UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS

MASTER'S THESIS

THE COST OF CAPITAL FOR HIGH-CAP EUROPEAN BANKS

Ljubljana, June 2018 FRANCESCO CIGUI

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INTRODUCTION

This Master’s thesis is a consequence of my strong interest for the 2016 European Union (hereinafter: EU) wide stress test carried out by the European Banking Authority (hereinafter: EBA). The objective of the 2016 wide stress test is to provide a shared analytical framework for the comparison of the resilience of European banks to adverse macroeconomic scenarios over the period that goes from 31 December 2015 to 31 December 2018. Whereas the objective of my Master’s thesis is to estimate the cost of capital analyzing the same sample of banks used by EBA in its 2016 EU-wide stress test.

The sample of banks is constructed to capture the largest banks in Europe in terms of total consolidated assets as of 31 December 2014. Therefore, only banks with assets greater than 30 billions of Euro (hereinafter: EUR) are included in the sample. The important feature is that each of the examined banks are directly supervised by EBA, and defined as a significant institution by the Single Supervisory Mechanism. My decision, to focus on significant institutions only, was guided by the strong impact those banks have on the society. The financial result of each high-cap European bank has an important role on the overall European financial stability, and so on the economic growth of Europe. The aim of this Master's thesis is to estimate the cost of capital for high-cap European banks applying the Fama-French three factor model (hereinafter: FF3). The FF3 is proved to have more explanatory power on stock returns than the capital asset pricing model (hereinafter: CAPM). Indeed, FF3 adds two sources of systematic risk to the one of CAPM. A much more precise estimate of the cost of capital is estimated once the size factor and the value factor are added to CAPM’s market factor.

The cost of capital in the high-cap European banking industry is a fundamental figure for many different reasons. The cost of capital is a useful benchmark for regulatory authorities in developing new policies aiming economic stability through the enhance of risk management. Moreover, managers use it as a measure of performance and investors need it as discount rate in valuing stocks. Given that the cost of capital is an estimation of the required rate of return, it is not directly observable from the market. The cost of capital is the amount asked by investors as compensation for the risk undertaken for allocating their funds within the bank. Equity capital is the first type of capital used to absorb losses, hence more expensive than other categories of bank's capital such as deposits, repurchase agreements, certificate of deposits, capital notes, and funding from the central bank.

The first part focuses on the theoretical framework of asset pricing models. Starting from Markowitz's intuition about the relationship between risk and return (Markowitz, 1952), which is known as modern portfolio theory, and proceeding with the theoretical development in the field by Tobin (1958) who is the first to expand the study of Markowitz (1952). Tobin introduces the risk-free rate concept, arguing that the first step of the portfolio selection process consists in choosing the optimal risky portfolio, and the second step consists in allocating the capital invested between the risk-free asset and the optimal risky portfolio. Treynor (1962), Sharpe (1964), Lintner (1965a, 1965b), and Mossin (1966) all independently extend the normative model of portfolio selection by developing a positive market equilibrium theory of asset prices under conditions of risk, known as the CAPM. According to CAPM the return on an asset is a linear function of the excess return of the market over the risk-free rate, namely the market risk premium (hereinafter: MRP). Ross (1976a, 1976b) improves the CAPM by assuming a factor structure which explains the return on stocks, the theory is known as arbitrage pricing theory. All the patterns of an asset return which are not predicted by the CAPM are called anomalies and are fundamental for the developing of multifactor models. Fama and French (1993) prove that the size anomaly and the value anomaly are risk factors which are not captured by the CAPM. The factors describing stock returns in the FF3 (1993) are the market factor, the small-minus-big (hereinafter: SMB) factor, and the high-minus-low (hereinafter: HML) factor.

In the second part FF3 is applied to the high-cap European banks. The sample of high-cap European banks includes all the publicly listed banks from the sample of banks already analyzed by EBA for its 2016 EU-Wide Stress Test. Hence consisting of 29 banks from 14 countries. Stock returns are calculated from stocks last prices. Dividends are not included to better reflect the extreme low profitability affecting the banking industry in the last decade. The 12 months Euro Interbank Offered Rate (hereinafter: Euribor) is used as the risk-free rate. Where 12 months it is the shortest maturity showing positive values throughout the entire period of the analysis. The value of the dependent variable is the excess stock returns obtained by the difference between each stock return and the rate of Euribor 12 months. The three explanatory variables used for the regressions are MRP, SMB, and HML. MRP is calculated as the difference between the value of the index used, which is Stoxx Europe 600, and the rate of Euribor 12 months. The dataset consists of monthly values for the period that goes from 31 January 2011 to 31 December 2015. The coefficients of each explanatory variable are estimated through the ordinary least squares (hereinafter: OLS) method. The cost of capital for high-cap European banks is estimated by multiplying the mean values of the three explanatory variables by the estimate of their respective coefficients.

The overall outcome of the regression analysis suggests that FF3 can be used to describe the excess stock returns of the high-cap European banking industry. All the banks which are included in the sample but two show a fair estimate of their cost of capital. In order for the cost of capital to be considered fair it has to be greater than 4.50%. Once setting the bottom limit at 4.50%, the sample's average cost of capital estimated through FF3 results to be 11.50%. The high-cap European bank showing the lowest cost of capital estimate is Banco de Sabadell from Spain (hereinafter: SAB SM), its cost of capital estimate is 4.90%. Whereas the high-cap European bank with the highest cost of capital estimate is Banca Monte dei Paschi di Siena (hereinafter: BMPS IM) from Italy, its cost of capital estimate is 24.13%. Hence, based on this Master's thesis results, the required rate of return's estimate for the high-cap European banks' sample can be properly estimated through FF3.

In the conclusion of this Master's thesis the estimated cost of capital and the return on equity are compared. Such comparison can be used as a measure of the yearly overall performance of each high-cap European bank. The bank shows an increase in its value if the spread between return on equity and cost of capital is positive, instead if the spread is negative the value of the bank has been destroyed. Therefore, the average spread between the estimated cost of capital and the return on equity of the high-cap European banks' sample reflects the overall performance of the European high-cap banking industry in year 2015, this value is -5.48%. Hence, the overall value of the European high-cap banking industry in 2015 is destroyed.

1 ASSET PRICING MODELS

1.1 Modern portfolio theory

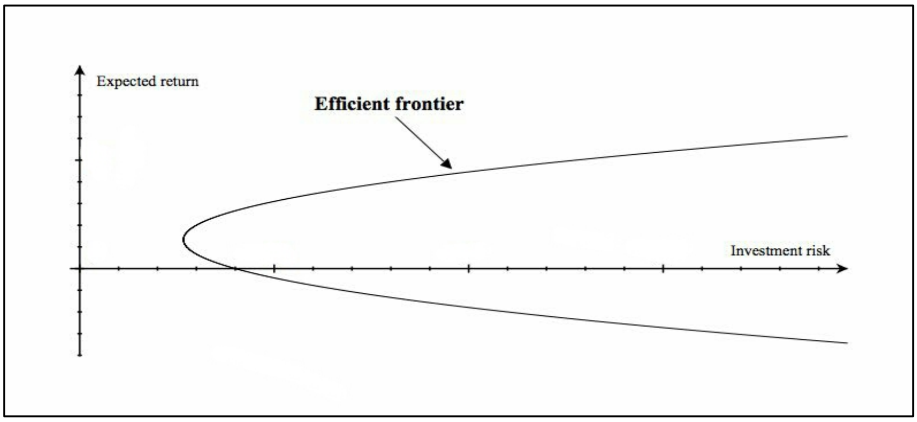
Modern portfolio theory is developed by Markowitz (1952). The concept is included in Markowitz's doctoral dissertation in statistics entitled ″Portfolio selection″ (Markowitz, 1952). The core idea of modern portfolio theory is to construct a portfolio which simultaneously maximizes the expected return and minimizes the investment risk. Tobin (1958) introduces the risk-free rate concept in Markowitz's framework improving the concept of portfolio selection. Tobin, implying all investors holding the same portfolio whichever their propensity toward risk, argues that adjustments toward risk are done by allowing each investor to choose what he thinks to be the best allocation among the risky asset and the risk-free asset. The resulting portfolio available to investors, namely the market portfolio, is formed by the risky asset and the risk-free asset.

1.1.1 Mean-variance criterion and the efficient frontier

The mean-variance criterion is an essential concept for the right interpretation of the efficient frontier of Markowitz. The efficient frontier is made by the set of efficient portfolios. An efficient portfolio maximizes the expected return given a specific level of risk by its definition, and represents the best combination of expected return and investment risk (Markowitz, 1952). The set of efficient portfolios which form the efficient frontier by combining the expected return of an investment to the investment risk is shown in Figure 1.

Usually the risk is measured as the variance of the financial assets return. The variance is the expected square deviation of a financial asset return from its expected value. Markowitz (1952) uses variance and volatility as interchangeably concepts, so high variance coincides with high volatility and low variance coincides with low volatility. The implication of a diversified portfolio of financial assets is that its variance is always smaller than the weighted average of individual financial asset variances (Frantz & Payne, 2009). Each portfolio is made by many financial assets which are all subject to a double source of risk (Markowitz, 1952). On one hand the unsystematic risk and on the other hand the systematic risk.

Figure 1. The efficient frontier



Own work.

The unsystematic risk does affect a single or a group of financial assets and it never affects the overall market performance (Ross, Westerfield, & Jaffe, 2002), therefore it is perceived as a micro-level form of risk. Theoretically the unsystematic risk can be reduced almost to zero by diversification across different industries and different asset classes. Nevertheless, in a more realistic environment, given the correlation between financial assets, the unsystematic risk will never disappear completely (Mangram, 2013). However, some practitioners, such as Frantz and Payne (2009) still argue that unsystematic risk can be completely removed from well diversified portfolio. In any case the saying "don't put all your eggs in one basket" perfectly describes the concept of diversification, the risk of breaking the eggs is reduced by increasing the number of baskets used.

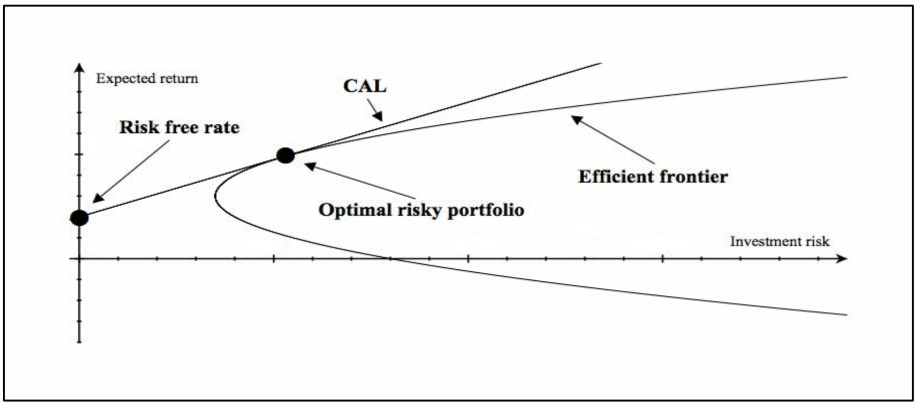
The systematic risk instead is a macro-level form of risk and it is a consequence of those macroeconomic conditions which hit the financial market as a whole. The systematic risk can't be reduced by means of diversification. Hence given the double nature of risk, the volatility of a portfolio's return can't be eliminated completely. Although diversification does not eliminate the risk completely, it may increase expected portfolio return without increasing the risk. According to Fabozzi, Gupta, and Markowitz (2002) the mean-variance criterion is a normative theory, hence a methodology which investors should follow once creating a portfolio.

1.1.2 Separation theorem

Tobin (1958) improves the asset pricing theory by introducing a risk-free asset into an investor's portfolio. A government bond is generally used as the risk-free asset, and the return on the same government bond is used as the risk-free rate. A risk-free asset and a risky portfolio are then required for the construction of a complete portfolio. From a graphical perspective the linear relationship between the rate of return of the risk-free asset and the optimal risky portfolio, both plotted against the risk, forms the capital allocation line (hereinafter: CAL). CAL is a crucial point in Tobin's research. An investor creates a complete portfolio by choosing the allocation of his investment between the risk-free asset and the optimal risky portfolio. The reason why the risky portfolio is optimal is that it consists in the tangent point between the efficient frontier and CAL. The slope of CAL is the reward to variability ratio. The reward to variability ratio is also called Sharpe-ratio (hereinafter: SR) and measures how much the expected return increases from a unit increase of the risk (Sharpe, 1994).

The separation theorem implies that the investor, in presence of a risk-free asset, always choose the efficient risky portfolio which is tangent to CAL, namely the optimal risky portfolio. The investor then is allowed to allocate the wealth invested according to his preferences. A risk averse investor lends at the risk-free rate and invests in the optimal risky portfolio. Instead a risk seeking investor borrows at the risk-free rate and invests in the risky portfolio. Tobin's separation theorem can be summarized in two steps. At first the identification of the optimal risky portfolio and secondly the allocation of the invested wealth between the risk-free asset and the optimal risky portfolio. The separation theorem is illustrated in Figure 2.

Figure 2. The separation theorem



Own work.

1.2 Classification of asset pricing models

Asset pricing theory is based on the concept that the price of an asset is equal to its expected discounted return (Markowitz, 1952). Asset pricing models are then classified depending on what the researcher is focusing on once trying to understand the nature of the asset's price. The distinction is made between absolute models and relative models. Absolute models explain the origin of an asset price by focusing on those factors which are considered sources of macroeconomic risk. Instead relative models predict the value of an asset by observing the price of other assets (Celik, 2012). An example of an absolute asset pricing model is given by the CAPM (Sharpe, 1964), whereas the Black-Scholes option model (Black &

Scholes, 1973) is a typical example of a relative asset pricing model. Moreover, there is a further distinction about asset pricing models. Each absolute asset pricing model is classified as being static or dynamic. The assumption made on the efficient frontier is the explanation of a model being classified as static or dynamic. If the efficient frontier is assumed to stay fixed throughout the investment period then the asset pricing model is static. Instead, if a shift of the efficient frontier is assumed during the period of the investment the asset pricing model is classified as dynamic (Mazzola & Gerace, 2015). The CAPM (Sharpe, 1964) is an example of static asset pricing model whereas the intertemporal asset pricing model (Merton, 1973) is an example of dynamic asset pricing model.

The objective of this Master's thesis is achieved by employing a model which is both absolute and static, therefore relative asset pricing models and dynamic asset pricing models are not further discussed. The cost of capital of the sample of high-cap European banks is here estimated by employing a static asset pricing model which is an empirical development of the CAPM (Sharpe, 1964), which is known as the FF3 (Fama & French, 1993).

1.3 Capital asset pricing model

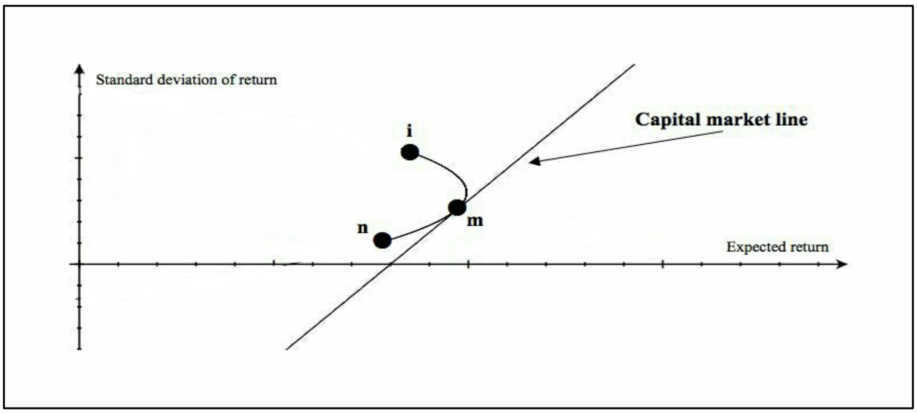
Treynor (1962) is the first author extending the normative model of investor behavior initially developed by Markowitz (1952). Beside Treynor a number of other researchers focus their studies on Markowitz's framework attempting to develop it. The name of the researchers, named according to the temporal framework of their researches, are Sharpe (1964), Lintner (1965a, 1965b) and Mossin (1966). Each one of the mentioned researchers published an article about a positive market equilibrium theory of asset prices which is influenced by risk, known as CAPM.

According to the framework of market equilibrium, the efficient portfolio of risky assets can be identified only once some essential assumptions are made. A straightforward consequence of CAPM's assumptions are their implications. One implication is that investors use Markowitz (1952) mean-variance algorithm to select the set of efficient portfolios. Moreover, investors can allocate their wealth in the risk-free assets depending on their attitude towards risk, hence a riskier investor will invest less in the risk-free asset than a risk averse investor does. Furthermore, the market portfolio is mean-variance efficient, thus the one with the highest Sharpe ratio (Sharpe, 1994). Another implication is that the return of an asset is completely determined by the market risk premium, beta coefficient, and the risk-free rate.

The CAPM, contrary to Tobin's separation theorem (1958), recognizes that an investor has many efficient risky portfolios in which invest. Such conclusion implies perfect positive correlation between the efficient risky portfolios. The positive perfect correlation results from the investors' attempt to purchase the portfolio of risky asset tangent to the investment opportunity curve, this process leads to the adjustment of capital asset prices. The investment opportunity curve represents the set of risky assets with the highest expected return given a specific level of standard deviation. Prices stop changing only once every kind of capital asset enters at least one of the portfolios which are laying on the capital market line. The capital market line, by maximizing investors utility, is tangent to the investment opportunity curve, and relates the risk-free rate to the efficient portfolio of risky assets. At the end of the process the investment opportunity curve becomes much more linear, and the efficient risky assets portfolios are assumed to have a linear relationship between expected return and the standard deviation of return. Hence the capital market line is made by efficient risky assets portfolios only.

As a consequence of being not diversified all the individual stocks are inefficient, laying above the capital market line, and set inside the investment opportunity curve. Figure 3 illustrates the relation between an individual stock called *i* and an efficient portfolio of risky assets which is called *m*. Where stock *i* is part of m. The curve *imn* is obtained by adding all the possible combination in terms of proportion of *i* and *m.* Denote *Y* as the proportion of asset *i* and denoting *(1-Y)* as the proportion of the portfolio of risky assets. Then a value of *Y=1* means total investment in *i* and a value of *Y=0* means a total investment in *m*. At point *n,* a negative value of *Y* is observed, suggesting that asset *i* is not included (Sharpe, 1964).

Figure 3. Relation between individual stock and efficient portfolio of risky assets



Own work.

Equilibrium requires all the curves that are constructed by all the possible combinations between an individual stock and an efficient portfolio of risky assets to be tangent to the capital market line. Regression analysis clarifies the economic implication of the tangency requirement. The total risk of an individual asset is described graphically by plotting the return of an individual stock against the return of an efficient portfolio of risky assets. The systematic risk is identified as being the slope of the regression line. The slope represents the response of the individual asset return to changes of the efficient portfolio of risky assets. Whereas the unsystematic risk is given by the standard error of the regression and it is uncorrelated with the return of the efficient portfolio of risky assets (Sharpe, 1964). The

CAPM is used by practitioners as a predictive model. To employ CAPM as a predictive model a number of data are required. These data are the historical data about market returns, stock returns, and risk-free rate. The difference between the market return and the risk-free rate is the MRP. According to CAPM the excess return on an asset is related to the MRP. The MRP is given by the expected return on the market minus the risk-free rate. The relationship is then described by a linear equation. Equation (1) shows the linear equation of CAPM, where $E(R_i)$ is the expected return on the stock, r_f is the risk-free rate, β_i is the coefficient estimate, and $E(R_m)$ is the expected return on the market. In (1) the expected return on stock is given by the risk-free rate plus the coefficient estimate multiplied by the MRP:

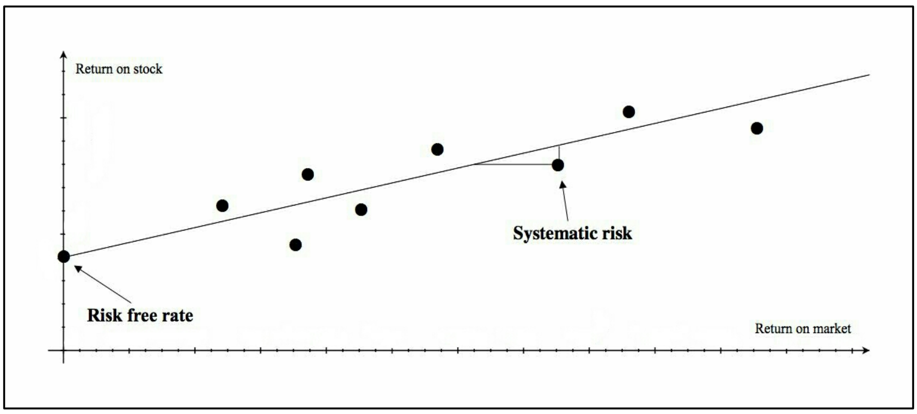
$$E(R_i) = r_f + \beta_i \left(E(R_m) - r_f\right) \quad (1)$$

The strength of the MRP affecting the expected return on stock is measured by the coefficient estimate. The coefficient estimate is obtained by dividing the covariance between the return on the stock and the return on the market by the variance of the return on the market. Equation (2) shows how to calculate the coefficient estimate, where the coefficient estimate is β_i, the covariance between the return on the stock and the return on the market is $Cov(R_i, R_m)$, and the variance of the return on the market is $Var(R_m)$:

$$\beta_i = \frac{Cov(R_i,R_m)}{Var(R_m)} \quad (2)$$

The OLS method is used to find the coefficient estimate. The OLS method consists in minimizing the squares of the differences between the historical returns on the stock and the linear function predicted by the OLS model. The OLS method is illustrated in Figure 4.

Figure 4. Ordinary least square method



Own work.

As a consequence of the linear relationship between the expected return of a stock and the market factor CAPM can be considered as an intuitive and logical asset pricing model. The restrictiveness of CAPM's assumptions makes the model simple to understand. The implications of equation (1) are tested empirically by many authors. An example is given by the early tests performed on two implications of the CAPM. The first implication tested concerns the positive risk premium. Whereas the second implication consists in using as proxy for the risk-free rate the expected return on a stock not correlated with the market. Friend and Bloom (1970), Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), Stambaught (1982) have poor empirical results once testing those implications. Hence, they invalidate the application of CAPM. Moreover Roll (1977) affirms that implications of (1) are not even suitable for testing. The Roll’s critique argues that a perfectly diversified market portfolio does not exist (Roll, 1977), which makes the CAPM unusable in practice. However beside being highly criticized CAPM still highly used in practice. Additionally, CAPM is both tested and extended in many different ways by a number of researchers.

The extensions of CAPM make use of different assumptions. Black (1972) in his zero-beta CAPM imposes no free lending and borrowing. Mayers (1973) with his non-marketable human capital CAPM introduces no traded assets. The intertemporal CAPM of Merton (1973) adds dynamic opportunities in investment. Solnik (1974), Stulz (1981), Adler and Dumas (1983) extended the framework to international investing (Perold, 2004). CAPM describes the market as the only variable with explanatory power over stock returns. Ross (1976a, 1976b) extended CAPM by assuming that each investor holds a unique portfolio with its own explanatory variables. The arbitrage pricing theory of Ross (1976a, 1976b) is fundamental for the development of those asset pricing models assuming more variables explaining stock returns.

The strict assumptions of CAPM and their implications are very important for the overall understanding of the model. At first all investors are assumed to be price takers, hence CAPM works in a perfectly competitive market environment where investors have perfect information about the market. Secondly the investment’s time horizon is assumed to be the same for all investors, thus investors are assumed to be myopic. Since the time horizon of the investment depends on the investors’ aptitude towards risk this second assumption is not realistic. The third assumption requires an environment with neither taxes nor transaction costs, clearly this assumption is not realistic too. The fourth assumption concerns the risk-free rate. All investors are allowed to borrow and lend at the same risk-free rate. The fourth assumption is generally speaking not realistic but once considering the zero-beta version of the CAPM. Fifth, being consistent with portfolio theory, all investors are assumed to use mean-variance portfolio selection. The sixth assumption concerns the market’s information that are available to investors, investors are assumed to have perfect information and homogeneous expectations about the market. Investors, according to the assumption of homogeneous expectations, share the same beliefs about the distribution of stock returns. The seventh and last assumption is about the composition of the market portfolio which determines the beta coefficient. The market portfolio is assumed to be made of all the publicly traded assets available (Sharpe, 1964).

1.4 Arbitrage pricing theory

Arbitrage pricing theory (hereinafter: APT) is developed by Ross (1976a, 1976b) and makes investors believe in the existence of a factor structure governing asset returns. The limitation of APT is that it does not specify which and how many factors should be included in the model. Ross (1976a, 1976b) argues that the preclusion of arbitrage opportunities over the static portfolio of assets creates a factor structure of asset returns. The underlying assumption is equilibrium of the assets' price. Hence in a market characterized by investors maximizing their utility the necessary condition for market equilibrium is a linear pricing relationship. The heuristic argument of Ross (1976a) is formalized by Huberman (1982) and generalized by Ingersoll (1984) just after few years from its development.

An interesting point of APT is that it is a generalization of the CAPM. The relationship between the mean variance efficiency of CAPM and the APT is described by many authors, one of them is Jobson (1982). The CAPM might be viewed as a special case of the APT in which the securities market line corresponds to one factor model. Building on that, according to APT, a mean variance efficient portfolio can always be constructed. As a consequence, APT can't be tested by looking for mean-variance efficient portfolios. Once testing APT a joint test must be used. The joint test concerns the factors used by the researcher to mimic for the systematic risk. APT holds if the factors used as proxy of systemic risk are proved to be both correct and related with asset prices. Not all factors can be included in an APT equation, thus for the factors to be included two properties are required. At first factors must explain most of the movement of asset returns, and the unexplained part of the movement related to asset returns has to be approximately uncorrelated across stocks. The cross-sectional approach is a very common tool for the empirical analysis of the risk premium of factors. Among the authors using a cross-sectional approach in testing APT are Chen, Roll, and Ross (1986). Whereas Jagannathan, Skoulakis and Wang (2002) test the APT through the generalized method of moments.

On the other hand, once selecting the factors to include in the APT equation, three approaches are used for the identification of such factors. The first approach is an algorithmic analysis of the estimated covariance of asset returns, the analysis can be done according to two different methods. Roll and Ross (1980), Chen (1983) and Lehman and Modest (1988) use factor analysis. Instead Chambarlain and Rothschild (1983) and Connor and Korajczyk (1986) use principal component analysis. The first step of the second approach is to estimate the covariance of asset returns. Then the researcher, in the second step, choose the factors according to his personal judgment, and in the last step he estimates the coefficients of individual factors. Fama and French (1993) are an example of researchers using the second approach. Researchers using the third approach choose the factors according to their personal judgment, and then analyze the explanatory power of factors on asset returns. Researchers using the third approach are Chan, Chen, and Hsieh (1985) and Chen, Roll, and Ross (1986). Both studies use macroeconomics factors and financial variables factors.

The applications of APT are principally three: evaluation of the performance of funds, asset allocation, and estimation of the cost of capital. The overall results of the researches about APT obtain better results in describing data than CAPM. However, in some cases the outperformance of APM might be a consequence of the application of wrong tests about factors (Huberman & Wang, 2008). Even if it might be misused, APT still a very flexible and practical theory to rely on once describing asset returns. The linear equation of APT relates an asset return with the sources of systematic risk. Equation (3) describes APT, where $E(R_a)$ is the expected return on an asset, r_f is the risk-free rate, β_{ak} is the coefficient of the asset to the explanatory variable, f_k is the explanatory variable, and ε_a is the unsystematic risk:

$$E(R_a) = r_f + \sum_{k=1}^{k} \beta_{ak} f_k + \varepsilon_a \tag{3}$$

ATP improves CAPM by adding different sources of systematic risk beside the market. Hence researchers are free to add other proxies for systematic risk. Those risk factors which are proved to have explanatory power over the return of an asset can be included in equation (3). APT overcome CAPM's weakness of finding in the market factor the only source of systematic risk. However APT does not reveal which factors have to be included and how many factors there are, therefore the choice is up to the researcher.

