{B/M}$, but taking B/M instead of size into account (Fama & French, 2015). The variable name "high minus low" is a good descriptor of how the HML is calculated:

$$HML = \frac{S/H + B/H}{2} - \frac{S/L + B/L}{2}$$

The next factor explained is based on the work of Carhart (1997) and is meant to take the risk in excess return related to momentum into account. This explanatory variable is related to the model specified in equation 3. The momentum variable is calculated by taking the simple average of the winner minus the simple average of the losers.

$$MOM = \frac{S/W + B/W}{2} - \frac{S/L + B/L}{2}$$

The SMB_{OP} is, as $SMB_{B/M}$, initially divided by market capitalization into small and big stocks by the median. The second portioning is with respect to operational profitability creating 6 portfolios. Small equity firms with weak, neutral and robust profitability and the same for large firms. Calculating the SMB_{OP}, we have followed the same procedure as when creating $SMB_{B/M}$ by taking the simple average difference between small and big firms in accordance with Fama & French (2015).

$$SMB_{OP} = \frac{S/W + S/N + S/R}{3} - \frac{B/W + B/N + B/R}{3}$$

The SMB_{INV} follows the same method as $SMB_{B/M}$ and SMB_{OP} but the second sorting with respect to growth in total assets. Creating SMB_{INV} we also take the average difference between small and big firms, (Fama & French, 2015).

$$SMB_{INV} = \frac{S/A + S/N + S/C}{3} - \frac{B/A + B/N + B/C}{3}$$

The SMB variable for FF5, (SMB_{FF5}), was calculated using 18 portfolios, instead of the 6 in $SMB_{B/M}$, see equation 4. for the full model specification. This is due to the inclusion of operational profitability and investments. The SMB now includes all previous mentioned SMB:s, $SMB_{B/M}$, SMB_{OP} and SMB_{INV}. By summarizing these variables and dividing by three, this new SMB_{FF5} is created which is a measurement of risk in excess return regarding size (Fama & French, 2017).

$$SMB_{FF5} = \frac{SMB_{B/M} + SMB_{OP} + SMB_{INV}}{3}$$

The same approach was followed when creating HML and the additional variables in the FF5 model, the Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA). RMW was calculated by taking the simple average difference between the robust portfolio minus the weak portfolios, Fama & French (2015).

$$RMW = \frac{S/R + B/R}{2} - \frac{S/W + B/W}{2}$$

In accordance with Fama & French's (2015) approach, CMA was then calculated the same way as RMW and HML but with regards to conservative and aggressive portfolios:

$$CMA = \frac{S/C + B/C}{2} - \frac{S/A + B/A}{2}$$

Again, it is worth noting how the portfolios featured in the flowchart of Figure 1. serve as the ingredients for the explanatory variables in each model featured in equation 2, 3, and 4. Once all the necessary portfolios and variables had now been created, the statistical analysis could begin.

3.4 Statistical Tests

This section outlines the statistical tests applied to evaluate how well the data fulfills the assumptions of time series regressions. It also describes what measures that were performed to ensure that the data conformed to the assumptions of the analyses that were later used.

This assessment was initiated by checking the distribution of the explanatory variables and portfolios. As mentioned earlier, some previous studies use log normal returns for the portfolios, thereby handling potential problems related to the distribution of this data. However, such transformations were deemed unnecessary with this specific data set.

An investigation of multicollinearity was also conducted. For this, the variance inflation factor (VIF) was used. The VIF measures how much of the variation there is in an independent variable that is explained by the other independent variables in the model at hand. More formally, the VIF value for the i:th independent variable in the model is given by:

$$VIF_i = \frac{1}{1 - R_i^2}$$

Where R_i^2 is ESS/RSS for the i:th independent variable. A rather conservative criterion regarding the VIF-value was applied, only accepting a $R_i^2 < 0.8$. To asses the assumption of a constant variance in the error terms, a version of Lagrange Multiplier (LM) test called the Studentized Breusch-Pagan was used. This test was used prior to the Breusch-Pagan test (Breusch & Pagan, 1979) following Koenkers (1981) argument. The Studentized Breush-Pagan test is generally not as sensitive to the kurtosis of the distribution in the error term as the Breusch Pagan test. The Studentized Breusch-Pagan (BP) test approximately follows the χ^2 distribution with the null hypothesis of a constant variance in the error term over time:

$$H_0 : \sigma^2_{\epsilon_1} = \sigma^2_{\epsilon_2} = \sigma^2_{\epsilon_3} = ... = \sigma^2_{\epsilon}$$

The test is calculated by first squaring the residuals of the model at hand and then running a regression on the squared residuals with the independent variables of the initial model as explanatory variables. The R^2 from the model with the squared residuals as the dependent variables are then multiplied with the number of observations. The product results in a χ^2 value which is compared to a critical χ^2-value. As noted by Greene (2011) the tests for heteroscedasticity does not give any certain evidence about the variation in the error terms, which is why we also inspected at the plots of the error terms over time. To moderate the problem of heteroscedastic error terms, robust linear models were used to not underestimate the standard errors of the parameters in line with Greene's (2011) and Gujarati's (2009) recommendations.

To further examine the assumptions, the autocorrelation of the variables and error terms were inspected. The autocorrelation as assessed by using the autocorrelation function (acf) in R and the Breusch-Godfrey (BG) test of serial correlation. The BG test of autocorrelation is a LM test and very similar to BP test and is in the same way approximately χ^2 distributed (Greene, 2011). Instead of squaring the residuals from the model at hand as we did when investigating heteroscedasticity, the regular residuals are used instead by running a regression on them with the explanatory variables of the model and then testing the correlation between all the lags. The null hypothesis of the BG test is the correlations between the lags are equal and equal to zero (Gujarati, 2009):

$$H_0 : \rho_1 = \rho_2 = \rho_3 = ... = \rho_p = 0$$

To evaluate the performance of the models the $\overline{R^2}$ in the output of the linear model was used as the benchmark, see formal definition below (Gujarati, 2009). $\overline{R^2}$ penalizes for the number of parameters and is, therefore, a preferable performance measure when comparing models with different numbers of parameters (Gujarati, 2009; Cryer & Chan, 2008).

$$\overline{R^2} = 1 - \frac{SS_{res}/(n-k)}{SS_{total}/(n-1)}$$

The R^2, F-statistic and standard errors of the error terms were also reported as measures of comparisons and guidelines. The next chapter will highlight the specific results of the models.

4 Data Analysis and Model Validation

In this chapter, three aspects of the empirical portfolio data analysis are considered. The first section is focused on validating the assumptions of the asset pricing models, the second concerns the performance of those models and the third is focused on parameter estimations in each of the models. From the standpoint of statistics, the paradigm here is time series regression. The research questions of this thesis are addressed in the second and third section by first evaluating the models' performance and then going into the specific parameters of the individual portfolios.

