UNIVERSITY OF TURKU
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Do Multi-Factor Models Explain European Portfolio Returns Better than the CAPM During 2000–2025?

An Empirical Analysis Using the Fama–French Factor Model

Accounting and Finance
Bachelor's thesis

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☐ **I have not used any AI-based tools.**

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Abstract

This thesis examines how well different asset pricing models explain portfolio returns in European equity markets during 2000–2025. The study is motivated by the long discussion in finance about whether stock returns can be explained mainly by market risk, as suggested by the CAPM, or whether additional factors are needed. Earlier research has often focused on the United States, while European markets have been given less attention, even though they differ from U.S. markets in many ways.

The empirical analysis uses monthly data from the Kenneth R. French Data Library. The data consists of 25 European portfolios formed on size and book-to-market ratios, with the Fama–French factor series. The thesis compares three asset pricing models: the CAPM, the Fama–French three-factor model, and the Fama–French five-factor model. The models are estimated using time-series regression analysis, and their performance is analyzed using explanatory power, factor coefficients, and intercept terms.

The results show that the market factor remains the most important factor in all of the models in European equity markets. At the same time, multi-factor models explain portfolio returns more accurately than the CAPM. The average explanatory power increases from the CAPM to the three-factor model, and the five-factor model provides the highest explanatory power overall. However, the improvement from the three-factor model to the five-factor model is relatively small. The size factor shows relatively steady support in the broader models, while the value factor remains quite weak during the sample period in the European market data. The profitability and investment factors increase the model's explanatory power, but their effects are not strong across the portfolios. The results ultimately show that the models do not perform equally well for all European portfolios, and differences can be seen especially across book-to-market groups.

Overall, the findings support the view that stock returns in European equity markets are explained better by several factors than by solely market risk. At the same time, the results suggest that factor effects are not constant and may depend on the market, portfolio type, and time period.

Keywords: asset pricing, CAPM, Fama–French three-factor model, Fama–French five-factor model, factor investing, European equity markets

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Tiivistelmä

Tässä kandidaatintutkielmassa tarkastellaan, kuinka hyvin eri hinnoittelumallit selittävät osakesalkkujen tuottoja Euroopan osakemarkkinoilla vuosina 2000–2025. Tutkimuksen taustalla on rahoitustieteessä pitkään jatkunut keskustelu siitä, voidaanko osakkeiden tuottoja selittää pääasiassa markkinariskillä CAPM-mallin mukaisesti vai tarvitaanko lisäksi muita tekijöitä. Aiempi tutkimus on keskittynyt usein Yhdysvaltoihin, kun taas Euroopan markkinat ovat saaneet vähemmän huomiota, vaikka ne eroavat Yhdysvaltain markkinoista monin tavoin.

Empiirisessä analyysissä hyödynnetään Kenneth R. French Data Librarystä saatua kuukausittaista aineistoa. Aineisto koostuu 25 eurooppalaisesta salkusta, jotka on muodostettu yritysten koon ja tasearvo–markkina-arvo-suhteen perusteella, sekä Fama–French-faktoriaineistosta. Tutkielmassa vertaillaan kolmea hinnoittelumallia: CAPM-mallia, Fama–Frenchin kolmen faktorin mallia sekä Fama–Frenchin viiden faktorin mallia. Mallit estimoidaan aikasarjaregressioanalyysillä, ja niiden toimivuutta arvioidaan selitysasteen, faktorikertoimien sekä vakiotermien avulla.

Tulokset osoittavat, että markkinatekijä säilyy tärkeimpänä yksittäisenä tekijänä kaikissa malleissa Euroopan osakemarkkinoilla. Samalla monifaktorimallit selittävät portfoliotuottoja tarkemmin kuin CAPM-malli. Keskimääräinen selitysaste kasvaa CAPM-mallista kolmen faktorin malliin siirryttäessä, ja viiden faktorin malli antaa kokonaisuutena korkeimman selitysasteen. Kolmen faktorin mallista viiden faktorin malliin siirtymisestä saatava lisähyöty jää kuitenkin melko pieneksi. Kokotekijä saa suhteellisen vakaata tukea laajemmissa malleissa, kun taas arvotekijä jää tarkastelujaksolla melko heikoksi Euroopan markkina-aineistossa. Kannattavuus- ja investointitekijät parantavat mallin selitysvoimaa, mutta niiden vaikutukset eivät ole vahvoja kaikissa portfolioissa. Tulokset osoittavat myös, etteivät mallit toimi yhtä hyvin kaikissa eurooppalaisissa portfolioissa, vaan eroja esiintyy erityisesti book-to-market-ryhmien välillä.

Kokonaisuutena havainnot tukevat näkemystä siitä, että osaketuottoja Euroopan osakemarkkinoilla selittävät paremmin useat tekijät kuin pelkkä markkinariski. Samalla tulokset viittaavat siihen, etteivät faktorivaikutukset ole pysyviä, vaan ne voivat riippua markkinasta, portfoliotyypistä ja tarkastelujaksosta.

Avainsanat: hinnoittelumallit, CAPM, Fama–Frenchin kolmen faktorin malli, Fama–Frenchin viiden faktorin malli, faktorisijoittaminen, Euroopan osakemarkkinat

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1 Introduction

1.1 Background and Significance of the Research Topic

Stock markets are very important for the economy. They give investors the opportunity to invest their money and own a part of a company, so they can enjoy the benefits of the company's success. Understanding how the stock market functions and how returns are formed has always interested investors. They want to understand why some stocks earn higher returns than others. This information is also important for financial institutions, because their decisions depend on future return expectations.

In recent years, financial markets have become more important in everyday investing. Many individuals invest in stocks, either on their own through a broker or by using, for example, mutual funds or exchange-traded funds. During the last few decades, factor investing has gotten more attention. Many investment products use strategies related to the use of factors, such as size or profitability. Ang (2014) states that an important decision is deciding how much risk to take and which factor risk premiums to use.

Several earlier studies use stock market and factor data from the United States, but European markets are also important. There are many large and globally listed companies in the European stock market and a wide variety of different exchanges. At the same time, European markets have structural differences that make them different from the United States. Because of this, analyzing return models in equity markets is important. This allows us to assess whether existing research findings are still valid in a different environment.

1.2 Research Problem, Objectives, and Delimitation

Even though stock return research dates back a long time, it’s still not entirely clear which model best explains how stocks perform in different markets. Many still use models like the Capital Asset Pricing Model (CAPM), but some research has found that adding more factors can help explain stock returns better (Fama & French 2015). This is why comparing simpler and more complex models in the same market is useful. Most of the research done for factor investing has been done in the United States market. This creates a need for research: we need to test how well common models can explain stock returns in the European markets.

The main research question of the study is: Do multi-factor models explain portfolio returns better than the CAPM in European equity markets? The study is limited to European stock market data and covers the period from the beginning of 2000 to the end of 2025. The empirical analysis compares how well the CAPM, the Fama–French three-factor, and the Fama–French five-factor models perform and how well they explain stock returns in European markets. Other factor models are not included in this study.

1.3 Research Methods and Structure of the Study

This study is based on a quantitative research method, and it uses numerical data to compare how well different asset pricing models perform. Empirical analysis is done using regression analysis. This allows the examination of the relationship between the factors and returns. The results are compared using data from the regression models. The final conclusions of the study are based on the results obtained, and they are compared with previous research.

The study has five main chapters. The first chapter introduces the topic and research question and gives basic information about the study. The second chapter presents the theoretical framework. The third chapter explains the data and methods used in the study. The fourth chapter presents the empirical results. The final chapter includes the conclusions, limitations, and suggestions for future research.

