UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER THESIS

NET WORKING CAPITAL AS A FACTOR OF STOCK RETURNS: AN EMPIRICAL ANALYSIS OF STOXX EUROPE 600 INDEX STOCKS

Ljubljana, June 2022 JAKA GOLOB

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LIST OF ABBREVIATIONS

APT – Arbitrage pricing theory
B/M – Book to market ratio
CAL – Capital allocation line
CAPM – Capital asset pricing model
CCC – Cash conversion cycle
CMA – Conservative minus aggressive
E/P – Earnings yield
FE – Fixed effects
FF 3-factor model – Fama French three factor model
FF 5-factor model – Fama French five factor model
GRS – Gibbons Ross Shanken
HML – High minus low

NACE – Nomenclature of Economic Activities
NOP – Net operating ratio
NWC – Net working capital
NWC ratio – Net working capital ratio
NYSE – New York stock exchange
OLS – Ordinary least squares
PR1YR – Prior one-year return
RMW – Robust minus weak
ROA – Return on assets
SMB – Small minus big
SML – Security market line
TML – Tight minus loose
UK – United Kingdom
US – United States

INTRODUCTION

The majority of literature in the field of corporate finance has focused on long term allocations of assets and liabilities, the most popular being capital structure, investments, dividends, and company valuation. This is surprising, considering that short term asset investments and resources with maturities with less than a year, account for a large part of a company's balance sheet (García-Teruel & Martínez-Solano, 2007). As an example, García-Teruel and Martínez-Solano (2007) state that in their sample of small and medium sized Spanish companies, current assets represent 69 % of assets and current liabilities present 52 % of liabilities. This evidence suggests that more attention should be given to analysis on short allocations of assets and liabilities.

Net working capital (hereinafter referred to as NWC) is a source of short-term liquidity. Its primary objective is to ensure that companies have enough liquidity to carry out their operations and at the same time meet their obligations. On the other hand, having too much NWC can also have a negative side. Having more assets tied up in NWC leaves less available assets to invest elsewhere (García-Teruel & Martínez-Solano, 2007). In this sense having the right amount of NWC can represent a trade-off. The challenge in managing NWC is to consider both sides of the balance sheet and try to favourably balance risk and returns (Zariyawati, Annuar, Taufiq & Rahim, 2009).

In the master thesis I research NWC and its impact on future returns of stocks included in the Stoxx Europe 600 index. I provide two hypotheses. The first hypothesis states that the NWC scaled by total assets (hereinafter referred to as NWC ratio), as an independent variable, can additionally help explain variations in stock returns when using asset pricing models. I compare the ability of the Fama French five factor model (hereinafter referred to as FF 5-factor model) and my own 6-factor model, where the NWC ratio is added as a factor to explain differences in future portfolio excess returns. The model with a better ability to explain differences in excess returns will have lower pricing errors. The models will be tested on 10 NWC ratio sorted portfolios and 25 SIZE-NWC ratio double sorted portfolios. I compare the pricing errors of the FF 5- factor model to the pricing errors obtained by my own 6-factor model. The evaluation will be based on the Gibbons Ross Shanken (hereinafter referred to as GRS) test statistic where we test if the pricing errors of all portfolios are jointly zero. The model whose GRS test statistic will be lower, will indicate that its pricing errors are jointly closer to zero and more accurately explain future excess returns. To give support to the GRS test statistic, I also compare the models based on adjusted R-squared and absolute mis-pricing error.

The second hypothesis states that NWC ratio as an independent variable will have a negative effect on future excess stock returns, thus implying that firms with lower values of NWC ratio will yield higher than average future returns. The validity of the relation is tested by using the Fama Macbeth procedure on my 6-factor model using 10 NWC ratio single sorted portfolios and 25 SIZE-NWC ratio double sorted portfolios as test assets. If the coefficient corresponding to the NWC ratio factor shows a positive relation between the variables and is statistically significant, we cannot reject the hypothesis.

My master thesis consists of two parts. The first is theoretical. Firstly, I present an overview of NWC. Next, I present previous studies tied to NWC and profitability, and compare their findings. I continue with the presentation of the most famous asset pricing models. Then I present time series and cross-sectional analysis procedures. I finish the theoretical part, by presenting the most common criteria used when comparing performance of different asset pricing models.

The second part is empirical. Firstly, I present the Stoxx Euro 600 index. I then explain the process of data gathering and preparation and provide variable definitions and summary statistics of the sample. I continue with the presentation of the methodology used and explain the structure of my models. In the last part I present the results of the research and assess the research questions. I discuss the possible reasons for this outcome and end with the conclusion.

1 NET WORKING CAPITAL

In this section I provide a detailed description of NWC. I present all the definitions of NWC that are used in literature. I explain arguments for having low and high NWC. Lastly, I present a summary of important studies regarding NWC and its effect on future profitability of companies.

1.1 Measures of net working capital

There are several studies which measure the effects of NWC on profitability. Some studies use the working capital definition, some use the definition of NWC that is consistent with how it is used in this thesis, and some studies use the cash conversion cycle (Hereinafter referred to as CCC) measure when assessing links to profitability.

The broadest definition is the working capital definition. It shows how much cash and liquid assets are available to meet short-term requirements from current liabilities. According to accounting standards short term assets and liabilities are those which will be converted into cash (for assets) or become due (for liabilities) within one year. The working capital formula is presented below (Preve & Sarria-Allende, 2010):

$$NWC = Current\ assets - Current\ liabilities \quad (1)$$

Current assets of the firm are composed of the following accounts (Preve & Sarria-Allende, 2010):

– Accounts receivable
– Inventory
– Cash holdings

Current liabilities of the firm are composed of the following accounts (Preve & Sarria-Allende, 2010):

– Accounts payable
– Credits from employees
– Tax authority credits
– Short term financial debt

Most of the relevant research in the field takes into account a narrower definition of NWC capital where NWC consists of:

– Accounts receivable
– Inventory
– Accounts payable

Inventory is composed of raw materials and goods, which is needed to ensure that the company operates normally. Inventory measures the sum of the cost of all raw materials the company has and all the costs the company had while producing the goods it has in stock (Preve & Sarria-Allende, 2010).

Accounts receivable is when companies allow customers additional time to pay invoices for the goods or services obtained. It represents the dollar amount of goods and services for which the company has not received payment yet (Preve & Sarria-Allende, 2010).

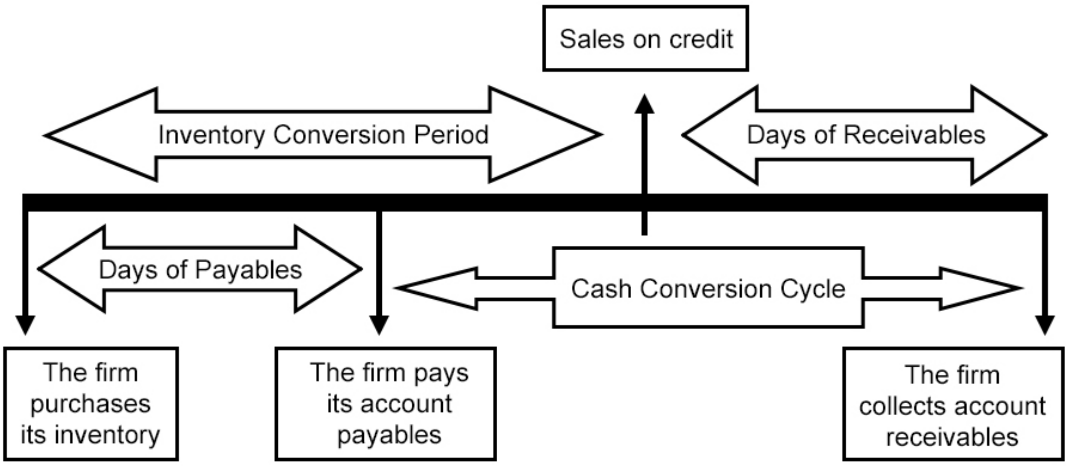
Accounts payable is the opposite of accounts receivable, where suppliers enable the company additional time to pay for the received services or goods. The dollar amount of goods and services received for which the company has not paid yet, is represented as accounts payable (Preve & Sarria-Allende, 2010).

Following this definition, the NWC is calculated as the sum of inventory and accounts receivable minus accounts payable. In this master thesis this is the definition that is going to be used. Since firms are of different sizes, I control for differences in size by scaling firms NWC by its total assets which is represented below as the NWC ratio.

$$NWC\ ratio = \frac{accounts\ receivable + inventory - \ accounts\ payable}{Total\ assets} \quad (2)$$

Many researchers study NWC from the perspective of the CCC, which represents the length of time between payment for materials or services that are needed in the production process of products and collecting payments associated with the sale of these products (Preve & Sarria-Allende, 2010).

Figure 1: Cash conversion cycle



Adapted from Preve & Sarria-Allende (2010, p. 68).

From figure 1 we can see that the CCC is calculated as the sum of the inventory conversion period and days for receivables minus the days for payables (Nobanee, Abdullatif & AlHajjar, 2011).

The inventory conversion period measures the average time needed to convert raw materials into goods and selling them. The calculation is shown below (Nobanee, Abdullatif & AlHajjar, 2011):

$$inventory\ conversion\ period = \frac{inventory}{cost\ of\ good\ sold} * 365 \qquad (3)$$

Days for receivables measure the average time between the sale of goods and collection of payments. The calculation is shown below (Nobanee, Abdullatif & AlHajjar, 2011):

$$days\ for\ receivables = \frac{accounts\ receivable}{sales} * 365 \qquad (4)$$

Days for payables measure the average time between when the materials are purchased and when they are paid for. The calculation is shown below (Nobanee, Abdullatif & AlHajjar, 2011):

$$days\ for\ payables = \frac{accounts\ payable}{cost\ of\ goods\ sold} * 365 \tag{5}$$

The relation between the CCC and NWC can be seen from equations (2), (3), (4), (5) above. The higher the NWC the longer the CCC. This relationship is useful when comparing studies on NWC to studies on CCC.

1.2 Advantages of high and low NWC

NWC can represent a significant amount of a company's balance sheet. For example, in his study from 1997, Deloof (2003) states that accounts receivable represented 17 %, inventory represented 10 %, and accounts payable represented 13 % of total assets in Belgian firms. Similarly, Kieschnick, Laplante & Moussawi (2013) state that NWC represents 27 % of assets in United States (hereinafter referred to as US) corporations. From this we can conclude that components of NWC represent a significant part of a company's balance sheet and that managers should devote considerable time to managing NWC.

Both low and high NWC have advantages. Essentially the level of NWC represents a trade-off. If firms lower the amount of NWC, less capital is locked up which can then be used to invest in profitable opportunities and provide the firm with sufficient liquidity. But by doing so the company has less disposable resources to ensure that its business runs smoothly (Afrifa, 2016).

1.2.1 Advantages of high NWC

Lazaridis and Tryfonidis (2006) state that high accounts receivable can help a company secure new customers and enhance existing relationships with customers. Granting companies trade credit helps them gain customers who otherwise could not afford to buy products, gives customers the ability to check the quality of the product before paying, and can influence buyers to acquire products at a time when there is low demand for products in the market.

Having high amounts of inventory can prevent possible interruptions in the production process due to unavailability of resources, protect the company from the risk of scarcity of supply, and can also protect the company from price fluctuations of supplies (García-Teruel & Martínez-Solano, 2007).

Moreover, firms might obtain an important discount for early payments by reducing supplier financing, and with that, accounts payable (Baños-Caballero, García-Teruel & Martínez-Solano, 2019).

1.2.2 Advantages of low NWC

On the other hand, there are also advantages to having low NWC. Deloof (2003) states that low NWC levels enable the firm to invest these resources in other projects that can enhance the value of the firm more than the additional investment in NWC.

Granting less trade credit to companies can also put firms at lower counterparty risk. (Kieschnick, Laplante & Moussawi, 2013). Having lower inventory levels enables the firm to reduce costs such as warehouse rent, insurance, and security expenses. Having higher accounts payables offers an alternative source of financing for the company, while allowing the firm to be more flexible with its payments and enabling the firm to check the quality of received goods (García-Teruel & Martínez-Solano, 2007).

Lower NWC levels also allow firms to save on financing cost. If a firm has higher NWC, then a firm needs to finance higher NWC levels by raising finance. External financing is much more expensive than internal financing. It can be especially harmful for smaller firms who are usually more in need of financing, as there is more information asymmetry between investors and companies, leading to even higher borrowing cost (Afrifa, 2016).

1.3 Previous Studies

Studies monitored the effect of net working capital on profitability or the relation between CCC length and profitability. Profitability was either measured by the company's future profits or future excess returns. Although a lot of research has been done in the field of NWC, I am not aware of any study using linear factor models to draw conclusions, but some studies use different forms of panel data models to study the relationship between NWC and profitability. Nevertheless, I use these studies as a reference point for my research.

Deloof (2003) studied the relationship between profitability of Belgian companies and their accounts receivable, inventory, and accounts payable. He studied the effect of the CCC components on net operating ratio (hereinafter referred to as NOP), which is defined as gross operating income scaled by total assets. The method used is the fixed effects (hereinafter referred to as FE) model. He found a negative relationship between NOP and Days for payables, Days for receivables and inventory conversion period, and concluded that managers can increase profitability by minimizing accounts receivables and inventory to a reasonable minimum.

Mathuva (2010) studied the relationship between profitability of the companies listed on the Nairobi Stock Exchange and their accounts receivable, inventory, and accounts payable. He studied the effect of the CCC components on NOP using the FE model and pooled ordinary least squares. He found a positive relationship between NOP and Days for payables, negative relationship between NOP and Days for receivables and inventory conversion period. Mathuva concluded that companies can increase profitability by carefully reducing the investment in NWC to a reasonable minimum.

Gill, Biger and Mathur (2010) studied the relationship between profitability of US manufacturing companies and their accounts receivable, inventory, and accounts payable. They studied the effect of CCC components on NOP using the weighted least squares model, and found a negative relationship between profitability and accounts receivable. For inventory and accounts payable, their findings were not statistically significant.

García-Teruel and Martínez-Solano (2007) studied the relationship between profitability of Spanish medium and small sized companies and their accounts receivable, inventory, and accounts payable. They studied the effect of the CCC components on return on assets (hereinafter referred to as ROA), by using panel data methodology and found a negative relationship between profitability and accounts receivable, and inventory. For accounts payable, their findings were not statistically significant.

Lazaridis and Tryfonidis (2006) studied the relationship between profitability of firms listed on the Athens stock exchange and their accounts receivable, inventory, and accounts payable. They studied the effect of the CCC components on NOP and found a negative relationship between NOP and Days for payables, Days for receivables, and inventory conversion period.

Hill, Kelly and Highfield (2010) studied which factors influence the choice of the optimal NWC level. Their sample consisted of 3,343 companies from the Compustat database. They studied the net effect of NWC rather than studying each of the components separately. This decision was based on the fact that assets and liabilities should be managed together rather than separately. They measured the relationship between NWC scaled by sales and several variables using the FE model. They found that NWC is positively related to cash flow and size, while it is negatively related to sales growth, sales volatility, book to market ratio (hereinafter referred to as B/M), and financial distress. The study confirmed that NWC is not significantly related to market share and gross profit margin. The study concluded that multiple factors influence the optimal level of NWC.

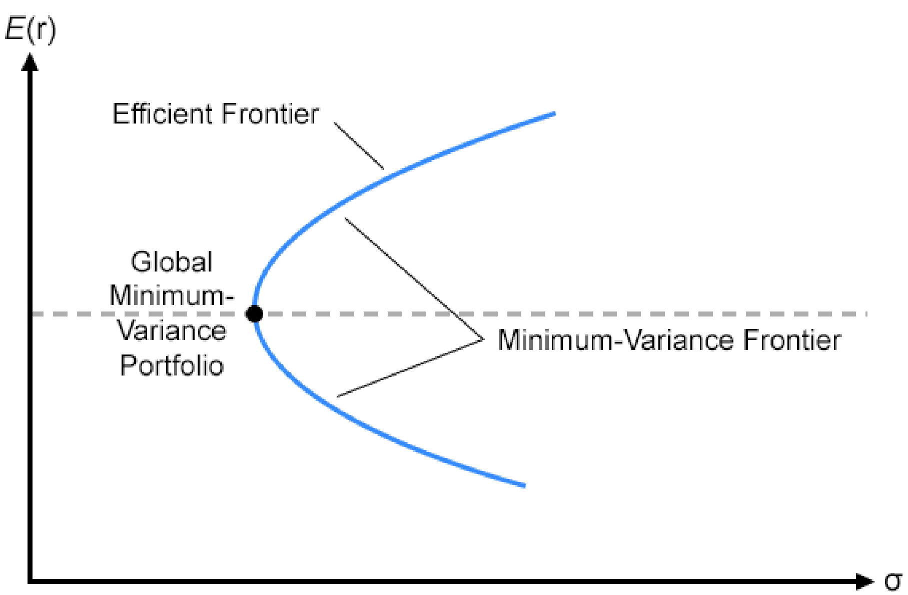
Baños-Caballero, García-Teruel and Martínez-Solano (2014) studied the relationship between profitability and NWC of the United Kingdom (hereinafter referred to as UK) firms. The paper proposes that there exists a U-shape relationship between NWC and profitability, implying the existence of an optimal level of NWC. They use a non-linear panel model where profitability is regressed on the length of the CCC and the square of the length of the CCC. The study confirms the U-shape relationship between NWC and profitability, which indicates that there exsists an optimal level of NWC that balances benefits and risks. The authors also conclude that firms that are more financially constrained have a lower optimal NWC level than those that are less constrained.