4.1 Model Assumptions

Specific model assumptions were assessed by inspecting the individual portfolios and variables. First, the normal distribution of the excess returns over time was examined. The dependent variables for the models were all deemed to conform to approximate normal distributions.

Additional assessments indicated that some of the portfolios show that time had a statistically significant impact. The variables that seemed symptomatic of time dependence were therefore adjusted by saving the residuals of the regressions, where the response variable is the variable showing time dependence and the predictor is the time variable. The residuals were then used as the new dependent variables, now representing the seasonally adjusted portfolios.

Next, the presence of serial correlation in the portfolios and variables was investigated. The acf plots showed no serious signs of serial correlation in the error terms here. However, a few of the regressors showed ghost correlation on some lags but this is expected. Consistent with the acf of the error terms, the BG test indicated no significant disturbance. The BG tests, the plots of time adjustment and the acf plots are currently excluded from the Appendix due to the lacking evidence of interference.

The adjusted variables can now be used to asses the models. The VIF of the models showed no sign of disturbing multicollinearity. The correlation plot over all variables showed results in line with the VIF, no problematic multicollinearity, see Table 4, 5 and 6 in the Appendix for VIF-values of the independent variables. The correlation plot was excluded to minimize redundancy. Next, the error terms of the models were investigated. The acf of the error terms show no sign of serial correlation and the BG test show no evidence of contradiction. Plots of all the error terms for the models against time were also inspected. These plots showed no clear evidence of heteroscedasticity, which is why they are also excluded from the Appendix. However, when conducting the BP tests, some results were significant, see table 7, 8 and 9 in Appendix. However, all the models that showed significant results were re-run with robust standard errors to not underestimate the standard errors of the parameters. This procedure will be highlighted in the tables of the next section.

4.2 Performance Measures

At this stage, we have seasonally adjusted, homoscedastic and non-serial correlated models ready for interpretation. The models display mixed results, fluctuating from as low as 0.26 to a high of 0.84 in adjusted explanatory rate. Reviewing the tables approximately half of the explanatory variables are significant in the models. The more significant models, models where all or all except one independent variable are statistically significant, does not fluctuate as much but still quite much. The low is at approximately 0.5 and the high, as previously mentioned, 0.84 of adjusted $\overline{R^2}$.

Going into the specific models, the FF5 shows on average a higher $\overline{R^2}$ than the FF3 and the CFFM. The CFFM shows on average similar $\overline{R^2}$ to the FF3. The FF5 average performance is 0.58 in $\overline{R^2}$ with a top notation of 0.84, the CFFM average performance is 0.50 with a top notation of 0.67 and the FF3 average is 0.48 with a highest notation of 0.67.

A more detailed report of the performance will ensue in the next three recitals, starting with the FF3. The results below can also be found in table 1, 2 and 3. The variation explained by FF3 in portfolios sorted on size and B/M is in relation, to portfolios sorted on Operational Profitability and Investment, higher but the explanatory rate in some of the models are low. The FF3 $\overline{R^2}$ fluctuates between 0.37 and 0.68 on the size and B/M, 0.39 and 0.6 in the size and Operational Profitability and 0.26 and 0.55 on the size and Investments portfolios. The FF3 show statistical significance for all of the explanatory variables in three of the regressions. The one that presented $\overline{R^2}$ of 0.67 is the portfolio sorted on small stock and low B/M, the second highest $\overline{R^2}$ of 0.68 is small stock with high B/M and the third is the S/R portfolios with an $\overline{R^2}$ of 0.6.

The next model to report results is the CFFM, which presents similar results to the FF3, as mentioned earlier. The CFFM also show difficulties capture behaviour of the portfolios sorted on size and Operational Profitability or Investment. In comparison, the CFFM presents two models where all factors are significant at a 5% level. The dependent variables of the models are the same as in FF3, which is the S/L and B/H portfolios with an $\overline{R^2}$ of 0.69 and 0.53 respectively. The momentum factor of the CFFM cannot capture the variation of the excess returns in the S/R portfolios. The S/M portfolio almost show full significance, the momentum presents a p-value $< 10\%$ significance with an $\overline{R^2}$ of 0.54. The B/N portfolio show the second highest $\overline{R^2}$ with 67% of the variation explained, but only two factors are significant. The significant variables are the market and momentum factor.

The last model performance to look into is the FF5. The results of the FF5 does not follow the pattern presented in the FF3 or the CFFM. The performance of the model does not show any pronounceable pattern as of which portfolios that were explained the best. There is no model that shows significance in all factors. The model manages to capture the variation of the S/W portfolio the best with an $\overline{R^2}$ of 0.85, without the CMA factor significant. The second highest $\overline{R^2}$ with 0.74 belongs to the S/A portfolio.

The models presenting the third highest $\overline{R^2}$ is hard to distinguish, as the $\overline{R^2}$ of the B/N portfolio is 0.680 and the $\overline{R^2}$ of the S/C portfolio is 0.678. The results display low $\overline{R^2}$ in the B/H, even though four out of the five factors are significant, leaving the CMA insignificant. The difference between B/H and S/W is that the *Fama French Five Factor alpha* is insignificant.

4.3 Parameter Estimations

Continuing with reporting the results about the factors, we will mainly focus on the SMB, HML, MOM, RMW and CMA, since the market premium is not the main scope of this thesis. We find that the SMB of the FF5 is the best factor of the models. The SMB of the FF5 display as the most consistent factor of the models, with the most significant factors (Fama & French, 2015, 2017; Novy-Marx, 2013; Titman *et al.,* 2004).

Digging deeper into the analysis of the FF3, we interpret the individual parameters for each of the portfolios, starting with the ones sorted on size and B/M, see Table 1 on the next page. In the portfolios, we can see the same patterns as mentioned earlier in the $SMB_{B/M}$ regarding the decrease in value of the parameters as the B/M of the portfolios increase. In opposite of the $SMB_{B/M}$, the HML parameters increase as the B/M of the portfolios increase, as mentioned earlier. Three of the *Fama French Three Factor alphas* show statistical significance at a 5% level and are close to zero or can be interpreted as zero (Fama & French, 2015).

Continuing the analysis by presenting the parameters of the portfolios sorted on Operational Profitability. The size factor for portfolios sorted on size and Operational Profitability in the FF3 show $p < 5\%$ significant result in all the small stock portfolios, while none of the big stock portfolios manages this. The small stock returns alleviate with the increase of Operational Profitability, although positive, in the $SMB_{B/M}$. Further, the HML only presents one significant factor, which is in the model run on S/R. The parameter displays a negative correlation between small stock robust returns and HML. This indicates that the S/R portfolio shows the same variation as a portfolio heavily invested in low B/M stock. One of the alphas show a $p < 5\%$ significance.

At last, parameters of the FF3 are interpreted for portfolios sorted on size and Investment. The small stock parameters of $SMB_{B/M}$ show high significance and a positive correlation to all portfolios sorted on Investments. The S/A and S/C present similar parameter estimation values just above 1, while the S/M parameter of the $SMB_{B/M}$ is 0.434. The only significant parameter of HML belongs to the S/M portfolio and it is negative. As the portfolios sorted on size and Operational Profitability, one of the alphas shows a $p < 5\%$ significance.