2 Theoretical Framework

2.1 Efficient Market Hypothesis

In finance theory, there has been an effort to understand how security prices are formed, and which factors explain differences in returns (Sharpe 1964; Lintner 1965). A central question has been whether the prices fully reflect the information available in the market, or whether it is possible to identify and predict some return patterns. Since the early stages of investing, many different investment models have been developed to explain price fluctuations and predict investment returns. Many of these are still in use today, but most have been replaced by newer models. The efficient market hypothesis (EMH) has become a central starting point in this research tradition, according to which all available information is quickly reflected in security prices. According to this theory, stocks reflect all available information, and for this reason, the market cannot be beaten. New information is reflected in prices quickly, and expected returns based on publicly known information should disappear. (Fama 1970; Malkiel 2003.)

The idea of the efficient market hypothesis is related to the idea of a random walk in asset prices. If new information enters the market unpredictably and gets reflected in prices right away, then future price changes should also be difficult to predict. Fama (1965) states that if stock prices follow a random walk, meaning that past price movements cannot be used to predict future trends, it is not possible to predict future prices appropriately. This means that technical analysis should not give any information about future price changes. Samuelson presents a similar idea, showing that if asset prices are based on discounted future values, prices should follow a random path. In addition, he notes that even skilled investors find it hard to consistently beat the market average return. (Fama 1965; Samuelson 1973.)

According to Fama (1970), the efficient market hypothesis can be divided into three different forms: weak-form, semi-strong form, and strong-form efficiency. When a market is weak-form efficient, prices reflect all historical price information. In this case, technical analysis does not work systematically, as past returns cannot predict future returns. According to semi-strong efficiency, prices contain all publicly available information. These include, among others, financial statements, analyses, and news. Strong efficiency includes all information, including insider information, in which case even insiders cannot achieve excess returns in the market. However, strong efficiency is considered an unrealistic assumption in securities markets (Malkiel 2003). Even though there is uncertainty about the form classification, it provides a clear way to separate different levels of market efficiency. It also helps to understand in which situations the potential return patterns could be exploited and in which they could not. (Fama 1970.)

The efficient market hypothesis has been important in finance research because it gives an understanding of how prices should behave in the stock market. The idea is based on the presumption that the information spreads very quickly, and it is reflected in prices immediately. In such a situation, it is very difficult to consistently achieve excess returns using only publicly available information. This applies to both technical and fundamental analysis. For this reason, the EMH is often used as a starting point when evaluating whether observed returns are significant or not. Even if markets are not fully efficient, the hypothesis still gives a useful benchmark. (Malkiel 2003.)

Another challenge to the efficient market hypothesis comes from behavioral finance, which examines how investors actually make their decisions. Barberis et al. (1998) develop a model in which investor behavior can lead to both underreaction and overreaction in stock prices. In their model, underreaction is related to conservatism, in which investors react to new information too slowly. On the contrary, overreaction occurs when investors overemphasize the recent stock market trends and patterns and base their decisions on them. These behavioral patterns help to understand why return anomalies may occur in the data, and suggest that market efficiency cannot be fully implemented in the short term. (Barberis et al. 1998.)

Although the efficient market hypothesis remains highly central and widely used today, it has received criticism for its characteristics and limitations. Many studies have identified so-called market anomalies in the model, which suggest that certain characteristics of stocks, such as valuation level, firm size, and market risk, systematically affect return differences (Fama & French 1993). Based on these findings, newer and more modern models have been developed in finance research that explain returns better using multiple variables (Fama & French 1993; 2015). The efficient market hypothesis serves as a central starting point for factor investing research, but if markets are not fully efficient, it can be expected that certain systematic factors, such as risk factors, explain return differences.

2.2 CAPM and Its Limitations

Alongside the efficient market hypothesis, models have been developed that aim to explain the returns of securities using different risk factors. One of the most common of these models is the Capital Asset Pricing Model (CAPM), which was originally developed by Sharpe (1964) and

Lintner (1965). This model is based on the idea that the expected return of a security is determined by its systematic risk, which is measured by the beta coefficient. According to the model, an investor is only rewarded for market risk, meaning risk that cannot be diversified away. Thus, securities with higher beta coefficients, on average, offer higher returns than investment assets with lower beta. The CAPM can be expressed in a form where the expected return of a security consists of the risk-free rate and the product of the market risk premium and beta. The model emphasizes the linear relationship between expected return and risk. (Sharpe 1964; Lintner 1965.)

Even though the CAPM is widely used, it is built on quite strong assumptions. Investors are assumed to be fully rational and risk-averse, and markets are assumed to be efficient and without transaction costs (Sharpe 1964). On top of this, all investors are assumed to have access to the same information, to have well-diversified stock portfolios, and to be able to lend at a common risk-free rate (Fama & French 2004). As discussed earlier, fully efficient markets may be difficult to achieve in real markets, which contradicts this model (Malkiel 2003). The assumptions of the CAPM are not fully realistic, but they keep it simple. In real markets, investors behave differently, as they prefer different kinds of portfolios, and some have more information than others. Markets also have frictions, such as taxes and trading costs, that affect the return.

Although the CAPM provides a clear theoretical estimate of the relationship between return and risk, empirical research has shown that the model is not able to explain all return differences. Early studies by Fama and MacBeth (1973) found that the relationship between beta and average returns was not as significant as the traditional model predicts. Black et al. (1972) also present evidence against the traditional CAPM by showing that the relationship between beta and returns is flatter than predicted. This suggests that the model is, as such, too simple, since higher risk has not always been associated with higher returns. This provides evidence that beta may not be sufficient to explain differences in stock returns.

Later studies made this view even stronger by showing that other firm characteristics also tend to be related to average returns. Banz (1981) reports that smaller firms earned higher average risk-adjusted returns than larger firms. Fama and French (1992) find that size and book-to-market equity explain average stock returns more accurately than solely the market beta. In their later three-factor model, they set size and value as risk factors to help explain return differences (Fama & French 1993). These findings suggest that the market risk factor alone is not sufficient to fully explain stock return differences.

The CAPM model has also received criticism related to how it can be tested in practice. One main issue is the market portfolio used in the model, which cannot be fully observed. Because of this, many empirical studies use stock market indices as proxies, even though these indices only include a portion of all available assets. Roll (1977) argues that “the theory is not testable unless the exact composition of the true market portfolio is known and used in the tests” (Roll 1977). This means that the CAPM cannot be fully tested if all relevant assets are not included in the market portfolio. A true market portfolio should include not only stocks but also bonds, real estate, and other assets. For this reason, models that use a simplified market proxy may generate weak results that are caused by measurement problems instead of the CAPM itself. This is one of the most well-known challenges of the CAPM.

The CAPM still gives a useful starting point to understanding the relationship between return and risk. The model is simple, which makes it relatively easy to understand and use. However, later evidence suggests that the model is not enough on its own. Since it has many limitations, more advanced models have been developed that also include more factors instead of only the market risk (Fama & French 2015). These models aim to use key factors to better explain the return patterns in financial markets.

2.3 The Emergence and Development of Factor Investing

As a result of the limitations of the Capital Asset Pricing Model, alternative models have been developed in finance research that aim to evaluate returns more accurately using multiple variables. In these models, the expected return is not calculated solely based on market risk, but several risk factors are used in its calculation. Because of this, new models were created with the intention of including several factors that would explain the returns instead of just one.