1.5 Anomalies

Kuhn (1970) use the term anomaly for those patterns which are not described by a central paradigm theory. The efficient market hypothesis assumes that the expected return on an asset depends on its risk (Fama, 1970). According to efficient market hypothesis framework, every pattern of an asset returns lacking a risk based explanation is an anomaly. So CAPM anomalies are all those time-series and cross-sectional patterns of an asset average returns which are not predicted by the model (Fama & French, 2008). Researchers test return on stocks in many different ways and in a number of markets. The result is an increasing number of anomalies year after year.

There are two common methods used to find anomalies, both of them are widely used and accepted. The first approach is to sort stock returns according to the supposed anomaly variable, whereas the second approach consists in using the anomaly variable to explain the cross section of average stock returns by means of regression analysis (Fama & French, 2008). Sorting stock returns on the anomaly variable is used to check for differences in the pattern of stock returns across different stocks. On the other hand, the second approach which is regression analysis results helpful in making statistical inference about the relation between stock returns and the anomaly variable. The result of regression analysis gives an estimate of the marginal effect of an anomaly variable on the stock return. Fama and French (2008) find in a method used by researchers for the application of the sorting approach the shortcoming of the sorting approach. This method consists in sorting stocks according to the value of the anomaly variable in equal-weight decile portfolios. A problem emerges as a consequence that researchers usually focus on the hedge portfolio return which is constructed from long-short positions in the most extreme deciles. Once all the stocks of a market index are used, the equal weight hedge portfolios might be dominated by microcaps. Fama and French (2008) define microcaps all the stocks with market cap below the 20th percentile of the New York Stock Exchange (hereinafter: NYSE). Even if the sum of the market capitalization of microcap of the NYSE and the National Association of Securities Dealers Automated Quotation (hereinafter: NASDAQ) is approximately 3% of the total capitalization of the stock markets, microcaps represents almost 60% of the total number of stocks (Fama & French, 2008). Moreover, with respect to the more capitalized stocks, microcaps have a greater cross-section's dispersion of the anomaly variables (Fama & French, 2008). A greater dispersion means that for extreme portfolios the number of microcaps is even higher than 60% of total stocks.

Fama and French (2008) use a method which mitigates of microcaps. The method consists in analyzing the stock returns on three different portfolios, where stocks are sorted by size. By sorting stocks between microcaps, small stocks, and big stocks, is much easier to recognize the effect of an anomaly variable over stock returns. In the case of Fama and French (2008) the breakpoints are the 20th percentile of the NYSE's market-cap which separates microcaps from small stocks, and the 50th percentile of the NYSE's market-cap which distinguishes small stocks from big stocks. Then an anomaly is identified every time an abnormal stock return is observed with approximately the same magnitude in each of the three size portfolios.

Microcaps, beside representing a potential problem under the sorting approach, might be a problem for the regression analysis approach. Given that the values of both the anomaly variables and stock returns are generally more extreme for microcaps than for more capitalized stocks, then the estimated coefficients might be misleading. The problem can be solved by sorting stocks according to their market capitalization. Three portfolios are created microcaps, small stocks, and big stocks. Then to each portfolio correspond a regression. Formal inference on the relation between the average stock return and an anomaly variable across size groups is given by the mean slope resulting from each size group's regression (Fama & French, 2008). In the case an anomalous pattern in stock return is limited to microcaps it means that probably such anomaly pattern is not realizable. One of the reason for which an anomaly pattern is limited to microcaps is that trading microcaps is very expensive (Fama & French, 2008).

1.5.1 Value anomaly

Graham and Dodd (1934) are the first to use investment strategies constructed on the value effect. The value anomaly is given by a positive cross-sectional relationship between a stock returns and the ratio of a fundamental measure to the market stock price. In literature, the fundamental measures most used to describe the value anomaly are the book value of common equity per share, and the earning per share. Ball (1978) explains the link between stock returns and earnings, and demonstrates empirically that a value variable like the earnings to price ratio (hereinafter: E/P) can explain a portion of the systematic risk not caught by CAPM. Basu (1977) argues that E/P have explanatory power over stock returns listed on the NYSE stocks for the period 1957-1975. Basu (1977) focuses his research on portfolios consisting of stocks exhibiting high earnings' yield, low earnings' yield, and random earnings' yield.

Reinganum (1981) by focusing his research on both the NYSE and the American Stock Exchange (hereinafter: AMEX) over the period 1957-1979 confirms and broaden the result of Basu (1977). Another research of Basu (1983) confirms that the firms listed in the NYSE with high E/P have a higher average stock return with respect to firms with low E/P for the period 1962-1978. The method used by Basu (1983) differ from the one adopted by Reinganum (1981) in the sense that returns are controlled for the effect of risk. As a matter of fact, Basu (1983) constructs earning's yield portfolios by taking into account differences in their systematic risk, and differences in their total risk. Basu (1983) takes into account adjustment for risk differences to avoid the mistake of not observing an abnormal earning's yield in the case an abnormal earning's yield exists. Reinganum (1981) on the other hand doesn't adjust its earning's yield portfolios for systematic risk.

E/P results to be a proxy of the systematic risk not captured by CAPM even outside the United States of America (hereinafter: U.S.). Levis (1989) examine E/P variable in the United Kingdom (hereinafter: U.K.) over the period 1961-1985. Aggarwal, Rao, and Hiraki (1990) test E/P in Japan over the period 1974-1983. Chou and Johnson (1990) suggest that E/P describes stock returns in the Taiwanese stock market. All the mentioned authors find a strong cross-sectional relationship between E/P and stock returns. Beside E/P, there is evidence in literature that another value anomaly has explanatory power on stock returns. This anomaly is the book to price ratio (hereinafter: B/P). Graham and Dodd (1934) argue that the difference between the market price per share and the book price per share has to be considered as an indicator of price return. DeBondt and Thaler (1987) and Fama and French (1992) find a strong positive relation between B/P and U.S. stock returns. Evidence of B/P factor explaining stock returns is present in different stock exchanges. Capaul, Rowley, and Sharpe (1993) find a positive relation between B/P and stock returns in the stock exchange of U.K., Japan, France, Germany, and Switzerland. According to the available literature, stocks with high B/P ratio are outperforming stocks with low B/P ratio.

1.5.2 Size anomaly

The size anomaly describes the relation between stock returns and the market value of common equity. Banz (1981) tests the size anomaly to the stocks listed on the NYSE for the period 1931-1975. The result demonstrates that stocks of small companies outperform the stocks of highly capitalized companies. Banz (1981) retrieves all the relevant information, such as monthly stock prices, monthly stock returns, and shares outstanding from the University of Chicago, precisely from the Center for Research in Security Prices (hereinafter: CRSP). Banz (1981) classifies stocks in five different portfolios according to their market value. Once the size portfolios are constructed, stocks are sorted based on their estimated betas into other five portfolios. The betas are estimated using five years of monthly historical data. The proportions of the market are calculated every five years too. Proportions of the market are calculated by multiplying the stock price times the shares outstanding. Moreover the 25 portfolios are updated once a year and regressions are run on monthly basis (Banz, 1981). Banz (1981) comes up with the conclusion that the size effect is not linear in the market proportions. As a matter of fact, the smallest companies listed on the NYSE are those more effected by the size effect. Furthermore, the magnitude of the size factor's coefficient is not stable across an analysis made on sub-periods consisting of ten years each.

The size of a company might not be a risk factor but a proxy for some unknown true risk factors which are correlated with size (Banz, 1981). For Reinganum (1981) the E/P ratio results to be a proxy for the size effect, but the contrary is not true. The impact of the size effect being related to the structure of the stock market differ across different stock markets (Reinganum, 1990). However, a number of researches focusing on countries different from the U.S. confirm the result obtained by Banz (1981). Examples are given by tests on the stock exchange of Japan (Garza-Gomez, Hodoshima, & Kunimura, 1998), Belgium, France and U.K. (Corhai, Hawawini, & Michel, 1987).

The size effect might be caused by the higher transaction costs and illiquidity of small listed companies (Banz, 1981). Moreover, to investors are available only a small number of information about small companies. Hence, small companies might be perceived as undesired by investors (Klein & Bawa, 1977). Some investors might think to have not enough information about small companies. For this kind of investors not holding stocks of small companies is preferred. And given that stock sought by all investors have lower return than stock sought by few investors, then stocks of small firms have higher returns (Banz, 1981).

1.5.3 Momentum anomaly

Momentum is a temporal pattern of the stock market. According to which stocks with high returns over a period of three months to one year have a higher than expected probability to outperform stocks with low returns for the next three months to one year period (Jagadeesh & Titman, 1993). Stocks with high return are called winners whereas stocks with low return are called losers. A momentum portfolio is made up by ranking the stocks according to the previous months returns, and long position is taken in the winner stocks and short position is taken in the loser stocks. One of the most notable authors of the early literature about relative strength strategies consisting in buying past winners and selling past losers is Levy

(1967). Levy (1967) states that a strategy consisting of buying stocks with current prices being higher than their last 27 weeks average prices leads to abnormal return. The result of the research made by Jagadeesh and Titman (1993) goes in the same direction of Levy's research. Jagadeesh and Titman (1993) disclose a strategy consisting of buying past winners and selling past losers at the same time too.

The portfolio constructed on the strategy of Jagadeesh and Titman (1993) generates significant abnormal returns if it is hold for a period not lower than three months and up to one year. For a holding period which is greater than one year the portfolios' abnormal return becomes negative, and it persists to be negative until the 31st month. The research accounts for all the traded stocks of the NYSE and the AMEX for the period 1965-1989. The stock returns are retrieved from the CRSP's daily return file. Jagadeesh and Titman (1993) examines a total of 16 strategies, where stocks are picked according to their return over the past four quarters for a holding period varying from one to four quarters. The abnormal profits generated by the strategies are apparently independent from the market factor. The strategy showing the highest average compounded excess return per year, precisely 12.01%, is the one where stocks are chosen according to their six months past returns and where stocks are hold for six months (Jagadeesh & Titman, 1993).

Carhart (1997) adds the momentum factor to FF3 (Fama & French, 1993). The momentum factor is built coherently with the strategy of buying winners and selling losers. The Carhart's four factor model is consistent with a model of market equilibrium with four risk factors. Carhart (1997) research focuses on the persistence in mutual fund performance. Monthly data about equity funds for the period 1962-1993 are obtained from Micropal/Investment Company Data in the case the mutual fund survived or disappeared after 1989. Instead if the fund disappeared before 1989 data are retrieved from FundScope Megazine, the Wall Street Journal, and other reports (Carhart,1997). The total number of equity funds included in the sample constructed by Carhart (1997) is 1,892 diversified equity funds. The categories of equity funds forming the sample are long-term growth, growth and income, and aggressive growth. The number of equity funds in each category almost corresponds to the number of equity funds in the other categories. Note that some categories of equity funds are excluded from the research. The excluded equity funds are the sector funds, the balanced funds, and the international funds (Carhart, 1997). Carhart (1997) mentions that the yearly average number of equity funds is 509, with a yearly average total net asset of United States Dollar (hereinafter: USD) 218 million, and a yearly average traded assets' percentage of 77.3%.

Carhart (1997) tests the superiority of his four-factor model over CAPM. Finding that the four-factor model is able to explain variation in returns in a much better way with respect CAPM. Additionally, the momentum factor constructed by Carhart (1997) has a statistically significant coefficient, is positive in value, persists over time and is not explained by other factors. The result obtained from the research of Carhart (1997) suggests that by going long in last year's top decile equity funds and simultaneously going short in last year's bottom decile equity funds there is a yearly return on the portfolio of 8%. Moreover, those funds experiencing higher return last year are supposed to have higher than average expected return the following year (Carhart, 1997).

Beside Carhart's research on the persistence in mutual fund performance (Carhart, 1997), there is not a rational evidence to use the momentum factor as a proxy of systematic risk. Avramov and Chordia (2006) show how the momentum factor is not able to describe the stock returns of the listed companies belonging to both the NYSE-AMEX and the NASDAQ over the period 1962-2002. The average number of stocks in the sample is 2,070, and data are retrieved from CRSP (Avramov & Chordia, 2006). At first glance the abnormal profit of momentum anomaly seems the right risk premium for such systematic risk. But the profit is not lasting for more than one year from the portfolio's creation. Some authors try to explain momentum according to behavioral theories or rational frameworks. Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999) develop behavioral theories arguing the transient nature of momentum. Instead Johnson (2002) introduce a mechanism to generate the momentum factor, and it is extended by Sagi and Seasholes (2007).

1.5.4 Illiquidity anomaly

By defining liquidity as the investors' ability to trade an asset quickly and without incurring high costs, a debate among academics is whether illiquid assets have an abnormal return compared to more liquid assets. One of the first relevant researches about the explanatory power of illiquidity on stock returns is made by Amihud and Mendelson (1986). The illiquidity factor used by Amihud and Mendelson (1986) is given by the stocks' bid-ask spread. The sample consists of monthly returns of stocks listed on the NYSE for the period 1961-1980. Data about stock returns are retrieved from the CRSP, whereas data about the bid-ask spreads are retrieved from Fitch's Stock Quotations on the NYSE (Amihud & Mendelson, 1986). The result of the research shows a positive relation between illiquidity and expected return. The average portfolio returns increase with the increase of their bid-ask spread, moreover the effect of bid-ask spread doesn't vanish once a firm size factor is added to the regression equations (Amihud & Mendelson, 1986).

Eleswarapu and Reinganum (1993) test for monthly seasonality in the relation between returns and bid-ask spreads. The sample used by Eleswarapu and Reinganum (1993) consists of all stocks listed on the NYSE for the period 1961-1990. Data about stock returns are provided by the CRSP, bid-ask spread data for the period 1961-1979 are taken from Stoll and Whaley (1983), and bid-ask spread data for the period 1980-1990 are taken from Fitch Investors Service. Eleswarapu and Reinganum (1993) show that the liquidity premium exists only in January. Hence the result of the research carried out by Amihud and Mendelson (1986) is very different from the result of the research made by Eleswarapu and Reinganum (1993). But both researches find an anomaly in the bid-ask spread.

Some researchers such as Brennan and Subrahmanyam (1996) argue that the bid-ask spread is a bad proxy for illiquidity. Beside bid-ask spread, the illiquidity factor can be described by the shares' turnover ratio. Chan and Faff (2003) are among those using the turnover ratio as proxy for the illiquidity factor. The shares' turnover ratio is measured as the ratio of the total number of shares traded over a period of time by the average number of shares outstanding in that period (Chan & Faff, 2003). Another proxy for the illiquidity factor is provided by the strength of volume related return reversals (Pastor and Stambaugh, 2003). Pastor and Stambaugh analyze data obtained from CRSP for the period 1966-1999. Their sample consists of stocks from the NYSE and AMEX. The result of the research shows an abnormal return for the stocks with a high sensitivity to aggregate liquidity once compared to stocks with low sensitivity to aggregate liquidity.

The result of other researches about the existence of the illiquidity factor suggest that the illiquidity factor is not able to explain stock returns. An example is given by Avramov, Chordia, and Goyal (2006), they conclude that the liquidity factor does not explain stock returns. The sample used by Avramov, Chordia, and Goyal (2006) is made of monthly stock returns of stocks listed on the NYSE, the AMEX, and the NASDAQ over the period 1962-2002. Avramov, Chordia, and Goyal (2006) calculate the liquidity factor by taking the difference between the weighted average return on stocks with high sensitivities to liquidity and the weighted average return on stocks with low sensitivities to liquidity.

All the mentioned researches about the liquidity factor explaining stock returns don't take into account a measure of liquidity that assumes trading costs to be asymmetric for purchases and sales. Authors considering asymmetries in the trading cost structure are Brennan, Chordia, Subrahmanyam, and Tong (2012). Their research shows that the demand for liquidity and immediacy is higher on the sell side than on the buy side, meaning that the illiquidity premium appears more often on the sell side than on the buy side.

1.5.5 Profitability anomaly

Novy-Marks (2013) makes use of regression analysis to test whether profitability measures have explanatory power over stock returns. The profitability measures used by Novy-Marks (2013) are gross profits to asset ratio, earnings to book equity ratio, and free cash flow to book equity ratio. Gross profit is measured as revenues minus cost of goods sold, and according to Novy-Marks (2013) it reflects true economic profitability. Data are retrieved from Compustat for the period 1963-2010, and the sample is composed by all stocks but those of financial companies listed on the NYSE and the AMEX (Novy-Marks, 2013). The regressions' outcome show that gross profits is the profitability measure which better explain cross section of returns. Earnings to book equity ratio and free cash flow to book equity ratio have much less explanatory power on returns. Moreover, earnings to book equity ratio and free cash flow to book equity ratio are subsumed by the gross profitability variable (Novy-Marks, 2013). Novy-Marks (2013) uses alternative earning variables such as earnings before interest, taxes, depreciation, and amortization (hereinafter: EBITDA) to asset ratio and selling, general, and administrative expenses (hereinafter: XSGA) to asset ratio. The regressions' outcome suggests that gross profits to asset subsumes the explanatory power of both EBITDA to asset ratio and XSGA to asset ratio (Novy-Marks, 2013). However, both variables have explanatory power both jointly and individually. According to Novy-Marks (2013) the more profitable companies have higher average return than the unprofitable companies.

Consistently with the result obtained by Novy-Marks (2013), Fama and French (2015) find a profitability factor having explanatory power over stock returns. The method of Fama and French (2015) consists in sorting stocks in 25 different portfolios. Stocks are sorted in the 25 portfolios according to two dimensions. Where the two dimensions are size and profitability quintiles. The profitability variable is given by the ratio between operating profit and book equity observed at the end of each fiscal year (Fama & French, 2015). The operating profitability variable used by Fama and French (2015), being defined as annual sales minus cost of goods sold, interest expense, and selling, general, and administrative expense, is from an accounting point of view operating profitability minus interest expense. Fama and French (2015) find that stocks exhibiting the highest operating profitability have higher average return with respect to stocks with the lowest operating profitability. The result holds for whichever size quintile.

1.5.6 Calendar anomaly

A calendar anomaly occurs every time that stock returns have a time varying pattern predicted by calendar turning point. Meaning that stock markets reacts differently according to hours, days, weeks, and months (Rossi, 2015). Rossi (2015) in summarizing all the studies on the calendar anomalies realizes that the majority of researches are about three calendar effects, namely January effect, day of the week effect, and turn of the month effect. Rozeff and Kinney (1976) investigates the monthly returns on the stocks listed on the NYSE for the period 1904-1974. The result of their research shows that the monthly average return in January is higher with respect the other months of the year (Rozeff & Kinney, 1976).

Agrawal and Tondon (1994) conduct a test on 18 of the most industrialized countries but U.S., their findings suggest a higher stock returns in January for most of the countries. The stock exchanges analyzed belong to the following countries: Australia, Belgium, Brazil, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Singapore, U.K., Switzerland, and Sweden. Further tests on the January anomaly are made by Barone (1990), and Mylonakis and Tserkezos (2008). Barone (1990) finds seasonal higher average returns in January in Italy for the period 1975-1989. Furthermore, Mylonakis and Tserkezos (2008) find that the January anomaly is present in the Athens Stock Exchange over the period 1985-2001. The January anomaly is represented by higher average stock returns than stock returns observed on the other months of the year.

Other scholars such as French (1980), Jaffe, Westerfiled, and Ma (1989), and Wang, Li, and Erickson (1997) all find a day of the week anomaly in the stocks listed on the NYSE. Negative stock returns on Mondays and positive stock returns on Fridays are observed. Additionally, the stock returns on Mondays are much lower than average stock returns on different days and the stock returns on Fridays are much higher than average stock returns on different days.

Moreover, some researches once focusing on the calendar anomaly find out a turn of the month anomaly which effect stocks listed on the NYSE. Among those Ariel (1987), and Lakonishok and Smidt (1988). Ariel (1987) analyzed the period 1963-1981 whereas Lakonishok and Smidt (1988) focus their test on the period 1897-1986. Both share the same conclusion about abnormal stock returns trend. The shared result of Lakonishok and Smidt (1988) and Ariel (1987) consists in observing higher stock returns at the end of one month and at the beginning of the following month. Where for higher stock returns is meant higher than the stock returns observed on the other days of the month.

1.6 Fama-French three factor model

Fama and French (1992, 1993) prove that two anomalies of the CAPM have explanatory power over stocks returns. The first article about FF3 is published by Fama and French in 1992, while the second one in 1993. The two articles are different in terms of the asset returns explained, the variables used to explain returns, and the approach used. In an integrated market one single model should be able to describe the return on both stocks and bonds. In their second research about FF3, Fama and French by including all the stocks available from the U.S. stock markets and all the bonds supplied by the U.S. government are coherent with the integrated market assumption. Indeed, two term-structure variables are added in their second research. The two term-structure variables are specifically used to describe bond returns.

Being return on bonds affected by the interest rates' unexpected volatility the first term-structure variable is a proxy for the unexpected fluctuation in interest rates. Fama and French (1993) call this variable Term. Term is calculated as the difference between the monthly return of the U.S. long-term government bond and the return of the one-month Treasury bill rate. The one-month Treasury bill rate is used as proxy of the expected return on bonds because the difference between the long-term bond returns and the short-term bond returns is a proxy of the unexpected variation in the long-term bond returns caused by fluctuations in interest rates. The second term-structure variable is a proxy of corporate bonds' default risk. The magnitude of default risk affecting corporate bonds depends on the economic conditions. So, default risk changes according to shifts in economic conditions. The term-structure variable used by Fama and French (1993) as proxy for default risk is called Def. Def is calculated as the difference between a market portfolio of long-term returns on corporate bonds and the long-term returns on government bonds.

A very important difference between the two researches about FF3 consists in the approach used once testing the model. In the first research (Fama & French, 1992) the U.S. stock market is tested using the cross-section regression of Fama and MacBeth (1973). Cross-section regression consists in regressing the cross-section of stock returns over those factors which are identified as being proxy for systematic risk. Given that the second research (Fama & French, 1993) includes bond returns it is not possible to use the cross-section regression approach. Hence, Fama and French (1993) in their second research about FF3 employ the time-series regression approach of Black, Jensen, and Scholes (1972).

The time-series regression approach consists of regressing the dependent variable on the explanatory variables which are mimicking for systematic risk. In the case of Fama and French (1993) the dependent variable is the excess return on both stocks and bonds, whereas the explanatory variables are size factor, value factor, and two term-structure factors. A further important issue related to time-series regressions is that the explanatory variables are return or excess returns on portfolios mimicking systematic risk. The slope of the time-series regression represents a factor loading. The factor loading represents the sensitivity of both return on stocks and return on bonds to common risk factors. Fama and French (1993) calculate the excess return as the difference between stock returns and the one month Treasury bill rate, and the difference between bond returns and the one month Treasury bill rate. The regressions of a specified asset pricing model should produce an intercept equal to zero (Merton, 1973).

The results obtained by Fama and French (1993) in their second research about FF3 need attention, and so are going to be described in detail. The Term factor and Def factor explain a big portion of both variation in return on government bonds and variation in return on corporate bonds. Moreover, size factor and value factor are important proxy for systematic risk for stocks, explaining the majority of variation in the return on stocks. Furthermore, the intercept resulting from the regression between the portfolios of stocks and the risk factors is close to zero. Hence, confirming that the market factor, the size factor, and the value factor are able to describe stock returns. The effects of the term-structure factors on stock returns are similar to the effects of the term-structure factors on bond returns. In both cases the term-structure factors capture variation in returns. Moreover, the regressions' slopes are similar (Fama & French, 1993).

The U.S. bond market and the U.S. stock market results to be linked through the term-structure factors. The term-structure factors explain the variation in the return on bonds only but for low-grade corporate bonds. The variation in the return on low-grade corporate bonds is explained by the stock-market factors too. Instead, the stock-market factors explain the return on bonds when they are regressed alone from Term factor and Def factor. Indeed, once the term-structure factors are included in the regressions of bonds then the stock-market factors lose their explanatory power over the return on bonds. Moreover, variation in stock returns is explained by at least three stock-market factors. Namely the market factor, the size factor, and the value factor (Fama & French, 1993). Equation (4) shows the relation between the return on the seven bond portfolios used as dependent variable and the two term-structure factors which are used as explanatory variables. Where $E(R_b)$ is the expected return on bond, R_f is the risk-free rate, β^b_{Term} is the coefficient estimate of the explanatory variable Term, $(Term)$ is the explanatory variable Term, β^b_{Def} is the coefficient estimate of the explanatory variable Def, and (Def) is the explanatory variable Def:

$$E(R_b) - R_f = \beta^b_{Term}(Term) + \beta^b_{Def}(Def) \tag{4}$$

In the U.S. stock market FF3 has a much higher explanatory power over stock returns than CAPM (Fama & French, 1993). By adding to the market factor of CAPM the size and value anomalies, the explanatory power on stock returns drastically increases. The size variable is represented by the market equity (hereinafter: ME) of a company whereas the value variable is the book to market equity ratio (hereinafter: BE/ME). ME is obtained by multiplying the stock price with the number of shares at the end of June of a specific year. The two variables are represented by two portfolios. The first portfolio is named SMB, and includes ME values. Whereas the second portfolio is named HML, and includes BE/ME values. The data sample includes all the stocks of AMEX and NYSE from 31 July 1963 to 31 December 1991. Stocks of NASDAQ are also included in the data sample but for the period 31 July 1972 to 31 December 1991. The sample includes all the stocks but those belonging to both financial companies and companies with negative book equity (Fama & French, 1993). Equation (5) represents the relation between the stock returns and the three stock-market factors. Where $E(R_i)$ is the expected return on stock, R_f is the risk-free rate, β^i_m is the coefficient estimate of the explanatory variable MRP, $E(R_m)$ is the expected return on the stock market, β^i_{SMB} is the coefficient estimate of the explanatory variable SMB, (SMB) is the explanatory variable SMB, β^i_{HML} is the coefficient estimate of the explanatory variable HML, and (HML) is the explanatory variable HML:

$$E(R_i) - R_f = \beta^i_m\big(E(R_m) - R_f\big) + \beta^i_{SMB}(SMB) + \beta^i_{HML}(HML) \tag{5}$$

1.6.1 Link between the U.S. stock-market and the U.S. bond-market

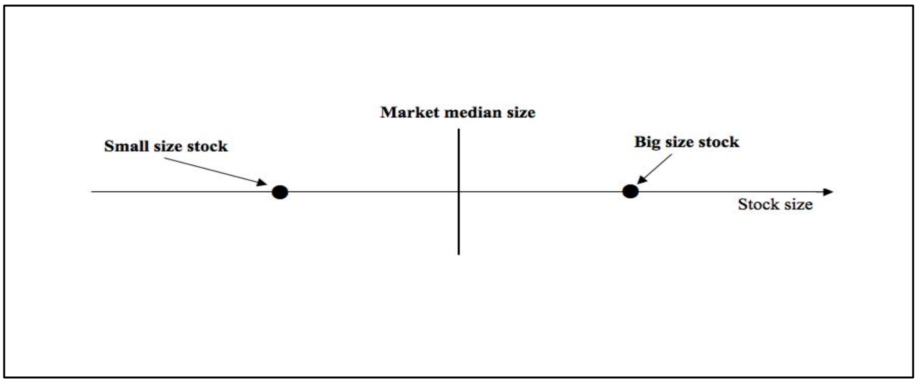
Fama and French (1993) in their research show that a single asset pricing model works for both the U.S. bond-market and the U.S. stock-market. FF3 works as a single asset pricing model in the U.S. because the bond-market and the stock-market are integrated. The link between the two U.S. markets is going to be described in detail even if the bond-market is not the subject matter of this Master thesis. The reason is that having a complete view of the theory about the model is a must. The result of the five-factor regression used to describe stock returns shows that Term and Def have no effect on stock returns. But the common variation between stock returns and bond returns is given by the two bond-market factors once there are regressed alone (Fama & French, 1993).

1.6.2 Stock-market factors

Fama and French (1993) use as proxy for the market risk the excess stock-market return. So, the market factor is given by the excess market return which is calculated as the difference between the value-weighted portfolio of stocks and the one month Treasury bill. Note that the value-weighted portfolio of stocks is the result of six portfolios constructed on ME-(BE/ME) and those stocks having a negative value of BE hence excluded from the six ME-(BE/ME) portfolios. On the other hand, the SMB portfolio and the HML portfolio are both constructed by ranking the sample of stocks on the values of the size variable and on the values of the value variable.