Afrifa (2016) builds on the previously mentioned study. The paper focuses on estimating the relationship between NWC scaled by sales and profitability measured as ROA. The paper estimated this relationship based on the sample of medium and small companies in the UK. The study uses a nonlinear panel model, where ROA is regressed on NWC scaled by sales and squared NWC scaled by sales. The study finds that firms with cash flows below the sample median have a negative relationship with NWC and should reduce the investment in working capital. Firms with sufficient cash flows (above the median), exhibit a positive relationship with NWC and should strive to increase investment in NWC.

2 ASSET PRICING MODELS

Harry Markowitz laid the groundwork for the Capital asset pricing model (hereinafter referred to as CAPM) in 1952. He generalized the problem of constructing an optimal portfolio from N risky assets, introducing the concept of the efficient frontier, a graph of lowest possible variances for a range of different portfolio expected returns. Given any future expected returns, the minimum variance portfolio can be calculated by finding the optimal combinations of weights of assets, based on future expected returns, variances and covariances of the N assets. The main assumptions are that investors are averse to risk, choose portfolios with the smallest variance given expected returns, and have the same expectations about future expected returns, their variances and covariances (Bodie, Kane & Marcus, 2008).

Figure 2: The efficient frontier

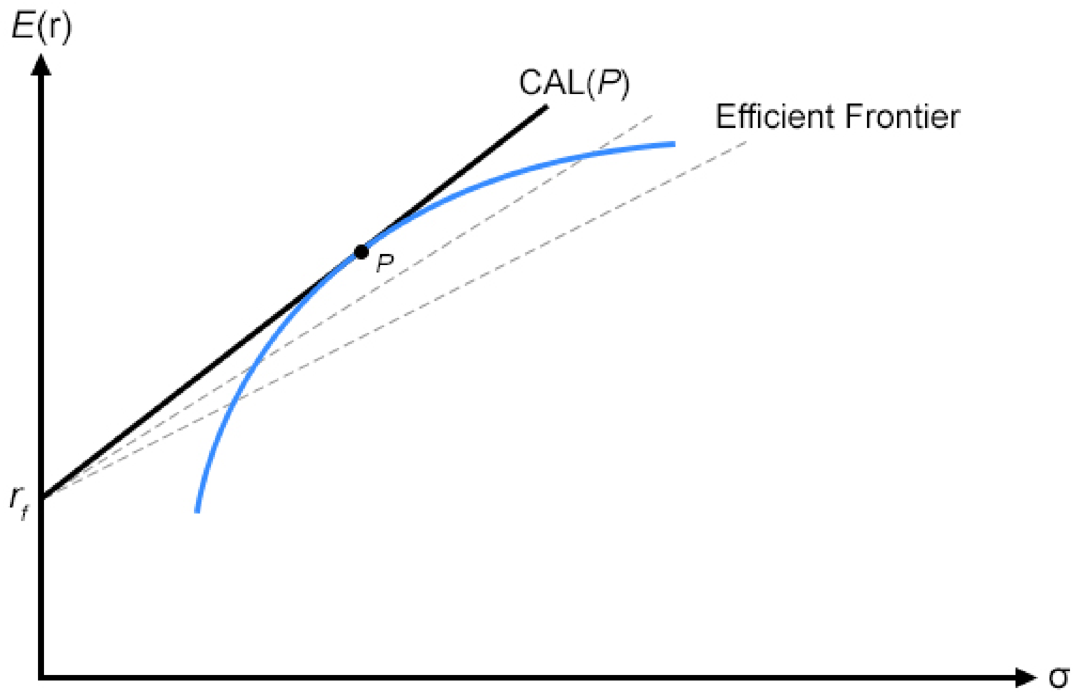


Adapted from Bodie, Kane & Marcus (2008, p. 210).

Only the portfolios that lie on the global minimum variance portfolio and higher present the efficient frontier. For each value of standard deviation, we obtain two different expected return values. Since one is higher than the other, while they both bear the same amount of risk, only the upper part of the Minimum variance frontier is efficient (Bodie, Kane & Marcus, 2008).

The shape of the efficient frontier changes when there exists a risk-free asset and short selling is not prohibited. The efficient line is now represented by the capital allocation line (hereinafter referred to as CAL) that is tangent to the efficient frontier and passes through the risk-free-rate of return. Portfolios on the CAL are combinations of investment in the risk-free asset and the risky portfolio that is represented by the tangency point P. Since the risk-free asset bears zero risk, the risk of the portfolio is proportional to the share invested in the risky portfolio. As a consequence, the efficient frontier is represented by a straight line, where different points on the line represent different combinations of the risk-free asset and the risky portfolio (Bodie, Kane & Marcus, 2008).

Figure 3: The capital allocation line



Adapted from Bodie, Kane & Marcus (2008, p. 210).

2.1 Capital asset pricing model

The CAPM, which can be considered as a cornerstone of financial economics, was developed in 1964 in articles by William Sharpe, John Lintner and Jan Mossin. In order for

CAPM to hold, several simplifying assumptions most hold. Below are summarized the assumptions that are needed for CAPM to hold (Bodie, Kane & Marcus, 2008):

- Investors take the price as given and act as though their trades do not affect security prices.
- Investors plan one holding period ahead and ignore everything that might happen after the holding period.
- Investors trade only financial assets that are publicly traded and can borrow or lend them at the risk-free-rate.
- Investors do not pay transaction costs or taxes when trading securities.
- Investors are rational and use the Markowitz selection model to make investment decisions.
- Investors have the same economic view of the world and derive the same inputs for the Markowitz model. A consequence of this is that all investors derive the same efficient frontier and risky portfolio.

Since all investors hold the same portfolio of risky assets consisting of the same assets in the same proportions, the portfolio of risky assets must represent a share of the value-weighted market portfolio. Each asset's weight in the portfolio must be its market value divided by the total market value of all assets. Since the portfolios that the investors derive are all the same and on the efficient frontier, the weighted sum of all their portfolios which is the market portfolio, should also be on the efficient frontier, where the individuals only differ in the proportion of money they allocate to the portfolio of risky assets and the proportion they allocate to the risk-free-asset. The main conclusion is that if the market portfolio lies on the efficient frontier, then the linear relation that holds for portfolios on the efficient frontier in the presence of the risk-free asset must also hold for the market portfolio as well. The CAPM model is presented below (Fama & French, 2004):

$$E(R_i) = R_f + \left(E(R_m) - R_f\right)\beta_{iM}, \quad i = 1, . . . \ , N. \tag{6}$$

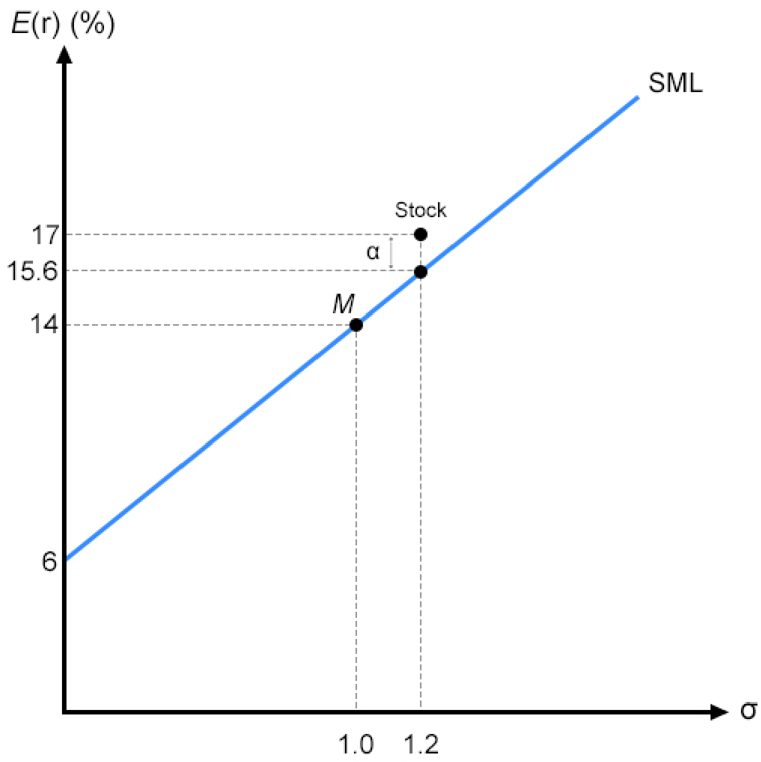
N represents the number of assets, $E(R_i)$ the expected return of some asset i, R_f presents the return of the risk free asset, $E(R_m)$ the expected return of the market portfolio, β_{iM} represents the market beta of asset i, which is the covariance of its returns with market returns divided by the variance of market returns (Fama & French, 2004).

$$\beta_{iM} = \frac{cov(R_i, R_m)}{\sigma^2(R_m)} \tag{7}$$

The risk of the market portfolio $(\sigma^2(R_m))$, is measured as the weighted average of the covariance risk of each asset $(cov(R_i,\ R_m))$. β_{iM} represents the covariance risk of asset i relative to the weighted average covariance risk of N assets. The higher its covariance risk is compared to the average covariance risk, the higher its future return will be. $R_m - R_f$ should thus be interpreted as the risk premium per unit of beta (Fama & French, 2004).

The relationship between assets' market betas and their expected return is represented by the security market line (hereinafter referred to as SML) shown below (Bodie, Kane & Marcus, 2008):

Figure 4: The security market line



Adapted from Bodie, Kane & Marcus (2008, p. 289).

The slope of the SML equals the risk premium of the market. According to the CAPM, the expected returns of securities should lie on the SML, where their expected return depends on their market beta. If CAPM assumptions are violated and not all investors have the same expectations about the future, then it can happen that investor's expectations of future returns differ from expected returns predicted by the CAPM. The difference in returns predicted by the CAPM and returns expected by investors is called »Alpha«. Assets with expected returns above the SML have a positive alpha and are perceived as under-priced. Assets with expected returns below the SML have a negative alpha and are perceived as overpriced (Bodie, Kane & Marcus, 2008).

Jensen (1968) shows that the CAPM can be extended to several periods. In this setting investors are allowed to have different holding periods, where trading can take place continuously. The multi-period model is shown below Jensen (1968):

$$E(R_{it}) = R_{ft} + \beta_{iM}\left(E(R_{mt}) - R_{ft}\right) \quad (8)$$

In the equation (8), t denotes the time period. Jensen (1968) states that the model in equation (8), can be used to test the validity of the CAPM on single assets or portfolios, since the CAPM should hold in all periods.

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\big(E(R_m) - R_f\big) + u_{it} \quad (9)$$

In equation (9), α_i represents the intercept term of asset i in the time series regression, where the excess returns of asset i is regressed on the market excess returns. U_{it} represents the error term and its expected value is zero ($E(u_{it}) = 0$). The difference between the asset's average excess return and the average excess return predicted by the CAPM is α_i and represents the average time series mis-pricing error. For the CAPM to hold, α_i should be zero for all assets Jensen (1968).

2.2 Multifactor models

The CAPM involves only one explanatory factor of returns. Over the years several contradictions of the CAPM have been observed, which might not come as a surprise given the simplicity of the model and the restricting assumptions that do not hold in the real world. Given the contradictions between the CAPM and reality, researchers have added more explanatory variables to the CAPM.

In reality it is hard to believe that returns can be explained by one explanatory factor. The market factor, which represents the only factor in CAPM, combines several sources of risk like the business cycle, inflation, interest rates, and many more. When estimating regression models with only one factor, we thus make the wrong assumption that all stocks have equal relative sensitivities to the risk factors, that are all combined in one factor. Multifactor models can thus allow for better descriptions of future returns and can be used in risk management. With multifactor models we can easily measure exposure to different risk factors of interest, and then construct portfolios that can hedge the exposures to these risks (Bodie, Kane & Marcus, 2008).

2.2.1 Arbitrage pricing theory

Multifactor models are based on arbitrage pricing theory (hereinafter referred to as APT) developed by Stephen Ross in 1976. As in CAPM, APT uses the SML to link expected returns to risk. The difference between CAPM and APT is that APT uses less restricting assumptions for the validity of the SML. The assumptions that are needed for APT to hold are summarized below (Bodie, Kane & Marcus, 2008):

- Returns of securities can be described by a factor model.
- Markets function well enough so that arbitrage opportunities do not persist.
- Enough securities exist such that idiosyncratic risk can be diversified away.

Based on these assumptions, Ross (1973) provides the following derivation of APT and multifactor models. For the sake of simplicity let's assume that we first derive a single factor model and then generalize it to a multifactor case.

First let's form an arbitrage portfolio consisting of n assets where the amount that is invested long in assets comes from short sales, which means that in order to construct the portfolio, no wealth is needed. The return of the portfolio is given below:

$$R_p = \eta \mathrm{E(R)} + \eta\beta\delta + \eta\varepsilon \tag{10}$$

$\mathrm{E}(R)$ represents the vector of expected returns of assets in the portfolio, η the vector of asset weights, δ the deviations of the factor from its expected value, β the vector of β_i which is a vector of each company's sensitivities to the δ factor, and ε the vector of error terms.

Since we assume that we construct a portfolio of many assets such that idiosyncratic risk can be diversified away, the error term becomes negligible and approaches 0 as n gets larger. This holds for all large portfolios where all asset weights approach 0 as n gets larger (more assets are added) and are small enough such that non-systematic variance becomes negligible.

$$R_p = \eta E(R) + \eta\beta\delta \tag{11}$$

The arbitrage portfolio can always be constructed in a way such that we eliminate systematic risk as well.

$$\eta\beta = 0 \tag{12}$$

Equations (11) and (12) imply that the portfolio return should be equal to 0. Since all sources of risk have been eliminated, we are able to earn the certain return $\eta\mathrm{E(R)}$. If this return is not 0, then the no arbitrage assumption is violated, since we would be able to earn a certain return with 0 investment and 0 risk. It follows that all vectors η that are orthogonal to β and ε, are also orthogonal to E(R). From this we can conclude that E(R) must be a linear combination of β and ε. As a consequence, there exists such constants a and E_0, such that for all companies i in the portfolio

$$E(R_i) = E_0 + a\beta_i \tag{13}$$

If this relation does not hold, then an arbitrage opportunity exists. Also, if there exists a riskless asset with return ρ, then $\mathrm{E}_0 = \rho$. If this would not be the case, an arbitrage opportunity would again exist.

Ross (1973) states that the CAPM can be considered a special case of equation (13), where δ is normalized such that aβ = 1, where equation (13) is then transformed to:

$$E(R_i) = E_0 + (a - E_0)\, \beta_i \tag{14}$$

Ross (1973) states than the one factor model can be easily extended to a k factor model.

$$\begin{gathered} E(R_i) = E_0 + E(\lambda_1)\beta_{i1} + \cdots + E(\lambda_k)\beta_{ik} \\ where\ \lambda_i = a_i - E_0 \end{gathered} \tag{15}$$

To show that equation (15) holds, it is important to understand how a factor portfolio can be formed. A factor portfolio is any well-diversified portfolio that has a beta exposure of 1 to one of the factors and 0 to all other factors. It can always be constructed since we assume that there exist many more assets than factors. The exposure of some random portfolio to different factors will be equal to the portfolio's beta coefficients corresponding to those factors according to equation (15). We can create an alternative portfolio (R_{alt}) where we invest into factor portfolios, where the share invested in each factor portfolio is exactly equal to the corresponding beta coefficient of the before mentioned random portfolio and the rest into the risk-free asset. By construction the two portfolios have the same exposures to risk factors which means that they should have the same return or there exists an arbitrage opportunity. The following example where a two-factor model is used as an example, clearly shows the logic of the proof (Bodie, Kane & Marcus, 2008).

$$\begin{gathered} E(R_{alt}) = E(a_{alt1})\beta_{alt1} + E(a_{alt2})\beta_{alt2} + E_0(1 - \beta_{alt1} - \beta_{alt2}) \\ E(R_{alt}) = E_0 + E(a_{alt1} - E_0)\beta_{alt1} + E(a_{alt2} - E_0)\beta_{alt2} \end{gathered} \tag{16}$$

To test the APT in equation (15) Roll & Ross (1980) use the two-step procedure from Fama & MacBeth (1973) which is described in more detail in section 2.5. The test they use is the following:

Suppose there exist k factors and i test assets.

$$H_0: There\ exist\ non\ zero\ constants\ (E_0, \lambda_1, \cdots, \lambda_k) \tag{17}$$

Such that

$$E(R_i) = E_0 + \lambda_1\beta_{i1} + \cdots + \lambda_k\beta_{ik}, \quad for\ all\ i\ assets \tag{18}$$

The two-step procedure is used to estimate the k different factor λ, which can be interpreted as factor risk premiums. The tested APT model is not rejected if the joint hypothesis

$$\lambda_1 = \cdots = \lambda_k = 0 \tag{19}$$

is rejected.

