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TESTING THE CAPM AND THE FAMA-FRENCH 3-FACTOR MODEL ON U.S. HIGH-TECH STOCKS

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Master's Thesis in Finance

Lund University School of Economics and Management

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May 24, 2017

Abstract

This master's thesis tests the capital asset pricing model (CAPM) and the Fama-French 3-factor model (FF3FM) for the U.S. high-tech industry. For a total sample of 120 U.S. high-tech companies we run OLS time-series regressions for both models by using return and accounting data from 2002 to 2016. It is found that on average, the CAPM is not sufficient in explaining average excess returns for our sample of U.S. high-tech stocks, indicated by significant abnormal returns in the time-series regressions. However, the FF3FM eliminates the significance of the abnormal returns, or at least lowers the significance of the time-series regressions intercepts. Hence, it is found that the latter model outperforms the traditional CAPM for our sample of U.S. high-tech stocks, indicated by lower significance of the alpha terms as well as increasing adjusted R^2 values in the time-series regressions. The higher explanatory power of the FF3FM compared to the CAPM is mainly caused by the high significance of the size factor measured by the SMB (small-minus-big) variable, which confirms a negative size premium for U.S. high-tech stocks. The book-to-market factor represented by the HML (high-minus-low) variable does not seem to contribute to explain average excess returns, which is concluded from an insignificant average regression coefficient. Since the FF3FM proves to be an improvement towards the traditional CAPM, it can be recommended to apply the former model as a valuation and decision making tool for U.S. high-tech stocks. However, these results only hold for stable economic periods as the research results show that during economic turmoil both models are not sufficient in explaining the respective average excess returns.

Keywords: CAPM, Fama-French Three-Factor Model, U.S. high-tech stocks

Acknowledgements

We would like to express our sincere gratitude to our main supervisor, Charlotte Christiansen, for her support, guidance and valuable feedback during the writing of this master's thesis. Without her help and vast expertise, this research paper would not be of the same quality and sophistication as it is today.

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1. Introduction

The chapter introduces this thesis by giving background information about the U.S. high-tech industry and by addressing the significance of the topic. Furthermore, it explains the purpose of this research, proposes research limitations and gives an outline of subsequent chapters and subjects covered in this paper.

1.1 Background

The capital asset pricing model (CAPM) is the most widely used asset pricing model in financial economics, serving companies all over the world as a decision-making tool for e.g. valuation purposes, investment decisions or capital budgeting. The model is applied to determine the costs of equity, which is a key input to the discount rate used in company valuation or financial decision making, the WACC (weighted average cost of capital). Obviously, an accurate and precise calculation of the cost of equity is therefore a crucial incentive to every business.

However, research by Fama and French in the 1990's has shown that the traditional CAPM is not sufficient in explaining average stock returns (Fama & French, 1992 and 1993). In their papers, Fama and French introduce two additional risk factors, namely size and book-to-market (value). In combination with the market risk, these factors prove to be more accurate in explaining average stock returns. They suggest that small companies as well as companies with a high book-to-market equity ratio yield on average higher returns than their opponents. The model is commonly known as the Fama-French 3-factor model (FF3FM).

In their research, Fama and French focus on the entire U.S. stock market by using all NYSE, AMEX and NASDAQ stocks from 1963 to 1991 (Fama & French, 1993). This paper however, only considers U.S. high-tech stocks from 2002 to 2016. Due to different characteristics of high-tech companies compared to companies from other industries, the assumption is valid that also asset pricing models behave differently in this industry. Furthermore, this master's thesis addresses the performance of the respective asset pricing models before, during and after the recent financial crisis in the U.S.

In the context of this thesis, high-tech is defined as a technology that applies the latest technological advancements, or the so called "cutting-edge technology". The definition of high-tech changes constantly – what is considered high-tech today could be an old technology tomorrow. However, high-tech usually refers to technologies that are fully or partially related to computer engineering such as robots, machine learning and bioinformatics.

The high-tech industry is generally characterized by high productivity and notable sensitivity to economic fluctuations, i.e. high volatility and high systematic risk. The unique risk of the high-tech companies is caused by the fact that it is their task to produce cutting-edge technology that is often related to technological uncertainty (Kohers & Kohers, 2000). This characteristic significantly contributes to the “high risk, high reward” nature of the industry. Thus, investors often have higher expectations for their investments in high-tech companies which obviously should affect the expected returns estimated by asset pricing models. In general, the products and services in the high-tech industry are easily scalable, which means that the companies that break through can make substantial profits in a short time whereas their competitors might get bankrupt in a moment. Technological advancements create new business opportunities destroying already existing businesses.

To overcome the ever-changing nature of the industry, high-tech companies frequently use mergers and acquisitions as their initial growth and survival strategy. Therefore, another characteristic of the high-tech industry is its high number of M&A transactions. As Mchawrab (2016) points out, the high-tech industry recorded a volume of $713 billion in transactions during the year 2015. In this context, asset pricing models are widely used to calculate the cost of equity.

It is worth noting that the high-tech industry is an important part of the U.S. economy. Wolf and Terrell (2016) point out that the high-tech industries are an essential part of the U.S economy as they provide about 12% of all the jobs and almost 23% of all the output. This portion is expected to increase in the coming years which makes the high-tech industry particularly interesting for this master’s thesis.

1.2 Research purpose

Since asset pricing models are commonly used by high-tech companies to determine the required rate of return for investment projects and especially for calculating the cost of equity as part of M&A activities, the purpose of this master’s thesis is to investigate the performance of the CAPM and the FF3FM with regards to U.S. high-tech stocks. Especially, the objectives of the research are to reveal if the models have significant explanatory power in explaining the average excess returns of U.S. high-tech stocks, and if yes, if the FF3FM provides more reliable results than the CAPM. Additionally, it is focused on the question if these models can produce reliable results during times of economic turmoil.

To conduct the research, the following research questions will be answered during this thesis:

- Does the FF3FM outperform the CAPM in explaining the average excess returns for our sample of U.S. high-tech stocks from 2002 to 2016?

- Are the CAPM and the FF3FM sufficient in explaining average stock returns in the U.S. high-tech industry from 2002 to 2016?

- Do the models produce sufficient results for the sample of U.S. high-tech stocks before, during and after the most recent financial crises in the U.S.?

By answering the research questions, this research tries to provide new insights and guidance into the use of asset pricing models for the U.S. high-tech industry.

1.3 Limitations

The first limitation in this research is the focus of investigations on the U.S. high-tech industry only. Therefore, we are neither able to make inferences about the model performances in other U.S. industries nor about high-tech industries in other countries.

Furthermore, because of the characteristics of the U.S. high-tech industry it was not possible to include all U.S. high-tech companies. This is because high-tech companies are often relatively young and there is a substantial amount of M&A activities in the industry. Therefore, stock and accounting data is not frequently available for every U.S. high-tech company for the time period from 2002 to 2016. This reduces the sample size of this research significantly and decreases the regression inferences.

In relation to the previous limitation, the time period under consideration is limited to 15 years which is relatively short compared to e.g. the research conducted by Fama and French (1992 and 1993). In this context, we chose to work with a balanced panel, i.e. monthly observations of all variables for the entire sample size.

In the time-series regressions, we limit our research to ordinary least squares (OLS) regressions which assume a linear relationship between the independent and dependent variables. This assumption, however, simplifies the relationship and does not mirror the "true" relationship between the variables. Thus, other more advanced regression methods could result in better outcomes.

Additionally, the research is limited to the CAPM and FF3FM only. Other models, e.g. the Carhart-4-factor-model and the Fama-French-five-factor-model include additional risk factors, which this research does not take into consideration.

1.4 Thesis outline

The structure of this paper is as follows: Chapter 2 provides the theoretical background to this thesis, explaining in detail the traditional CAPM and the FF3FM as well as its evolution. In chapter 3, the literature review, previous research results and ideas related to the research topic are presented. Chapters 4, 5 and 6 focus on the empirical part, shedding light on the methodology, the data at hand and the empirical results of the time-series regressions. In chapter 7, we present our research conclusions and suggest potential future research opportunities.

2. Theoretical background

The chapter provides the theoretical background to understand the principles of the conducted research. It explains the CAPM and the FF3FM as well their assumptions about the risk factors in detail and serves as an overview of the theory needed to follow the subsequent analysis.

2.1 Markowitz Modern Portfolio Theory

With his research paper from 1952, Harry Markowitz lies the groundwork for modern portfolio theory. He introduces the concept of risk aversion and points out that rational investors make investment decisions according to two variables: the mean return (or expected return) and the variance. Because the variance of portfolio returns is associated with risk, an investor should always choose the portfolio with less variance, given the same expected return. It follows that investors will only take additional risk, if this risk is compensated by an increase in expected return. In Markowitz' model, expected portfolio return and variance are determined as follows:

Expected portfolio return: $E(R) = \sum X_i E(R_i)$, where X_i is the relative amount invested in security i, and $E(R_i)$ is the expected return of security i (Markowitz, 1952).

Portfolio return variance: $V(R) = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_{ij} X_i X_j$, where $X_i \; and \; X_j$ are the relative amounts invested in security i and j, and σ_{ij} is the covariance between R_i and R_j (Markowitz, 1952).

Markowitz points out that an investor desires an efficient portfolio, i.e. a portfolio with maximum expected return for a given variance and a portfolio with minimum variance (MV) for a given expected return. According to Markowitz, all possible portfolio combinations as well as efficient combinations can be represented by Figure 1 (Markowitz, 1952):

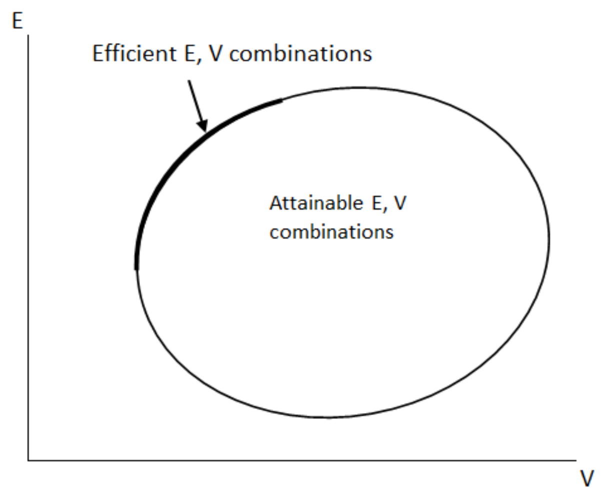

Figure 1: Attainable and efficient E, V combinations

Additionally, there is always a portfolio available which has zero variance, i.e. a risk-free portfolio. If the risk-free (RF) portfolio is smaller than the minimum variance portfolio, then the expected return of a portfolio can be represented by a linear combination of the risk-free portfolio and an efficient portfolio (Markowitz, 1952). In fact, Markowitz suggests that the efficient set of portfolios is equal to the market portfolio, Figure2:

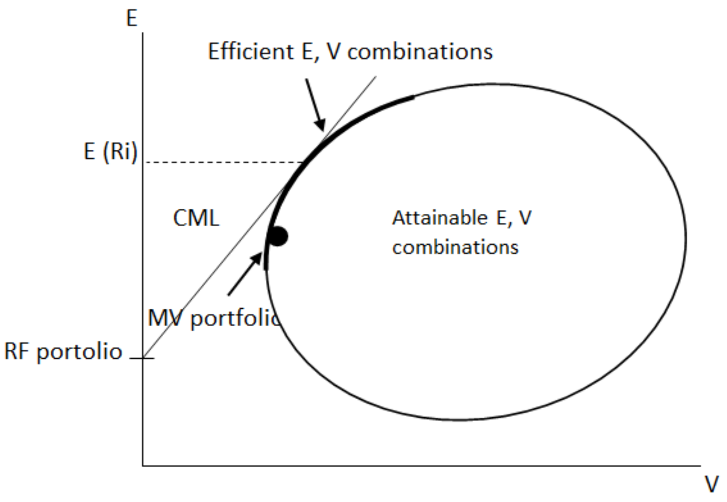

Figure 2: MV portfolio, RF portfolio and CML

The line which combines the risk-free portfolio and the market portfolio is called the capital market line (CML).