Table 1: *Estimates of the three factors and alpha for the FF3 model run on 18 portfolios over the time period July 2012- June 2018. The portfolios represented are the value-weighted excess returns of S/L, B/L, S/N, B/N, S/H, B/H, S/W, B/W, S/N, B/N, S/R, B/R, S/A, B/A, S/M, B/M, S/R, B/R. The explanatory variables are seasonally adjusted and presented in the parentheses are the robust standard errors of the estimates.*

	Dependent variable																	
	$r_{s/l}-rf$	$r_{b/l}-rf$	$r_{s/n}-rf$	$r_{b/n}-rf$	$r_{s/h}-rf$	$r_{b/h}-rf$	$r_{s/w}-rf$	$r_{b/w}-rf$	$r_{s/n}-rf$	$r_{b/n}-rf$	$r_{s/r}-rf$	$r_{b/r}-rf$	$r_{s/a}-rf$	$r_{b/a}-rf$	$r_{s/m}-rf$	$r_{b/m}-rf$	$r_{s/c}-rf$	$r_{b/c}-rf$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$\beta_{1,i}$	0.901***	0.663***	0.860***	0.782***	0.636***	0.884***	1.021***	0.917***	0.712***	0.671***	0.846***	0.783***	0.981***	1.167***	0.613***	0.964***	0.89***	0.77***
	(0.101)	(0.131)	(0.114)	(0.073)	(0.136)	(0.132)	(0.233)	(0.126)	(0.121)	(0.089)	(0.103)	(0.102)	(0.181)	(0.246)	(0.083)	(0.144)	(0.197)	(0.119)
$\beta_{2,i}$	0.750***	−0.192	0.692***	−0.046	0.926***	−0.329**	1.223***	−0.191	0.675***	−0.164*	0.521***	0.048	1.129***	−0.113	0.435***	−0.158	1.043***	−0.036
	(0.099)	(0.127)	(0.108)	(0.068)	(0.135)	(0.127)	(0.236)	(0.123)	(0.119)	(0.083)	(0.099)	(0.100)	(0.186)	(0.245)	(0.081)	(0.138)	(0.191)	(0.115)
$\beta_{3,i}$	−0.476***	−0.314***	−0.203**	−0.052	0.782***	0.368***	−0.089	0.178*	0.072	−0.015	−0.322***	−0.156*	0.002	0.134	−0.151**	0.112	−0.091	−0.087
	(0.078)	(0.099)	(0.084)	(0.053)	(0.105)	(0.099)	(0.185)	(0.096)	(0.093)	(0.065)	(0.077)	(0.078)	(0.146)	(0.191)	(0.063)	(0.108)	(0.149)	(0.090)
Constant	−0.001**	0.001**	0.001*	−0.0005**	0.001*	−0.001	−0.0004	−0.001	0.001	0.001*	−0.001**	−0.0005	−0.001*	0.002**	0.0001	−0.001*	−0.001	0.00005
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.0005)	(0.001)	(0.0004)
Observations	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72
R^2	0.691	0.370	0.599	0.667	0.682	0.522	0.392	0.489	0.505	0.519	0.606	0.485	0.481	0.267	0.553	0.443	0.421	0.408
Adjusted R^2	0.677	0.342	0.581	0.652	0.668	0.501	0.366	0.467	0.483	0.498	0.589	0.462	0.458	0.235	0.533	0.419	0.396	0.382
Res. Std. Er. (df = 68)	0.003	0.003	0.003	0.002	0.004	0.003	0.006	0.003	0.003	0.002	0.003	0.003	0.005	0.007	0.002	0.004	0.005	0.003
F Statistic (df = 3; 68)	50.72***	13.29***	33.81***	45.40***	48.65***	24.73***	14.64***	21.72***	23.08***	24.45***	34.89***	21.34***	21.04***	8.27***	28.01***	18.06***	16.49***	15.65***

Note: *p<0.1; **p<0.05; ***p<0.01

The next model under investigations is the CFFM, see Table 2. Which in broad strokes show similar results to the FF3, as expected since, as mentioned earlier, the model is similar in most ways. Initiating the analysis with the B/M portfolios for the CFFM, we can see that the size effect is present in the $SMB_{B/M}$ but not the value effect. The value effect in HML is not consistent since the S/N show a lower parameter value than the S/L. The additional variable in this model, the momentum factors show a significant result for half of the portfolios. S/L and B/H show negative parameters, while the B/N display a positive parameter. One of the alphas in the models above show significant results and it is close to zero.

Moving on, the CFFM run on Portfolios sorted on size and Operational Profitability does not show compelling evidence of explaining variation in excess returns of the portfolios. Similar to the FF3 the $SMB_{B/M}$ show significant results for the small stock portfolios. The parameters belonging to the $SMB_{B/M}$ follow the same pattern, positive but decreasing as the operational profitability increases. The momentum factor does not show any significance under 5%. As the portfolios sorted on size and B/M only one alpha of the models presents significant results at 5% level. There is one significant alpha and it is close to zero.

The last regressions of the CFFM are run on portfolios sorted on size and Investments. The $SMB_{B/M}$ presents similar results to the FF3 sorted on size and Investments. In table # we can see that the S/A and S/C portfolios show parameters of the same magnitude and that the S/M is a bit modest in relation to the other two portfolios but still positive. It is only one HML variable that shows a significant effect on the portfolios at a 5% level, which is the HML of the S/M portfolio. The parameter of S/M is moderately negative. The momentum factor of sorts displays three significant results under 5% and one under 10%. The small and big aggressive portfolios show positive parameters and a $p < 5\%$. The small conservative presents a negative parameter and also a $p < 5\%$. The S/M show a parameter close to zero and a $p < 10\%$. The models run on portfolios sorted on size and Investment show two significant alphas, at a 5% level.

