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Master in Economics

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Abstract

This paper aims to test whether the three-factor model by Fama and French (1993) is applicable on the global banking/financial industry. The Fama and French three-factor model is an extension of the Capital Asset Pricing Model (CAPM) which predicts expected return rate using a systemic market risk factor. Fama and French (1993) argued the CAPM was not sufficient and added a size risk factor and value risk factor. Although the model has been proven in multiple researches, it is also important to observe that it consistently excludes financial firms from its sample. This could be considered as a shortcoming, as the financial industry represents a large fraction of the economy. Therefore, in this paper we assess the efficiency of 3 risk factors of the Fama and French model for predicting expected returns for financial institutions in the United States, the European Union, and Japan.

The findings show that there is indeed a correlation between the three factors and the expected returns of financial institutions. The results show a correlation between financial institutions with a small market capitalization and a low book-to-market ratio and higher expected returns. This is contrary to the popular belief of the Fama and French model where firms with small market capitalizations and high book-to-market ratios are considered to cause higher expected returns.

Keywords: Fama and French Three-factor Model; Expected Returns; Financial Industry; Market Risk; Size Risk; Value Risk.

JEL Classification: G0; G12

Resumo

Esta dissertação tem como objetivo testar se o modelo dos 3 fatores de Fama and French (1993) é aplicável ao setor global da indústria financeira. O modelo dos 3 fatores de Fama e French é uma extensão da Capital Asset Pricing Model (CAPM), a qual tenta estimar os retornos utilizando um fator de risco sitemático. Fama e French (1993) argumenta que a CAPM apenas não é suficiente para medir retornos e, consequentemente, adiciona um fator relacionado ao tamanho de uma empresa e um fator relacionado ao risco do valor de uma empresa. Apesar de o modelo ter sido utilizado em vários estudos desde a sua origem, é importante notar que as empresas financeiras são comumente excuídas do modelo. Isto pode ser considerado como um defeito, já que o setor financeiro representa uma parte significante da economia. Portanto, nesta dissertação avaliamos a eficiência do modelo em retornos nos setores financeiros do Japão, Estados Unidos e União Europeia.

Os resultados dos testes indicam que existe uma correlação entre os 3 fatores e as taxas de retorno de empresas financeiras. Ademais, os resultados demostram que empresas com um tamanho maior e um book-to-market ratio baixo tendem a ter retornos mais altos. Contraditório às indicações populares do modelo, em qual considera-se que um empresas de um tamanho menor e um book-to-market ratio alto tendem ser relacionado a retornos mais altos.

Palavras-chave: Fama and French modelo dos 3 fatores; Taxas de Retorno; Indústria Financeira; Risco de Mercado; Risco de Tamanho; Risco de Valor.

Classificão JEL: G0; G12

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CHAPTER 1

Introduction

This paper aims to test whether the three-factor model by Fama and French (1993) is applicable on the financial industry when predicting expected portfolio returns. The Fama and French three-factor model is an extension of the Capital Asset Pricing Model (CAPM). This model predicts expected return rate by the use of a systemic market risk factor. However, Fama and French (1993) argue that only a systematic risk factor is insufficient for measuring expected return risks. Hence, Fama and French (1993) added a size risk factor and value risk factor, resulting in the creation of the three-factor model by these authors.

Various studies confirm the efficiency of the Fama and French model for measuring expected portfolio returns. For instance, Fama and French (1993), Banz (1981) explain that firm size has an influence on expected returns, as their outcomes show that firms with a lower market capitalization generally account for higher return rates. In addition, Fama and French (1993), Stattman (1980) and Rosenberg, Reid and Lanstein (1985) find that portfolios with higher book-to-market ratios also have a correlation to higher expected portfolio returns.

Nevertheless, Fama and French (1993) consistently excluded financial institutions from their sample, as they argue that the amount of leverage generally existent in financial firms would influence the outcomes. Financial firms have also been consistently left out by researchers applying the Fama and French model in their studies. This can be considered controversial due to the fact that the financial industry accounts for a substantial part of the economy and plays a major role in financing other industries. Furthermore, there is no solid proof yet that this high leverage actually changes the outcomes of the Fama and French model. For example, Modigliani and Miller (1963) demonstrate that leverage indeed changes the risk profile of firms, but does not necessarily invalidate the principles of the CAPM. Meaning that more research into the correlation of the three factors of the Fama and French model and financial firms is highly recommended.

As a result, in this Dissertation we try to fill the gap in the academic literature by applying the Fama and French three-factor model to financial firms. We will do this by looking at yearly data between 2007 and 2021 from financial institutions in the United States, the European Union and Japan. Then we will categorize these financial institutions into 6 categories based on their size and book-to-market value. Next, before applying the data to the Fama and French model, we will perform some tests in order to verify that the data complies with the procedures.

Subsequently, to obtain our empirical results, we will perform time series regressions to find the correlation of the risk factors to the expected portfolio returns.

The remainder of the paper will start with a literature review in chapter 2; next, in chapters 3 and 4, the data and methodology used for this paper will be described and explained. Chapter 5 presents the main empirical results of the present research, followed by the estimation results in chapter 6. Finally, in Chapter 7, the main conclusions are presented.

