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Is Default Risk Systematic?

An Augmentation of the Fama and French Three-Factor Model with Credit-Default Swap Spreads

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Abstract

Title: Is Default Risk Systematic? An Augmentation of the Fama and French Three-Factor Model with Credit-Default Swap Spreads.

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Key words: DEFAULT RISK, FAMA AND MACBETH, EQUITY PRICING, SYSTEMATIC RISK, FACTOR MIMICKING PORTFOLIO TECHNIQUE.

Purpose: The purpose of the study is to quantitatively verify the systematic property of default risk and to statistically test if adding a default risk factor to the Fama and French Three-Factor Model can enhance its performance.

Methodology: The applied method is derived from the Fama and French Three-factor methodology and enhancing it with an additional default risk factor. The study employs Credit-Default Swap spreads as a proxy for default risk and applies factor mimicking portfolio technique to model the underlying risk factors. Regression analysis is applied to both the constructed portfolios and the entire data sample with the risk factors as independent variables after which the results are statistically tested for significance via cross-sectional regression analysis in line with Fama Macbeth methodology.

Data Sample: The data sample includes 101 firms listed on the European iTraxx, spread over different countries within the EU-area. Monthly observations have been utilized from 2004-07-01 to 2010-10-01.

Conclusion: Adding an additional default risk factor to the three-factor model does not improve its performance. The results show no statistical significance for any of the four tested factors. Therefore, the systematic property of default risk, value, size or market risk cannot be confirmed.

Sammanfattning

Uppsatsens titel: Is Default Risk Systematic? An Augmentation of the Fama and French Three-Factor Model with Credit-Default Swap Spreads.
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Fem nyckelord: FAMA OCH MACBETH, AVKASTNING, SYSTEMATISK RISK, KONKURSRISK, ”FACTOR MIMICKING PORTFOLIO”-TEKNIK.
Syfte: Syftet med uppsatsen är att kvantitativt fastställa den systematiska egenskapen hos konkursrisk och att testa huruvida en utökning av Fama och French tre-faktor-modellen kan förbättra dess precision.
Metod: Den applicerade metoden är gjord i linje med den traditionella tre-faktor-metodiken samt en utökning av denna med en konkursriskfaktor. Studien använder credit-default swap spreads som proxy för konkursrisk och applicerar ”factor mimicking portfolio”-teknik för att simulera de underliggande riskfaktorerna. Regressionsanalyser tillämpas på både konstruerade portföljer samt individuella företag med de konstruerade faktorerna som oberoende variabler. Resultatens statistiska signifikans testas med hjälp av tvärsnittsregressioner i linje med Fama MacBeth-metodik.
Data: Den empiriska datan inkluderar 101 företag från det europeiska iTraxx-indexet fördelade över Europa. Månatliga observationer har gjorts från 2004-07-01 till 2010-10-01.
Slutsats: En utökning av Fama och French tre-fakto- modellen med ytterligare en konkursriskfaktor förbättrade inte modellens precision. Studiens resultat kan inte påvisa statistisk signifikans för någon av de fyra testade faktorerna. Därmed kan den systematiska egenskapen hos faktorerna storlek, värde, marknadsrisk och konkursrisk inte bekräftas.

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1. Introduction

This paper will discuss whether corporate risk of default is priced in equity returns and whether credit-default swap spread is an adequate measurement of default risk. Section 1.1 contains a brief introduction to current circumstances followed by a review of the European positioning and problem discussion in sections 1.2 and 1.3. Furthermore, in section 1.4 the purpose of the thesis will be presented followed by delimitations and weaknesses in section 1.5. Section 1.6 will contain the thesis outline.