2.2.2 Fama French 3-factor model

Banz (1981) found that the CAPM is missspecified. On average, small New York stock exchange companies (hereinafter referred to as NYSE) had significantly larger risk adjusted returns compared to the large NYSE companies, ranging over a period of 40 years from 1936 -1975.

On the other hand, Basu (1983) found that during the 1963-79 time period, the returns of NYSE companies appeared to have been related to earnings yield (hereinafter referred to as E/P) and size. He found that, on average, high E/P companies earn higher risk-adjusted returns than low E/P companies. He noted that the size effect is a proxy for earnings yield, and that its power as an explanatory factor is a consequence of its relation to earnings yield.

Fama and French (1992) examined the CAPM anomolies mentioned before. They found a weak relationship between the average excess returns and market beta during 1941-1990. They studied the joint role of size, market return, E/P, leverage, and B/M factors. They found that when used alone, size, E/P, leverage, and B/M all have explanatory power. When used together, size, and B/M seem to absorb the roles of leverage and E/P in explaining average returns.

Based on previous studies, Fama and French (1993) proposed a model with 3 explanatory variables. In this model average excess returns depend on market return, size (measured as the company's market capitalization), and B/M (measured as the company's book value divided by its market capitalization)

The Small minus Big (hereinafter referred to as SMB) factor tries to capture the fact that small companies yield, on average, higher excess returns than big companies. The SMB factor is constructed by taking long positions in small companies and financing those positions with taking short positions in large companies (Bali, Engle & Murray, 2016).

The High minus Low (hereinafter referred to as HML) factor tries to capture the fact that companies with high book values compared to their market value tend to have, on average, higher returns than companies with low book values compared to their market values. The HML factor is constructed by taking long positions in firms with high values of B/M and financing those positions by taking short positions in firms with low values of B/M (Bali, Engle & Murray, 2016).

The model more commonly known as the »Fama French three factor model« (hereinafter referred to as FF 3-factor model) is specified below (Fama & French, 1993):

$$E(R_i) = R_f + \left(E(R_m) - R_f\right)\beta_{iM} + E(SMB)\beta_{iSMB} + E(HML)\beta_{iHML} \tag{20}$$

In equation (20) E(SMB) represents the expected return of the SMB factor and β_{iSMB} the SMB factor beta value of asset i. E(HML) represents the expected return of the HML factor and β_{iHML} the HML factor beta value of asset i.

The model was criticized by Black (1993), who states that the use of size and B/M as factors is not supported by theory and that factors like HML or SMB have proven to be inconsistent. He explained that the results could be due to the fact that some data sets can be used many times by researchers and can uncover returns purely by chance.

Fama and French implemented the FF 3-factor model in different markets all over the world, while also testing the model during different time periods, thus dismissing such effects as mentioned by Black (1993). Although the size and value factors are not straight-forward candidates for risk factors, the hope of Fama and French was that these two factors would be proxies for some variables yet unknown. They point out that firms with high B/M are also more likely to experience financial distress, and firms with small market capitalization tend to be more dependent on changes in business conditions. Size and B/M all are also convenient risk factors, as there is a long time series available for these variables (Bodie, Kane & Marcus, 2008).

2.2.3 Carhart 4-factor model

Carhart (1997) improved the FF 3-factor model by adding one additional factor. He claimed that neither the CAPM nor FF 3-factor model were able to explain the cross-sectional variation returns in portfolios sorted based on momentum. He constructed the prior one-year return (hereinafter referred to as PR1YR) factor, which tried to capture the fact that stocks with high returns over the past year tend to, on average, outperform stocks with low returns in the past year. PR1YR is constructed by taking long positions in companies with high returns over the past year and financing those positions by taking short positions in companies with low returns over the past year.

He found that his 4-factor model reduces the time series mis-pricing errors of the CAPM and the FF-3 factor. The four-factor model is presented below (Carhart, 1997):

$$E(R_i) = R_f + \left(E(R_m) - R_f\right)\beta_{iM} + E(SMB)\beta_{iSMB} + E(HML)\beta_{iHML} + E(PR1YR)\beta_{iPR1YR} \tag{21}$$

In the equation above, E(PR1YR) represents the expected return of the PR1YR factor and β_{iPR1YR} the PR1YR factor beta value of asset i.

2.2.4 Fama French 5-factor model

Novy-Marx (2013) and Titman Wei and Xie (2004), found evidence that the FF-3 factor model is incomplete. They state that its main drawback is that the factors of the model fail to capture much of the variation of the average excess returns that relate to investment of firms.

Fama and French (2015) added that the robust minus weak (hereinafter referred to as RMW) and conservative minus aggressive (hereinafter referred to as CMA) factor to the FF-3 factor model. They found that the model containing the CMA and RMW has lower time series mis-pricing errors than the FF-3 model.

The CMA factor tries to capture the fact that companies that have a more conservative investment strategy, tend to have, on average, higher returns than companies that have a more aggressive investment strategy. The CMA factor is constructed by taking long positions in companies with low investments and financing those positions by taking short positions in companies with high investments (Fama & French, 2015).

The RMW factor tries to capture the fact that companies that have higher operating profitability tend to have, on average, higher returns than companies with low operating profitability. The RMW factor is constructed by taking long positions in companies with high operating profitability and financing those positions by taking short positions in companies with low operating profitability (Fama & French, 2015).

The model frequently referred to as the »FF 5-factor model« is presented below (Fama & French, 2015):

$$E(R_i) = R_f + \left(E(R_m) - R_f\right)\beta_{iM} + E(SMB)\beta_{iSMB} + E(HML)\beta_{iHML} + E(CMA)\beta_{iCMA} + E(RMW)\beta_{iRMW} \quad (22)$$

In the equation above, E(CMA) represents the expected return of the CMA factor and β_{iCMA} the CMA factor beta value of asset i. E(RMW) represents the return of the RMW factor and β_{iRMW} the RMW factor beta value of asset i.

2.2.5 6-factor NWC model

For the purpose of the master thesis, I construct a 6-factor model that adds the NWC ratio factor to the existing Fama and French 5 factor model. The factor is added because the FF 5-factor model fails to capture variation of average excess returns that relate to NWC.

The NWC factor tries to capture the fact that companies that have low NWC tend to have higher returns on average than companies with high NWC. The NWC factor is constructed by taking long positions in companies with low NWC and financing those positions by taking short position in companies with high NWC. The 6-factor model is presented below:

$$E(R_i) = R_f + \left(E(R_m) - R_f\right)\beta_{iM} + E(SMB)\beta_{iSMB} + E(HML)\beta_{iHML} + E(CMA)\beta_{iCMA} + E(RMW)\beta_{iRMW} + E(NWC)\beta_{iNWC} \tag{23}$$

In the equation above, E(NWC) represents the expected return of the NWC factor and β_{iNWC} the NWC factor beta value of asset i.

2.3 Time series factor analysis

Time series factor analysis can be used to examine the cross-sectional relation between variables. The general approach is to form portfolios of assets, where the assets are assigned to portfolios based on values of some sorting variable in period t. In the next period t+1 we examine the returns of the ranked portfolios where we try to determine if the variation in the returns of portfolios is due to the variation in the sorting variable or due to the variation of some known factors that explain excess returns (Bali, Engle & Murray, 2016).

In the first step of the analysis, we rank all assets with available data into portfolios in each time period based on some sorting variable that may have the ability to explain differences in returns. The detailed portfolio formation procedure is presented in 4.1 (Bali, Engle & Murray, 2016).

The next step is to calculate the returns of portfolios in the period following the portfolio formation period for each time period. Equally weighted or market capitalization weighted returns of assets in portfolios can be used to calculate portfolio returns. In the case of equally weighted returns, the portfolio return is calculated as the arithmetic average of asset returns. In the case of market capitalization weighted returns, asset returns are weighted by the ratio of their market capitalization and the sum of market capitalizations of all assets in the portfolio. The average returns calculation for a market capitalization weighted returns of portfolio k in time t is given below (Bali, Engle & Murray, 2016):

$$\overline{Y}_{k,t} = \frac{\sum_{i \in P_{i,t}} Y_{i,t} W_{i,t}}{\sum_{i \in P_{i,t}} W_{i,t}} \tag{24}$$

In the equation above, $\overline{Y}_{k,t}$ is the average return of portfolio k in time t, $i \in P_{i,t}$ represents the set of all assets included in the portfolio in time t, $Y_{i,t}$ represents the return of asset i in time t and $W_{i,t}$ represents the company market capitalization of asset i in time t.

After calculating the average return of each portfolio k in each time period t, we subtract the return of a risk-free-asset (for example a short-term government bond). The difference between the return of an asset and the return of a risk-free asset is called the excess return (Bali, Engle & Murray, 2016).

In addition to calculating the average returns of portfolios in each time period, we also calculate the return of the difference portfolio in each time period. The difference portfolio in time t presents the difference in returns between portfolios with the highest and the lowest values of the sort variables in time t-1. The difference portfolio calculation is presented below (Bali, Engle & Murray, 2016):

$$\bar{Y}_{diff,t} = \bar{Y}_{n,t} - \bar{Y}_{1,t} \tag{25}$$

In the equation above n represents the portfolio with the highest values of the sort variable in time t-1. The next step is to calculate the time series means of portfolio returns for each of the n portfolios and also for the difference portfolio. The time series average return for portfolio k is defined as (Bali, Engle & Murray, 2016):

$$\bar{Y}_k = \frac{\sum_{t=1}^{T} \bar{Y}_{k,t}}{T} \tag{26}$$

The time series average return for the difference portfolio is defined as:

$$\bar{Y}_{diff} = \frac{\sum_{t=1}^{T} \bar{Y}_{diff,t}}{T} \tag{27}$$

In the equation above, T is the number of periods in the sample.

The time series average excess return of each portfolio serves as an estimate of the true average excess returns of assets in each of the portfolios in the average time period. The time-series mean of the difference portfolio estimates the difference in average returns in the average period between portfolios with the highest and the lowest value of the sorting variable (Bali, Engle & Murray, 2016).

To assess whether there is a cross sectional relation between the sort variable and returns, we examine whether the time series average excess return of the difference portfolio is statistically distinguishable from 0. Additionally, we can examine whether the time series average returns vary monotonically across portfolios. The more monotonic the pattern is, the stronger the indication that the results from the difference portfolio are not due to chance. Since assets (stocks) in general exhibit positive average excess returns, testing whether asset excess returns are statistically different from zero, will usually lead to the conclusion that average excess returns are statistically distinguishable from zero (Bali, Engle & Murray, 2016).

We need to identify if excess returns of portfolios persist after adjusting them for their sensitivity to risk factors. Risk factors are variables that exhibit the power to explain variation of average stock returns. The way to adjust for exposure to risk factors is to use a time series regression. For each portfolio k, we run a time series regression where portfolio excess returns are regressed on risk factor excess returns. Popular models of risk adjustment are the CAPM, FF-3 factor model, or FF-5 factor model (Bali, Engle & Murray, 2016).

If the average excess return of the difference portfolio is now insignificant and we fail to detect a pattern in average returns across portfolios, then the variation in returns across portfolios was due to exposure to risk factors. If this is not the case, then we can construct risk factors mimicking returns associated with the sort variable and test whether adding the risk factor to existing asset pricing models can help improve their accuracy (Bali, Engle & Murray, 2016).

It also needs to be considered that the time series might exhibit autocorrelation or heteroskedasticity. If the data exhibits autocorrelation and heteroskedasticity then it means that the ordinary least squares (hereinafter referred to as OLS) assumptions are violated; namely, the assumption that error terms are uncorrelated and that they exhibit constant variance. The consequence of this is that the coefficient standard errors are not calculated appropriately. This leads to an incorrect conclusion in terms of t-statistics and p-values (Bali, Engle & Murray, 2016).

The Newey-West method adjusts the variance covariance matrix of the estimated coefficients for heteroskedasticity and autocorrelation (up to a specified order of autocorrelation). The square root of diagonal elements of the covariance matrix now represent variance of the coefficients. Autocorrelation is handled by adding off-diagonal elements (Bali, Engle & Murray, 2016).

2.4 Evaluating performance of models

If we are able to show that some variable has the ability to explain variation in asset excess returns, we can construct a risk factor associated with the explanatory variable (the construction of most common risk factors is explained in 4.2). We can compare whether the addition of a new risk factor can increase the accuracy of an existing model. R-squared, adjusted R-squared, absolute mis-pricing error, and the GRS test statistic proposed by Gibbons, Ross and Shanken (1989), are the most common criteria for comparing performance of different factor models in literature.

For simplicity let’s assume that we formed n different portfolios based on some sort variable. We perform the following time series regression test for each of the n portfolios using standard asset pricing models.

$$R_{i,t} - R_{f,t} = \alpha_i + \left(R_{M,t} - R_{f,t}\right)\beta_{iM} \sum_{r=2}^{l} F_r \beta_{ir} + \varepsilon_{i,t} \quad (28)$$

In equation (28), l denotes the number of factors and F_r denotes the r-th factor. In the next step we perform the same time series regression test but add an additional risk factor to the model.

$$R_{i,t} - R_{f,t} = \alpha_i + \left(R_{M,t} - R_{f,t}\right)\beta_{iM} + \sum_{r=2}^{l+1} F_r \beta_{ir} + \varepsilon_{i,t} \tag{29}$$

The next section provides different performance measures which can be used to compare the accuracy of the proposed models

2.4.1 R-squared

R-squared is one of the most common criteria when assessing model fit. R-squared measures the proportion of total variation that is due to variation in regressors. The formula for R-squared is shown below (Greene, 2003):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} e_i^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{30}$$

In the equation above, e_i^2 is the variation of residuals, y represents the dependant variable, and n represents the number of observations. The R-squared value is always between 0 and 1. When R-squared equals 0 the regressors exhibit zero explanatory power. If R-squared equals 1, then the regressors explain all the variation of the dependant variable (Greene, 2003).

2.4.2 Adjusted R-squared

The biggest shortcoming of the R-squared measure is that R-squared cannot decrease when a new variable is added to the model. By adding additional variables to the model, the R-squared will continue to raise to its limit of 1 regardless of whether the newly added variable has any explanatory power. Since the goal is to compare an existing model like the FF 5-factor model and a model where an additional variable is added to the FF 5- factor model, using R-squared is not appropriate, as it will always results in a higher R-squared for factor models with additional variables (Greene, 2003).

This shortcoming is addressed by the adjusted R-squared. Adjusted R-squared penalises the loss of degrees of freedom. As a consequence, the adjusted R-squared can also decline when a new variable is added to existing models. Whether the newly added variable positively or negatively effects the adjusted R-squared value, depends on whether the contribution it brings to the model fit, offsets the correction that is due to the loss of one additional degree of freedom.

The relation between adjusted R-squared and R-squared is shown below (Greene, 2003):

$$\overline{R^2} = 1 - \frac{n-1}{n-K}(1 - R^2) \tag{31}$$

In the equation above, K represents the number of variables and n represents the number of observations. To measure performance based on adjusted R-square, we obtain the k adjusted R-squared values from the k different time series regression and calculate the average of the k adjusted R-squared value for both models that we are comparing. The model that has a higher adjusted R-squared is considered more accurate.

2.4.3 Absolute mis-pricing error

The accuracy of asset pricing models can also be measured with the absolute mis-pricing error, which represents the excess returns that cannot be explained by risk factors. The error should be as close to zero as possible. To measure performance based on the absolute mis-pricing error, we obtain the intercepts of each of the n time series regressions, since intercepts represent the mis-pricing error. Since the mis-pricing error for each portfolio can either be negative or positive, taking the average value of positive and negative mis-pricing errors could result in the average mis-pricing error being closer to zero than it actually is. For this reason, the average mis-pricing error is calculated as the average of absolute values of mispricing error of the k portfolios.

2.4.4 GRS test

The most common method for evaluating asset pricing model performance is the GRS test.