Data are divided into two group of BE values. The market index median BE is used as reference point to split stocks into two different groups, namely small and big. BE is measured as share price times shares outstanding as of the end of June of each year. The two stock portfolios constructed according to BE values are described by Figure 5.

Figure 5. Stocks classified by size

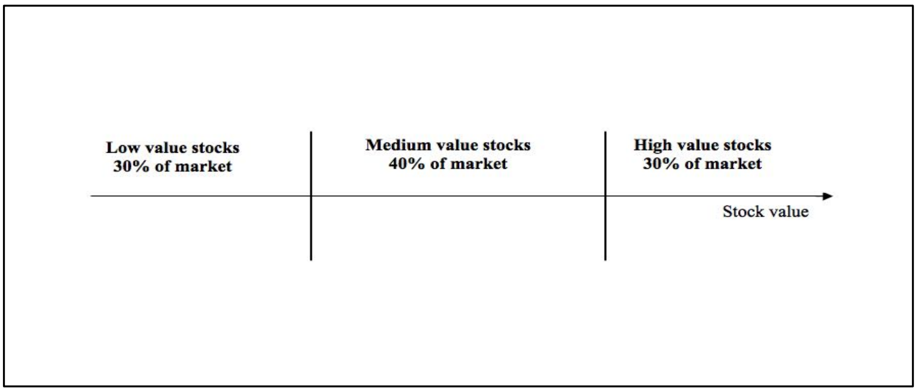


Own work.

Stocks are further classified according to BE/ME values. Three groups based on BE/ME are then formed. The low BE/ME group is made of the lowest 30% stocks, the medium BE/ME group is made of the middle 40% stocks, and the high BE/ME group is made of the highest 30% stocks (Fama & French, 1993). The three groups are formed at yearly basis at the end of each June. The BE value used in June of year t is the one from last fiscal year-end (t-1). ME is measured as shares outstanding times stock price. The reference period of both values is year-end of (t-1).

Observing small BE/ME values is a common feature of growth stocks. Growth stocks are those stocks with high share price relative to BE. Growth stocks have persistent high earnings on assets, hence perceived as a source of capital gain by some investors. Another feature of growth stocks is that they don't pay dividends, earnings are reinvested instead (Fama & French, 1993). The result is that growth stocks are often overvalued. High BE/ME are called value stocks. Value stocks are usually linked to persistent low earnings on assets. Persistent low earnings signal the distress of a company. Hence the share price of a value stock is generally low (Fama & French, 1992). Value stocks are considered undervalued by a value investor. Stocks belonging to the medium BE/ME group are called neutral stocks, hence half way from being considered both growth stocks and value stocks. The three stock portfolios constructed according to BE/ME values are described by Figure 6.

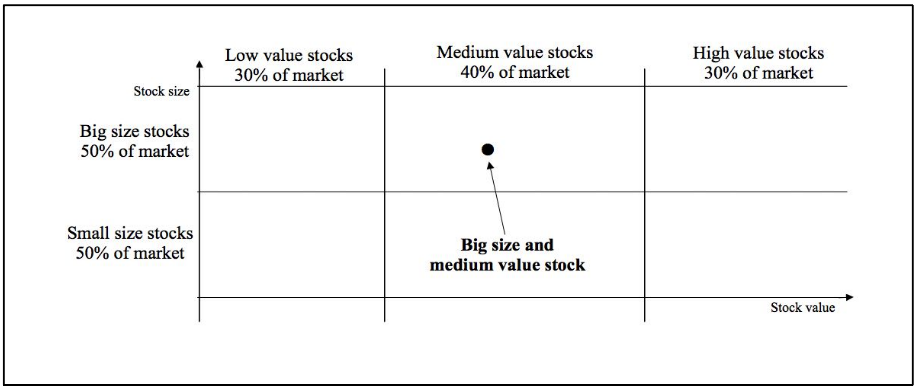
Figure 6. Stocks classified by value



Own work.

Sorting stocks in two BE portfolios and in three BE/ME portfolios is an arbitrary choice (Fama & French, 1993). The next step consists in the creation of six value-weighted portfolios. The six value-weighted portfolios are created on yearly basis at the end of June of year t from the combination of the two portfolios formed on BE and the three portfolios formed on BE/ME (Fama & French, 1993). The six value-weighted portfolios are named small BE and low BE/ME, small BE and medium BE/ME, small BE and high BE/ME, big BE and low BE/ME, big BE and medium BE/ME, big BE and high BE/ME. The six value-weighted portfolios are shown in Figure 7.

Figure 7. The six value-weighted portfolios



Own work.

Value weighted portfolios are used because able to catch differences in the return behavior of those stocks differing both in BE and BE/ME. Moreover, since the return variances are negatively related to size, a value-weighted portfolio minimizes the variance (Fama & French, 1993). Hence, each value-weighted portfolio represents a realistic investment opportunity. The portfolios include all the stocks having positive BE in year (t-1) and for which ME year-end data are available for (t-1) and June of year t. The resulting SMB values and HML values are calculated on daily, weekly or monthly frequency. So, SMB and HML are calculated according to the need of the researcher. Since the value of BE for year (t-1) is disclosed during the first quarter of year t, the stock returns are calculated starting from July of year t. Fama and French (1993) define BE as the difference between book value of equity and book value of preferred stock. Where book value of equity is gross of deferred taxes and investment tax credit.

1.6.3 Computation of size variable and value variable

SMB is given by the difference between the average monthly return on the three small portfolios and the average monthly return on the three big portfolios (Fama & French, 1993). The SMB portfolio is described by equation (6). Where SMB is the size variable, $R_{s/l}$ is the stock return on the small BE and low BE/ME portfolio, $R_{s/m}$ is the return on the small BE and medium BE/ME portfolio, $R_{s/h}$ is the return on the small BE and high BE/ME portfolio, $R_{b/l}$ is the return on the big BE and low BE/ME portfolio, $R_{b/m}$ is the return on the big BE and medium BE/ME portfolio, and $R_{b/h}$ is the return on the big BE and high BE/ME portfolio:

$$SMB = \frac{(R_{s/l}+R_{s/m}+R_{s/h})}{3} - \frac{(R_{b/l}+R_{b/m}+R_{b/h})}{3} \tag{6}$$

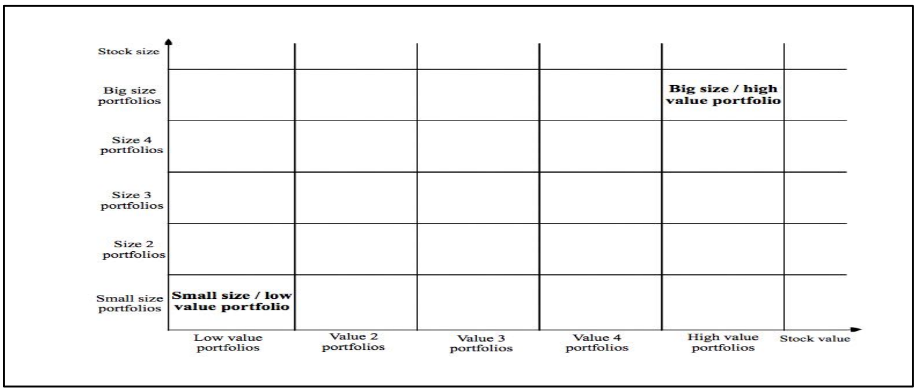
On the other hand, HML is given by the difference between the average monthly return on the high BE/ME portfolios and the average monthly return on the low BE/ME portfolios (Fama & French, 1993). Differently from SMB, medium BE/ME portfolios are not used to calculate HML. The HML portfolio described by equation (7). Where $R_{s/h}$ is the return on the small BE and high BE/ME portfolio, $R_{b/h}$ is the return on the big BE and high BE/ME portfolio, $R_{s/l}$ is the return on the small BE and low BE/ME portfolio, and $R_{b/l}$ is the return on the big BE and low BE/ME portfolio:

$$HML = \frac{(R_{s/h}+R_{b/h})}{2} - \frac{(R_{s/l}+R_{b/l})}{2} \tag{7}$$

1.6.4 The returns explained

Fama and French (1993) use bond returns and stock returns as dependent variables for the regressions analysis. The bonds analyzed are government bonds with two different maturities and five groups of corporate bond portfolios. The two maturities of the government bonds are from one year to five years, and from six years to ten years. The corporate bonds instead are classified in five categories according to Moody's rating, namely Aaa, Aa, A, Baa, and low-grade. Since the objective of this Master's thesis is to use FF3 on stock returns, more attention is given to stock returns used as dependent variable. Hence, the return on stocks explained are monthly values of the excess returns on 25 portfolios of stocks. The 25 portfolios are constructed according to BE values and BE/ME values. Stocks are divided in five BE portfolios and five BE/ME portfolios. The five BE portfolios rank stocks according to their BE value, from the smallest in size to the largest in size. BE portfolios are Small, 2, 3, 4, and Big. Whereas the five BE/ME portfolios rank stocks depending on their BE/ME value, from the lowest in BE/ME value to the highest in BE/ME value. BE/ME portfolios are Low, 2, 3, 4, and High (Fama & French, 1993). The elements of the 25 portfolios are the result from the intersection between BE portfolios and BE/ME portfolios. Figure 8 shows the 25 portfolios of the explained stock returns.

Figure 8. The 25 portfolios of stock returns



Own work.

The stocks used as dependent variables are retrieved from the same market indices as the stocks used as explanatory variables. Namely NYSE, Amex, and NASDAQ. BE and BE/ME portfolios are formed at yearly basis on June. The stocks forming the five size portfolios have a BE value which is calculated at yearly basis at the end of June. Whereas the five BE/ME portfolios are made of BE value and ME value calculated at yearly basis at year end of each year (t-1) (Fama & French, 1993).

1.6.5 Average excess return and factor premiums

The average excess returns of the dependent variable are important values for a better understanding of the return ranges explained by explanatory variables. Average excess return is the difference between the average stock return and the average risk-free rate. The monthly excess returns on the 25 portfolios resulting from BE and BE/ME combinations range from 0.32% to 1.05% (Fama & French, 1993). There is evidence that the higher BE the lower the stock returns. Exception made for the average return on the smallest BE/ME quintile which tends to increase with the increase of the BE quintiles. Moreover, the higher BE/ME the higher the stock returns. As a matter of fact, in every size quintile the average return increases with the increase of BE/ME. The monthly spread in average returns between highest and lowest BE/ME portfolios for each BE category ranges from 0.19% to 0.62%. The high variation in stock returns causes large average returns to be non-statistically significant different from zero. But high variation in stock returns partially vanishes as a consequence to the common factors in stock returns (Fama & French, 1993). Hence high variation in stock returns doesn't represent a problem for the suitability of FF3 once the intercept of the time-series regressions is tested to be non-statistically significant different from zero. Table 1 shows the average excess return on the 25 portfolios constructed on the combinations between five BE portfolios and five BE/ME portfolios.

Table 1. Average excess return on the 25 stock portfolios (in %)

BE quintiles	**BE/ME quintiles**				
	Low	2	3	4	High
Small	0.39	0.70	0.79	0.88	1.01
2	0.44	0.71	0.85	0.84	1.02
3	0.43	0.66	0.68	0.81	0.97
4	0.48	0.35	0.57	0.77	1.05
Big	0.40	0.36	0.32	0.56	0.59

Source: E.F. Fama & K.R. French, *Common risk factors in the returns on stocks and bonds*, 1993, p. 15, Table 3.

The other category of assets used as dependent variable by Fama and French (1993) are bonds. The average value of each of the seven bond portfolios is very low. However, the bond portfolios showing the highest average excess returns are government bonds with six to ten years maturity and Baa corporate bonds. Both of them have an average excess return of 0.14% (Fama & French, 1993). Values of the monthly average excess returns of the seven bond portfolios are shown in Table 2.

Table 2. Average excess return on the seven bond portfolios (in %)

Government 1-5 years	**Government 6-10 years**	**Aaa**	**Aa**	**A**	**Baa**	**Low-grade**
0.12	0.14	0.06	0.07	0.08	0.14	0.13

Source: E.F. Fama & K.R. French, *Common risk factors in the returns on stocks and bonds*, 1993, p. 14, Table 2.

The time-series regression method requires the premiums of the common risk factors to be averaged. The average premium of each common risk factor is the average value of each explanatory variable. Hence, values of the three stock-market factors and values of the two bond-market factors are averaged (Fama & French, 1993). The average premium on the stock-market factors ranges from 0.27% to 0.43%. Where the market factor average premium is 0.43%, the average size premium is 0.27%, and the premium of the value factor is 0.40%. On the other hand, the bond-market factors show much lower average premiums. The average premium of Term factor is just 0.06%. Whereas, the average premium of Def factor is 0.02%, so even lower than the Term factor. Table 3 shows the average premium on each of the explanatory variables of the time-series regressions. Hence, the average premium on each of the three stock-market factors and the average premium on each of the two bond-market factors.

Table 3. Average premium on the explanatory variables (in %)

MRP	**SMB**	**HML**	**Term**	**Def**
0.43	0.27	0.4	0.06	0.02

Source: E.F. Fama & K.R. French, *Common risk factors in the returns on stocks and bonds*, 1993, p. 14, Table 2.

Fama and French (1993), by giving a first look to the factor premiums, argue that the low average premiums of the bond-market factors might be good to explain bond returns, but not stock returns. And that the higher average premiums of the stock-market factors might be good to explain stock returns.

1.6.6 Testing Fama-French three factor model on the U.S. market

Fama and French (1993) test FF3 on the U.S. stock-market and on the U.S. bond-market in two ways. At first the explanatory variables are tested to see whether they are capturing common variation in returns. Two figures are extremely helpful to check whether explanatory variables are able to capture common variation in returns in time-series regressions. These figures are the coefficient estimate of each explanatory variable and r-squared (hereinafter: R^2) of each time-series regression (Fama & French, 1993). Secondly the average premiums of the risk factors are tested to understand if they have explanatory power over stock returns and bond returns. The results of time-series regressions describe the ability with which the three stock-market factors and of the two bond-market factors capture common variation in returns.

The dependent variable of all the time-series regressions is the monthly excess return on each of the 25 portfolios constructed on BE values and BE/ME values, and each of the seven bond portfolios. Data are collected for the period 31 July 1963 to 31 December 1991. The first set of regressions consist of regressing the dependent variables on the two bond-factors alone. Fama and French (1993) argue that Term factor and Def factor capture the common variation in stock returns and bond returns only if used alone. As a matter of fact, all the

Term coefficient estimates are high. Once excess returns on stocks are used as dependent variable the Term coefficient estimates range from 0.77% to 1.05%. And by using excess return on bonds as the dependent variable the Term coefficient estimates range from 0.45% to 1.02%. Def coefficient estimates are high too. For the time-series regressions having the excess return on stocks as dependent variable the Def coefficient estimates range from 0.73% to 1.52%. Whereas for the time-series regressions having excess return on bonds as dependent variable the Def coefficient estimates range from 0.25% to 1.10% (Fama & French, 1993). There are some interesting patterns in both Term coefficient estimates and Def coefficient estimates.

The Term factor captures unexpected shifts in the interest rates. So, not surprisingly the Term coefficient estimate is much stronger for long-term government bonds than for short-term government bonds. The coefficient estimate is 0.72% for long-term bonds against 0.45% of the short-term bonds. Whereas the Term coefficient estimate for portfolios of corporate bonds ranges from 0.99% to 1.02%, so pretty much constant. The only exception concerns low-grade corporate bonds, which have a Term coefficient estimate of 0.81%. On the other hand, Def factor is mimicking for default risk. The time-series regression results show that the smaller the size of a company the higher is the coefficient estimate of Def. Hence, Def coefficient estimates for the smallest companies range from 1.39% of those with low BE/ME values to 1.52% of those with high BE/ME values. Moreover, Def coefficient estimates for the biggest companies range from 0.78% of those having low BE/ME values to 0.89% of those with high BE/ME values. Rationally Def coefficient estimates for the two portfolios consisting of government bonds are low. The coefficient estimate of short-term government bonds is 0.25% and the coefficient estimate of long-term government bonds is 0.27%. Def coefficient estimates increase for portfolios consisting of corporate bonds instead, ranging from 0.96% to 1.10% (Fama & French, 1993).

From the value of R^2 is clear how Term and Def are missing to explain a big portion of the variation of the excess returns on stocks and the variation of excess return on low-grade bonds. Indeed R^2 of stocks portfolios is ranging from 0.06 to 0.21, and R^2 for the low-grade bonds is 0.49. Instead R^2 for all the other categories of bonds is ranging from 0.79 to 0.98 (Fama & French, 1993). So, Term and Def capture almost all the variation on excess returns of all bond portfolios but low-grade bond portfolio.

To test for common variation in excess return when stock-market variables are used as the explanatory variables in the time-series regressions three steps are required (Fama & French, 1993). At first dependent variables are regressed on MRP only. In the second step, the dependent variables are regressed on SMB and HML. Whereas in the third step the dependent variables are regressed on the three stock-market variables all together. The first two steps might be helpful to explain the results achieved in the third step, but here only the results of the third step are going to be described in detail. However, important patterns of the first step are the low R^2 of both government bonds and corporate bonds. R^2 of corporate bonds ranges from 0.14 to 0.30, which is higher than R^2 of government bonds but still low. Whereas R^2 of stock portfolios ranges from 0.61 to 0.92, so MRP seems to capture a big portion of the excess return on stocks. The second step shows that SMB and HML are not able to capture the variation in excess bond returns, R^2 is 0 for all bond portfolios but the low-grade one which R^2 is 0.04. But once SMB and HML are regressed on the 25 stock portfolios their ability to capture variation in returns change. Indeed, SMB and HML capture common variation in stock returns. R^2 ranges from 0.04 to 0.65. So, leaving some variation in stock returns to be explained by MRP (Fama & French, 1993).

In the third step the 25 stock portfolios and the seven bond portfolios are regressed against the three stock-market factors together. Once used together MRP, SMB, and HML seems to partially explain the variation in the excess returns on bond portfolios. R^2 for the seven bond portfolios ranges from 0.10 of short-term government bonds to 0.33 of low-grade bonds. Fama and French (1993) argue that this unexpected result is a consequence of covariation between bond-market factors and the three stock-market factors. The most important regressions in the third step are those regarding excess returns on stocks. As a matter of fact, the three stock-market factors once used together catch almost all variation in the excess return of stocks. R^2 is higher than 0.90 in 21 out of 25 stock portfolios, however R^2 for the remaining four stock portfolios is higher than 0.82. An interesting pattern is related with MRP coefficient estimates. MRP coefficient estimates where much lower or much higher than one in the first step. In the third step are all converging to one instead. MRP coefficient estimates in the third step range from 0.91% to 1.18%. The convergence to one is probably due to the correlation between market risk premium and SMB or HML (Fama & French, 1993).

At this point the dependent variables are regressed on five factors. The five factors are the two bond-market factors and the three stock-market factors. The results confirm that stock-market factors capture common variation in stock excess returns and that bond-market factors capture common variation in bond excess returns. The coefficient estimates of MRP, SMB, and HML which results from the time-series regression of the 25 stock portfolios used as dependent variables are not effected by Term and Def. Moreover, the coefficient estimates of Term and Def resulting from the time-series regressions of the seven bond portfolios used as dependent variables are not effected by MRP, SMB, and HML.

The time-series regressions using 25 stock portfolios as dependent variable and five explanatory variables have the coefficient estimate of Term converging to zero and also the coefficient estimate of Def converging to zero. Furthermore, the time-series regressions using seven bond portfolios as dependent variable and five explanatory variables have the coefficient estimate of MRP converging to zero, the coefficient estimate of SMB converging to zero, and also the coefficient estimate of HML converging to zero. But for the low-grade bond portfolio which has a coefficient estimate different from zero. The result obtained by the research of Fama and French (1993) show that MRP, SMB, and HML have explanatory power over stock returns, and that stock returns are linked to bond returns through some common variation in the Term factor and in the Def factor. The link is partially captured by MRP, so Term and Def are partially included in MRP. The intercepts of time-series regressions are used to test how well the average premiums of the explanatory variables explain stock returns and bond returns. The intercept of time-series regressions using 25 stock portfolios as dependent variable converges to zero when moving from time-series regressions with one stock-market explanatory variable to time-series regressions with three stock-market explanatory variables. Table 4 shows the intercept values resulting from the time-series regressions having as dependent variable the excess return on the 25 stock portfolios and as explanatory variables the three stock-market factors, namely MRP, SMB and HML.

Table 4. Intercepts from excess stock return of 25 stock portfolios and three stock-market factors (in %)

BE quintiles	**BE/ME quintiles**				
	Low	2	3	4	High
Small	-0.34	-0.12	-0.05	0.01	0.00
2	-0.11	-0.01	0.08	0.03	0.02
3	-0.11	0.04	-0.04	0.05	0.05
4	0.09	-0.22	-0.08	0.03	0.13
Big	0.21	-0.05	-0.13	-0.05	-0.16

Source: E.F. Fama & K.R. French, *Common risk factors in the returns on stocks and bonds*, 1993, p. 37, Table 9a.

Moreover, the intercepts are close to zero even when Term and Def are added to MRP, SMB, and HML. But the average value of Term and the average value of Def are both too low. Hence, only MRP, SMB, and HML are working well in explaining the cross-section of average stock returns. Furthermore, Table 5 shows the intercepts resulting from the time-series regressions having Term and Def as explanatory variables and excess return on the seven bond portfolios as the dependent variable. Their values are close to zero as well. Thus, Term and Def are good factors in explaining bond returns. Term and Def are related to business conditions and hence vary through time (Fama & French, 1993).

Table 5. Intercepts from excess bond return of seven bond portfolios and two bond-market factors (in %)

Government 1-5 years	**Government 6-10 years**	**Aaa**	**Aa**	**A**	**Baa**	**Low-grade**
0.08	0.09	-0.02	0.00	0.00	0.06	0.06

Source: E.F. Fama & K.R. French, *Common risk factors in the returns on stocks and bonds*, 1993, p. 37, Table 9b.

1.6.7 Outperformance of the Fama-French three factor model over the capital asset pricing model

The FF3 model since its development is tested a number of times and in different ways by many researchers. The result of the majority of these tests shows that FF3 outperforms CAPM in the ability of describing stock returns. CAPM is a subject of criticism among researchers. Among critics of CAPM we find D. H. Bower, R. S. Bower, and Logue (1984) which show that the market premium does not explain the total systematic risk of a stock average return. Their advice is to incorporate different factors in addition to MRP. Moreover, the result obtained by D. H. Bower et al. (1984) is in line with APT developed by Ross (1976a, 1976b). The difference between the two is the way in which the result is achieved. D. H. Bower et al. (1984) focus on CAPM, instead APT is an evolution of CAPM focusing on different sources of systematic risk beside MRP. Chan, Hamao, and Lakonishok (1991), Capaul, Rowley, and Sharpe (1993), and Davis, Fama, and French (2000) argue that FF3 outperforms CAPM. Their researches are focus on the BE/ME factor. The results of numerous researches conducted by Fama and French (1992, 1993, 1995) argue that CAPM is inferior with respect to their FF3. Fama and French (1992, 1993, 1995) show how CAPM does not properly explain the variation in average stock returns, and that other proxy for systematic risk must be add to MRP.

Empirical evidence about the outperformance of FF3 over CAPM outside U.S. is given by a number of researchers. Fama and French (1998) provide an international evidence of the validity of FF3 too. Whereas, Arshanapalli, Coggin, and Doukas (1998) show that FF3 explains stock returns for the period 1975-1995 in the stock markets of U.S., Canada, Austria, Belgium, Denmark, France, Germany, U.K., Netherlands, Norway, Spain, Sweden, Switzerland, Australia, Hong Kong, Japan, Malaysia, and Singapore. Moreover, Liew and Vassalou (2000) test the validity of FF3 for the period 1978-1996 in the stock markets of Australia, Canada, France, Germany, U.S., Japan, Netherlands, Switzerland, U.K., and Italy. The result confirms the ability of FF3 to explain stock returns better than CAPM in those ten countries.

Moreover, FF3 is tested on developing countries. An example is given by Taneja (2010). Taneja (2010) applied FF3 to the Indian capital market for the period 2004-2009, the result shows all the factors to be significantly related to stock returns. Among other authors there are Drew and Veeraraghavan (2002) analyzing the Kuala Lumpur stock exchange, Hardianto and Suherman (2009) analyzing the Indonesian stock exchange for the period 2000-2004, and Al-Mwalla (2012) analyzing the Amman stock market for the period 1999-2010.

On the other hand, some researches argue that FF3 have no effect on stock returns in emerging countries. Authors evidencing that the three stock-market factors of FF3 have no explanatory power over stock returns of the stock-market of emerging countries are Senthilkumar (2009), Eraslan (2013), and Chandra (2015). Senthilkumar (2009) tests FF3 in

India for the period 2002-2008, Eraslan (2013) tests FF3 in Turkey for the period 2003-2010, and Chandra (2015) tests FF3 in Indonesia for the period 2010-2013. To conclude all the mentioned literature described here reveals that FF3 outperforms CAPM in explaining stock returns of stock-markets belonging to different developed countries. An exception is made for some emerging countries, where the ability of FF3 in describing stock return is not clear.

2 FAMA-FRENCH THREE FACTOR MODEL FOR HIGH CAP EUROPEAN BANKS

2.1 Sample of high-cap European banks

The sample of high-cap European banks which is used in this Master's thesis coincides with the sample of banks constructed for the 2016 EU-wide stress test. The EU-wide stress test is coordinated by EBA in cooperation with the European Systemic Risk Board. The objective of EBA's EU-wide stress test is to assess the resilience of a set of EU banks to adverse macroeconomic shocks for the period 31 December 2015 to 31 December 2018, and it is based on 2015 year-end figures.

The shocks emerging in the adverse macroeconomic scenario are created by the European Systemic Risk Board and the European Central Bank in cooperation with the EBA and the European Commission. Banks, during the exercise, are subject to stress test a set of risk which are affecting their ability to meet financial obligations. The impact of the adverse scenario on the solvency of banks is captured by the following risks: credit risk including securitizations; market risk, counterparty credit risk, credit valuation adjustment; operational risk including conduct risk.

Banks are required to use their own statistical models to access the impact of credit risk. Credit risk is measured as capital impairments and risk exposure amounts caused by counterparties default. The parameters starting value has to be estimated at first. The second step consists with the estimation of the impact of shocks on the risk parameters. The last step regards the computation of the impairment flows which is used as basis for provision. Market risk also affects the positions of available for sale securities and fair value options securities. Moreover, the hedge accounting portfolios are assessed at their fair value and are subject to the market risk methodology.

The 2016 EU-wide stress test is exercised on the largest EU banks in terms of their consolidated assets as of 2014 year-end figures. All the sample banks are significant institutions of the EU, hence directly supervised by the European Central Bank. The Single Supervisory Mechanism classifies as significant those banks with consolidated assets exceeding EUR 30 billions. The 2016 EU-wide stress test is carried out on 51 banks. Where 37 banks are from SSM countries. Moreover, 14 banks are from the Denmark, Hungary, Norway, Poland, U.K., and Sweden. Norway is a member of the European Economic Area.

Since 22 high-cap banks are not publicly listed companies, then FF3 is applied on a sample of 29 high-cap banks. Table 6 shows the country of origin, the name, the ticker symbol, and the currency of the 29 sample banks on which FF3 is applied.