1.1 Background

The development of stock returns is, according to most theory, associated with systematic risk. The standard asset pricing models used today such as the Fama and French (1993) three-factor model, an enhancement of the CAPM model, developed by Sharpe, Lintner, Treynor and Mossin in the 1960s, and the Arbitrage Pricing Theory (Ross, 1976) all stem from the assumption that idiosyncratic risk is not to be considered when pricing assets. The logic entails that rational investors are only to be compensated for the non-diversifiable risk as they are expected to diversify away the idiosyncratic risk (Byström, 2007). Stock prices do, however, react whenever new information specifically related to an underlying asset is released to the market as stock price and return reflect a vast amount of available information. The release of unforeseeable information can either be of systematic nature, thereby being priced in the market, or be of idiosyncratic nature. The result is investors being exposed to not only the macroeconomic environment but also the performance and development of specific firms included in a portfolio. Investor expectations of future return on equity are thus subject to risk events, which may alter the manner in which future return on equity is characterized.

CAPM attributes excess return on risky assets to market risk. The robustness of this conclusion has however on several occasions been challenged, suggesting that there are additional factors that command significant risk premiums. Merton (1973) investigated this relationship with his Intertemporal CAPM theory. Investors want to hedge against non-diversifiable risk factors which systematically alter the return of risky assets. Chen *et al.* (1986) confirmed the significance of the market portfolio, attributing a large portion of the return of assets to it. The study conducted by Chen *et al.*, however, also determines the market portfolio's insignificance when controlling for additional risk factors, a finding further investigated by Fama and French (1992) and Fama and French (1993).

The discussion of which factors apart from market risk command significant risk premiums thereby being systematic, is of importance to the investment community. Fama and French (1992) attributed a majority of the explained stock return to size and market-to-book ratio, adding these two factors to the CAPM model, thereby creating the Fama and French (1993) three-factor model. The reason behind the factors' relevance is still debated. However, certain studies suggest that they serve as proxies for default risk (Fergusson and Shockley, 2003).

To determine the systematic nature of default risk has been attempted in several studies, which vary in researched market, proxy employed and applied method. While certain studies find a statistically significant relationship, others refute it, leaving the field with inconclusive and contradicting results. Byström (2005) put forth the suitability of CDS spreads as a proxy for default risk, a conclusion serving as the foundation for this paper.

By utilizing traditional methodology, developed by Fama and French (1992), and augmenting it by adding an additional default risk factor derived from CDS spreads on the European market, this study aims to contribute to existing theory in the field.

1.2 Positioning of Current Study

There are several attempted explanations behind the explanatory nature, among them Lakoniskoh *et al.* (1994), who suggest the value factor serves as an investor bias in earnings growth extrapolation. Fergusson and Shockley (2003), however, suggest that both the value and size factor serve as proxies for leverage levels, thus retaining an element of default risk.

There have been several attempts to incorporate default risk in to the traditional asset pricing models in order to verify a systematic property. The main difference between the studies relies on what proxy for default risk is utilized. While certain authors derive the proxy from structural models, e.g. Gharghori *et al.* (2009), who utilized option-based models, others derive the default proxy from available market information, such as bond spreads (Anginer and Yildizhan, 2010). Previous studies also exhibit different hypotheses. Vassalou and Xing (2004), for example, examine the performance of classical asset pricing models after being altered with a default risk factor while Ferson and Campbell (1991) focus on the relationship between default risk and equity returns.

1.3 Problem Discussion

Earlier literature, such as Fama and French (1993) and Ogden *et al.* (2003), claim that market capitalization is an a appropriate default risk indicator, due to e.g. larger firms having easier access to external finance. However, with recent scandals such as Enron or Lehman Brothers bankruptcies, size might be questioned regarding its role as default risk indicator. Vassalou and Xing (2004) claim that size indeed serves as a proxy for default risk, but only for firms that are highly risky. The book-to-market ratio works likewise. Furthermore, Vassalou and Xing find that high default risk firms do not generate higher returns than firms with low default risk, unless the firms are small or have high book-to-market values, indicating that default risk is not priced. Instead of only focusing on size and value, this thesis examines the usage of CDS spreads as default risk proxy. CDS spreads offer information about credit risk and is constantly priced by the market, and following the footsteps of Byström (2005), it is reasonable to expect that the CDS market is highly correlated with the equity market.