Table 2: *Estimates of the four factors and alpha for the CFFM run on 18 portfolios over the time period July 2012- June 2018. The portfolios represented are the value-weighted excess returns of S/L, B/L, S/N, B/N, S/H, B/H, S/W, B/W, S/N, B/N, S/R, B/R, S/A, B/A, S/M, B/M, S/R, B/R. The explanatory variables are seasonally adjusted and the robust standard errors of the estimates are presented in the parentheses.*

	Dependent variable																	
	$r_{s/l}-rf$	$r_{b/l}-rf$	$r_{s/n}-rf$	$r_{b/n}-rf$	$r_{s/h}-rf$	$r_{b/h}-rf$	$r_{s/w}-rf$	$r_{b/w}-rf$	$r_{s/n}-rf$	$r_{b/n}-rf$	$r_{s/r}-rf$	$r_{b/r}-rf$	$r_{s/a}-rf$	$r_{b/a}-rf$	$r_{s/m}-rf$	$r_{b/m}-rf$	$r_{s/c}-rf$	$r_{b/c}-rf$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$\beta_{1,i}$	0.881***	0.666***	0.863***	0.796***	0.645***	0.857***	0.981***	0.901***	0.734***	0.678***	0.849***	0.799***	1.011***	1.223***	0.632***	0.956***	0.821***	0.772***
	(0.101)	(0.132)	(0.116)	(0.077)	(0.133)	(0.124)	(0.235)	(0.126)	(0.122)	(0.087)	(0.101)	(0.103)	(0.183)	(0.234)	(0.081)	(0.146)	(0.171)	(0.117)
$\beta_{2,i}$	0.783***	−0.199	0.690***	−0.070	0.907***	−0.284**	1.290***	−0.188	0.643***	−0.163*	0.524***	0.028	1.071***	−0.208	0.412***	−0.151	1.158***	−0.040
	(0.098)	(0.129)	(0.110)	(0.067)	(0.137)	(0.125)	(0.235)	(0.125)	(0.119)	(0.085)	(0.101)	(0.101)	(0.185)	(0.238)	(0.081)	(0.140)	(0.173)	(0.117)
$\beta_{3,i}$	−0.509***	−0.307***	−0.202**	−0.027	0.801***	0.323***	−0.157	0.175*	0.104	−0.015	−0.326***	−0.136*	0.061	0.231	−0.128**	0.105	−0.207	−0.083
	(0.077)	(0.102)	(0.087)	(0.053)	(0.108)	(0.098)	(0.185)	(0.098)	(0.094)	(0.067)	(0.080)	(0.080)	(0.145)	(0.187)	(0.063)	(0.111)	(0.137)	(0.092)
$\beta_{4,i}$	−0.130**	0.029	0.005	0.097**	0.075	−0.176**	−0.265*	−0.011	0.123*	−0.002	−0.013	0.077	0.228**	0.377**	0.092*	−0.027	−0.453***	0.015
	(0.060)	(0.080)	(0.068)	(0.041)	(0.084)	(0.077)	(0.145)	(0.077)	(0.073)	(0.052)	(0.062)	(0.062)	(0.114)	(0.147)	(0.050)	(0.087)	(0.107)	(0.072)
Constant	−0.001**	0.001**	0.001*	−0.0004**	0.001*	−0.001	−0.001	−0.001	0.001	0.001*	−0.001**	−0.0005	−0.001*	0.002**	0.0002	−0.001*	−0.001**	0.0001
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.0005)	(0.001)	(0.0004)
Observations	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72
R^2	0.711	0.371	0.599	0.692	0.686	0.556	0.421	0.490	0.525	0.519	0.606	0.496	0.511	0.333	0.574	0.444	0.543	0.409
Adjusted R^2	0.694	0.333	0.575	0.674	0.667	0.530	0.387	0.459	0.496	0.490	0.583	0.466	0.481	0.293	0.549	0.411	0.516	0.373
Res. Std. Er. (df = 67)	0.003	0.003	0.003	0.002	0.004	0.003	0.006	0.003	0.003	0.002	0.003	0.003	0.005	0.006	0.002	0.004	0.005	0.003
F Statistic (df = 4; 67)	41.23***	9.88***	24.99***	37.69***	36.57***	20.99***	12.19***	16.06***	18.48***	18.07***	25.81***	16.51***	17.48***	8.36***	22.60***	13.39***	19.93***	11.58***

Note: *p<0.1; **p<0.05; ***p<0.01

The final section of the analysis will focus on the FF5 model, see Table 3. Initiating the investigation with the B/M portfolios. The SMB show strong significance for the small stock portfolios, but weak for the big stock. All of the small stock portfolios are significant but only one of the big portfolios stock show significance, the B/H. The parameters of the SMB increase as the B/M in the portfolios rises, inconsistent with the FF3 and CFFM. The SMB also show signs of the size effect. Next, the HML presents similar results to previous models on B/M portfolios. Five out six factors show a statistical significant result, only leaving the HML for B/N portfolio insignificant. The parameters increase as the B/M of the portfolios increases, disregarding the size. Although, the effect is stronger within the small stock than the big stock portfolios as the B/M increases. Further, the RMW factor performs poorly with only one significant factor for the B/L portfolio. The parameter of the significant RMW factor is negative. At last, the CMA presents three significant factors at a 5% and one at a 10% level. The portfolios showing significance in the CMA factor at a 5% level are B/L, S/N and S/H. The 10% level is to the B/N. All the parameters are negative of the CMA factors. The alphas of in the models, show significance in three of the six models and are all are close to zero.

The portfolios sorted on size and Operational Profitability are now evaluated. Five out of the six SMB factors display significant results, leaving only the SMB of the B/R insignificant. The small stock shows a positive sign with a decrease in value of the parameters as the Operational Profitability of the portfolios increase. There are two HML significant at a 5% and one at a 10% level. The significant variables belong to small stock portfolios, the neutral portfolio is the one with moderately significant HML. The parameter's for S/W and S/R are negative and fairly of the same magnitude. The S/N parameter is positive, close to 0.15. The RMW variables of the FF5 show significant results in five out of six models, one at a 10% the rest at a 1% level. The parameters value of the RMW increase as the profitability in the portfolios increases. The CMA present significance in three models, which is the big robust and neutral portfolios. All the parameters are negative, fairly the same size and close to zero, fluctuating between the absolute value of 0.2 and 0.1. There are four significant alphas, $p < 5\%$, and all can be interpreted as zero.

The last FF5 models reported are run on portfolios sorted on size and Investments. The SMB of the models show similar results to the models with portfolios sorted on size and OP, where five out of the six factors are significant. Although one of them show significance at a 10% level. The parameters of the SMB show positive signs for the small portfolios and negative signs for the big portfolios. The HML explains variation poorly in the portfolios sorted on size and Investment, only presenting one significant factor for the S/M portfolio at a 10% level. The parameter is negative.

The fourth factor of the FF5, RMW, explain variation in the portfolios sorted on size and investments somewhat better than the HML but still quite poor. It is only two factors in the RMW, belonging to the portfolios B/A and S/C, that present significant results under the 5% level. The B/M show a significance level of 10% and all the parameters are negative. The CMA factor is the second best factor, after the market factor, explaining variation in the portfolios sorted on market equity and Investment with 5 significant factors. It is only the B/M portfolio that shows insignificant results for the CMA. The aggressive portfolios present negative parameters whereas the conservative show positive parameters. The S/M portfolios show a negative value of the parameter. The two statistically significant alphas can be interpreted as zero.