Based on these findings, the Fama–French three-factor model was developed (Fama & French 1993). They show that, in addition to market risk, firm size and book-to-market ratios help to explain differences in stock returns. Their model includes the market factor, the size factor (SMB), and the value factor (HML). This was an important step in financial research and the start of the development of multifactor investing models. Later, the model was further expanded into the Fama–French five-factor model (Fama & French 2015). This model added the profitability and investment factors to the previous three-factor model. The purpose was to explain the differences in stock returns more precisely than the previous model. This shows that asset pricing models change when more empirical data is available.

Additionally, financial research identified other factors outside of the traditional Fama–French factor models. As more studies were published, the number of proposed return factors increased significantly. Harvey et al. (2016) note that hundreds of factors have been presented in the literature and argue that many reported findings may be unreliable because of multiple testing.

One of the best-known examples is the momentum factor. This factor describes the relationship between past return development and future returns (Jegadeesh & Titman 1993). This factor became one of the most widely used factors in research as well as practical investing. The Carhart four-factor model was introduced in 1997, which expanded the previous three-factor model, adding the momentum factor (Carhart 1997).

Factor investing has not remained only a theoretical approach, but it is also widely utilized in practical investment activities. A wide variety of investment funds and ETFs build their investment strategies based on factors such as value, size, momentum, and low volatility. The aim of these strategies is to use previously observed return differences and achieve better returns relative to risk. Asness et al. (2019) find that “high-quality stocks have high risk-adjusted returns”, which supports using quality-based investing strategies. Also, Baker et al. (2011) report that during the timeframe of their study, “low risk consistently outperformed high risk over the period”, which has later increased the popularity of low-volatility-based investing.

2.4 Key Stock Market Factors

In factor investing, multiple different factors are usually used, based on which different investment strategies are formed. The most well-known factors are based on the Fama–French three- and five-factor models, but based on other research, widely recognized factors have also been formed, which are used today extensively around the world. The most common use of factors is in stock markets, but they can also be utilized, for example, in currency markets.

2.4.1 Value Factor

The value factor is one of the most commonly used factors and is widely visible in everyday investment activities. The value factor is based on the idea that undervalued stocks perform, on average, better than overvalued stocks. Valuation level is often measured using various ratios, such as price-to-earnings or book-to-market. A high book-to-market ratio indicates a low valuation, whereas a low ratio indicates that the stock is priced highly relative to its book value. Empirical research shows that the book-to-market ratio can explain return differences between stocks. In the Fama–French three-factor model, the value factor (HML) is represented by the difference between high book-to-market and low book-to-market stocks. This made value factor investing a central part of today's asset pricing models and research. (Fama & French 1993.)

The effectiveness of the value factor can be explained in several different ways. One explanation is that low-valued stocks are riskier than highly valued stocks, and therefore investors expect higher returns from them. On the other hand, it is also possible that investors underestimate poorly performing stocks, in which case these undervalued stocks may later generate above-average returns due to their low price.

2.4.2 Size Factor

The size factor is based on the observation that, on average, small firms have historically generated higher returns than large firms. Firm size is generally measured by its market capitalization, where firms with low market value are classified as small firms and firms with high market value are classified as large firms, and this also serves as the basis for the size factor. The size factor is based on the finding that small firms have, on average, earned higher returns than large firms. In the Fama–French model, it is represented by SMB, which measures the difference in return between small and large firms. (Fama & French 1993.)

The phenomenon is also referred to in finance theory as the small-firm effect, which was documented in studies by Banz (1981), already before the Fama–French three-factor model. The phenomenon can be explained in several different ways. One possible explanation is that small firms have significant potential to grow multiple times in value, whereas large firms typically do not experience such substantial growth. This means that small firms tend to be much riskier, thus less attractive to risk-averse investors. At the same time, investors require higher returns from riskier investments. Small firms are often associated with greater uncertainty and may be more sensitive to market movements, while they can be harder to buy or sell. Amihud and Mendelson (1986) show that assets with lower liquidity may have higher expected returns, because investors require compensation for higher trading costs. In addition, small firms may have stronger growth potential, since it is often easier to grow significantly from a low-value level compared to an already highly valued firm.

2.4.3 Quality Factor

The quality factor, also referred to as the profitability factor, is based on the idea that high-quality firms, on average, generate higher returns than lower-quality firms. Quality refers to a firm’s ability to generate stable and profitable earnings, usually over a longer time period. It can also be associated with a strong financial position. Such firms are able to efficiently utilize their resources and generate higher returns and profits relative to their assets, which is central to the quality factor. Empirical research has also shown that profitable firms generate significantly higher returns than unprofitable firms, even though their valuation multiples are on average higher. (Novy-Marx 2013.)

The findings of Novy-Marx (2013) became well-known later when the quality factor was included in the Fama–French five-factor model, where the profitability factor was included as the RMW factor. In the model, this factor compares firms with strong profitability to firms with weak profitability. (Fama & French 2015.)

The effectiveness of the quality factor can be justified in several different ways. One explanation for the profitability is that high-quality firms tend to generate stable earnings year after year, making their future cash flows easier to evaluate. This also provides investors with a sense of security, especially during uncertain times. On the other hand, it is possible that markets do not recognize all high-quality firms, and in such cases, high-quality firms may be undervalued. Piotroski (2000) finds that financially strong high book-to-market firms generated substantially higher returns than financially weak firms. In such situations, investment assets that generate above-average returns may be found, which is why investment strategies based on the quality factor are very popular today.

2.4.4 Investment Factor

The investment factor refers to the observation that companies that invest less perform, on average, better than companies that invest more. In research, investment usually means an increase in a firm's assets. In the Fama–French five-factor model, this factor is represented by CMA (Conservative Minus Aggressive), which measures the return difference between firms with conservative and aggressive investing strategies. (Fama & French 2015.)

Earlier research before the implementation of the investment factor in the five-factor model also supports this idea. Cooper et al. (2008) find that a firm's asset growth is strongly negatively correlated with abnormal returns. They also mention that asset growth still serves as an important predictor of return when other factors are included. Similar evidence has been documented in other studies. For example, Hou et al. (2015) present an empirical q-factor asset pricing model that includes market, size, investment, and profitability factors. They later state that this model explains average stock returns well.

The investment factor is very important because it connects the company's strategic decisions with the stock returns. Investments are often made from the profit earner earlier, so firms with strong profits may invest more in the future. At the same time, the investment can give information on the future returns, and therefore it is essential to include it in models.

2.4.5 Additional Factors

In addition to the most common factors in Fama–French factor models, research has identified other factors that may help explain stock returns. Two well-known examples are momentum and low volatility. These factors are not included in the Fama–French three- or five-factor models but have since become highly popular in both research and practice.

The momentum factor is based on the observation that stocks that have performed well recently often continue their good performance in the future, especially in the short term. This also implies that stocks that have performed poorly recently tend to continue to perform poorly in the near future, particularly over a short time horizon. Momentum is typically measured by examining stock returns over recent months and using this information to form investment strategies. Empirical research has shown that such strategies have historically generated significantly higher returns (Jegadeesh & Titman 1993).

The effectiveness of the momentum factor can be criticized from several perspectives. For example, it is clear that a stock cannot continue rising indefinitely, but markets experience changes at certain intervals, during which the majority of stocks may decline. Another critical aspect relates to investor behavior. Many investors prefer investing in stocks that have performed well recently, as they are optimistic that the increase in stock prices will continue in the future. In this case, they base their investment decisions specifically on past stock price development, which, according to the efficient market hypothesis, should not be possible (Fama 1970). However, stocks that have recently performed poorly are often overlooked by investors because they do not appear very attractive. In a value-based investment strategy, such stocks may offer excellent investment opportunities, as their valuation may be significantly below their true value.

