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The five-factor model in The Netherlands

Measuring the effectiveness of different factor models in the Dutch stock market

Bachelorscriptie economie en bedrijfseconomie

Auteur: Eduard Th.J. Jansen

Studentnummer: 375670

Scriptiebegeleider: Dr. J. Kil

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ABSTRACT

This research attempts to answer the question: How does the five-factor model by Fama & French (2015) perform in predicting returns on the stock market of The Netherlands, and does it perform better than the three-factor model and CAPM? The first question is answered by constructing portfolios based on different company-specific characteristics. The research shows differences in stock returns of the different portfolios, although regression analysis shows little effectiveness of the risk factors in explaining stock returns. Based on this, the effectiveness of the five-factor model in the Dutch stock market cannot be validated. The added value of the five-factor model over the three-factor model and the CAPM is clear: the explanatory power increases by several different measures: a GRS test is performed, along with the comparison of the absolute α values and R^2 values. The findings can be interpreted in different manners. The increased explanatory power of the five-factor model over the three-factor model and CAPM suggests the search for the correct risk factors needs to be continued. On the other hand, the disappointing performance of the five-factor model in an absolute sense possibly suggests that the factor-based approach is an inappropriate one when it comes to explaining Dutch stock returns.

Keywords: stock pricing, stock returns, factor model, risk factor

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Table of contents

1. Introduction

Explaining stock returns has been a topic of interest for both financial researchers and investors. The mysteriously high returns not being explained by traditional economic models has been referred to as the ‘equity premium puzzle’ (Mehra & Prescott, 1985). In line with the efficient market hypothesis (EMH) (Fama, 1970), theory states that risk is at the basis of explaining these returns and has prompted researchers to come up with models to capture this. The well-known capital asset pricing model (CAPM) uses a single factor β to explain systematic risk (Sharpe, 1964). Research showing that this single factor cannot capture all risk (Reinganum, 1981) has inspired researchers to find more risk-based factors that explain stock returns. Fama and French (1993) expanded on the CAPM and developed a three-factor model. A more recent and widely used model is the five-factor model that captures a market risk factor, along with size, book-to-market ratio (B/M), profitability and investing attitude (Fama & French, 2015).

The five-factor model was originally developed, tested and validated on US stock exchanges, specifically the NYSE, AMEX and NASDAQ (Fama & French, 2015; 2016). But how well does it work on markets with different investors and firms with different characteristics? The Dutch stock market is characterized by being small in market capitalization, with a small group of companies making up most of the value of the 25 companies of the AEX, the main Dutch stock index. Calendar anomalies such as the January effect, persistent abnormal returns in December and the turn-of-the-month effect have been documented to occur (Gultekin & Gultekin, 1983; Van der Sar, Calendar Effects on the Amsterdam Stock Exchange, 2003). Furthermore, it is suggested that contrarian momentum-based strategies yield higher returns (Doeswijk, 1997). These findings suggest a Dutch violation of the efficient market hypothesis (Fama, 1970). Based on this notion one can argue whether the Dutch stock returns can be explained with a factor-based model. However, the five-factor model has been shown to have explanatory power in Europe as a whole and in the United States (Fama & French, 2016) even though many markets, including the US, have experienced the same anomalies (Gultekin & Gultekin, 1983; Jegadeesh & Titman, 1993; Hawawini & Keim, 1995). These conflicting observations ask for more research on risk-based explanations in markets where ‘irrational’ behavior seems to be present.

Fama and French continue their search of more risk factors to explain stock market returns and hesitate to accept that behavioral traits may have a stronger influence on stock returns. This research attempts to answer the question: How does the five-factor model by Fama & French (2015) perform in predicting returns on the stock market of The Netherlands, and does it perform better than the three-factor model and CAPM?

The research shows differences in stock returns of stock portfolios based on different characteristics, although it is difficult to statistically distinguish a clear pattern based on risk factors. Based on this, the effectiveness of the five-factor model in the Dutch stock market cannot be validated. The added value of the five-factor model over the three-factor model and the CAPM is clear: the explanatory power increases by several different measures. The findings can be interpreted in different manners. The increased explanatory power of the five-factor model over the three-factor model and CAPM suggests the search for the correct risk factors needs to be continued. On the other hand, the disappointing performance of the five-factor model in an absolute sense possibly suggests that the factor-based approach is an inappropriate one when it comes to explaining Dutch stock returns.

This paper is structured as follows: section 2 is a literature review that gives an overview on different factors that have been claimed to explain stock returns. It also touches on the empirical evaluation of the five-factor model in different markets. Lastly it contains a section on the characteristics of returns in the Dutch stock market. Section 3 describes the data that is used for the research and explains the methodology used. It shows how portfolios are constructed to calculate risk factors, and how the performance of models can be compared. The data section also contains tables with descriptive statistics which are discussed. Special attention is given to differences in average returns between portfolios, and different returns during the global economic crisis. Section 4 presents the results of the research and discusses whether this is in line with the expectations and existing literature. The last section gives a brief conclusion of the paper.

2. Literature review

Factors predicting stock returns

A belief in finance theory, shared by Fama and French in their works, is that stock returns are to a certain extent compensation for stockholder risk. Sharpe (1964) attempted to show that all returns could be explained by a single systematic risk factor in his capital asset pricing model (CAPM), as seen in equation 1.

$$ER_i = R_f + \beta_i(ER_m - R_f) \quad \textbf{(1)}$$

In equation 1, ER_i represents the expected return on investment i, and ER_m represents the expected return on a market portfolio. R_f is the risk-free rate. Lastly, β_i captures the amount of market risk exposure. As can be seen in the formula, risk and expected return have a positive relationship. However, the CAPM has been shown to not fully predict stock returns, thus not fully capturing the risk exposure in β. For example, research has shown that portfolios based on firm size and P/E ratio generate systematically different returns, implying there are other factors that influence risk (Reinganum, 1981).

Fama & French factors

Fama & French (1992) observed that several fundamental factors were suggested to have explanatory power. Research showed relationships between returns and market value (Banz, 1981; Reinganum, 1981), the debt-to-equity ratio (Bhandari, 1988), the book-to-market (B/M) ratio (Stattman, 1980; Rosenberg, Reid, & Lanstein, 1985) and earnings-to-price ratio (Basu, 1983; Reinganum, 1981). Most of these factors have in common that they refer to the market value of the companies. To avoid multicollinearity and to reach parsimony, Fama and French (1993) add market value (also referred to as size) and B/M to the CAPM to develop a three-factor model (equation 2) to more accurately explain stock returns.

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB + h_i HML + e_{it} \quad \textbf{(2)}$$

In equation 2, R_{it} represents the return of i in period t. R_{Ft} is the risk-free rate in the same period. R_{Mt} is the return on the market portfolio. SMB (small-minus-big) is a size-related factor. The size effect[1], or small firm effect, holds that firms with smaller market capitalization generate higher returns than large firms, and thus implies that there is a negative relationship between size and abnormal returns. There are many hypothetical explanations for this effect, but none can adequately explain the presence of the effect (Van Dijk, 2011). HML (high-minus-low) is related to the book-to-market (B/M) ratio. Firms with a high B/M ratio are often referred to as value stocks. Firms with low B/M ratio are referred to as growth or glamour stocks. The value effect states that value stocks outperform growth stocks. Possible explanations for this are based on mispricing and suboptimal

[1] Despite claims that the size effect has been dead since the 1980s, size still has an influence on stock returns and is therefore included in the three-factor and five-factor models (Van Dijk, 2011)

investor behavior (Lakonishok, Shleifer, & Vishny, 1994) or on increased risk associated with high B/M (Fama & French, 1993).

Research shows that more factors have explaining power. It is shown that, despite higher valuations, firms with high profits-to-assets have greater returns (Novy-Marx, 2013). More explanatory power can be assigned to investment. Expected investment (expressed as asset growth) has a negative influence on the return (Aharoni, Gundy, & Zeng, 2013; Titman, Wei, & Xie, 2004). This can be explained through 'empire building' tendencies of managers, which means that managers make investment decisions with personal motives rather than only for the adding of value (Titman, Wei, & Xie, 2004). The five-factor model by Fama & French (2015) expands on the three-factor model of equation 2, and is shown below in equation 3

$$R_i - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{it} \quad \textbf{(3)}$$

with a profitability factor RMW (robust-minus-weak) and an investment attitude factor CMA (conservative-minus-aggressive, implying less investment leads to higher returns) added. Interestingly, they acknowledge that HML could be ommitted if parsimony was pursued. This is line with earlier research that showed a strong correlation between size and B/M-ratio (Chan, Karceski, & Lakonishok, 1998).