CHAPTER 2

Literature Review

The Fama and French 3-factor model is well-known for predicting expected portfolio returns (Fama & French, 2004). In fact, the Fama and French models is an asset pricing model that expands on the Capital Asset Pricing Model (CAPM) by adding two variables, namely a size risk factor and a value risk factor to the systemic risk factor of the CAPM (Fama & French, 1993). The formula is based on the assumption that investors require a certain level of returns in compensation for the systemic risk they suffer. Hence, requiring a higher return rate for riskier investments (Fama & French, 2004). The Capital Asset Pricing Model was introduced by William Sharpe (1964) and John Lintner (1965) and was based upon the work of Markowitz (1945) regarding his portfolio selection theory [1]. Over the years the CAPM gained a vital role in empirical studies and in predicting expected portfolio returns (Fama & French, 1993). The CAPM formula was set up as follows:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_{is}(R_{mt} - R_{ft}) \tag{1}$$

Where:
R_{it} = *Average return on portfolio i at time t.*
R_{ft} = *Risk free rate of return at time t.*
R_{mt} = *Total market return at time t.*
$R_{it} - R_{ft}$ = *Expected excess return.*
$R_{mt} - R_{ft}$ = *Excess on the return on the market.*
$\beta_{im,is,ih}$ = *Factor coefficients.*

Although the CAPM is of great importance, it also shows contrasting results on whether systematic risk can fully explain these portfolio returns. For example, Banz (1981) found that on average portfolios of small sized firms show higher returns than expected. Bhandari (1988) discovered that in stocks there is a correlation between high debt-to-equity ratios and relatively higher expected returns than calculated by the CAPM. Furthermore, Stattman (1980) and Rosenberg, Reid and Lanstein (1985) also show the existence of a correlation between firms with a high book-to-market ratio and higher returns.

As a result, Fama and French (2004) argued that market volatility was not the only risk factor necessary to measure returns. Fama and French (1993) further stated that it is necessary to add at least two more factors to the model, namely a size factor and a value factor. This Fama and French model is based on the following formula:

[1] William Sharpe was awarded a Nobel prize in 1990 for his contributions to the CAPM (Nobel Prize, 1990).

$$R_{it} - R_{ft} = \alpha_{it} + \beta_{im}(R_{mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \epsilon_{it} \quad (2)$$

Where:
R_{it} = *Average return on portfolio i at time t.*
R_{ft} = *Risk free rate of return at time t.*
R_{mt} = *Total market return at time t.*
$R_{it} - R_{ft}$ = *Expected excess return.*
$R_{mt} - R_{ft}$ = *Excess on the return on the market.*
SMB = *Size premium (Small Minus Big).*
HML = *Value premium (High Minus Low).*
$\beta_{im,is,ih}$ = *Factor coefficients.*

The size factor is based upon a firm's market capitalization where excess returns are measured of small stocks over big stocks, also known as small minus big (SMB) effect. The value factor is based on the book-to-market ratio of a company, which is predicted by measuring firms with a high book-to-market against firms with a lower ratio, the high minus low (HML) effect (Fama & French, 1993). As mentioned before by Banz (1981), Fama and French (1993) explain that firms with a lower market capitalization generate higher return rates over the long term than larger firms do. Regarding the value factor, some might argue that firms with a low book-to-market value show higher returns, as these stocks are considered more volatile and have more growth potential (Baldridge, 2022). However, similar to Stattman (1980) and Rosenberg, Reid and Lanstein (1985), Fama and French (1993) actually found that over the long run firms with a high book-to-market ratio have higher expected returns. This is due to the fact that investors see these value portfolios as riskier and with less growth potential (Fama and French, 1993). This lack of growth potential might cause managers to take riskier decisions or reorganize their portfolios in order to increase potential future growth (Fidanza & Morresi, 2018).

However, it is noticeable that Fama and French only select non-financial firms in their research and, thereby, exclude financial firms from their testing procedures (Fama & French, 1993). This is also the case for many other subsequent academic literature that have used the Fama and French model in their researches (Baek & Bilson, 2014). Fama and French (1993) argue that financial firms should not be included as these types of firms generally have a very high level of leverage. Nevertheless, the financial industry is a vital part of the economy in many parts of the world. For example, in 2021 the financial service industry accounted for 21 per cent of the total GDP of the United States (Statista, 2022). Therefore, it is of importance to find a fitting model to predict expected return rates in this industry. Previously it was thought that the interest rate would be an important factor to be added to the CAPM when applied to financial institutions. However, Giliberto (1985) finds that various researches demonstrate that the interest rate is not a reliable factor to predict return rates.

Some researches have tried to apply to apply the Fama and French model to financial institutions. These papers find conflicting outcomes because some industry-specific characteristics actually influence the results of the Fama and French three-factor model. For example, some papers argue that the size effect is affected by the assumption that big financial institutions suffer from less risk as they are more diversified (Fidanza & Morresi, 2018). On the contrary, some researches such as Demsetz and Strahan (1997) state that these institutions operate with lower levels of capital and, as a result, take on more risks. In addition, the too big to fail policy, which still exists in some cases, also leads to riskier behaviour as these financial institutions become less afraid of possible repercussions (Kelleher, 2022). For instance, this risky behaviour of some of these too big to fail institutions was a major reason behind the financial crisis (Young, 2022). On the other hand, Gandhi and Lustig (2015) argue that large financial institutions require a lower level of risk premium, as governments would apply certain protections to large banks that would take away some of the risks that they face. This would overdo the fact that these large banks show much higher levels of leverage. On the other hand, Barber and Lyon (1997) find that the factors that influence the size effect are quite similar between financial and non-financial institutions. Hence, these authors argue that small financial institutions face more risk and can expect higher return rates. Baek and Nilson (2014) also find similar results regarding the effect of the three factors. However, it finds that the ability to measure the excess return variability is lesser for financial firms. Baek and Nilson (2014) argues that this the effect of the higher leverage ratios of financial institutions, which makes them more volatile to changes in interest rates.