Table 6. Sample banks on which Fama-French three factor model is applied

Country	**Name**	**Ticker**	**Currency**
Austria	Erste Group Bank AG	EBS AV	Euro
Belgium	KBC Group NV	KBC BB	Euro
Denmark	Danske Bank	DANSKE DC	Danish Krone
	Jyske Bank	JYSK DC	Danish Krone
France	BNP Paribas S.A.	BNP FP	Euro
	Societe Generale S.A.	GLE FP	Euro
Germany	Commerzbank AG	CBK GR	Euro
	Deutsche Bank AG	DBK GR	Euro
Hungary	OTP Bank Nyrt.	OTP HB	Hungarian Forint
Ireland	Allied Irish Banks plc	ALBK ID	Euro
Italy	Banca Monte dei Paschi di Siena S.p.a.	BMPS IM	Euro
	Intesa Sanpaolo S.p.a.	ISP IM	Euro
	UniCredit S.p.a.	UCG IM	Euro
	Unione di Banche Italiane S.p.a.	UBI IM	Euro
Netherlands	ING Group N.V.	INGA NA	Euro
Norway	DNB Bank Group	DNB NO	Norwegian Krone
Poland	Powszechna Kasa Oszczednosci Bank Polski	PKO PW	Polish Zloty
Spain	Banco Bilbao Vizcaya Argentaria S.A.	BBVA SM	Euro
	Banco de Sabadell S.A.	SAB SM	Euro
	Banco Popular Espanol S.A.	POP SM	Euro
	Banco Santander S.A.	SAN SM	Euro
Sweden	Nordea Bank-group	NDA SS	Swedish Krone
	Skandinaviska Enskilda Banken-group	SEBA SS	Swedish Krone
	Svenska Handelsbanken-group	SHBA SS	Swedish Krone
	Swedbank-group	SWEDA SS	Swedish Krone
United Kingdom	Barclays Plc	BARC LN	Pound Sterling
	HSBC Holdings Plc	HSBA LN	Pound Sterling
	Lloyds Banking Group Plc	LLOY LN	Pound Sterling
	The Royal Bank of Scotland Group Plc	RBS LN	Pound Sterling

Data source: Bloomberg Finance L.P. (2018), *Company overview of high-cap European banks*, 2017.

The fundamental assumption of the EU-wide stress test is the static balance sheet. The static balance sheet assumption imposes that all the assets and liabilities which mature during the period of the test must be replaced with similar assets and liabilities. The replaced instruments must be similar in terms of type, maturity, and credit quality. Banks are also assumed to have zero growth, keep the same business mix, and keep the same business model throughout the exercise. The consequences of adverse macroeconomic scenarios are reported in terms of Common Equity Tier 1 (hereinafter: CET1) capital. CET1 is defined by

Basel III as the sum of common shares issued by the bank and consolidated subsidiaries, share premium resulting from the issue of instruments, and share earnings. The starting CET1 ratio as of year-end 2015 of the sample banks is 13.2%. CET1 ratio is calculated by EBA as the ratio between CET1 and risk weighted assets. In 2015 CET1 ratio increased by 200 basis points with respect to the sample of banks analyzed by EBA in 2014. The negative scenario of the 2016 EU-wide stress test has a negative impact on CET1 ratio of 380 basis points. Therefore, on date 31 December 2018 which is the end of the shocks period, the CET1 ratio for the 2016 EU-wide stress test's sample of banks decreased to 9.4%.

2.2 Method

In this Master's thesis FF3 is used to estimate the cost of capital for high-cap European banks. FF3 finds little application in the banking industry. But some researchers suggest that the model works well in explaining the stock returns of banks. For example, Barber and Lyon (1997) find that FF3 has the same explanatory power on stock returns of both financial and non-financial companies listed on the NYSE for the period 1973-1994. Moreover, Schuermann and Stiroh (2006) analyze a sample of banks with reference period 1997-2005 using different asset pricing models. The result shows that FF3 is the best asset pricing model in explaining stock returns (Schuermann & Stiroh, 2006). Even Baek and Bilson (2015) argue that FF3 describes the stock returns of banks. Their research is based on a sample of financial companies listed in the U.S., and the period of the analysis is 1963-2012. So, the just mentioned researches suggest that FF3 is an asset pricing model able to describe the stock returns of banks.

An essential step for the estimation of the cost of capital of the high-cap European banks concerns the choice of data input. Data input consists in the variables used for the FF3 equation. Equation (8) shows the FF3 equation used to describe the high-cap European bank stock excess returns. Where $E(R_i)$ is the expected stock return on bank, R_{E12m} is the rate of Euribor 12 months, β^i_{SXXP} is the coefficient estimate of MRP, R_{SXXP} is the return on Stoxx Europe 600, β^i_{SMB} is the coefficient estimate of SMB, SMB is the size variable, β^i_{HML} is the coefficient estimate of HML, and HML is the value variable:

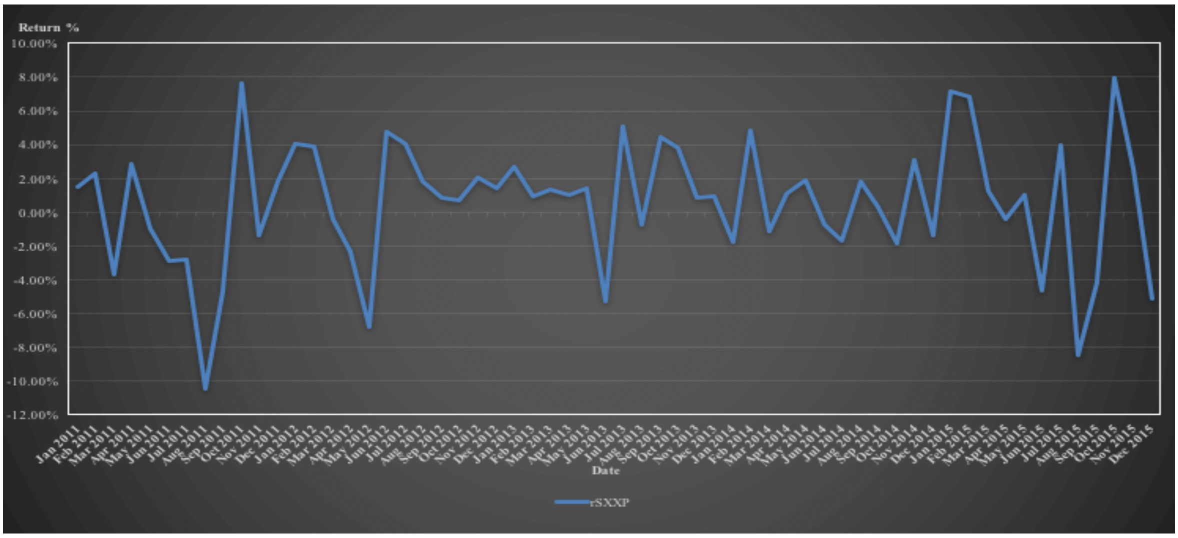
$$E(R_i) - R_{E12m} = \beta^i_{MRP}\left((R_{SXXP}) - (R_{E12m})\right) + \beta^i_{SMB}(SMB) + \beta^i_{HML}(HML) \qquad (8)$$

Hence, stock index, risk-free rate, SMB, HML, and the length of historical data have to be explained at first. The historical data length is five years. The reference period of data goes from 31 January 2011 to 31 December 2015. So, time-series regressions are employed using 60 months of historical data. All the data of each variable are monthly values. The dependent variable is the stock excess return of each high-cap European bank. Whereas, the three explanatory variables are MRP, SMB, and HML. Moreover, MRP is here calculated as the difference between the return on stock index and the risk-free rate. Whereas, the stock index is Stoxx Europe 600. And the risk-free rate is Euribor 12 months.

2.2.1 Market index

One of the three explanatory variables of FF3 is MRP, which is the value of the stock index return over the risk-free rate. Stoxx Europe 600 is a stock index constructed on a fix number of 600 companies and made of high-cap, mid-cap, and small-cap companies from 17 European countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Luxemburg, Netherlands, Norway, Portugal, U.K., Sweden, Switzerland, and Spain. Moreover 28 out of 29 high-cap European banks are components of Stoxx Europe 600. Powszechna Kasa Oszczednosci Bank Polski (hereinafter: PKO PW) is the only bank which is not part of Stoxx Europe 600. However, since Poland is part of the Euroean economy, Stoxx Europe 600 is a proper index also for PKO PW. Monthly returns of Stoxx Europe 600 for the period 31 December 2010 to 31 December 2015 are retrieved from Bloomberg (Bloomberg L.P., 2017). Figure 9 shows the historical return on Stoxx Europe 600.

Figure 9. Monthly return on Stoxx Europe 600



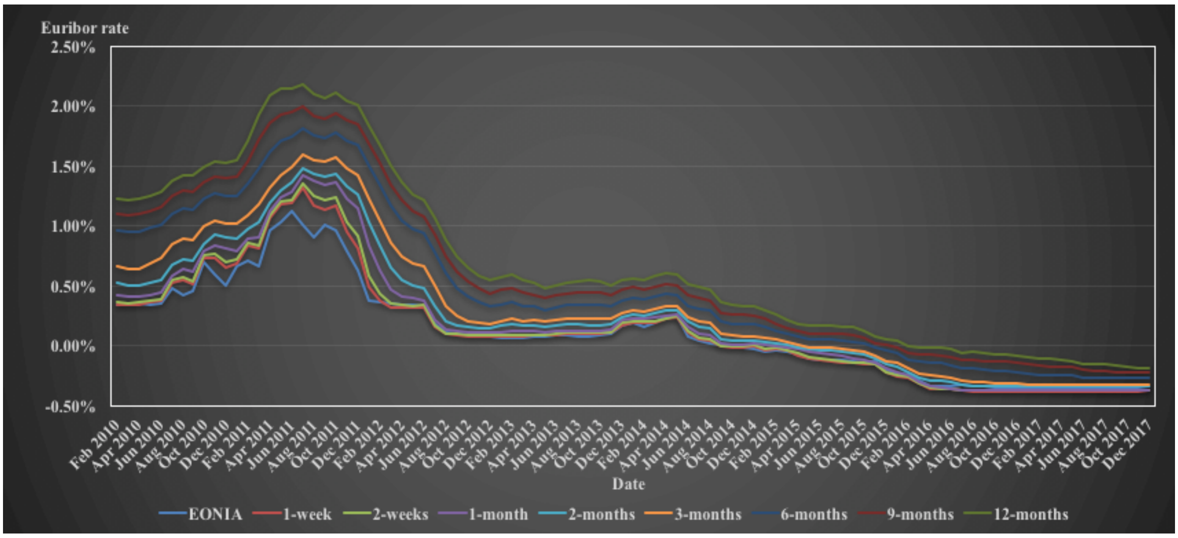
Data source: Bloomberg Finance L.P. (2018), *Return on Stoxx Europe 600,* 2017; own calculation.

2.2.2 Risk- free rate

The risk-free rate is the rate of return of a zero-risk investment. U.S. government bonds and German government bonds with maturities ranging from 20 to 30 years are commonly used as risk-free assets. Usually the maturity of the risk-free rate asset reflects the maturity of overall investments of a company. The FF3 regression applied in this Master’s thesis does not use government bonds as the risk free-rate, this is mainly due to the fact that the European banking industry has an internal rate for deposits among banks. Hence, since this research is based on the high-cap European banking industry, Euribor 12 months is used as the risk-free rate. The 12 months maturity is the Euribor rate with the shortest maturity having positive values for the entire reference period which goes from 31 December 2010 to 31 December

2015. Thus, a total of 60 monthly rates are collected. Monthly rates of Euribor 12 months are retrieved from Bloomberg (Bloomberg L.P., 2017). Euribor is the daily rate at which banks of the Economic and Monetary Union offer term deposits in the Euro interbank market to other Economic and Monetary Union banks and it is published by the European Money Market Institute (hereinafter: EMMI). There are 9 Euribor maturities: Euro Overnight Index Average (hereinafter: EONIA), one week, two weeks, one month, two months, three months, six months, nine months, and 12 months. A panel of 20 banks contribute to Euribor, and half of them are part of the sample of high-cap European banks (EMMI, 2016). Namely BNP Paribas, Societe Generale, Deutsche Bank, Intesa San Paolo, Monte dei Paschi di Siena, UniCredit, ING Group, Banco Bilbao Vizcaya Argentaria, Banco Santander, and Barclays. To be part of the panel banks contributing to Euribor, a bank must be an active participant in the euro money markets in the euro-zone or an active participant in the euro money markets worldwide. Moreover, a bank to be qualified as a panel member must hold a significant volume in euro-interest rate related instruments (EMMI, 2016). Historical Euribor rates are shown in Figure 10. Euribor rates are decreasing for all maturities since the last quarter of 2011.

Figure 10. Historical Euribor rates



Data source: Bloomberg Finance L.P. (2018), *Last price of Euribor*, 2017; own calculation.

2.2.3 Size factor and value factor

Monthly European values of SMB and HML for the period 31 January 2011 to 31 December 2015 are retrieved from the data library of K.R. French (2017). SMB is constructed by dividing European stocks according to their size. The market cap at the end of June of each year is the reference point for the classification of stocks in small and big. Where top 90% market cap represents big stocks. Whereas bottom 10% market cap identifies small stocks. HML is created by identifying three BE/ME groups among big stocks. The 30th and 70th percentiles of BE/ME for big stocks are used as reference points. The next step consists in the identification of six portfolios. The six portfolios are constructed from the interaction of two size portfolios and three BE/ME portfolios. Then the monthly value of SMB is obtained from equation (6) and the monthly value of HML is calculated from equation (7). The European values of SMB and HML include all listed companies of Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal, and Sweden.

2.3 Empirical analysis

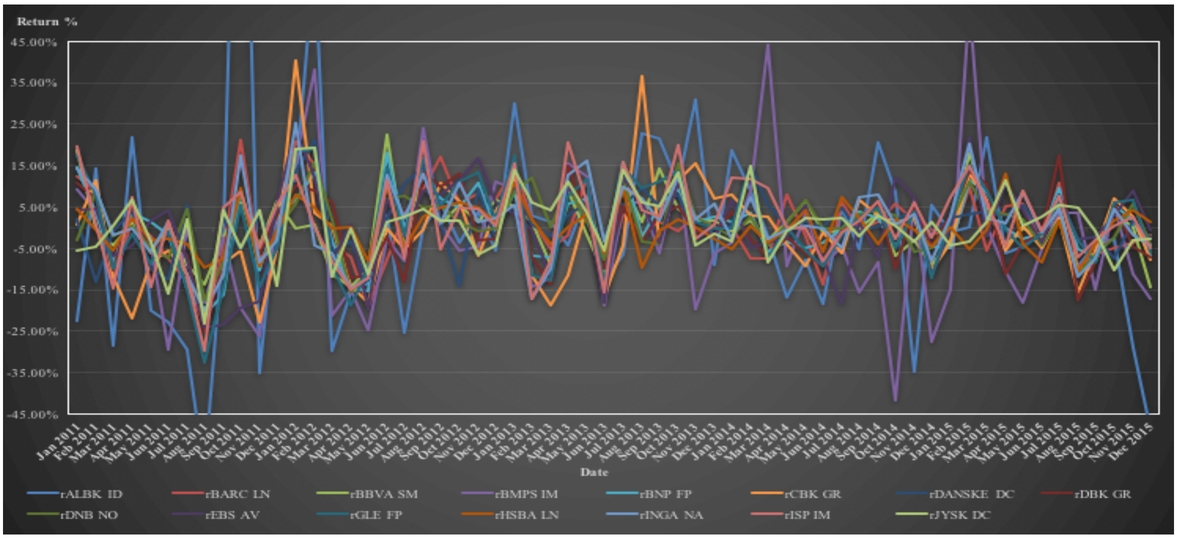
2.3.1 Stock returns

Monthly stock excess returns on each sample bank is used as dependent variable of FF3. The monthly values of bank stock returns are calculated as the difference of the monthly stock last price at time t and the monthly stock last price at time (t-1), divided by the monthly stock last price at time (t-1). Dividends are excluded from the calculation of bank stock returns to catch the extremely low profitability of the European banking industry since 2008 (KPMG, 2016). Monthly last prices of bank stocks range from 31 December 2010 to 31 December 2015, and are retrieved from Bloomberg (Bloomberg L.P., 2017). The exchange rate applied to non-EUR currencies is the one effective on date 31 December 2015. The Swedish Krona (hereinafter: SEK) to EUR is EUR 0.108971. The British Penny (hereinafter: GBp) to EUR is EUR 0.013586 instead. The Danish Krone (hereinafter: DKK) to EUR is EUR 0.134035. The Norwegian Krone (hereinafter: NOK) to EUR is EUR 0.103935. The Polish Zloty (hereinafter: PLN) to EUR is EUR 0.233873. And the Hungarian Forint (hereinafter: HUF) to EUR is EUR 0.003166. Equation (9) shows the calculation of the monthly stock returns. Where R_t^i is the monthly return on the bank stock at time t, PXL_t^i is the monthly last price of the bank stock at time t, and PXL_{t-1}^i is the monthly last price of the bank stock at time (t-1):

$$R_t^i = \frac{(PXL_t^i - PXL_{t-1}^i)}{PXL_{t-1}^i} \tag{9}$$

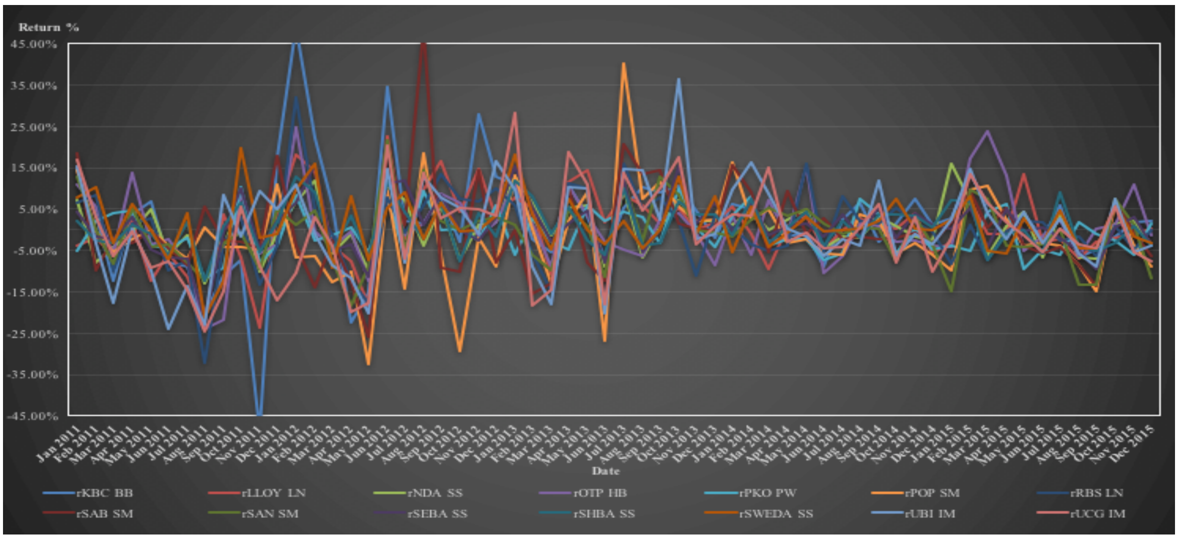
Historical monthly returns of each high-cap European bank for the period 31 January 2011 to 31 December 2015 are shown in Figure 11 and Figure 12. The sample of high-cap European banks is here split in to two different groups. Group-1 is shown in Figure 11, and group-2 is shown in Figure 12. The high-cap European banks in group-1 are Allied Irish Bank (hereinafter: ALBK ID), Barclays (hereinafter: BARC LN), Banco Bilbao Vizcaya Argentaria (hereinafter: BBVA SM), BMPS IM, BNP Paribas (hereinafter: BNP FP), Commerzbank (hereinafter: CBK GR), Danske Bank (hereinafter: DANSKE DC), Deutsche Bank (hereinafter: DBK GR), DNB Bank Group (hereinafter: DNB NO), Erste Group Bank (hereinafter: EBS AV), Societe Generale (hereinafter: GLE FP), HSBC Holdings (hereinafter: HSBA LN), ING Group (hereinafter: INGA NA), Intesa Sanpaolo (hereinafter: ISP IM), and Jyske Bank (hereinafter: JYSK DC). Whereas the high-cap banks in group-2 are KBC Group (hereinafter: KBC BB), Lloyds Banking Group (hereinafter: LLOY LN), Nordea Bank-group (hereinafter: NDA SS), OTP Bank (hereinafter: OTP HB), PKO PW, Banco Popular Espanol (hereinafter: POP SM), The Royal Bank of Scotland group (hereinafter: RBS LN), SAB SM, Banco Santander (hereinafter: SAN SM), Skandinaviska Enskilda Banken-group (hereinafter: SEBA SS), Svenska Handelsbanken Group (hereinafter: SHBA SS), Swedbank Group (hereinafter: SWEDA), Unione di Banche Italiane (hereinafter: UBI IM), and UniCredit (hereinafter: UCG).

Figure 11. Monthly return on high-cap European banks group-1



Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Figure 12. Monthly return on high-cap European banks group-2



Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

2.3.2 Market risk premium

MRP is defined as the excess return on stock over the risk-free rate which is required by an investor to invest in a diversified portfolio (JP Morgan Chase, 2008). There are different ways to calculate MRP, but the most common one is the historical realized return method. Equation (10) shows the calculation of MRP through the historical realized return method which is given by the difference between monthly returns on Stoxx Europe 600 and monthly returns on Euribor 12 months. Where MRP_t is the monthly value of MRP at time t, R_{SXXP_t} is the monthly return on Stoxx Europe 600 at time t, and R_{E12m_t} is the rate of Euribor 12 months at time t:

$$MRP_t = R_{SXXP_t} - R_{E12m_t} \tag{10}$$

The historical realized return method is used as a consequence that it focuses on historical data. However, beside the historical realized return method other methods used by researchers to estimate the MRP are the dividend discount method (hereinafter: DDM) and the constant Sharpe-ratio method (JP Morgan Chase, 2008). DDM is used to estimate the implied cost of equity capital and two inputs are required. The first input is the price and the second input is the expected dividend stream of a stock index. To obtain an estimate for future dividends, earnings must be forecasted at first. The next five years earnings are expected to grow according to market estimates. Whereas, earnings after five years are assumed to growth in perpetuity as the long-term nominal GDP rate. Then the dividend payout ratio must be calculated too. Usually the historical average dividend payout ratio is used for the short-term forecast. On the other hand, the dividend payout ratio in the long-term is assumed to approach 80%. Which highlights the decline of the investment opportunities over time (JP Morgan Chase, 2008). The equation for the market cost of equity capital through DDM is described by (11). Where P_t is price at time t, DIV_t is dividend forecast at time t, and $(1 + cost\ of\ equity)^t$ is one plus the implied cost of equity at the power of t:

$$P_t = \sum_{t=1}^{\infty} \frac{DIV_t}{(1+cost\ of\ equity)^t} \tag{11}$$

Then MRP is calculate as the difference between DDM implied cost of equity capital and the risk-free rate. MRP through DDM is shown in equation (12). Where MRP_{DDM} is MRP through DDM, $CEC_{DDMimplied}$ is the cost of equity capital implied from DDM, R_f is the risk-free rate:

$$MRP_{DDM} = CEC_{DDMimplied} - R_f \tag{12}$$

A further method used for the estimation of MRP is the constant Sharpe-ratio method. The SR is generally used as a measure of excess return per unit of risk. The risk is usually measured and defined as the implied volatility of the portfolio. The longer the period of historical data the more precise SR estimate. Equation (13) shows the SR. Where SR is the Sharpe-ratio, R_p is the return on the portfolio, R_f is the risk-free rate, and σ_p is the volatility of the portfolio:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{13}$$

MRP is then obtained by multiplying the constant Sharpe-ratio by an estimate of the market's future volatility. Note that the SR is assumed to be constant over time even if it might not be the real case. Equation (14) shows how to obtain an estimate of MRP using SR. Where MRP_{SR} is MRP through SR, SR_m is the stock-market SR, and σ_m is the volatility of the portfolio:

$$MRP_{SR} = SR_m \times \sigma_m \tag{14}$$

The future volatility of the market is an estimate very difficult to obtain. There is not a clear way to do it. A method employed to estimate the future volatility of the market concerns the use of indices measuring the implied volatility of stock-market options (JP Morgan Chase, 2008).

2.3.3 Dataset of the multiple linear regressions

Three explanatory variables are used to explain stock returns. Namely MRP, SMB, and HML. Each of them proxy for systematic risk. After regressing the dependent variable on the three explanatory variables, a beta-coefficient (hereinafter: β) is estimated. Each explanatory variable has one β. The β of MRP to bank i is β_{MRP_i} , the β of SMB to bank i is β_{SMB_i}, and the β of HML to bank i is β_{HML_i}. β represents the change in the expected stock return per unit increase in the associated explanatory variable with the other explanatory variables held constant. β_{MRP_i}, β_{SMB_i}, and β_{HML_i} are estimated through OLS method. OLS is used in linear regression analysis and minimizes the sum of the squares of the differences between the observed sample values and the values predicted by a linear function of explanatory variables (Gujarati & Porter, 2009).

A total of 29 multiple linear regressions are run, one for each high-cap European bank. For each multiple linear regression one dependent variable is regressed on three explanatory variables. The regressions' outcome is three β for high-cap European bank. The dependent variable is given by the difference between monthly return on stocks and monthly Euribor 12 months rates. Whereas the explanatory variables employed are monthly values of MRP, SMB, and HML. Monthly values of the explanatory variables and monthly values of the risk-free rate do not change across multiple linear regressions. The reference period of data is 31 January 2011 to 31 December 2015, for a total of 60 months.

2.3.4 Coefficient estimates

Classical theory of statistical inference is based on two branches, namely estimation and hypothesis testing (Gujarati & Porter, 2009). According to the first branch, if the assumptions of the Classical Linear Regression Model (hereinafter: CLRM) are satisfied, then OLS estimator is the Best Linear Unbiased Estimator (hereinafter: BLUE). The OLS estimator is said to be BLUE as a consequence of the following properties. The BLUE estimator is the one with minimum variance in the class of linear unbiased estimators, hence best. The BLUE estimator is a linear function of the dependent variable. The BLUE estimator is unbiased since its expected value is equal to the true value of β.

The seven assumptions made by CLRM concern the variables and the error term (Gujarati & Porter, 2009). Linearity of the regression model is the first assumption. According to the first assumption the parameters of the model are linear, whereas the dependent and explanatory variables might be non-linear. CLRM's second assumption tells that the explanatory variables have to be non-random. So, fixed in repeated samples. Or in the case that the explanatory variables change with the dependent variable, hence having stochastic explanatory variables, then the explanatory variables have to be independent from the error term. The third assumption concerns the error term, the mean value of the error term is assumed to be zero. Homoscedasticity of the error term is the fourth assumption. The fourth assumption requires the error term to have constant variance for whichever value of the explanatory variables. The fifth assumption presumes the error terms to be not correlated between them. Hence the deviation of the values of an explanatory variable doesn't have to show any pattern. The sixth assumption requires the number of the observations to be greater than the number of the parameters and thus of the explanatory variables. According to the last assumption, the seventh one, there should be variability in the values of each explanatory variable. Assumptions of CLRM might be perceived as unrealistic, but what is important are the predictions based on CLRM's assumptions (Gujarati & Porter, 2009).

Hypothesis testing instead is used to know how close β estimates are to the true βs. The β estimates are random variables, so their values change according to the sample used. As a consequence of being a random variable, β estimates follow a probability distribution. The classical normal linear regression model assumes that the residuals follow a normal probability distribution. Since β estimates are a linear function of the residuals, then β estimates are normally distributed too.

Hypothesis testing is based on a null hypothesis (hereinafter: H_0) and on an alternative hypothesis (hereinafter: H_1). The H_0 assumes β to be equal to zero. Whereas H_1 assumes β to be different from zero. The level of significance (hereinafter: α) is set at 0.05, so H_0 is rejected for p-values smaller than 0.05, and H_0 is not rejected for p-values greater than 0.05. Rejecting H_0 entails that the coefficient of the explanatory variable is statistically significant different from zero, hence there is evidence of a statistical relationship between the explanatory variable and the dependent variable. However, a statistical relationship does not imply causation. Furthermore the H_0 of each β is rejected or not rejected but never accepted. Then it is not possible to conclude that an explanatory variable is not related to the dependent variable even in the case of a non-statistically significant coefficient (Gujarati & Porter, 2009).