The interpretation of the factors is based on an important assumption by Fama and French (1992; 1993; 2015). The goal is to have factors that represent the risk related to a certain factor. The assumption made by Fama and French is that returns are a proxy for this risk. The factors therefore show the difference in returns between firms with a large amount and a small amount of a certain factor (in this case size, B/M, profitability or investment).

Macroeconomic factors

Chen, Roll and Ross (1986) were one of the first to find that stocks are (in part) priced according to their exposure to macroeconomic factors. They find that interest rates, expected and unexpected inflation, industrial production growth and bond prices are sources of risk that are priced in stock portfolios. There is more empirical support for priced macroeconomic factors: inflation (both in consumer price index and producer price index), and M1[2] also directly influence the return on the market portfolio (Flannery & Protopapadakis, 2002). However, findings are contradictory. In their evaluation of factors, Chan et al. (1998) find that macroeconomic factors have little impact at all: industrial production growth, real interest rate, slope of the yield curve, change in expected inflation and unexpected inflation are surprisingly useless in explaining return covariation[3]. In their findings only default premium and maturity premium have decent explanatory power. Chan et al. (1998, p.

[2] M1 is the absolute value of the most liquid portion of the money supply in an economy, containing currency and assets that can be quickly converted into cash.
[3] Chan et al. (1998) research the covariance between returns of portfolios formed based on different factors and expected returns. The reasoning behind this is that if the covariance is large, the underlying factors are good at explaining the overall returns.

175) could not explain these poor results other than with measurement errors. Whether macroeconomic factors exist or not, Fama and French build their models solely on firm-specific factors, as these represent diversifiable unsystematic exposures to risk. One could argue that systematic macroeconomic factors are captured in *b*.

Momentum factors

De Bondt and Thaler (1985) were one of the first to suggest that stock prices, like individuals, overreact to information. This overreaction would eventually lead to a correction, suggesting that contrarian strategies could lead to abnormal returns. A portfolio based on this potential violation of the efficient market hypothesis (EMH), consisting of past losers, performs significantly better than a portfolio that consists of winners, and this effect lasts from three to five years (De Bondt & Thaler, 1985). However, there is no agreement that these abnormal returns are caused by momentum (and thus by overreactive behavior of investors). Some suggest the risk of the investments changes during the period and the high returns are simply a reward for the increased risk (Chan K. C., 1988; Ball & Kothari, 1989). A risk-based suggestion is that losers experience an increase in relative leverage, resulting in an increase in systematic risk. It has also been suggested that the losers are of smaller size and that it is simply the size effect that is behind the high returns (Zarowin, 1990). Chopra, Lakonishok and Ritter (1992) provide a different theory. They suggest small investors overreact more and invest more in small firms, resulting in a stronger overreaction effect in small firms.

Later research considers the size effect and still finds a momentum effect, albeit a different (shorter) one (Jegadeesh & Titman, 1993). This one year-momentum effect shows that losers outperform winners only in the first three to twelve months after portfolio formation, and this is not due to changes in risk.

Carhart (1997) observed that the three-factor model could not explain variation in momentum-sorted portfolios (Fama & French, 1993). Carhart expanded the three-factor model with a momentum factor to create a four-factor model as seen below:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB + h_i HML + p_i PR1YR_t + e_{it} \quad \textbf{(4)}$$

where *PR1YR* is the one-year momentum as described by Jegadeesh and Titman (1993). The models of Fama and French (1993; 2015) do not use momentum factors. However, they do acknowledge that the addition of momentum factors in some cases performs better than the CAPM and three-factor model (Fama & French, 2012).

Evaluation of the five-factor model

To test the five-factor model (Fama & French, 2015) outside the USA, Fama & French (2016) applied it to four regions: North America, Europe, Asia Pacific and Japan. For the first three geographies, they find that returns increase with *SMB*, *RMW* and *CMA*. These results are as expected. In Japan however, profitability and investment do not strongly influence returns (Kubota &

Takehara, 2018), and in Europe investment is also redundant (Fama & French, 2016). Additionally, the model has trouble explaining the excessively low returns of small stocks with low profit and aggressive investment attitude (Fama & French, 2016). A clear explanation for these findings was not given and the authors ask for additional research.

Criticism on Fama and French

The strong focus of Fama and French on firm-specific attributes and the seemingly all-important role of risk on variations in returns has often been criticized. The assumption that risk is solely at the basis of stock returns is an important one with respect to the efficient market hypothesis. Van der Sar (2018) states there are three ways of looking at return anomalies: the statistical view, the risk view (supported by Fama and French) and the behavioral view. In the first view, predictive value is unjustly assigned to empirical relations which only exist due to statistical errors such as data snooping and survivor bias. The risk view, which has been extensively described already, states that the firm-specific characteristics are proxies for risk and therefore justify an excess return. The third view states that the differences in returns are the result of systematic mispricing in the market, without there necessarily being an increased risk. This behavioral view contrasts strongly with the EMH and therefore the risk view. As an example for behavior-based returns, the value effect has been said to be a result of overreaction in the market, without there being adequate risk to counter the abnormal returns (Lakonishok, Shleifer, & Vishny, 1994).

The factor construction method of Fama and French has also been criticized. Recall that the Fama-French method uses return differences and interprets this as risk exposure, thus directly implying the one on one relation between risk and return. This method has been questioned before, as a return relationship does not necessarily represent a risk relationship. To illustrate this, Ferson, Sarkissian and Simin (1999) create portfolios based on the first letter of a firm's name and show return differences, even though it is hard to imagine that the letters in the name of a company have any influence on risk whatsoever. Daniel and Titman (1997) have argued that covariation in stock returns are due to similar characteristics such as country or industry, and not due to distress factors. It has also been shown (and this has been partially confirmed by Fama and French (2016) themselves) that the same portfolio distinctions cannot be made in an international context, even though one would expect so in an integrated international market (Hawawini & Keim, 1995).

Explaining Dutch stock returns

Overall research shows that there is reason to believe that the Dutch stock market is inefficient. It is unlikely that complete efficiency is required for a factor-based model to have explanatory value, but inefficiency certainly shows that the factors are not the single thing explaining returns. For example, the five-factor model has been tested and validated in the US, even though many anomalies, such as momentum and calendar anomalies, have been observed in the US (De Bondt & Thaler, 1985; Lakonishok & Smidt, 1988). The Dutch stock market shows calendar anomalies such as the January effect, abnormally high returns in December, the turn-of-the-month effect and the twist-on-the-Monday effect (Van der Sar, Calendar Effects on the Amsterdam Stock Exchange, 2003; Gultekin & Gultekin, 1983). These effects imply that the time of year, month, week or even day have an effect on the returns, even though it is difficult to imagine that these have an influence on risk exposure. These findings are incompatible with the EMH.

Previous research has suggested that the size effect is not present in the Dutch stock market in the observed period 1976-1994 (Doeswijk, 1997). The same research shows that a contrarian momentum-based strategy on the AEX yields abnormal returns, without this being a compensation for higher risk. One of the measures of undervaluation used is high B/M, suggesting a high B/M yields higher return (in line with the expectations of Fama and French (1993; 2015)). The possibility of gaining abnormal returns with a momentum-based strategy is more evidence that the EMH is not applicable to the Dutch stock market.

These incompatibilities of the Dutch stock market with the EMH can be the meaning of two things, both of which impair the theoretical effectiveness of the five-factor model. Either it means that the used factors do not fully capture the risk (and that the, perhaps hypothetical, correct factors are subject to seasonality themselves), or it means that the returns cannot be explained by risk and are determined by other (perhaps behavioural) influences. However, it seems that, in line with the validation of the five-factor model in the inefficient US market, a certain degree of inefficiency does not necessarily render the model useless. The five-factor model is expected to have low explanatory power in the Dutch market due to the inefficiencies of this market, although the contrary would not be surprising, based off the US-based evidence.