CHAPTER 3

Data

This paper investigates a sample of company data from financial institutions in the United States, the European Union, and Japan. The company data obtained for this paper consists of the following variables: (i) average return on equity, (ii) market capitalization, (iii) share price, and (iv) the book value per share, of which the latter two are used to calculate the book-to-market ratio. This information was all retrieved from the database Bank Focus. Only institutions that had data available data for all the selected variables and time periods are included in our sample. The specific regions named above were selected as these were the only regions with at least 50 institutions that passed the criteria. A sample of at least 50 companies is actually necessary in order to have a sufficient number of observations in order to construct the 6 portfolios of the Fama and French model. Also, it was also necessary to include multiple regions instead of focusing on one, as one region would not provide sufficient observations due to data limitations regarding the time interval. The time interval chosen comprises yearly data from 2007 to 2021. Yearly data is used as most data for financial institutions is only provided on a yearly basis. Our time period is somewhat limited due to the reason that Bank Focus, for most variables, only provides data for the period between 2007 and 2021. Also, choosing the maximum time period available provided the paper with more observations, as the inclusion of more observations increases the validity of the research results.

Besides company data, it is also necessary to obtain the risk-free rates and expected market risk returns that compose the market risk factors in the CAPM. For the United States both of these rates are retrieved from Kenneth R. French's own data library (French, 2022). Here Fama and French (1993) provide the risk-free rate based on the 1-year US treasury bill rate (French, 2022). The expected market return Fama and French (1993) derive from the average yields of the NYSE, AMEX, and NASDAQ exchanges (French, 2022). Regarding the European Union, the yearly return on the STOXX Europe 600 index rate will be used (The Wall Street Journal, 2022). The Stoxx Europe 600 index is composed of company stocks from the following European countries: Austria, Belgium, Denmark, Finland, France, Germany Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, the United Kingdom, and Switzerland. The Stoxx Europe 600 is therefore a good measurement for the European market returns (STOXX, 2022). Due to the lack of a bond rate that represents the EU as a whole and covers all the necessary time periods, the EURIBOR rate was chosen to represent the risk-free rate. For Japan the yearly return rate on the Nikkei stock exchange is obtained to define the excess return rate (MacroTrends, 2022). To obtain the risk-free rate for Japan, the Japanese 1 year bond is used (Trading Economics, 2020).

CHAPTER 4

Methodology

4.1. Factor Construction

Before running the test to analyse the data, it is necessary to construct the factors of the Fama and French 3-factor model. The market risk variables from the CAPM model can be directly derived from the databases. The average portfolio return rate - SMB and HML - need to be calculated beforehand. The average portfolio return rate is calculated simply by taking the average return rate of all companies for each year and region separately. The calculations for the SMB and HML factors are a bit more sophisticated. Firstly, the companies in the sample will be divided by market capitalisation, representing the company's size, while book-to-market represents the company's value. Based on these factors the companies will be sorted into 6 portfolios. The companies are first split in half based on their size using the median market capitalisation of the companies in the sample. The companies are then categorized as "Big", in case they have a market capitalisation higher than the median, and categorized as "Small", in case of a below median market capitalisation. Then the companies are categorized into 3 categories based on the book-to-market value. The companies that have a book-to-market in the first 30th percentile are categorized as "Low", the ones that fall above the 70th percentile are categorized as "High" and the companies that fall between the 30th and 70th percentile will be listed as "Medium". When joining these two divisions we construct the 6 portfolios, as can be seen in Table 4.1 below:

Table 4.1

Fama and French 6 portfolios overview

	Below Median Market Capitalization	Above Median Market Capitalization
Under 30th percentile Book-to-Market	Small-Low	Big-Low
30th to 70th percentile Book-to-Market	Small-Medium	Big-Medium
Above 70th percentile Book-to-Market	Small-High	Big-High

Source: Fama and French (1993).

After constructing the portfolios, the SMB and HML are calculated by the two formulas below:

$$SMB = 1/3\,(Small - Low + Small - Medium + Small - High) - 1/3\,(Big - Low + Big - Medium + Big - High) \quad (3)$$

$$HML = 1/2\,(Small - High + Big - High) - 1/2\,(Small - Low + Big - Low) \quad (4)$$

4.2. Regression Analysis

After the 3 factors of the Fama and French model are constructed, it is time to do the testing. For this paper, the ordinary least square (OLS) multiple regression is being used to estimate the time-series (Fama & French, 1993). Fama and French (1993) have used both time series regressions and cross-sectional regressions in the past. However, the choice for time series regression was made as research shows that this is a slightly more accurate test of model validity (Lam, 2005). Time-series regression helps us in measuring on what degree expected returns are linked to the 3 factors of the Fama and French model (Goyal & Jegadeesh, 2017). Firstly, we will do a regression of the overall model to see the overall impact of the 3 factors. Next, we will do regressions on the average returns of each of the 6 portfolios to measure the effect of the factors on each portfolio individually. The regressions are all performed in Stata 17.

Nevertheless, before estimating the regressions, we will perform some tests to confirm that our data is clear of nonstationarity, autocorrelation, heteroscedasticity, and multicollinearity in our data. We try to avoid these as best as possible, as this would decrease the suitability of the data and our test results (Cochrane, 2005). These tests are also conducted in Stata 17.

Firstly, we will start by verifying if our data is stationary. Stationarity implies that data points have means, variances and covariances that do not change over time (Gurajati, 2014). In other words, in order to have stationarity, the statistical properties of a system do not change over time (Rasheed, 2020). Stationarity is important as it facilitates the analysis regarding the specific impact of a variable, and for example, to state whether test results are not influenced by trends or seasonality (Radečić, 2020). When the opposite occurs, it means that the data is non-stationary. This means that non-stationary data often show means, variances, and covariances that change over time and behaviours such as trends and seasonality. Consequently, the time series data in this case becomes less predictable (Iordanova, 2022). In case there is non-stationarity, the data should be slightly transformed so that it can convert to stationary data (Rasheed, 2020). To find out whether our time series are stationary, we will perform the Augmented Dickey-Fuller (ADF) unit root test (Elliot et al., 1996). In case our data suffers from non-stationarity, we will have to apply the KPSS test in order to define what type of non-stationarity we are dealing with. This test is used to define whether the time series follows a deterministic trend or whether if it is difference stationary (Kwiatkowski et al., 1992). In case of a deterministic trend, we will transform the data using detrending to remove the trend (Iordovana, 2022). On the contrary, if there is difference stationarity, we will use differencing to transform the data (Iordovana, 2022).