The GRS test builds on the idea of mispricing errors. The GRS evaluates if the mis-pricing errors of n portfolios are jointly statistically indistinguishable from zero. The null hypothesis states that all pricing errors equal zero, while the alternative hypothesis states that at least 1 pricing error is nonzero (Diether, 2001):

The GRS test statistic is given below (Diether, 2001):

$$\left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}^{T}\hat{\Sigma}^{-1}\hat{\alpha}}{1+\hat{u}^{T}\hat{\Omega}^{-1}\hat{u}}\right] \sim F(N, T-N-L) \tag{32}$$

In the equation above:

- T represents the sample size (number of time periods)
- N represents number of tested portfolios
- L represents number of risk factors

– $\hat{\alpha}$ is the N × 1 vector of the intercept estimates from performing the time series regression in equation (28)
– $\hat{\Sigma}$ is the T × N unbiased estimator of the covariance matrix of the residuals from performing the time series regression in equation (28). Residuals are stacked into a matrix of size T × N ($\hat{\varepsilon}$) shown below:

$$\hat{\varepsilon} = \begin{bmatrix} \hat{\varepsilon}_{11} & \hat{\varepsilon}_{12} & \cdots & \cdots & \hat{\varepsilon}_{1N} \\ \hat{\varepsilon}_{21} & \hat{\varepsilon}_{22} & \cdots & \cdots & \hat{\varepsilon}_{2N} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \hat{\varepsilon}_{T1} & \hat{\varepsilon}_{T2} & \cdots & \cdots & \hat{\varepsilon}_{TN} \end{bmatrix} \tag{33}$$

– The unbiased estimator of the residual covariance matrix calculated as presented below:

$$\hat{\Sigma} = \frac{\hat{\varepsilon}^T \hat{\varepsilon}}{T - L - 1} \tag{34}$$

– $\bar{u}$ represents a L x 1 vector of sample means of factor portfolios:

$$\bar{u} = \begin{bmatrix} \bar{F}_1 \\ \bar{F}_2 \\ \vdots \\ \vdots \\ \bar{F}_N \end{bmatrix} \tag{35}$$

– $\hat{\Omega}$ is the NxN unbiased estimator of the covariance matrix of the factor portfolios returns. First we stack the factor excess returns into a matrix of size T X L:

$$F = \begin{bmatrix} F_{11} & F_{12} & \cdots & \cdots & F_{1L} \\ F_{21} & F_{22} & \cdots & \cdots & F_{2L} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ F_{T1} & F_{T2} & \cdots & \cdots & F_{TL} \end{bmatrix} \tag{36}$$

– The unbiased estimate of the factor covariance matrix is then computed as:

$$\hat{\Omega} = \frac{(F - \bar{F})^T (F - \bar{F})}{T - 1} \tag{37}$$

Where:

$$\bar{F} = \begin{bmatrix} \bar{F}_1 & \bar{F}_2 & \cdots & \cdots & \bar{F}_L \\ \bar{F}_1 & \bar{F}_2 & \cdots & \cdots & \bar{F}_L \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \bar{F}_1 & \bar{F}_2 & \cdots & \cdots & \bar{F}_L \end{bmatrix} \tag{38}$$

The GRS test statistic from equation (32) follows a non-central F-distribution with N and T-N-L degrees of freedom and is centered on zero in the null hypothesis. (Kim & Shamsuddin, 2017)

The easiest way to understand the logic of the test is to rewrite the test statistics in terms of Sharpe-ratios (derivation can be found in the appendix of Gibbons, Ross and Shanken (1989)). The Sharpe-ratio represents the excess return of a portfolio per one-unit volatility measured in terms of standard deviation of the excess returns. The optimal Sharpe ratio of L factor portfolios can be interpreted as the slope of the efficient frontier (Kamstra & Shi, 2021). The Sharpe-ratio version of the statistic is presented below (Gibbons, Ross and Shanken (1989)):

$$\left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\sqrt{1+\hat{\theta}_{N+L}^2}}{\sqrt{1+\hat{\theta}_L^2}}\right]-1\sim F(N,T-N-L) \qquad (39)$$

In the equation above, $\hat{\theta}_{N+L}^2$ is the optimal Sharpe-ratio of the N assets and L factor portfolios, while $\hat{\theta}_L^2$ represents the optimal Sharpe-ratio of L factor portfolios only. The L factor portfolios are mean variance efficient, if the optimal portfolio consisting of only the L factor portfolios will have the same slope of the efficient frontier as the optimal portfolio that can be constructed from L factor portfolios and N test assets (sorted portfolios). Thus, bigger the difference between the Sharpe-ratios the farther away the test statistic is from 0 and higher the likelihood that the test rejects the null hypothesis. Thus, in terms of comparing models, the model with the lowest GRS score has the biggest ability to explain the tested portfolio returns (Kamstra & Shi, 2021).

It must be pointed out that the GRS test makes assumptions about regression residuals. It assumes that the regression residuals are normally distributed, which is usually not a valid assumption for stock returns. Nevertheless Affleck-Graves and McDonald (1989) state that the test is reasonably robust to non-normality of the residuals (Cochrane, 2005).

The GRS also assumes that the residuals are uncorrelated and homoskedastic while the residuals can be correlated across assets (Cochrane, 2005). Homoskedasticy and independence of residuals can be disputed, but since the goal is to ensure comparability to Fama & French (2015), who use the GRS statistic as measure of performance, I also use the GRS statistic. There also exists a correction for autocorrelation and heterosekdasticy which can be found in Cochrane (2005).

2.5 Fama MacBeth Procedure

The procedure was first implemented by Fama & MacBeth (1973). The procedure represents an alternative technique for examining the cross-sectional relationship between variables. It enables us to examine the relation between the dependant and many independent variables at the same time (Bali, Engle & Murray, 2016).

The setting is the same as described in section 2.3 time series. In each time period we assign assets into portfolios based on some chosen variable, calculate portfolio returns in the following period and subtract the risk-free rate

In the first part of the analysis, we perform time series regressions where we regress portfolio excess returns on risk factor excess returns. For each portfolio we obtain estimates of portfolio excess return sensitivities to risk factors (factor loadings) (Cochrane, 2005).

$$R_{i,t} - R_{f,t} = \alpha_i + \left(R_{M,t} - R_{f,t}\right)\beta_{iM} + \sum_{r=2}^{k} F_{r,t}\beta_r + \varepsilon_{i,t} \quad t=1, . . . ,T \tag{40}$$

In the second step we make the assumption that the estimated factor loadings do not vary over time. In every time period we run a cross sectional regression, where we regress excess portfolio returns on previously estimated portfolio specific factor loadings. The regression equation is specified below (Cochrane, 2005).

$$R_{i,t} - R_{f,t} = \gamma_t + \lambda_{1,t}\beta_i + \sum_{r=2}^{k} \lambda_{r,t}\beta_r + \varepsilon_{i,t} \qquad i=1, . . . ,N \tag{41}$$

In the equation above, $\lambda_{r,t}$ represents the risk premium of factor r in time t. By doing the cross-sectional regression for period t, we obtain risk premium for each of the risk factors in period t. Risk premium represents excess returns associated with undertaking 1 unit of factor risk (Cochrane, 2005).

In the last step we take the time series averages of cross section risk premium estimates for each factor. The interpretation of the obtained estimate is that it represents the average premium per period, for bearing 1 unit of factor risk (Cochrane, 2005).

$$\overline{\lambda_r} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{r,t} \tag{42}$$

We use the variation of the estimated cross-sectional coefficients over time to assess the standard errors and significance of their time series average. The usual threshold for determining significance of coefficients is the 95 % confidence interval, which corresponds to a t-statistic value that is higher than 1.96. If the t-statistic is higher than 1.96, it indicates a cross sectional relationship between two variables.

Below are the expressions for calculating the variance of the time series average risk premium (Cochrane, 2005).

$$\sigma^2(\hat{\lambda}) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\lambda}_t - \hat{\lambda})^2 \tag{43}$$

It also has to be taken into account that the standard errors of the estimates are not entirely correct. This is due to the fact that regression inputs in the cross-sectional regression were portfolio specific sensitivities that were not given but were previously estimated in the time series regression (Cochrane, 2005).

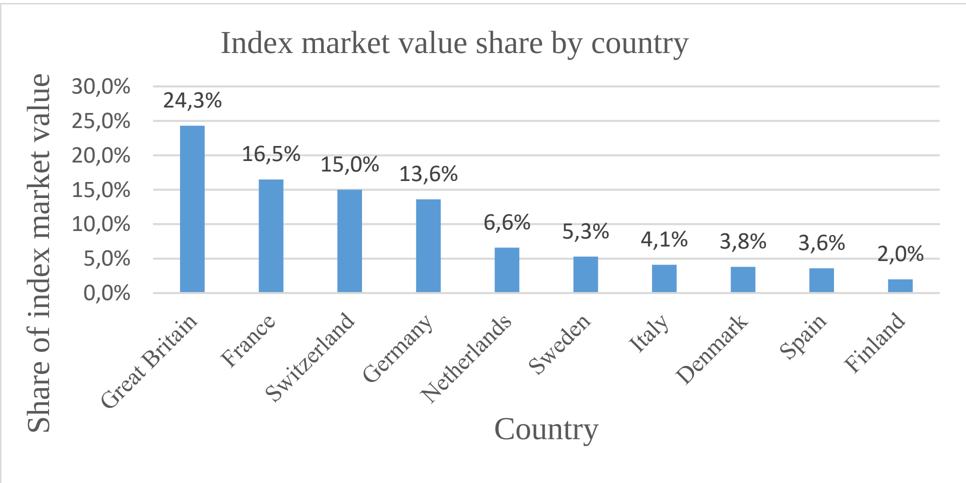
3 DATASET

Understanding the data we are working with is one of the key aspects to performing a good analysis. In this section I provide general information about the researched index, the different biases the researcher is prone to, and the description and summary of the data and variables used in the analysis.

3.1 Stoxx Euro 600 Index

The data for the analysis was taken from the Stoxx Europe 600 index, which was introduced in 1998. The index constituents represent around 90 % of the market capitalization of the European stock market. Stoxx Europe is an index composed of the largest European companies, from 17 different European countries, where companies from Great Britain (24, 3 %), France (16,5 %), Switzerland (15,0 %) and Germany (13,6 %) represent 69,4 % of the index market value (Quontigo, 2022b).

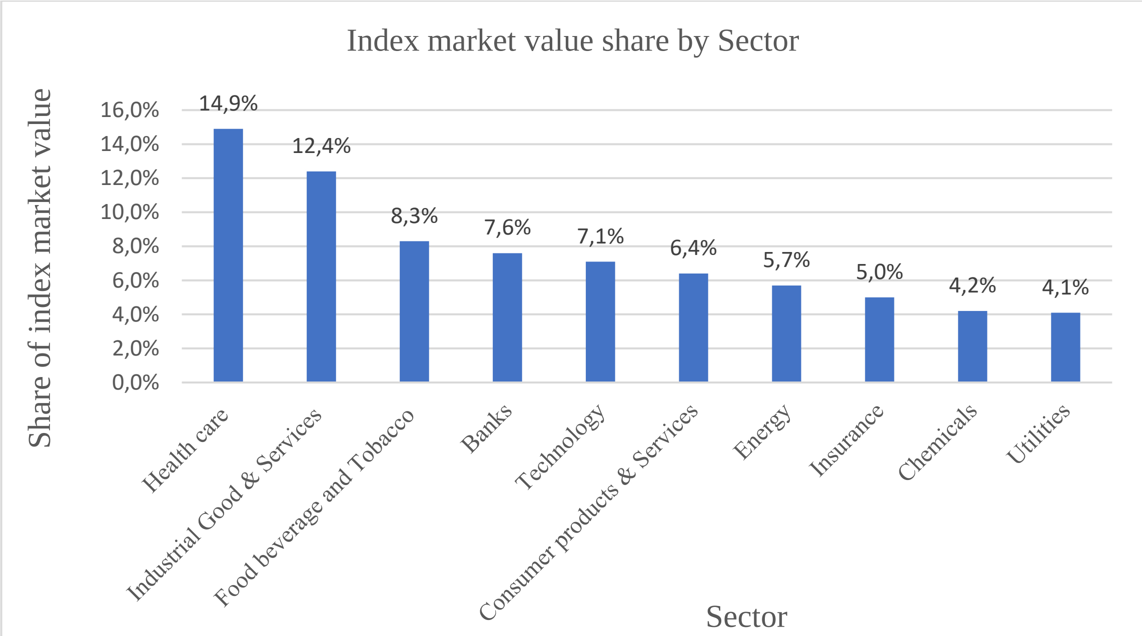
Figure 5: Stoxx Europe market value share by country



Adapted from Quontigo (2022b).

The index is also diversified in terms of represented sectors. Health care (14,9 %), Industrial Good & Services (12,4 %) and Food beverage and tobacco sector (8,3 %) represent 35,6 % percent of the index market value (Quontigo, 2022b).

Figure 6: Stoxx Europe market value share by sector



Adapted from Quontigo (2022b).

The index is composed of 600 companies at each point in time. The composition of the index is reviewed 4 times a year in March, June, September, and December. The selection of the companies at each revision time is based on the most recent data on the last trading day of the previous month (Quontigo, 2022a).

To be included in the selection process, the companies must have at least 1 million euros of average daily trading volume measured over a time span of 3 months. All stocks that are eligible based on the average daily trading volume criteria are ranked based on their market capitalization (Quontigo, 2022a).

From the stocks that meet the criteria, the largest 550 in terms of market capitalization are automatically included in the index. Among the companies ranked between 551 and 750, 50 largest companies that are also current components of the index are chosen. If the number of selected stocks is still below 600, the largest stocks that remain are chosen (Quontigo, 2022a).

3.2 Biases

Before downloading the data, researchers need to consider data biases, namely the »survivorship bias«, »look-ahead-bias«, and »data snooping bias«, because these biases can have a big impact on results if not taken care of properly.

In this setting survivorship bias occurs when researchers only include current constituents of STOXX Europe 600 in the sample. This would lead to a wrong conclusion because we would only include the companies that have survived and avoided bankruptcy. In terms of returns this would mean that we would overestimate average returns of portfolios, because the poor performing companies would be excluded from the sample (Bodie, Kane & Marcus, 2008).

Fixing this issue is not straightforward. Fortunately, there is a »joiner and leaver list« available on the DataStream website from which I obtained my data. The list includes listing and delisting dates for every company that has ever joined the STOXX Europe 600 index. All the companies on this list were included in the sample. I downloaded the time series of returns for all these companies. The returns were set to 0 in the periods when the companies were not part of the index, which was done with the help of the listing and delisting dates. With this I ensured that none of the companies were excluded from the sample, while including only companies that were listed in the index in each time period.

I also had to account for the look-ahead-bias, which occurs when researchers use data that was not available during the period being studied. To correct for this bias, I employ the solution from Fama & French (1993). In factor analysis, portfolio formation plays a key role, where companies are sorted into portfolios based on variables of the researcher's choice. The key issue is the portfolio formation time. Usually, it takes some time for variables based on which portfolios are formed to be publicly available. For this reason, the portfolio formation period takes place in June of every year, to make sure that most of the data from annual reports is available.

Data snooping bias also presents serious problems for researchers. Lo and MacKinlay (1990) stated that the usual problem in economics research is that future research is often motivated by successful and failed past research. As a result, only a few studies are free of the influence of such biases from previous research. The degree of such biases increases with number of published papers performed on a single data set. The more times the data set is used and tested in different models, the higher the likelihood that patterns emerge. Since stock market prices are one of the most frequently studied topics in finance, it seems that tests of asset pricing models are especially susceptible to this.

In the case of my research, I conclude that I am not susceptible to the data snooping bias. First, no previous research on NWC used factor models to derive results. Second, most of the research field does not focus on the actual NWC values but rather the cash conversion cycle. Lastly the data set on which I performed the analysis was custom made, and not inspired by any other study.

3.3 The sample

My sample consists of all the companies that were part of STOXX Europe 600 index for at least 1 month from the beginning of August 1999 to September 2021. The data was obtained from the DataStream database. The first sample consisted of 1798 companies.

I begin by applying filters to the data. Following the example of Fama and French (1993), I exclude financial firms from the sample. The argument for the exclusion of financial firms is strong, particularly because financial firms mostly do not have inventory, while the role of accounts payable and accounts receivable is different from the role they have in non-financial companies.

The exclusion was done by selecting a filter based on the Nomenclature of Economic Activities (hereinafter referred to as NACE). Companies that had NACE classifications with the values 64, 65, 66, represented financial companies and were thus excluded, which left 1397 companies in the sample. All the calculations and results presented in the following chapters were done using the R programming language.

3.4 Variable definitions

The data was obtained using the Datastream database and Kenneth Frenchs Data library. The variable definitions are the following:

- Stock returns are obtained on a monthly basis using the »Total return« indicator in Datastream. The Total return indicator incorporates the daily price change measured in percent and any relevant dividends for the specified period to calculate the return for the specified period.
- The market capitalizations are obtained using the »Company Market capitalization« indicator in Datastream. The data is obtained on a monthly basis, every end of June, and at the end of each fiscal year. The Company Market Capitalization represents the sum of market value for all relevant share types. Market value is calculated by multiplying the shares type by latest price.
- Common equity will serve as a proxy for book value. Common equity is obtained at the end of every fiscal year using »Common shareholder equity«. This is the total shareholder's equity minus Preferred Stock and Redeemable Preferred Stock
- Total assets are obtained every fiscal year using the »Totals assets« indicator. Total assets represent the total assets reported by the respective company in the balance sheet.
- Operating profit is obtained every fiscal year using the »Operating profit« indicator. Operating profit is defined as the difference between the company’s revenues, and its costs and expenditures that occur directly because of the company’s regular operations.
- Accounts receivable is obtained at the end of every fiscal year using the »Accounts receivable« indicator. Accounts receivable represents the sum of all claims that are held against customers for goods sold or services rendered.

- Amounts payable is obtained every fiscal year end using the »Amounts payable« indicator. Amounts payable is the total amount owed to creditors or suppliers for materials and merchandise acquired, or for services provided within the normal operations of the business
- Inventory is obtained every fiscal year using the »Inventory« indicator. Inventory is defined as the raw materials, work in progress good, and completely finished goods that are considered ready or will be ready for sale.
- The proxy for the risk-free interest rate will be the US 1-month treasury rate. The risk-free rate was obtained from Kenneth French's data library. I chose the US 1-month treasury instead of a European treasury, because the US 1-month treasury rate was used when Fama and French tested their models on European market data and I wanted to make it comparable to the methodology of Fama and French.