2.2 Sharpe-Lintner CAPM

Based on the research of Markowitz (1952), we know that an investor should try to minimize the variance of a portfolio for a given expected return and maximize the expected return of a portfolio for a given variance. The original capital asset pricing model (CAPM) is based on the research of Sharpe (1964) and Linter (1965) and captures the ideas of Markowitz and the capital market line, i.e. that an investor can achieve any expected portfolio return by combining the zero-variance portfolio and the market portfolio. Sharpe and Lintner extend this research and suggest that the expected return of an asset i can be expressed as a linear function of the risk-free rate of return plus the asset's systematic risk (the beta) times the expected market premium. Furthermore, the model relies on several assumptions such as homogeneity of investor expectations, and a common pure rate of interest for borrowing and lending (Sharpe, 1964).

The idea of the model is that the expected excess returns of an asset i can be explained by only one risk factor, which is the market factor. The systematic risk determines the sensitivity of the asset i towards market volatility and can be defined as:

$$\beta_{im} = \frac{cov(R_{i,}R_m)}{var(R_m)} \tag{1}$$

where $cov(R_{i,}R_m)$ is the covariance between the return on asset i and the market return, and $var(R_m)$ is the variance of the market return. Mathematically, the CAPM can be expressed as:

$$E(R_{it}) = R_{ft} + \beta_{im}\big(E(R_{mt}) - R_{ft}\big) \tag{2}$$

where $E(R_{it})$ is the expected return of asset i at time t, R_{ft} is the risk-free rate of return at time t, β_{im} is the asset's systematic risk and $E(R_{mt})$ is the expected return of the market portfolio at time t.

2.3 Arbitrage Pricing Theory

The arbitrage pricing theory (APT) was developed by Ross (1976) as an alternative to the traditional mean-variance CAPM. Ross motivates the model with the fact that the assumptions underlying the mean-variance CAPM are hard to justify – e.g. normality of returns or quadratic preferences. Additionally, according to Ross, the empirical research on the topic has questioned the conclusions and the assumptions of the mean-variance CAPM theory. He mentions that these shortages and the restrictiveness of the assumptions in the model had been well known at the time, but the simplicity of the mean-variance CAPM explains the popularity of the model (Ross, 1976; Roll, 1977; Roll & Ross, 1980).

According to Roll and Ross (1980), there are two significant differences between the APT and the original Sharpe "diagonal" model, which they position as the main influence behind the CAPM. First, the logic behind the arbitrage pricing theory is that asset returns are explained utilizing changes in various macroeconomic factors. This diversifies the APT from the CAPM, which relies on one explanatory variable. Secondly, the APT shows that every equilibrium in the model will be determined by a linear relationship between each asset's expected returns and it's returns response loadings on the common factors (company-specific variables or macroeconomic variables). The APT loosens the CAPM assumption that the market portfolios must be mean-variance efficient (Roll & Ross, 1980).

It is worth noting, that the APT does not specify which factors should be used, which in some cases could be a drawback of the model as it might lead to arbitrary selection of the variables. Furthermore, since in the APT the number of betas to estimate is higher than in the CAPM, it could be argued that APT is harder to apply in practice, and that the APT might be more vulnerable to statistical disturbances (Roll & Ross, 1980).

2.4 Fama-French Three-Factor Model

Since the traditional CAPM often fails in empirical tests, the three-factor-model by Fama and French (1992 and 1993) was designed. The FF3FM captures the relation between expected excess returns and the market premium as well as two additional factors, the book-to-market equity and company size measured by market capitalization.

In their prestigious research paper "Common risk factors in the returns on stocks and bonds" (1993), Fama and French extended their previous research from 1992, where they introduced the factors size and book-to-market and conducted their asset pricing tests based on cross-sectional regressions. In their 1993 paper, however, the researchers applied the time-series regression approach introduced by Black, Jensen and Scholes (1972).

Even though the usage of size and book-to-market might seem arbitrary, Fama and French motivate these choices by the fact that those factors are related to economic fundamentals. According to their paper, high book-to-market equity, i.e. a low stock price related to the book value, is related to low earnings on assets, whereas low book-to-market equity, i.e. a high stock price related to the book value, is related to high profitability (Fama & French, 1993).

Additionally, size proved to be also connected to profitability, i.e. earnings on assets. They point out that by controlling for book-to-market equity, it happened to be the smaller firms which had lower earnings on assets when compared to bigger firms. Fama and French justify this size effect by the economic recession in the early 1980's which turned into a period of lower growth for small companies, whilst big companies experienced substantial growth. Until then, smaller firms were only marginally less profitable than bigger firms. Thus, Fama and French deduct that economic turmoil and the state of the economy affect the earnings of the small companies substantially (Fama & French, 1993).

Fama and French point out that because it is possible for small companies to realize long periods of earnings depression that does not account for the big companies, the size of the company in fact is related to a risk factor. They state that this risk factor might be able to explain the negative relation between company size and average returns. In a similar manner, they use relative profitability to motivate the positive relationship between book-to-market equity and average returns (Fama & French, 1993).

The attraction of the FF3FM lies in the fact that the results of the model can be used in various financial applications. The conclusions can be used for example in selecting portfolios, evaluating portfolios, and estimating the cost of capital (Fama & French, 1993).

The FF3FM can be written as:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + e_{it} \tag{3}$$

Where R_{it} is the return on portfolio i, R_{ft} is the risk-free return, $R_{it} - R_{ft}$ is the expected excess return on portfolio i, $(R_{\mathrm{m}t} - R_{ft})$ is the expected excess return on the market portfolio, $s_i SMB_t$ is the is the expected return on the mimicking portfolio for the size risk factor, and $h_i HML_t$ is the expected return on the mimicking portfolio on the value (book-to-market equity) risk factor.

3. Literature review

Chui and Wei (1998) test the CAPM and FF3FM in the five Pacific-Basin emerging markets: Hong-Kong, Korea, Malaysia, Taiwan, and Thailand. They find that the CAPM does not sufficiently explain expected returns in these regions. Book-to-market equity proves to be significant in the markets of Hong-Kong, Korea and Malaysia, whilst size can explain expected returns in all markets excluding Taiwan. This is in line with the Fama and French research from 1992, indicating that market beta is not sufficient in explaining expected stock returns. However, there is a strong relationship between expected returns and two additional risk factors, size and book-to-market (Chui & Wei, 1998).

Gaunt (2004) finds that the FF3FM provides significantly better explanatory power compared to the CAPM in the Australian market. In his study, Gaunt uses a dataset containing of monthly stock returns and accounting data from 1991 to 2000. After modifying the data, he ends up with 108 monthly returns for 25 size/BM portfolios. Gaunt uses a total sample of 6,814 companies, where the smallest number of companies (531) is from 1992 and the largest number of companies (876) from 1997. He finds that with regards to the CAPM, the beta risk is higher for smaller companies and for companies with lower book-to-market ratios. Gaunt mentions that this discovery is in line with the findings of Fama and French (1993). Gaunt further finds that even though the smallest stock portfolio (lowest quantile) produces large positive abnormal returns, they are not statistically significant. Despite this surprising result, he finds slight evidence that the size effect holds for the rest of the five quantiles. Additionally, he suggests a little indication of a book-to-market effect, with abnormal returns increasing monotonically when moving from lowest to highest book-to-market portfolios. This finding is also in line with Fama and French (1993) as Gaunt states. Gaunt summarizes that his research shows that the FF3FM contributes with a higher explanatory power for Australian stock returns than the CAPM. However, whereas Fama and French (1993) find that in the U.S. both additional risk factors contribute notably to the model, Gaunt states that in the Australian market most of the superior explanatory power of the FF3FM is explained due to the size factor (Gaunt, 2004).

In their 2011 study, Aguenaou, Abrache and El Kadiri focus on the Moroccan stock market to find out if there are signs of the pervasive market, size, and value factors in the market. Using a monthly data set of 48 stocks over a five-year period from 2005 to 2009 the researchers find evidence of significant value and market risk factors existing in the market, which is in line with FF3FM. They also realize that for the Moroccan stock market, the high book-to-market stocks perform better in comparison to low book-to-market stocks, which further supports the

Fama and French findings. However, they also find that companies that are smaller in size do not earn higher returns than their bigger peers, meaning that the bigger firms experienced a positive size premium. This finding is not in line with the FF3FM, and the researchers conclude that the model does not completely hold in the Moroccan stock market. They motivate this inconsistency with the fact that the Moroccan stock market is illiquid when it comes to small cap stocks. The researchers mention that when looking at the results in the emerging markets, it is important to keep in mind that these markets are often characterized by inefficiencies such as liquidity problems, high volatility and low trading volumes that could affect the results of asset pricing models (Aguenaou, Abrache & El Kadiri, 2011).

Blanco (2012) tests the CAPM and the FF3FM in the American market for NYSE stocks. He constructs six different portfolios according to size and book-to-market equity. Blanco uses an extensive data set from July 1926 to January 2006, resulting in 955 monthly observations. He applies time series regressions to test the model and finds out that the FF3FM performs empirically better in comparison to the CAPM in the analyzed market and the sample period. However, he underlines that the results vary depending on the way the portfolios are created, and this should be taken in to account while interpreting the results (Blanco, 2012).

Eraslan (2013) studies the FF3FM on the Istanbul Stock Exchange using monthly stock market observations from 2003 to 2010. He constructs nine portfolios to investigate the variations on excess portfolio returns using the market risk factor, the size factor and the value factor as the explanatory variables. Eraslan finds that even though the FF3FM can explain the variations in the portfolio returns to some extent, the market risk factor has more firm effect on the portfolio returns than the size risk factor and value risk factor. Eraslan states that factors such as the time period, number of portfolios, and the economic crisis (hitting Turkey in 2001) could be the reason that causes his results to show weak evidence for the FF3FM when comparing to previous research conducted in the Istanbul Stock Exchange (Eraslan, 2013).

Loughran (1997) enhances the research of Fama and French (1992 and 1993) by evaluating returns for the book-to-market factor across firm size and different seasons. His sample includes returns for most of the firms listed on NYSE, Amex and NASDAQ from 1963 to 1995. His initial research question covers the findings from Malkiel (1995), that returns from growth funds are not significantly different from returns for value funds. In his research, Loughran finds out that the book-to-market factor in the Fama and French research can be reduced to firstly to extremely low average returns by small growth stocks during months excluding

January, and secondly a seasonality effect for high book-to-market firms in January. Additionally, it is found that for firms in the higher size quintiles (which contain over 90% of market capitalization), book-to-market has no explanatory power. Because fund managers mostly invest in large firms, there is no significant difference in returns for value and growth funds. Loughran suggests that it is only possible to exploit a value strategy when concentrating on the firms in the small size quintiles. This, however, is only accomplishable for fund managers with few assets under management and thus not often applicable (Loughran, 1997).

Knez and Ready (1997) extend the FF3FM by including robust regression estimators and by focusing on the robustness of the estimated risk premiums for book-to-market and size. In their paper, Knez and Ready try to find out whether the estimates are driven by a small subset of firms or months, arguing that using a robust regression technique called least trimmed squares (LTS) would allow them to capture these observations, when comparing them with the results from the least squares regressions. The dataset in their study consists of monthly observations from July 1963 to December 1990 resulting in 330 monthly observations. Knez and Ready only use size and book-to-market as predictors. They motivate this choice by the success of these variables in the Fama and French (1992) study. Knez and Ready find that the negative relation between the firm size and average return is mainly caused by a couple of extreme returns that occurred during the months in question. They point out, that when only one percent of each month's extreme values are ruled out, they find a significant positive relation between the firm size and average returns. They conclude, that the difference in the results obtained by the robust Fama-MacBeth procedure (trimming) and those obtained by using the normal least squares regressions can be explained by the positive skewness in the return distribution. The researchers state that this is particularly evident for small young firms, as the investors in these companies are in most cases expecting a loss, whereas a small portion of these investments lead to significant profits (Knez & Ready, 1997).