Table 3: *Estimates of the five factors and alpha for the FF5 run on 18 portfolios over the time period July 2012- June 2018. The portfolios represented are the value-weighted excess returns of S/L, B/L, S/N, B/N, S/H, B/H, S/W, B/W, S/N, B/N, S/R, B/R, S/A, B/A, S/M, B/M, S/R, B/R. All explanatory variables are seasonally adjusted. The robust standard errors of the estimates are presented in the parentheses.*

	Dependent variables																	
	$r_{s/l}-rf$	$r_{b/l}-rf$	$r_{s/n}-rf$	$r_{b/n}-rf$	$r_{s/h}-rf$	$r_{b/h}-rf$	$r_{s/w}-rf$	$r_{b/w}-rf$	$r_{s/n}-rf$	$r_{b/n}-rf$	$r_{s/r}-rf$	$r_{b/r}-rf$	$r_{s/a}-rf$	$r_{b/a}-rf$	$r_{s/m}-rf$	$r_{b/m}-rf$	$r_{s/c}-rf$	$r_{b/c}-rf$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$\beta_{1,i}$	.893***	.607***	.821***	.766***	.621***	.826***	.858***	.856***	.692***	.631***	.893***	.785***	.863***	.921***	.587***	.928***	.945***	.791***
	(.113)	(.127)	(.099)	(.074)	(.0146)	(.121)	(.124)	(.121)	(.111)	(.083)	(.104)	(.106)	(.133)	(.187)	(.083)	(.145)	(.143)	(.118)
$\beta_{2,i}$	.654***	−.125	.697***	−.102	.910***	−.381***	.971***	−.337***	.766***	−.174**	.538***	.096	1.238***	−.492***	.398***	−.271*	.893***	−.147
	(.112)	(.129)	(.098)	(.068)	(.141)	(.125)	(.122)	(.119)	(.109)	(.084)	(.103)	(.099)	(.133)	(.183)	(.082)	(.142)	(.145)	(.116)
$\beta_{3,i}$	−.420***	−.406***	−.209***	−.053	.873***	.230**	−.349***	.072	.145*	−.075	−.199**	−.113	−.003	−.064	−.128*	.043	−.062	−.074
	(.087)	(.101)	(.077)	(.053)	(.111)	(.098)	(.095)	(.094)	(.085)	(.066)	(.081)	(.078)	(.104)	(.143)	(.064)	(.111)	(.114)	(.091)
$\beta_{4,i}$	−.025	−.179*	−.158*	.036	.129	−.381***	−1.209***	−.327***	.178*	−.112	.257***	.183**	−.057	−.336**	.025	−.200*	−.420***	−.019
	(.092)	(.107)	(.081)	(.056)	(.117)	(.104)	(.101)	(.099)	(.090)	(.069)	(.085)	(.082)	(.110)	(.151)	(.068)	(.117)	(.120)	(.096)
$\beta_{5,i}$	−.029	−.154**	−.136**	−.074*	−.203**	.009	−.097	.018	−.262***	−.104**	.025	−.109*	−.616***	−.770***	−.169***	.005	.462***	.141**
	(.064)	(.073)	(.056)	(.039)	(.081)	(.071)	(.069)	(.068)	(.062)	(.048)	(.059)	(.057)	(.076)	(.104)	(.047)	(.081)	(.083)	(.066)
Constant	−.001*	.001**	.001***	−.0005**	.001	−.0002	.001**	−.0002	.0005	.001**	−.001***	−.001**	−.001**	.002***	.0002	−.001	−.001	.0001
	(.0004)	(.0004)	(.0003)	(.0002)	(.0005)	(.0004)	(.0004)	(.0004)	(.0004)	(.0003)	(.0003)	(.0003)	(.0004)	(.001)	(.0003)	(.0005)	(.0005)	(.0004)
Observations	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72
R^2	.650	.414	.702	.703	.686	.582	.855	.564	.629	.561	.616	.545	.763	.633	.587	.472	.701	.455
Adjusted R^2	.623	.369	.680	.680	.662	.550	.844	.531	.600	.528	.587	.510	.745	.605	.556	.432	.678	.414
Res. Std. Er. (df = 66)	.003	.003	.003	.002	.004	.003	.003	.003	.003	.002	.003	.003	.003	.005	.002	.004	.004	.003
F Statistic (df = 5; 66)	24.47***	9.32***	31.12***	31.20***	28.78***	18.35***	77.96***	17.01***	22.34***	16.88***	21.18***	15.81***	42.54***	22.73***	18.80***	11.78***	30.94***	11.04***

Note: *p<0.1; **p<0.05; ***p<0.01

5 Discussion

This section evaluates and discusses the results in the previous chapter in relation to the work of other scholars. The second and third section concerns critical considerations and future research on the topic of this thesis.

Let's start with the model validation. The absence of time dependence is expected since growth in price was used as a measure for returns. As a measure, this takes away the time trend of the variables (Gujarati, 2009). The variables that still present some time dependence were not deemed as problematic. This tendency might be due to coincidence or because of time dependence in the variables (Cryer & Chan, 2008). The normal distribution of the dependent variables is somewhat skewed in some of the portfolios. This could be an explanation to the absent significance in some of the factors or the larger standard deviation of the parameters (Koenker, 1981).

On average, the FF5 shows a higher $\overline{R^2}$ than the two other models, with a top note of 0.84 in $\overline{R^2}$. These results are in line with the findings in Fama & French (2015; 2017) and Sundqvist (2017). The model achieving this result is small stock with low Operational Profitability, S/W. The models present similar results with the same significant variables, which also is expected since the models are similar. The similarity in the performance of the FF3 and CFFM is due to the underperformance of the momentum factor in the CFFM. Even though the momentum factor is significant, as we can see in the CFFM run on portfolios sorted on Size and Investments, the momentum only contributes 0.3 in $\overline{R^2}$. If we investigate this further, the contribution is rather poor for every significant momentum factor. These results are similar to Fama & French's (2012) study on the European market but inconclusive with Foye (2016). The difference between our analysis and Foye (2016) is that he also uses portfolios sorted on momentum, which might be one reason for the different results. However, this is still an open question since Fama & French (2012) does this as well while without showing convincing evidence of a present momentum. We will continue by discussing the specific factors and then evaluate the model validation.

Starting with the SMB. The models show mixed results of a significant size premium. We start by evaluating the FF3 and the CFFM. The models show similar results for all $SMB_{B/M}$ factors, which is expected since the factors are the same. Yet, the result of the $SMB_{B/M}$ is somewhat confusing. The problem is not the sign of the parameters but the insignificance of the factors making it hard to argue for a negative correlation between market equity and value-weighted excess returns. Another problem is that the expected value effect on the portfolios sorted on size and B/M is inconsistent. Theoretically, we expect the value stock to outperform growth stock (Carhart, 1997). For some specific sizes, this is not the case. To echo Fama & French (2017), a possible explanation for the absence of value effect within the size might be due to the fact that each size group is quite homogeneous, which makes it hard for the model to distinguish and capture the behaviour of the specific portfolios.