Another well-known factor is low volatility. The low-volatility factor is based on the observation that low-risk stocks have historically generated returns as high as, or even higher than, high-risk stocks. This contradicts traditional finance theory, according to which higher risk is always associated with higher expected return. Volatility refers to the fluctuation in the price of a stock, so the higher the volatility, the more the price changes. Stocks with low volatility are typically more stable and less sensitive to market changes and fluctuations. Despite this, their returns have not lagged behind those of higher-risk investments. (Baker et al. 2011.)

The low-volatility phenomenon has been explained, among other things, by investor behavior and their market actions. Investors may prefer high-volatility securities when seeking high returns, which can lead to the overpricing of these securities, in which case low-risk assets may be undervalued and offer excellent investment opportunities. In addition, not all investors are able to use leverage without limitations, which reduces the possibility of fully exploiting low-volatility securities (Frazzini & Pedersen 2014). Based on these findings, the low-volatility strategy has become an established part of modern investment practice.

2.5 Previous Research and Hypotheses

A significant amount of international research has been conducted on factor investing over several decades. Traditional finance theory and the first models focused solely on the market risk, as CAPM suggests that expected returns depend on the beta (Sharpe 1964). Later research found that there are multiple factors that can help to explain stock returns.

Studies have shown that certain characteristics, such as profitability, firm market value, and past price development, explain differences in stock returns. For example, Fama and French (1993) demonstrated in their study that the size factor explains differences in returns. Later, they expanded their model by adding profitability and investment factors (Fama & French 2015). In addition, later research has confirmed that the momentum factor is a significant factor of returns (Jegadeesh & Titman 1993).

Even though factor investing has been studied quite extensively, a large portion of the research is based on large, liquid markets, particularly the United States markets. European markets have had less research, and factors may perform differently across regions and time periods. The European markets are less integrated than those in the United States, and European companies tend to rely more on bank lending than equity markets. In addition, European households are less likely to invest in capital markets than American households. Lastly, venture capital availability is also lower in Europe, which makes it useful to study how factors explain returns in European markets. (European Central Bank 2025.)

Based on the above, it is justified to examine how factor investing strategies and phenomena function in the European markets and to what extent the results align with previous research. For this purpose, the following hypotheses are set in the study:

H1: Multi-factor models explain portfolio returns better than the CAPM in European equity markets.

H2: The Fama–French five-factor model provides higher explanatory power than the three-factor model.

H3: Market risk remains the most important individual factor, but size, value, profitability, and investment factors also help explain returns.

Testing these hypotheses requires empirical research that examines the relationship between factors and stock market returns. The following chapter describes the data and the methods used to study this relationship.

3 Data and Methods

3.1 Description of the Data

The data used in this study consists of portfolio return data and Fama–French factors. The subject of the study is a set of portfolios representing European stock markets, and their returns are explained using different factor models.

The portfolio data used in the study consists of 25 portfolios formed on size and book-to-market ratios. These portfolios are obtained from the Kenneth French Data Library, which is widely used in empirical finance research. The portfolios include firms from European stock markets, and they are constructed by sorting companies based on their market capitalization and book-to-market ratios. This results in portfolios that represent different types of firms, such as small and large companies, as well as value and growth stocks. (French 2026).

The portfolios are divided into categories using two characteristics. First, the companies are sorted into five groups based on their market capitalization value, from smallest to largest. Then they are also divided into five groups based on their book-to-market ratios, from low to high. By combining the two categories, a total of 25 portfolios are formed in a 5 x 5 structure. Each portfolio then represents companies of a specific firm size and value. (French 2026.)

The portfolios are named based on their characteristics. The abbreviations ME and BM refer to market equity and book-to-market ratio. For example, portfolio ME1 BM2 refers to a company in the smallest size group and the second-lowest book-to-market ratio group. ME5 BM4 is the portfolio with the largest companies and the second-highest book-to-market ratio. SMALL LoBM refers to small firms that have the lowest book-to-market ratios, while BIG HiBM refers to large firms with the highest book-to-market ratios.

The portfolios' returns are value-weighted monthly returns. This means that firms with larger market capitalization have a bigger impact on the portfolio returns. For this reason, the portfolios reflect more realistic market conditions than equal-weighted portfolios. The data is used in the study as a measure of portfolio returns. The study examines excess returns of the portfolios, which are calculated by subtracting the risk-free rate from the portfolio returns. The risk-free rate is obtained from the Fama–French dataset. This approach allows the analysis to focus only on returns that are related to risk factors, rather than returns that are explained by risk-free investments.

The explanatory variables consist of Fama–French factors, which have been downloaded from the Data Library maintained by Kenneth French. The dataset includes the variables of the five-factor model: market risk premium (Mkt-RF), size factor (SMB), value factor (HML), profitability factor (RMW), and investment factor (CMA). The risk-free rate is also included in the dataset.

Fama–French factors are constructed as differences between portfolio returns. For example, the SMB (Small Minus Big) factor measures the return difference between small and large firms, and the HML (High Minus Low) factor measures the return difference between firms based on high and low book-to-market ratios. In addition, the RMW (Robust Minus Weak) factor measures the return difference between firms with high and low profitability, and the CMA factor (Conservative Minus Aggressive) measures the return difference between firms that invest conservatively and those that invest aggressively. The dataset contains monthly data, which smooths out sudden fluctuations in the market and thus makes the data more reliable. (Fama & French 1993; Fama & French 2015.)

3.2 Research Period

The data used in the study covers the period from the beginning of January 2000 to the end of December 2025, and the dataset contains 312 monthly observations. The selected time period is based on the availability of the portfolio data from the Kenneth French Data Library. A period of over 26 years is sufficiently long to conduct a reliable analysis.

The selected time period covers multiple market conditions, during which stock markets have experienced significant fluctuations and returns have varied considerably. The research period includes, among other events, the dot-com crash in the early 2000s, which affected technology stocks in particular and the global financial crisis of 2008 and 2009, during which stock markets experienced large declines. It also includes the subsequent euro area debt crisis, the immediate market panic caused by the COVID-19 pandemic, and the rapid recovery of stock markets that followed. The final years of the period also reflect rising interest rates, geopolitical tensions, and inflation.

The selected research period covers both bull and bear market periods. This makes the results more reliable, as market conditions may affect the performance of factors. A longer time period allows for a more comprehensive analysis of how well different factor models explain returns over time. (Fama & French 2015.)

3.3 Construction of Factors

The factors used in this study are based on pre-constructed Fama–French factor models, downloaded from the Kenneth French Data Library database. The factors in this study are not constructed from individual stocks but are based on ready-made monthly factor datasets. The purpose of these factors is to capture different sources of systematic risk in stock markets. The size factor reflects differences between small and large firms, while the value factor describes differences between value and growth stocks. The profitability and investment factors extend this framework by considering firm characteristics related to earnings and investment decisions. (Fama & French 1993; Fama & French 2015.)

The market factor (Mkt-RF) represents the excess return of the market portfolio over the risk-free rate. The SMB factor describes the difference in returns between small and large firms, while the HML factor describes the difference between value and growth stocks. The RMW factor measures the effect of profitability on returns, and the CMA factor measures the effect of investment decisions on returns.

Since the study uses pre-constructed factor series, the results do not depend on individual factor construction methods. This improves the reliability of the results and allows comparison with previous studies. However, it should be noted that the factors are based on European stock markets and, therefore, may not fully capture all characteristics of specific regional markets.