3.5 Variable summary

Understanding the data, we are dealing with is a key aspect when performing statistical analysis. Below is a basic summary of the data that was used in the analysis.

Table 1: Summary statistics

Variable	Mean	Median	Maximum	Minimum
Market return (in %)	0,60	1,02	13,29	-12,93
Market capitalization (in $)	14.157.366.670,00	5.646.793.600,00	1.078.802.668.796,00	3.291.938,00
B/M	1,01	0,43	547,81	0,01
Operating profitability	0,19	0,09	161,25	-198,11
Change in investment (in %)	9,77	5,41	4583,82	-93,72
NWC ratio (in %)	13,02	9,07	160,27	55,19
Risk-free rate (in %)	0,13	0,08	0,56	0,00

Source: Own work.

Definitions of variables in table 1 are given below:

- Market return represents the monthly return of the Stoxx Euro 600 index in time t, which is calculated as the market capitalization weighted average of stock returns, where only companies that are index constituents in time t are included in the calculation.
- The market capitalization represents the company market capitalization at the end of June in time t.
- B/M is defined as December t-1 common equity divided by December t-1 company market capitalization.
- Operating profitability is defined as December t-1 operating profit divided by December t-1 common equity.
- Change in investment is defined as the difference between December t-1 and December t-2 total assets, divided by December t-2 assets.
- NWC ratio is defined as December t-1 NWC divided by December t-1 total assets.
- Risk-free rate represents each month's US 1-month treasury rate.

Between the beginning of August 1999 and September 2021, companies that were included in the STOXX EUROPE 600 index had, on average, a market capitalization of 14,16 billion dollars, B/M of 1,01, operating profitability of 0,19, change in investment of 9,77 %, NWC ratio of 13,02 %, while the average risk-free rate was 0,13 %.

The companies' median values were 5,6 billion dollars for market capitalization, 0,43 for B/M, 0,09 for operating profitability, 5,41 % for change in investment, 9,07 % for NWC ratio and the median risk free-rate was 0,08 %

Big differences between the variable's median and mean values together with some extremely high values indicate that the data is positively skewed, where the high mean value is influenced by extreme values.

The average market returns in the period were 0,6 % per month, while the median return of the market was 1,02 %, which indicates that the returns of the market are negatively skewed.

4 FACTOR AND PORTFOLIO FORMATION

The way portfolios are created in asset pricing models is very important as there are numerous possibilities to form portfolios. The first CAPM tests were mostly unsuccessful due to the fact that they were regressing individual stocks on the market factor. The consequence of that was that there was too much dispersion to accurately measure the beta coefficients. Fama and MacBeth (1973) solved this problem by grouping stocks into portfolios. The estimated beta coefficients are estimated more accurately because the portfolio exhibits less residual variance. Beta coefficients of portfolios are more stable over time compared to stocks and are easier to estimate accurately (Cochrane, 2005)

4.1 Portfolio formation

The most important decision to be made is how many portfolios to use and choosing the appropriate breakpoints. As the number of portfolios increases the number stocks in each portfolio declines. A smaller number of stocks in each portfolio decreases the accuracy of the estimated mean in each portfolio. If we increase the number of stocks in each portfolio, this improves the accuracy of the estimated mean in each portfolio. This results in a smaller number of portfolios, which decreases the dispersion of the sorting variable. As a result of smaller dispersion, it is harder to detect the cross-sectional relation between the dependent and sort variable as the values of the sort variables do not differ a lot if we form a small number of portfolios (Bali, Engle & Murray, 2016).

The number of sort variables also has an important implication. In this master thesis, I will conduct tests on portfolios that were formed based on NWC ratio, and on portfolios that were formed based on two variables, SIZE (company market capitalization) and NWC.

4.1.1 NWC Portfolios

Each end of June, 10 portfolios are formed based on the NWC ratio, where the ratio is calculated as NWC in December t-1 divided by December t-1 total assets. Included in one of the 10 portfolios for July of year t to June of t+1 are all companies from my sample that were listed on Stoxx Europe 600 index at the end of June in time t, had inventory data for December t-1, accounts payables data for t-1, accounts receivables for t-1, and total assets for t-1.

The period t breakpoints which are used to group assets into portfolios are determined based on percentiles of the cross-sectional distribution of NWC ratio in period t. Since I form 10 portfolios, there are 9 breakpoints. The first breakpoint is calculated as the first decile of the NWC ratio distribution in time. The k-th breakpoint is calculated as k-th decile.

4.1.2 NWC ratio-SIZE portfolios

Next, I create portfolios based on two sort variables, SIZE and NWC ratio. I create 25 different portfolios using independent sorts. Included in one of the 25 double sorted portfolios for July of year t to June of t+1 are all companies from my sample that were listed on Stoxx euro 600 index at the end of June in time t, had market capitalization data for June of t, inventory data for December t-1, accounts payables data for t-1, accounts receivables for t-1, and total assets for t-1.

The first step in forming 25 double sorted portfolios is to divide companies into groups for each of the sort variables. For both sort variables I divide the companies into 5 groups based on their cross-sectional distribution in each time t. The breakpoints, based on which the companies are sorted into groups, are the 20^{th}, 40^{th},60^{th}, and 80^{th} percentile of respective distributions. The companies are now grouped into portfolios based on the intersection of the 5 NWC ratio sorted portfolios and 5 size sorted portfolios, which results in 25 different portfolios based on SIZE and NWC ratio.

If there is a high positive correlation between the sort variables, then portfolios containing high value of both variables or low values of both variables will contain more elements than other portfolios. Similarly, a high negative correlation between both sort variables adds more variables to portfolios with high values of one sorting variable and a low value of the other sort variable. The researchers needs to take this into account when constructing portfolios as a sufficient number of assets should be included in each portfolio, to ensure that the estimate of the average return is sufficiently accurate (Bali, Engle & Murray, 2016)

4.2 Factor formation

Next, I construct 6 risk factors that explain asset returns. Five of the factors are constructed according to Fama and French (2015): market factor, SML factor, HML factor, CMA factor, and RMW factor. I also add the NWC ratio factor.

The market factor for a given month consists of all the companies included in our sample that were included in the Stoxx Europe 600 index in the given month and had an available market capitalization for the previous month. The market factor excess return is calculated as the value weighted return minus the risk-free rate.

Next, I construct the HML factor. The HML factor for July of year t to June of t+1 includes all companies from my sample that were listed on the Stoxx Europe 600 index at the end of June in time t, had market capitalization data for June of t, positive market capitalization data in December of t-1, and common equity data for December t-1. B/M is calculated as the ratio of t-1 common equity and t-1 market capitalization.

Companies are divided into 3 groups based on B/M and into two groups based on market capitalization. The companies below the 30th B/M percentile are assigned to the Value group, the companies between the 30th and the 70th percentile represent the Neutral B/M group while the rest of the companies present the Growth B/M group. The companies are assigned to 2 size groups based on the median of the market capitalization, where companies below the median are classified as small and companies above it are classified as big. I form 6 portfolios by taking the intersection of size and B/M (the company that has a high market capitalization and low B/M is assigned to the Big Growth portfolio).

The next step is to calculate value weighted returns for each of the 6 portfolios. To approximate returns that mimic taking exposure to the HML factor, I create a zero-cost mimicking portfolio comprised of short positions of stocks with low B/M and long positions of high B/M (that are financed by the short positions).

The return calculation is specified below:

$$HML = \frac{1}{2}(Small\ value + Big\ value) - \frac{1}{2}(Small\ growth + Big\ growth) \tag{44}$$

I proceed by constructing the RMW factor. The RMW factor for July of year t to June of t+1 includes all companies from my sample that were listed on Stoxx Europe 600 index at the end of June in time t, had market capitalization data for June of t, operating profit for t-1, and common equity data for t-1. Operating profitability is calculated as the ratio of operating profit and common equity.

The companies are assigned to 3 operating profitability groups and 2 size groups. The operating profitability breakpoints are the 30th and 70th percentile, while the size group formations follow the same rule as in the HML case. Companies below the 30th percentile are classified as Weak, the companies between the 30th and the 70th percentile as Neutral, and the rest as Robust. I form 6 portfolios, by taking the intersection of size and operating profitability groups.

The next step is to calculate value weighted returns for each of the 6 portfolios. To approximate returns that mimic taking exposure to the operating profitability, I create a zero-cost mimicking portfolio comprised of short positions of stocks with low operating profitability and long positions of stocks with high operating profitability (that are financed by the short positions). The return calculation is specified below:

$$RMW = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}\ (Small\ Weak + Big\ Weak) \tag{45}$$

Next, I construct the CMA factor. The CMA factor for July of year t to June of t+1 includes all companies from my sample that were listed on Stoxx Europe 600 index at the end of June in time t, had market capitalization data for June of t, total assets data for t-1, and t-2 total asset data. Investment is calculated as the asset difference between t-1 total assets and t-2 assets divided by t-2 total assets.

The companies are assigned to 3 investment groups and 2 size groups. The investment breakpoints are the 30th and 70th percentile, while the size group formations follow the same rule as in the HML case. Companies below the 30th investment percentile are classified as Conservative, the companies between the 30th and the 70th percentile as Neutral and the rest as Aggressive. I form 6 portfolios, by taking the intersection of size and investment groups.

The next step is to calculate value weighted returns for each of the 6 portfolios. To approximate returns that mimic taking exposure to the investment factor, I create a zero-cost mimicking portfolio comprised of short positions of stocks with high investment and long positions of stocks with low investments (that are financed by the short positions).

The return calculation is specified below:

$$CMA = \frac{1}{2}(Small\ Conservative + Big\ Conservative) - \frac{1}{2}(Small\ Aggressive + Big\ Aggressive) \tag{46}$$

Lastly, I construct the Tight minus loose (hereinafter referred to as TML) factor. I set the definition for the TML factor by myself but I follow the example of factors constructed in Fama and French (2015). The TML factor for July of year t to June of t+1 includes all companies from my sample that were listed on Stoxx Europe 600 index at the end of June in time t, had market capitalization data for June of t, inventory data for t-1, accounts payables data for t-1, accounts receivables for t-1, and total assets for t-1. NWC ratio is calculated as NWC in t-1 divided by t-1 total assets.

The companies are assigned to 3 NWC groups and 2 SIZE groups. The NWC breakpoints are the 30th and the 70th percentile, while the SIZE group formations follow the same rule as in the HML case. Companies below the 30th percentile are classified as Loose, the companies between the 30th and the 70th percentile as Neutral and the rest as Tight. I form 6 portfolios, by taking the intersection of SIZE and NWC groups.

The next step is to calculate value weighted returns for each of the 6 portfolios. To approximate returns that mimic taking exposure to the NWC, I create a zero-cost mimicking portfolio comprised of short positions of stocks with high NWC ratios and long positions of stocks with low NWC ratios (that are financed by the short positions). The return calculation is specified below:

$$TML = \frac{1}{2}(Small\ Tight + Big\ Tight) - \frac{1}{2}(Small\ Loose + Big\ Loose) \tag{47}$$

Lastly, I create value weighted returns for the SMB factor. To approximate returns that mimic taking exposure to SMB factor, I create a zero-cost mimicking portfolio comprised of short positions of stocks with big market capitalizations and long positions of stocks with small market capitalization (that are financed by the short positions). I calculate the SMB factor for portfolios ranked based on HML, RMW, CMA and TML.

The SMB_{HML} factor for stocks rated based on HML:

$$SMB_{HML} = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth\ ) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth\ ) \tag{48}$$

The SMB_{CMA} factor for stocks rated based on CMA:

$$SMB_{CMA} = \frac{1}{3}(Small\ Conservative + Small\ Neutral + \ Small\ Aggresive) - \frac{1}{3}(Big\ Conservative\ + Big\ Neutral + Big\ Aggresive\ ) \tag{49}$$

The SMB_{RMW} factor for stocks rated based on RMW:

$$SMB_{RMW} = \frac{1}{3}(Small\ Robust\ + Small\ Neutral + Small\ Weak\ ) - \frac{1}{3}(Big\ Robust\ + Big\ Neutral + Big\ Weak\ ) \tag{50}$$

The SMB_{TML} factor for stock rated based on TML:

$$\mathrm{SMB}_{TML} = \frac{1}{3}(Small\ Risky + Small\ Neutral\ Small\ Safe) - \frac{1}{3}(Big\ Risky + Big\ Neutral + Big\ Safe\ ) \tag{51}$$

The overall SMB factor is calculated as the equally weighted average of the SMB factors stated above:

$$SMB = 1/4(SMB_{HML} + \ SMB_{RMW} + SMB_{TML} + SMB_{CMA}) \tag{52}$$

4.2.1 Average factor returns

After calculating the excess returns of factor portfolios, I present some basic statistics about the constructed data, such as the average number of observations, arithmetic mean return, and geometric mean return.

Table 2: Factor portfolios summary statistics

Factor portfolio	**Average number of observations**	**Arithmetic mean return per month (in %)**	**Geometric mean return per month (in %)**
Market	368	0,61	0,52
SMB	358	0,34	0,32
HML	364	0,13	0,09
RMW	363	0,22	0,18
CMA	366	0,05	0,01
TML	339	-0,51	-0,54

Source: Own work.

From table 2 we can see that the average number of companies included in factor portfolios ranges from 339 (TML) to 368 (Market). The average monthly arithmetic return ranges between -0,51% (TML) to 0,61 % (Market) per month, whereas the average monthly geometric return ranges between -0,54 % (TML) and 0,52 % (Market). The negative average monthly returns for the TML factor are surprising since it should exhibit positive average returns.

4.2.2 Factor correlations

It is also important to provide correlations between variables used in the regressions. Firstly, the correlations between variables can give us an indication about the relationship between pairs of variables. Secondly, it can reveal potential issues in statistical analysis. If both the variables are included in the regression and are very highly correlated, it can be hard to distinguish between the effects of the variables which can lead to high standard errors of coefficient estimates (Bali, Engle & Murray, 2016)

I present the Pearson correlation. If the relation between the variables is linear then the Pearson correlation is interpreted as the percentage variation in X that is related to variation Y, which can be negative or positive. The Pearson correlation values are between 1 and -1, where 1 indicates a perfect positive linear relation, 0 indicates no linear relationship, and -1 indicates a perfect negative linear relationship (Bali, Engle & Murray, 2016)

Table 3: Factor returns correlation matrix

Factor	**Market**	**SMB**	**HML**	**RMW**	**CMA**	**TML**
Market	1,00	0,15	0,27	-0,19	-0,02	-0,27
SMB	0,15	1,00	0,27	-0,07	0,17	-0,16
HML	0,27	0,27	1,00	0,41	0,66	0,01
RMW	-0,19	-0,07	0,41	1,00	0,45	0,26
CMA	-0,02	0,17	0,66	0,45	1,00	0,09
TML	-0,27	-0,16	0,01	0,26	0,09	1,00

Source: Own work.

From table 3 we can see that the highest positive correlation is exhibited between returns of the HML factor and returns of the RMW factor (0,66), and the highest negative relationship is exhibited between TML factor returns and market factor returns (-0,27). TML factor returns also exhibit a negative correlation with SMB returns (-0,16), almost no correlation to the HML factor returns and a positive correlation with CMA factor returns (0,26) and RMW factor returns (0,09).

5 RESULTS

In this section I provide the model specifications for the time series and Fama MacbBeth regression models and present the obtained results. Time series regression is performed using the FF 5-factor model and the 6-factor model, while the Fama Macbeth regression is performed using only the 6-factor model.