In their 1998 paper, Chui and Wei also find a January effect of large firms in Hong-Kong and small firms in Korea. The opposite direction of the size effect in these two regions is explained by the composition of investors in both countries, i.e. mainly institutional investors in Hong-Kong (large stocks) and mainly individual investors in Korea (small stocks). As both groups tend to buy high amounts of stocks in January, the demand pressure increases the returns of these stocks. Also, Chui and Wei find that book-to-market is significant for all months except January (Chui & Wei, 1998).

Kim (1995) examines the significance of the CAPM and the size factor after controlling for the errors-in-variables (EIV) problem. He motivates that the two-step estimation method of Fama and French lead to the EIV problem, i.e. an underestimation of the beta coefficient and an overestimation of the other regression coefficients (e.g. size and book-to-market). Kim points out that it is important to clarify if the weak relationship between expected returns and market beta in the cross-sectional regression is because of the model itself or because of the EIV bias. He finds that without any EIV correction, the relationship between expected returns and market beta is insignificant, which is in line with previous research by Fama and French. However, after controlling for EIV the beta coefficient and its significance increase, resulting in an intercept being insignificant from zero, i.e. the CAPM holds. However, although the size coefficient decreases after the EIV correction it remains significant, which still indicates a misinterpretation of the CAPM (Kim, 1995).

Kothari et al. (1995) provide evidence that the Fama and French results could be influenced by a combination of survivorship bias in the COMPUSTAT database affecting the high book-to-market stocks' performance. They further argue that the bias affects the period-specific performance of both low book-to-market and high book-to-market stocks. According to the researchers, the bias could be caused by the spuriously inflated data, which is firstly occurring since several years of data for the surviving firms was included when COMPUSTAT added data for the companies in the first place. Secondly, the bias could be caused by missing data in the COMPUSTAT database, which would be available at other sources such as Center for Research in Securities Prices. Kothari et al. point out that for the latter group of companies there is evidence that the probability of facing financial distress is relatively high (Kothari et al., 1995).

In his paper "On Persistence in Mutual Fund Performance" from 1997, Carhart introduces the momentum factor as an extension to the CAPM and FF3FM. A stock shows momentum if it obtains the tendency to further rise after an increase and to further decline after a decrease. In his research Carhart finds that the four-factor model, i.e. market, size, book-to-market, and momentum, almost completely explain risk-adjusted portfolio returns. However, mutual funds that follow a momentum strategy only earn significantly higher returns before accounting for transaction costs. After expenses, individual mutual funds earn significantly lower returns because the costs from pursuing a momentum strategy reduce the gains. His sample consists of monthly observations for 1,892 diversified equity funds from 1962 to 1993 and Carhart tests the CAPM against the four-factor model. He finds that the CAPM is not sufficient in explaining the portfolio returns, which is consistent with the findings by Fama and French. However, when performing the four-factor model, the results show insignificant abnormal returns for the model, concluding a high explanatory power of the model. What is more, Carhart noticed significantly higher R^2 for the four-factor model. Additionally, Carhart finds that overall, the market factor, size and momentum explain most of the variation in portfolio returns, whereas the book-to-market factor is almost insignificant in his research. It is worth noting that another important feature of Carhart's research is the independence of the results from the survivorship bias as it is accounted for in the dataset (Carhart, 1997).

Other recent research has attempted to question which factors to use as the additional factors. One of these alternative models was represented by Chen and Zhang (2010) who state that the traditional Fama-French model (1993) is not capable of explaining many cross-sectional patterns and anomalies. As an example of these patterns, Chen and Zhang mention for instance the negative relation between the average returns and asset growth, and the positive relation between average returns and earnings surprises. Because of these shortcomings, Chen and Zhang introduce a "new" three-factor-model. In their model, similarly to Fama and French, Chen and Zhang have the expected return on portfolio j in excess of the risk-free rate on the left-hand-side. In their model these returns are explained by the sensitivity of its returns to the three factors on the right-hand-side of the regression: the market excess return (the market factor), the difference between the returns of the portfolios consisting of low- and the high-investment stocks (a low-minus-high investment factor), and finally, the difference between the returns on a portfolio of stocks with high returns on assets and the portfolios of stocks with low returns on assets (a high-minus-low ROA factor). They find that their three-factor-model outperforms traditional asset pricing models like the CAPM and FF3FM and that it can be used to calculate values for the expected returns in practice (Chen & Zhang, 2010).

The research by Chen and Zhang (2010) has been extended by Fama and French in their 2015 paper "A five-factor asset pricing model". In addition to the factors according to the FF3FM, they introduce two new factors, investment and profitability. The investment factor is captured by the difference between the returns for low minus high investment stocks, and profitability is measured by the difference between the returns for robust minus low profitability stocks. For a sample of monthly observation for all U.S. NYSE, AMEX, and NASDAQ stocks from 1963 to 2013, Fama and French test the FF3FM against the five-factor model. The main result of their research is that the five-factor model performs significantly better than the FF3FM suggesting support for the new factors, investment and profitability. Additionally, they find that when using the five-factor model, the HML factor of the FF3FM becomes obsolete for explaining average returns, as according to Fama and French the explanatory HML return is covered by the other factors (Fama & French, 2015).

4. Methodology

The chapter explains the methods used to conduct the research. Firstly, it is presented how the factor mimicking portfolios for the factors SMB and HML are constructed, which together with the market premium represent the independent variables in the CAPM and FF3FM time-series regressions. Secondly, the same is shown for constructing the portfolios for the independent variable, the excess returns for the U.S. high-tech stocks. Finally, it is explained how the two models are tested and what regressions are run.

4.1 Constructing portfolios: Explanatory variables

To mimic the common risk factors of size and book-to-market equity, the Fama and French approach of constructing six portfolios sorted according to ME and BE/ME is used (Fama & French, 1993). In this context, the SMB (small minus big) portfolio is supposed to mimic the risk factor according to the size of the company and the HML (high minus low) portfolio is supposed to mimic the risk factor according to the book-to-market equity of the company.

In the first place, it is worth noting that we are constructing the factor mimicking portfolios for SMB and HML from our own data sample of high-tech stocks. This is necessary to investigate on the industry specific effect of the factors on the expected portfolio returns and to avoid a dimensionality problem in the time-series regressions. In many other research papers, the SMB and HML data is directly gathered from the Fama and French website, containing the entire U.S. stock market data, i.e. stock return and accounting data for many different industries. As we are only investigating on the high-tech industry, this approach would probably lead to different regression results as the proposition of small and big firms as well as high book-to-market and low book-to-market firms is different with regards to the overall U.S. stock market than for the high-tech industry only.

In each year t in July from 2002 until 2015 all stocks are sorted according to the market capitalization of the company. Then, the median size is determined to split the stocks into two different portfolios. One portfolio with high market cap stocks, big (B), and the other portfolio with low market cap stocks, small (S).

The same principle is applied to the stocks sorted by book-to-market equity ratio (BE/ME) in each year t in January from 2002 until 2015. Fama and French (1993) use end of year t-1 data to sort their stocks according to BE/ME. Using beginning of year t data is basically the same procedure with the same logical intention, i.e. to ensure that the market has access to the accounting data of t-1 and book equity is known in July of year t (Fama & French, 1993). The stocks are sorted according to the 70% and 30% quantiles resulting in three different portfolios at time t, high (H), medium (M), and low (L). The reasoning for dividing the stocks into three BE/ME portfolios instead of two, as for size (ME), is that book-to-market equity proved to exhibit stronger power in explaining average stock returns than size (Fama & French, 1992). In addition, companies with negative BE are excluded from this research.

Out of the sorted size and BE/ME portfolios and the respective intersections, six portfolios are constructed: SL, SM, SH, BL, BM, and BH. These portfolios are visualized in the following table:

Table 1: Six portfolios according to size and BE/ME (Fama & French, 2017)

	Median ME	
	Small High	Big High
70th BE/ME percentile		
	Small Medium	Big Medium
30th BE/ME percentile		
	Small Low	Big Low

As an example, notice that the Small High portfolio consists of stocks, which appear in the small size portfolio as well in the high-book-to-market portfolio after sorting according to size and BE/ME. Also note that each company is present in one of the two size portfolios and in one of the three BE/ME portfolios. The equal-weighted monthly returns of these portfolios are calculated for each year from July in year t until June in t+1. In July t+1, the portfolios are reformed according to size and BE/ME.

The monthly return for the SMB portfolio is calculated by taking the average return of the three small portfolios (SH, SM, SL) minus the average return on the three big portfolios (BH, BM, BL). Hence, SMB is the average return of the portfolios with small market cap stocks minus the average return of the portfolios with big market cap stocks, after controlling for BE/ME. Thus, SMB excludes the influence of BE/ME by focusing solely on the behavior of small and big stocks (Fama & French, 1993). Mathematically, SMB for each month t can be determined as follows:

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

In the same manner, the monthly return of the HML portfolio is calculated by taking the average return of the two high portfolios (SH, BH) minus the average return of the two low portfolios (SL, BL). Hence, HML is the average return of the portfolios with high BE/ME minus the average return of the portfolios with low BE/ME. Also, HML should be free of size influences and solely focuses on the behavior of high and low BE/ME stocks (Fama & French, 1993). Mathematically, HML for each month t can be determined as follows:

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

Note that for calculating the return on the HML portfolio, the two medium portfolios (SM and BM) are excluded. This is because the Fama and French research shows that the HML factor works most properly when it is defined in the presented manner (Fama & French, 1993).

In their research paper from 1993, Fama and French use value-weighted portfolios because most of the investment portfolios are in fact value-weighted. Thus, this approach is supposed to be the most "realistic" one. Note that in this research equal-weighted portfolios are used. Firstly, this is because of the simplicity and straightforward mathematical application of equal-weighted portfolios in comparison to value-weighted portfolios. Secondly, as we are only using equal weighted portfolios, the overall regression results should not significantly differ from using value-weighted portfolios. Also, there is no such evidence that specifically prefers value-weighted portfolio over equal-weighted portfolios. Finally, recent research has shown that equal-weighted portfolios outperform value-weighted portfolios in terms of mean returns (Plyakha, Uppal & Vilkov, 2012). Therefore, using equal-weighted portfolios enables to gain additional insight into the explanatory power of the CAPM and FF3FM.

Finally, the monthly excess return on the market portfolio over the risk-free rate of return is calculated to represent the market risk factor. In this context, the S&P500 value-weighted index is chosen, which is supposed to capture the performance of the U.S. stock market. The value-weighted index is chosen as this index is usually used for representing the U.S. market, also in previous research. As the value-weighted index and the equal-weighted index show a correlation of almost 98% during the sample period, it is assumed that the regression results do not significantly differ. The monthly market excess return is calculated by the monthly market return minus the monthly risk-free rate of return.

The risk-free rate of return is determined by the yield of the one-month U.S. T-bill. As the rates are usually presented on an annual basis, the annual interest rate was transformed by the following formula into monthly rates:

$$RF_{monthly} = (1 + RF_{yearly})^{\frac{1}{12}} - 1) \qquad (6)$$

4.2 Constructing portfolios: Dependent variable

The explained excess returns in the time-series regressions are determined by 25 stock portfolios sorted by size and book-to-market equity. The reason why portfolios formed on size and book-to-market equity are used to represent the explained variable, is that this research tries to determine whether the SMB and HML portfolios capture common risk factors in stock returns related to size and book-to-market equity (Fama & French, 1993). Also, the 25 portfolios will produce a wide range of average returns, which can be used to test CAPM and FF3FM in the time-series regressions (Fama & French, 1993).