3.4 Portfolio Formation

The portfolios used in this study are obtained from the Kenneth French Data Library and are not constructed manually. The dataset consists of 25 portfolios formed on size and book-to-market ratios. Each portfolio represents a specific group of firms based on their characteristics, which allows for a more detailed analysis compared to using a single market index.

The portfolios are formed by sorting firms into five groups based on their market capitalization and five groups based on their book-to-market ratios. This results in 25 portfolios that represent combinations of small and large firms as well as value and growth firms. For example, the "SMALL LoBM" portfolio includes small firms with low book-to-market ratios, while the "BIG HiBM" portfolio includes large firms with high book-to-market ratios. (Fama & French 1993.)

In the empirical analysis, portfolio returns are described using excess returns. These are calculated by subtracting the risk-free rate from the portfolio returns. The risk-free rate is obtained from the

Fama–French dataset. This makes it possible to focus on returns that are explained by risk factors, rather than returns that are due to risk-free investments.

3.5 Research Methods

The research method used in this study is quantitative, in which the relationship between portfolio returns and factor variables is analyzed using linear regression. The aim of the analysis is to determine to what extent the selected risk factors are able to explain the returns of the portfolios representing European stock markets. The regression is conducted as a time-series regression, which means that it uses monthly observations to calculate how returns and factors are related over time. This approach makes it possible to capture variation across different market conditions and to observe how the relationships change during different periods. Regression analysis makes it possible to examine the effect of multiple factors simultaneously and thereby determine the relationship between the stock portfolio and risk factors. Regression analysis can also be used to determine whether the observations are statistically significant.

The regression analysis is carried out using the Ordinary Least Squares (OLS) method, which is a fundamental and widely used approach in finance research. The regression models are constructed in Excel using the data analysis tool. This tool calculates the estimated coefficients, standard errors, t-statistics, p-values, and coefficients of determination automatically based on the input data. The method minimizes the sum of squared errors of the model, which produces the best possible estimates of the relationships between variables. This makes it possible to examine the relationship between risk factors and the portfolios, showing their impact and how well they explain differences in portfolio returns. This OLS method is well-suited for this study, as it allows for convenient examination of the effect of multiple factors on the stock portfolios.

The performance of the models is evaluated using the key statistics obtained from the regression analysis. The most important statistic describing the relationship between the stock portfolios and risk factors is the coefficient of determination (R^2). This indicates what percentage of the portfolio's returns can be explained by the model's risk factors. In addition, the adjusted coefficient of determination (Adjusted R^2) is examined, which, compared to the standard R^2, also takes into account the number of variables and adjusts the model accordingly. The overall fit of the model is tested using the F-test, and individual factors are tested using t-tests. The p-value provided by the model indicates whether the results are statistically significant or not. A 5% level is commonly used as the threshold for statistical significance. These statistics make it possible to assess how well the model explains the relationship between the stock portfolios and risk factors, and which factors are most significant.

3.6 Models

The study includes several asset pricing models used to examine the returns of the stock portfolio. The purpose of these models is to evaluate how well different sets of risk factors are able to explain the variation in portfolio returns. The models are estimated using the same dataset and time period, which allows for a direct comparison of their explanatory power. In this way, the analysis focuses on whether adding additional factors improves the ability of the models to describe returns.

The first model examined is the Capital Asset Pricing Model (CAPM), in which the portfolio's excess return is explained solely by market risk. The model assumes that the market portfolio is the key factor explaining return differences. In this study, the CAPM serves as a benchmark model for the other models, allowing for comparison of how much different risk factors improve the explanatory power. The regression form of the CAPM used in the analysis is presented in Equation (1):

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(MKT_t - R_{ft}\right) + \varepsilon_{it} \tag{1}$$

The second model is the Fama–French three-factor model, which extends the CAPM by including the size factor (SMB) and the value factor (HML). These additional factors show differences between small and large firms and between value and growth stocks. Analyzing this model helps to examine whether these commonly used factors improve the explanation of portfolio returns. The regression model is shown in Equation (2):

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(MKT_t - R_{ft}\right) + \beta_{SMB,i}SMB + \beta_{HML,i}HML + \epsilon_i \tag{2}$$

The third model is the traditional and extensively studied Fama–French five-factor model, which extends the previous three-factor model by adding the quality and investment factors. The added RMW and CMA factors describe the effects of profitability and investment on returns. The extended model shows how much the additional factors affect returns when the previous model's factors are still included. If including additional factors leads to higher explanatory power and more consistent results, this suggests that the extended models provide a better estimate of portfolio returns. The regression model used for the five-factor model is presented below. (Fama & French 2015.)

$$R_{it} - R_{ft} = \alpha_i + \beta_i(MKT_t - R_{ft}) + \beta_{SMB,i}SMB + \beta_{HML,i}HML + \beta_{RMW,i}RMW + \beta_{CMA,i}CMA + \epsilon_i \quad (3)$$

Comparing these models with each other makes it possible to determine how much the inclusion of additional factors affects the explanatory power of the models. If the extended models provide a better fit and reduce unexplained returns, it indicates that multiple factors are needed to describe stock returns more accurately (Fama & French 1993; Fama & French 2015).

4 Empirical Results

4.1 Description of the Data

The examination of the data shows that the excess returns of the portfolios vary significantly over the study period. In some months, excess returns can be strongly positive or negative, reflecting the volatility of stock markets and their sensitivity to changes in the economy as well as market cycles. In particular, during the financial crisis, large negative returns can be observed. During market recovery phases, there are longer upward periods, during which excess returns are strongly positive.

The returns of the factors also vary considerably over the study period. No factor is consistently positive or negative throughout the entire period. As expected, the market risk factor behaves relatively similarly to the general market index, but other factors, such as value, quality, and investment, vary more across different time periods. The effect of different factors depends on market conditions, where certain characteristics of firms make a significant difference. The variation in the data provides a good basis for regression analysis, as it allows for a clearer examination of which factors have a greater impact on returns and how large their effect is at different points in time.

4.2 Results of the CAPM Model

The results of the CAPM model show that the model explains a moderate amount of the variation in portfolio returns. Table 1 presents the regression results for all 25 portfolios, including estimated alphas, betas, and coefficients of determination. The average coefficient of determination (R^2) is 0.854, indicating that the market risk alone explains a large part of portfolio returns, but not all of it. The explanatory power varies across different portfolios, with R^2 ranging from 0.729 to 0.949. In general, higher values are found in larger portfolios, while some of the smaller portfolios show lower levels of explanatory power.

Table 1. CAPM Regression Results for the 25 European Portfolios

The table reports CAPM regression results for 25 European portfolios formed on size and book-to-market ratios. ME refers to market equity (firm size), and BM refers to the book-to-market ratio. Alpha is the intercept term, Beta (Mkt-RF) measures sensitivity to market risk, and R^2 indicates the model's explanatory power. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Portfolio	Alpha	p-value	Beta (Mkt-RF)	R^2
SMALL LoBM	-0.599***	0.001	0.989	0.729
ME1 BM2	-0.195	0.191	0.979	0.793
ME1 BM3	-0.007	0.959	0.962	0.824