Next, an autocorrelation test will be performed to measure the degree of correlation of a given variable over different time intervals (Smith, 2022). Having autocorrelation in data is a problem as it represents a correlation between an error term in one period with an error term in another period. It is preferable to avoid having correlation in error terms, as it can lead to misleading results (Dotis-Georgiou, 2019). It is commonly considered that the Durban-Watson statistic is the most used method to test for autocorrelation (Kenton, 2022). However, various studies point out that the Breusch-Godfrey actually provides superior results to the Durbin-Watson test (Gujarati, 2004). Research shows that in models with lagged dependent variables, the Breusch-Godfrey test appeared to be to the most adequate to test autocorrelation (Uyanto, 2022).

Afterwards, we will test whether the data faces any heteroscedasticity issues. The problem of heteroscedasticity exists whenever the variance of the error term is not constant. This unequal spread in data results in OLS estimations being neither unbiased nor having minimum variance (Gujarati, 2004). To test for heteroskedasticity, two tests are used, namely the Breusch-Pagan test and the White test (Breusch & Pagan, 1979) (White, 1980). These tests check whether the residuals of a regression have changing variance (XLSTAT, 2022).

Lastly, a multicollinearity test is also conducted. Multicollinearity occurs when two or more independent variables are highly correlated with each other (Hayes, 2022). When inputs influence each other, they actually are no longer independent. As a result, it becomes complicated to isolate and analyse their individual effects on the dependent variable (Potters, 2022). To measure the degree of multicollinearity in the adopted dataset, the Variance Inflation Factor (VIF) is also computed. The VIF calculates the number of inflated variances caused by multicollinearity (CFI, 2022).

Chapter 5

Empirical Results

5.1. Estimation Results

Table 5.1 shows a number of statistics from the data that we have used for our research (descriptive statistics). Firstly, it easily noticeable that the portfolios with a low book-to-market ratio have a higher average return rate. This is contrary to Fama and French (1993), and to the outcomes present in existing literature (Stattman,1980; Rosenberg, Reid and Lanstein (1985). On the other hand, the other assumption of the Fama and French (1993), stipulating that small firms would have higher returns than big size firms, seems to be less noticeable.

Table 5.1

Descriptive statistics of the time series

	Small-Low	Small-Medium	Small-High	Big-Low	Big-Medium	Big-High	Market Risk Factor	SMB	HML
Mean	10,21	7,00	4,71	11,07	6,86	3,42	7,58	0,19	-6,58
Median	11,46	6,52	4,85	12,40	6,84	3,50	7,87	-0,07	-5,87
Standard Deviation	5,29	3,58	3,89	4,51	3,75	4,98	18,40	1,77	4,58
Sample Variance	28,01	12,80	15,09	20,33	14,04	24,85	338,56	3,13	21,01
Kurtosis	8,55	4,70	6,31	3,64	6,03	5,71	4,11	2,41	3,26
Skewness	-1,84	-0,33	-1,33	-0,20	-0,71	-0,91	-0,41	0,013	-0,04
Minimum	-12,11	-4,87	-9,24	-0,55	-6,79	-14,60	-44,07	-3,80	-19,06
Maximum	19,19	16,39	11,69	23,73	15,98	14,60	56,62	3,55	4,69
Observations	45	45	45	45	45	45	45	45	45

Source: Performed by author in STATA

Furthermore, it can be observed that the standard deviations for the 6 portfolios, SMB and HML are relatively low, with values varying around 2 to 5 per cent. Beforehand, it was expected that the portfolios with a low book-to-market might suffer from higher volatility (Fama and French, 1993). The statistics also prove that the two portfolios with the lowest book-to-market ratio have higher returns. Nevertheless, it is very surprising to observe that the "Big-High" portfolio shows a higher standard deviation also. When looking more in-depth into the data file, it is possible to observe that companies in the "Big-High" portfolio were significantly more impacted by the financial crisis, showing relatively high negative returns for 2009. The only variable with a standard deviation showing a significant higher value is the Market Risk Premium. This could mean that the overall market was more volatile over the chosen time periods than the volatility of the financial firms included in the sample. Furthermore, the descriptive statistics also show a rather high sample variance, especially for the market risk factor. This variance is most probably a result of the financial crisis that occurred during the chosen time period.

5.2. Stationarity Tests

In this section we will discuss the stationarity results that we obtained by applying the Augmented Dickey-Fuller (ADF) to the variables in our sample. We will look at the data from each region separately [2]. When applying the ADF test we will try to answer the following hypotheses:

Null hypothesis: The times series variable under consideration is non-stationary

Alternative hypothesis: The times series variable under consideration is stationary

(Elliot et al., 1996)

As mentioned in the methodology section, should variables that show non-stationarity be found, we will also apply the KPSS test. In order to verify whether we are dealing with a deterministic trend non-stationarity or difference non-stationarity, we will answer the following hypotheses:

Null hypothesis: The times series variable under consideration is deterministic trend non-stationary

Alternative hypothesis: The times series variable under consideration is difference non-stationary

(Kwiatkowski et al., 1992)

5.2.1. Stationarity tests USA

Table 5.2

ADF Test Results USA

Country	Variables	p-value	T-statistic	Critical value 1%	Critical value 5%	Critical value 10%
USA	Small-Low	0.1589	-2.342	-3.750	-3.000	-2.630
USA	Small-Medium	0.2080	-2.195	-3.750	-3.000	-2.630
USA	Small-High	0.3904	-1.780	-3.750	-3.000	-2.630
USA	Big-Low	0.0819	-2.656	-3.750	-3.000	-2.630
USA	Big-Medium	0.3191	-1.928	-3.750	-3.000	-2.630

2 The tests were performed separately for each country, because the ADF test does not function in Stata when the data of all three regions is uploaded in one file.