5.1 Time series regression model specifications

To answer the first hypothesis, I perform time series regression tests. NWC ratio sorted and NWC ratio-SIZE double sorted portfolios will be regressed on the FF 5-factor model and the 6-factor model, where the TML factor is added to the FF 5-factor model. The goal is to compare the performance of both models to see if the 6-factor can help in explaining the 10 single and 25 double sorted portfolio excess returns. The time series regression test for single and double sorted portfolios are presented below in equations (53), (54), (55) and (56).

$$\mathrm{R_{i,t} - R_{f,t} = \alpha_i + (R_{M,t} - R_{f,t})\beta_{i1} + SMB_t\beta_{i2} + HML_t\beta_{i3} + CMA_t\beta_{i4} + RMW_t\beta_{i5} + \varepsilon_{i,t}} \tag{53}$$

$$\mathrm{R_{i,t} - R_{f,t} = \alpha_i + (R_{M,t} - R_{f,t})\beta_{i1} + SMB_t\beta_{i2} + HML_t\beta_{i3} + CMA_t\beta_{i4} + RMW_t\beta_{i5} + TML_t\beta_{i6} + \varepsilon_{i,t}} \tag{54}$$

Where t = 1999-07...2021-08 and i = 1...10

$$\mathrm{R_{i,t} - R_{f,t} = \alpha_i + (R_{M,t} - R_{f,t})\beta_{i1} + SMB_t\beta_{i2} + HML_t\beta_{i3} + CMA_t\beta_{i4} + RMW_t\beta_{i5} + \varepsilon_{i,t}} \tag{55}$$

$$R_{i,t} - R_{f,t} = \alpha_i + (R_{M,t} - R_{f,t})\beta_{i1} + SMB_t\beta_{i2} + HML_t\beta_{i3} + CMA_t\beta_{i4} + RMW_t\beta_{i5} + RMS_t\beta_{i6} + \varepsilon_{i,t} \tag{56}$$

Where t = 1999-07...2021-08 and i = 1...25

5.2 Fama-MacBeth Regressions model specifications

To answer the second hypothesis, I use the Fama-Macbeth regression analyses. The analysis was performed on 10 NWC ratio and 25 NWC ratio-SIZE sorted portfolios using the 6-factor model. The goal is to determine the relationship between future excess returns of the portfolios and the TML factor. The beta inputs for regressing the 10 single sorted portfolios are the beta coefficients that were obtained in equation (53).

$$R_{i,t} - R_{f,t} = \gamma_i + \lambda_{1,t}\beta_{i1} + \lambda_{2,t}\beta_{i2} + \lambda_{3,t}\beta_{i3} + \lambda_{4,t}\beta_{i4} + \lambda_{5,t}\beta_{i5} + \lambda_{6,t}\beta_{i6} + \varepsilon_{i,t} \tag{57}$$

Where t = 1999-07...2021-08 and i = 1...10

The risk premium and their standard errors are obtained according to equations (42) and (43). The beta coefficient inputs for regressing the 25 double portfolios are the beta coefficients that were obtained in equation (55).

$$R_{i,t} - R_{f,t} = \gamma_i + \lambda_{1,t}\beta_{i1} + \lambda_{2,t}\beta_{i2} + \lambda_{3,t}\beta_{i3} + \lambda_{4,t}\beta_{i4} + \lambda_{5,t}\beta_{i5} + \lambda_{6,t}\beta_{i6} + \varepsilon_{i,t} \tag{58}$$

Where t = 1999-07...2021-08 and i = 1...25

The risk premium and the standard errors are obtained according to equations (40) and (41).

5.3 Time series regression results

I start the time series analysis by first computing the time series averages for the 10 NWC ratio ranked portfolios. I want to assess if there exists a pattern in future excess returns related to different levels of NWC ratio.

Table 4: Single sorted portfolio average returns

Decile	**Average monthly return (in %)**
1	0,35
2	0,32
3	0,34
4	0,53
5	0,36
6	0,62
7	0,55
8	0,66
9	0,80
10	0,85
(1-10)	-0,50

Source: Own work.

From

Table 4 we can see that returns across portfolios seem to be increasing almost monotonically with the NWC ratio. The lowest NWC ratio portfolio had an average excess return of 0,5 % per month, while the highest NWC ratio portfolio had an average monthly excess return of 0,85 %. The difference portfolio had an average excess return of -0,50 % per month.

The data suggest that there could be some cross-sectional relation between future excess returns and NWC ratio. But to make an assessment we need to adjust the average portfolio excess returns for the exposure to risk factors. The results presented in Table 5 correspond to the regression equation (53), where the FF 5-factor model is used for risk adjustment, α represents the risk adjusted excess returns (mispricing errors), $|\alpha|$ represents the absolute mispricing errors ,and Adj. R represents the adjusted R-squared.

Table 5: Performance measures corresponding to equation (53)

Portfolio	**Statistic**	**α (%)**	**$\|\alpha\|$ (%)**	**Adj. R**
1	Coefficient	-0,23	0,23	0,81
	T-statistic	-1,77		
	P-Value	0,08		
2	Coefficient	0,05	0,05	0,72
	T-statistic	0,29		
	P-Value	0,77		
3	Coefficient	-0,02	0,02	0,79
	T-statistic	-0,18		
	P-Value	0,86		
4	Coefficient	0,1	0,1	0,77
	T-statistic	0,72		
	P-Value	0,47		
5	Coefficient	-0,08	0,08	0,81
	T-statistic	-0,65		
	P-Value	0,51		
6	Coefficient	-0,01	0,01	0,84
	T-statistic	-0,1		
	P-Value	0,92		
7	Coefficient	-0,11	0,11	0,79
	T-statistic	-0,85		
	P-Value	0,4		
8	Coefficient	0,17	0,17	0,8
	T-statistic	1,06		
	P-Value	0,29		

To be continued

Table 6: Performance measures corresponding to equation (53) (cont.)

Portfolio	**Statistic**	$\boldsymbol{\alpha}$ **(%)**	$\boldsymbol{|\alpha|}$**(%)**	**Adj. R**
9	Coefficient	0,03	0,03	0,77
	T-statistic	0,15		
	P-Value	0,88		
10	Coefficient	0,45	0,45	0,68
	T-statistic	1,64		
	P-Value	0,10		
Average			**0,13**	**0,78**
			GRS Test statistics	**1,19**
			P-value	**0,29**

Source: Own work.

Table 7: Performance measures for the difference portfolio

Difference portfolio (1-10)	**Coefficient**	-0,68
	T-statistic	-2,66
	P-Value	0,01

Source: Own work.

As we can see from Table 7, the risk-adjusted average excess return of the difference portfolio is -0,68 % per month and is statistically significant with a p-value of 0,01. The fact that the results prove that the average excess return of the difference portfolio is statistically distinguishable from 0, indicates that there exists a cross sectional relation between NWC ratio and future excess returns. On the other hand, we can also observe that the pattern that arises does not monotonically increase across NWC ratio portfolios. The only thing that can be said about the pattern of excess returns across portfolios is that the 5 portfolios with higher NWC ratio values seem to have higher average excess returns than the 5 portfolios with lower values of the NWC ratio. In this sense, the lack of monotonicity does not seem to give support to the findings concluded from the difference portfolio.

As we can see from Table 5, the 5-factor model has an average absolute misspricing error of 0,125 % per month, where the highest measured error is in the highest NWC ratio portfolio (0,45%) and the lowest measured in portfolio 6 (0,01%). In terms of adjusted R-squared, we can see that the highest value was observed in portfolio 6 (0,84) and the lowest was observed in portfolio 10 (0,68), while the average adjusted R-squared was 0,78. The GRS statistic provides a test score of 1,19 with a p-value of 0,29. Based on this p-value the conclusion is that we cannot reject the null hypothesis that all pricing errors are jointly 0.

I continue by performing the same exercise, only using the 6-factor model. Below in Table 8 are the results of the time series regression corresponding to equation (54). The 10 single sorted portfolios are regressed on the 6-factor model.

Table 8: Performance measures corresponding to equation (54)

Portfolio	Statistic	α (%)	$\lvert\alpha\rvert$ (%)	Adj. R
1	Coefficient	-0,11	0,11	0,85
	T-statistic	-0,92		
	P-Value	0,36		
2	Coefficient	0,27	0,27	0,81
	T-statistic	1,49		
	P-Value	0,14		
3	Coefficient	0,1	0,10	0,83
	T-statistic	1,01		
	P-Value	0,31		
4	Coefficient	0,09	0,09	0,77
	T-statistic	0,65		
	P-Value	0,52		
5	Coefficient	-0,14	0,14	0,82
	T-statistic	-1,12		
	P-Value	0,26		
6	Coefficient	-0,07	0,07	0,85
	T-statistic	-0,57		
	P-Value	0,57		
7	Coefficient	-0,14	0,14	0,79
	T-statistic	-0,98		
	P-Value	0,33		
8	Coefficient	0,08	0,08	0,82
	T-statistic	0,55		
	P-Value	0,58		
9	Coefficient	-0,13	0,13	0,81
	T-statistic	-0,65		
	P-Value	0,52		
10	Coefficient	0,23	0,23	0,75
	T-statistic	0,99		
	P-Value	0,33		
Average			**0,14**	**0,81**
			GRS Test statistics	**0,96**
			P-value	**0,48**

Source: Own work.

The model has an average absolute mis-pricing error of 0,14 % per month, where the highest error is measured in the highest NWC ratio portfolio (0,23%) and the lowest is measured in portfolio 6 (0,07%). The average mis-pricing error is higher (+ 0,01% pp.) than in the 5-

factor model, from which we can conclude that based on the criteria of the absolute mis-pricing error, the 5-factor model explains the returns better than the 6-factor model. The highest observed adjusted R-squared values were observed in portfolio 1 and 6 (0,85) while the lowest was observed in portfolio 10 (0,75). The average R-squared value is 0,81, which is higher (+ 0,03) than in the 5-factor model. Based on the criteria of the Adjusted R-squared, the 6-factor model explains the excess returns better than the 5-factor model. Lastly, I compare the models based on the GRS statistic. The GRS statistic in the 6-factor model is 0,96 with a corresponding p-value of 0,48. The lower GRS statistic value compared to the 5-factor model (1,19) indicates that the 6-factor model is better in explaining NWC ratio sorted excess returns.

Next, following the example of Fama & French (2015), I test the performance of the models on SIZE ratio-NWC double sorted portfolios. The results presented in the table below correspond to the regression equation (55), where FF 5-factor model is used for risk adjustment.

Table 9: Performance measures corresponding to equation (55)

SIZE / NWC	**Statistic**	**1**	**2**	**3**	**4**	**5**
1	α (%)	0,18	-0,17	-0,23	0,13	-0,11
	T-statistic	0,69	-0,73	-1,30	0,90	-0,73
	P-Value	0,49	0,46	0,19	0,37	0,47
	$\lvert\alpha\rvert$ (%)	0,18	0,17	0,23	0,13	0,11
	Adj-R	0,65	0,71	0,73	0,76	0,75
2	α (%)	-0,51	-0,14	-0,05	0,13	-0,03
	T-statistic	-2,36	-0,92	-0,29	0,91	-0,22
	P-Value	0,00	0,40	0,80	0,40	0,80
	$\lvert\alpha\rvert$ (%)	0,51	0,14	0,05	0,13	0,03
	Adj-R	0,69	0,73	0,71	0,81	0,77
3	α (%)	0,06	0,19	0,03	-0,01	-0,06
	T-statistic	0,27	1,13	0,17	-0,07	-0,57
	P-Value	0,79	0,26	0,86	0,94	0,57
	$\lvert\alpha\rvert$ (%)	0,06	0,19	0,03	0,01	0,06
	Adj-R	0,67	0,78	0,76	0,80	0,84
4	α (%)	0,13	0,06	0,01	0,04	-0,09
	T-statistic	0,58	0,36	0,09	0,18	-0,68
	P-Value	0,56	0,72	0,93	0,86	0,50
	$\lvert\alpha\rvert$ (%)	0,13	0,06	0,01	0,04	0,09
	Adj-R	0,69	0,79	0,77	0,68	0,81
5	α (%)	0,13	0,38	0,08	0,26	0,45
	T-statistic	0,90	2,62	0,41	0,96	1,49
	P-Value	0,37	0,01	0,68	0,34	0,14
	$\lvert\alpha\rvert$ (%)	0,13	0,38	0,08	0,26	0,45
	Adj-R	0,80	0,86	0,74	0,69	0,68
Average	**$\lvert\alpha\rvert$ %**	**0,15**	**GRS test statistic**			**1,08**
	Adj-R	**0,75**	**P-value**			**0,36**

Source: Own work

In table 9, we can see that the 5-factor model has an average absolute misspricing error of 0,15 % per month, where the highest pricing error is 0,45%, and the lowest measured error is 0,01 %. In terms of adjusted R-squared, we can see that the highest observed value is (0,84) and the lowest observed value is 0,68, while the average adjusted R-squared is 0,75. The GRS statistic test score is 1,08 with a p-value of 0,36. Based on this p-value the conclusion is that we cannot reject the null hypothesis that all pricing errors are jointly 0.

I continue by performing the same exercise, only using the 6-factor model. Below in Table 10 are the results of the time series regression corresponding to equation (56). Twenty-five double sorted NWC ratio-SIZE sorted portfolios are regressed on the 6-factor model

Table 10: Performance measures corresponding to equation (56)

<table>
<tr><th>SIZE / NWC</th><th>Statistic</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th></tr>
<tr><td rowspan="5">1</td><td>α (%)</td><td>0,27</td><td>-0,09</td><td>-0,09</td><td>0,22</td><td>0,09</td></tr>
<tr><td>T-statistic</td><td>1,09</td><td>-0,39</td><td>-0,59</td><td>1,48</td><td>0,68</td></tr>
<tr><td>P-Value</td><td>0,28</td><td>0,70</td><td>0,55</td><td>0,14</td><td>0,50</td></tr>
<tr><td>$|\alpha|$ (%)</td><td>0,27</td><td>0,09</td><td>0,09</td><td>0,22</td><td>0,09</td></tr>
<tr><td>Adj-R</td><td>0,66</td><td>0,72</td><td>0,77</td><td>0,78</td><td>0,84</td></tr>
<tr><td rowspan="5">2</td><td>α (%)</td><td>-0,42</td><td>-0,08</td><td>-0,01</td><td>0,17</td><td>0,03</td></tr>
<tr><td>T-statistic</td><td>-1,96</td><td>-0,58</td><td>-0,07</td><td>1,24</td><td>0,22</td></tr>
<tr><td>P-Value</td><td>0,05</td><td>0,56</td><td>0,94</td><td>0,22</td><td>0,83</td></tr>
<tr><td>$|\alpha|$ (%)</td><td>0,42</td><td>0,08</td><td>0,01</td><td>0,17</td><td>0,03</td></tr>
<tr><td>Adj-R</td><td>0,70</td><td>0,73</td><td>0,71</td><td>0,81</td><td>0,78</td></tr>
<tr><td rowspan="5">3</td><td>α (%)</td><td>0,02</td><td>0,17</td><td>-0,03</td><td>-0,10</td><td>-0,11</td></tr>
<tr><td>T-statistic</td><td>0,07</td><td>0,96</td><td>-0,22</td><td>-0,62</td><td>-1,01</td></tr>
<tr><td>P-Value</td><td>0,94</td><td>0,34</td><td>0,83</td><td>0,54</td><td>0,31</td></tr>
<tr><td>$|\alpha|$ (%)</td><td>0,02</td><td>0,17</td><td>0,03</td><td>0,10</td><td>0,11</td></tr>
<tr><td>Adj-R</td><td>0,67</td><td>0,78</td><td>0,77</td><td>0,81</td><td>0,84</td></tr>
<tr><td rowspan="5">4</td><td>α (%)</td><td>0,08</td><td>0,03</td><td>-0,07</td><td>-0,01</td><td>-0,13</td></tr>
<tr><td>T-statistic</td><td>0,35</td><td>0,20</td><td>-0,52</td><td>-0,06</td><td>-1,05</td></tr>
<tr><td>P-Value</td><td>0,73</td><td>0,84</td><td>0,61</td><td>0,95</td><td>0,29</td></tr>
<tr><td>$|\alpha|$ (%)</td><td>0,08</td><td>0,03</td><td>0,07</td><td>0,01</td><td>0,13</td></tr>
<tr><td>Adj-R</td><td>0,69</td><td>0,79</td><td>0,79</td><td>0,69</td><td>0,82</td></tr>
<tr><td rowspan="5">5</td><td>α (%)</td><td>0,04</td><td>0,26</td><td>-0,07</td><td>0,07</td><td>0,16</td></tr>
<tr><td>T-statistic</td><td>0,28</td><td>2,10</td><td>-0,41</td><td>0,31</td><td>0,63</td></tr>
<tr><td>P-Value</td><td>0,78</td><td>0,04</td><td>0,68</td><td>0,76</td><td>0,53</td></tr>
<tr><td>$|\alpha|$ (%)</td><td>0,04</td><td>0,26</td><td>0,07</td><td>0,07</td><td>0,16</td></tr>
<tr><td>Adj-R</td><td>0,81</td><td>0,89</td><td>0,78</td><td>0,74</td><td>0,77</td></tr>
<tr><td rowspan="2">Average</td><td>$|\alpha|$ %</td><td colspan="2">0,11</td><td colspan="2">GRS test statistic</td><td>0,89</td></tr>
<tr><td>Adj-R</td><td colspan="2">0,77</td><td colspan="2">P-value</td><td>0,62</td></tr>
</table>

Source: Own work.

In terms of the absolute mis-pricing error the 5-factor model produces an average absolute mis-pricing error of 0,11 % per month, where the highest measured error is 0,42 % and the lowest measured is 0,01 % . The average misspricing error is lower than in the 5-factor model

(-0,04 pp.), from which we can conclude that based on the criteria of the absolute pricing error, the 6-factor model explains the returns better than the 5-factor model. The highest observed adjusted R-squared value is (0,89) while the lowest observed is 0,66. The average R-squared value is 0,77 which is higher (+ 0,02) than in the 5-factor model. Based on the criteria of the adjusted R-squared, the 6-factor model explains the returns better than the 5-factor model. Lastly, I compare the models based on the GRS statistic. The GRS statistic in the 6-factor model is 0,89 with a corresponding p-value of 0,62. The lower GRS statistic value compared to the 5-factor model (1,08) indicates that the 6-factor model is better in explaining NWC ratio sorted returns.

5.4 Fama MacBeth results

To answer the second hypothesis I used the Fama MacBeth regression analysis to see if NWC ratio positively impacts future excess returns in 10 NWC ratio single sorted portfolios and 25 NWC ratio-SIZE double sorted portfolio.