The portfolios are constructed in a similar manner as the six size and book-to-market portfolios. In each year t in July from 2002 until 2015 all stocks are sorted according to the market capitalization and the book-to-market equity ratio of the company. Market capitalization is measured in July in year t and book-to-market equity is measured in January in year t. The logic behind this procedure is the same as for the construction of the six size and book-to-market portfolios. Then, each of the sorted size and book-to-market portfolios is divided into five sub-portfolios according to the following quantiles: 20%, 40%, 60%, and 80%. According to these intersections, 25 portfolios are constructed in each year t in July by combining the five size portfolios and the five book-to-market portfolios. This procedure results in a 5x5 matrix of stock portfolios, which is visualized in table 2:

Table 2: 5x5 matrix of 25 high-tech stock portfolios formed on size and BE/ME

Size	Low	2	3	4	High
Small	SL	S2	S3	S4	SH
2	2L	22	23	24	2H
3	3L	32	33	34	3H
4	4L	42	43	44	4H
Big	BL	B2	B3	B4	BH

BE/ME

The portfolios are reformed in each in year in July. Given the 25 portfolios, the monthly excess returns can be calculated by subtracting the risk-free rate of return from the equal-weighted portfolio returns. The result is a time-series of monthly excess returns of the 25 dependent high-tech stock portfolios from July 2002 to June 2016.

4.3 Regressions and model tests

To test and compare the explanatory power of the CAPM and the FF3FM with regards to the excess returns of the high-tech stocks, OLS time-series regressions are run. According to Fama and French (1993), time-series regressions are suitable for studying asset pricing issues for two reasons:

First, because we are interested to see if assets are priced rationally, variables like market, size and book-to-market equity should track the sensitivity for risk factors in returns. Thus, time series regressions can give us insights if the assets are priced rationally. Additionally, the slopes and adjusted R^2 values show whether the risk factors capture shared variation in asset returns (Fama & French, 1993).

Second, as the time-series regressions are structured in a way that on the left-hand-side they use excess returns and on the right-hand-side they use excess returns or returns on zero-investment portfolios, we can interpret the estimated intercepts as a return metric. Further, the estimated intercepts work as a formal test for how well different combinations of the factors take the cross-section of average returns into account (Fama & French, 1993).

As explained before, the dependent variable in both the CAPM and FF3FM regressions is represented by the excess returns on the 25 high-tech stock portfolios formed on size and book-to-market. For the CAPM, the independent variable is represented by the market excess return, and for the FF3FM by the market excess return and the returns of the two factor mimicking portfolios SMB and HML.

For each of the regression components, i.e. the independent and dependent variables, monthly observations are available for the entire time period. In this research, time-series regressions are run for five different time intervals (explained in chapter 5). For each time interval, the time-series regressions are run for both the CAPM and FF3FM. For each model per time interval, the 25 portfolio returns formed on size and book-to-market must be tested. Additionally, we also run overall time-regressions for both models for the different time periods, i.e. average regressions. In total this adds up to 312 time-series regressions.

A well-known stylized fact of stock return data is heteroscedasticity, i.e. the variance of the error terms in the time-series regressions is not constant over time. To obtain consistent OLS estimates, i.e. make the right inferences from the p-values, and thus to overcome the problem of heteroscedasticity, we use Whites robust standard errors in our time-series regressions.

After running the regressions, the models are tested with regards to the significance of their intercept and the respective risk factors. In other words, it is tested if the coefficients of the intercept and the risk factors are significantly different from 0, i.e. the null and alternative hypotheses can be determined as follows:

H0: $\alpha = 0$ H1: $\alpha \neq 0$

H0: $\beta = 0$ H1: $\beta \neq 0$

Thus, if the null hypotheses hold it can be concluded that the models are sufficient in explaining the excess returns of the U.S. high-tech stocks because the model does not produce significant abnormal returns and the risk factors are sufficient in explaining these excess returns. This statistical concept is captured by the p-values of the coefficients in the regression outputs. During this research, the significance is divided into three levels and marked by stars for reasons of clarity and comprehensibility:

1. Very significant: ***p<0.01 = Significant at the 1% level
2. Significant: **p<0.05 = Significant at the 5% level
3. Weakly significant: *p<0.1 = Significant at the 10% level

5. Data

The chapter presents the data that is used for conducting the research. Firstly, the time period of the research is explained. Secondly, the sample as well as constructed portfolios are presented. Finally, descriptive statistics of the sample is provided as well as additional information with regards to the data.

5.1 Time period

For this research, a time-period of 15 years is chosen which ensures an adequate amount of data and validity of the regression results. In fact, the data consists of 168 monthly observations from July 2002 to June 2016. The entire period is divided into three sub-periods: The Pre-crisis (July 2002 to November 2007), the Subprime/Financial Crisis (December 2007 to July 2009), and the Post-crisis (August 2009 to June 2016). To control for the aftermath of the dotcom bubble, we further run time-series regressions on a dataset from which both the subprime crisis and the dotcom bubble (ended in October 2002 as defined by Zhang et al. (2016)) are excluded. Looking at different periods allows us to test the CAPM and the FF3FM in different economic circumstances and gives insights into the explanatory power of these models and their components over time. Figure 3 presents the monthly average returns of our sample of U.S. high-tech stocks over the entire sample period as well the different time periods:

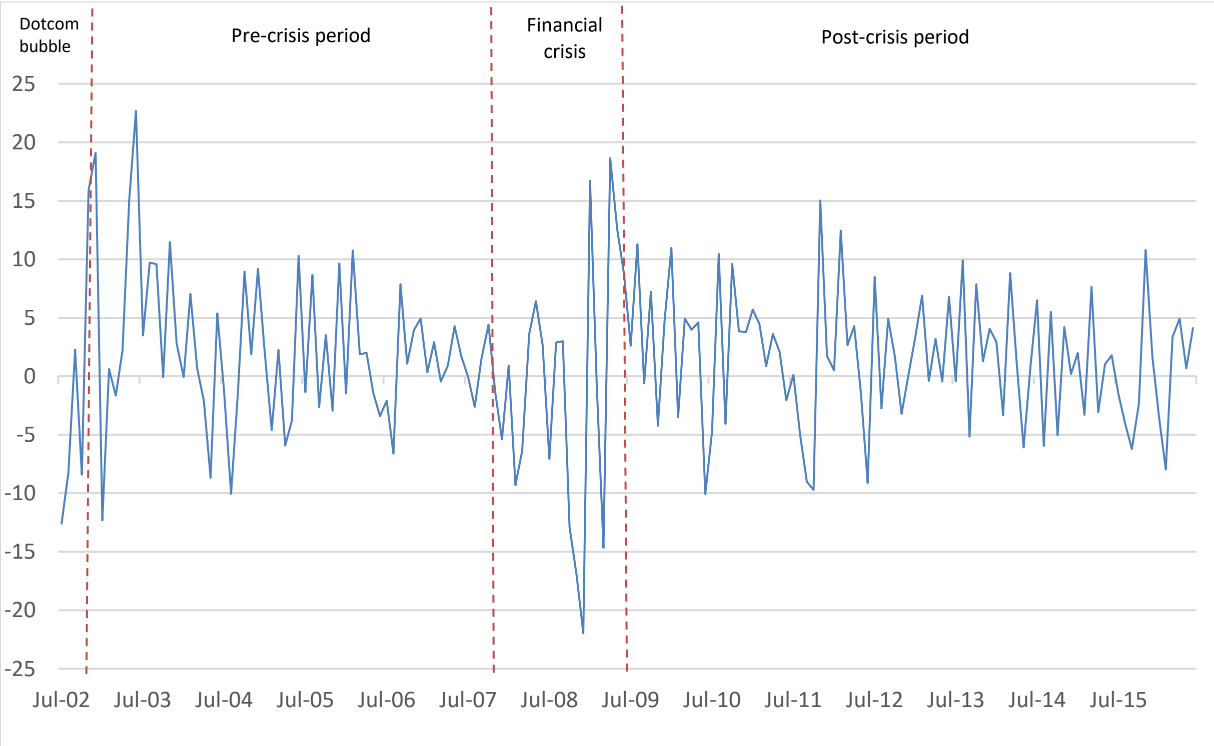

Figure 3: Monthly average returns for the sample of U.S. high-tech stocks over the entire period

5.2 Sample

5.2.1 Sample construction

The initial sample consisted of 1,810 U.S. high-tech stocks out of four sub-industries which are perceived to be high-tech: Software and Computer Services (725 firms), Technology Hardware & Equipment (369 firms), Pharmaceuticals and Biotechnology (672 firms), and Mobile Telecommunication (44 firms). For the time period from 2002 to 2016 (15 years), monthly returns of these stocks as well as monthly observations of the respective market capitalization and the market-to-book equity ratios were gathered from DATASTREAM.

Due to missing values during the research period of either of the three variables (return, market capitalization, or market-to-book equity) around half of the sample size was lost. These missing values did mainly occur because of the comparably young age of high-tech companies compared to other industries as well as high M&A activities in the high-tech industry. Also, the research was designed to reach a balanced panel for the subsequent time-series regressions. Additionally, another 750 firms were lost because of unreasonable data which included the following phenomena: Frequent monthly returns of zero, zero market capitalization, and high increases in return up to 6000% due to non-trading and/or previous returns close to zero. Also, firms with a negative book-value of equity were excluded from this research (Fama & French, 1993). After reconstructions, the total sample size resulted in 120 U.S. high-tech firms with monthly observations over the time period from 2002 to 2016, which equals 21,600 observations.

It is worth noting that our sample might suffer from a survivorship bias as defined by Kothari et al. (1995). As already pointed out in the literature review, a survivorship bias can influence the performance of high book-to-market firms as well as it can affect the period-specific performance of both low book-to-market and high book-to-market stocks. As our sample period is quite long with 15 years and due the exclusion of many firms because of bankruptcy, missing data and M&A activities, our sample is most likely biased towards older high-tech companies. This destroys the characteristic of the high-tech industry to a certain extent and should be kept in mind when reading this paper.

5.2.2 Regression components and data sources

In order to test for the CAPM and the FF3FM, the research requires monthly observations for 5 variables: Each individual stock return at time t, the risk-free rate of return at time t, the market return at time t, the market capitalization of each stock at time t, and the book-to-market equity ratio at time t-1.

The individual stock return at t is given by the stock price at time t divided by the stock price at t-1 and further transformed by subtracting 1. The risk free-rate of return is represented by the monthly rate of the 1-month U.S. T-bill and the market returns are captured by the S&P500 market index. Market capitalization at time t is calculated by the individual stock price at time t multiplied by the number of outstanding shares of the company. Finally, the book-to-market equity ratio at t-1 is given by the book equity at t-1 divided by the market equity at t-1. In this research, the book-to-market equity is calculated by 1/market-to-book value. The entire dataset is gathered from DATASTREAM.

5.2.3 Portfolio characteristics

For the time-series regressions, 25 high-tech stock portfolios as well as the factor mimicking portfolios SMB and HML are formed in each year t from 2002 to 2016. Due to an even number of 120 companies in the final sample, each small and big portfolio consists of 60 companies. Respectively, the three book-to-market portfolios consist of 36, 48 and 36 companies according to the 30% and 70% percentile. For the time-series regressions, the equal-weighted monthly returns of the six portfolios SL (96 companies), SM (108 companies), SB (96 companies), BL (96 companies), BM (108 companies), and BH (96 companies) are calculated, which results in a time-series of 168 monthly return observations of SMB and HML from July 2002 to June 2016.

Additionally, the portfolios formed according to size and book-to-market equity are divided into the 20%, 40%, 60%, and 80% quantiles, resulting in 5 portfolios of 24 companies for both size and book-to-market. Each independent portfolio, e.g. SL, therefore consists of 48 companies. For the regressions, the equal-weighted portfolio returns are calculated in each month from July 2002 to June 2016. Subtracting the risk-free rate of return from the portfolio returns results in a time-series of 168 monthly excess returns of the 25 portfolios.

In the same manner, the excess returns of the S&P500 market index are calculated by subtracting the risk-free rate of return from the monthly index returns. The result is a time-series of 168 monthly observations of S&P500 excess returns from July 2002 to June 2016.

5.3 Descriptive statistics

5.3.1 Dependent variable: 25 high-tech stock portfolios

In table 3, the descriptive statistics of the 25 high-tech stock portfolios formed on size and book-to-market equity are presented. The table shows that because of the chosen quantiles, each portfolio contains on average the same number of companies, 48.