3. Data & methodology

Data

This paper tests the effectiveness of the five-factor model in the Dutch stock market. The market is characterized by it being small, both in number of listed companies and in market capitalization. The main Dutch stock index, the AEX, contains 25 companies of which the market capitalization ranges between US$300 billion and US$4,5 billion. Those numbers are small compared to, for example, the S&P 500, whose 500 constituents range between a market capitalization of US$1050 billion and US$7 billion[4]. Because of the small amount of companies in the AEX index, no exclusions will be made based on company-specific characteristics[5] and all will be considered in this research.

Data from 1999 until now is used, to create portfolios containing stocks from 2000 until 2017. The recent time period has been chosen to give more insight in the current and more recent factors behind stock returns, which are more interesting to investors, rather than the full historical developments. This period features high volatilities due to the economic crisis of 2008 and the period around it, and stocks in this period are expected to be less rationally priced (based on risk) and are expected to be more heavily influenced by behavioral factors than other periods. This would of course diminish the effectiveness of the five-factor model. Despite this, the available literature gives no special attention the economic crises of 2008 or other time periods. The only observation made is that risk factor exposures are sometimes different in periods of poor market performance (Chiah, Chai, Zhong, & Li, 2016). This means that the crisis may have an influence on the average risk exposures of portfolios over time, but for regression analysis this poses no problems.

Each year, the stocks which the AEX contains are put into portfolios. Although no stocks are excluded purely because of their characteristics, not all stocks are counted. As will be described in the variables section, the accounting information of December of year t-1 is used, as that is when the fiscal year ends. This information is applicable to period t. Monthly returns are used from July in year t until June in year t+1 (e.g. a 2017 portfolio relates to a portfolio formed in June 2017 with returns from July 2017 – June 2018). This six-month delay is to make sure that the characteristics are known to investors and is conform the Fama-French methodology (Fama & French, 1993; 2015). Because of this, only the companies that are listed in the full period of December t-1 until June t+1 are used. This means that, due to companies dropping in and out of the AEX index, and thus not being listed for a full formation period, the portfolios contain less than the usual 25 firms. The AEX constituents of the period December 1999 until June 2018 are retrieved from CompuStat Global of the Wharton

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[4] Market capitalization of index constituents as of July 2019.

[5] Some research excludes financial institutions from the dataset due to their atypical debt structures (Fama & French, 1992).

Research Data Services (WRDS). This results in a list of 71 companies that have been part of the index during this time period. For each of these firms stock price, market capitalization, total assets, total liabilities and EBIT are retrieved from Thomson One Datastream. This data is used to compute the factors as described in the variables section. Due to missing or incorrect data, KLM Royal Dutch Airlines (pre-merger with Air France), Royal Dutch Petroleum N.V. (pre-Shell merger in 2005, after which Royal Dutch Shell enters the index, for which the correct data is available), Corus Group PLC and TNT Express N.V. are not counted.

Variables

The US T-Bill 3 Month rate is used as the risk-free rate. The annualized risk-free rate is converted into a monthly number with $R_{Ft} = R_{F,annual}^{1/12}$. The market rate used is the value-weighted monthly return on the AEX index[6].

Size is simply expressed as market capitalization (*M*). That is stock price times the amount of ordinary stock outstanding. The book value is defined as the book value of equity: total assets (*TA*) minus total liabilities (*TL*). The book-to-market ratio is then defined as

$$\frac{B}{M} = \frac{TA - TL}{M} \quad \textbf{(5)}$$

Operating profitability is defined as

$$OP = \frac{EBIT}{B} \quad \textbf{(6)}$$

with *EBIT* standing for earnings before interest and tax, and *B* expressing book value in the same way as in equation 5.

Investment is expressed as asset growth. This is in line with Chiah et al. (2016) and Fama and French (2015). Following these studies, the factor is defined as

$$INV = AG_t = \frac{TA_t}{TA_{t-1}} - 1 \quad \textbf{(7)}$$

with TA_t as total assets in year *t*.

The variables *OP* and *INV* used for portfolio formation (formation happens at the end of June) are calculated using data of the end of December of year t-1. This is because the accounting data used to calculate the variables is released in December at the end of the fiscal year. It is common practice to also use the *B/M* of the end of the fiscal year. However, Asness and Frazzini (2013) argue this is inaccurate and unnecessary, since up-to-date market value for public firms is always available. Therefore, the B/M ratio is calculated using the M of the date of portfolio formation.

[6] In the actual weighting of the AEX index, Euronext caps the weight of invidual firms at 15% so a single stock cannot have a too strong influence on the performance of the index. For example, the market capitalization of Royal Dutch Shell is around 28% of the total market capitalization of the 25 AEX index, as of August 2019.

Methodology

This section describes the methodology used in this research, which is largely based on the method as developed by Fama and French (1992; 1993; 2015) and will rely on elements that are common practice in this type of research.

Portfolio formation

Portfolios for the five-factor model are used for two different goals and will be constructed in two different ways. These portfolio returns will be used in the regression, using equation 3. The explanatory results are referred to as the right-hand side (RHS) factors and are developed using the differences between returns of portfolios and are to be interpreted as risk associated with these differences. Different portfolios are created generating left-hand side (LHS) returns that are to be explained by the RHS risk factors.

RHS factors (explanatory variables)

The explanatory variables are calculated with the use of 2 x 3 portfolios. This means that the portfolios are based on two company characteristics (e.g. Size x B/M), of which the first is divided into 2 categories (e.g. Size: the 50% of companies with the largest size vs. the 50% with the smallest size), and the second is divided into 3 categories (e.g. B/M: the 30% of companies with the highest B/M, the 30% with the lowest B/M, and the 40% in between. This will be explained in more detail in the next paragraph. Different breakpoints (e.g. 2 x 2 or 2 x 2 x 2 x 2) can be used, but it has been shown that the model's performance is not sensitive to how the factors are defined (Fama & French, 2015). It is important to understand the interpretation of the factors. The factors show the return difference that a certain attribute causes and, as reasoned by Fama and French (1992; 1993; 2015), therefore mimic the risk related to these attributes. For example, the Size factor is expressed as SMB (small-minus-big) and shows the difference between the returns, and thus risk, of portfolios with small stocks and portfolios with big stocks. Similarly, the HML factor shows the difference in returns between value (high B/M) and growth/glamour stocks (low B/M), RMW shows the difference in returns between high- and low-profit firms and CMA shows how much more returns are generated by conservatively investing firms than by aggressively investing firms.

For the years 2000 to 2017, portfolios are formed in which the AEX stocks are divided. Every year at the end of June, the stocks are put into categories. Each June, the portfolios are made up again. The 50% of stock above that month's median market capitalization are put in the big (B) category, the lower 50% are in the small (S) category. For factors HML, RMW and CMA there are three categories: above the 70th percentile, below the 30th percentile and a neutral category in between. Using these classifications, 2 x 3 portfolios are created. For example, we get an SH portfolio that contains companies that fall in the small category, and in the high B/M category. Using this method, six Size-B/M portfolios, six Size-OP portfolios and six Size-Inv portfolios are obtained, reaching a total 18 portfolios per year. For 17 years this leads to 306 portfolios. For each stock the average monthly return for that year is retrieved, and after being value-weighted these are combined into average monthly portfolio returns for each year. The returns are used to create the factors used later in the regression analysis. A more detailed explanation of the factor calculation can be found in table 1.

Table 1

Stocks are allocated and put into categories. For the market capitalization, stocks are allocated to small (S) or big (B). For the book-to-market ratio, stocks are allocated to high (H), neutral (N), or low (L). For the operating profitability, stocks are allocated to robust (R), neutral (N), or weak (W). For the investment attitude, stocks are allocated to conservative (C), neutral (N), or aggressive (A). For each year's portfolio the factors are calculated as described below.