5.4.1 Single sorted portfolios

First, I assess the relationship between the regression variables and 10 NWC ratio sorted portfolios. The results of the Fama MacBeth regression are shown below in Table 11.

Table 11: Results corresponding to equation (57)

Factor	Coefficient	Standard Error	T-Value	P-value
Intercept	2,546	1,570	1,622	0,105
Market	-1,706	1,592	-1,072	0,284
SMB	-0,561	0,676	-0,830	0,407
HML	-0,759	1,040	-0,730	0,466
CMA	0,252	0,675	0,373	0,709
RMW	-0,471	0,904	-0,521	0,603
TML	-0,459	0,212	-2,167	0,030

Source: Own work.

The only statistically significant coefficient is TML, with a value of -0,459. The coefficient presents the average risk premium per unit of TML factor risk. Investing in the TML factor would bear an average monthly excess return of -0,459 %. We can thus observe that on average companies with lower NWC ratio levels experience future negative returns whereas higher levels of NWC ratio coincide with positive future returns. This is due to the fact that the TML factor is constructed by having long exposure to companies with low NWC ratio and short selling companies with high NWC ratio values. The high model intercept of 2,546 impacts the regression result as factors such as market, SMB, and HML, which are known to positively impact future excess returns are all negative.

5.4.2 Double sorted portfolios

I also test the relation between NWC ratio and future excess returns on 25 NWC ratio-SIZE double sorted portfolios. The results of the Fama MacBeth regression are show below in Table 12.

Table 12: Results corresponding to equation (58)

Factor	Coefficient	Standard Error	T-Value	P-value
Intercept	-0,563	0,858	-0,657	0,511
Market	1,061	0,913	1,162	0,245
SMB	0,324	0,136	2,382	0,017
HML	0,285	0,364	0,783	0,434
CMA	0,144	0,365	0,396	0,692
RMW	0,208	0,344	0,604	0,546
TML	-0,426	0,160	-2,654	0,008

Source: Own work.

The only two coefficients that are statistically significant are TML (0,008) and SMB (0,017). Investing in the TML factor would bear an average monthly excess return of - 0,426 %. We can thus observe that on average companies with lower NWC ratio levels experience future negative excess returns, whereas higher levels of NWC ratio coincide with positive future excess returns. SMB has a positive effect on future excess returns with an average monthly risk premium of 0,324 % per unit of Size risk. This indicates that smaller companies tend to have higher future excess returns. In contrast to the previous regression results, other coefficients (although insignificant) exhibit a positive risk premium which is consistent with literature findings.

5.5 Conclusion from results

In this section I provide the answers regarding my research questions. I discuss the possible reason for the obtained results. Based on my results I provide motivation and ideas for further research on NWC.

5.5.1 Evaluation of hypothesis 1

The first hypothesis stated that the NWC ratio can help reduce mis-pricing errors in asset pricing models. I tested whether the 6-factor model, containing the NWC ratio factor reduces the errors of the FF 5-factor model. Firstly, the comparison was performed on 10 NWC ratio single sorted portfolios. Based on the results of the GRS statistic and adjusted R-squared the 6-factor model performed better than the FF 5-factor model. Based on the criteria of the absolute mis-pricing error the FF 5-factor model performed better than the 6-factor model. Secondly, the comparison was performed on 25 NWC ratio-SIZE double sorted portfolios. Based on the results of all 3 measures, the 6-factor model performed better than the FF 5-

factor model. Based on this I cannot reject the first hypothesis that the NWC ratio can help explain differences in future excess stock returns.

5.5.2 Evaluation of hypothesis 2

The second hypothesis states that firms with lower NWC tend to yield higher than average future returns. I tested the validity of the relationship by implementing the Fama MacBeth procedure. The analysis was performed on 10 NWC ratio single sorted portfolios and 25 NWC ratio-SIZE double sorted portfolios. Both analyses indicate a significant negative relationship between low NWC ratio and future excess returns. Based on this I rejected the second hypothesis.

5.5.3 Discussion of results

Although no analysis of NWC has been done using factor models, it is useful to compare their results with other studies. Since most of the studies study whether NWC impacts future returns positively or negatively, most of the focus will be on discussing the results of the second hyphothesis.

Most of the literature reports a positive relation between low NWC levels and future excess returns. Deloof (2003) studied a sample of 1009 Belgian firms, García-Teruel and Martínez-Solano (2007) studied a sample of 8872 small and medium sized firms, while Lazaridis and Tryfonidis (2006) studied 131 firms listed on the Athens stock exchange. They studied firms that are, on average, much smaller than my sample, since average total assets in my sample amount to 13,6 Billion dollars, while, for example, in the sample of García-Teruel and Martínez-Solano (2007), the average total assets of the sample are 7,0 million dollars. This difference in the size of companies could be the key reason for differences in the findings.

Investment in working capital depends on several financial factors. The most important financial factors are availability of internal finance, company availability to access capital markets, and the cost of obtaining financing in capital markets (Afrifa, 2016). Hill, Kelly and Highfield (2010) show that NWC investment is positively related to cash flow availability and company size.

NWC investment can be financed internally or externally. Firms with good credit ratings and good access to capital markets have greater ability to finance themselves externally. Larger firms have better access to external financing than smaller firms. Since analysts monitor larger firm more frequently than smaller firms, this leads to larger information asymmetry in smaller firms. The consequence of higher information asymmetry are higher costs of financing for smaller firms (Hill, Kelly & Highfield, 2010).

Baños-Caballero, García-Teruel and Martínez-Solano (2014) hypothesised that there could be a non-linear connection between firm performance and NWC, based on the fact that NWC exhibits positive and negative effects. They found that firms with less financial constrains have a higher optimal NWC than firms with more constrains.

The most important finding for explaining the results of this master thesis are from Afrifa (2016), who found that in firms with cash flow availability above the sample median, NWC exhibits a positive relationship with firm value.

Based on the conclusions of the mentioned studies I have reason to believe that the positive relationship between NWC ratio and future excess returns are due to firm size and financing ability of the firms, since the firms included in my sample are the largest firms in Europe, consequentially with good financing abilities. The other studies do not exhibit this effect because they study much smaller companies (usually from a single country), with consequentially poorer financing capabilities. Since larger companies exhibit much better financing conditions, it lets them benefit from increased NWC investment without risking financial distress.

5.5.4 Further research

Since this study provides results that are significant, it would seem logical to test the model on different datasets. The researcher would need to find a dataset consisting of comparably large companies for the comparison to make sense. Two possible choices would be to study some US stock index like the The Standard and Poor's 500 index or combining some large companies from Asian markets. It would be interesting to see if the positive relationship holds in those markets and whether the risk premium differs across those markets, since US companies have better access to capital markets than Europe and much better access to capital markets than Asian companies.

It would also be interesting to perform the analysis during the recession and expansionary periods and compare the results. Since access to capital markets and cost of financing is much worse during recession periods than expansionary periods, it would be natural to expect that the significance of the positive relationship would fade during recession periods, or even turn negative.

Some studies (see for example Afrifa (2016)) have shown that optimal NWC ratio varies across industries; hence, it would make sense to perform the analysis on large companies from different industries where the NWC ratio risk premium could be compared across different industries.

CONCLUSION

The main goal of the master thesis was to study the effect of NWC on company future excess returns. Understanding the effect of NWC is important since NWC can represent a significant proportion of a company’s balance sheet and is needed for everyday operations.

I researched whether NWC ratio as an asset pricing factor can help reduce mispricing errors in asset pricing models, since no research papers have studied the role of NWC as an asset pricing factor. This was done using time series data from companies included in the Stoxx Europe 600 index during the 1999-2021 period. I tested the performance of the FF 5-factor against the performance of the 6-factor model, which was constructed by adding the NWC ratio factor to the FF-5 factor model. As test assets I used 10 NWC ratio single sorted portfolios and 25 SIZE-NWC ratio double sorted portfolios. The main criteria for comparing the performance of two asset pricing models is the GRS test statistic, which tests whether the pricing errors of all portfolios are jointly equal to zero. I found that the 6-factor model exhibits lower GRS test statistic on both double and single sorted portfolios than the 5-factor model. These findings are reinforced by results obtained from comparing models using the absolute pricing error and adjusted R-squared. Based on these results, I cannot reject the hypothesis that the NWC ratio as an explanatory factor can help reduce mispricing errors in existing factor models.

In the second part of the analysis, I studied the effect of NWC on company future excess returns. Based on literature findings I tried to show that there exists a negative relationship between the NWC ratio and future excess returns, which means that companies should strive to reduce NWC to a reasonable minimum, to achieve positive future excess returns. The effect of NWC on future excess returns was studied with the Fama MacBeth procedure using the 6-factor model containing the NWC ratio factor. As test assets I used 10 NWC ratio single sorted portfolios and 25 SIZE-NWC ratio double sorted portfolios.

In both cases I found a statistically significant positive relation between NWC ratio and future excess returns, which is not in line with the findings of previous studies. The reason for this lies in the sample of observed companies; my sample consisted of much bigger companies than the ones found in most of the literature. The consequence of this is that these companies exhibit much better financing conditions, which lets them benefit from increased NWC investment without risking financial distress. Based on this I reject the second hypothesis.

In light of big global uncertainties such as the Covid crisis, the war in Ukraine, high inflation, and supply chain issues, it would be interesting to repeat this study by using the data from recession periods, to see whether this positive relationship fades or even becomes negative, which would help large companies manage NWC investment in times of economic downturn.

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APPENDIX

Appendix 1: Povzetek (Summary in Slovene language)

Neto obratni kapital predstavlja pomemben vir kratkoročne likvidnosti podjetja. Neto obratni kapiital zagotavlja, da ima podjetje na voljo dovolj kratkoročnih sredstev, da opravlja dejavnosti povezane z svojim poslovanjem in obenem poravna vse svoje obveznosti. Obenem pa je lahko prevelika količina neto obratnega kapitala za podjetje neučinkovita, saj kot posledica investiranja v neto obratni kapital, podjetje sredstev ne more investirati drugam. Kljub temu večji del literature na tem področju ugotavlja, da nižji delež neto obratnega kapitala v celotnih sredstvih pozitivno vpliva na bodoče delniške donose.

V svoji magistrski nalogi sem preučeval vpliv neto obratnega kapitala na prihodnje donose podjetji vključenih v Stoxx Euro 600 indeks med letoma 1999-2021. Analizo sem opravil s pomočjo linearnih faktorskih modelov, saj jih za analizo neto obratnega kapitala ni uporabil še nihče.

Postavil sem dve raziskovalni vprašanj. V sklopu prvega raziskovalnega vprašanja sem preučeval ali lahko delež neto obratnega kapitala v celotnih sredstvih kot faktor delniških donosov pomaga dodatno pojasniti nihanja v delniških donosih. Podjeta so bila razvrščena v portfelje glede na njihov delež neto obratnega kapitala v celotnih sredstvih, razvrščena pa so bila tudi na podlagi velikosti in deleža neto obratnega kapitala v celotnih sredstvih hkrati. Primerjal sem natančnost Fama & French 5-faktorskega modela in 6-faktorkega modela, kjer je bil 5-faktorskemu modelu dodan faktor, ki temelji na deležu neto obratnega kapitala. Uporabljena je bila metoda analize časovnih vrst. Natančnost se je presojala na podlagi GRS statistike. Rezulatati so pokazali da je imel 6-faktorski model v obeh primerih (enojno in dvojno razvrščenih podjetj), manjšo napako kot 5-faktorski model. Na podlagi tega lahko zaključimo, da lahko neto obratni kapital kot faktor dodatno pripomore k pojasnevanju bodočih delniških donosov.

V sklopu drugega raziskovalnega vprašanja sem preučeval ali delež neto obratnega kapitala v celotnih sredstvih kot faktor delniških donosov pozitivno ali negativno vpliva na bodoče delniške donose. Za analizo sem uporabil portfelje, kjer so bila podjetja sortirana glede na delež obratnega kapitala v celotnih sredstvih in velikosti podjetji hkrati. Analiza je bila opravljena z Fama MacBeth regresijsko metodo. V nasprotju z literaturo, z uporabo 6-faktorskega modela pridem do rezultata, da višji delež obratnega kapitala pozitivno vpliva na bodoče delniške donose. Drugačni rezultati so verjetno posledica izbranega vzorca podjetji, ki vključuje večinoma velika podjetja. Ostale raziskave večinoma uporabljajo vzorec majhnih podjetji. Večja podjetja imajo praviloma več denarnih sredstev in boljše pogoje financiranja, zato imajo lahko korist od višjega deleža neto obratnega kapitala.

Appendix 2: Single sorted returns regressed on the FF 5-factor model

Below are presented the full results from equation (53), where 10 NWC ratio single sorted excess returns are regressed on the FF-5 model.

Table 1: Single sorted returns regressed on the FF 5-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	Adj-R
	Coef.	-0,23	1,03	0,02	-0,25	0,22	0,24	0,81
	T-Stat.	-1,77	29,53	0,35	-4,09	3,81	3,47	0,00
1	P-Value	0,08	0,00	0,73	0,00	0,00	0,00	0,00
	Coef.	0,05	0,95	-0,29	0,22	-0,13	-0,37	0,72
	T-Stat.	0,29	15,12	-2,17	1,43	-0,91	-2,36	0,00
2	P-Value	0,77	0,00	0,03	0,15	0,36	0,02	0,00
	Coef.	-0,02	0,91	-0,08	0,13	-0,10	-0,16	0,79
	T-Stat.	-0,18	15,53	-1,17	1,02	-1,07	-1,52	0,00
3	P-Value	0,86	0,00	0,24	0,31	0,28	0,13	0,00
	Coef.	0,10	0,88	-0,14	0,06	0,08	0,13	0,77
	T-Stat.	0,72	19,97	-1,19	0,57	0,99	1,59	0,00
4	P-Value	0,47	0,00	0,24	0,57	0,32	0,11	0,00
	Coef.	-0,08	0,94	-0,31	0,02	0,11	0,30	0,81
	T-Stat.	-0,65	26,72	-3,73	0,23	1,59	3,56	0,00
5	P-Value	0,51	0,00	0,00	0,82	0,11	0,00	0,00
	Coef.	-0,01	1,04	0,24	-0,18	0,07	0,26	0,84
	T-Stat.	-0,10	29,29	3,56	-2,40	1,04	3,17	0,00
6	P-Value	0,92	0,00	0,00	0,02	0,30	0,00	0,00
	Coef.	-0,11	1,08	0,29	-0,24	0,23	0,09	0,79
	T-Stat.	-0,85	26,49	2,92	-2,53	2,41	0,87	0,00
7	P-Value	0,40	0,00	0,00	0,01	0,02	0,39	0,00
	Coef.	0,17	0,98	0,15	0,21	0,02	-0,24	0,80
	T-Stat.	1,06	20,91	1,62	1,81	0,27	-2,04	0,00
8	P-Value	0,29	0,00	0,11	0,07	0,79	0,04	0,00
	Coef.	0,03	1,21	0,52	0,04	0,18	-0,19	0,77
	T-Stat.	0,15	19,72	3,35	0,26	1,09	-1,09	0,00
9	P-Value	0,88	0,00	0,00	0,79	0,28	0,28	0,00
	Coef.	0,45	1,08	0,17	0,03	-0,40	-0,28	0,68
	T-Stat.	1,64	15,65	0,84	0,23	-2,05	-1,59	0,00
10	P-Value	0,10	0,00	0,40	0,82	0,04	0,11	0,00

Source: Own work.

Appendix 3: Single sorted returns regressed on the 6-factor model

Below are presented the full results from equation (54), where 10 NWC ratio single sorted excess returns are regressed on the FF-5 model.