USA	Big-High	0.1582	-2.344	-3.750	-3.000	-2.630
USA	Market Risk Factor	0.0037	-3.730	-3.750	-3.000	-2.630
USA	SMB	0.0138	-3.325	-3.750	-3.000	-2.630
USA	HML	0.1861	-3.681	-3.750	-3.000	-2.630

Source: Performed by author in STATA

Table 5.2 displays the results of the Augmented Dickey-Fuller in the USA. Most p-values are above 0.05, and therefore, the null hypothesis of non-stationarity cannot be rejected. This means that non-stationarity has been detected in these specific variables. Only the variables "Market Risk Premium" and "SMB" have a p-value<0.05. As a result, these variables show stationarity and further research into these variables will not be necessary. However, for the variables exhibiting non-stationarity we will need to apply the KPSS test, as can be seen below, to discover what type of non-stationarity we are dealing with.

Table 5.3

KPSS Test Results USA

Variable	Relevant T-statistic	Critical value 10%	Critical value 5%	Critical value 2,5%	Critical value 1%
Small-Low	0.137	0.119	0.146	0.176	0.216
Small-Medium	0.0848	0.119	0.146	0.176	0.216
Small-High	0.0755	0.119	0.146	0.176	0.216
Big-Low	0.114	0.119	0.146	0.176	0.216
Big-Medium	0.0756	0.119	0.146	0.176	0.216
Big-High	0.117	0.119	0.146	0.176	0.216
HML	0.108	0.119	0.146	0.176	0.216

Source: Performed by author in STATA

As can be seen in Table 5.3, all variables have a relevant t-statistic value lower than the 5 per cent critical value of 0.146. Therefore, we cannot reject the null hypothesis for any of the variables. This means that these variables have deterministic non-stationarity trends. Hence, a detrending procedure is applied in order to transform this data into stationarity data.

Table 5.4

KPSS Test Result USA After Detrending

Variable	p-value	T-statistic	Critical value 1%	Critical value 5%	Critical value 10%
Small-Low	0.0028	-3.807	-3.750	-3.000	-2.630
Small-Medium	0.0037	-3.927	-3.750	-3.000	-2.630
Small-High	0.0025	-3.839	-3.750	-3.000	-2.630
Big-Low	0.0028	-3.807	-3.750	-3.000	-2.630
Big-Medium	0.0009	-4.115	-3.750	-3.000	-2.630
Big-High	0.0001	-4.694	-3.750	-3.000	-2.630
HML	0.0121	-3.369	-3.750	-3.000	-2.630

Source: Performed by author in STATA

After applying the detrending method, we obtained the following results that can be seen in Table 5.4. We see that after detrending, the corresponding p-value<0.05 for all the variables under consideration. This means that the data has successfully been transformed into stationarity data.

5.2.2. Stationarity Tests Eu

Table 5.5

ADF Test Results EU

Country	Variables	p-value	T-statistic	Critical value 1%	Critical value 5%	Critical value 10%
EU	Small-Low	0.0014	-4.750	-3.750	-3.000	-2.630
EU	Small-Medium	0.0001	-2.238	-3.750	-3.000	-2.630
EU	Small-High	0.0054	-3.681	-3.750	-3.000	-2.630
EU	Big-Low	0.0000	-6.517	-3.750	-3.000	-2.630
EU	Big-Medium	0.0000	-5.279	-3.750	-3.000	-2.630
EU	Big-High	0.0000	-5.484	-3.750	-3.000	-2.630
EU	Market Risk Factor	0.0000	-5.276	-3.750	-3.000	-2.630
EU	SMB	0.1928	-2.238	-3.750	-3.000	-2.630
EU	HML	0.0044	-3.681	-3.750	-3.000	-2.630

Source: Performed by author in STATA

In Table 5.5 we can observe in the Table that for all variables, except the SMB factor, the corresponding p-value is below 0.05. This means that we can safely reject the null hypothesis in these and conclude that these variables are stationary. On the contrary, this also means that we cannot reject the null hypothesis in the case of SMB. Hence, we conclude that the variable SMB shows non-stationarity. This means we will have to follow the steps to transform SMB into a stationary variable.

Table 5.6

KPSS Test Result SMB EU

Lag Order – Test Statistic	Critical value 10%	Critical value 5%	Critical value 2,5%	Critical value 1%
0 – 0.159 1 – 0.152 2 – 0.166	0.119	0.146	0.176	0.216

Source: Performed by author in STATA

In Table 5.6, it is possible to observe the results of the KPSS test that we used to determine whether we are dealing with a deterministic trend or difference non-stationarity. Here we can see that t-statistic values fall between 0.146 and 0.176. In other words, the test statistic value falls between 5 per cent and 2.5 per cent. This means we can reject the null hypothesis as the value is below 0.05. Therefore, the series exhibits difference non-stationarity, and the differencing method is then applied in order to transform the data.