Sort	Breakpoints	Factor calculation
Size portfolios	Median size	$SMB_{B/M}$ = [(SH + SN + SL) – (BH + BN + BL)]/3
		SMB_{OP} = [(SR + SN + SW) – (BR + BN + BW)]/3
		SMB_{INV} = [(SC + SN + SA) – (BC + BN + BA)]/3
		SMB = ($SMB_{B/M}$ + SMB_{OP} + SMB_{INV})/3
2 x 3 sort on Size-B/M	30^{th} and 70^{th} percentile	HML = [(SV – SG) + (BV – BG)]/2
2 x 3 sort on Size-OP	30^{th} and 70^{th} percentile	RMW = [(SR + BR) – (SW + BW)]/2
2 x 3 sort on Size-Inv	30^{th} and 70^{th} percentile	CMA = [(SC + BC) – (SA + BA)]/2

Descriptive statistics of RHS factors

The factors, of which the definition has been described in the previous section, can be found for each year in table 2.

Table 2: Descriptive statistics of RHS factors

Below are the RHS factor for each year that are to be used in the regression: the market factor and SMB, HML, RMW and CMA, calculated in the way described in table 1.

	SMB	HML	RMW	CMA
2000	2,42%	-3,24%	7,12%	1,84%
2001	0,78%	1,48%	0,91%	-0,42%
2002	1,35%	-2,72%	-1,45%	0,91%
2003	1,95%	-1,68%	2,07%	0,68%
2004	0,31%	1,18%	0,19%	-0,22%
2005	0,91%	0,13%	1,31%	1,23%
2006	0,52%	-1,88%	1,49%	1,47%
2007	1,66%	-0,75%	-0,74%	2,19%

2008	1,41%	-1,58%	-0,75%	0,59%
2009	1,08%	-0,67%	1,19%	-0,67%
2010	-0,14%	2,27%	-1,19%	-2,33%
2011	-0,25%	-2,73%	3,51%	-2,24%
2012	2,12%	-0,65%	0,79%	-0,67%
2013	1,14%	0,83%	0,37%	-0,37%
2014	0,88%	-1,92%	1,49%	1,48%
2015	-0,98%	-3,00%	2,03%	-3,11%
2016	1,27%	0,30%	-0,35%	1,17%
2017	0,14%	0,07%	-1,09%	0,03%
Mean	0,92%	-0,81%	0,94%	0,09%

In table 2 are the RHS factors for each year. The return differences are to be interpreted as the risk associated with each factor. The SMB factor confirms expectations. Small firms, on average, have a 0,92% higher monthly return than large firms. As was described in the literature section, this is consistent with the size effect. The HML factor gives a result that is not in line with the expectations about B/M ratio. Per the literature, high B/M or value stocks are expected to give higher returns than low B/M or growth stocks (Rosenberg, Reid, & Lanstein, 1985; Stattman, 1980). Here the complete opposite is observed. In the researched period, Dutch stocks with a high B/M value have generated 0,81% less average monthly return than low B/M stocks. The RMW factor gives less surprising results: firms with robust operating profitability perform better than firms with weak operating profitability. The highest 30% return 0,94% more per month on average than the lowest 30%. The CMA factor, which is one of the less logical factors, does not give a strong indication of the presence of a real 'investment effect'. The mean is slightly positive and is close to zero. This is in line with Fama and French (2016), who find that *CMA* is redundant in Europe. Apparently the Dutch stock market does not reward conservatively investing firms with a large positive return. Perhaps managers of Dutch firms have less empire building ambitions, or perhaps they have more constraints on their investment behavior. The latter could be the result of the customary (and until 2013 legally required) two-tier board structure of Dutch companies, as opposed to one-tier board structures that are standard in the US.

As was discussed in the data section, different economic climates (such as the crisis in and around 2008) can cause the factor exposures to change (Chiah, Chai, Zhong, & Li, 2016). For *SMB*, there is a strong increase in 2007, which drops off again in 2010. *HML* experiences a large drop in 2006 and a strong increase in 2010. *RMW* drops heavily in 2007, goes up in 2009 and then goes up and down in the year after. For *CMA*, the values in the years directly after 2008 are strongly negative, compared to the positive values of before. However, when looking at the other values, these increases and decreases happen not exclusively in and around the financial crisis, and no conclusions can be drawn without further statistical analysis on the influence of time period or economic climate on risk exposure.

LHS returns

To calculate the returns created by the variables, new portfolios are created, to be used in the left-hand side (LHS) of the regression (see equation 3). There are two variations. Portfolios are created with 2 x 2 sorts and with 3 x 3 sorts. This means that for the 2 x 2 portfolios, these are based on two company characteristics (e.g. Size-B/M), which are both divided into 2 categories (e.g. Size: the 50% of companies with the largest size vs. the 50% with the smallest size). For 3 x 3 sorts this is the same, except that there are 3 categories and the breakpoints are at 33% and 66%. The 3 x 3 amount was chosen since there are only 25 stocks to divide and a certain degree of diversification within the portfolios is preferred (low amounts of firms are observed in table 3). Fama and French (2015) use up to 5 x 5 sorts when evaluating these models. However, for some time periods there are empty 3 x 3 sort portfolios, which is not only a problem in terms of diversification, but missing values also refrain us from performing certain statistical tests. For this reason, a dataset without missing values is needed, hence the 2 x 2 portfolios. Another reason to perform regression analysis on two different ways of portfolio formation is a check for the robustness of the findings. The testing of different LHS portfolio sorts was done before by Carvalho Coolen (2018), with 3 x 3 and 4 x 4 sorts.

The 3 x 3 portfolios are constructed in the same way as the portfolios used for RHS factor calculation in the previous section. At the end of June of each year, portfolios are made using the current market value, but with the other accounting variables of the end of fiscal year t-1. However, for the construction of the 3 x 3 portfolios, 33rd and 66th percentile breakpoints are used. 9 portfolios are constructed for each of Size-B/M, Size-OP and Size-Inv, so 27 in total.

The construction of the 2 x 2 portfolio works the same as for the 3 x 3 portfolios. The only difference is that for the 2 x 2 portfolios the median is used as a breakpoint for all variables. There are 4 portfolios for Size-B/M, Size-OP and Size-Inv, so 12 in total.

Descriptive statistics of LHS portfolios

This section shows the descriptive statistics of the LHS portfolios that will be used as response variables in the regression analysis. The first thing discussed will be the average division of the AEX constituents over the portfolios and an overview of the excess returns of the portfolios follows.

Table 3: Average number of securities in LHS portfolios

Portfolios have been created with allocations based on breakpoints in size, B/M, operating profitability and investment. This leads to 27 3 x 3 portfolios and 12 2 x 2 portfolios. The portfolios are constructed again in June of the years 2000-2017, giving 18 observations per portfolio. The average amount of stocks in the portfolios can be seen in panels A, B and C for the 3 x 3 portfolios, and in panels D, E and F for the 2 x 2 portfolios.

Panel A: 3 x 3 Size-B/M portfolios

	High	Neutral	Low
Small	2,4	2,4	2,1
Neutral	1,7	2,4	2,9
Big	2,4	2,2	2,0

Panel D: 2 x 2 Size-B/M portfolios

	High	Low
Small	4,7	5,9
Big	5,2	4,8

Panel B: 3 x 3 Size-OP portfolios

	Robust	Neutral	Weak
Small	1,3	2,2	3,4
Neutral	2,3	2,6	2,2
Big	2,2	2,9	1,4

Panel E: 2 x 2 Size-OP portfolios

	Robust	Weak
Small	4,2	6,4
Big	5,8	4,2

Panel C: 3 x 3 Size-Inv portfolios

	Conservative	Neutral	Aggressive
Small	2,8	2,1	2,1
Neutral	2,3	2,5	2,2
Big	1,8	2,5	2,3

Panel F: 2 x 2 Size-Inv portfolios

	Conservative	Aggressive
Small	6,0	4,6
Big	4,6	5,4

Table 3 shows the amount of stock the portfolios contain on average in the years 2000-2017. In panels A, B and C it can be seen that the average amount of stocks in the 3 x 3 portfolios is very low, issuing concerns over a lack of diversification. In the actual data, the maximum amount of stocks found in one 3 x 3 portfolio is 6, with the minimum being 0. Since certain statistical tests cannot be performed with empty portfolios, and the returns cannot be assumed to be zero or another approximate value, 2 x 2 sort portfolios are also constructed. As expected, the average amount of stocks in these portfolios, as seen in panels D, E and F of table 3, is higher, leading to better (yet still not optimal) diversification. Also, for each year the individual 2 x 2 portfolios contain at least 2 firms and at most 9 firms. The amount of companies in the portfolios is evenly spread, which is to be expected since allocations are based on relative variables and not absolute values. Still, there are some values that deserve to be mentioned. The most numerous category is for both sorts the small size-weak profitability portfolio. This can be explained by the relation between (retained) profits and company value. The smallest portfolios are small size-robust profitability and large size-weak profitability, which can of course be explained through the same mechanism.