2.3.5 Interpretation of the regression coefficients

The regression outcome of each of the 29 high-cap European banks consists of three β. The regressions link the excess return on the high-cap European banks with three explanatory variables, namely MRP, SMB, and HML. Then, equation (8) is used for each of the 29 regressions. The way the explanatory variable coefficients are interpreted is the same for each bank. The coefficients β_{MRP_i}, β_{SMB_i}, and β_{HML_i} represent the impact of MRP, SMB, and HML on each sample bank. Moreover, the confidence interval approach, the t-test, and the p-value of β are all used to test whether coefficient estimates are in line with some hypothesis about the true coefficient parameter. The underlying H_0 and H_1 used for hypothesis testing are the same for each coefficient and for all banks:

- $\mathrm{H_0}: \beta_{\mathrm{MRP_i}} = 0$ and $\mathrm{H_1}: \beta_{\mathrm{MRP_i}} \neq 0$;
- $\mathrm{H_0}: \beta_{\mathrm{SMB_i}} = 0$ and $\mathrm{H_1}: \beta_{\mathrm{SMB_i}} \neq 0$;
- $\mathrm{H_0}: \beta_{\mathrm{HML_i}} = 0$ and $\mathrm{H_1}: \beta_{\mathrm{HML_i}} \neq 0$.

Whereas the F-test is used to test FF3 model as a whole. Thus H_0 and H_1 of the F-test are:

- $\mathrm{H_0}$: all the βs equal to 0;
- $\mathrm{H_1}$: at least one β different from 0.

The strength of the explanatory variable coefficients, namely β_{MRP_i}, β_{SMB_i}, and β_{HML_i} is subjective to each bank, but all βs are interpreted as follows:

- if average MRP increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of bank i increases/decreases by β_{MRP_i}% points;
- if average SMB increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of bank i increases/decreases by β_{SMB_i}% points;
- if average HML increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of bank i increases/decreases by β_{HML_i}% points.

Given that the mathematical expectations modeled are on average, the term average is used in the interpretation. Moreover, the mathematical expectation modeled are conditional to other explanatory variables, hence the term *ceteris paribus* is included in the interpretation.

Ceteris paribus is a Latin expression for "other things equal". Among the sample of high-cap European banks there are two banks exhibiting substantially different results in terms of interpretation and hypothesis testing. The two banks are BMPS IM and SHBA SS.

Before interpreting the regression outcome of BMPS IM and the regression outcome of SHBA SS, the items of Figure 13 which shows the regression outcome of BMPS IM and Figure 14 which shows the regression outcome of SHBA SS are going to be described. R is the sample correlation coefficient, R measures the degree of association between two variables. Instead R-square is the coefficient of determination, and measures the proportion of the dependent variable's total variance which is described by the explanatory variables (Gujarati & Porter, 2009). Equation (15) shows how to calculate R-square, where R^2 is R-square, ESS is explained sum of squares, and TSS is total sum of squares:

$$R^2 = \frac{ESS}{TSS} \tag{15}$$

Adjusted R-square adjusts R-square when many explanatory variables are used. Equation (16) shows how to calculate adjusted R-square, where $AdjR^2$ is adjusted R-square, RSS is residual sum of squares, $(n - 1)$ is the number of observation minus one, TSS is total sum of squares, and $(n - p - 1)$ is the number of observation minus the number of explanatory variables and minus one:

$$AdjR^2 = 1 - \frac{RSS/_{(n-1)}}{TSS/_{(n-p-1)}} \tag{16}$$

S is the standard error of the regression, and tells on average how far values of the dependent variable are from the regression line in absolute terms. Moreover, N is the total number of observations. The analysis of variance is represented by the F-test. Where df are the degrees of freedom, SS is the sum of squares. The value appearing from the combination of the label named Regression and SS is the explained sum of square. Whereas the value appearing from the combination between Residual and SS is the residual sum of squares. The result of the sum of explained sum of squares and residual sum of squares is the total sum of squares. MS is the average sum of square given the degrees of freedom, and it is calculated as the ratio between the sum of squares and degrees of freedom. F is the F-test statistic, the F-test statistic is the result of the ratio between the between group variability and the within group variability. The higher the F-test statistic the greater the evidence against H_0.

Moreover, the p-level is a measure of the strength of evidence against H_0. The p-value is the lowest level of significance at which H_0 can be rejected. The p-value is the probability of getting a t-statistic equal or higher than the one observed. The smaller the p-value the greater the evidence against H_0. Each coefficient represents the mean change in the dependent variable for one unit change in the explanatory variable holding the other explanatory variables constant. The market model argues that the mean value of the regression intercept in an efficient market is zero. Standard error of the coefficient represents the standard deviation of the coefficient. The smaller the standard error of the coefficient the more precise is the explanatory variable coefficient estimated through the model. LCL is the lower confidence level of the coefficient (Gujarati & Porter, 2009). The calculation is shown in equation (17), where LCL is the lower confidence interval, $E(\beta)$ is the expected value of the coefficient, $t_{\alpha/2}$ is the value from the t-table given the degrees of freedom and the level of significance, and $SE_{E(\beta)}$ is the standard error of the expected value of the coefficient:

$$LCL = E(\beta) - t_{\alpha/2} \times SE_{E(\beta)} \tag{17}$$

On the other hand, UCL is the upper confidence level of the coefficient. Equation (18) shows how to calculate the upper confidence level, where UCL is the upper confidence level, $E(\beta)$ is the expected value of the coefficient, $t_{\alpha/2}$ is the value from the t-table given the degrees of freedom and the level of significance, and $SE_{E(\beta)}$ is the standard error of the expected value of the coefficient:

$$UCL = E(\beta) + t_{\alpha/2} \times SE_{E(\beta)} \tag{18}$$

The confidence interval approach states that if β of H_0 falls in the confidence interval then H_0 is not rejected, on the other hand if β of H_0 falls outside the confidence interval then H_0 is rejected (Gujarati & Porter, 2009). The t-stat is the test statistic of β of the t-test. Equation (19) shows how to obtain the t-stat, where $t - stat$ is the t-statistic, β_i is the coefficient estimate, β_{H_0} is the coefficient under the null hypothesis, and $SE\beta_i$ is the standard error of the coefficient estimate:

$$t - stat = \frac{\beta_i - \beta_{H_0}}{SE\beta_i} \tag{19}$$

The t-stat follows a t-distribution with (n-1) degrees of freedom. The t-test, also known as test of significance approach, is used to test hypothesis as an alternative to the confidence interval approach. According to the test of significance approach, H_0 is rejected if the t-stat lies in the critical region. Instead if t-stat lies in the not rejection region the H_0 is not rejected. The region of not rejection area is the (1- α) probability that β is within the two critical values assuming H_0 to be the true parameter (Gujarati & Porter, 2009). Where α is the level of significance. T(5%) is the critical value from two-tailed t-table with 95% confidence interval and 59 df. H_0(5%) is the level of significant, hence the probability of rejecting the true hypothesis, which is known as type one error. H_0 is rejected for p-level lower than 0.05. For now, the research is conducted at micro level only. An overall view at macro level is going to be discussed later on. Figure 13 shows the elements of the regression outcome of BMPS IM. Figure 13 the βs, the related hypothesis testing and the resulting linear equation.

Figure 13. Banca Monte dei Paschi di Siena S.p.a. regression outcome

Linear Regression

Regression Statistics	
R	0.65385
R-square	0.42752
Adjusted R-squa	0.39686
S	0.13264
N	60

E(rBMPS IM - rE12M) = - 0.023 + 1.42749 * E(MRP) + 2.22308 * E(SMB) + 3.42476 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.73582	0.24527	13.94021	6.67085E-7
Residual	56.	0.9853	0.01759		
Total	59.	1.72111			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**-0.023**	0.01737	-0.0578	0.0118	-1.32373	0.19097	**not rejected**
MRP	**1.42749**	0.51136	0.40312	2.45186	2.79158	0.00716	**rejected**
SMB	**2.22308**	1.05832	0.10301	4.34315	2.10057	0.04019	**rejected**
HML	**3.42476**	0.76374	1.8948	4.95472	4.48417	0.00004	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

The interpretation of the regression coefficient estimates shown in Figure 13 for BMPS IM is the following:

- if average MRP increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of BMPS IM increases by 1.42749% points;
- if average SMB increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of BMPS IM increases by 2.22308% points;
- if average HML increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of BMPS IM increases by 3.42476% points;

The estimates of β_{MRP_i}, β_{SMB_i}, and β_{HML_i} for BMPS IM are all statistically significant different from zero. Indeed, by setting the level of significance at 5%, the p-value of each coefficient estimate is lower than 5%. Moreover, the ability of the three explanatory variables to explain the monthly excess returns of BMPS IM is confirmed by the confidence interval approach and the t-test. According to the confidence interval approach H_0 is rejected for all three β. As a matter of fact, in each of the three hypothesis tests the $H_0$of β equal to zero falls out from the confidence interval. Even the t-test suggests that the three β are statistically significant different from zero. The absolute value of the t-stat of each coefficient is greater than 2, which means that H_0 can be rejected. This rule of thumb, called 2-t, and according to which H_0 of β equal to zero is rejected in the case that the t-stat is greater than 2 in absolute value. This rule of thumb only works in the case in which the degrees of freedom are greater than 20 and the level of significance must be set at 5%

(Gujarati & Porter, 2009). The model as a whole explains 42.75% of BMPS IM monthly excess return's variance. According to the F-test the relationship between the model and BMPS IM monthly excess returns is highly statistically significant different from 0. Indeed, the p-value is very small, its value is 0.0000007. And the value of the F-statistics is 13.94021. On the other hand, Figure 14 shows the elements of the regression outcome of SHBA SS. Figure 14 include the βs, the related hypothesis testing and the resulting linear equation.

Figure 14: Svenska Handelsbanken-group regression outcome

Linear Regression

Regression Statistics	
R	0.65358
R-square	0.42716
Adjusted R-squa	0.39648
S	0.0437
N	60

E(rSHBA SS - rE12M) = 0.00347 + 0.97089 * E(MRP) + 0.27599 * E(SMB) + 0.03989 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.07973	0.02658	13.91972	6.78665E-7
Residual	56.	0.10692	0.00191		
Total	59.	0.18665			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00347**	0.00572	-0.00799	0.01494	0.60709	0.54624	**not rejected**
MRP	**0.97089**	0.16845	0.63344	1.30833	5.76367	3.67229E-7	**rejected**
SMB	**0.27599**	0.34863	-0.42239	0.97438	0.79166	0.4319	**not rejected**
HML	**0.03989**	0.25159	-0.46411	0.54388	0.15853	0.87461	**not rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

The interpretation of the regression coefficient estimates obtained in Figure 14 for SHBA SS is the following:

- if average MRP increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of SHBA SS increases by 0.97089% points;
- if average SMB increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of SHBA SS increases by 0.27599% points;
- if average HML increases by 1% point then on average, *ceteris paribus*, the estimated cost of capital of SHBA SS increases by 0.03989% points;

Apparently, the F-test suggests that the model as a whole is able to explain SHBA SS monthly excess return. Indeed, the p-value of the F-test is extremely low its value is 0.0000007. But the result of tests conducted on each estimate are different. The confidence interval approach, the T-test, and p-values all suggest that the estimates of β_{SMB_i}, and β_{HML_i} for SHBA SS are not statistically significant different from zero. Whereas the estimate of β_{MRP_i} is statistically significant different from zero. Hence the misleading result of the F-test is driven by the very low probability of β_{MRP_i} to be equal to zero. Moreover, β_{SMB_i}, and β_{HML_i} are not statistically significant different from zero as a consequence that their estimates are very close to zero. However, results might be biased by the reference period of inputs. Thus, even if coefficients are not statistically significant different from zero for the period 2011-2015, coefficients might be statistically significant different from zero once FF3 is tested for a different period.

2.3.6 Average values of the explanatory variables

The expected value of each explanatory variable is needed to successfully estimate the impact of the three risk factors on the cost of capital for the sample of high-cap European banks. Usually the longer the period of historical data, the more precise is the computation of the expected value. Moreover, the same reference period must be applied to all explanatory variables. So, it is not possible to use data prior to year 1999. Just because the date of the creation of Euribor rates coincides with the introduction of EUR currency, which is year 1999. Hence the expected values used for the estimation of the cost of capital for high-cap European banks consist of data with reference period 1999-2015. The expected value of MRP is the mean value of the difference between the yearly return on Stoxx Europe 600 and yearly rate of Euribor 12 months for the period 1999-2015. Whereas the expected values of SMB and HML correspond to the mean value of the yearly values of SMB and HML for the period 1999-2015. Calculation of average MRP is shown in Table 7 whereas calculation of average SMB and average HML are shown in Table 8.

Table 7. Average market risk premium

Year	Rsxxp	E12m	MRP
2015	0.06793	0.00060	0.06733
2014	0.04350	0.00325	0.04025
2013	0.17370	0.00556	0.16814
2012	0.14370	0.00542	0.13828
2011	-0.11338	0.01947	-0.13285
2010	0.08634	0.01507	0.07127
2009	0.27995	0.01248	0.26747
2008	-0.45601	0.03049	-0.48650
2007	-0.00170	0.04745	-0.04915
2006	0.17814	0.04028	0.13786
2005	0.23464	0.02844	0.20620
2004	0.09507	0.02356	0.07151
2003	0.12822	0.02305	0.10517
2002	-0.31962	0.02749	-0.34711
2001	-0.16971	0.03341	-0.20312
2000	-0.05191	0.04749	-0.09940
1999	0.35920	0.03876	0.32044
Average	0.03989	0.02366	0.01622

Data source: Bloomberg Finance L.P. (2018), *Return on Stoxx Europe 600*, 2017; Bloomberg Finance L.P. (2018), *last price of Euribor 12 months*, 2017; own calculation.

Table 8. Average size variable and average value variable

Year	SMB	HML
2015	0.10820	-0.16680
2014	-0.02100	-0.04930
2013	0.08570	0.09350
2012	0.01010	0.02140
2011	-0.07560	-0.12430
2010	0.10160	-0.07980
2009	0.14350	0.02610
2008	-0.06480	-0.03470
2007	-0.09160	0.00200
2006	0.07670	0.09840
2005	0.05840	0.09430
2004	0.08250	0.10850
2003	0.13480	0.21060
2002	0.08350	0.21090
2001	0.00910	0.26080
2000	-0.05760	0.27900
1999	0.15160	-0.23090
Average	0.04324	0.04234

Data source: Kenneth R. French (2018), *Fama/French European 3 Factors*, 2017; own calculation.

2.4 Result

The estimated cost of capital is calculated by adding together the estimates of the three risk factors, namely MRP, SMB, and HML. The estimate of the market factor is obtained by multiplying β_{MRP_i} by average MRP, the size factor is estimated by multiplying β_{SMB_i} by average SMB, and the value factor is estimated by multiplying β_{HML_i} by average HML. Hence the cost of capital of each European high-cap bank results from the combination of β and average value of the explanatory variables, which are obtained from Table 7 and Table 8. The outcome of the 29 multiple linear regressions is the β of the explanatory variables, hence the estimated cost of capital is ready to be estimated by using equation (8). However, the estimated cost of capital is computed by adding the intercept values to the values of the risk factors too. The role of the intercept still not clear in literature. But it is generally accepted that accordingly to the market model the intercept is zero in an efficient market.

The cost of capital is estimated employing two different approaches regarding βs. The first approach make use of statistically significant βs and of statistically non-significant βs. On the other hand, the second approach make use of statistically significant βs only. For both approaches values of the estimated cost of capital which are lower than 4.5% suggest that FF3 is not usable for those banks. However, FF3 might be successfully employed also for those banks by using a different reference period of the inputs. The threshold is subjectively set at 4.5%, which reflects the overall extremely low profitability of the European banking industry since 2008 (KPMG, 2016). βs, average values of the explanatory variables, and the intercept of each bank included in the sample of high-cap European banks are shown in Table 9, where the cells of statistically significant β values are highlighted in light blue.

Table 9. Coefficient estimates and average values of explanatory variables

Ticker	E (intercept)	E (beta MRP)	Mean(MRP)	E (beta SMB)	Mean(SMB)	E (beta HML)	Mean(HML)
ALBK ID	-0.00191	3.09207	0.01622	0.34073	0.04324	0.97417	0.04234
BARC LN	0.00129	1.39404	0.01622	1.09312	0.04324	1.05045	0.04234
BBVA SM	0.00325	0.78794	0.01622	-0.92773	0.04324	1.87140	0.04234
BMPS IM	-0.02300	1.42749	0.01622	2.22308	0.04324	3.42476	0.04234
BNP FP	0.00729	1.22025	0.01622	-0.14078	0.04324	1.75286	0.04234
CBK GR	0.01378	1.59539	0.01622	2.65312	0.04324	1.62179	0.04234
DANSKE DC	0.00394	1.19291	0.01622	1.26613	0.04324	0.34801	0.04234
DBK GR	-0.00249	1.20959	0.01622	-0.17203	0.04324	1.59563	0.04234
DNB NO	0.00425	1.25700	0.01622	0.45416	0.04324	0.51609	0.04234
EBS AV	0.00185	1.54167	0.01622	1.89921	0.04324	1.30231	0.04234
GLE FP	0.01287	1.63326	0.01622	0.46871	0.04324	2.48336	0.04234
HSBA LN	-0.00563	0.71280	0.01622	-0.07992	0.04324	0.59883	0.04234
INGA NA	0.01572	1.23498	0.01622	-0.00256	0.04324	1.87075	0.04234
ISP IM	0.01853	1.09225	0.01622	-0.43583	0.04324	2.50122	0.04234
JYSK DC	0.00094	0.92669	0.01622	1.56099	0.04324	0.47101	0.04234
KBC BB	0.02537	1.77928	0.01622	2.03099	0.04324	1.87648	0.04234
LLOY LN	0.00533	1.13105	0.01622	1.22429	0.04324	1.47498	0.04234
NDA SS	0.00171	1.22343	0.01622	0.53444	0.04324	0.26471	0.04234
OTP HB	0.00567	1.24635	0.01622	1.15315	0.04324	1.15643	0.04234
PKO PW	-0.01162	0.46913	0.01622	0.77006	0.04324	0.62401	0.04234
POP SM	-0.01135	0.68323	0.01622	-0.16153	0.04324	2.22485	0.04234
RBS LN	0.00179	1.09713	0.01622	0.93221	0.04324	1.87995	0.04234
SAB SM	0.00415	0.39732	0.01622	-1.15026	0.04324	2.08081	0.04234
SAN SM	-0.00381	0.66620	0.01622	-0.94053	0.04324	2.01531	0.04234
SEBA SS	0.00803	1.16013	0.01622	0.49436	0.04324	0.87817	0.04234
SHBA SS	0.00347	0.97089	0.01622	0.27599	0.04324	0.03989	0.04234
SWEDA SS	0.01003	1.22281	0.01622	0.30089	0.04324	0.26276	0.04234
UBI IM	0.01242	1.18517	0.01622	0.35686	0.04324	2.82157	0.04234
UCG IM	0.00231	0.94774	0.01622	-0.51814	0.04324	3.26830	0.04234

Note. Statistically significant coefficient estimates are highlighted in light blue.

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Table 9 shows that β_{MRP} is statistically significant for 27 of 29 sample banks. Whereas β_{SMB} is statistically significant for 10 out of 29 sample banks. β_{HML} is statistically significant for 22 out of 29 sample banks. Table 10 shows the cost of capital estimates for each of the high-cap European banks. Values in Table 10 are obtained from Table 9 by summing together the values of MRP factor, SMB factor, HML factor and intercept for each of the 29 sample banks. In Table 10 the cells of the cost of capital estimates lower than 4.5% are highlighted in red, and cells of average cost of capital estimate values are highlighted in orange. Moreover, the cost of capital estimates lower than 4.5% are excluded from the calculation of the average cost of capital estimates of Table 10.

Table 10. Cost of capital estimate for high-cap European banks (in %)

	E (cost of capital)	
Ticker	**All p-values**	**Significant betas**
ALBK ID	10.42	4.82
BARC LN	11.56	6.84
BBVA SM	5.52	5.52
BMPS IM	24.13	24.13
BNP FP	9.52	10.13
CBK GR	22.30	22.30
DANSKE DC	9.28	7.80
DBK GR	7.72	8.47
DNB NO	6.61	2.46
EBS AV	16.41	16.41
GLE FP	16.48	14.45
HSBA LN	2.78	3.13
INGA NA	11.48	11.50
ISP IM	12.33	14.21
JYSK DC	10.34	8.35
KBC BB	22.15	22.15
LLOY LN	13.91	13.91
NDA SS	5.59	2.16
OTP HB	12.47	12.47
PKO PW	5.57	2.24
POP SM	8.69	8.29
RBS LN	13.95	9.92
SAB SM	4.90	9.23
SAN SM	5.17	5.17
SEBA SS	8.54	6.40
SHBA SS	3.28	1.92
SWEDA SS	5.40	2.99
UBI IM	16.65	15.11
UCG IM	13.37	15.61
Average	11.50	11.88

Note. Cost of capital estimates lower than 4.5% are highlighted in red, and average cost of capital estimate values are highlighted in orange.

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

From the first approach, which is the approach in which all β are used for the calculation of the cost of capital estimate, the banks with an estimated cost of capital lower than 4.5% are

HSBA LN and SHBA SS. Using the second approach instead, the approach where only statistically significant β are used for the calculation of the cost of capital estimate, the number of banks with a cost of capital lower than 4.5% increases to six. Namely DNB NO, HSBA LN, NDA SS, PKO PW, SHBA SS, and SWEDA SS. Table 11 shows the average values of β_{MRP}, β_{SMB}, β_{HML}, and the intercept estimate. Values in Table 11 are calculated considering the sample of high-cap European banks but not considering those banks that according to the two different approaches have a cost of capital estimate lower than 4.5%.

Table 11. Average risk factors and average intercept (in%)

Approach	**Cost of capital**	**Intercept**	**Market factor**	**Size factor**	**Value factor**
All p-values	11.50	0.39	1.97	2.45	6.68
Significant betas	11.88	0.44	1.94	2.28	7.21

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Once considering the cost of capital estimates using the all p-values approach, and at the same time not taking into consideration those banks exhibiting an estimated cost of capital lower than 4.5%, the value factor alone increases the cost of capital estimate by 6.68% on average, whereas the size factor increases the cost of capital estimate by 2.45% on average, and the market factor brings to the cost of capital estimate 1.97% on average only. The average intercept is 0.39%. Given that the average value of the intercept approaches zero, then the market is efficient. Moreover, once using the significant betas approach the average values are very similar to the all p-values approach.

By focusing on the result of the all p-values approach, the high-cap European banks with an estimated cost of capital higher than 20% are BMPS IM, CBK GR, and KBC BB. Instead the banks with an estimated cost of capital lower than 6% but higher than 4.5% are BBVA SM, NDA SS, PKO PW, SAB SM, SAN SM, and SWEDA SS. According to Damodaran (2017) the cost of capital for the European banking industry on date 4 January 2016 is 11.33%. Damodaran's estimate is in line with the average estimate of the cost of capital which is obtained in this Master's Thesis. The resulting average cost of capital for high-cap European banks through FF3 is 11.50%. Whereas the average cost of capital using statistically significant β only is 11.88%.

CONCLUSION

The results of this Master’s thesis show that FF3 can be successfully employed to estimate the cost of capital for the sample of high-cap European banks. Moreover, it is evident that FF3 outperforms CAPM. Focusing on the outcome obtained by the all p-values approach, the market factor explains less than a quarter of the total systematic risk captured by FF3. There is no doubt that the market factor is an essential part of the total systematic risk. But its average effect on the sample of high-cap European banks is just 17.14% of the FF3 risk factors' total average effect, low for being considered the only source of systematic risk. Hence, the size factor and the value factor on average explain the remaining 82.86% of the systematic risk captured by FF3. Precisely 21.32% by the size factor and 58.11% by the value factor. An important role of the cost of capital is that its value can be compared to return on equity (hereinafter: ROE). ROE is a measure of profitability, describing how much profit is generated from the shareholder's capital. The difference between ROE and cost of capital is used as measure of overall performance. A ROE value higher than the cost of capital is a positive signal suggesting that the bank increased in value. Whereas a ROE value lower than the cost of capital is a warning. If the difference between ROE and cost of capital is negative then the value of the high-cap European bank has been destroyed.

To evaluate the performance of the high-cap European banks two measures are required. The first measure is the 2015 annualised ROE, which is retrieved from Bloomberg (Bloomberg L.P., 2017). Whereas the second measure is the cost of capital estimates, which is estimated in this Master’s thesis through FF3 as of 31 December 2015. Moreover, the cost of capital estimates used for the comparison are those calculated through the all p-values approach.

The Country's average performance of the high-cap banks is obtained by sampling the banks according to their Country of origin. The worst performing banks are the German banks, with an average decrease in value of -18.41%. The difference between ROE and estimated cost of capital is similar for both German banks, the value creation of CBK GR is -18.38% and the value creation of DBK GR is -18.44%. U.K. banks come just after the German ones. The average decrease in value of the high-cap U.K. banks is -14.22%. The difference between ROE and the estimated cost of capital is -17.57% for RBS LN, -12.81% for LLOY LN, and -12.28% for BARC LN. The average performance of the high-cap Italian banks does not differ much from the U.K. banks. As a matter of fact, the average value creation of Italian high-cap banks is -12.71%. In Italy, there is the worst sample bank in terms of value creation. Namely BMPS IM with a change in value of -19.08%. The results for the others Italian banks are -15.47% for UBI IM, -9.90% for UCG IM, and -6.41% for ISP IM. KBC BB from Belgium, with -10.62%, experiences a decrease in the overall value too. Even the two French high-cap banks show negative results. Precisely -10.25% for GLE FP and -2.07% for BNP FP.

The negative trend hit Hungary, Austria, Netherlands, and Denmark as well, but in a less harsh way. The results show -7.37% for OTP HB, -7.12 for EBS AV, -3.39% for INGA NA, -1.74% for JYSK DC, and -0.83% for DANSKE DC. The overall value of the Spanish high-cap banks was destroyed too, the average result is -1.24%. Even if the Spanish overall result is negative, has to be mentioned that the only Spanish bank with a significant negative result is Banco POP SM with -7.85%. Instead SAN SM creates value for 1.90%, and SAB SM has a positive value creation of 1.03%. Whereas the value of BBVA SM is neither created nor destroyed, for this last high-cap Spanish bank the spread between ROE and cost of capital is -0.04%. The value of the remaining high-cap European banks increased. The result is positive in Ireland with 1.98% for ALBK ID, in Poland with 3.44% for PKO PW, in Norway with 7.71% for DNB NO, and in Sweden with 7.68% for SWEDA SS, 6.44% for NDA SS, 3.42% for SEBA SS.

Considering the sample of high-cap European banks as a whole, the average value creation of the high-cap European public banking industry in 2015 is -5.48%. Hence, exception made for 8 out of 27 banks, the management of the publicly listed high-cap European banks in the year 2015 is not able to generate enough profit to cover the cost of capital estimated through FF3.

REFERENCE LIST

1. Adler, M., & Dumas, B. (1983). International portfolio choice and corporation finance: a synthesis. *Journal of Finance*, *38*(3), 925-984.
2. Aggarwal, R., Rao, R., & Hiraki, T. (1990). Regularities in Tokyo stock exchange security returns: P/E, size, and seasonal influences. *Journal of Financial Research*, *13*(3), 249-263.
3. Agrawal, A., & Tandon, K. (1994). Anomalies or illusions? Evidence from stock markets in eighteen countries. *Journal of International Money and Finance*, *13*(1), 83-106.
4. Al-Mwalla, M. (2012). Can book-to-market, size and momentum be extra risk factors that explain the stocks rate of return: evidence from emerging market. *Journal of Finance, Accounting and Management*, *3*(2), 42-57.
5. Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*(2), 223-249.
6. AnalystSoft Inc. (2018). (2017). *Regressions of high-cap European banks*. Walnut, California: AnalystSoft Inc..
7. Ariel, R. (1987). The monthly effect in stock returns. *Journal of Financial Economics*, *18*(2), 161-174.
8. Arshanapalli, B. G., Coggin, T. D., & Doukas J. (1998). Multifactor asset pricing analysis of international value investment strategies. *The Journal of Portfolio Management*, *24*(4), 10-23.
9. Avramov, D., & Chordia, T. (2006). Asset pricing models and financial market anomalies. *The Review of Financial Studies*, *19*(3), 1001-1040.
10. Avramov, D., Chordia, T., & Goyal, A. (2006). Liquidity and autocorrelations in individual stock returns. *The Journal of Finance*, *61*(5), 2365-2394.
11. Baek, S., & Bilson, J. F. O. (2015). Size and value risk in financial firms. *Journal of Banking & Finance*, *55*(21), 295-326.
12. Ball, R. (1978). Anomalies in relationships between securities' yields and yield-surrogates. *Journal of Financial Economics*, *6*(2-3), 103-126.
13. Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3-18.
14. Barber, B. M., & Lyon, J. D. (1997). Firm size, book-to-market ratio, and security returns: a holdout sample of financial firms. *The Journal of Finance*, *52*(2), 875-883.
15. Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307-343.
16. Barone, E. (1990). The italian stock market: efficiency and calendar anomalies. *Journal of Banking & Finance*, *14*(2-3), 483-510.
17. Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis. *Journal of Finance*, *32*(3), 663-682.

18. Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: further evidence. *Journal of Financial Economics, 12*(1)*,* 129-156.
19. Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business*, *45*(3), 444-455.
20. Black, F., Jensen, M. C., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests. In *Studies in the Theory of Capital Markets* (pp. 79-121). New York: Praeger.
21. Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *The Journal of Political Economy*, *81*(3), 637-654.
22. Bloomberg Finance L.P. (2018). (2017a). *Company overview of high-cap European banks*. New York: Bloomberg Finance L.P. (2018).
23. Bloomberg Finance L.P. (2018). (2017b). *Last price of Euribor*. New York: Bloomberg Finance L.P. (2018).
24. Bloomberg Finance L.P. (2018). (2017c). *Monthly last price of high-cap European banks*. New York: Bloomberg Finance L.P. (2018).
25. Bloomberg Finance L.P. (2018). (2017d). *Return on Stoxx Europe 600*. New York: Bloomberg Finance L.P. (2018).
26. Bloomberg Finance L.P. (2018). (2017e). *ROE of high-cap European banks*. New York: Bloomberg Finance L.P. (2018).
27. Bower, D. H., Bower, R. S., & Logue, D. E. (1984). Arbitrage pricing theory and utility stock returns. *The Journal of Finance*, *39*(4), 1041-1054.
28. Brennan, M. J., Chordia, T., Subrahmanyam, A., & Tong, Q. (2012). Sell-order liquidity and the cross-section of expected stock returns. *Journal of Financial Economics*, *105*(3),523-541.
29. Brennan, M. J., & Subrahmanyam, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, *41*(3), 441-464.
30. Capaul, C., Rowley, I., & Sharpe, W. F. (1993). International value and growth stock returns. *Financial Analysts Journal*, *49*(1), 27-36.
31. Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57-82.
32. Celik, S. (2012). Theoretical and empirical review of asset pricing models: A structural synthesis. *International Journal of Economics and Financial Issues*, *2*(2), 141-178.
33. Chamberlain, G., & Rothschild, M. (1983). Arbitrage, factor structure, and mean variance analysis on large asset markets. *Econometrica*, *51*(5), 1281-1304.
34. Chan, K. C., Chen, N. F., & Hsieh, D. A. (1985). An explanatory investigation of the firm size effect. *Journal of Financial Economics*, *14*(3), 451-471.
35. Chan, H. W., & Faff, R. W. (2003). An investigation into the role of liquidity in asset pricing: Australian evidence. *Pacific-Basin Finance Journal*, *11*(5), 555-572.
36. Chan, L. K. C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock return in Japan. *Journal of Finance*, *46*(5), 1739-1764.

37. Chandra, T. (2015). Testing Fama and French three factor models in Indonesia stock exchange. *International Business Management*, *9*(6), 1025-1034.
38. Chen, N. F. (1983). Some empirical tests of the theory of arbitrage pricing. *Journal of Finance*, *38*(5), 1393-1414.
39. Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock markets. *Journal of Business*, *59*(3), 383-403.
40. Chou, S., & Johnson, K. H. (1990). An empirical analysis of stock market anomalies: evidence from the Republic of China and Taiwan, in S. G. Rhee & R. P. Chang (eds), *Pacific-Basin Capital Markets Research, vol. I* (pp. 283-312). Amsterdam: Elsevier.
41. Connor, G., & Korajczyk, R. (1986). Performance measurement with the arbitrage pricing theory: a framework for analysis. *Journal of Financial Economics*, *15*(3), 373-394.
42. Corhai, A., Hawawini, G., & Michel, P. (1987). Seasonality in the risk-return relationship: some international evidence. *The Journal of Finance*, *42*(1), 49-68.
43. Damodaran, A. (2017). *Cost of Capital by Industry.* Retrieved July 27, 2017 from http://pages.stern.nyu.edu/~adamodar/New_Home_Page/dataarchived.html#discrate
44. Davis, J. L., Fama, E. F., & French, K. R. (2000). Characteristics, covariances and average return: 1929-1997. *The Journal of Finance*, *55*(1), 389-406.
45. DeBondt, W. F. M., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, *42*(3), 557-581.
46. Drew, M. E., & Veeraraghavan, M (2002). Closer look at the size and value premium in emerging markets: evidence from the Kuala Lumpur stock exchange. *Asian Economic Journal*, *16*(4), 337-351.
47. Eleswarapu, V., & Reinganum, M. R. (1993). The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics*, *34*(3), 373-386.
48. Eraslan, V. (2013). Fama and french three-factor model: evidence from Istanbul stock exchange. *Business and Economics Research Journal*, *4*(2), 11-22.
49. European Banking Authority (2016, February 24). *2016 EU-Wide Stress Test Methodological Note*. London, UK: European Banking Authority, 2016.
50. European Banking Authority (2016, July 7). *Risk Dashboard Q1 2016*. London, UK: European Banking Authority.
51. European Money Market Institute (2016, June 1). *Euribor Code of Conduct*. Brussels, Belgium: EMMI.
52. European Money Market Institute (2017, May 10). *Euribor Panel Banks' Adherence to the Euribor Code of Conduct*. Brussels, Belgium: EMMI.
53. Fabozzi, F., Gupta., F., & Markowitz, H. (2002). The legacy of modern portfolio theory. *Journal of Investing*, *13*(3), 7-22.
54. Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance*, *25*(2), 383-417.
55. Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427-465.

56. Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *53*(6), 1975-1999.
57. Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance*, *50*(1), 131-155.
58. Fama, E. F., & French, K. R. (1998). Value versus growth: the international evidence. *The Journal of Finance*, *53*(6), 1975-1999.
59. Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, *63*(4), 1653-1678.
60. Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.
61. Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607-636.
62. Fama/French European 3 Factors. (N.D.) In *Kenneth R. French data library.* Retrieved July 12, 2017, from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International
63. Frantz, P., & Payne, R. (2009). *Corporate finance*. Chapter 2. London, UK: University of London Press.
64. French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, *8*(1), 55-69.
65. Friend, I., & Blume, M. (1970). Measurement of portfolio performance under uncertainty. *American Economic Review*, *60*(4), 607-636.
66. Garza-Gomez, X., Hodoshima, J., & Kunimura, M. (1998). *Financial Analyst Journal*, *54*(6), 22-34.
67. Graham, B., & Dodd, D. L. (1934). *Security analysis*. New York: McGraw-Hill.
68. Gujarati, D. N., & Porter, D. C. (2009). Two-variable regression model: the problem of estimation. In D. N., Gujarati & D. L. Porter (5th ed.), *Basic Econometrics* (pp.55-96). New York: McGraw-Hill.
69. Hardianto, D., & Suherman (2009). Testing the fama-french three factor model in indonesia. *Finance Bank Journal*, *13*(2), 198-208.
70. Haugen, R. A., & Baker, N. (1996). Commonality in the determinants of expected stock return. *Journal of Financial Economics*, *41*(3), 401-439.
71. Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, *54*(6), 2143-2184.
72. Huberman, G. (1982). A simple approach to arbitrage pricing theory. *Journal of Economic Theory*, *28*(1), 183-191.
73. Huberman, G., & Wang, Z. (2008). Arbitrage pricing theory. In S. N. Durlauf & L. E. Blume (2nd ed.), *The New Palgrave Dictionary of Economics*. London, UK: Palgrave Macmillan.
74. Ingersoll, J. (1984). Some results in the theory of arbitrage pricing. *Journal of Finance*, *39*(4), 1021-1039.

75. Jaffe, J. F., Westerfield, R., & Ma, C. (1989). A twist on the Monday effect in stock prices: evidence from the US and foreign stock markets. *Journal of Banking and Finance*, *13*(4-5), 641-650.
76. Jagadeesh, N., & Titman, S. (1993). *Journal of Finance*, *48*(1), 65-91.
77. Jagannathan, R., Skoulakis, G., & Wang, Z. (2002). Generalized method of moments: application in finance. *Journal of Business and Economic Statistics*, *20*(4), 470-481.
78. Jobson, J. (1982). A multivariate linear regression test of the arbitrage pricing theory. *Journal of Finance*, *37*(4), 1037-1042.
79. Johnson, T. C. (2002). Rational momentum effects. *The Journal of Finance*, *57*(2), 585-606.
80. JP Morgan Chase (2008). *The Quest for MRP*. New York: JP Morgan Chase.
81. Klein, R., & Bawa, V. S. (1977). The effect of limited information and estimation risk on optimal portfolio diversification. *Journal of Financial Economics*, *5*(1), 89-111.
82. Kmenta, J. (1971). *Elements of Econometrics*. New York: MacMillan.
83. KPMG International (2016, October). *The Profitability of EU Bank.* Netherlands: KPMG International.
84. Kuhn, T. S. (1970). *The structure of scientific revolutions* (2nd ed.). Chicago: University of Chicago Press.
85. Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety year perspective. *The Journal of Financial Studies*, *1*(4), 403-425.
86. Lehman, B., & Modest, D. (1988). The empirical foundations of the arbitrage pricing theory. *Journal of Financial Economics*, *21*(2), 213-254.
87. Levis, M. (1989). Stock market anomalies: a re-assessment based on the UK evidence. *Journal of Banking & Finance*, *13*(4-5), 675-696.
88. Levy, R. A. (1967). Relative strength as a criterion for investment selection. *The Journal of Finance*, *22*(4), 595-610.
89. Liew, J., & Vassalou M. (2000). Can book-to-market, size and momentum be risk factors that predict economic growth. *Journal of Financial Economics*, *57*(2), 221-245.
90. Lintner, J. (1965a). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, *20*(4), 587-615.
91. Lintner, J. (1965b). The valuation of risky assets and the selection of risky investments in stock portfolios and capital budget. *Review of Economics and Statistics*, *47*(1), 13-37.
92. Mangram, M. E. (2013). A simplified perspective of the Markovitz portfolio theorem, *Global Journal of Business Research*, *7*(1), 59-70.
93. Markowitz, H. M. (1952). Portfolio selection, *Journal of Finance*, *7*(1), 77-91.
94. Mayers, D. (1973). Nonmarketable assets and the determination of capital asset prices in the absence of a riskless asset. *Journal of Business*, *46*(2), 258-267.
95. Mazzola, P., & Gerace, D. (2015). A comparison between a dynamic and static approach to asset management using CAPM models on the Australian securities market. *Australasian Accounting, Business and Finance Journal*, *9*(2), 44-58.

96. Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, *41*(5), 867-887.
97. Mossin, J. (1966). Equilibrium in a capital asset market, *Econometrica*, *34*(4), 768-783.
98. Mylonakis, J. & Tserkezos, D. (2008). The January effect results in the Athens Stock Exchange (ASE). *Global Journal of Finance and Banking Issues*, *2*(2), 44–55.
99. Novy-Marx, R. (2013). The other side of value: the gross profitability premium. *Journal of Financial Economics*, *108*(1), 1-28.
100. Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock return. *Journal of Political Economy*, *111*(3), 642-685.
101. Perold, A. F. (2004). The capital asset pricing model. *Journal of Economic Perspectives*, *18*(3), 3-24.
102. Reinganum, M. R. (1981). Misspecification of capital asset pricing: empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics*, *9*(1), 19-46.
103. Reinganum, M. R. (1990). Market microstructure and asset pricing: an empirical investigation of NYSE and NASDAQ securities. *Journal of Financial Economics*, *28*(1-2), 127-147.
104. Roll, R. (1977). A critique of the asset pricing theory's tests Part 1: On past and potential testability of the theory. *Journal of Financial Economics*, *4*(2), 129-176.
105. Roll, R., & Ross, S. (1980). An empirical investigation of the arbitrage pricing theory. *Journal of Finance*, *35*(5), 1073-1103.
106. Ross, S. (1976a). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), 341-360.
107. Ross, S. (1976b). Risk, return and arbitrage. In I. Friend & J. Bicksler (1st ed.), *Risk Return in Finance* (pp. 189-218). Cambridge, Massachusetts: Ballinger.
108. Ross, S., Westerfield, R., & Jaffe, J. (2002). Capital market theory: An overview. In *Corporate finance* (6th ed.) (pp.226-247). NY: Mc Graw-Hill.
109. Rossi, M. (2015). The efficient market hyphotesis and calendar anomalies: a literature review. *International Journal of Managerial and Financial Accounting*, *7*(3-4), 285-296.
110. Rozeff, S., & Kinney, W. (1976). Capital market seasonality: the case of stock returns. *Journal of Financial Economics*, *3*(4), 379-402.
111. Sagi, J. S., & Seasholes, M. S. (2007). Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics*, *84*(2), 389-434.
112. Schuermann, T., & Stiroh, K. J. (2006). *Visible and Hidden Risk Factors for Banks* (Staff Report No. 252). New York: Federal Reserve Bank of New York.
113. SenthilKumar, G. (2009). Behaviour in stock return in size and market-to-book ratio-evidence from selected Indian industries. *International Research Journal of Finance and Economics*, *33*(10), 142-153.
114. Sharpe, W. F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of finance*, *19*(3), 425-442.

115. Sharpe, W. F. (1994). The Sharpe ratio, *The Journal of Portfolio Management*, *21(1)*, 49-58.
116. Solnik, B. H. (1974). An equilibrium model of the international capital market. *Journal of Economic Theory*, *8*(4), 500-524.
117. Stambaugh, R. F. (1982). On the exclusion of assets from tests of the two-parameter model: a sensitivity analysis. *Journal of Financial Economics*, *10*(3), 237-268.
118. Stoll, H., & Whaley, R. E. (1983). Transaction costs and the small firm effect. *Journal of Financial Economics*, *12*(1), 57-79.
119. STOXX Limited (2017). *STOXX Index Methodology Guide (Portfolio Based Indices)*. Zurich, Switzerland: STOXX Limited
120. Stulz, R. M. (1981). A model of international asset pricing. *Journal of Financial Economic*, *9*(4), 383-406.
121. Taneja, Y. P. (2010). Revisiting fama french three-factor model in indian stock market. *The Journal of Business Perspective*, *14*(4), 267-274.
122. Tobin, J. (1958). Liquidity preference as behaviour toward risk. *Review of economic Studies*, *25*(2), 65-86.
123. Treynor, J. L. (1962). Toward a theory of market value of risky assets. In R. A. Korajczyk, *Asset pricing and portfolio performance: models, strategy, and performance metrics* (ch.2). London, U.K.: Risk Publications.
124. Wang, K., Li, Y., & Erickson, J. (1997). A new look at the Monday effect. *Journal of Finance*, *52*(5), 2171-2186.

APPENDIXES

TABLE OF APPENDIXES

APPENDIX A: List of abbreviations

ALBK ID – Allied Irish Banks plc
AMEX – American Stock Exchange
BARC LN – Barclays Plc
BBVA SM – Banco Bilbao Vizcaya Argentaria S.A.
BE/ME – Book to market equity ratio
BLUE – Best Linear Unbiased Estimator
BMPS IM – Banca Monte dei Paschi di Siena S.p.a.
BNP FP – BNP Paribas S.A.
B/P – Book to price ratio
CAL – Capital allocation line
CAPM – Capital asset pricing model
CBK GR – Commerzbank AG
CET1 – Common equity tier 1
CLRM – Classical linear regression model
CRSP – Center of Research in Security Prices
DANSKE DC – Danske Bank
DBK GR – Deutsche Bank AG
DDK – Danish Krone
DDM – Dividend discount method
DNB NO – DNB Bank Group
EBA – European Banking Authority
EBITDA – Earnings before interest, taxes, depreciation, and amortization
EBS AV – Erste Group Bank AG
EMMI – European Money Market Institute
EONIA – Euro overnight index average
E/P – Earnings to price ratio
EU – European Union
EURIBOR – Euro Interbank Offered Rate
EUR – Euro
FF3 – Fama-French three factor model
GBp – British Penny
GLE FP – Societe Generale S.A.
HML – High-minus-low
HSBA LN – HSBC Holdings Plc
HUF – Hungarian Forint
INGA NA – ING Group N.V.
ISP IM – Intesa Sanpaolo S.p.a.
JYSK DC – Jyske Bank
KBC BB – KBC Group AV
LLOY LN – Lloyds Banking Group Plc

ME – Market equity
MRP – Market risk premium
NASDAQ – National Association of Securities Dealers Automated Quotation
NDA SS – Nordea Bank-group
NOK – Norwegian Krone
NYSE – New York Stock Exchange
OLS – Ordinary least squares
OTP HB – OTP Bank Nyrt.
PKO PW - Powszechna Kasa Oszczednosci Bank Polski
PLN – Polish Zloty
POP SM – Banco Popular Espanol S.A.
RBS LN – The royal Bank of Scotland Group Plc
ROE – Return on equity
SAB SM – Banco de Sabadell S.A.
SAN SM – Banco Santander S.A.
SEBA SS – Skandinaviska Enskilda Banken-group
SEK – Swedish Krona
SHBA SS – Svenska Handelsbanken-group
SMB – Small-minus-big
SWEDA SS – Swedbank-group
SR – Sharpe-ratio
UBI IM – Unione di Banche Italiane S.p.a.
UCG IM – UniCredit S.p.a.
U.K. – United Kingdom
U.S. – United States of America
USD – United States Dollar
XSGA – Selling, general, and administrative expenses
$\alpha -$ Level of significance
$\beta -$ Beta coefficient
$H_0 -$ Null hypothesis
$H_1 -$ Alternative hypothesis
$R^2 -$ r-squared

APPENDIX B: Monthly last prices of high-cap European banks in EUR

Table 1. Monthly last prices of ALBK ID, BARC LN, BBVA SM, BMPS IM, BNP FP, CBK GR, DANSKE DC, and DBK GR (in EUR)

Date	ALBK ID	BARC LN	BBVA SM	BMPS IM	BNP FP	CBK GR	DANSKE DC	DBK GR
31.12.2015	6.660	2.974	6.739	123.200	52.230	9.572	24.823	20.104
30.11.2015	13.000	3.032	7.856	148.600	56.110	10.380	25.400	21.626
30.10.2015	18.250	3.152	7.840	167.200	55.260	10.101	24.998	22.671
30.09.2015	18.750	3.317	7.580	159.200	52.460	9.432	27.008	21.451
31.08.2015	19.500	3.552	8.263	187.300	56.270	9.980	27.611	23.415
31.07.2015	21.500	3.926	9.214	180.600	59.310	11.810	28.442	28.415
30.06.2015	21.000	3.539	8.792	174.600	54.150	11.540	26.378	24.187
29.05.2015	21.250	3.668	8.993	184.500	54.930	12.140	26.713	24.548
30.04.2015	22.250	3.469	9.000	225.030	56.440	12.100	25.333	25.514
31.03.2015	23.750	3.296	9.408	251.480	56.570	12.800	24.595	28.782
27.02.2015	19.500	3.490	8.980	250.666	52.090	11.980	23.671	26.084
30.01.2015	19.500	3.181	7.600	162.770	46.775	10.600	22.933	22.952
31.12.2014	19.750	3.308	7.854	191.255	49.260	10.988	22.437	22.299
28.11.2014	18.750	3.331	8.638	264.095	51.560	12.260	22.786	23.394
31.10.2014	28.750	3.272	8.908	247.411	50.140	11.980	21.834	22.261
30.09.2014	26.500	3.090	9.551	424.831	52.520	11.830	21.472	24.687
29.08.2014	22.000	3.049	9.210	463.082	51.380	11.500	21.365	23.281
31.07.2014	23.250	3.066	9.219	549.350	49.500	10.775	21.620	22.830
30.06.2014	22.250	2.891	9.309	575.800	49.545	11.480	20.628	22.946
30.05.2014	27.250	3.356	9.404	632.140	51.370	11.620	20.628	25.308
30.04.2014	29.500	3.426	8.845	610.018	54.110	12.820	20.373	27.010
31.03.2014	35.500	3.171	8.718	673.842	55.990	13.350	20.239	27.649
28.02.2014	36.250	3.425	8.995	467.621	59.460	13.020	19.194	29.803
31.01.2014	33.250	3.702	8.860	429.479	57.450	12.650	16.728	30.645
31.12.2013	28.000	3.695	8.948	446.007	56.650	11.710	16.674	29.517
29.11.2013	30.750	3.691	8.794	474.995	55.250	10.950	16.728	30.083
31.10.2013	23.500	3.581	8.629	592.472	54.540	9.470	17.197	30.385
30.09.2013	21.250	3.607	8.260	521.274	50.000	8.490	15.910	28.900
30.08.2013	17.500	3.556	7.220	555.856	47.415	8.780	15.146	27.972
31.07.2013	14.250	3.613	7.118	522.291	48.635	6.420	13.846	28.943
28.06.2013	15.250	3.495	6.445	495.846	41.975	6.707	13.135	27.520
31.05.2013	17.500	4.022	7.247	611.543	45.325	8.039	15.200	30.586
30.04.2013	16.250	3.590	7.370	543.905	42.310	7.659	14.342	29.794
28.03.2013	17.000	3.654	6.763	470.418	40.040	8.646	13.940	25.963
28.02.2013	16.750	3.853	7.431	536.531	43.105	10.650	14.248	30.049
31.01.2013	16.250	3.778	7.325	627.054	46.210	12.042	14.127	32.356
31.12.2012	12.500	3.293	6.960	573.910	42.585	10.725	12.820	28.049
30.11.2012	13.250	3.087	6.524	515.934	42.945	10.329	13.182	28.845
31.10.2012	12.750	2.855	6.437	541.616	38.810	11.077	12.063	29.747
28.09.2012	13.250	2.696	6.113	573.656	36.980	10.411	14.033	26.317
31.08.2012	12.500	2.300	6.073	569.587	34.555	9.394	13.806	23.925
31.07.2012	12.500	2.108	5.324	458.721	30.170	9.454	12.063	21.094
29.06.2012	16.750	2.044	5.629	498.897	30.335	9.970	10.910	24.261
31.05.2012	16.250	2.213	4.602	512.374	25.725	9.992	10.662	24.780
30.04.2012	18.750	2.739	5.106	682.233	30.350	12.221	12.231	28.006
30.03.2012	22.250	2.952	5.967	803.779	35.575	14.211	12.666	31.837
29.02.2012	31.750	3.075	6.729	1,019.663	36.635	14.151	13.471	30.041
31.01.2012	19.250	2.668	6.674	737.666	32.370	13.680	11.125	27.568
30.12.2011	17.250	2.209	6.680	640.531	30.350	9.745	9.778	25.057
30.11.2011	16.250	2.262	6.274	633.157	29.470	10.299	10.321	24.376
31.10.2011	25.000	2.451	6.562	860.229	32.850	13.373	9.986	26.104
30.09.2011	10.000	2.025	6.180	1,065.687	30.050	14.173	10.528	22.294
31.08.2011	10.250	2.143	6.338	1,090.861	35.870	15.512	10.294	24.142
29.07.2011	25.000	2.799	7.349	1,331.155	45.465	19.820	13.471	32.246
30.06.2011	35.500	3.218	8.090	1,328.613	53.230	22.341	12.767	34.604
31.05.2011	46.000	3.472	8.115	1,885.494	54.220	23.642	14.610	35.217
29.04.2011	57.500	3.543	8.660	1,966.071	53.430	25.785	16.218	37.464
31.03.2011	47.250	3.483	8.561	1,891.940	51.610	33.031	15.615	35.455
28.02.2011	66.250	4.014	8.946	2,075.655	56.580	37.419	15.740	39.481
31.01.2011	58.000	3.687	8.967	1,997.227	54.600	33.547	18.109	36.860
31.12.2010	75.000	3.284	7.560	1,828.553	47.610	33.289	17.737	33.284

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Table 2. Monthly last price of DNB NO, EBS AV, GLE FP, HSBA LN, INGA NA, ISP IM, and JYSK DC (in EUR)

Date	DNB NO	EBS AV	GLE FP	HSBA LN	INGA NA	ISP IM	JYSK DC
31.12.2015	11.412	28.910	42.570	7.285	12.450	3.088	41.832
30.11.2015	11.890	29.040	45.180	7.194	12.995	3.248	43.039
30.10.2015	11.246	26.670	42.310	6.896	13.235	3.168	44.379
30.09.2015	11.506	25.940	39.850	6.775	12.650	3.156	49.472
31.08.2015	12.306	26.555	43.455	7.047	13.645	3.254	49.834
31.07.2015	13.844	27.290	44.800	7.876	15.490	3.502	47.556
30.06.2015	13.595	25.475	41.870	7.745	14.810	3.252	45.063
29.05.2015	14.187	26.415	42.525	8.460	14.975	3.282	43.896
30.04.2015	13.927	25.380	44.705	8.805	13.795	3.016	43.776
31.03.2015	13.480	22.935	44.970	7.798	13.645	3.166	39.259
27.02.2015	12.971	23.420	41.315	7.843	13.355	2.984	38.696
30.01.2015	11.672	19.225	35.835	8.282	11.120	2.598	40.063
31.12.2014	11.506	19.235	34.990	8.269	10.830	2.422	41.926
28.11.2014	12.108	21.780	39.890	8.654	11.780	2.478	41.403
31.10.2014	12.878	20.310	38.415	8.688	11.410	2.338	42.891
30.09.2014	12.503	18.135	40.420	8.506	11.310	2.406	42.690
29.08.2014	12.015	19.530	38.555	8.858	10.465	2.264	41.417
31.07.2014	11.641	19.255	37.555	8.646	9.745	2.230	42.368
30.06.2014	11.662	23.620	38.255	8.055	10.260	2.256	41.430
30.05.2014	11.672	25.490	42.265	8.548	10.275	2.458	40.572
30.04.2014	10.924	24.190	44.800	8.207	10.235	2.460	39.607
31.03.2014	10.820	24.800	44.705	8.254	10.275	2.460	39.916
28.02.2014	11.319	25.710	48.375	8.555	10.570	2.246	43.561
31.01.2014	11.028	27.005	42.080	8.518	9.840	2.010	37.919
31.12.2013	11.277	25.330	42.220	8.999	10.100	1.794	39.205
29.11.2013	11.267	25.910	42.335	9.264	9.558	1.780	39.782
31.10.2013	10.965	25.975	41.820	9.267	9.383	1.831	41.564
30.09.2013	9.489	23.360	36.830	9.095	8.351	1.525	36.699
30.08.2013	9.874	24.255	33.115	9.184	8.215	1.485	34.916
31.07.2013	10.201	22.830	30.215	10.160	7.680	1.426	32.946
28.06.2013	9.141	20.400	26.400	9.266	7.000	1.231	28.952
31.05.2013	9.921	24.931	30.860	9.862	7.232	1.459	30.614
30.04.2013	9.796	23.678	27.580	9.558	6.232	1.377	29.528
28.03.2013	8.902	21.618	25.630	9.544	5.537	1.142	26.539
28.02.2013	8.886	24.548	29.410	9.937	6.158	1.243	25.453
31.01.2013	7.941	24.658	33.275	9.737	7.449	1.502	23.992
31.12.2012	7.317	23.902	28.340	8.789	7.061	1.300	21.057
30.11.2012	7.333	22.499	27.805	8.664	6.910	1.294	21.982
31.10.2012	7.400	19.275	24.525	8.271	6.816	1.239	23.523
28.09.2012	7.301	17.276	22.100	7.789	6.149	1.183	23.108
31.08.2012	6.922	15.977	21.050	7.433	6.082	1.250	22.719
31.07.2012	6.600	14.654	18.010	7.254	5.381	1.033	21.754
29.06.2012	6.127	14.868	18.410	7.623	5.266	1.118	21.178
31.05.2012	5.727	13.903	16.060	6.922	4.671	1.003	20.909
30.04.2012	6.413	17.306	17.860	7.542	5.327	1.143	23.590
30.03.2012	7.608	17.201	21.965	7.538	6.247	1.344	23.657
29.02.2012	7.457	18.738	24.250	7.544	6.658	1.461	26.834
31.01.2012	6.434	16.704	20.365	7.197	6.958	1.460	22.464
30.12.2011	6.085	13.515	17.205	6.671	5.560	1.294	18.899
30.11.2011	6.111	12.759	18.080	6.718	5.739	1.228	21.982
31.10.2011	6.751	15.520	21.100	7.403	6.260	1.291	21.097
30.09.2011	6.174	19.260	20.000	6.751	5.333	1.190	22.210
31.08.2011	6.730	25.220	23.360	7.290	6.025	1.134	21.312
29.07.2011	8.169	33.218	34.735	8.077	7.520	1.616	27.732
30.06.2011	7.816	35.964	40.920	8.402	8.489	1.836	27.223
31.05.2011	8.434	34.467	41.240	8.624	8.379	1.803	32.436
29.04.2011	8.866	33.945	45.160	8.904	8.900	2.103	33.549
31.03.2011	8.819	35.422	45.850	8.709	8.931	1.958	31.404
28.02.2011	9.001	38.053	50.950	9.211	9.087	2.292	31.230
31.01.2011	8.263	36.412	47.230	9.247	8.324	2.279	32.772
31.12.2010	8.512	34.959	40.220	8.846	7.280	1.904	34.715