The FF5:s SMB show more significant variables which makes it easier to evaluate and we can see that the returns decrease with the growth in market equity for portfolios sorted on Book/Market, Operational Profitability and Investments portfolios. The results from the FF5 is inconsistent with the results in Foye (2016) who says that the size effect is country specific and does not show presence in the European market as a whole which is also in line with Fama & French (2012). As we outlined in the Background - there is a debate in previous research regarding whether the size effect is present or not. In this thesis, the focus regards a country-specific or Swedish size effect. Van Dijk (2011) states the question: If the size premium is dead due to a lack of empirical and theoretical research on the matter? Horowitz *et al.* (2000), Dimson & Marsh (2001) and Foye *et al.* (2013) show results that would affirmatively answer the question but there is also proof for a significant size premium (Bhatnagar & Ramlogan, 2012). Foye (2016), as previously mentioned, evaluated 18 countries in Europe where most of them show the presence of a size premium and Heston *et al.* (1999) evaluated 12 countries in Europe also showing similar results. Based on the results in this thesis the value and profitability effect is also present in the SMB. This is in line with Foye (2016) and Fama & French (2017). In the portfolios sorted on size and Investment, we can see the opposite of the findings in Fama & French (2015). The aggressive stock is meant to represent firms that invest heavily due to previously poor performance, thereby the expectation is that the conservative investments stocks will outperform the aggressive investments stocks (Fama & French, 2017).

Moving on to evaluate the value premium. Approximately half of the HML factors show statistically significant results, the portfolios sorted on size and B/M show more significant factors than the other portfolios. This is expected since the factor is created to take variation in excess return belonging to B/M into account.

The expectation is that the value of the parameter will increase as the B/M increases in the portfolios. The results are in line with this expectation and we can argue for a present value premium. A present value premium has been confirmed by most of the previous research. To our knowledge, there are few scholars questioning the HML factor. The more frequently asked questions concerns whether the $FF3$ is an exhaustive model of excess returns as mentioned by Fama & French (2015), Novy-Marx (2013) and Titman *et al.,* (2004).

The next factor regards momentum which only concerns the CFFM, equation (3) in the second chapter. This factor does not show any convincing evidence of presence in this context, with most of its coefficients insignificant. The CFFM run on portfolios sorted on size and investments are the ones with the highest significant rates. The values of the parameters show that the aggressive portfolios mimic variations of a portfolio heavily invested in winning stock and the contrary for the conservative stock. What we expect is that the conservative stock presents higher returns and lower volatility than the aggressive stock (Fama & French, 2015). The aggressive portfolios are meant to represent stocks that have performed poorly and now invest heavily, hence the higher volatility and what might be an answer to the reversed momentum. Overall, the momentum factor in this thesis shows no strong contribution to the model which in line with previous research where they use portfolios not sorted on momentum as dependent variables. Further, the CFFM shows no sign of difficulty explaining excess returns in small stocks in the momentum factor. In contrary to the statement by Fama & French (2012). They imply that the unexplained variation is due to the modest total market influence of small stocks. Yet, this can be contrasted to Gregory *et al.,* (2013) that present results of more significant momentum factors, excluding small firms.

The next factor to evaluate is the RMW belonging to the FF5. In summary, the RMW factor does a fair job explaining the excess returns of the portfolios sorted on size and operational profitability or investment. However, the factor does a very poor job explaining variation in excess returns of the portfolios sorted on size and B/M or Investments. The RMW seems redundant in the context of B/M portfolios, with no significant factors at a 5% level. The results on portfolios sorted in size and Investments are fairly confusing, showing a reversed profitability effect between aggressive and conservative stock. The profitability effect is clearly present on the portfolios sorted on operational profitability, where we expect a positive correlation between excess returns and the increase of profitability. Theoretically, the effect is to be stronger within small stocks since they are more volatile than big stocks, see Table 3. The results here are similar to those of Novy-Marx (2013), results on US data in Fama & French (2015) and with the results on European data in Fama & French (2017). However, the results are inconclusively presented in the Scandinavian market shown in Sundqvist (2017). The latter points out that the profitability effect is weaker and with no discernible difference between big and small companies. One possible explanation might be because of ineffective pricing of small stocks in the Scandinavian markets. The results in Fama & French (2017) on the European market show similar results as the findings in this thesis.

The CMA is the last factor to discuss. The overall performance is mixed, where half of the factors are significant. As we mentioned in the former chapter, the CMA showed no significance in the model displaying the highest $\overline{R}^2$ and the overall assessment of the factor is conclusive with Fama & French (2017) and Racicot and Rentz (2017). As a factor the CMA seems redundant. Fama & French (2017) make the same conclusion for portfolios sorted on size B/M and Operational profitability but it performs well on the portfolios sorted on size and Investment. The results show evidence of the effect presented in Titman *et al.,* (2004) where the aggressive portfolios are expected to show a negative CMA parameter and the conservative portfolios are expected to show a positive CMA parameter. The effect is also expected to be stronger among the small stocks because of their more volatile behavior, which is in line with the results presented in Table 3.

5.1 Critical Considerations

On a general level, when statistical analyses are performed we employ mathematical facts to deal with empirical problems. For example, if we want to know whether the means of two groups differ we can use the facts of the groups' distribution (on the variable of interest along with some additional assumptions) to say whether the difference in means between the groups is more or less likely to be attributable to chance rather than to some factual difference. However, while an objective yardstick is always preferable some choices still miss readily available factual arguments. In this thesis, at least two points could have been addressed with a more objective yardstick in terms of statistics: The size of the collected sample and the choice of the time period under analysis.

Now, the time period was not arbitrary. As mentioned previously it was selected with respect to the long-lasting noise of the financial crises of 2008.

The sample size is a more complex subject. In a simple case where we try to make inferences about a single parameter in a population, the precision of this parameter estimation will be a function of the sample size. However, in the context of this thesis no a priori objective criterion was used when the decision was made to randomly select ($n = 90$) companies from the current population of ($N = 372$) publicly listed companies on the SSE. A larger sample along with an evaluation of portfolios sorted on more measures would have made the results of this thesis more reliable. As a research topic, evaluating returns using Fama & French and other asset pricing models demands a very wide approach and to take on many general assumptions of the market and its actors at hand. A topic such as this might be a bit too wide for a thesis such as this one. The sorting of the dataset was work intensive but there are yet more aspects that could be investigated. This means that several other variations of portfolios could have been investigated. More inferential tests could perhaps also be performed to draw even more solid conclusions from the data. In addition, another interesting topic would have been to investigate the dependencies between portfolios but this lands in the basket of future research.

5.2 Future Research

The literature that was reviewed in this thesis combined with the results that were obtained opened up many interesting disagreements between scholars. One of the most obvious debates concerns the presence (or lack of it) of the size effect. Further research on the subject of the FF5 is also needed. For example, using portfolios sorted on different measures applied to the SSE and using the full population of the SSE. In future iterations of this kind of a thesis the following amendments are worth considering. In Barvels *et al.,* (2015) we can see how they use industry standard portfolios which adds additional clarity to the results. Foye (2016) made an evaluation of the momentum factor on country-specific data, using momentum portfolios. Those portfolios were not analyzed here. Yet, the interest in this factor is also outlined in Fama & French (2017), where they state that an additional momentum factor is expected to further evaluate the FF5. As previously stated, an investigation of the dependencies between portfolios which probably accounts for a lot of variation in the data could be a fruitful endeavor.