Table 4: Return statistics for LHS portfolios

For each portfolio formed in June of the years 2000-2017, the average value-weighted monthly returns in excess of the risk-free rate of the following year (July *t* – June *t+1*) is calculated. For each portfolio there are 18 observations, one for each year. The averages of the returns of these observations can be seen below. All values are return percentages per month.

Panel A: 3 x 3 Size-B/M portfolios

Mean	High	Neutral	Low
Small	0,16	0,20	0,72
Neutral	-0,07	0,56	0,01
Big	-0,90	-1,17	0,39

Std. dev.	High	Neutral	Low
Small	2,04	3,20	2,29
Neutral	1,88	1,54	2,11
Big	2,43	2,01	1,46

Panel D: 2 x 2 Size-B/M portfolios

Mean	High	Low
Small	-0,61	-0,38
Big	-1,20	-0,54

Std. dev.	High	Low
Small	1,26	0,79
Big	0,91	1,14

Panel B: 3 x 3 Size-OP portfolios

Mean	Robust	Neutral	Weak
Small	0,87	0,24	0,42
Neutral	0,12	0,66	-0,02
Big	0,47	-1,25	-1,80

Std. dev.	Robust	Neutral	Weak
Small	2,22	2,55	1,70
Neutral	2,23	1,89	2,27
Big	1,46	2,12	2,71

Panel E: 2 x 2 Size-OP portfolios

Mean	Robust	Weak
Small	-0,36	-0,57
Big	-0,36	-1,57

Std. dev.	Robust	Weak
Small	1,40	0,83
Big	0,79	0,99

Panel C: 3 x 3 Size-Inv portfolios

Mean	Conservative	Neutral	Aggressive
Small	0,74	0,20	0,32
Neutral	0,70	-0,16	0,12
Big	-0,74	-0,65	-0,28

Std. dev.	Conservative	Neutral	Aggressive
Small	2,23	2,45	1,69
Neutral	2,07	1,93	1,97
Big	2,51	1,77	2,12

Panel F: 2 x 2 Size-Inv portfolios

Mean	Conservative	Aggressive
Small	-0,57	-0,34
Big	-0,96	-0,63

Std. dev.	Conservative	Aggressive
Small	1,14	0,92
Big	1,42	1,00

Return statistics for the LHS portfolios are described in table 4. Although no strongly supported statistical conclusions can be drawn, the values are interesting to consider. Looking at the returns generally, AEX constituents have performed badly in the period 2000-2017, showing negative average returns. Now let us consider the 3 x 3 sorts in panels A, B and C, starting with the size variable which is present in all portfolios. With few exceptions, portfolios containing large firms perform worse than portfolios containing small or neutral-sized firms. Conversely, portfolios containing small firms perform better than portfolios containing big or neutral-sized firms. This is in line with expectations per the size effect (Banz, 1981). The second variable to be discussed is the B/M ratio in panel A. High B/M firms, or value stocks, perform badly. Low B/M firms, also known as growth or glamour stocks, perform better. However, a very clear pattern cannot be observed, with neutral-Size neutral-B/M stocks performing better, and large-Size neutral-B/M stocks performing much worse. Per the value effect low B/M firms are expected to perform better, something which cannot be concluded from these values. The third variable to discuss is operating profitability in panel B. With the N-N portfolio being the only exception, portfolios containing firms with robust profitability perform better, as expected. The fourth and last variable to be discussed is the variable representing investment attitude in panel C. It is again hard to distinguish a clear pattern for this variable. For small and neutral-sized firms, those with a conservative approach to investment perform better than those that invest aggressively, and vice versa. However, firms with a neutral investment attitude perform even worse. More surprisingly, the effect is the complete opposite for big firms: large corporations with a conservative investment attitude perform worse than those with a neutral or aggressive investment attitude. One could expect to see higher volatility in the aggressive investment portfolio due to the risk involved in investments, but this is not seen in the table.

It must be noted that for the 3 x 3 portfolios, very large standard deviations are observed, something which can be caused by the small diversification in the portfolios. The 2 x 2 portfolios contain more stocks so will possibly have lower standard deviations. However, it must be understood that the 2 x 2 cannot show complex patterns due to there being only two allocations possible per variable. When considering the 2 x 2 sort-portfolios in Panels D, E and F next, it appears that small firms perform better (or less badly) than large firms, confirming the size premium. The only exception is that robust operating profitability seems to dismiss a size effect, with large and small firms performing almost equally in this allocation. As with the 3 x 3 sorts, there is no value effect seen in panel D, but rather a premium for growth stocks. In panel E the stocks are sorted on operating profitability. Robust operating profitability has a strong positive effect on the returns. As mentioned before this is the only category in which small firms do not outperform large firms. Panel F shows again the unexpected positive effect on returns of aggressive asset growth.

Compared to table 3 where the average amount of stocks per portfolio is described, it was observed that portfolios with small-Size robust-OP and big-Size weak-OP were the smallest. In table 4 it shows that these are also the portfolios that have the best and worst returns, respectively.

Model performance

Ultimately, the desire is to know if the five-factor model is an improvement over the three-factor model and the CAPM in explaining stock returns. The models are compared based on the joint α (using GRS), average α, mean R^2 and adjusted R^2. Equation 3 states the formula for the five-factor model:

$$R_i - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{it}$$

Equation 2 for the three-factor model:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB + h_i HML + e_{it}$$

And equation 1 for the CAPM:

$$ER_i - R_f = a_i + \beta_i(ER_m - R_f)$$

If the factors fully capture the returns, intercept α must have value 0. Therefore, for each model must be tested whether the intercept significantly differs from 0. To test this hypothesis, a GRS test is run (Gibbons, Ross, & Shanken, 1989) per the methodology of Fama and French (2015). If the GRS statistic for this test equals zero, it can be concluded that $\alpha_i = 0 \forall i$. The GRS statistic is calculated as follows:

$$GRS = \left(\frac{T}{N}\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \sim F(N, T-N-L) \quad \textbf{(8)}$$

where $\hat{\alpha}$ is an N x 1 vector of intercepts, $\hat{\Sigma}$ is an unbiased estimate of the residual covariance matrix, $\bar{\mu}$ is an L x 1 vector of the sample means of the factor portfolios and $\hat{\Omega}$ is an unbiased estimate of the covariance matrix of the factor portfolios. However, as the necessary assumption of normally distributed ε is not necessarily fulfilled and the sample size is small, the following variant is used:

$$GRS = \left(\frac{T-N-K}{N}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{f}'\hat{\Omega}^{-1}\bar{f}}\right] \sim F(N, T-N-K) \quad \textbf{(9)}$$

This variant is a refinement for smaller samples and takes in account that Σ may differ across samples (Cochrane, 2014). The GRS statistic should return a value of zero if all the α are jointly zero, and an increase in α would show an increase in the GRS value.

Regression

To test the influence of the calculated factors SMB, HML, RMW and CMA, regression analysis is performed according to equation 3:

$$R_i - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{it}$$

The factors have been defined every year in the way explained before. For each year, the returns used will be those of the LHS portfolios, both 2 x 2 sorts and 3 x 3 sorts. The regression is run for 27 3 x 3 portfolios and 12 2 x 2 portfolios, where each portfolio has 18 observations.

4. Results & discussion

Model performances compared

In table 5 the CAPM, three-factor model and five-factor model are compared using the two GRS test statistics, the corresponding *p* values, the mean intercept coefficient and the mean adjusted R^2 value.

Table 5: Comparison of CAPM, three-factor model and five-factor model
The GRS test statistic and corresponding *p* value for both the usual GRS test and the variant for small samples, mean α, mean R^2 and mean adjusted R^2. Some regressions returned negative adjusted R^2 values, these are interpreted to be zero. For the five-factor model, only 2 x 2 sort portfolios are used for the regression as some 3 x 3 sort portfolios returned missing values because of them containing no stocks.