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Table 3. Monthly last price of KBC BB, LLOY LN, NDA SS, OTP HB, PKO PW, POP SM, RBS LN (in EUR)

Date	KBC BB	LLOY LN	NDA SS	OTP HB	PKO PW	POP SM	RBS LN
31.12.2015	57.670	0.993	10.167	18.996	6.392	2.730	4.103
30.11.2015	56.500	0.991	10.532	19.218	6.303	2.992	4.108
30.10.2015	55.400	1.002	10.298	17.334	6.698	3.109	4.315
30.09.2015	56.370	1.021	10.156	17.112	6.883	2.924	4.280
31.08.2015	59.170	1.051	10.919	17.055	6.955	3.428	4.576
31.07.2015	63.460	1.130	11.714	18.189	6.834	3.749	4.649
30.06.2015	59.940	1.158	11.268	17.730	7.278	3.899	4.776
29.05.2015	61.050	1.192	12.085	18.046	7.643	4.028	4.691
30.04.2015	58.880	1.051	11.573	19.012	8.443	4.187	4.599
31.03.2015	57.560	1.064	11.475	16.792	7.952	4.089	4.619
27.02.2015	54.220	1.073	12.259	13.566	7.624	3.690	4.989
30.01.2015	47.715	1.002	11.475	11.556	8.031	3.368	4.924
31.12.2014	46.495	1.030	9.905	12.066	8.363	3.732	5.358
28.11.2014	46.000	1.092	10.151	12.556	8.782	3.965	5.371
31.10.2014	42.750	1.048	10.320	12.870	8.759	4.096	5.271
30.09.2014	42.165	1.044	10.232	13.234	9.275	4.348	5.002
29.08.2014	43.375	1.036	9.927	13.107	8.946	4.262	4.929
31.07.2014	40.670	1.009	10.113	12.901	8.326	4.110	4.827
30.06.2014	39.750	1.009	10.276	13.766	8.817	4.378	4.462
30.05.2014	43.670	1.058	10.755	15.365	9.495	4.648	4.709
30.04.2014	43.910	1.024	10.238	13.332	9.706	4.754	4.060
31.03.2014	44.650	1.014	10.004	13.525	9.935	4.916	4.225
28.02.2014	45.980	1.121	10.009	12.629	10.325	4.686	4.455
31.01.2014	43.855	1.132	9.557	13.424	9.542	4.580	4.619
31.12.2013	41.250	1.072	9.442	12.981	9.219	3.934	4.593
29.11.2013	42.000	1.052	9.235	14.212	9.624	3.837	4.445
31.10.2013	40.150	1.053	9.045	14.310	9.554	3.760	4.994
30.09.2013	36.315	1.000	8.445	13.772	8.677	3.560	4.890
30.08.2013	33.280	0.986	8.407	13.421	8.960	3.187	4.534
31.07.2013	30.150	0.930	8.996	14.342	8.700	2.965	4.315
28.06.2013	28.605	0.858	8.173	15.054	8.326	2.113	3.716
31.05.2013	30.690	0.844	8.957	15.513	8.141	2.889	4.573
30.04.2013	29.800	0.738	8.462	14.994	7.694	2.651	4.161
28.03.2013	26.870	0.662	8.042	13.566	8.080	2.593	3.743
28.02.2013	28.410	0.740	8.156	14.880	8.326	2.983	4.401
31.01.2013	29.035	0.702	7.644	14.668	8.099	2.978	4.664
31.12.2012	26.150	0.651	6.767	13.139	8.630	2.628	4.409
30.11.2012	23.165	0.632	6.636	12.917	8.139	2.880	4.011
31.10.2012	18.110	0.551	6.566	13.139	8.347	2.932	3.750
28.09.2012	18.670	0.528	7.078	12.332	8.326	4.146	3.492
31.08.2012	17.285	0.453	6.674	11.331	8.326	4.419	3.075
31.07.2012	17.040	0.412	6.931	11.160	7.601	3.727	2.903
29.06.2012	16.665	0.423	6.473	11.303	8.092	4.346	2.925
31.05.2012	12.390	0.345	5.852	10.568	7.484	3.973	2.715
30.04.2012	14.610	0.421	6.495	12.062	7.905	5.886	3.297
30.03.2012	18.810	0.457	6.555	12.123	7.858	6.556	3.755
29.02.2012	17.730	0.475	6.952	12.658	7.952	7.509	3.793
31.01.2012	14.495	0.416	6.206	12.705	8.150	8.019	3.617
30.12.2011	9.731	0.352	5.803	10.188	7.512	8.579	2.742
30.11.2011	8.300	0.337	5.846	10.555	7.816	7.726	2.852
31.10.2011	16.230	0.441	6.500	11.211	8.490	8.119	3.292
30.09.2011	17.500	0.474	6.124	10.283	7.694	8.482	3.191
31.08.2011	19.700	0.456	6.375	13.139	8.478	8.848	3.297
29.07.2011	24.680	0.589	7.312	17.255	9.617	8.801	4.849
30.06.2011	27.100	0.666	7.410	18.885	9.823	9.459	5.225
31.05.2011	29.390	0.706	7.890	19.313	10.281	9.849	5.788
29.04.2011	27.520	0.805	7.514	20.009	10.688	9.866	5.634
31.03.2011	26.535	0.789	7.530	17.574	10.220	10.110	5.542
28.02.2011	30.300	0.842	7.846	18.616	9.820	10.678	6.135
31.01.2011	29.255	0.858	8.532	17.619	9.624	10.705	5.663
31.12.2010	25.500	0.893	7.971	15.893	10.138	9.359	5.308

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Table 4. Monthly last price of SAB SM, SAN SM, SEBA SS, SHBA SS, SWEDA SS, UBI IM, UCG IM (in EUR)

Date	SAB SM	SAN SM	SEBA SS	SHBA SS	SWEDA SS	UBI IM	UCG IM
31.12.2015	1.616	4.483	9.742	12.303	20.388	5.909	25.733
30.11.2015	1.726	5.083	10.107	12.793	21.053	6.138	27.838
30.10.2015	1.738	5.016	9.796	12.662	21.369	6.491	29.466
30.09.2015	1.623	4.666	9.737	13.066	20.149	6.043	27.913
31.08.2015	1.877	5.370	10.739	13.785	21.075	6.634	29.216
31.07.2015	2.049	6.181	11.333	14.384	22.034	7.044	30.243
30.06.2015	2.139	6.161	11.551	13.185	21.064	6.858	30.193
29.05.2015	2.269	6.377	11.475	13.992	21.794	7.086	31.922
30.04.2015	2.359	6.645	11.529	13.999	21.184	6.796	32.323
31.03.2015	2.242	6.902	10.995	14.141	22.459	6.943	31.721
27.02.2015	2.230	6.426	11.464	15.256	23.647	6.681	29.792
30.01.2015	2.038	5.862	10.886	14.268	21.860	5.824	26.234
31.12.2014	2.003	6.881	10.848	13.316	21.304	5.681	26.735
28.11.2014	2.072	7.130	10.734	13.229	21.315	5.890	29.792
31.10.2014	2.089	6.912	10.309	12.790	21.282	5.952	28.865
30.09.2014	2.129	7.486	10.505	12.332	19.800	6.348	31.371
29.08.2014	2.176	7.465	9.944	11.900	19.397	5.666	29.516
31.07.2014	2.211	7.423	10.102	12.121	19.321	5.895	29.366
30.06.2014	2.263	7.505	9.731	11.881	19.310	6.024	30.644
30.05.2014	2.201	7.400	9.900	12.354	19.397	6.438	32.047
30.04.2014	2.225	7.049	9.758	11.852	18.819	6.538	32.273
31.03.2014	2.036	6.807	9.682	11.798	18.928	6.519	33.225
28.02.2014	2.155	6.458	9.824	12.168	19.724	5.995	28.890
31.01.2014	1.974	6.305	9.219	11.318	18.667	5.161	27.963
31.12.2013	1.707	6.399	9.241	11.478	19.724	4.705	26.961
29.11.2013	1.708	6.435	8.674	11.071	18.253	4.750	26.760
31.10.2013	1.701	6.432	8.554	10.665	18.416	4.861	27.762
30.09.2013	1.675	5.929	7.421	9.985	16.313	3.563	23.613
30.08.2013	1.462	5.252	7.415	10.330	16.346	3.479	21.438
31.07.2013	1.290	5.404	7.840	10.752	17.130	3.042	20.506
28.06.2013	1.069	4.821	6.985	9.778	16.760	2.652	18.031
31.05.2013	1.220	5.449	7.584	10.407	17.348	3.323	22.020
30.04.2013	1.324	5.401	7.247	10.694	17.381	3.021	19.845
28.03.2013	1.201	5.156	7.132	10.116	16.150	2.739	16.688
28.02.2013	1.380	5.715	7.339	10.211	16.945	3.344	19.504
31.01.2013	1.633	6.077	6.947	9.444	16.346	3.666	23.834
31.12.2012	1.635	6.000	6.021	8.442	13.839	3.342	18.572
30.11.2012	1.776	5.817	5.835	8.591	13.393	2.863	17.940
31.10.2012	1.554	5.694	5.993	8.253	13.403	2.890	17.068
28.09.2012	1.730	5.700	5.993	8.939	13.447	2.741	16.196
31.08.2012	1.904	5.577	5.525	8.387	12.630	2.543	15.775
31.07.2012	1.283	4.869	5.454	8.594	12.924	2.255	13.871
29.06.2012	1.269	5.135	4.878	8.235	11.834	2.450	14.934
31.05.2012	1.056	4.224	4.381	7.374	11.246	2.135	12.418
30.04.2012	1.426	4.642	4.943	7.911	12.128	2.674	15.064
30.03.2012	1.632	5.675	5.122	7.661	11.202	3.029	18.822
29.02.2012	1.676	6.125	5.395	8.071	12.336	3.315	19.574
31.01.2012	1.944	5.852	4.661	7.410	10.646	3.347	18.993
30.12.2011	2.024	5.774	4.369	6.575	9.715	3.018	21.190
30.11.2011	1.718	5.507	4.273	6.458	9.802	2.878	25.513
31.10.2011	1.800	6.075	4.486	6.825	10.009	2.631	27.989
30.09.2011	1.852	6.122	4.073	6.397	8.347	2.671	26.487
31.08.2011	1.900	6.314	4.097	6.331	9.508	2.465	31.108
29.07.2011	1.800	7.205	5.243	7.210	12.052	3.199	41.257
30.06.2011	1.966	7.832	5.634	7.087	11.584	3.700	48.188
31.05.2011	2.058	8.128	6.026	7.537	12.499	4.868	52.116
29.04.2011	2.065	8.480	6.331	7.617	12.488	5.399	57.364
31.03.2011	2.129	8.057	6.135	7.519	11.769	5.381	57.562
28.02.2011	2.170	8.788	6.277	7.766	12.150	6.533	61.490
31.01.2011	2.410	8.803	6.380	7.980	11.028	6.751	59.707
31.12.2010	2.035	7.798	6.113	7.806	10.221	5.846	51.093

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

APPENDIX C: Monthly last prices of high-cap European banks in local currencies

Table 5. Monthly last prices of high-cap Swedish banks (in SEK)

Date	NDA SS	SEBA SS	SHBA SS	SWEDA SS
30.12.2015	93.300	89.400	112.900	187.100
30.11.2015	96.650	92.750	117.400	193.200
30.10.2015	94.500	89.900	116.200	196.100
30.09.2015	93.200	89.350	119.900	184.900
31.08.2015	100.200	98.550	126.500	193.400
31.07.2015	107.500	104.000	132.000	202.200
30.06.2015	103.400	106.000	121.000	193.300
29.05.2015	110.900	105.300	128.400	200.000
30.04.2015	106.200	105.800	128.467	194.400
31.03.2015	105.300	100.900	129.767	206.100
27.02.2015	112.500	105.200	140.000	217.000
30.01.2015	105.300	99.900	130.933	200.600
30.12.2014	90.900	99.550	122.200	195.500
28.11.2014	93.150	98.500	121.400	195.600
31.10.2014	94.700	94.600	117.367	195.300
30.09.2014	93.900	96.400	113.167	181.700
29.08.2014	91.100	91.250	109.200	178.000
31.07.2014	92.800	92.700	111.233	177.300
30.06.2014	94.300	89.300	109.033	177.200
30.05.2014	98.700	90.850	113.367	178.000
30.04.2014	93.950	89.550	108.767	172.700
31.03.2014	91.800	88.850	108.267	173.700
28.02.2014	91.850	90.150	111.667	181.000
31.01.2014	87.700	84.600	103.867	171.300
30.12.2013	86.650	84.800	105.333	181.000
29.11.2013	84.750	79.600	101.600	167.500
31.10.2013	83.000	78.500	97.867	169.000
30.09.2013	77.500	68.100	91.633	149.700
30.08.2013	77.150	68.050	94.800	150.000
31.07.2013	82.550	71.950	98.667	157.200
28.06.2013	75.000	64.100	89.733	153.800
31.05.2013	82.200	69.600	95.500	159.200
30.04.2013	77.650	66.500	98.133	159.500
28.03.2013	73.800	65.450	92.833	148.200
28.02.2013	74.850	67.350	93.700	155.500
31.01.2013	70.150	63.750	86.667	150.000
28.12.2012	62.100	55.250	77.467	127.000
30.11.2012	60.900	53.550	78.833	122.900
31.10.2012	60.250	55.000	75.733	123.000
28.09.2012	64.950	55.000	82.033	123.400
31.08.2012	61.250	50.700	76.967	115.900
31.07.2012	63.600	50.050	78.867	118.600
29.06.2012	59.400	44.760	75.567	108.600
31.05.2012	53.700	40.200	67.667	103.200
30.04.2012	59.600	45.360	72.600	111.300
30.03.2012	60.150	47.000	70.300	102.800
29.02.2012	63.800	49.510	74.067	113.200
31.01.2012	56.950	42.770	68.000	97.700
30.12.2011	53.250	40.090	60.333	89.150
30.11.2011	53.650	39.210	59.267	89.950
31.10.2011	59.650	41.170	62.633	91.850
30.09.2011	56.200	37.380	58.700	76.600
31.08.2011	58.500	37.600	58.100	87.250
29.07.2011	67.100	48.110	66.167	110.600
30.06.2011	68.000	51.700	65.033	106.300
31.05.2011	72.400	55.300	69.167	114.700
29.04.2011	68.950	58.100	69.900	114.600
31.03.2011	69.100	56.300	69.000	108.000
28.02.2011	72.000	57.600	71.267	111.500
31.01.2011	78.300	58.550	73.233	101.200
30.12.2010	73.150	56.100	71.633	93.800

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Table 6. Monthly last prices of high-cap U.K. banks (in GBp)

Date	BARC LN	HSBA LN	LLOY LN	RBS LN
31.12.2015	218.900	536.200	73.070	302.000
30.11.2015	223.200	529.500	72.960	302.400
30.10.2015	232.000	507.600	73.730	317.600
30.09.2015	244.150	498.700	75.160	315.000
28.08.2015	261.450	518.700	77.380	336.800
31.07.2015	288.950	579.700	83.200	342.200
30.06.2015	260.500	570.100	85.240	351.500
29.05.2015	270.000	622.700	87.770	345.300
30.04.2015	255.300	648.100	77.380	338.500
31.03.2015	242.600	574.000	78.280	340.000
27.02.2015	256.900	577.300	79.000	367.200
30.01.2015	234.150	609.600	73.750	362.400
31.12.2014	243.500	608.600	75.820	394.400
28.11.2014	245.150	637.000	80.350	395.300
31.10.2014	240.800	639.500	77.130	388.000
30.09.2014	227.450	626.100	76.870	368.200
29.08.2014	224.450	652.000	76.270	362.800
31.07.2014	225.700	636.400	74.250	355.300
30.06.2014	212.800	592.900	74.250	328.400
30.05.2014	247.000	629.200	77.860	346.600
30.04.2014	252.200	604.100	75.360	298.800
31.03.2014	233.400	607.500	74.650	311.000
28.02.2014	252.100	629.700	82.530	327.900
31.01.2014	272.500	627.000	83.300	340.000
31.12.2013	271.950	662.400	78.880	338.100
29.11.2013	271.700	681.900	77.400	327.200
31.10.2013	263.600	682.100	77.530	367.600
30.09.2013	265.500	669.400	73.580	359.900
30.08.2013	261.743	676.000	72.550	333.700
31.07.2013	265.946	747.800	68.470	317.600
28.06.2013	257.217	682.000	63.160	273.500
31.05.2013	296.014	725.900	62.110	336.600
30.04.2013	264.237	703.500	54.330	306.300
28.03.2013	268.948	702.500	48.690	275.500
28.02.2013	283.590	731.400	54.470	323.900
31.01.2013	278.047	716.700	51.660	343.300
31.12.2012	242.391	646.900	47.915	324.500
30.11.2012	227.241	637.700	46.495	295.200
31.10.2012	210.152	608.800	40.575	276.000
28.09.2012	198.467	573.300	38.830	257.000
31.08.2012	169.276	547.100	33.310	226.300
31.07.2012	155.189	533.900	30.355	213.700
29.06.2012	150.432	561.100	31.100	215.300
31.05.2012	162.856	509.500	25.380	199.800
30.04.2012	201.607	555.100	31.010	242.700
30.03.2012	217.311	554.800	33.605	276.400
29.02.2012	226.318	555.300	34.935	279.200
31.01.2012	196.342	529.700	30.620	266.200
30.12.2011	162.625	491.050	25.905	201.800
30.11.2011	166.505	494.500	24.825	209.900
31.10.2011	180.407	544.900	32.495	242.300
30.09.2011	149.046	496.900	34.865	234.900
31.08.2011	157.729	536.600	33.595	242.700
29.07.2011	205.995	594.500	43.350	356.900
30.06.2011	236.894	618.400	49.000	384.600
31.05.2011	255.554	634.800	52.000	426.000
28.04.2011	260.773	655.400	59.250	414.700
31.03.2011	256.385	641.000	58.090	407.900
28.02.2011	295.460	678.000	61.960	451.600
31.01.2011	271.350	680.600	63.180	416.800
31.12.2010	241.698	651.100	65.700	390.700

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Table 7. Monthly last prices of high-cap Danish banks (in DDK)

Date	DANSKE DC	JYSK DC
30.12.2015	185.200	312.100
30.11.2015	189.500	321.100
30.10.2015	186.500	331.100
30.09.2015	201.500	369.100
31.08.2015	206.000	371.800
31.07.2015	212.200	354.800
30.06.2015	196.800	336.200
29.05.2015	199.300	327.500
30.04.2015	189.000	326.600
31.03.2015	183.500	292.900
27.02.2015	176.600	288.700
30.01.2015	171.100	298.900
30.12.2014	167.400	312.800
28.11.2014	170.000	308.900
31.10.2014	162.900	320.000
30.09.2014	160.200	318.500
29.08.2014	159.400	309.000
31.07.2014	161.300	316.100
30.06.2014	153.900	309.100
28.05.2014	153.900	302.700
30.04.2014	152.000	295.500
31.03.2014	151.000	297.800
28.02.2014	143.200	325.000
31.01.2014	124.800	282.900
30.12.2013	124.400	292.500
29.11.2013	124.800	296.800
31.10.2013	128.300	310.100
30.09.2013	118.700	273.800
30.08.2013	113.000	260.500
31.07.2013	103.300	245.800
28.06.2013	98.000	216.000
31.05.2013	113.400	228.400
30.04.2013	107.000	220.300
27.03.2013	104.000	198.000
28.02.2013	106.300	189.900
31.01.2013	105.400	179.000
28.12.2012	95.650	157.100
30.11.2012	98.350	164.000
31.10.2012	90.000	175.500
28.09.2012	104.700	172.400
31.08.2012	103.000	169.500
31.07.2012	90.000	162.300
29.06.2012	81.400	158.000
31.05.2012	79.550	156.000
30.04.2012	91.250	176.000
30.03.2012	94.500	176.500
29.02.2012	100.500	200.200
31.01.2012	83.000	167.600
30.12.2011	72.950	141.000
30.11.2011	77.000	164.000
31.10.2011	74.500	157.400
30.09.2011	78.550	165.700
31.08.2011	76.800	159.000
29.07.2011	100.500	206.900
30.06.2011	95.250	203.100
31.05.2011	109.000	242.000
29.04.2011	121.000	250.300
31.03.2011	116.500	234.300
28.02.2011	117.429	233.000
31.01.2011	135.104	244.500
30.12.2010	132.328	259.000

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

Table 8. Monthly last prices of the high-cap banks from Norway, Poland, and Hungary

Date	DNB NO	PKO PW	OTP HB
30.12.2015	109.800 NOK	27.330 PLN	6,000.000 HUF
30.11.2015	114.400 NOK	26.950 PLN	6,070.000 HUF
30.10.2015	108.200 NOK	28.640 PLN	5,475.000 HUF
30.09.2015	110.700 NOK	29.430 PLN	5,405.000 HUF
31.08.2015	118.400 NOK	29.740 PLN	5,387.000 HUF
31.07.2015	133.200 NOK	29.220 PLN	5,745.000 HUF
30.06.2015	130.800 NOK	31.120 PLN	5,600.000 HUF
29.05.2015	136.500 NOK	32.680 PLN	5,700.000 HUF
30.04.2015	134.000 NOK	36.100 PLN	6,005.000 HUF
31.03.2015	129.700 NOK	34.000 PLN	5,304.000 HUF
27.02.2015	124.800 NOK	32.600 PLN	4,285.000 HUF
30.01.2015	112.300 NOK	34.340 PLN	3,650.000 HUF
30.12.2014	110.700 NOK	35.760 PLN	3,811.000 HUF
28.11.2014	116.500 NOK	37.550 PLN	3,966.000 HUF
31.10.2014	123.900 NOK	37.450 PLN	4,065.000 HUF
30.09.2014	120.300 NOK	39.660 PLN	4,180.000 HUF
29.08.2014	115.600 NOK	38.250 PLN	4,140.000 HUF
31.07.2014	112.000 NOK	35.600 PLN	4,075.000 HUF
30.06.2014	112.200 NOK	37.700 PLN	4,348.000 HUF
30.05.2014	112.300 NOK	40.600 PLN	4,853.000 HUF
30.04.2014	105.100 NOK	41.500 PLN	4,211.000 HUF
31.03.2014	104.100 NOK	42.480 PLN	4,272.000 HUF
28.02.2014	108.900 NOK	44.150 PLN	3,989.000 HUF
31.01.2014	106.100 NOK	40.800 PLN	4,240.000 HUF
30.12.2013	108.500 NOK	39.420 PLN	4,100.000 HUF
29.11.2013	108.400 NOK	41.150 PLN	4,489.000 HUF
31.10.2013	105.500 NOK	40.850 PLN	4,520.000 HUF
30.09.2013	91.300 NOK	37.100 PLN	4,350.000 HUF
30.08.2013	95.000 NOK	38.310 PLN	4,239.000 HUF
31.07.2013	98.150 NOK	37.200 PLN	4,530.000 HUF
28.06.2013	87.950 NOK	35.600 PLN	4,755.000 HUF
31.05.2013	95.450 NOK	34.810 PLN	4,900.000 HUF
30.04.2013	94.250 NOK	32.900 PLN	4,736.000 HUF
27.03.2013	85.650 NOK	34.550 PLN	4,285.000 HUF
28.02.2013	85.500 NOK	35.600 PLN	4,700.000 HUF
31.01.2013	76.400 NOK	34.630 PLN	4,633.000 HUF
28.12.2012	70.400 NOK	36.900 PLN	4,150.000 HUF
30.11.2012	70.550 NOK	34.800 PLN	4,080.000 HUF
31.10.2012	71.200 NOK	35.690 PLN	4,150.000 HUF
28.09.2012	70.250 NOK	35.600 PLN	3,895.000 HUF
31.08.2012	66.600 NOK	35.600 PLN	3,579.000 HUF
31.07.2012	63.500 NOK	32.500 PLN	3,525.000 HUF
29.06.2012	58.950 NOK	34.600 PLN	3,570.000 HUF
31.05.2012	55.100 NOK	32.000 PLN	3,338.000 HUF
30.04.2012	61.700 NOK	33.800 PLN	3,810.000 HUF
30.03.2012	73.200 NOK	33.600 PLN	3,829.000 HUF
29.02.2012	71.750 NOK	34.000 PLN	3,998.000 HUF
31.01.2012	61.900 NOK	34.850 PLN	4,013.000 HUF
30.12.2011	58.550 NOK	32.120 PLN	3,218.000 HUF
30.11.2011	58.800 NOK	33.420 PLN	3,334.000 HUF
31.10.2011	64.950 NOK	36.300 PLN	3,541.000 HUF
30.09.2011	59.400 NOK	32.900 PLN	3,248.000 HUF
31.08.2011	64.750 NOK	36.250 PLN	4,150.000 HUF
29.07.2011	78.600 NOK	41.120 PLN	5,450.000 HUF
30.06.2011	75.200 NOK	42.000 PLN	5,965.000 HUF
31.05.2011	81.150 NOK	43.960 PLN	6,100.000 HUF
29.04.2011	85.300 NOK	45.700 PLN	6,320.000 HUF
31.03.2011	84.850 NOK	43.700 PLN	5,551.000 HUF
28.02.2011	86.600 NOK	41.990 PLN	5,880.000 HUF
31.01.2011	79.500 NOK	41.150 PLN	5,565.000 HUF
30.12.2010	81.900 NOK	43.350 PLN	5,020.000 HUF

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of high-cap European banks*, 2017; own calculation.