Not surprisingly, the portfolios in the largest size quintile have the largest fractions of market value. The market value (size) is decreasing throughout the sample, where the smallest quintile averages about 10% of the total market value in the portfolios. In contrast, the portfolios in the largest size quintile average 54.36%. Note, that the stocks in the largest size and lowest BE/ME quintile alone, account for over 13 % of the entire market value in the portfolios.

Furthermore, in each size quintile, the average market value (and average percentage fraction) decreases from lower to higher BE/ME quantiles. This is mainly due to independent size and book-to-market sorts of high-tech stocks to form the portfolios. This means that the highest BE/ME quintile is tilted towards the smallest stocks (Fama & French, 1993).

Table 3: Descriptive statistics for 25 high-tech stock portfolios

Descriptive statistics for 25 stock portfolios formed on size and book-to-market equity: July 2002 - June 2016. 14 years										
	Book-to-market equity (BE/ME) quitiles									
Size quintiles	Low	2	3	4	High	Low	2	3	4	High
	Average of annual averages of firm size					Average of annual BE/ME ratios for portfolio				
Small	13176,1	13058,9	3928,3	1508,0	794,1	0,45	0,51	0,57	0,65	0,90
2	13401,1	13283,9	4153,4	1733,0	1019,2	0,34	0,40	0,45	0,54	0,78
3	13891,8	13774,6	4644,1	2223,7	1509,9	0,30	0,36	0,42	0,50	0,75
4	15563,9	15446,7	6316,1	3895,8	3181,9	0,28	0,34	0,39	0,48	0,72
Big	41667,4	41550,1	32419,6	29999,3	29285,4	0,22	0,29	0,34	0,42	0,67
	Average of annual percent of market value in portfolio					Average of annual number of firms in portfolio				
Small	4,27%	3,93%	1,14%	0,49%	0,28%	48	48	48	48	48
2	4,34%	4,00%	1,21%	0,56%	0,35%	48	48	48	48	48
3	4,49%	4,15%	1,36%	0,71%	0,50%	48	48	48	48	48
4	5,02%	4,68%	1,89%	1,24%	1,03%	48	48	48	48	48
Big	13,12%	12,78%	9,99%	9,34%	9,13%	48	48	48	48	48

Table 4 presents the descriptive statistics for the excess returns based on 25 portfolios formed on size and BE/ME. The portfolio returns range from 0.99 to 1.71 per month. Furthermore, table 4 verifies the well-known findings by Fama and French (1992) that there is a negative relationship between size and average return, and a positive relationship between BE/ME and average return. This can be observed as average portfolio returns tend to increase moving from the big to the small size quantiles. In the same manner portfolio returns tend to increase moving from the low to the high BE/ME quantiles. However, there are some outliers of these trends, which make both factors not entirely consistent throughout the sample.

Another problem (Merton, 1980) which can be observed is the high standard deviation of stock returns. For the excess returns on the 25 portfolios the standard deviations range from 6.2% to 7.76%. The consequence is that large average returns are often not significantly different from zero (Fama & French, 1993). However, due to the common risk factors in returns, which absorb most of the variation in stock returns, the high volatility of stock returns will not decrease the power of the asset-pricing tests (Fama & French, 1993).

Table 4: Descriptive statistics for the excess returns on the 25 high-tech stock portfolios

Descriptive statistics for excess returns on 25 portfolios formed on size and BE/ME										
	Book-to-market equity (BE/ME) quitiles									
Size quintiles	Low	2	3	4	High	Low	2	3	4	High
	Means					Standard deviations				
Small	1,35	1,27	1,42	1,40	1,60	6,91	6,62	7,05	7,76	7,65
2	1,20	1,33	1,27	1,10	1,44	7,25	7,55	7,40	7,46	7,30
3	1,14	1,15	1,18	1,18	1,50	7,04	7,13	7,15	7,40	6,75
4	1,10	1,12	1,16	1,15	1,71	6,83	6,89	6,94	7,19	7,30
Big	0,99	1,13	1,05	1,04	1,49	6,20	6,37	6,18	6,42	6,01

5.3.2 Independent variables

Table 5 presents the summary statistics for the average returns of the explanatory factors market, SMB and HML, and provides a perspective with regards to the average returns of the 25 dependent portfolios in Table 4. RM-RF, SMB and HML represent the independent variables which are included in the time-series regressions. The average return of the market factor is around 0.43% per month, around 0.3% per month for the size factor, and 0.165% per month for the book-to-market factor. From an investment point of view, these returns are quite substantial if cumulated over a year: Around 5% for the market factor, 3.6% for the size factor, and around 2% for the book-to-market factor. These returns are significantly lower in comparison to the returns on the 25 portfolios, however, also exhibit lower volatility, i.e. the standard deviations are much lower. The correlation of the risk factors is covered in chapter 6.

Table 5: Summary statistics for the monthly explanatory return variables

Summary statistics for the monthly explanatory returns (in percent): July 2002 to June 2016, 168 observations									
			Autocorrelation for lag			Correlations			
Name	Mean	Std	1	2	3				
						RM	RM-RF	SMB	HML
RM	0,531	4,710	0,034	-0,098	0,094				
RM - RF	0,432	4,715	0,036	-0,095	0,097	0,9996	1,00		
SMB	0,291	2,031	0,002	0,104	-0,005	0,1944	0,1936	1,00	
HML	0,165	1,430	0,052	-0,020	-0,026	0,1435	0,1446	0,3747	1,00

6. Empirical Results and Interpretation

The chapter presents the results from the OLS time-series regressions that have been run for the excess returns on U.S. high-tech stocks for the CAPM and the FF3FM. First, we show our main findings and overall results. Second, we focus on the variation of the models across different time periods. Finally, we compare our results to previous research presented in the literature review.

6.1 Main findings

Table 6 presents the overall time-series regressions results, i.e. the alphas, regression coefficients, adjusted R^2 values and the significance level of the specific risk factors for the CAPM and FF3FM. Here, the coefficients can be interpreted as average coefficients of the regressions on all 25 dependent portfolios of excess returns, and are comparable among different time periods. Overall, it can be observed that the FF3FM performs better than the CAPM. This can be concluded because of decreasing significance of the regression intercepts, the alphas, and increasing R^2 values. As an example, we notice that the significance of the abnormal return decreases from the 1% level to the 5% level when focusing on the entire sample period regression. Additionally, also the value of the abnormal return decreases from 0.73% to 0.54% which indicates a better explanatory power of the FF3FM. Furthermore, the adjusted R^2 value increases from 0.76 to 0.82. The same observations can be made for the specific time periods, where the significance of the alphas entirely disappears after using the FF3FM and always significantly decreases in value. This is accompanied by increasing R^2 values for almost all periods. The improving performance of the FF3FM compared to the CAPM is mainly caused by the high significance of the SMB factor at the 1% level. The HML factor, however, does not seem to play an important role when explaining average excess returns for U.S. high-tech stocks, concluded from insignificant average coefficients for all periods.

Table 6: Average coefficients, alphas, and significance level for different time periods

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
Entire period	0.7260***	1.2321***	0.7643	0.5385**	1.1700***	0.8335***	-0.1704	0.8199
Pre-crisis	0.8570*	1.7032***	0.6892	0.4244	1.6109***	0.8056***	0.0148	0.7642
Crisis	1.6801**	1.1425***	0.9067	1.5974**	1.1481***	0.3182	-0.3265	0.9015
Post-crisis	0.2647	1.1714***	0.7982	0.2228	1.1240***	0.8416***	0.0605	0.8650
Crisis exc (1)	0.4985*	1.3252***	0.7128	0.2879	1.2635***	0.8918***	-0.0801	0.7951
Crisis exc (2)	0.5090*	1.3331***	0.6952	0.3352	1.2499***	0.8903***	-0.0526	0.7837

*** p<0.01, **p<0.05, *p<0.1

(1) the sub-prime crisis excluded (2) the dotcom bubble and the sub-prime crisis excluded

It is important to notice that these general observations do not apply to the financial crisis period and the post-crisis period. The variations of the models across time periods is covered in detail in Chapter 6.2.

For both the CAPM and FF3FM, the market factor is highly significant at the 1% level in all time periods. Especially in the post-crisis period, the market factor, i.e. the CAPM, is on average sufficient in explaining expected excess returns due to an insignificant intercept. The beta coefficients range from 1.14% to 1.7% for the CAPM and from 1.12% to 1.61% for the FF3FM. In all periods except from the pre-crisis period the betas range from 1.14% to 1.33% for the CAPM and from 1.12% to 1.26% for the FF3FM, i.e. they are significantly above 1. This seems to be an intuitive result as the high-tech industry is generally more sensitive to market changes and in this context perceived to be "riskier" than other industries, indicated by a higher beta.

The coefficients for the size factor range on average from 0.81% to 0.89% across all periods, except for the financial crisis. In this context, the average coefficient for the size factor during the entire period was 0.83. It can be concluded that the companies categorized as "small" by their market cap earn higher returns in comparison to their bigger peers. This is well in line with the well-known Fama and French research. The HML coefficients range from -0.32 to 0.06, with an average of -0.17 and are significantly lower than the SMB coefficients. However, the HML factors are not significant in any of the regressions.

Table 7 presents the regression results for the CAPM and FF3FM for all 25 high-tech stock portfolios for the entire sample period from July 2002 to June 2016. Looking at the adjusted R^2 values for the CAPM we can see that the explanatory power of the model tends to increase when we move from small to big quantiles. As an example, in the small quantile the adjusted R^2 values range from 0.53 to 0.66, whereas in the big quantile from 0.71 to 0.79. Importantly, in the small quantile the SMB and HML factors will have their best opportunity for high marginal explanatory power. This can be observed by looking at the R^2 values on the FF3FM for the small quantile, and comparing these values with the corresponding CAPM R^2 values. For the small quantile, the percentage difference between the adjusted R^2 values of the CAPM and FF3FM is clearly most eminent, as it is also stated by Fama and French (1993).

Importantly, it can be observed that the beta coefficients are all significant at the 1% level, ranging from 1.07 to 1.34. Nonetheless, the CAPM produces significant alpha values for all 25 portfolios, i.e. returns that are not explained by the market factor only. Hence, the CAPM does not hold.

Table 7: CAPM and FF3FM for the entire sample period

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
SL	0.8881**	1.0747***	0.5346	0.6176**	0.9833***	1.4774***	-0.7244**	0.6900
S2	0.7903**	1.1141***	0.6282	0.6195**	1.0590***	0.5541*	0.2019	0.6591
S3	0.9096***	1.1693***	0.6087	0.5934*	1.0659***	1.2327***	0.0143	0.7282
S4	0.8248**	1.3358***	0.6565	0.3931	1.1964***	1.4310***	0.4585*	0.8191
SH	1.0638***	1.2307***	0.5723	0.6116**	1.0848***	1.4854***	0.5041*	0.7543
2L	0.6444**	1.2844***	0.6950	0.4620*	1.2201***	1.3683***	-1.1371***	0.8246
22	0.7599**	1.3215***	0.6789	0.5450*	1.2478***	1.3239***	-0.8372***	0.7844
23	0.7108**	1.2933***	0.6772	0.4243	1.1985***	1.2668***	-0.2480	0.7823
24	0.5251*	1.3244***	0.6998	0.2716	1.2414***	1.0029***	-0.0141	0.7688
2H	0.8908***	1.2808***	0.6831	0.5775**	1.1799***	1.0059***	0.3897	0.7769
3L	0.5942**	1.2540***	0.7051	0.5115*	1.2239***	0.8938***	-0.9915***	0.7705
32	0.6004**	1.2725***	0.7067	0.5088*	1.2404***	0.6737**	-0.5479**	0.7364
33	0.6377**	1.2586***	0.6872	0.4530	1.1977***	0.7870***	-0.1082	0.7294
34	0.6071**	1.3243***	0.7098	0.3742	1.2481***	0.9099***	0.0071	0.7676
3H	0.9986***	1.1529***	0.6467	0.8105**	1.0929***	0.5178*	0.3840	0.6817
4L	0.5573**	1.2575***	0.7526	0.5261**	1.2438***	0.6099***	-0.8489***	0.7905
42	0.5790**	1.2615***	0.7446	0.5860**	1.2621***	0.2242	-0.4388	0.7498
43	0.6148**	1.2576***	0.7291	0.4825*	1.2144***	0.5051***	0.0246	0.7478
44	0.5782**	1.3256***	0.7541	0.3963	1.2667***	0.6220***	0.1596	0.7863
4H	1.1679***	1.2482***	0.6486	0.8129***	1.1370***	0.6839**	1.2359***	0.7708
BL	0.4922**	1.1447***	0.7566	0.5209**	1.1499***	0.4893***	-1.0490***	0.8098
B2	0.6229**	1.1779***	0.7583	0.6192**	1.1737***	0.4392**	-0.7397***	0.7856
B3	0.5552**	1.1458***	0.7625	0.4824**	1.1213***	0.3791***	-0.1628	0.7729
B4	0.5106**	1.2146***	0.7943	0.3897*	1.1749***	0.4875***	-0.0221	0.8146
BH	1.0266***	1.0761***	0.7121	0.8738***	1.0271***	0.4671***	0.2309	0.7421
	N: 168			N: 168				

After including the SMB and HML factors to the overall regressions, it can be observed that the FF3FM clearly outperforms the CAPM as we find significant increases in the adjusted R^2 values, ranging from 0.66 to 0.82. Additionally, the significance of the intercept decreases in 16 out of 25 cases, where in 6 cases, the model produces no significant abnormal return at all.