	GRS	*p* value	GRS (alt.)	*P* value	Mean α	Mean R^2	Mean adj. R^2
CAPM	6,530	0,025	5,804	0,032	-0,00650	4,825%	2,221%
3-factor	7,588	0,061	5,902	0,085	-0,00637	20,738%	10,068%
5-factor	71,590	0,092	68,813	0,094	-0,00729	30,067%	13,615%

Recall that the GRS test tests whether the α values are jointly zero for a certain model, with H_0: the intercepts α_i are not significantly different from 0. The *p* value is significant for the CAPM, indicating that the null hypothesis can be rejected for the CAPM. The null hypothesis is accepted for the three-factor and five-factor model, indicating that joint α_i is zero and that the factors accurately capture returns. The increasing p-values show that the five-factor model is an improvement over the three-factor model, which is an improvement over the CAPM. It is surprising to see that the GRS statistic seems to increase instead of decrease when moving from the CAPM to the three-factor to the five-factor model. The *p* value is expected to decrease with higher GRS. The increase of the GRS statistic implies that α increases with the adding of factors and that the added factors make the models less accurate when purely looking at the value of α. The absolute mean α increases with the adding of factors, which confirms the conclusions drawn with the GRS test. Although present, the increase is minimal. The R^2 gives a more hopeful statistic for the five-factor model. The amount of explained variability increases when adding factors to the model. The adjusted R^2 is considered to confirm the added value of the factors. All things considered, the GRS test is not very conclusive in comparing the three models. Although it indicates an increase in joint α, it does not indicate how much and the absolute value of mean α suggests the change could be minimal and perhaps the result of statistical or measurement errors. Easier to interpret are the R^2 and adjusted R^2, which show that the five-factor model is an improvement over the three-factor model and the CAPM.

Regression results

3 x 3 sorts

In this section the regression results are presented for the 27 3 x 3 LHS portfolios. In table 6 are intercept α, its *t*-statistic and the R^2 of the regression. The coefficients and *t* statistics for *b, s, h, r* and *c* can be found in appendix A, table 1. In portfolios without a return for a certain year (because they contained no stocks), that year is not used in the regression.

Table 6: Intercept values for 3 x 3 portfolios

The 27 portfolios (3 x 3 sorts) regressed on $R_M - R_f$, SMB, HML, RMW and CMA (factors constructed using 2 x 3 portfolios). Each of the portfolios has 18 observations, one for each year 2000 – 2017. * = significant at 5%.

Panel A: Size-B/M

α	High	Neutral	Low
Small	0,00502*	-0,00635	0,00271
Neutral	-0,00375	0,00331	0,00884
Big	-0,00360	-0,00213	-0,00075

t	High	Neutral	Low
Small	2,41785	-0,60501	0,38012
Neutral	-0,69836	0,77308	1,44949
Big	-0,76320	-0,26651	-0,16787

R^2	High	Neutral	Low
Small	0,96455	0,58741	0,66193
Neutral	0,72887	0,70390	0,68007
Big	0,85512	0,47643	0,70948

Panel B: Size-OP

α	Robust	Neutral	Weak
Small	-0,00077	0,00481	0,00365
Neutral	0,01291*	0,00497	-0,01503*
Big	0,00331	-0,01082*	0,00190

t	Robust	Neutral	Weak
Small	-0,10469	0,69069	1,07172
Neutral	2,29247	0,83074	-2,44586
Big	1,54405	-2,49852	0,21937

R^2	Robust	Neutral	Weak
Small	0,64565	0,76890	0,84562
Neutral	0,75510	0,66719	0,77332
Big	0,91663	0,86036	0,68091

Panel C: Size-Inv

A	Conservative	Neutral	Aggressive
Small	-0,00056	-0,00209	0,00618
Neutral	-0,00742	0,00510	-0,00222

t	Conservative	Neutral	Aggressive
Small	-0,08143	-0,27612	1,23313
Neutral	-1,62026	0,77406	-0,38345

Big	-0,00818	-0,00111	-0,00406	Big	-0,87061	-0,23059	-1,28952

R^2	Conservative	Neutral	Aggressive
Small	0,63890	0,65558	0,76950
Neutral	0,83590	0,55209	0,71311
Big	0,49474	0,71647	0,91530

Panel A shows see the intercepts of the Size-B/M portfolio regressions. Only one significant t-value is observed, for small value firms, meaning that for eight out of nine Size-B/M portfolios, regression intercept α is not significantly different from 0. Panel B shows see three values that are significantly different from 0. However, it is hard to recognize a pattern in the significant values. Neutral sized firms with weak and robust profitability, and small firms with neutral profitability have significant intercepts *α*. In panel C there are no significant values. High R^2 values ranging from 48% to 96% can be seen, indicating that a large part of the variation in returns in the all portfolios is explained by the model. These findings are strong support for the five-factor model's explanatory power.

Coefficients *α*, *b* (for the market factor), *s* (SMB), *h* (HML), *r* (RMW), *c* (CMA) and their corresponding *t* values for the 3 x 3 sort portfolios can be found in appendix A, table 1. Coefficient *α* has already been discussed. Panel A shows that the market coefficients *b* are significant at the 1% level, with the exception of the *b*-coefficient of portfolio B-N, which is not significant. This is interpreted as the excess market return having strong influence on the returns of stocks in the portfolios. Since this factor is the only factor in the CAPM model, the other factors should have added value according to Fama and French (1993; 2015). However, the other factors do not give many significant coefficients. The few significant coefficients are concentrated in the small size-high B/M portfolio. It has coefficients *s*, *h* and *c* which are significant at 1% and all positive, in line with expectations. It seems that for these S-H firms, returns can be well explained by the exposure to risk factors SMB, HML and CMA. However, operating profitability does not have a significant influence on returns. Panel B again shows 1%-significant market factor coefficients, with one exception in B-W which is significant at the 5% threshold. As with the Size-B/M portfolios, these Size-OP portfolios do not seem to be predicted by factors other than the market factor. The *s* value is significant for two out of nine portfolios, and *r* is significant for one out of nine portfolios. It is difficult to distinguish a clear pattern in these significant coefficients. Panel C shows the coefficients for the nine Size-Inv portfolios. Again, the market factor has significant positive values, with seven portfolios having *b*-factors significant at 1% and the other two at 5%. There is only one other significant value: *s* for the N-C portfolio.

2 x 2 sorts

In this section the regression results are presented for the 12 2 x 2 LHS portfolios. Table 7 shows intercept α, its *t*-statistic and the R^2 of the regression.

Table 7: Intercept values for 2 x 2 portfolios

The 12 portfolios (2 x 2 sorts) regressed on $R_M - R_f$, SMB, HML, RMW and CMA (factors constructed using 2 x 3 portfolios). Each of the portfolios has 18 observations, one for each year 2000 – 2017. * = significant at 5%.

Panel A: Size-B/M

α	High	Low
Small	-0,0064	-0,0075*
Big	-0,0057	-0,0098

t	High	Low
Small	-1,3241	-2,8592
Big	-1,8382	-1,7833

R²	High	Low
Small	0,4417	0,5760
Big	0,5612	0,1079

Panel B: Size-OP

α	Robust	Weak
Small	-0,0089	-0,0065
Big	-0,0031	-0,0115*

t	Robust	Weak
Small	-1,3916	-1,8903
Big	-0,7955	-3,2269

R²	Robust	Weak
Small	0,1974	0,3382
Big	0,0425	0,5103

Panel C: Size-Inv

α	Aggressive	Conservative
Small	-0,0069	-0,0084
Big	-0,0116	-0,0012

t	Aggressive	Conservative
Small	-1,2707	-1,9446
Big	-1,6316	-0,3365

R²	Aggressive	Conservative
Small	0,1344	0,1629
Big	0,0450	0,4905

As with the 3 x 3 sort portfolios, the 2 x 2 sort portfolios mostly show values of α that are not significantly different from zero. This means the five-factor model provides an accurate description of the determinants of excess monthly returns. The first significant value is the intercept coefficient of the S-L portfolio. This implies that the five-factor model is slightly less accurate in describing the returns of small growth stocks. The same goes for the second significant value in the B-W portfolio: the model performs worse for small firms with weak profitability. The coefficient value is surprisingly large for this B-W portfolio and makes one wonder if the returns of these firms need additional or different explanatory variables to be explained fully. Lastly, smaller R^2 values are observed for the 2 x 2 sort portfolios than for the 3 x 3 sort portfolios. This is as expected, as less portfolios means a more diverse group of firms together. The R^2 values of the B-R and B-A portfolios are surprisingly small. It is difficult to draw strong conclusions from R^2 due to the limited sample size.