ME1 BM4	0.158	0.192	0.927	0.839
SMALL HiBM	0.413***	0.001	0.896	0.811
ME2 BM1	-0.314*	0.071	1.059	0.767
ME2 BM2	0.070	0.598	1.034	0.844
ME2 BM3	0.190	0.116	0.998	0.858
ME2 BM4	0.258**	0.030	0.998	0.863
ME2 BM5	0.435***	0.001	1.004	0.831
ME3 BM1	-0.139	0.404	1.100	0.795
ME3 BM2	0.105	0.363	1.042	0.879
ME3 BM3	0.177	0.101	1.025	0.889
ME3 BM4	0.234**	0.032	1.022	0.886
ME3 BM5	0.400***	0.002	1.054	0.851
ME4 BM1	0.013	0.921	1.035	0.850
ME4 BM2	0.183*	0.059	1.003	0.905
ME4 BM3	0.174**	0.035	0.997	0.928
ME4 BM4	0.240**	0.017	1.055	0.907
ME4 BM5	0.212	0.119	1.123	0.859
BIG LoBM	-0.133	0.287	0.868	0.811
ME5 BM2	0.097	0.223	0.908	0.920
ME5 BM3	-0.045	0.525	1.019	0.949
ME5 BM4	0.089	0.337	1.030	0.916
BIG HiBM	0.027	0.865	1.207	0.836

The estimated market betas are very close to one for most of the portfolios, which is in line with the predictions of CAPM theory (Sharpe 1964; Fama & French 1993). Most beta values tend to be between 0.9 and 1.1, meaning that the portfolios move largely in line with the overall stock market. There are still some differences between the portfolios. For example, the BIG HiBM portfolio has a beta of 1.207, while the BIG LoBM portfolio has a lower beta of 0.868, indicating that not all portfolios are equally sensitive to market movements.

The intercept terms provide additional information about the model's performance. Out of the 25 portfolios, 8 have statistically significant alphas at the 5% level. Statistically significant alpha values suggest that portfolio returns are different from the model's predicted level. Jensen (1968) interpreted alpha as abnormal performance relative to the model. Some of these values are relatively high, as seen in portfolios such as SMALL HiBM and ME2 BM5, where the alphas are positive and statistically significant. At the same time, the SMALL LoBM portfolio shows a negative and significant alpha, indicating that the abnormal returns are not consistent across different portfolios. The average alpha across all 25 portfolios is 0.082, which clearly differs from zero.

Additional information can be obtained by analyzing the results across portfolio groups. When portfolios are grouped by size, the differences are relatively small. Table 2 shows that the average alpha is 0.041 for small portfolios and 0.086 for large portfolios, and the number of significant alphas is slightly higher among small portfolios. This indicates that the model performs quite similarly in the different size groups.

Table 2. CAPM Alphas by Portfolio Size

The table reports average alphas and the number of statistically significant alphas (p < 0.05) for portfolios grouped by size.

Group	Average alpha	Significant alphas (p<0.05)
Small	0.041	4
Big	0.086	2

Clearer differences appear when the portfolios are grouped by book-to-market ratios. As shown in Table 3, portfolios with high book-to-market ratios have a significantly higher alpha compared to low book-to-market portfolios. Also, most of the statistically significant alphas are found in high book-to-market portfolios, while low book-to-market portfolios show only a slight sign of abnormal returns. This can be analyzed as the CAPM systematically underestimating returns for high-value portfolios. This type of pattern aligns with earlier empirical findings in the asset pricing literature. For example, Fama and French (1992) show that firms with high book-to-market ratios tend to earn higher average returns, while the CAPM fails to explain these differences (Fama & French 1992). Similar evidence has been reported in later studies, where the value effect is still a persistent pattern in stock returns (Fama & French 1993; Fama & French 2015). However, value factor's importance tends to reduce when additional factors are included (Fama & French 2015).

Table 3. CAPM Alphas by Book-to-Market

The table reports average alphas and the number of statistically significant alphas (p < 0.05) for portfolios grouped by book-to-market ratios.

Group	Average alpha	Significant alphas (p<0.05)
Low BM	-0.091	1
High BM	0.247	6

Looking across portfolios, the alphas do not appear to be randomly distributed, but rather depend on certain portfolio characteristics. For instance, several higher book-to-market portfolios show positive alphas, while some lower book-to-market portfolios show negative values, meaning that the market factor alone is not capable of capturing all of the systematic differences.

Overall, the CAPM model captures the general relationship between market risk and returns, but still leaves a big part of the observed variation unexplained. The amount of significant alphas across all the portfolios indicates that a single-factor model cannot fully describe stock market returns. This makes it relevant to examine whether multi-factor models provide a better explanation for returns.

4.3 Results of the Fama–French Three-Factor Model

The results of the Fama–French three-factor model show that the model's explanatory power increases clearly compared to the CAPM model. The average coefficient of determination (R^2) is 0.949, which is noticeably higher than in the CAPM model. Across portfolios, the values are consistently high, and most of them are above 0.93. This indicates that adding the size and value factors improves the model's ability to explain variation in portfolio returns. The market beta remains close to one for most of the portfolios and continues to be statistically significant. This is similar to the CAPM results, where market risk already explained a large part of the observed returns. The interpretation does not change much in this model.

Contrary to the CAPM results, the intercept terms show a difference. The number of statistically significant alphas increases to 10 portfolios, but the average alpha is close to zero at only 0.001. This difference is extremely important. Even though some of the individual portfolios still show abnormal returns, their effects seem to cancel out when the portfolios are examined together. In the CAPM model, the average alpha was clearly positive, but in this model practically zero. This finding suggests that the three-factor model captures more patterns leading to systematic returns. The coefficients of the additional factors in the model give more insight into the results. The size factor (SMB) is positive for most portfolios, and the average SMB coefficient is quite high at 0.550. This shows that smaller firms tend to earn higher returns than larger firms during the sample period, but the effect varies across portfolios and is not as strong in all size groups.

The results of the value factor (HML) show a more complicated pattern. The average coefficient of HML is close to zero at 0.014, which shows that the value effect is very weak. However, there are clear differences between the portfolios. Portfolios with high book-to-market values tend to have positive HML values, and low book-to-market portfolios often have negative values. Despite this, the overall effect of the value factor is not significant during the sample period.

The three-factor model explains the portfolio returns better than the CAPM model. When comparing these results with the previous model, the main differences are increased explanatory power and a decrease in average alpha. The three-factor model is more capable of explaining the returns, even though not all of them. This indicates that adding additional factors tends to improve the overall performance of the model. The full regression model results for the three-factor model are presented in Appendix 1.

4.4 Results of the Five-factor Model

The results of the Fama–French five-factor model show that the explanatory power increases further when additional factors are added. The average coefficient of determination (R^2) is 0.953, which is slightly higher than in the three-factor model. The improvement is not very large, but values tend to be consistently high across all portfolios. Most R^2 values are close to or above 0.95, which means that the model is able to explain most of the variation in portfolio returns.

The market factor remains important in this model, like in the previous ones. The estimated betas are still close to one for most portfolios, and the overall interpretation does not change much compared to the previous models. Portfolio returns continue to move with the market. Since the additional factors capture some of the variation, the role of the market factor is less dominant.

The intercept terms demonstrate a clear improvement compared to the previous models. The number of statistically significant alphas decreases to 6 portfolios, with the average alpha being at just 0.028, indicating that the five-factor model is able to explain an even larger part of the abnormal returns. Even though some portfolios still have significant alphas, the overall pattern is closer to zero than in the CAPM model and slightly closer than in the three-factor model.

On an individual factor level, the size factor (SMB) remains positive on average, with a value of 0.548. The size factor effect is quite stable in the data, as the results are similar to those of the three-factor model. However, the value factor (HML) has an average value close to zero at only 0.003. It loses its power to explain returns when profitability and investment factors are included in the model. This kind of result is also seen in earlier studies, where the importance of the value factor decreases after including additional factors (Fama & French 2015). But the profitability (RMW) and investment (CMA) factors give additional explanation for the results. The RMW coefficient has an average value of -0.062, and the average CMA is also negative at -0.021. This indicates that the effects of profitability and investment are contrary to expectations. In this sample, these factors may behave differently in European markets compared to the original U.S.-based evidence.