In this context, the SMB factor is highly significant at the 1% level in 19 out of the 25 portfolios. For the remaining six portfolios, there is only one portfolio where SMB has no significance at the 10% level. Fama and French (1993) noticed in their research that the slopes on SMB stocks decrease monotonically from smaller to bigger size quantiles for each book-to-market quantile. In our research, this is completely true for two out of five book-to-market quantiles and partly true for the rest, with one to two inconsistencies in the trend.

Additionally, we can observe that the HML slopes experience negative values in the low book-to-market portfolios and increase when moving to high book-to-market portfolios. It is worth noting, however, that HML coefficients are significant in only 11 out of 25 portfolio regressions, where the low book-to-market portfolios are always highly significant. Furthermore, we find that by adding the SMB and HML factors to the regressions, the beta values tend to approach closer to 1.0 in 23 out of 25 portfolios. Fama and French interpret this result by the correlation between the market, and SMB and HML respectively. For our data, the correlation with the market is 0.19 for SMB and 0.14 for HML (see table 5).

Table 5 presents the correlation between the three different independent variables, the market premium, SMB and HML. Although the three factors are correlated to a certain extent, this correlation is minor, i.e. the highest correlation is 0.37 for SMB and HML. Hence, the regression results are accurate in describing the separate effects of the different factors on the expected portfolio returns and multicollinearity should not be an issue in our time-series regressions (Fama & French, 1993).

In table 7 it can be observed that the intercepts for the smaller size portfolios exceed the intercepts for the bigger size portfolios. Additionally, when comparing the intercepts between the CAPM and the FF3FM, we find that the alphas tend to decrease when we add the SMB and HML factors. This makes sense as the FF3FM performs better than the CAPM and thus produces lower abnormal returns.

The overall time-series regression for the FF3FM for the entire sample period produces an average beta of 1.17, table 6. The market itself gains an average return of 0.43%, which can be found in table 5. Hence, the average monthly contribution of a high-tech stock to the expected return is around 0.503%, which can be interpreted as the premium of being a high-tech stock rather than a stock from another industry.

The slopes for the SMB portfolios result in an average of 0.83, whilst the average return on the SMB portfolios is 0.291. Thus, the risk premium on small stocks increase the expected average return of a U.S. high-tech stock by 0.241% per month.

Similarly, this applies to the HML portfolio which result in an average of -0.17. Having an average HML return of 0.165, the risk premium on high market-to-book stocks reduces the expected average return by 0.028.

6.2 Variation of the models across time periods

Since we are running OLS time-series regressions for the CAPM and the FF3FM separately for specific time periods, it is possible to find out more about the behavior and the explanatory power of these models during different economic situations with regards to U.S. high-tech stocks. Due to simplicity reasons, this section only describes the behavior and changes in the models for two out of the 25 portfolios, S3 and 44. A detailed overview of the entire regression results can be found in the appendix.

Table 8 presents the regression results for the CAPM and FF3FM for the portfolios S3 and 44 for the pre-crisis period, i.e. July 2002 until November 2007. For the S3 portfolio, the CAPM produces a significant abnormal return of 1.33% at the 5% level with an R^2 value of around 0.49. On the other hand, the CAPM produces an insignificant alpha for the 44-portfolio with an R^2 value of around 0.69. In both cases the market factor is significant at the 1% level, resulting in beta coefficients highly above 1, i.e. 1.58 and 1.87 respectively.

As expected due to previous analyses, the FF3FM performs better than the CAPM, especially with regards to the S3-portfolio. It results in insignificant abnormal returns and increases the R^2 up to 0.7. In a similar manner, the FF3FM increases the R^2 of the 44-portfolio regression to 0.76. In both cases, this improvement is mainly due to the highly significant SMB factor, whilst the HML factor stays insignificant. It is important to mention that although the CAPM produces an insignificant alpha for the 44-portfolio, i.e. the CAPM holds, there is still a misspecification in the model. This can be concluded from the increasing R^2 values when using the FF3FM as well as the fact that the significance of the size factor decreases the alphas and the market betas.

Table 8: CAPM and FF3FM for S3 and 44 in the pre-crisis period

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
S3	1,3313**	1,5823***	0,4892	0,4996	1,4738***	1,3124***	0,4927	0,7026
44	0,5632	1,8731***	0,6983	0,0934	1,8299***	0,6791***	0,4000	0,7600
	N: 65			N: 65				

*** p<0.01, **p<0.05, *p<0.1

By having a closer look at the betas in the pre-crisis period in comparison to other time periods (see also table 6), these betas are significantly higher. It could be argued that if we assume efficient markets, the subsequent financial crisis is already anticipated and priced in the model as the market expects economic turmoil in the future. Asset pricing models should respond to that by increasing betas and hence, increasing expected excess returns of U.S. high-tech stocks.

As opposed to the pre-crisis data, table 9 shows the regression results of the CAPM and FF3FM during the financial crisis, or subprime mortgage crisis in the U.S. from December 2007 to July 2009. It is interesting to observe that during this period, the FF3FM does not outperform the

CAPM. For both portfolios, the adjusted R^2 values of the regressions even decrease from 0.78 to 0.75 and from 0.89 to 0.88 respectively when including the SMB and HML factors. Additionally, it can be observed that neither the SMB factor nor the HML factor shows any significance. Hence, the significant abnormal return of the S3-portfolio cannot be eliminated using the FF3FM. Only the market factor is still highly significant at the 1% level, which also causes the insignificant alpha for the 44-portfolio, i.e. the CAPM holds for this particular portfolio during the financial crisis. However, this can only be an exception as on average both models produce significant abnormal returns during this period (see table 6).

Table 9: CAPM and FF3FM for S3 and 44 during the financial crisis

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
S3	2,5273**	1,0908***	0,7782	2,5287**	1,1193***	0,102	-0,3205	0,7527
44	1,4191	1,2515***	0,8911	1,3211	1,2125***	0,205	0,1341	0,8795
	N: 20			N: 20				

*** p<0.01, **p<0.05, *p<0.1

By looking closer at the alpha terms, we can observe that during the financial crisis both the CAPM and the FF3FM produce comparably high abnormal returns, ranging from 1.32% to 2.53% for the S3 and 44 portfolios. This can also be observed in table 6 for the average abnormal returns during the crisis. In comparison, during other periods and the ones excluding the financial crisis and the aftermath of the dotcom bubble, abnormal returns were significantly lower. This is economically intuitive due to high uncertainty and unpredictability of financial markets during economic turmoil. Also with regards to the limited explanatory power of the CAPM and FF3FM during financial crises, these higher abnormal returns seem to be a reasonable result. Finally, it can be argued that the high sensitivity of the high-tech industry to market changes contribute to the high abnormal returns observed in the data.

Interestingly, also the relationship between small firms and higher expected returns seems to disappear during economic turmoil caused by the subprime crisis. As compared to other time periods, the coefficients for the SMB factor is significantly lower during the crisis-period, however, not significant anymore. This result could be motivated with the fact that for larger and more established companies it might be easier to cope with economic uncertainty and distress, hence, maintaining expected returns.

During the post-crisis period from August 2009 to June 2016, table 10, it can be observed that using only the CAPM already produces insignificant alphas and R^2 values of 0.69 and 0.76 for the S3 and the 44-portfolio respectively. In both cases the market factor is significant at the 1% level. However, using the FF3FM improves the regression results as it increases the R^2 values in both cases and decreases the alphas. Hence, the high significance of the SMB factor at the 1% level still discovers a misspecification of the CAPM. For both portfolios, it can be observed that the HML factor is either insignificant or just significant at the 10% level, which is in line with previous observations.

Table 10: CAPM and FF3FM for S4 and 44 in the post-crisis period

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
S3	0,0291	1,1602***	0,6904	-0,0065	1,0898***	1,3028***	-0,0844	0,8209
44	0,3069	1,205***	0,7670	0,2180	1,1740***	0,4231***	0,4439*	0,7988
	N: 83			N: 83				

*** p<0.01, **p<0.05, *p<0.1

To get a picture of how both models would perform without periods of economic turmoil, regression results of the CAPM and FF3FM for S3 and 44 are presented in the tables 11 and 12. The OLS time-series regressions exclude return data from the financial crisis, table 11, and additionally from the aftermath of the dotcom bubble, table 12. Both results are quite similar and show the same significance of the specific factors in each model. Particularly, it can be observed that in each case the FF3FM outperforms the CAPM by increasing the R^2 values and in producing insignificant alphas after having significant abnormal returns in the CAPM (for S3 in table 11 and for 44 in table 12). Also, the CAPM shows insignificant alphas in two cases, which are, however, further corrected downwards in the FF3FM. In both scenarios, the market factor as well as the size factor are highly significant at the 1% level. Again, the HML factor shows no significance in the regression results and does not seem to have an impact on the explanatory power of the FF3FM. The beta coefficients range from 1.27 to 1.40, which again is an indication of the relatively high sensitivity of high-tech stocks to market changes and is in line with the industry characteristics.

Table 11: CAPM and FF3FM for S3 and 44 for the entire period excl. the financial crisis

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
S3	0.5877*	1.2726***	0.558864	0.2108	1.1809***	1.3787***	0.1111	0.7458
44	0.3820	1.4039***	0.695493	0.1582	1.3625***	0.6682***	0.2421	0.7471
	N: 148			N: 148				

*** p<0.01, **p<0.05, *p<0.1

Table 12: CAPM and FF3FM for S3 and 44 for the entire period excl. the financial crisis and the end of the dotcom bubble

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
S3	0.5447	1.3072***	0.5476	0.2325	1.1821***	1.3668***	0.1376	0.7381
44	0.4780*	1.3688***	0.6649	0.2797	1.3069***	0.7009***	0.2546	0.7285
	N: 144			N: 144				

*** p<0.01, **p<0.05, *p<0.1

It can be summarized that during economic turmoil, the FF3FM does not seems to help explaining expected returns of U.S. high-tech stocks, given decreasing R^2 values, remaining significance of abnormal returns and insignificant SMB and HML factors. In this context, the alphas have their highest values during the financial crisis, which occur due to lower explanatory power of the CAPM and the FF3FM as well as higher return volatility in the market. Prior to the financial crisis, the FF3FM outperforms the CAPM where the market betas indicate an anticipation of future economic risk. Also after the crisis-period the FF3FM outperforms the CAPM. However, in the post-crisis period the CAPM already holds by producing insignificant abnormal returns. Nevertheless, the FF3FM can increase the explanatory power and corrects the misspecification of the CAPM.