Next, the factor coefficients *b*, *s*, *h*, *r*, *c* and their corresponding *t* values will be discussed. These can be found in table 2 of appendix A. In panel A the values for the Size-B/M portfolios are seen. The *b* coefficients are again positive, in line with expectations. Surprisingly, the highly significant influence of the market factor that was observed with the 3 x 3 portfolios does not return for 2 x 2 portfolios, where none of the *b* coefficients are significant. The size effect is also minimally present, with only one out of four values significant, and with one strongly negative value the coefficients seem random. The B/M factor has significant values for the two small-firm portfolios. The coefficient values are quite interesting, with a significantly negative influence of B/M on high B/M firms, and a significantly positive influence of B/M on low B/M firms. This implies that the return of value stocks is negatively correlated with the risk associated with high B/M. Conversely, growth stocks' returns are positively correlated with risk of high B/M. One of four *r* values is significant: that of the S-H portfolio, with a strong negative value. This negative value is also seen in the other H portfolio and turns positive for both L portfolios, although not significantly. The *c* values are all close to zero and insignificant and seem to be meaningless. In panel B there is only one significant result for the market risk factor. The operating profitability also shows a significant value, a small negative coefficient for B-W portfolios. None of *s, h* or *c* are significant. The Size-Inv portfolios show even fewer exciting results, with no significant values being observed.

5. Conclusion

This research has the intention of showing the effectiveness of the five-factor model in The Netherlands and comparing it with the three-factor model and CAPM. First, the differences in returns between different sorts of stocks were observed in several descriptive statistics. In the construction of the RHS portfolios it was seen that, in line with the size effect, small firms outperform large firms by 0,92% per month. Operating profitability also has a positive influence on the average monthly return. Instead of a value premium for high B/M stocks, the complete opposite was observed in something that can be called a growth premium. The findings for the investment factor seem to confirm what Fama and French (2016) found in European markets: CMA has no clear effect. In the construction of the LHS portfolios there are similar findings. The size effect seems to occur, with portfolios containing large firms performing worse than portfolios containing small or neutral-sized firms. Again, the presence of a value effect cannot be derived from the observations. Profitability continues to generate higher returns, and investment has an ambiguous effect. The data section shows that market performance during the crisis of around 2008 does not have a clear effect on the findings, or on the risk exposures.

Second, we see if the observations have any statistical basis. When regressing average monthly returns on R_M-R_f, *SMB*, *HML*, *RMW* and *CMA*, only the market factor has a significant effect on the monthly returns. Reducing the credibility of the five-factor model even more, the findings regarding the effects of the market factor are not robust, as only in the 3 x 3 sort portfolios significant results are detected, and not in the 2 x 2 sort portfolios. Overall all factors, with the exception of the market factor, seem to perform very poorly in describing excess monthly returns.

Third, the models are compared. The joint αs of the five-factor model and three-factor model are zero according to the GRS test, indicating that the factors describe a large portion of the variation in returns. R^2 and adjusted R^2 increase when adding new factors which shows that more variation is explained when adding factors. Overall, the five-factor model seems to be an improvement over the three-factor model and CAPM.

The findings can be used to answer the research question: how does the five-factor model by Fama & French (2015) perform in predicting returns on the stock market of The Netherlands, and does it perform better than the three-factor model and CAPM? Although average returns show some interesting differences, it cannot be stated with solid statistical arguments that the risk factor are a driving force behind variation in stock returns. The added value of the five-factor model over the CAPM and three-factor model can be confirmed. The findings can be interpreted in a few ways. Either the Dutch stock market asks for different risk factors to determine the stock returns (this is supported by the increase of explanatory power when adding new factors), or the findings confirm the suggestion raised in the introduction: that stock returns in the Dutch market, which knows many behavior-based anomalies, cannot be described by “rational” fundamental risk factors.

6. Limitations

The research and its finding have been limited by the amount of stocks used, in a theoretical and practical way. An often-heard criticism of the AEX index in the public debate is that it is not fully representative of the Dutch economy, and in the same way it is not fully representative of the whole Dutch stock market as intended in this research. Adding the 25 stocks of the AMX, or the 50 stocks of the AMX and AScX combined could possibly give different results. This expansion could potentially show even less support for the five-factor model, as one could expect that these smaller stocks are even less rationally priced based on risk. The expansion could give more flexibility in portfolio formation. 75 stocks instead of 25 could see a move from 2 x 2 and 3 x 3 portfolios to 4 x 4 portfolios or keep the smaller sorts but with more diversification in the portfolios. Another limitation is the lack of observations (only 18) in each portfolio, with one from every year from 2000 to 2017. This does not have to be solved by going back further in time but can rather easily be expanded by moving to monthly, weekly or even daily observations. This would have allowed the statistical conclusions drawn from the regressions to be more robust, and this would also greatly improve the usefulness of the GRS test to compare the different models.

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Appendix A

Table 1: Slope coefficients for 3 x 3 sort portfolios

The 27 portfolios (3 x 3 sorts) regressed on $R_M - R_f$, SMB, HML, RMW and CMA (factors constructed using 2 x 3 portfolios). Each of the portfolios has 18 observations, one for each year 2000 – 2017. * = significant at 5%. ** = significant at 1%.

Panel A: Size-B/M

α	High	Neutral	Low
Small	0,00502*	-0,00635	0,00271
Neutral	-0,00375	0,00331	0,00884
Big	-0,00360	-0,00213	-0,00075

t	High	Neutral	Low
Small	2,41785	-0,60501	0,38012
Neutral	-0,69836	0,77308	1,44949
Big	-0,76320	-0,26651	-0,16787

b	High	Neutral	Low
Small	0,6919**	1,6410**	1,2230**
Neutral	0,9704**	0,7524**	0,9037**
Big	1,3445**	0,5191	0,7059**

t	High	Neutral	Low
Small	8,4388	3,8958	4,0645
Neutral	4,7422	4,3820	3,6924
Big	7,0989	1,7103	4,1328

s	High	Neutral	Low
Small	0,6080**	1,3245	0,6687
Neutral	0,8640	0,7643	-1,0932
Big	0,2340	-1,3659	0,3738

t	High	Neutral	Low
Small	3,1741	1,3481	0,9900
Neutral	1,7767	1,9085	-1,9152
Big	0,5297	-1,8220	0,9051

h	High	Neutral	Low
Small	0,6758**	-0,1611	-0,9141
Neutral	0,1321	0,1446	-0,0153
Big	0,1441	-0,2406	-0,2062

t	High	Neutral	Low
Small	7,6096	-0,3497	-2,9550
Neutral	0,5799	0,7702	-0,0572
Big	0,6958	-0,6564	-1,1331

r	High	Neutral	Low
Small	-0,1725	0,0162	-0,3588
Neutral	-0,0205	-0,1202	0,3884
Big	-0,2347	0,3538	0,2485

t	High	Neutral	Low
Small	-2,5173	0,0449	-1,4773
Neutral	-0,1153	-0,8163	1,8505
Big	-1,4453	1,3638	1,7726

c	High	Neutral	Low
Small	0,3866**	-0,3140	-0,1963
Neutral	-0,2362	-0,1926	0,3601
Big	-0,1500	0,4743	-0,0603

t	High	Neutral	Low
Small	3,3952	-0,5558	-0,5025
Neutral	-0,8192	-0,8360	1,0971
Big	-0,5904	1,1016	-0,2455