In general, the five-factor model provides the best fit among the other models. The increase in explanatory power is relatively small compared to the three-factor model, but the lower amount of significant alphas indicates that the model captures return patterns more accurately. At the same time, not all factors have a strong effect, especially in the latter two models. The full regression model results for the five-factor model are presented in Appendix 2.

4.5 Comparison of Results with Previous Research

The results of this study can be compared to the finance literature, in which the explanation of stock returns has been examined using factor models. One of the key findings is the strong and statistically significant role of the market risk factor in all models. This is consistent with previous research, in which the market factor forms a central component of multifactor models and, together with other factors, explains stock returns (Fama & French 2015; Hou et al. 2015). Although additional risk factors are included in the model, the market factor remains an important variable.

With regard to the three-factor model, the explanatory power increases clearly, in line with previous studies. Fama and French (1993) show that including size and value factors in the model improves its ability to explain differences in returns. A similar pattern is seen in this study, where the R^2 increases significantly, and the average alpha decreases close to zero. However, the amount of significant alphas does not disappear completely, which is also reported in earlier studies, explaining that no single model can explain all of the variation in stock returns (Fama & French 1993; Fama & French 2015).

With regard to the size factor, early research found that small firms generated higher risk-adjusted returns (Banz 1981), but later literature has shown that its strength varies across different time periods and markets (Fama & French 2015). A similar pattern is found in the results of this study. The SMB coefficient is, on average, positive in both the three- and five-factor models, which is in line with earlier studies. At the same time, the effect is not equally strong in all portfolios, suggesting that the size effect may be present but not constant.

The five-factor model improves the overall fit and accuracy of the model, as the number of statistically significant alphas is lower than in the previous models, and the explanatory power is the highest. This is in line with the findings of Fama and French (2015), in which profitability and investment factors are shown to improve the model’s ability to explain differences in stock returns. At the same time, the results at the individual factor level are less clear. The average coefficients for profitability (RMW) and investment (CMA) are slightly negative, but the effects are not strong or consistent across all portfolios. This indicates that the expected effects are not clearly visible in the data. Previous research has found that more profitable firms tend to earn higher returns and that firms with lower investment levels tend to outperform (Fama & French 2015; Cooper et al. 2008), but the results of this study show only limited evidence for these patterns.

5 Conclusions

5.1 Key Findings

The main findings of this study relate to how different asset pricing models explain returns in European equity markets during the period 2000–2025. In all models, the market risk factor is clearly the most important individual factor. The market beta is close to one in most portfolios, and the market factor remains statistically significant in the whole analysis. This shows that general market movements are still a key driver of stock returns. When the multi-factor models are compared to the single-factor CAPM model, the explanatory power clearly increases. The average R^2 of the CAPM model is 0.854, while the three-factor model increases it to 0.949, meaning that adding two more factors to the single-factor model increases the average by 0.095. The five-factor model provides the highest average R^2 at 0.953, a slight increase from the previous model. This means that adding size, value, profitability, and investment factors truly seems to help explain portfolio returns better than using market risk alone. However, the increase from the three-factor model to the five-factor model is quite small. This finding aligns well with earlier studies where adding additional factors improves the total explanatory power of the model (Fama & French 1993; Fama & French 2015).

The intercept terms also give valuable information about the model performance. In the CAPM model, several portfolios show statistically significant alpha values, which suggests that the single-factor CAPM model is not fully capable of explaining all the return differences. In the three-factor model, the average alpha declines close to zero, which can be seen as an improvement in the model's performance. Moving to the five-factor model, the number of statistically significant alphas declines further. This indicates that models seem to be able to explain more of the returns when additional explanatory factors are added. But after adding profitability and investment factors, the number of alphas does not go to zero, indicating that the model is still not perfect. Studies have shown similar situations, where the explanatory power increases but the model cannot fully eliminate abnormal returns (Fama & French 2015; Hou et al. 2015).

The individual factor results are quite mixed. The size factor is mostly positive in both the three-factor and five-factor models, meaning that small firms have generally done a little better during the review period. On the contrary, the value factor shows weaker results. Its average coefficient is close to zero, and it becomes less important in the five-factor model. This can be interpreted as the value factor not having as big an effect in European markets as in the United States. Also, since the model includes two new factors in addition to the three-factor model, it can lose its significance compared to the other factors.

Adding the profitability and investment factors to the three-factor model adds some explanatory power, but the improvement is not strong as stated above. The coefficients of these factors are not strong on average, which means that their effects in the European markets do not seem as significant as in the United States market. Fama and French (2015) report that profitable firms and firms that do not invest aggressively have, on average, higher returns. This pattern cannot be seen from the conducted analysis. A possible explanation for the less clear value is the differences in the European markets' structure and the chosen timeframe.

The portfolios also have clear differences between them. The results are not identical across all 25 portfolios. An interesting observation is that when comparing the portfolios by the book-to-market ratio, the explanatory power (R^2) is, on average, the lowest in the portfolios with the lowest and highest book-to-market values, and highest in the middle ones. This can be clearly observed in the CAPM model, but when moving to the three- and then five-factor models, it seems to change. In the five-factor model, the BM1-portfolios seem to have the lowest explanatory power, and the BM5-portfolios the highest. This indicates that when adding multiple factors to the model, it tends to explain return patterns better for firms with high book-to-market ratios than for firms with low book-to-market ratios. The explanatory power of each portfolio for the three- and then five-factor models can be seen in Appendix 1 and Appendix 2.

The hypotheses receive support. The first hypothesis is supported, since multi-factor models explain returns better than the single-factor CAPM model. The second hypothesis is also supported, as the five-factor model has the highest explanatory power among the other models. However, the improvement of the five-factor model over the three-factor model is not significant. The third hypothesis is partly supported. While the market risk remains through all the models as the most important factor, the additional factors do not show equally great or consistent improvements.

The thesis supports the view that stock returns are explained better by models including multiple factors, instead of the market risk alone. At the same time, factor effects are not the same. The size factor was the second most significant additional factor in the multiple-factor models. The value factor showed the weakest overall performance, and its importance reduced further when the model was expanded to five factors.

5.2 Limitations of the Study

When interpreting the results of the study, it is important to keep in mind the limitations. The study uses 25 pre-constructed portfolios of individual stocks. This reduces the impact of single companies' stock valuation movements and gives an overview of the market. It might also make some return patterns look smoother and less dramatic than they actually are. Because of this, some effects might seem weaker than in some other portfolios. Another important limitation to consider is that the study covers the years from 2000 to 2025, which includes, among others, the dot-com crash, the financial crisis, and the COVID-19 pandemic. These events can affect how the factors perform and how well the models work. This result applies to the last 26 years, including all the market movements. The results might be different if the study used data only from, for example, the last 10 years. After all, a longer time frame usually gives a more accurate and reliable result.

This study also uses factor data from the Kenneth French Data Library. The data is commonly used in finance research, which might give results that align more with the financial literature. If the portfolios for this study were constructed from scratch using different methods, the results could differ. There are also some limitations with the regression models used in the study. Linear regression, which was used, assumes that the relationship between the variables stays the same during the whole time period. In reality, market conditions change, and the effect might be non-linear.

Lastly, the study is based on historical returns. Just because historical data may show patterns in returns does not mean that it will be similar in the future. Financial markets are always changing, and so is investors' behavior. This study’s results are based on data, and it does not guarantee that similar results will continue in the future.