6 Conclusion

To summarize the answer to the first research question: The FF5 outperformed both the CFFM and its predecessor FF3 comparing the $\overline{R^2}$ of the models. This is a testimony to the relevance of the new model and is also in line with previous research (Fama & French, 2017). The second research question concerned which of the factors in the models that would be the best predictors of excess return. In this context, it is hard to decisively distinguish which of the models that outperform the other. The results show that the FF3 and the CFFM are fairly good at explaining the portfolios sorted on size and B/M while doing an overall poor job at explaining variation in portfolios sorted on size and Operational Profitability or Investments. Here, the FF5 is better and more consistent. The SMB of the FF5, where all the SMB portfolios are included presents more consistent results where most of the SMB factors are present. The other factors of the models are overall fair at explaining variation in the portfolios sorted on the measure of the factor. For example, the small aggressive portfolio shows a significant CMA factor and the big robust portfolio show a significant RMW factor. The problem is that the factors are not on average good predictors for other portfolios sorted on a different factor measure. The conclusion is that the FF5 is the best of the three models but there is still a lot of variation unexplained in the excess returns of the portfolios, which needs to be evaluated further to make proper assessments. With this in mind, any particular suggestions for investors are to be done with caution. The size factor of the FF5 is the explanatory variable we find the most consistent evidence for and could supposedly be used as a benchmark for evaluating the influence of market capitalization on value-weighted excess returns. On a final statistical note, introducing multivariate models accounting for interdependence between portfolios would probably result in better prediction properties. In closing, we will leave this humbling task to a more advanced study somewhere is the future.

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8 Appendix

The tables and figures below are part of the auxiliary statistical analysis that was performed to validate the results of this thesis. On the last two pages, a complete list of all the included companies can be found.

Table 4: *FF3 - VIF values of the factors*

OMXS30	$SMB_{B/M}$	HML
1.012	1.025	1.030

Table 5: *CFFm - VIF values of the factors*

OMXS30	$SMB_{B/M}$	HML	MOM
1.021	1.050	1.074	1.075

Table 6: *FF5 - VIF values of the factors*

OMXS30	$SMB_{B/M}$	HML	RMW	CMA
1.060	1.167	1.140	1.287	1.070

Table 7: *FF3 - Studentized Breusch-Pagan tests*

Model	BP-values	Degrees of freedom	p-values
$FF3_{S/L}$	10.897	3	0.0123*
$FF3_{B/L}$	2.297	3	0.5131
$FF3_{S/N}$	7.7113	3	0.0524
$FF3_{B/N}$	3.5494	3	0.3144
$FF3_{S/H}$	3.6542	3	0.3013
$FF3_{B/H}$	17.292	3	0.0006***
$FF3_{S/W}$	2.9578	3	0.3982
$FF3_{B/W}$	5.2539	3	0.1541
$FF3_{S/N}$	3.0937	3	0.3774
$FF3_{B/N}$	1.1419	3	0.767
$FF3_{S/R}$	6.6797	3	0.0828
$FF3_{B/R}$	3.9445	3	0.2675
$FF3_{S/A}$	8.8752	3	0.0310*
$FF3_{B/A}$	0.41189	3	0.9378
$FF3_{S/M}$	11.683	3	0.0086**
$FF3_{B/M}$	1.7192	3	0.6327
$FF3_{S/C}$	3.1343	3	0.3714
$FF3_{B/C}$	3.3897	3	0.3354

Note: *p<0.05; **p<0.01; ***p<0.001

Table 8: *CFFM - Studentized Breusch-Pagan tests*

Model	BP-values	Degrees of freedom	p-values
$CFFM_{S/L}$	5.831	4	0.2121
$CFFM_{B/L}$	2.5347	4	0.6384
$CFFM_{S/N}$	8.2629	4	0.0824
$CFFM_{B/N}$	5.2174	4	0.2657
$CFFM_{S/H}$	3.413	4	0.4912
$CFFM_{B/H}$	14.92	4	0.0049**
$CFFM_{S/W}$	5.0568	4	0.2815
$CFFM_{B/W}$	6.1557	4	0.1878
$CFFM_{S/N}$	3.079	4	0.5447
$CFFM_{B/N}$	1.7957	4	0.7733
$CFFM_{S/R}$	6.8261	4	0.1454
$CFFM_{B/R}$	4.2012	4	0.3795
$CFFM_{S/A}$	9.8991	4	0.0422*
$CFFM_{B/A}$	4.9044	4	0.2972
$CFFM_{S/M}$	9.9583	4	0.0411*
$CFFM_{B/M}$	2.4538	4	0.6529
$CFFM_{S/C}$	11.203	4	0.0244*
$CFFM_{B/C}$	3.9952	4	0.4067

Note: *p<0.05; **p<0.01; ***p<0.001

Table 9: *FF5 - Studentized Breusch-Pagan tests*

Model	BP-values	Degrees of freedom	p-values
$FF5_{S/L}$	6.8094	5	0.2352
$FF5_{B/L}$	5.8168	5	0.3245
$FF5_{S/N}$	13.796	5	0.0170*
$FF5_{B/N}$	2.6646	5	0.7515
$FF5_{S/H}$	2.9144	5	0.7132
$FF5_{B/H}$	7.8927	5	0.1622
$FF5_{S/W}$	5.9984	5	0.3064
$FF5_{B/W}$	4.8081	5	0.4397
$FF5_{S/N}$	3.0708	5	0.6891
$FF5_{B/N}$	3.0198	5	0.6969
$FF5_{S/R}$	10.851	5	0.0544
$FF5_{B/R}$	9.624	5	0.0866
$FF5_{S/A}$	4.8971	5	0.4286
$FF5_{B/A}$	14.855	5	0.0110*
$FF5_{S/M}$	5.2786	5	0.3828
$FF5_{B/M}$	5.8163	5	0.3245
$FF5_{S/C}$	1.7923	5	0.8771
$FF5_{B/C}$	3.9666	5	0.5542

Note: *p<0.05; **p<0.01; ***p<0.001

Table 10: *First 45 companies that were included in the random sample* ($n = 90$)