6.3 Comparison to previous research findings

In general, it can be said that previous research on asset pricing models tends to agree on the result that the FF3FM provides a higher explanatory power than the CAPM. This result is supported by research done by e.g. Fama and French (1992 and 1993), Gaunt (2004) and Blanco (2012) who test the CAPM and FF3FM in the U.S. as well as the Australian market. This is in line with our research results, where the FF3FM outperforms the CAPM considering the entire sample period as well as almost every separate time period. This pattern only breaks during the crisis period, where the additional factors do not help increasing the explanatory power of the model, especially because of the insignificance of the SMB factor. The reasons for this result have been explained in the previous section.

Additional research by Chui and Wei (1998), and once again Fama and French (1992 and 1993), show that the CAPM is not sufficient in explaining average excess returns in the Pacific-Basin emerging markets as well as in the U.S. Also, this result can be generally confirmed by our research where we find that except from the post-crisis period, the CAPM always produces significant abnormal returns. Using the FF3FM reduces the significance of the abnormal returns, decrease the values of the abnormal returns and increase the adjusted R^2 values for the regressions. However, there is still some evidence in favor of the CAPM, for example the research done by Eraslan in 2013. He tests the CAPM and FF3FM on the Istanbul stock exchange and finds that the CAPM has stronger explanatory power than the FF3FM.

As already mentioned, the CAPM does not produce significant abnormal returns in the post-crisis period. However, the FF3FM still increase the R^2 value of the regression and decreases the value of the abnormal return. Additionally, the SMB factor is still significant at the 1% level for this period. This result is similar to the outcome of the research done by Kim (1995). He suggests that although the CAPM produces an insignificant alpha, there is still a misinterpretation in the model due to a significant SMB factor, which can be confirmed by our research results.

In his research from 1997, Carhart finds that overall, the market factor, size and momentum explain most of the variation in portfolio returns, whereas the book-to-market factor is almost insignificant in his research. Similarly, Fama and French (2015) find that the HML factor becomes obsolete when extending the model with additional risk factors such as investment and profitability, whereas Loughran (1997) discovers that book-to-market has no explanatory power for firms in the higher size-quantiles. Also, Gaunt (2004) tests the CAPM and the FF3FM in the Australian stock market and he finds that the FF3FM outperforms the CAPM. Especially, he finds that the improving explanatory power of the FF3FM is mainly caused by the size factor rather than the HML factor. These results can be strictly confirmed by our research, where we find that on average only the SMB factor is significant and contributes to explain excess returns of U.S. high-tech stocks. In fact, the SMB factor is significant at the 1% level in 19 out of 25 portfolios, e.g. in the regression for the entire time period. In comparison, the HML factor is on average not significant in explaining excess returns, in none of the time periods. However, there is still evidence that support the presence of a premium for high book-to-market companies like the Fama and French research as well as Aguenaou, Abrache and El Kadiri (2011).

As already pointed out, our regression results confirm a return premium for smaller firms, i.e. a negative size premium. In fact, the direction of the size premium has been a highly-discussed topic in previous research and lacks clear consensus. While some research papers have confirmed a negative size premium, e.g. Fama and French (1992), other research papers have demonstrated signs of a positive size premium, e.g. Aguenaou, Abrache and El Kadiri (2011). The latter test for the FF3FM in the Moroccan stock market and find that bigger firms earn on average higher returns than smaller firms, which is not in line with our results. A reason for this could be that the underlying data and especially the sample period significantly affects the direction of the size premium, which should be considered when testing asset pricing models. Hence, a period of economic turmoil – such as the dotcom bubble or the subprime crisis – could be more favorable periods for bigger companies, affecting the direction of the relationship.

7. Conclusion

7.1 Main conclusions

In consideration of the respective research questions it can be concluded that for the sample of U.S. high-tech companies at hand the FF3FM outperforms the CAPM in explaining average excess returns of U.S. high-tech stocks. This result can be confirmed for the entire sample period from 2002 to 2016 as well as for almost all specific time periods, where the FF3FM reduces the significance of the alpha terms and increases the adjusted R^2 values. However, the FF3FM does not outperform the CAPM during the financial crisis, in fact it even decreases the explanatory power of the model.

Furthermore, we confirm the frequent result that the CAPM is not sufficient in explaining average excess returns of U.S. high-tech stocks. Although the market factor itself is highly significant throughout the entire sample period, the model produces significant abnormal returns which indicate a misspecification and lack of explanatory power of the CAPM. In comparison, the FF3FM eliminates the significance of the abnormal returns in the specific periods before and after the financial crisis as well as it decreases the value of the alpha terms.

For the entire sample period, the FF3FM is not sufficient in explaining average returns of the U.S. high-tech stocks, but it reduces the significance of the abnormal returns significantly compared to the CAPM. In this context, it is important to mention that the FF3FM eliminates the significant alpha terms of the CAPM when we exclude the return data of the crises periods from the time-series regressions, i.e. the FF3FM holds.

The higher explanatory power of the FF3FM is mainly caused by the high significance of the SMB factor. Hence, we confirm the well-known result of a negative size premium for U.S. high-tech stocks, i.e. holding small-cap U.S. high-tech stocks increases the expected returns compared to holding large-cap stocks. Although we find patterns in the data of increasing returns with higher book-to-market quantiles, the HML factor is on average not significant in our time-series regression. This leads to the conclusion that book-to-market equity does not contribute significantly to explain average returns of U.S. high-tech stocks.

Finally, our findings suggest that the CAPM and the FF3FM do not sufficiently work during times of economic turmoil as both models produce significant abnormal returns. In fact, the FF3FM has an even lower explanatory power compared to the CAPM, which results due to the insignificant SMB and HML factors during this period.

7.2 Application and Recommendation

As indicated in the previous section, the FF3FM is an improvement towards the traditional CAPM for the U.S. high-tech industry. Especially, during stable economic times the FF3FM is a reliable model for calculating expected returns for U.S. high-tech stocks. Even during periods where the CAPM holds, the FF3FM adds explanatory power and makes the calculation of expected returns more precise. It is therefore recommended to apply the FF3FM as a decision making and valuation tool for the U.S. high-tech industry rather than using the traditional CAPM. This is of course accompanied by the need of additional information and resources since the FF3FM requires more input than the CAPM.

In general, the FF3FM can be applied to every business application that requires the calculation of expect returns for U.S. high-tech stocks. This encompasses for example the estimation of abnormal returns in an event study, measuring portfolio performance or estimating the cost of capital for valuation purposes (Fama & French, 1993). Since for our sample of U.S. high-tech stocks the three risk factors are not highly correlated, the average coefficients of the overall time-series regressions (Table 6) fairly represent the separate effect of the respective risk factors on the expected returns for U.S. high-tech stocks. A detailed calculation can be found at the end of section 6.1.

However, we recommend financial analysts to be careful when using asset pricing models during times of economic turmoil, since our results show that neither the CAPM nor the FF3FM works sufficiently during that period. This is of course caused by the high return volatility as well as uncertainty in the entire market, which makes both models unreliable with high significant abnormal returns. However, these high abnormal returns also indicate investment opportunities for market beaters that are certainly associated with higher risk during times of economic turmoil.

7.3 Future research

Taking the multidimensional nature of the recent research on asset pricing models into account, it is important to suggest relevant future research topics for the U.S. high-tech industry. As already mentioned there might be a substantial survivorship bias present in this study due to the characteristics of the high-tech industry. Conducting research with a focus on the survivorship bias would be an interesting approach with further insights into the effects of this bias towards the model performances.

Another self-evident option to deepen our understanding of the research topic would be to add additional explanatory variables as suggested by Carhart (1997) and Fama and French (2015), and similarly by replacing the original size and value factors in the traditional FF3FM with other variables as suggested by Chen and Zhang (2010).

Furthermore, Blanco (2012) states that the regression results are affected by how the portfolios are formed, and Eraslan (2013) mentions that the number of the portfolios affects the results when comparing the CAPM to the FF3FM. Hence, a future research possibility could be to use different techniques for forming the portfolios, and varying the number of portfolios which might have a different effect on the explanatory power of the models.

As pointed out in the literature review, there are also repeating anomalies and seasonality effects that might be presents in the underlying data, such as a January effect defined by Chui and Wei (1998) and Loughran (1997). Obviously, an interesting approach would be to focus on these seasonality effects for U.S. high-tech stock data as our research does not cover this topic.

Finally, Eraslan (2013) points out that the research period is one of the reasons which undoubtedly affects the performance of the FF3FM and the CAPM. Therefore, changing the time period under consideration, and perhaps trying to increase the number of observations, would be a lucrative future research opportunity.

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9. Appendix

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
SL	1,1988*	1,5644***	0,50583	0,4962	1,3671***	1,4716***	-0,2958	0,7173
S2	0,5593	1,4156***	0,51165	0,2675	1,4947***	0,0581	0,9624**	0,5546
S3	1,3313**	1,5823***	0,48917	0,4996	1,4738***	1,3124***	0,4927	0,7026
S4	1,0825*	1,7073***	0,51395	0,1114	1,598***	1,4725***	0,6927**	0,7757
SH	1,6873***	1,5933***	0,47183	0,793*	1,4683***	1,4397***	0,4736	0,7106
2L	0,8841	1,8546***	0,6285	0,4297	1,6169***	1,3299***	-0,9334***	0,7712
22	0,9838*	2,2001***	0,6699	0,4389	1,9815***	1,3687***	-0,6756	0,7822
23	1,0271*	1,8849***	0,6037	0,4327	1,7369***	1,1801***	-0,1228	0,7149
24	0,4543	1,8152***	0,6072	0,0535	1,7521***	0,6694	0,165	0,6462
2H	1,1424*	1,5639***	0,5098	0,6045	1,5411***	0,6859	0,63802	0,5914
3L	0,6655	1,7913***	0,6163	0,3994	1,5893***	0,9946***	-0,9697**	0,7012
32	0,4576	2,0289***	0,6724	0,2007	1,9068***	0,7097	-0,4449	0,7008
33	0,7883	1,8127***	0,6009	0,3867	1,7009***	0,838**	-0,1628	0,6529
34	0,5464	1,9343***	0,6382	0,001	1,8156***	1,0239***	0,0026	0,7246
3H	0,8868	1,5059***	0,5178	0,5288	1,5163***	0,3689	0,5966	0,5511
4L	0,6882	1,7332***	0,6949	0,5009	1,6052***	0,6514***	-0,587*	0,7339
42	0,5088	1,8981***	0,7050	0,5298	1,8681***	0,079	-0,2327	0,6975
43	0,8164	1,7556***	0,6532	0,4921	1,7124***	0,5148**	0,1861	0,6795
44	0,5632	1,8731***	0,6983	0,0934	1,8299***	0,6791***	0,4	0,7600
4H	1,5787***	1,2529***	0,3875	0,9253*	1,3252***	0,4898	1,4488***	0,5678
BL	0,5768	1,4818***	0,6665	0,534	1,3274***	0,5789***	-0,9776***	0,7333
B2	0,6678	1,8281***	0,7416	0,5297	1,6942***	0,6161**	-0,6992**	0,7792
B3	0,7398*	1,5031***	0,6660	0,5553	1,4392***	0,4278*	-0,1589	0,6811
B4	0,4641	1,6258***	0,7217	0,1401	1,5633***	0,5807***	0,0555	0,7655
BH	1,1252***	1,3719***	0,6093	0,6667	1,3484***	0,5986***	0,5165*	0,7062
	N: 65			N: 65				