Table 2: Single sorted returns regressed on the 6-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	TML	Adj-R
1	Coef.	-0,11	1,08	0,10	-0,28	0,21	0,22	0,39	0,85
	T-Stat.	-0,92	32,22	1,45	-4,89	3,32	3,22	6,04	0,00
	P-Value	0,36	0,00	0,15	0,00	0,00	0,00	0,00	0,00
2	Coef.	0,27	1,05	-0,16	0,17	-0,14	-0,40	0,70	0,81
	T-Stat.	1,49	16,43	-1,17	1,40	-1,45	-3,56	10,44	0,00
	P-Value	0,14	0,00	0,24	0,16	0,15	0,00	0,00	0,00
3	Coef.	0,10	0,97	0,00	0,10	-0,11	-0,18	0,41	0,83
	T-Stat.	1,01	17,87	-0,05	0,89	-1,58	-1,95	6,11	0,00
	P-Value	0,31	0,00	0,96	0,38	0,11	0,05	0,00	0,00
4	Coef.	0,09	0,88	-0,14	0,07	0,08	0,13	-0,03	0,77
	T-Stat.	0,65	19,27	-1,23	0,59	1,01	1,62	-0,44	0,00
	P-Value	0,52	0,00	0,22	0,56	0,31	0,11	0,66	0,00
5	Coef.	-0,14	0,92	-0,34	0,03	0,11	0,31	-0,18	0,82
	T-Stat.	-1,12	24,58	-4,50	0,43	1,89	3,95	-3,08	0,00
	P-Value	0,26	0,00	0,00	0,66	0,06	0,00	0,00	0,00
6	Coef.	-0,07	1,02	0,20	-0,16	0,07	0,27	-0,19	0,85
	T-Stat.	-0,57	30,62	2,68	-2,16	1,08	3,44	-2,86	0,00
	P-Value	0,57	0,00	0,01	0,03	0,28	0,00	0,00	0,00
7	Coef.	-0,14	1,07	0,28	-0,23	0,24	0,10	-0,09	0,79
	T-Stat.	-0,98	25,56	2,65	-2,58	2,55	0,94	-1,14	0,00
	P-Value	0,33	0,00	0,01	0,01	0,01	0,35	0,26	0,00
8	Coef.	0,08	0,94	0,10	0,23	0,03	-0,22	-0,26	0,82
	T-Stat.	0,55	19,59	1,01	1,96	0,30	-1,85	-3,22	0,00
	P-Value	0,58	0,00	0,32	0,05	0,76	0,07	0,00	0,00
9	Coef.	-0,13	1,14	0,42	0,07	0,19	-0,16	-0,54	0,81
	T-Stat.	-0,65	21,14	2,63	0,59	1,57	-1,00	-5,12	0,00
	P-Value	0,52	0,00	0,01	0,55	0,12	0,32	0,00	0,00
10	Coef.	0,23	0,98	0,03	0,08	-0,38	-0,24	-0,72	0,75
	T-Stat.	0,99	15,58	0,15	0,61	-2,51	-1,67	-5,30	0,00
	P-Value	0,33	0,00	0,88	0,54	0,01	0,10	0,00	0,00

Source: Own work.

Appendix 4: Double sorted returns regressed on the FF 5-factor model

Below are presented the results from equation (55), where 25 SIZE-NWC ratio double sorted excess returns are regressed on the FF-5 model. I break down the results in five tables for the results to be more clearly seen. In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 1.

Table 3: Double sorted returns regressed on the FF 5-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	Adj-R
1	Coef.	0,18	1,00	1,14	0,15	-0,14	-0,21	0,65
	T-Stat.	0,69	11,86	7,90	1,03	-1,16	-1,16	0,00
	P-Value	0,49	0,00	0,00	0,30	0,25	0,25	0,00
2	Coef.	-0,51	0,93	1,42	0,16	-0,13	-0,20	0,69
	T-Stat.	-2,36	15,14	9,45	1,15	-0,83	-1,39	0,00
	P-Value	0,0	0,00	0,00	0,25	0,41	0,17	0,00
3	Coef.	0,06	0,98	0,96	0,06	0,00	-0,02	0,67
	T-Stat.	0,27	13,73	6,83	0,38	0,01	-0,13	0,00
	P-Value	0,79	0,00	0,00	0,70	0,99	0,90	0,00
4	Coef.	0,13	1,06	1,20	-0,03	0,26	0,07	0,69
	T-Stat.	0,58	16,96	6,81	-0,20	1,87	0,40	0,00
	P-Value	0,56	0,00	0,00	0,84	0,06	0,69	0,00
5	Coef.	0,13	1,06	1,39	-0,05	0,13	-0,22	0,80
	T-Stat.	0,90	16,98	13,66	-0,50	1,22	-1,55	0,00
	P-Value	0,37	0,00	0,00	0,62	0,22	0,12	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group, but are included in the SIZE group 2.

Table 4: Double sorted returns regressed on the FF 5-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	Adj-R
1	Coef.	-0,17	1,00	0,46	0,11	0,25	0,03	0,71
	T-Stat.	-0,73	17,11	3,75	0,87	1,62	0,18	0,00
	P-Value	0,46	0,00	0,00	0,38	0,11	0,86	0,00
2	Coef.	-0,14	0,89	0,74	-0,08	0,04	0,16	0,73
	T-Stat.	-0,92	17,91	8,12	-0,73	0,46	1,23	0,00
	P-Value	0,4	0,00	0,00	0,46	0,65	0,22	0,00
3	Coef.	0,19	1,00	0,87	0,03	0,03	-0,14	0,78
	T-Stat.	1,13	15,45	8,83	0,27	0,33	-1,11	0,00
	P-Value	0,26	0,00	0,00	0,79	0,74	0,27	0,00
4	Coef.	0,06	1,01	0,84	0,10	0,12	-0,35	0,79
	T-Stat.	0,36	22,82	7,17	0,93	1,20	-2,93	0,00
	P-Value	0,72	0,00	0,00	0,35	0,23	0,00	0,00
5	Coef.	0,38	1,09	1,02	0,08	-0,02	-0,07	0,86
	T-Stat.	2,62	30,01	10,14	0,80	-0,18	-0,84	0,00
	P-Value	0,01	0,00	0,00	0,43	0,85	0,40	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 3.

Table 5: Double sorted returns regressed on the FF 5-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	Adj-R
1	Coef.	-0,23	0,89	0,49	0,04	0,05	0,05	0,73
	T-Stat.	-1,30	18,98	6,68	0,59	0,59	0,46	0,00
	P-Value	0,19	0,00	0,00	0,56	0,55	0,65	0,00
2	Coef.	-0,05	0,97	0,36	-0,15	0,11	0,32	0,71
	T-Stat.	-0,29	21,28	3,08	-1,48	0,97	3,71	0,00
	P-Value	0,8	0,00	0,00	0,14	0,33	0,00	0,00
3	Coef.	0,03	0,93	0,62	-0,11	0,20	0,30	0,76
	T-Stat.	0,17	19,39	6,84	-1,30	2,12	2,35	0,00
	P-Value	0,86	0,00	0,00	0,20	0,03	0,02	0,00
4	Coef.	0,01	0,97	0,72	-0,12	0,15	0,13	0,77
	T-Stat.	0,09	24,64	8,54	-1,45	1,87	1,15	0,00
	P-Value	0,93	0,00	0,00	0,15	0,06	0,25	0,00
5	Coef.	0,08	1,01	0,65	-0,16	0,08	0,13	0,74
	T-Stat.	0,41	19,68	4,60	-1,51	0,52	0,97	0,00
	P-Value	0,68	0,00	0,00	0,13	0,60	0,33	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 4.

Table 6: Double sorted returns regressed on the FF 5-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	Adj-R
1	Coef.	0,13	0,89	0,28	0,11	-0,03	0,04	0,76
	T-Stat.	0,90	20,70	3,35	0,74	-0,37	0,25	0,00
	P-Value	0,37	0,00	0,00	0,46	0,71	0,80	0,00
2	Coef.	0,13	0,95	0,18	0,36	0,00	-0,26	0,81
	T-Stat.	0,91	24,85	2,32	4,20	-0,03	-2,79	0,00
	P-Value	0,4	0,00	0,02	0,00	0,97	0,01	0,00
3	Coef.	-0,01	1,03	0,44	0,13	0,13	0,13	0,80
	T-Stat.	-0,07	20,20	6,11	1,17	1,49	1,05	0,00
	P-Value	0,94	0,00	0,00	0,24	0,14	0,30	0,00
4	Coef.	0,04	1,05	0,28	0,10	0,39	-0,19	0,68
	T-Stat.	0,18	13,87	1,92	0,84	2,00	-1,04	0,00
	P-Value	0,86	0,00	0,06	0,40	0,05	0,30	0,00
5	Coef.	0,26	1,05	0,61	0,18	-0,22	-0,19	0,69
	T-Stat.	0,96	12,40	3,22	0,97	-1,68	-1,19	0,00
	P-Value	0,34	0,00	0,00	0,33	0,09	0,23	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 5.

Table 7: Double sorted returns regressed on the FF 5-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	Adj-R
1	Coef.	-0,11	1,00	-0,44	-0,04	0,08	-0,17	0,75
	T-Stat.	-0,73	21,00	-4,73	-0,44	0,82	-1,37	0,00
	P-Value	0,47	0,00	0,00	0,66	0,41	0,17	0,00
2	Coef.	-0,03	0,88	-0,30	0,06	-0,07	0,06	0,77
	T-Stat.	-0,22	16,76	-2,93	0,90	-0,98	0,88	0,00
	P-Value	0,8	0,00	0,00	0,37	0,33	0,38	0,00
3	Coef.	-0,06	0,95	-0,26	-0,10	0,06	0,33	0,84
	T-Stat.	-0,57	31,28	-4,16	-1,27	0,86	4,06	0,00
	P-Value	0,57	0,00	0,00	0,21	0,39	0,00	0,00
4	Coef.	-0,09	1,08	-0,07	-0,06	0,18	-0,07	0,81
	T-Stat.	-0,68	28,33	-0,91	-0,70	2,75	-0,72	0,00
	P-Value	0,50	0,00	0,36	0,48	0,01	0,47	0,00
5	Coef.	0,45	1,23	-0,47	0,31	-0,44	-0,52	0,68
	T-Stat.	1,49	16,67	-2,27	1,87	-2,28	-2,60	0,00
	P-Value	0,14	0,00	0,02	0,06	0,02	0,01	0,00

Source: Own work.

Appendix 5: Double sorted returns regressed on the 6-factor model

Below are presented the results from equation (56), where 25 SIZE-NWC ratio double sorted excess returns are regressed on the FF-6 model. I break down the results in five tables for the results to be more clearly seen. In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 1.

Table 8: Double sorted returns regressed on the 6-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	TML	Adj-R
1	Coef.	0,27	1,05	1,19	0,13	-0,15	-0,22	0,30	0,66
	T-Stat.	1,09	13,06	7,90	0,92	-1,40	-1,25	2,01	0,00
	P-Value	0,28	0,00	0,00	0,36	0,16	0,21	0,05	0,00
2	Coef.	-0,42	0,97	1,48	0,14	-0,14	-0,22	0,29	0,70
	T-Stat.	-1,96	14,56	9,51	1,01	-1,01	-1,54	2,52	0,00
	P-Value	0,05	0,00	0,00	0,31	0,31	0,12	0,01	0,00
3	Coef.	0,02	0,95	0,93	0,08	0,00	-0,01	-0,16	0,67
	T-Stat.	0,07	13,84	6,60	0,47	0,03	-0,08	-1,36	0,00
	P-Value	0,94	0,00	0,00	0,64	0,97	0,93	0,18	0,00
4	Coef.	0,08	1,03	1,16	-0,02	0,26	0,08	-0,18	0,69
	T-Stat.	0,35	16,89	6,47	-0,12	1,90	0,46	-1,65	0,00
	P-Value	0,73	0,00	0,00	0,91	0,06	0,65	0,10	0,00
5	Coef.	0,04	1,02	1,33	-0,03	0,13	-0,21	-0,30	0,81
	T-Stat.	0,28	15,94	13,09	-0,34	1,42	-1,38	-3,02	0,00
	P-Value	0,78	0,00	0,00	0,74	0,16	0,17	0,00	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 2.

Table 9: Double sorted returns regressed on the 6-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	TML	Adj-R
1	Coef.	-0,09	1,04	0,51	0,09	0,25	0,02	0,25	0,72
	T-Stat.	-0,39	18,30	3,64	0,79	1,41	0,10	2,57	0,00
	P-Value	0,70	0,00	0,00	0,43	0,16	0,92	0,01	0,00
2	Coef.	-0,08	0,92	0,77	-0,10	0,03	0,15	0,19	0,73
	T-Stat.	-0,58	17,66	8,66	-0,81	0,44	1,11	2,32	0,00
	P-Value	0,56	0,00	0,00	0,42	0,66	0,27	0,02	0,00
3	Coef.	0,17	0,98	0,86	0,03	0,03	-0,14	-0,09	0,78
	T-Stat.	0,96	15,41	8,54	0,33	0,36	-1,05	-1,13	0,00
	P-Value	0,34	0,00	0,00	0,74	0,72	0,30	0,26	0,00
4	Coef.	0,03	1,00	0,83	0,11	0,13	-0,35	-0,08	0,79
	T-Stat.	0,20	22,41	7,16	0,95	1,23	-2,80	-1,14	0,00
	P-Value	0,84	0,00	0,00	0,34	0,22	0,01	0,26	0,00
5	Coef.	0,26	1,04	0,94	0,11	-0,01	-0,05	-0,42	0,89
	T-Stat.	2,10	32,46	9,51	1,18	-0,10	-0,68	-5,56	0,00
	P-Value	0,04	0,00	0,00	0,24	0,92	0,50	0,00	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 3.

Table 10: Double sorted returns regressed on the 6-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	TML	Adj-R
1	Coef.	-0,09	0,95	0,58	0,01	0,04	0,03	0,44	0,77
	T-Stat.	-0,59	20,12	7,15	0,16	0,46	0,22	5,89	0,00
	P-Value	0,55	0,00	0,00	0,87	0,64	0,83	0,00	0,00
2	Coef.	-0,01	0,98	0,38	-0,16	0,11	0,32	0,11	0,71
	T-Stat.	-0,07	21,65	2,97	-1,57	0,89	3,50	1,00	0,00
	P-Value	0,94	0,00	0,00	0,12	0,38	0,00	0,32	0,00
3	Coef.	-0,03	0,90	0,58	-0,10	0,20	0,31	-0,19	0,77
	T-Stat.	-0,22	18,03	6,62	-1,24	2,44	2,65	-2,88	0,00
	P-Value	0,83	0,00	0,00	0,22	0,02	0,01	0,00	0,00
4	Coef.	-0,07	0,93	0,66	-0,10	0,15	0,15	-0,29	0,79
	T-Stat.	-0,52	21,21	7,56	-1,10	2,20	1,28	-3,55	0,00
	P-Value	0,61	0,00	0,00	0,27	0,03	0,20	0,00	0,00
5	Coef.	-0,07	0,94	0,55	-0,12	0,09	0,16	-0,50	0,78
	T-Stat.	-0,41	20,66	4,37	-1,22	0,82	1,34	-7,05	0,00
	P-Value	0,68	0,00	0,00	0,23	0,41	0,18	0,00	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 4.

Table 11: Double sorted returns regressed on the 6-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	TML	Adj-R
1	Coef.	0,22	0,93	0,34	0,09	-0,03	0,02	0,28	0,78
	T-Stat.	1,48	20,14	4,39	0,67	-0,50	0,16	3,52	0,00
	P-Value	0,14	0,00	0,00	0,50	0,62	0,87	0,00	0,00
2	Coef.	0,17	0,98	0,20	0,35	-0,01	-0,26	0,15	0,81
	T-Stat.	1,24	24,29	2,69	3,94	-0,08	-2,82	2,51	0,00
	P-Value	0,22	0,00	0,01	0,00	0,94	0,01	0,01	0,00
3	Coef.	-0,10	0,99	0,38	0,15	0,14	0,15	-0,30	0,81
	T-Stat.	-0,62	19,34	4,94	1,43	1,84	1,23	-3,69	0,00
	P-Value	0,54	0,00	0,00	0,15	0,07	0,22	0,00	0,00
4	Coef.	-0,01	1,03	0,25	0,11	0,39	-0,18	-0,17	0,69
	T-Stat.	-0,06	12,49	1,63	0,93	2,14	-0,95	-1,27	0,00
	P-Value	0,95	0,00	0,11	0,35	0,03	0,34	0,21	0,00
5	Coef.	0,07	0,96	0,50	0,22	-0,20	-0,16	-0,60	0,74
	T-Stat.	0,31	12,12	2,70	1,35	-1,76	-1,09	-4,94	0,00
	P-Value	0,76	0,00	0,01	0,18	0,08	0,28	0,00	0,00

Source: Own work.

In the table below are presented the results of portfolios that vary in the NWC ratio group but are included in the SIZE group 5.

Table 12: Double sorted returns regressed on the 6-factor model

Port.	Stat.	α	MKT	SMB	HML	CMA	RMW	TML	Adj-R
1	Coef.	0,09	1,09	-0,31	-0,09	0,07	-0,20	0,65	0,84
	T-Stat.	0,68	23,06	-2,97	-1,25	0,82	-2,15	8,51	0,00
	P-Value	0,50	0,00	0,00	0,21	0,41	0,03	0,00	0,00
2	Coef.	0,03	0,91	-0,26	0,04	-0,07	0,05	0,21	0,78
	T-Stat.	0,22	17,49	-2,64	0,62	-1,08	0,72	4,21	0,00
	P-Value	0,83	0,00	0,01	0,53	0,28	0,47	0,00	0,00
3	Coef.	-0,11	0,93	-0,29	-0,08	0,06	0,34	-0,16	0,84
	T-Stat.	-1,01	30,02	-4,62	-1,15	0,92	4,43	-2,62	0,00
	P-Value	0,31	0,00	0,00	0,25	0,36	0,00	0,01	0,00
4	Coef.	-0,13	1,06	-0,10	-0,05	0,18	-0,06	-0,15	0,82
	T-Stat.	-1,05	25,80	-1,22	-0,62	2,81	-0,66	-1,93	0,00
	P-Value	0,29	0,00	0,23	0,54	0,01	0,51	0,06	0,00
5	Coef.	0,16	1,10	-0,65	0,38	-0,42	-0,47	-0,96	0,77
	T-Stat.	0,63	17,64	-3,76	2,53	-3,00	-3,33	-9,32	0,00
	P-Value	0,53	0,00	0,00	0,01	0,00	0,00	0,00	0,00

Source: Own work.