Name of the stock	List	Market	Symbol	ISIN
Björn Borg AB	SMALL	Con. Goods	BORG	SE0011036821
Nilörngruppen AB ser. B	SMALL	Con. Goods	NIL B	SE0007100342
Electra Gruppen AB	SMALL	Con. Services	ELEC	SE0001572520
RNB RETAIL AND BRANDS AB	SMALL	Con. Services	RNBS	SE0005223674
Sportamore AB	SMALL	Con. Services	SPOR	SE0004777241
Midway Holding AB ser. A	SMALL	Financials	MIDW A	SE0000122657
BioInvent International AB	SMALL	Health Care	BINV	SE0000789711
Dedicare AB ser. B	SMALL	Health Care	DEDI	SE0003909282
Feelgood Svenska AB	SMALL	Health Care	FEEL	SE0000381840
GHP Specialty Care AB	SMALL	Health Care	GHP	SE0002579912
Immunicum AB	SMALL	Health Care	IMMU	SE0005003654
Moberg Pharma AB	SMALL	Health Care	MOB	SE0003613090
NeuroVive Pharmaceutical AB	SMALL	Health Care	NVP	SE0002575340
Nuevolution AB	SMALL	Health Care	NUE	SE0007730650
Balco Group AB	SMALL	Industrials	BALCO	SE0010323998
Christian Berner Tech Trade AB ser. B	SMALL	Industrials	CBTT B	SE0006143129
Consilium AB ser. B	SMALL	Industrials	CONS B	SE0000236382
eWork Group AB	SMALL	Industrials	EWRK	SE0002402701
NCAB Group AB	SMALL	Industrials	NCAB	SE0011167956
Precise Biometrics AB	SMALL	Industrials	PREC	SE0001823303
Pricer AB ser. B	SMALL	Industrials	PRIC B	SE0000233934
Projektengagemang Sweden AB ser. B	SMALL	Industrials	PENG B	SE0011337666
Railcare Group AB	SMALL	Industrials	RAIL	SE0010441139
Semcon AB	SMALL	Industrials	SEMC	SE0000379497
Viking Supply Ships AB ser. B	SMALL	Industrials	VSSAB B	SE0010820613
Anoto Group AB	SMALL	Technology	ANOT	SE0010415281
Empir Group AB ser. B	SMALL	Technology	EMPIR B	SE0010769182
Enea AB	SMALL	Technology	ENEA	SE0009697220
Micro Systemation AB ser. B	SMALL	Technology	MSAB B	SE0000526626
MultiQ International AB	SMALL	Technology	MULQ	SE0000353898
Lucara Diamond Corp	MID	Basic Materials	LUC	CA54928Q1081
Lundin Gold Inc.	MID	Basic Materials	LUG	CA5503711080
Bulten AB	MID	Con. Goods	BULTEN	SE0003849223
Haldex AB	MID	Con. Goods	HLDX	SE0000105199
Boozt AB	MID	Con. Services	BOOZT	SE0009888738
Byggmax Group AB	MID	Con. Services	BMAX	SE0003303627
Dustin Group AB	MID	Con. Services	DUST	SE0006625471
SAS AB	MID	Con. Services	SAS	SE0003366871
Corem Property Group AB ser. B	MID	Financials	CORE B	SE0010714287
Fast Partner AB pref.	MID	Financials	FPAR PREF	SE0011309236
Hoist Finance AB	MID	Financials	HOFI	SE0006887063
Magnolia Bostad AB	MID	Financials	MAG	SE0007074505
NP3 Fastigheter AB	MID	Financials	NP3	SE0006342333
Platzer Fastigheter Holding AB ser. B	MID	Financials	PLAZ B	SE0004977692
Svolder AB ser. B	MID	Financials	SVOL B	SE0010663310

Table 11: *Remaining 45 companies that were included in the random sample* ($n = 90$)

Name of the stock	**List**	**Market**	**Symbol**	**ISIN**
BioArctic AB ser. B	MID	Health Care	BIOA B	SE0010323311
Biotage AB	MID	Health Care	BIOT	SE0000454746
Camurus AB	MID	Health Care	CAMX	SE0007692850
Capio AB	MID	Health Care	CAPIO	SE0007185681
Medicover AB ser. B	MID	Health Care	MCOV B	SE0009778848
Medivir AB ser. B	MID	Health Care	MVIR B	SE0000273294
Oncopeptides AB	MID	Health Care	ONCO	SE0009414576
Concentric AB	MID	Industrials	COIC	SE0003950864
Ferronordic Machines AB	MID	Industrials	FNM	SE0005468717
Gunnebo AB	MID	Industrials	GUNN	SE0000195570
Opus Group AB	MID	Industrials	OPUS	SE0001696683
Troax Group AB	MID	Industrials	TROAX	SE0006732392
HMS Networks AB	MID	Technology	HMS	SE0009997018
Knowit AB	MID	Technology	KNOW	SE0000421273
Tobii AB	MID	Technology	TOBII	SE0002591420
Holmen AB ser. A	LARGE	Basic Materials	HOLM A	SE0011090000
SSAB AB ser. A	LARGE	Basic Materials	SSAB A	SE0000171100
AAK AB	LARGE	Con. Goods	AAK	SE0011337708
"Electrolux, AB ser. A"	LARGE	Con. Goods	ELUX A	SE0000103806
Essity AB ser. B	LARGE	Con. Goods	ESSITY B	SE0009922164
Husqvarna AB ser. B	LARGE	Con. Goods	HUSQ B	SE0001662230
Swedish Match AB	LARGE	Con. Goods	SWMA	SE0000310336
"Hennes & Mauritz AB, H & M ser. B"	LARGE	Con. Services	HM B	SE0000106270
ICA Gruppen AB	LARGE	Con. Services	ICA	SE0000652216
LeoVegas AB	LARGE	Con. Services	LEO	SE0008091904
Modern Times Group MTG AB ser. A	LARGE	Con. Services	MTG A	SE0000412363
Bonava AB ser. A	LARGE	Financials	BONAV A	SE0008091573
Hemfosa Fastigheter AB pref	LARGE	Financials	HEMF PREF	SE0007126123
"Industrivärden AB ser. A"	LARGE	Financials	INDU A	SE0000190126
Intrum AB	LARGE	Financials	INTRUM	SE0000936478
Investor AB ser. A	LARGE	Financials	INVE A	SE0000107401
Investor AB ser. B	LARGE	Financials	INVE B	SE0000107419
Kinnevik AB ser. B	LARGE	Financials	KINV B	SE0008373906
Klövern AB pref.	LARGE	Financials	KLOV PREF	SE0006593927
Kungsleden AB	LARGE	Financials	KLED	SE0000549412
Pandox AB ser. B	LARGE	Financials	PNDX B	SE0007100359
Ratos AB ser. B	LARGE	Financials	RATO B	SE0000111940
Sagax AB ser. B	LARGE	Financials	SAGA B	SE0005127818
Skandinaviska Enskilda Banken ser. C	LARGE	Financials	SEB C	SE0000120784
Attendo AB	LARGE	Health Care	ATT	SE0007666110
Getinge AB ser. B	LARGE	Health Care	GETI B	SE0000202624
Fingerprint Cards AB ser. B	LARGE	Industrials	FING B	SE0008374250
Lifco AB ser. B	LARGE	Industrials	LIFCO B	SE0006370730
Loomis AB ser. B	LARGE	Industrials	LOOM B	SE0002683557
NCC AB ser. B	LARGE	Industrials	NCC B	SE0000117970