Table 5.7

ADF Test Results SMB EU After Differencing

Variables	p-value	T-statistic	Critical value 1%	Critical value 5%	Critical value 10%
SMB	0.0011	-4.065	-3.750	-3.000	-2.630

Source: Performed by author in STATA

Table 5.7 shows the results of the ADF test for SMB after we applied the differencing method. As p-value<0.05 we can conclude that the variable is now stationary. Therefore, we can conclude that we successfully transformed the data with the differencing method.

5.2.3. Stationarity Tests Japan

Table 5.8

ADF Test Results Japan

Country	Variables	p-value	T-statistic	Critical value 1%	Critical value 5%	Critical value 10%
Japan	Small-Low	0.0392	-2.956	-3.750	-3.000	-2.630
Japan	Small-Medium	0.0038	-2.238	-3.750	-3.000	-2.630
Japan	Small-High	0.0000	-3.681	-3.750	-3.000	-2.630
Japan	Big-Low	0.1356	-2.422	-3.750	-3.000	-2.630
Japan	Big-Medium	0.0246	-3.127	-3.750	-3.000	-2.630
Japan	Big-High	0.0391	-3.257	-3.750	-3.000	-2.630
Japan	Market Risk Factor	0.0158	-3.280	-3.750	-3.000	-2.630
Japan	SMB	0.0067	-3.566	-3.750	-3.000	-2.630
Japan	HML	0.0490	-2.890	-3.750	-3.000	-2.630

Source: Performed by author in STATA

Table 5.8 shows us the ADF results for our Japan data sample. Here we can see that almost all variables in the Japan sample pass the ADF test for stationarity by having a p-value under 0.05 and, therefore, rejecting the null hypothesis. Meaning that all these variables have stationary data. However, the variable “Big-Low” has a p-value of over 0.05. In this case we cannot reject the null hypothesis, which means that “Big-Low” shows non-stationarity. As a result, we will apply the KPSS test to this variable to see what type of stationarity we are dealing with.

Table 5.9

KPSS Test Result Big-Low Japan

Lag Order – Test Statistic	Critical value 10%	Critical value 5%	Critical value 2,5%	Critical value 1%
0 – 0.183 1 – 0.146	0.119	0.146	0.176	0.216

2 – 0.127	

Source: Performed by author in STATA

Looking at the test results, we see that we obtain a T-statistic value of 0.183 from the KPSS test. This means that we have a p-value below 0.025. As a result, we can reject the null hypothesis and conclude that we experience difference non-stationarity. Therefore, we will need to use the differencing method to transform the data.

Table 5.10

ADF Test Results Big-Low Japan After Differencing

Variables	p-value	T-statistic	Critical value 1%	Critical value 5%	Critical value 10%
Big-Low	0.0000	-6.233	-3.750	-3.000	-2.630

Source: Performed by author in STATA

In Table 5.11 we can see the ADF test results after we applied the differencing method to our variable. The ADF test now shows a p-value of 0.000, meaning we reject the null hypothesis of non-stationarity. As a result, we can conclude that we successfully transformed our non-stationary variable into stationarity using the differencing method.

5.3 Autocorrelation

In this section, we discuss the Breusch-Godfrey test results. This test is used for each region separately in order to determine whether autocorrelation exists in our data sample. With this test we have the following hypothesis:

Null hypothesis: there is no autocorrelation in the residual
Alternative hypothesis: there is autocorrelation in the residual

(Gujarati, 2004)

Table 5.11

Breusch-Godfrey Test Results

Country	p-value
USA	0.4462
EU	0.0595
Japan	0.1440

Source: Performed by author in STATA

In Table 5.11 above we see that the p-value of the Breusch-Godfrey test for the USA is 0.4462. As the p-value>0.05, we do not reject the null hypothesis. Hence, we can conclude that there is no autocorrelation in this case.

The results also show us that the p-value of the Breusch-Godfrey for the EU data is 0.0595. This value is slightly higher than 0.05 and, therefore, we cannot reject the null hypothesis. Meaning that there is no autocorrelation the EU data.

For Japan, the Breusch-Godfrey test shows a p-value of 0.1440. As p-value>0.05, we once again reject the null hypothesis. Consequently, we conclude that there is no autocorrelation.

5.4 Heteroscedasticity

When testing for heteroscedasticity we apply the following hypothesis:

Null hypothesis: Time series data exhibits Homoscedasticity

Alternative hypothesis: Time series data exhibits Heteroscedasticity

(Breusch-Pagan, 1979) (White,1980)

Table 5.12

Breusch-Pagan and White Test Result

Country	BP Test p value	White test p value
USA	0.8059	0.0534
EU	0.7853	0.3550
Japan	0.0728	0.0921

Source: Performed by author in STATA

Table 5.12 shows us the results for both the Breusch-Pagan test and the White test. As can be seen in the table both tests show p-values above 0.05 for all countries. Being that p-value>0.05, we can safely reject the null hypothesis in all cases. Therefore, we conclude that there is no existence of heteroscedasticity in any of the region's time series data.

5.5 Multicollinearity

The data is tested for multicollinearity, as per the following rule-of-thumb:

VIF equal to 1 = variables are not correlated

VIF between 1 and 5 = variables are moderately correlated

VIF greater than 5 = variables are highly correlated

(Glen, 2020)

In addition, in the case of a VIF above 4 or tolerance below 0.25, further research into the data should be considered (CFI, 2022).

Table 5.13

Variance Inflation Factor Test Results

Country	Variable	VIF
USA	SMB	1.09
USA	HML	1.08
USA	Market Risk Factor	1.03
USA	Mean VIF	1.07
EU	SMB	1.38
EU	HML	1.35

EU	Market Risk Factor	1.08
EU	Mean VIF	1.27
JAPAN	SMB	2.10
Japan	HML	1.73
Japan	Market Risk Factor	1.38
Japan	Mean VIF	1.74

Source: Performed by author in STATA

As can be seen in Table 5.13, the VIF results for the USA were all positive. The VIF test for all variables shows a value of almost 1. This means that the variables are very little correlated. Therefore, we can consider that no multicollinearity exists in the sample for the USA. This means that prediction results will not be affected, and that further investigation is not necessary.