APPENDIX D: Monthly values of the explanatory variables

Table 9. Monthly values of MRP, SMB, and HML

Date	MRP	SMB	HML
31.12.2015	-0.051504	0.038100	-0.012900
30.11.2015	0.026047	0.004800	-0.028100
30.10.2015	0.078580	-0.029600	-0.006400
30.09.2015	-0.042821	0.011300	-0.036200
31.08.2015	-0.086319	0.036800	-0.009400
31.07.2015	0.037825	-0.008100	-0.026300
30.06.2015	-0.048055	0.020300	0.002300
29.05.2015	0.008708	0.015900	-0.026900
30.04.2015	-0.005511	0.022200	0.002900
31.03.2015	0.010998	-0.004700	-0.003000
27.02.2015	0.066217	0.009800	0.019000
30.01.2015	0.068854	-0.015400	-0.034400
31.12.2014	-0.016814	0.022600	-0.022600
28.11.2014	0.027717	-0.012800	-0.017800
31.10.2014	-0.021705	-0.011700	-0.031900
30.09.2014	-0.000222	-0.022100	-0.003800
29.08.2014	0.013547	-0.009400	-0.008900
31.07.2014	-0.022061	-0.004800	0.001800
30.06.2014	-0.011794	0.000400	-0.014900
30.05.2014	0.013073	-0.006600	-0.005100
30.04.2014	0.004569	-0.021200	0.004400
31.03.2014	-0.016876	0.003300	0.019200
28.02.2014	0.042569	0.004800	0.003500
31.01.2014	-0.023076	0.036000	0.024900
31.12.2013	0.003974	0.005800	-0.001800
29.11.2013	0.003645	0.009500	-0.005200
31.10.2013	0.032882	-0.002500	0.043900
30.09.2013	0.038805	0.000900	0.012300
30.08.2013	-0.012994	0.027300	0.007100
31.07.2013	0.045724	-0.017800	0.025200
28.06.2013	-0.057982	0.023000	-0.027000
31.05.2013	0.009240	0.011100	0.029100
30.04.2013	0.004907	-0.015000	0.035700
29.03.2013	0.007774	-0.005600	-0.044700
28.02.2013	0.003900	0.021000	-0.034200
31.01.2013	0.020759	0.004700	0.042700
31.12.2012	0.008722	0.022800	0.031100
30.11.2012	0.014534	-0.024100	-0.005000
31.10.2012	0.000599	-0.007600	0.020100
28.09.2012	0.001611	0.013600	0.022600
31.08.2012	0.010505	-0.002300	0.034800
31.07.2012	0.031190	-0.011800	-0.026400
29.06.2012	0.035590	-0.045800	0.030100
31.05.2012	-0.080534	0.001700	-0.024200
30.04.2012	-0.036048	0.013100	-0.042400
30.03.2012	-0.017943	0.007200	-0.016200
29.02.2012	0.022813	0.013300	-0.004000
31.01.2012	0.022821	0.028200	0.007800
30.12.2011	-0.000893	-0.009400	-0.009800
30.11.2011	-0.034314	-0.027300	-0.032500
31.10.2011	0.055278	-0.033600	-0.011700
30.09.2011	-0.068222	-0.010700	-0.017300
31.08.2011	-0.125772	0.007000	-0.037000
29.07.2011	-0.049670	0.003500	-0.039800
30.06.2011	-0.050795	-0.014300	0.003000
31.05.2011	-0.030965	0.001700	-0.024100
29.04.2011	0.007241	-0.010800	-0.009800
31.03.2011	-0.056857	0.021500	-0.017000
28.02.2011	0.005254	-0.011800	0.008300
31.01.2011	-0.001067	-0.006300	0.053100

Data source: Bloomberg Finance L.P. (2018), *Monthly last price of Euribor 12 months*, 2017; Bloomberg Finance L.P. (2018), *Return on Stoxx Europe 600*, 2017; Kenneth R. French (2018), *Fama/French European 3 Factors*, 2017; own calculation.

APPENDIX E: Regression outcome of the high-cap European banks

Figure 1. ALBK ID regression outcome

Linear Regression

Regression Statistics

R	0.45428
R-square	0.20637
Adjusted R-square	0.16385
S	0.25935
N	60

E(rALBK ID - rE12M) = - 0.00191 + 3.09207 * E(MRP) + 0.34073 * E(SMB) + 0.97417 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.97943	0.32648	4.85395	0.00452
Residual	56.	3.76656	0.06726		
Total	59.	4.74599			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**-0.00191**	0.03397	-0.06995	0.06613	-0.05618	0.9554	**not rejected**
MRP	**3.09207**	0.9998	1.08923	5.0949	3.09269	0.00309	**rejected**
SMB	**0.34073**	2.06921	-3.80441	4.48586	0.16466	0.8698	**not rejected**
HML	**0.97417**	1.49326	-2.0172	3.96553	0.65238	0.51683	**not rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 2. BARC LN regression outcome

Linear Regression

Regression Statistics

R	0.68438
R-square	0.46837
Adjusted R-squa	0.43989
S	0.06931
N	60

E(rBARC LN - rE12M) = 0.00129 + 1.39404 * E(MRP) + 1.09312 * E(SMB) + 1.05045 *E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.23701	0.079	16.44558	8.75733E-8
Residual	56.	0.26902	0.0048		
Total	59.	0.50603			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00129**	0.00908	-0.01689	0.01948	0.14255	0.88716	**not rejected**
MRP	**1.39404**	0.2672	0.85878	1.9293	5.21725	2.73677E-6	**rejected**
SMB	**1.09312**	0.553	-0.01467	2.20092	1.97671	0.05301	**not rejected**
HML	**1.05045**	0.39908	0.251	1.8499	2.6322	0.01094	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 3. BBVA SM regression outcome

Linear Regression

Regression Statistics

R	0.8543
R-square	0.72984
Adjusted R-squa	0.71536
S	0.04261
N	60

E(rBBVA SM - rE12M) = 0.00325 + 0.78794 * E(MRP) - 0.92773 *E(SMB) + 1.8714 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.27461	0.09154	50.42698	0.
Residual	56.	0.10165	0.00182		
Total	59.	0.37626			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00325**	0.00558	-0.00793	0.01442	0.58178	0.56305	**not rejected**
MRP	**0.78794**	0.16425	0.45891	1.11696	4.79727	0.00001	**rejected**
SMB	**-0.92773**	0.33993	-1.60869	-0.24676	-2.72916	0.00847	**rejected**
HML	**1.8714**	0.24531	1.37998	2.36282	7.62864	3.16501E-10	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 4. BNP FP regression outcome

Linear Regression

Regression Statistics

R	0.86913
R-square	0.7554
Adjusted R-square	0.74229
S	0.04337
N	60

E(rBNP FP - rE12M) = 0.00729 + 1.22025 * E(MRP) - 0.14078 * E(SMB) + 1.75286 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.32531	0.10844	57.64685	0.
Residual	56.	0.10534	0.00188		
Total	59.	0.43065			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**0.00729**	0.00568	-0.00409	0.01867	1.28274	0.20487	**not rejected**
MRP	**1.22025**	0.1672	0.88531	1.55519	7.29816	1.11272E-9	**rejected**
SMB	**-0.14078**	0.34604	-0.83399	0.55242	-0.40684	0.68568	**not rejected**
HML	**1.75286**	0.24972	1.2526	2.25311	7.01918	3.2173E-9	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 5. CBK GR regression outcome

Linear Regression

Regression Statistics

R	0.67971
R-square	0.46201
Adjusted R-square	0.43319
S	0.09099
N	60

E(rCBK GR - rE12M) = - 0.01378 + 1.59539 * E(MRP) + 2.65312 * E(SMB) + 1.62179 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.39812	0.13271	16.03033	1.21417E-7
Residual	56.	0.46359	0.00828		
Total	59.	0.86171			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**-0.01378**	0.01192	-0.03765	0.0101	-1.15601	0.25258	**not rejected**
MRP	**1.59539**	0.35076	0.89273	2.29804	4.54839	0.00003	**rejected**
SMB	**2.65312**	0.72594	1.19889	4.10736	3.65473	0.00057	**rejected**
HML	**1.62179**	0.52388	0.57233	2.67125	3.09571	0.00306	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 6. DANSKE DC regression outcome

Linear Regression

Regression Statistics

R	0.58313
R-square	0.34004
Adjusted R-square	0.30469
S	0.06646
N	60

E(rDANSKE DC - rE12M) = 0.00394 + 1.19291 * E(MRP) + 1.26613 * E(SMB) + 0.34801 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.12745	0.04248	9.61803	0.00003
Residual	56.	0.24736	0.00442		
Total	59.	0.37481			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**0.00394**	0.0087	-0.0135	0.02137	0.45215	0.65291	**not rejected**
MRP	**1.19291**	0.25621	0.67965	1.70617	4.6559	0.00002	**rejected**
SMB	**1.26613**	0.53027	0.20387	2.32839	2.38771	0.02035	**rejected**
HML	**0.34801**	0.38267	-0.41857	1.1146	0.90943	0.36702	**not rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 7. DBK GR regression outcome

Linear Regression

Regression Statistics

R	0.7645
R-square	0.58447
Adjusted R-square	0.56221
S	0.06159
N	60

E(rDBK GR - rE12M) = - 0.00249 + 1.20959 * E(MRP) - 0.17203 * E(SMB) + 1.59563 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.29883	0.09961	26.25565	9.80221E-11
Residual	56.	0.21245	0.00379		
Total	59.	0.51128			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**-0.00249**	0.00807	-0.01865	0.01368	-0.30805	0.75919	**not rejected**
MRP	**1.20959**	0.23745	0.73392	1.68526	5.0941	4.27177E-6	**rejected**
SMB	**-0.17203**	0.49143	-1.15649	0.81243	-0.35006	0.72761	**not rejected**
HML	**1.59563**	0.35465	0.88519	2.30607	4.49922	0.00003	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 8. DNB NO regression outcome

Linear Regression

Regression Statistics

R	0.73191
R-square	0.53569
Adjusted R-square	0.51081
S	0.0499
N	60

E(rDNB NO - rE12M) = 0.00425 + 1.257 * E(MRP) + 0.45416 * E(SMB) + 0.51609 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.16087	0.05362	21.53604	2.10529E-9
Residual	56.	0.13944	0.00249		
Total	59.	0.30031			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00425**	0.00654	-0.00884	0.01734	0.65013	0.51826	**not rejected**
MRP	**1.257**	0.19237	0.87165	1.64236	6.53444	2.02787E-8	**rejected**
SMB	**0.45416**	0.39813	-0.34339	1.2517	1.14073	0.25884	**not rejected**
HML	**0.51609**	0.28731	-0.05946	1.09164	1.79628	0.07784	**not rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 9. EBS AV regression outcome

Linear Regression

Regression Statistics

R	0.68154
R-square	0.46449
Adjusted R-square	0.43581
S	0.08018
N	60

E(rEBS AV - rE12M) = 0.00185 + 1.54167 * E(MRP) + 1.89921 * E(SMB) + 1.30231 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.31226	0.10409	16.19136	1.0692E-7
Residual	56.	0.36	0.00643		
Total	59.	0.67225			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00185**	0.0105	-0.01919	0.02288	0.17571	0.86115	**not rejected**
MRP	**1.54167**	0.30909	0.92248	2.16085	4.98772	6.25915E-6	**rejected**
SMB	**1.89921**	0.63971	0.61772	3.1807	2.96887	0.00439	**rejected**
HML	**1.30231**	0.46165	0.37751	2.2271	2.82098	0.00661	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 10. GLE FP regression outcome

Linear Regression

Regression Statistics

R	0.88101
R-square	0.77618
Adjusted R-square	0.76419
S	0.05453
N	60

E(rGLE FP - rE12M) = 0.01287 + 1.63326 * E(MRP) + 0.46871 * E(SMB) + 2.48336 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.57752	0.19251	64.73206	0.
Residual	56.	0.16654	0.00297		
Total	59.	0.74406			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.01287**	0.00714	-0.00144	0.02718	1.80229	0.07688	**not rejected**
MRP	**1.63326**	0.21023	1.21212	2.0544	7.76887	1.85774E-10	**rejected**
SMB	**0.46871**	0.4351	-0.40291	1.34032	1.07724	0.28599	**not rejected**
HML	**2.48336**	0.31399	1.85435	3.11236	7.90893	1.09186E-10	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 11. HSBA LN regression outcome

Linear Regression

Regression Statistics

R	0.64109
R-square	0.41099
Adjusted R-square	0.37944
S	0.04418
N	60

E(rHSBA LN - rE12M) = - 0.00563 + 0.7128 * E(MRP) - 0.07992 * E(SMB) + 0.59883 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.07626	0.02542	13.02516	1.45349E-6
Residual	56.	0.10929	0.00195		
Total	59.	0.18555			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**-0.00563**	0.00579	-0.01723	0.00596	-0.97389	0.3343	**not rejected**
MRP	**0.7128**	0.17031	0.37164	1.05396	4.18543	0.0001	**rejected**
SMB	**-0.07992**	0.35247	-0.786	0.62616	-0.22673	0.82146	**not rejected**
HML	**0.59883**	0.25436	0.08928	1.10837	2.35423	0.02209	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 12. INGA NA regression outcome

Linear Regression

Regression Statistics

R	0.81538
R-square	0.66485
Adjusted R-square	0.6469
S	0.05556
N	60

E(rINGA NA - rE12M) = 0.01572 + 1.23498 * E(MRP) - 0.00256 * E(SMB) + 1.87075 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.34287	0.11429	37.03016	0.
Residual	56.	0.17284	0.00309		
Total	59.	0.51571			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.01572**	0.00728	0.00114	0.03029	2.16015	0.03506	**rejected**
MRP	**1.23498**	0.21417	0.80594	1.66402	5.76631	3.63646E-7	**rejected**
SMB	**-0.00256**	0.44326	-0.89051	0.88539	-0.00578	0.99541	**not rejected**
HML	**1.87075**	0.31988	1.22995	2.51154	5.84829	2.67989E-7	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 13. ISP IM regression outcome

Linear Regression

Regression Statistics

R	0.82476
R-square	0.68022
Adjusted R-square	0.66309
S	0.06105
N	60

E(rISP IM - rE12M) = 0.01853 + 1.09225 * E(MRP) - 0.43583 * E(SMB) + 2.50122 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.44395	0.14798	39.70704	0.
Residual	56.	0.20871	0.00373		
Total	59.	0.65266			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.01853**	0.008	0.00252	0.03455	2.31795	0.02413	**rejected**
MRP	**1.09225**	0.23535	0.6208	1.56371	4.64105	0.00002	**rejected**
SMB	**-0.43583**	0.48708	-1.41156	0.53991	-0.89477	0.37474	**not rejected**
HML	**2.50122**	0.3515	1.79707	3.20537	7.11576	2.22781E-9	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 14. JYSK DC regression outcome

Linear Regression

Regression Statistics

R	0.49676
R-square	0.24677
Adjusted R-square	0.20642
S	0.07297
N	60

E(rJYSK DC - rE12M) = 0.00094 + 0.92669 * E(MRP) + 1.56099 * E(SMB) + 0.47101 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.09768	0.03256	6.11544	0.00113
Residual	56.	0.29815	0.00532		
Total	59.	0.39583			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00094**	0.00956	-0.0182	0.02008	0.09829	0.92205	**not rejected**
MRP	**0.92669**	0.28129	0.36319	1.49019	3.29439	0.00171	**rejected**
SMB	**1.56099**	0.58217	0.39476	2.72723	2.68132	0.00962	**rejected**
HML	**0.47101**	0.42013	-0.37061	1.31263	1.12111	0.26703	**not rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 15. KBC BB regression outcome

Linear Regression

Regression Statistics

R	0.66206
R-square	0.43833
Adjusted R-square	0.40824
S	0.10469
N	60

E(rKBC BB - rE12M) = 0.02537 + 1.77928 * E(MRP) + 2.03099 * E(SMB) + 1.87648 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.47897	0.15966	14.56745	3.9582E-7
Residual	56.	0.61375	0.01096		
Total	59.	1.09273			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.02537**	0.01371	-0.00209	0.05284	1.85049	0.06952	**not rejected**
MRP	**1.77928**	0.40359	0.9708	2.58776	4.40866	0.00005	**rejected**
SMB	**2.03099**	0.83528	0.35772	3.70425	2.43151	0.01826	**rejected**
HML	**1.87648**	0.60278	0.66896	3.084	3.11302	0.00292	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 16. LLOY LN regression outcome

Linear Regression

Regression Statistics

R	0.67698
R-square	0.4583
Adjusted R-square	0.42928
S	0.06963
N	60

E(rLLOY LN - rE12M) = 0.00533 + 1.13105 * E(MRP) + 1.22429 * E(SMB) + 1.47498 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.22971	0.07657	15.79292	1.46604E-7
Residual	56.	0.27151	0.00485		
Total	59.	0.50122			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00533**	0.00912	-0.01294	0.0236	0.58431	0.56136	**not rejected**
MRP	**1.13105**	0.26843	0.59332	1.66878	4.21354	0.00009	**rejected**
SMB	**1.22429**	0.55556	0.11138	2.33721	2.20373	0.03167	**rejected**
HML	**1.47498**	0.40092	0.67184	2.27812	3.67898	0.00053	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 17. NDA SS regression outcome

Linear Regression

Regression Statistics

R	0.74966
R-square	0.56199
Adjusted R-square	0.53852
S	0.04313
N	60

E(rNDA SS - rE12M) = 0.00171 + 1.22343 * E(MRP) + 0.53444 * E(SMB) + 0.26471 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.13363	0.04454	23.95013	4.20705E-10
Residual	56.	0.10415	0.00186		
Total	59.	0.23777			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00171**	0.00565	-0.00961	0.01302	0.3025	0.76339	**not rejected**
MRP	**1.22343**	0.16625	0.89039	1.55647	7.35895	8.8287E-10	**rejected**
SMB	**0.53444**	0.34408	-0.15483	1.22371	1.55324	0.126	**not rejected**
HML	**0.26471**	0.24831	-0.23271	0.76213	1.06606	0.29097	**not rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 18. OTP HB regression outcome

Linear Regression

Regression Statistics

R	0.6538
R-square	0.42746
Adjusted R-square	0.39679
S	0.0715
N	60

E(rOTP HB - rE12M) = 0.00567 + 1.24635 * E(MRP) + 1.15315 * E(SMB) + 1.15643 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.21375	0.07125	13.93651	6.69161E-7
Residual	56.	0.28629	0.00511		
Total	59.	0.50004			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00567**	0.00936	-0.01309	0.02443	0.60579	0.5471	**not rejected**
MRP	**1.24635**	0.27564	0.69417	1.79853	4.52163	0.00003	**rejected**
SMB	**1.15315**	0.57048	0.01035	2.29595	2.02138	0.04803	**rejected**
HML	**1.15643**	0.41169	0.33171	1.98114	2.80898	0.00683	**rejected**

T (5%) 2.00324
LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 19. PKO PW regression outcome

Linear Regression

Regression Statistics	
R	0.48824
R-square	0.23838
Adjusted R-square	0.19758
S	0.04902
N	60

E(rPKO PW - rE12M) = - 0,01162 + 0,46913 *E(MRP) + 0,77006 * E(SMB) + 0,62401 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.04212	0.01404	5.84238	0.00152
Residual	56.	0.13456	0.0024		
Total	59.	0.17668			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**-0.01162**	0.00642	-0.02449	0.00124	-1.81065	0.07556	**not rejected**
MRP	**0.46913**	0.18897	0.09057	0.84769	2.48251	0.01607	**rejected**
SMB	**0.77006**	0.39111	-0.01341	1.55354	1.96894	0.05392	**not rejected**
HML	**0.62401**	0.28224	0.05861	1.18942	2.2109	0.03114	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 20. POP SM regression outcome

Linear Regression

Regression Statistics	
R	0.59244
R-square	0.35098
Adjusted R-square	0.31621
S	0.09477
N	60

E(rPOP SM - rE12M) = - 0.01135 + 0.68323 * E(MRP) - 0.16153 * E(SMB) + 2.22485 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.272	0.09067	10.09479	0.00002
Residual	56.	0.50297	0.00898		
Total	59.	0.77497			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**-0.01135**	0.01241	-0.03622	0.01351	-0.91464	0.3643	**not rejected**
MRP	**0.68323**	0.36535	-0.04865	1.41512	1.87007	0.0667	**not rejected**
SMB	**-0.16153**	0.75614	-1.67627	1.35321	-0.21362	0.83162	**not rejected**
HML	**2.22485**	0.54568	1.13173	3.31797	4.07724	0.00015	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 21. RBS LN regression outcome

Linear Regression

Regression Statistics	
R	0.70445
R-square	0.49626
Adjusted R-square	0.46927
S	0.07175
N	60

E(rRBS LN - rE12M) = 0.00179 + 1.09713 * E(MRP) + 0.93221 * E(SMB) + 1.87995 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.28398	0.09466	18.38924	1.99026E-8
Residual	56.	0.28826	0.00515		
Total	59.	0.57224			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**0.00179**	0.0094	-0.01704	0.02061	0.19034	0.84973	**not rejected**
MRP	**1.09713**	0.27659	0.54306	1.65121	3.96666	0.00021	**rejected**
SMB	**0.93221**	0.57244	-0.21452	2.07894	1.6285	0.10903	**not rejected**
HML	**1.87995**	0.4131	1.0524	2.70749	4.55079	0.00003	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 22. SAB SM regression outcome

Linear Regression

Regression Statistics

R	0.55221
R-square	0.30493
Adjusted R-square	0.26769
S	0.09841
N	60

E(rSAB SM - rE12M) = 0.00415 + 0.39732 * E(MRP) - 1.15026 * E(SMB) + 2.08081 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.23793	0.07931	8.18916	0.00013
Residual	56.	0.54235	0.00968		
Total	59.	0.78028			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**0.00415**	0.01289	-0.02167	0.02997	0.32206	0.74861	**not rejected**
MRP	**0.39732**	0.37938	-0.36268	1.15731	1.04726	0.29948	**not rejected**
SMB	**-1.15026**	0.78519	-2.72317	0.42266	-1.46495	0.14853	**not rejected**
HML	**2.08081**	0.56663	0.94571	3.21592	3.67223	0.00054	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 23. SAN SM regression outcome

Linear Regression

Regression Statistics

R	0.85607
R-square	0.73285
Adjusted R-square	0.71854
S	0.04192
N	60

E(rSAN SM - rE12M) = - 0.00381 + 0.6662 *E(MRP) - 0.94053 * E(SMB) + 2.01531 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.27001	0.09	51.20638	0.
Residual	56.	0.09843	0.00176		
Total	59.	0.36844			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**-0.00381**	0.00549	-0.01481	0.00718	-0.69471	0.49011	**not rejected**
MRP	**0.6662**	0.16162	0.34243	0.98997	4.12194	0.00013	**rejected**
SMB	**-0.94053**	0.3345	-1.61061	-0.27044	-2.81174	0.00678	**rejected**
HML	**2.01531**	0.24139	1.53174	2.49888	8.3486	2.07063E-11	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 24. SEBA SS regression outcome

Linear Regression

Regression Statistics

R	0.78367
R-square	0.61415
Adjusted R-square	0.59347
S	0.04374
N	60

E(rSEBA SS -rE12M) = 0.00803 + 1.16013 * E(MRP) + 0.49436 * E(SMB) + 0.87817 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.1705	0.05683	29.71081	1.26011E-11
Residual	56.	0.10712	0.00191		
Total	59.	0.27761			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	**H0 (5%)**
Intercept	**0.00803**	0.00573	-0.00344	0.01951	1.40235	0.16633	**not rejected**
MRP	**1.16013**	0.16861	0.82237	1.49789	6.88073	5.44728E-9	**rejected**
SMB	**0.49436**	0.34895	-0.20467	1.1934	1.41671	0.16211	**not rejected**
HML	**0.87817**	0.25182	0.37371	1.38264	3.48726	0.00096	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 25. SWEDA SS regression outcome

Linear Regression

Regression Statistics

R	0.68146
R-square	0.46438
Adjusted R-square	0.43569
S	0.05359
N	60

E(rSWEDA SS - rE12M) = 0.01003 + 1.22281 * E(MRP) + 0.30089 * E(SMB) + 0.26276 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.13945	0.04648	16.18407	1.07536E-7
Residual	56.	0.16084	0.00287		
Total	59.	0.30029			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.01003**	0.00702	-0.00404	0.02409	1.42832	0.15875	**not rejected**
MRP	**1.22281**	0.2066	0.80893	1.63669	5.91859	2.06133E-7	**rejected**
SMB	**0.30089**	0.4276	-0.55569	1.15747	0.70368	0.48455	**not rejected**
HML	**0.26276**	0.30858	-0.3554	0.88091	0.85152	0.39811	**not rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 26. UBI IM regression outcome

Linear Regression

Regression Statistics

R	0.79883
R-square	0.63812
Adjusted R-square	0.61874
S	0.07172
N	60

E(rUBI IM - rE12M) = 0.01242 + 1.18517 * E(MRP) + 0.35686 * E(SMB) + 2.82157 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.50793	0.16931	32.91652	2.12845E-12
Residual	56.	0.28804	0.00514		
Total	59.	0.79597			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.01242**	0.00939	-0.0064	0.03123	1.32205	0.19153	**not rejected**
MRP	**1.18517**	0.27648	0.63131	1.73903	4.2866	0.00007	**rejected**
SMB	**0.35686**	0.57222	-0.78943	1.50314	0.62364	0.5354	**not rejected**
HML	**2.82157**	0.41294	1.99435	3.6488	6.83283	6.53514E-9	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

Figure 27. UCG IM regression outcome

Linear Regression

Regression Statistics

R	0.88544
R-square	0.784
Adjusted R-square	0.77243
S	0.05364
N	60

E(rUCG IM - rE12M) = 0.00231 + 0.94774 * E(MRP) - 0.51814 * E(SMB) + 3.2683 * E(HML)

ANOVA

	d.f.	SS	MS	F	p-level
Regression	3.	0.58482	0.19494	67.75434	0.
Residual	56.	0.16112	0.00288		
Total	59.	0.74594			

	Coefficient	Standard Error	LCL	UCL	t Stat	p-level	H0 (5%)
Intercept	**0.00231**	0.00703	-0.01176	0.01638	0.32876	0.74357	**not rejected**
MRP	**0.94774**	0.20678	0.53351	1.36198	4.58328	0.00003	**rejected**
SMB	**-0.51814**	0.42796	-1.37546	0.33917	-1.21071	0.23109	**not rejected**
HML	**3.2683**	0.30884	2.64961	3.88699	10.58237	0.	**rejected**
T (5%)	2.00324						

LCL - Lower value of a reliable interval (LCL)
UCL - Upper value of a reliable interval (UCL)

Data source: AnalystSoft Inc. (2018), *Regressions of high-cap European banks*, 2017; own calculation.

APPENDIX F: Performance of the high-cap European banks

Table 10. Difference between ROE and cost of capital estimate of the high-cap European banks (in %)

Ticker	Spread	ROE	E (cost of capital)
ALBK ID	1.98	12.40	10.42
BARC LN	-12.28	-0.72	11.56
BBVA SM	-0.04	5.48	5.52
BMPS IM	-19.08	5.05	24.13
BNP FP	-2.07	7.45	9.52
CBK GR	-18.38	3.92	22.30
DANSKE DC	-0.83	8.45	9.28
DBK GR	-18.44	-10.72	7.72
DNB NO	7.71	14.32	6.61
EBS AV	-7.12	9.29	16.41
GLE FP	-10.25	6.23	16.48
INGA NA	-3.39	8.09	11.48
ISP IM	-6.41	5.92	12.33
JYSK DC	-1.74	8.60	10.34
KBC BB	-10.62	11.53	22.15
LLOY LN	-12.81	1.10	13.91
NDA SS	6.44	12.03	5.59
OTP HB	-7.37	5.10	12.47
PKO PW	3.44	9.01	5.57
POP SM	-7.85	0.84	8.69
RBS LN	-17.57	-3.62	13.95
SAB SM	1.03	5.93	4.90
SAN SM	1.90	7.07	5.17
SEBA SS	3.42	11.96	8.54
SWEDA SS	7.68	13.08	5.40
UBI IM	-15.47	1.18	16.65
UCG IM	-9.90	3.47	13.37
Average	-5.48	6.02	11.50

Data source: Bloomberg Finance L.P. (2018), *ROE high-cap European banks*, 2017; own calculation.

Table 11. Difference between ROE and cost of capital estimate of the high-cap European banks sampled by country of origin (in %)

Country	Ticker	Average spread
Austria	EBS AV	-7.12
Belgium	KBC BB	-10.62
Denmark	DANSKE DC, JYSK DC	-1.28
France	BNP FP, GLE FP	-6.16
Germany	CBK GR, DBK GR	-18.41
Hungary	OTP HB	-7.37
Ireland	ALBK ID	1.98
Italy	BMPS IM, ISP IM, UBI IM, UCG IM	-12.71
Netherlands	INGA NA	-3.39
Norway	DNB NO	7.71
Poland	PKO PW	3.44
Spain	BBVA SM, POP SM, SAB SM, SAN SM	-1.24
Sweden	NDA SS, SEBA SS, SWEDA SS	5.85
UK	BARC LN, LLOY LN, RBS LN	-14.22

Data source: Bloomberg Finance L.P. (2018), *ROE high-cap European banks*, 2017; own calculation.