5.3 Suggestions for Future Research

The results of this study create several ideas for future research. One direction for future research would be to examine the same models by using individual stock data instead of portfolio data. This could make the return patterns more visible and help to explain why some factors were not strongly significant in this study. Future research could also divide the 26-year time frame into shorter periods, and the data could be analyzed separately before the financial crisis, during the euro area debt crisis, and after the COVID-19 pandemic. This could give different results, since some periods represent more normal market conditions than others. Also, it would be interesting to find out how the factors perform, especially during large market movements and financial crises.

Future research could also focus on individual European countries instead of Europe as one combined market. The results would explain whether the factors' effects differ between countries such as Finland, Sweden, and Germany. Different market sizes and industry structures could lead to different results between countries. Future studies could also include models and factors that were not used in this study. For example, momentum and low-volatility factors are often discussed in studies. This could help explain stock returns better.

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Appendices

Appendix 1. Three-factor model regression results for the 25 European portfolios

Portfolio	Alpha	p-value	Beta (Mkt-RF)	SMB	HML	R²
SMALL LoBM	-0.596***	0.000	1.029	1.129	-0.392	0.907
ME1 BM2	-0.251***	0.002	1.002	1.050	-0.217	0.942
ME1 BM3	-0.105	0.139	0.972	0.969	-0.084	0.951
ME1 BM4	-0.012	0.832	0.919	0.930	0.108	0.966
SMALL HiBM	0.144***	0.008	0.865	0.906	0.365	0.968
ME2 BM1	-0.236***	0.005	1.114	1.062	-0.558	0.948
ME2 BM2	0.059	0.391	1.063	0.899	-0.280	0.959
ME2 BM3	0.048	0.400	0.997	0.934	0.037	0.969
ME2 BM4	0.038	0.498	0.976	0.849	0.258	0.970
ME2 BM5	0.122**	0.030	0.960	0.843	0.495	0.972
ME3 BM1	0.008	0.932	1.161	0.764	-0.627	0.931
ME3 BM2	0.097	0.180	1.065	0.715	-0.225	0.953
ME3 BM3	0.042	0.586	1.016	0.665	0.112	0.946
ME3 BM4	0.052	0.477	1.002	0.649	0.235	0.951
ME3 BM5	0.096	0.184	1.005	0.608	0.551	0.956
ME4 BM1	0.195**	0.020	1.090	0.340	-0.571	0.940
ME4 BM2	0.200**	0.019	1.019	0.353	-0.163	0.929
ME4 BM3	0.095	0.193	0.990	0.341	0.082	0.946
ME4 BM4	0.063	0.410	1.029	0.431	0.295	0.949
ME4 BM5	-0.092	0.270	1.066	0.415	0.617	0.948
BIG LoBM	0.157**	0.027	0.924	-0.322	-0.614	0.941
ME5 BM2	0.224***	0.001	0.928	-0.273	-0.222	0.947
ME5 BM3	-0.043	0.526	1.014	-0.165	0.053	0.953
ME5 BM4	-0.016	0.827	0.999	-0.182	0.325	0.947
BIG HiBM	-0.264***	0.008	1.134	-0.152	0.779	0.939

Appendix 2. Five-factor model regression results for the 25 European portfolios

Portfolio	Alpha	p-value	Beta (Mkt-RF)	SMB	HML	RMW	CMA	R²
SMALL LoBM	-0.340***	0.001	0.957	1.106	-0.471	-0.578	-0.243	0.926
ME1 BM2	-0.094	0.227	0.951	1.028	-0.229	-0.336	-0.213	0.950
ME1 BM3	0.020	0.781	0.934	0.954	-0.108	-0.275	-0.144	0.956

ME1 BM4	-0.010	0.872	0.928	0.939	0.065	-0.026	0.073	0.966
SMALL HiBM	0.140**	0.012	0.882	0.922	0.290	-0.029	0.140	0.969
ME2 BM1	-0.077	0.344	1.057	1.036	-0.551	-0.330	-0.252	0.955
ME2 BM2	0.149**	0.034	1.031	0.885	-0.280	-0.189	-0.135	0.961
ME2 BM3	0.039	0.510	1.006	0.942	0.009	0.005	0.062	0.969
ME2 BM4	-0.042	0.463	0.997	0.855	0.291	0.185	0.063	0.972
ME2 BM5	0.079	0.164	0.992	0.867	0.414	0.051	0.210	0.974
ME3 BM1	0.204**	0.028	1.072	0.713	-0.533	-0.366	-0.463	0.944
ME3 BM2	0.083	0.274	1.069	0.716	-0.221	0.032	0.013	0.953
ME3 BM3	-0.059	0.448	1.042	0.671	0.157	0.233	0.071	0.949
ME3 BM4	-0.047	0.523	1.029	0.658	0.266	0.223	0.093	0.954
ME3 BM5	0.082	0.276	1.015	0.616	0.524	0.016	0.069	0.957
ME4 BM1	0.302***	0.000	1.041	0.312	-0.517	-0.198	-0.257	0.945
ME4 BM2	0.180**	0.042	1.040	0.370	-0.230	0.009	0.150	0.930
ME4 BM3	0.014	0.853	1.025	0.360	0.052	0.156	0.177	0.949
ME4 BM4	0.008	0.918	1.050	0.442	0.284	0.109	0.102	0.950
ME4 BM5	-0.097	0.268	1.055	0.403	0.678	0.040	-0.103	0.949
BIG LoBM	0.132**	0.075	0.927	-0.324	-0.586	0.066	-0.012	0.941
ME5 BM2	0.096	0.120	0.988	-0.238	-0.294	0.233	0.321	0.957
ME5 BM3	-0.038	0.584	1.041	-0.137	-0.083	-0.077	0.236	0.956
ME5 BM4	-0.001	0.989	0.996	-0.182	0.312	-0.038	0.000	0.947
BIG HiBM	-0.023	0.797	1.035	-0.204	0.847	-0.475	-0.485	0.955

Appendix 3. Explanation of the use of Artificial Intelligence

Artificial Intelligence was used in a supportive role during the preparation of this bachelor's thesis. The tools were used mainly for structure planning, language support, idea generation, and technical assistance. I confirm that all final decisions, interpretations, analysis, and written content are my own responsibility.

1. Tool: OpenAI ChatGPT

Stage of use: Structure and heading planning, translation support, literature searching

Use of the tool: ChatGPT was used to help plan the structure of the thesis, improve the headings, and suggest clearer wording for some sentences. It was also used to suggest possible academic sources and search terms related to the topic. All suggested sources were checked independently before use. In the empirical part, ChatGPT was used to discuss regression results and to give suggestions for cleaning the dataset. It was also used to translate some words into English.

All outputs were checked, and I only used suggestions that I considered suitable and accurate.

Example of a prompt: What word could replace "moves" in the following sentence to make it more fitting and academic?

"As expected, the market risk factor moves relatively similarly to the general market index."

ChatGPT response: Better options for moves in this sentence:

behaves → best general academic choice

develops

performs

changes

corresponds (if meaning close relationship)

Best version: "As expected, the market risk factor behaves relatively similarly to the general market index."

2. Tool: Grammarly

Stage of use: Language editing

Use of the tool: Grammarly was used to check grammar, spelling, and sentence clarity in the English text. The tool was used only to improve language quality. The meaning and academic content of the text remained my own.

Final statement: AI tools were used only as support tools during the thesis process. They were not used to create the main arguments, final conclusions, or independent research contribution of this thesis. I take full responsibility for the entire content of this bachelor's thesis.