The VIF scores for the EU data are generally slightly higher than the USA. However, the scores are still fairly close to 1 and significantly below 5. Therefore, it can be said that the predictions do not suffer from multicollinearity and that further research is also not necessary for the EU sample.

The VIF scores for Japan are again slightly higher when compared to the USA's and EU's scores. The SMB factor is still very near the 1. The other two factors, HML and the Market Risk Premium, reach more near a VIF score of 2. Although these factors might show a slightly higher level of correlation, a VIF score around 2 is not something to worry about as it is still very far of a VIF of 4. Hence, we can safely assume that the sample does not suffer from multicollinearity and that, once again, further investigation will not be needed.

Chapter 6

Estimation Results

Table 6.1

Regression Results

F-statistic	8.92	
P-value	0.0001	
Adjusted R-square	0.3507	
Variable	Coefficient	P-value
Market Risk Factor	0.0984	0.000
SMB	-0.5248	0.028
HML	-0.1601	0.023
Consonant	5.5743	0.000

Source: Performed by author in STATA

Table 6.1 shows the general outcomes of the regression of the Fama and French model. The results show that the p-value<0.05, which means that the corresponding variables of the model are significant. This assumption can also be made individually for the data of all the 3 factors of the model and the intercept as well, as all the variables show a p-value<0.05. As a result, it is possible to conclude that there is a correlation between the expected returns and the 3 factors of the Fama and French model.

With a value of 0.3507, the results of the regression also show a rather low adjusted R-square. Baek and Bilsen (2014) found similar results for financial firms. Baek and Bilsen (2014) believe that this is caused as financial institutions generally have a higher debt to equity ratio, which leads to higher volatility regarding variation of interest rates. However, in this case the adjusted R-square value can also be explained by the limited time period used in the paper, during which also a financial crisis occurred. This likely caused relatively high variance in the data.

A key observation that can be made from the results is that the value factor shows a negative coefficient. This means that there is a negative correlation with portfolios with a high book-to-market ratio expected returns. This is an innovation in relation to the classical outcomes of Fama and French (1993), where the size factor has a positive correlation with the expected returns. Fama and French (1993) argue that companies with a high book-to-market value show higher expected returns, as they state that these firms are riskier. However, as also can be seen at the descriptive statistics section, our research shows that the portfolios with a low book-to-market value show the highest return. As a result, the negative coefficient of the value factor could be explained by this difference in outcomes.

In addition to the negative coefficient for the value factor, the size factor also shows a negative coefficient in our regression results. This is once again contrary to Fama and French (1993), who state that there is a positive relation between small size firms and higher expected returns. Although our descriptive statistics do not show a clear presence of a size effect, the regression results show that there is a correlation between big financial institutions and higher expected returns. According to these results big financial institutions are riskier and require a higher return rate to compensate. This can be explained by some of the results that were obtained during the literature review. Fama and French (1993) that smaller firms are riskier as they have less reserves to survive bad times. However, some specific characteristics of financial institutions cause a contrary effect. For example, it is said that these institutions operate with lower levels of capital and, as a result, take on more risks (Demsetz & Strahan, 1997). Another important factor is the too big to fail policy, which still exists in some cases, that also leads to riskier management behaviour as these financial institutions become less afraid of possible repercussions (Kelleher, 2022). For instance, this risky behaviour of some of these too big to fail institutions was a major reason behind the financial crisis (Young, 2022). During this crisis a number of banks, such as the Lehmann Brothers, had to file bankruptcy after their high-risk business models failed (Wiggins et al., 2019). As a result, investors might see these large institutions as more risky.

Table 6.2

Regression Results of the Coefficients for the 6 Portfolios

	α_{it}	β_{im}	β_{is}	β_{ih}
Small-Low	7.572	0.158*	-0.049	-0.312*
Small-Medium	5.203	0.074	-0.429	-0.203**
Small-High	2.212	0.0222	0.615*	-0.103
Big-Low	8.545	0.079*	-0.257	-0.458*
Big-Medium	5.018	0.102*	-1.011*	-0.094
Big-High	4.115	0.069***	0.316	-0.756*

Source: Performed by author in STATA

**Significant at 1 per cent*

***Significant at 5 per cent*

**** Significant at 10 per cent*

In Table 6.2 we can see the regression results for the significance of the factor coefficients when the 6 portfolios are regressed against the 3 factors of the Fama and French model. The outcomes of this test show somewhat mixed results. None of the 3 factors show statistical significance for all the 6 portfolios. The market risk factor shows it has an effect only on the “Small-Low”, “Big-Low” and “Big-Medium” portfolios, besides a less significant effect on the “Big-High” portfolio. Therefore, it seems that the market risk factor has slightly more effect on portfolios with larger market capitalizations. The size factor seems to have lesser effect on the portfolios. The size factor only shows significance for the “Small-High” and “Big-Medium” factors, which coincidentally also do not have much in common. Lastly, the value factor is the factor that shows the most significance towards the portfolios.