This study will not only focus on the quantitative verification of default risk, but also test the appropriateness of CDS spreads as a proxy for default risk. Although previous studies have arrived at contradicting result as to the systematic character of default risk, the employment of CDS spreads as a proxy for default risk is limited, mostly due to the CDS market being relatively new and has not existed long enough for previous studies to have tested the suitability of CDS spreads as default risk proxy, although some studies have been made. As Byström (2005) concluded CDS spreads to be a suitable proxy, this study will empirically test if the results can be improved.

While other forms of default risk estimation, such as the Merton (1974) model or the Altman (1968) z-score model, require complex calculations, CDS spreads are expressed as basis points above the risk-free interest rate. The pricing is therefore directly based on the probability of the underlying entity defaulting on payments, thereby in theory capturing the risk of default.

Pu *et al.* (2011) claim that the CDS spread should equal the probability of default times the expected loss in such an event, and that variables affecting these factors should determine the CDS spread. If the probability of default increases, the CDS spread should increase, *ceteris paribus*. However, defining default risk as the risk of not being able to fulfill debt obligations, several factors should affect a firm's default riskiness. The state of the economy, as well as firm-specific factors, such as capital structure, contribute to the riskiness of a firm. Feldhütter and Nielsen (2012) claim in their paper that default risk, represented by CDS spreads, includes an element of both systematic and idiosyncratic risk.

Thus, except for examining the properties of default risk, this thesis also contributes to the research by analyzing the risk components of CDS spreads and the role of the CDS market within equity pricing. As mentioned above, it is reasonable to expect that CDS spreads exhibit systematic risk factors and that CDS spreads proxy adequately for default risk.

To conclude, this thesis contributes to previous research by examining if default risk is systematic by using CDS spreads as proxy for default risk. If this is the case, default risk should affect equity returns.

1.4 Purpose

The purpose of this thesis is as follows:

To quantitatively examine whether default risk is a systematic factor in stock returns by utilizing CDS spreads as a proxy for default risk and by applying statistical processing to test the significance of the results.

This study includes methodology and approach derived from theory. The study will utilize the classical Fama and French (1993) three-factor asset pricing model augmented with an additional default risk factor, utilizing similar methodology employed by previous studies. The uniqueness of this study lies with the proxy employed as default risk, namely CDS spreads. This will be tested by means of mimicking the underlying risk factor by utilizing mimicking portfolio formation approach developed by Fama and French (1993) as well as the Fama and Macbeth (1973) cross sectional regression methodology.

The study aims to find answers to the following questions in order to receive a conclusion for the purpose of this thesis:

1. Will the adding of a default risk factor to the Fama and French (1993) three-factor model improve the accuracy of the model?
2. Is default risk a statistically significant systematically priced factor in equity returns?

1.5 Delimitations and Weaknesses of the Study

Byström (2007) claims that systematic risk is non-diversifiable and that idiosyncratic risk should not be priced. The current study follows this axiom within finance and assumes that firm-specific risk does not affect equity returns of a portfolio of assets. To make such an assumption is delimiting, as, if such risk were to be non-diversifiable, the study would not be able to show any significant results regarding pricing of default risk.

Using the Fama and French (1993) three-factor model is relatively straight-forward. However, the two factors added to CAPM, i.e. the size and value risk factors, are not theoretically developed. Fama and French could not fully explain why these factors explain equity returns. These factors are purely empirical. Missing a proper theoretical explanation of these factors is obviously a weakness in the current thesis, as well as in previous research.