*** p<0.01, **p<0.05, *p<0.1

Appendix 1: CAPM and FF3FM for the pre-crisis period

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
SL	0,8504	0,8181***	0,5635	0,591	0,7419**	0,6442	0,0459	0,5338
S2	2,5719***	1,0329***	0,7797	2,6597**	1,1245***	0,0298	-0,7664	0,7640
S3	2,5273**	1,0908***	0,7782	2,5287**	1,1193***	0,102	-0,3205	0,7527
S4	1,9522**	1,4107***	0,9008	1,5339**	1,2197***	0,7822**	0,8512*	0,9180
SH	0,3206	1,1228***	0,6833	-0,3305	0,7797**	1,0449	1,8485**	0,7427
2L	1,6829	1,1573***	0,8317	1,4344	1,197***	1,0421**	-1,2427*	0,8788
22	1,6554	1,109***	0,8320	1,4162	1,1522***	1,022**	-1,2539**	0,8838
23	1,6651	1,1649***	0,8427	1,3427	1,1496***	1,1003**	-0,8499	0,8836
24	1,8257	1,2686***	0,8404	1,3344	1,1611***	1,3595***	-0,3345	0,8868
2H	1,9051*	1,2479***	0,8599	1,5311*	1,1576***	1,0023**	-0,1565	0,8802
3L	1,7496**	1,1577***	0,8798	1,8063**	1,2262***	0,0547	-0,602	0,8714
32	1,8902**	1,1171***	0,8843	1,9532**	1,1933***	0,061	-0,6701	0,8786
33	1,7597**	1,1606***	0,8816	1,7434*	1,1752***	0,1138	-0,2193*	0,8681
34	1,9224*	1,2667***	0,8898	1,7285*	1,1871***	0,3965	0,292	0,8837
3H	2,6506***	1,0338***	0,7839	2,8139***	1,0943***	-0,358	-0,172	0,7642
4L	1,2766	1,1456***	0,8779	1,4231*	1,2541***	-0,1171	-0,7728	0,8746
42	1,3714*	1,0982***	0,8665	1,5311*	1,2153***	-0,132	-0,829**	0,8647
43	1,3167	1,1441***	0,8822	1,4011*	1,2014***	-0,087	-0,386	0,8708
44	1,4191	1,2515***	0,8911	1,3211	1,2125***	0,205	0,1341	0,8795
4H	1,8695*	1,3208***	0,8568	1,6752*	1,1826***	0,1764	0,9609**	0,8528
BL	1,4194*	1,1053***	0,8704	1,593**	1,2491***	-0,0812	-1,0908**	0,8782
B2	1,4119*	1,0501***	0,8615	1,6028**	1,2008***	-0,1177	-1,1134***	0,8721
B3	1,3295*	1,0962***	0,8862	1,4359*	1,1871***	-0,0394	-0,6998	0,8821
B4	1,4744*	1,2102***	0,9054	1,4016*	1,2043***	0,2392	-0,1642	0,8963
BH	2,1845**	0,9811***	0,7607	2,4614**	1,1151***	-0,4893	-0,6501	0,7546
	N: 20			N: 20				

*** p<0.01, **p<0.05, *p<0.1

Appendix 2: CAPM and FF3FM during the financial crisis

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
SL	0,2860	1,1505***	0,6100	0,3898	1,0728***	1,7342***	-1,035***	0,7815
S2	0,3732	1,1437***	0,6662	0,3457	1,0731***	1,3252***	-0,14	0,7962
S3	0,0291	1,1602***	0,6904	-0,0065	1,0898***	1,3028***	-0,0844	0,8209
S4	0,4735	1,1497***	0,6101	0,3661	1,0623***	1,4903***	0,3091	0,8004
SH	0,6431	1,1769***	0,5795	0,4958	1,0763***	1,6637***	0,5119*	0,8151
2L	0,0218	1,2286***	0,7586	0,1295	1,172***	1,3285***	-0,9645***	0,8695
22	0,0944	1,218***	0,8088	0,0725	1,1685***	0,925***	-0,0809	0,8768
23	0,051	1,2282***	0,7375	-0,0526	1,1609***	1,1031***	0,3765	0,8604
24	0,1886	1,2274***	0,7345	0,0846	1,1597***	1,1099***	0,3769*	0,8585
2H	0,3807	1,2462***	0,7189	0,2363	1,1658***	1,2766***	0,5842***	0,8935
3L	0,1204	1,1815***	0,7576	0,2302	1,1466***	0,9078***	-0,8802***	0,8158
32	0,198	1,1663***	0,8010	0,1782	1,1381***	0,5111***	0,0015	0,8215
33	0,1103	1,179***	0,7305	0,0102	1,1339***	0,6758***	0,4535	0,7932
34	0,2736	1,1783***	0,7423	0,1708	1,1332***	0,6717***	0,4709*	0,8075
3H	0,4653	1,1997***	0,7328	0,3239	1,1411***	0,8559***	0,6632***	0,8443
4L	0,1268	1,2087***	0,7714	0,2507	1,1883***	0,6559***	-0,9077***	0,8090
42	0,2291	1,1962***	0,8191	0,2202	1,1827***	0,2469*	-0,003	0,8203
43	0,1324	1,2022***	0,7593	0,0447	1,172***	0,4108**	0,4392	0,7891
44	0,3069	1,205***	0,7670	0,218	1,174***	0,4231***	0,4439*	0,7988
4H	0,7541*	1,2101***	0,6504	0,5294*	1,1313***	1,0776***	1,1204***	0,8462
BL	0,1407	1,0848***	0,7738	0,2957	1,0776***	0,4602***	-1,0519***	0,8254
B2	0,2425	1,0711***	0,8517	0,2666	1,0711***	0,0482	-0,158	0,8494
B3	0,1524	1,0843***	0,7900	0,0979	1,0676***	0,2163	0,2822	0,8000
B4	0,3266	1,0816***	0,8114	0,2701	1,0641***	0,2254	0,2924	0,8238
BH	0,4964**	1,1058***	0,8057	0,4009*	1,0757***	0,3919***	0,4915**	0,8483
	N: 83			N: 83				

*** p<0.01, **p<0.05, *p<0.1

Appendix 3: CAPM and FF3FM in the post-crisis period

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
SL	0.6706*	1.2649***	0.541228	0.4121	1.1444***	1.6108***	-0.7033***	0.7449
S2	0.4404	1.2238***	0.590161	0.1963	1.1918***	0.5768*	0.4425	0.6475
S3	0.5877*	1.2726***	0.558864	0.2108	1.1809***	1.3787***	0.1111	0.7458
S4	0.7133*	1.3112***	0.536000	0.2355	1.2129***	1.5409***	0.3832	0.7725
SH	1.0864***	1.2906***	0.509278	0.5903**	1.1897***	1.5860***	0.4136	0.7572
2L	0.3711	1.4077***	0.653036	0.2444	1.2957***	1.4004***	-1.0605***	0.8044
22	0.4345	1.5047***	0.652187	0.2319	1.4044***	1.3289***	-0.6289**	0.7683
23	0.4495	1.4153***	0.626148	0.1376	1.3302***	1.2479***	-0.0337	0.7555
24	0.2727	1.4020***	0.642053	0.0037	1.343***	0.9101**	0.1660	0.7219
2H	0.7032**	1.3334***	0.605371	0.3313	1.2770***	0.9675***	0.5697**	0.7337
3L	0.3284	1.3594***	0.648292	0.2932	1.2729***	1.0285***	-1.0434***	0.7415
32	0.2629	1.4240***	0.668009	0.1676	1.3668***	0.7411**	-0.4316	0.7062
33	0.3765	1.3626***	0.624839	0.1587	1.3034***	0.8693***	-0.0207	0.6900
34	0.3508	1.4036***	0.641302	0.0922	1.3378***	0.9800***	0.0363	0.7258
3H	0.6360**	1.2873***	0.619060	0.3543	1.2556***	0.6063*	0.5799**	0.6899
4L	0.3472	1.3607***	0.707176	0.3484	1.2984***	0.7180***	-0.8467***	0.7599
42	0.3127	1.4051***	0.715212	0.3103	1.3841***	0.2447	-0.2758	0.7173
43	0.4061	1.3615***	0.675366	0.2258	1.3258***	0.5662***	0.1624	0.7101
44	0.3820	1.4039***	0.695493	0.1582	1.3625***	0.6682***	0.2421	0.7471
4H	1.1212***	1.2134***	0.536179	0.6485**	1.1837***	0.7467**	1.2901***	0.7204
BL	0.3126	1.1997***	0.7029	0.4025*	1.1430***	0.5776***	-1.0884***	0.7762
B2	0,3881	1,2949***	0,7283	0.4002*	1.2506***	0.5012**	-0.6425***	0.7580
B3	0,3908	1,2041***	0,7053	0.2972	1.1748***	0.4175***	-0.0608	0.7233
B4	0,3558	1,2445***	0,7340	0.2204	1.2101***	0.5123***	0.019999	0.7659
BH	0,7624***	1,1789***	0,7015	0.5261**	1.1471***	0.5691***	0.4157**	0.7736
	N: 148			N: 148				

*** p<0.01, **p<0.05, *p<0.1

Appendix 4: CAPM and FF3FM for entire period excl. the financial crisis

	CAPM			FF3FM				
	a	RM - RF	Adj. R2	a	RM - RF	SMB	HML	Adj. R2
SL	0.5770	1.3190***	0.5435	0.3830	1.1647***	1.5789***	-0.6431**	0.7431
S2	0.4937	1.2183***	0.5667	0.2733	1.1711***	0.5726*	0.4890	0.6317
S3	0.5447	1.3072***	0.5476	0.2325	1.1821***	1.3668***	0.1376	0.7381
S4	0.7128*	1.3216***	0.5132	0.3039	1.1830***	1.5498***	0.4205*	0.7664
SH	0.9838**	1.3441***	0.5062	0.5636**	1.2049***	1.5614***	0.4629*	0.7554
2L	0.3371	1.4339***	0.6408	0.2616	1.2923***	1.3917***	-1.0262***	0.7953
22	0.5177	1.4864***	0.6252	0.3649	1.3531***	1.3564***	-0.6192**	0.7564
23	0.4799	1.4166***	0.6007	0.2238	1.2990***	1.2644***	-0.0298	0.7412
24	0.3457	1.3791***	0.6096	0.1136	1.2944***	0.9372**	0.1810	0.7021
2H	0.6813**	1.3487***	0.5849	0.3559	1.2666***	0.9648**	0.6027**	0.7217
3L	0.2948	1.3948***	0.6407	0.2973	1.2894***	1.0037***	-1.0143***	0.7317
32	0.3464	1.4141***	0.6457	0.2787	1.3396***	0.7480**	-0.4211	0.6877
33	0.3986	1.3768***	0.6065	0.2231	1.2963***	0.8663***	-0.0205	0.6743
34	0.4077	1.3980***	0.6150	0.1925	1.3064***	0.9938***	0.0436	0.7082
3H	0.6142**	1.3120***	0.6037	0.3655	1.2651***	0.5866*	0.6112**	0.6771
4L	0.3496	1.3678***	0.6915	0.3705	1.2920***	0.7107***	-0.8103***	0.7449
42	0.4406	1.3634***	0.6904	0.4389	1.3353***	0.2683	-0.2601	0.6935
43	0.4661	1.3467***	0.6481	0.3105	1.2948***	0.5818***	0.1681	0.6880
44	0.4780*	1.3688***	0.6649	0.2797	1.3069***	0.7009***	0.2546	0.7285
4H	1.0377***	1.2514***	0.5228	0.6093**	1.2008***	0.7215**	1.3413***	0.7174
BL	0.2588	1.2304***	0.7018	0.3608	1.1672***	0.5460***	-1.0364***	0.7705
B2	0.4579**	1.2786***	0.7084	0.4810**	1.2239***	0.5084**	-0.6191***	0.7405
B3	0.3947	1.2130***	0.6868	0.3180	1.1746***	0.4084***	-0.03900	0.7052
B4	0.3953*	1.2332***	0.7109	0.2772	1.1856***	0.5200***	0.0489	0.7481
BH	0.7118***	1.2036***	0.6914	0.5019**	1.1584***	0.5488***	0.4624**	0.7678
	N: 144			N: 144				

*** p<0.01, **p<0.05, *p<0.1

Appendix 5: CAPM and FF3FM for the entire period excl. the financial crisis and the dotcom bubble