Table 6.3

Comparison Regression Results Fama and French Model and CAPM

	Adjusted R-square		F-statistic		P-value		Intercept	
	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM
Small-Low	0.3513	0.2508	8.94	15.73	0.0001	0.0003	7.572	8.555
Small-Medium	0.2225	0.0807	5.20	4.86	0.0039	0.0328	5.203	5.989
Small-High	0.0858	-0.0049	2.38	0.78	0.0838	0.3810	2.212	2.345
Big-Low	0.4677	0.0376	13.89	2.72	0.0000	0.1066	8.546	10.097
Big-Medium	0.3778	0.1600	9.91	9.38	0.0000	0.0038	5.018	5.639
Big-High	0.4345	-0.0118	12.27	0.48	0.0000	0.4900	4.115	6.437

Source: Performed by author in STATA

Table 6.3 shows a comparison between the regression results for both the Fama and French 3 factor model and the CAPM against all 6 portfolios. Besides that, these regressions can also be considered as a robustness check on the baseline results by looking at the results for each portfolio specifically. Firstly, it can be observed that the Fama and French model shows much better results regarding the significance of the variables under consideration. All portfolios, except “Small-High”, show a p-value below 0.05. Even the portfolio “Small-High” portfolio still shows it is significant at 10 per cent. This actually reflects the fact that the adopted Fama and French model overall shows a fairly significant correlation with the expected returns of the portfolio. Secondly, even though the adjusted R-square shows less efficient for both models, it can be observed that the Fama and French model still has superior values to the CAPM. This means that according to the present Dissertation’s findings, the Fama and French model is better at explaining the variation observed in the dataset. Combining these observations, it can be concluded that the Fama and French model is more efficient in predicting expected return for the portfolio than the CAPM.

Chapter 7

Conclusions

The goal of this paper is to measure whether the Fama and French model is a valid predictor of expected returns of firms in the financial industry. Fama and French (1993) created this model by adding a size premium and value premium to the market risk factor of the Capital Asset Pricing Model (CAPM). Fama and French (1993) argue that the market risk factor does not fully explain expected returns, and that the size and value of a firm also have a significant influence. Their research shows that companies with a smaller size and high book-to-market ratio generally have higher expected returns. This coincides with the findings of the literature review herein described. However, financial institutions are often excluded from this testing, even though the financial industry is a vital part of the economy. Therefore, this paper tries to overcome the gap in existing literature by applying the Fama and French to financial institutions.

The paper uses yearly information of financial institutions between 2007 and 2021, using data extracted from the database Bank Focus. In order to have suffice observations for proper analysis this research uses data from financial institutions in Japan, the United States, and the European Union. The Fama and French three-factor model predicts expected returns by dividing companies into 6 portfolios based on market capitalization (size) and book-to-market-value (value). Besides performing a regression on the overall Fama and French model, the paper also performs regressions on the average returns of portfolios individually to measure the effect of the model on each portfolio.

The empirical results of this paper show some very interesting, although somewhat slightly mixed findings. When doing the regression of the Fama and French model we find that there is a significant correlation for all three factors. However, a key finding that was shown by the results is that the coefficient for both the size and the value factor were negative, contrary to what was predicted in the Fama and French (1993) paper. This effect can be explained by the riskier management approach that often exists in larger financial institutions. Hence, we conclude that financial institutions with a small market capitalization and a low book-to-market ratio have higher expected results. This conclusion coincides with the observed findings for the value factor when looking at the average expected results for each portfolio in the descriptive statistics section. Here a size effect was less present. We also observe that results for the adjusted R-square, for both the model regression and the 6 separate portfolio regressions were lower compared to the literature using non-financial firms. Meaning that the model has some difficulty in measuring the variances in the sample, which is likely caused due to the high debt to ratio of financial firms and the time period used in this research. Lastly, when comparing the results for the Frama and French model to the CAPM, we saw that the Fama and French showed more effective and better results in all the measures. Hence, we can conclude that adding the Fama and French size and value factors, improves the functionality of the CAPM.

Based on the outcomes of the paper we can make a number of recommendations. Firstly, for future research, it would be interesting to see how the outcomes would differ in case a larger time interval would be selected. The research was limited to yearly data from 2007 to 2021. This has very possibly caused somewhat low adjusted R-square values that were observed in the test results. It is very probable that the model was less proficient in efficiently measuring the variances over this small time period. Therefore, when selecting a longer time period, the model might very well be more efficient in predicting these variances over time. Researching a larger time period would also allow for the incorporation of more observations. This could give us the opportunity to also measure the effects of the Fama and French model on each of our selected geographical areas separately.

Secondly, the findings show that the Fama and French 3-factor model presents superior results compared than the CAPM, therefore a major recommendation involves using the Fama and French model when predicting expected returns in the financial industry. Even though the results of the Fama and French model show some imperfections, it shows sufficient proof to be considered a better measuring tool for financial institutions than the CAPM for the adopted time interval.

Third, although the overall regressions showed there is a correlation between size and expected returns, The outcomes show that it is recommended for investors to focus on financial institutions with a big market capitalization and a low book-to-market ratio, as both are correlated to obtain higher expected results. This might be seen as an innovation/extension in relation to the Fama and French (1993) recommendations for non-financial institutions, where smaller firms with a high book-to-market ratio are seen as more favourable. Some further investigation regarding the size factor may be advised, as the descriptive statistics and individual portfolio regressions show a slight significant relevance of the size factor. Regarding the value factor, results in the regressions and descriptive analysis show a stronger significance.

Lastly, another way to improve the results of the model would be to include an extra risk factor that would be more specific to the financial industry. For example, one of the major risks that financial institutions face is credit risk (CFI, 2022). Hence, adding an extra risk factor based on the expected default frequency from the KMV model could improve the explanatory model for banks (Kaelhofer, 2019). Li & Lin (2021) added this credit risk factor to the Fama and French three-factor model when researching non-financial institutions in China, where companies are on average heavily debt-financed, a characteristic that is also known for the financial industry. Their paper shows a correlation between firms with a high level of credit risk and higher expected returns. A similar correlation would be very possible when applied to the global banking/financial industry. The addition of this factor would increase the ability of the model to measure variance in the sample.

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