Adding a fourth factor to the Fama and French three-factor model is relatively common within capital asset pricing research. For example Carhart (1997) added momentum, i.e. recent stock performance correlates with near future performance, in addition to the original three factors. However, since the current thesis is examining the properties of default risk, and the momentum factor does not reveal information regarding default risk, this factor is ignored. The same goes for other factors that do not possess relevant information on default risk. However, this study will apply the same three factors that Fama and French (1993) used as these factors have repeatedly exhibited strong explanatory power on equity pricing.

CDS spreads are, however, as stated above, sensitive to information reaching the market. As opposed to structured models, such as the Merton (1974) model, the model employed in this study does not stem from financial reports or other given numbers or ratios. This makes the employed proxy sensitive for e.g. rumors and other misleading information. However, such information is often passing and the market reverses to a more stable level after reacting to such information.

The data sample of the current thesis consists of equity prices and CDS spreads of 101 European firms, all of which belonging to the iTraxx index[1]. By using CDS spreads as proxy for default risk, this thesis limits the research with respect to sample size. Since the iTraxx index is limited in so far as only large and stable firms are listed, the homogenous state of the entities may have an impact on the Fama and French (1993) methodology. The study discards all entities not having equity price or CDS price available for the entirety of the period. This fact affects the results of this thesis and may impose an element of survivorship bias. In a similar manner, size bias must be considered as a weakness. The size and stability required for a firm to uphold outstanding CDS contracts over a time period sufficient enough for empirical studies may have a negative effect on the explanatory power of the size and value factors. The study utilizes data retrieved from Thomson Reuters DataStream via CMA[2], whose cooperation seized in late 2010, limiting the time scope to the duration of the contract although a more extensive time scope is preferred.

1.6 Thesis Outline

In the following Section 2, the theoretical environment revolving around this thesis will be explored. First, the traditional asset pricing models will be introduced, followed by a more thorough introduction to the Fama and French (1993) three-factor model. Second, the previous studies and theory with regard to this thesis will be investigated in relation to the hypothesis employed. Section 3 will explain the chosen methodological approach including dependent portfolio formation, factor mimicking portfolio formation and how the concluded risk factors are tested with regard to the purpose. Section 4 will present the empirical findings arrived at by the methodology employed. Section 5 will contain a discussion of the empirical results and attempts to analyse them with respect to existing theory and hypothesis as well as suggestions for further research. Section 6 will contain the conclusions drawn from the results and analysis.

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[1] iTraxx is an index containing the CDS spreads of large European firms

[2] Credit Market Analysis Ltd.

2. Theory

This section will review previous and recent theory relating to the study. Initially the previous asset pricing models will be described, following the process leading up to the augmentation of the Fama and French (1993) three-factor model. This will be complemented by relevant research and theory relating to the study.

2.1 Idiosyncratic and Systematic risk.

Systematic risk (also referred to in literature as market risk) labels the risk that is non-diversifiable. Constructing a portfolio with all the stocks in the world would render the risk level of the portfolio significantly lower than the corresponding risks of the individual assets. Regardless of how large the market is, if we were to add or remove stocks from the portfolio, the remaining risk will always equal the respective non-diversifiable risk of the entire market. Each individual asset in the portfolio, however, consists of both systematic risk as well as idiosyncratic or diversifiable risk (also referred to in literature as unique risk or firm-specific risk). (Campbell *et al.,* 1997)

2.2 Asset Pricing Models

In the 1960s, an asset pricing model was developed by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966). The model was called Capital Asset Pricing Model, CAPM, and explained the return of assets as a function of the asset's exposure to the market risk (beta), i.e. the systematic risk. Systematic risk includes macroeconomic risk variables such as the state of the economy, political decisions and natural disasters.

Investors expect higher returns for riskier assets in order to be compensated for the risk taken. The regression was formulated as follows:

$$r_i - r_f = \alpha_i + \beta(r_m - r_f) \tag{1}$$

Treynor, Sharpe, Lintner and Mossin argue that the only explanatory variable is the systematic risk since idiosyncratic risk, i.e. asset-specific risk, is diversifiable from an investor perspective. Idiosyncratic risk refers to risk that for example an investor holding a portfolio of different firms is able to avoid. The authors therefore reasoned that idiosyncratic risk should not be priced according to CAPM.