Panel B: Size-OP

α	Robust	Neutral	Weak
Small	-0,0008	0,0048	0,0037
Neutral	0,0129*	0,0050	-0,0150
Big	0,0033	-0,0108	0,0019

t	Robust	Neutral	Weak
Small	-0,1047	0,6907	1,0717
Neutral	2,2925	0,8307	-2,4459
Big	1,5441	-2,4985	0,2194

b	Robust	Neutral	Weak
Small	1,3632**	1,4250**	0,5200**
Neutral	0,9197**	1,0004**	1,0862**
Big	0,9132**	1,2210**	0,9583*

t	Robust	Neutral	Weak
Small	3,9691	5,3557	3,7994
Neutral	4,0680	4,3939	4,6230
Big	10,6014	7,3937	2,8921

s	Robust	Neutral	Weak
Small	0,9131	0,2394	0,8368
Neutral	-1,2705	0,4885	2,1259
Big	0,0862	0,2196	-1,1591

t	Robust	Neutral	Weak
Small	1,3690	0,3722	2,6216*
Neutral	-2,4095	0,8687	3,7422**
Big	0,4292	0,5596	-1,4817

h	Robust	Neutral	Weak
Small	-0,8823	0,1561	0,0043
Neutral	0,2376	0,1140	-0,0435
Big	-0,2402	0,1441	0,0791

t	Robust	Neutral	Weak
Small	-2,0117	0,5507	0,0284
Neutral	0,9611	0,4147	-0,1737
Big	-2,5498	0,7833	0,2095

r	Robust	Neutral	Weak
Small	-0,4645	0,2118	-0,6070
Neutral	0,4707	-0,0331	-0,1534
Big	0,1507	0,2155	-0,4037

t	Robust	Neutral	Weak
Small	-1,4798	0,9697	-5,1725
Neutral	2,4282*	-0,1701	-0,7954
Big	2,0404	1,5006	-1,4461

c	Robust	Neutral	Weak
Small	-0,5307	0,2612	0,1774
Neutral	0,3445	0,2032	-0,7210
Big	0,0165	0,0093	0,1905

t	Robust	Neutral	Weak
Small	-1,4151	0,6826	0,9665
Neutral	1,1361	0,6290	-2,1335
Big	0,1429	0,0398	0,4322

Panel C: Size-Inv

α	Conservative	Neutral	Aggressive
Small	-0,0006	-0,0021	0,0062
Neutral	-0,0074	0,0051	-0,0022
Big	-0,0082	-0,0011	-0,0041

t	Conservative	Neutral	Aggressive
Small	-0,0814	-0,2761	1,2331
Neutral	-1,6203	0,7741	-0,3834
Big	-0,8706	-0,2306	-1,2895

b	Conservative	Neutral	Aggressive
Small	0,9843**	1,0211**	0,8775**
Neutral	1,4185**	0,7639*	0,9560**
Big	1,1019*	0,9423**	1,2154**

t	Conservative	Neutral	Aggressive
Small	3,5905	3,2269	4,0649
Neutral	6,6243	2,8875	4,3343
Big	2,8007	4,8808	9,6165

s	Conservative	Neutral	Aggressive
Small	1,3014	1,3445	0,0644
Neutral	1,5918	-0,4481	0,7332
Big	0,6994	-0,2650	0,4305

t	Conservative	Neutral	Aggressive
Small	2,0353	1,8041	0,1548
Neutral	3,8873	-0,7261	1,3988
Big	0,7548	-0,5886	1,4602

h	Conservative	Neutral	Aggressive
Small	-0,3343	0,4701	0,1884
Neutral	-0,4916	0,1630	0,0931
Big	0,0247	-0,0292	-0,2580

t	Conservative	Neutral	Aggressive
Small	-1,1151	1,4130	0,7288
Neutral	-2,0671	0,5636	0,3789
Big	0,0597	-0,1382	-1,8666

r	Conservative	Neutral	Aggressive
Small	-0,4166	-0,0017	0,0217
Neutral	-0,2279	0,1166	0,1073
Big	-0,1240	-0,0397	-0,0536

t	Conservative	Neutral	Aggressive
Small	-1,7722	-0,0067	0,1324
Neutral	-1,4108	0,5138	0,5593
Big	-0,3898	-0,2396	-0,4942

c	Conservative	Neutral	Aggressive
Small	0,1979	-0,1528	0,0434
Neutral	-0,3044	-0,0504	-0,4899
Big	0,3420	0,0290	-0,6770

t	Conservative	Neutral	Aggressive
Small	0,5382	-0,3766	0,1872
Neutral	-1,3034	-0,1421	-1,5765
Big	0,6781	0,1121	-3,9933

Table 2: Slope coefficients for 2 x 2 sort portfolios

The 12 portfolios (2 x 2 sorts) regressed on $R_M – R_f$, SMB, HML, RMW and CMA (factors constructed using 2 x 3 portfolios). Each of the portfolios has 18 observations, one for each year 2000 – 2017. * = significant at 5%. ** = significant at 1%.

Panel A: Size-B/M

α	High	Low
Small	-0,0064	-0,0075*
Big	-0,0057	-0,0098

t	High	Low
Small	-1,3241	-2,8592
Big	-1,8382	-1,7833

b	High	Low
Small	0,3209	0,0040
Big	0,1337	0,0456

t	High	Low
Small	1,6588	0,0375
Big	1,0770	0,2071

s	High	Low
Small	0,0229	0,5886*
Big	-0,4156	0,3835

t	High	Low
Small	0,0508	2,3817
Big	-1,4351	0,7467

h	High	Low
Small	-0,5805*	0,3024*
Big	0,0823	-0,1442

t	High	Low
Small	-2,7441	2,6101
Big	0,6062	-0,5987

r	High	Low
Small	-0,3848	0,0937
Big	-0,1489	0,0029

t	High	Low
Small	-2,3195	1,0315
Big	-1,3990	0,0154

c	High	Low
Small	-0,0579	-0,0754
Big	-0,0279	-0,2830

t	High	Low
Small	-0,2232	-0,5308
Big	-0,1675	-0,9581

Panel B: Size-OP

α	Robust	Weak
Small	-0,0089	-0,0065
Big	-0,0031	-0,0115**

t	Robust	Weak
Small	-1,3916	-1,8903
Big	-0,7955	-3,2269

b	Robust	Weak
Small	-0,1060	0,3010*
Big	-0,0773	0,1975

t	Robust	Weak
Small	-0,4135	2,1768
Big	-0,4878	1,3865

s	Robust	Weak
Small	0,7496	0,1116
Big	-0,1133	-0,2006

t	Robust	Weak
Small	1,2535	0,3459
Big	-0,3067	-0,6039

h	Robust	Weak
Small	0,2232	-0,2596
Big	-0,0177	-0,1359

t	Robust	Weak
Small	0,7960	-1,7172
Big	-0,1020	-0,8725

r	Robust	Weak
Small	-0,0011	-0,1469
Big	0,0276	-0,2953*

t	Robust	Weak
Small	-0,0052	-1,2393
Big	0,2028	-2,4180

c	Robust	Weak
Small	-0,1705	0,0287
Big	-0,0147	-0,1135

t	Robust	Weak
Small	-0,4959	0,1549
Big	-0,0692	-0,5942

Panel C: Size-Inv

α	Conservative	Aggressive
Small	-0,0069	-0,0084
Big	-0,0116	-0,0012

t	Conservative	Aggressive
Small	-1,2707	-1,9446
Big	-1,6316	-0,3365

b	Conservative	Aggressive
Small	0,1529	0,0250
Big	-0,0430	0,1412

t	Conservative	Aggressive
Small	0,7013	0,1444
Big	-0,1511	0,9645

s	Conservative	Aggressive
Small	0,3058	0,4419
Big	0,3094	-0,3262

t	Conservative	Aggressive
Small	0,6015	1,0951
Big	0,4655	-0,9549

h	Conservative	Aggressive
Small	-0,0150	-0,1298
Big	0,1474	-0,0859

t	Conservative	Aggressive
Small	-0,0630	-0,6859
Big	0,4731	-0,5367

r	Conservative	Aggressive
Small	-0,1376	0,0126
Big	0,0328	-0,2358

t	Conservative	Aggressive
Small	-0,7360	0,0847
Big	0,1343	-1,8778

c	Conservative	Aggressive
Small	0,0542	-0,2561
Big	-0,1729	-0,1269

t	Conservative	Aggressive
Small	0,1853	-1,1033
Big	-0,4525	-0,6458