This model has ever since functioned as a basic tool for explaining the relationship between risk and return on the stock market. However, the model is far from being empirically perfect and has been criticized over the years. The main criticism concerns the fact that CAPM only views risk as the asset's sensitivity to the market risk, and that this factor only explains 70% of the returns (Fama and French 1992). Later theories, for example the Arbitrage Pricing Theory, or the Fama-French Three-Factor model include several factors that explain the return of assets. However, CAPM can be empirically useful, and Koller *et al.* (2010) claim that CAPM is an adequate model when estimating companies' cost of capital.

An alternative model to CAPM was developed by Ross in 1976. This model is called the Arbitrage Pricing Theory and uses several factors as explanatory variables. These variables, however, are not defined in the model and may change in number or nature dependent on which asset to price. This model has limited usage empirically, and is more of a theoretical tool of explaining asset pricing. (Koller *et al.* 2010)

2.3 The Fama and French Three-Factor Model

Fama and French (1993) attempted to empirically explain the average return of stocks by identifying a set of common risk factors. The five main factors included the market risk, size, measured by market capitalization, value, measured by book-to-market ratio, leverage and finally price-to-earnings ratio. Based on historical, available market data in time series regressions, they found that the factors relating to size and book-to-market ratio adequately capture the cross-section of average stock returns, thereby deducing the risks associated with the two factors to retain an element of systematic nature.

By adding the two factors HmL ("High-minus-low", referring to book-to-market ratio) and SmB ("Small-minus-big", referring to market capitalization) to the traditional CAPM model, creating the Fama and French three-factor model, Fama and French managed to explain 90% of the diversified stock portfolio return in contrast to 70% with CAPM (Fama and French 1992).

Dividing the sample into two groups, with respect to the employed factor, will render two sets of equity yields. By subtracting the yield of the sample firms in the top 50^{th} percentile with the bottom 50^{th} percentile will equal the non-diversifiable risk and thereby represent the systematic aspect of the employed factor.

Fama and French presented the following regression:

$$r_i - r_f = \alpha_i + \beta\left(r_m - r_f\right) + b_s * SmB + b_v * HmL + \varepsilon_i \qquad (2)$$

Where r_i denotes the return of the asset, and r_f denotes the risk-free interest rate, i.e. the US one-month T-bill. The asset's exposure to the market risk premium is denoted by the beta, and the exposure to the size risk factor and the value risk factor is denoted by b_s and b_v, respectively. ε_i denotes the error term. The return of an asset is thus dependent on the exposure coefficient to various risk premiums, according to Fama and French's empirical findings.

Fama and French (1993) found that firms with high book-to-market ratios tend to exhibit low earnings on assets within a five-year time frame before and after the study is conducted. Similar results were found considering firm size, or market capitalization, where smaller firms proved to have higher earnings on assets relative to larger firms, implying a negative coefficient between size and stock return.

When devising the dependent variable portfolios based on excess portfolio return, Fama and French (1993) utilized a 50^{th} percentile split of the data range, dividing the value factor in *high* and *low* and dividing the market size factor into *big* and *small*. The corresponding firms' respective returns are then allocated to the respective portfolios, creating compounded returns to produce an average weighted portfolio return. When constructing the mimicking portfolio formation for the independent variables, the authors found a stronger influence of the value factor relative the size factor on the portfolios' expected average stock return. Fama and French (1993) therefore constructed a second split (30^{th} and 70^{th} percentiles) for the value factor data set and only one split at the 50^{th} percentile for the size factor thereby creating a 3x2 mimicking portfolio set up. From this reasoning, the authors were able to minimize the variance of the factors and more accurately distinguish the different behavior of the SmB (small-minus-big) and HmL (high-minus-low) stocks.

Using this model, it is possible to examine which return that a certain asset should be able to generate, and for firms it is possible to for instance calculate the cost of capital when issuing new shares.

However, criticism has been aimed towards the research of Fama and French. One example is the paper by Kothari *et al.* (1995). Kothari *et al.* present results that claim that the relation between returns and book-to-market equity is weaker than what was presented by Fama and French (1992), and that the latter research might be affected by survivorship bias.

Fama and French (1998) further point out that the value risk factor more heavily affects equity return than the size factor does, but add a global perspective to their previous findings. Value stocks outperform growth stocks and the difference between international high and low book-to-market portfolios equals 7.68 percent p.a. (Fama and French, 1998)

Griffin (2002) follows the footsteps of Fama and French (1998) and further examines whether the Fama and French (1993) three-factor model is appropriate to use when adding international factors. Griffin uses Japanese, U.K., Canadian and U.S. data. He collects data from the largest stock exchanges in the respective countries, and only uses data that describes returns from non-financial firms.

In his article, Griffin compares a regression using three world-factors with one regression that only includes domestic factors. When forming the international factors, Griffin uses the same types of factors that Fama and French (1993) use, i.e. one market factor, one size factor and one value factor. However, Griffin decomposes the factors into domestic and foreign ones, and uses one model that includes only domestic factors, one that includes only world factors, and one that includes both domestic and foreign factors.

By decomposing the factors into domestic and foreign, it is possible to examine the effects of domestic or international factors on equity returns. For example, Griffin claims that using either the domestic or the world model might lead to a declining result regarding explanations of equity returns, since the difference in expected return for U.S. stocks and portfolios amounts to 8.41%, depending on which model to use. (Griffin, 2002)

Griffin claims that none of the models used completely explains the equity returns. However, Griffin argued that domestic models better explain the returns than the world model. Furthermore, the model, which included both domestic and world factors had even further explanatory power as measured by higher R^2, but the economic importance is low.

Griffin concludes that the Fama and French (1998) world-factor model is not as accurate when explaining equity returns as domestic factors models. This is highly relevant for this study as it renders the data incompatible with the already available Fama and French factors (size, value and market risk) as they are derived from the American market. Therefore this study will create new factors based on traditional methodology on the European market.

Ferguson and Shockley (2003) suggested that the three factors employed by Fama and French (1992), namely size, value and market risk, all serve as proxies for default risk. The authors claimed that the three factors in fact complement each other as different aspects of default risk and therefore together capture the systematic aspects of default risk.

2.4 Default Risk and Equity Returns

The amount of studies addressing a possible link between risk of default and stock return is limited and provides inconclusive results.

Merton (1974) examined the linkage between credit risk and equity prices, and developed the Merton model. The Merton model helps calculating the probability of default for a specific asset or a specific firm. This model is used to evaluate companies' credit risk and to price securities. Furthermore, the model uses an option pricing theory approach to price the securities since the equity of a firm can be represented by a European call option of the firm's assets, held by the shareholders. The strike price of the call option equals the default barrier, since the equity is worthless if the firm value drops below the default barrier.

Rietz (1988) determined the excess equity returns to be compensation required by investors for being exposed to more significant systematic risk events, e.g.

economic recession. As such events typically result in a certain amount of corporate defaults, it could be argued that the risk of default contains a certain degree of systematic risk and thus has an impact on stock return. Contradictory to Rietz (1988), Altman (1968) determined that corporate defaults occurred as a result of idiosyncratic risks, which argues for default risk being of non-systematic risk character.

The more recent studies attempt to confirm the existence, or non-existence, of a relationship between equity returns and default risk. The studies utilize similar methodological framework, yet vary in researched markets and proxies utilized for risk of default. When consolidating the information, one is unable to confirm any significant relationship as the studies present contradicting results.

Vassalou and Xing (2004) attempted to assess whether default risk was priced on the stock market. The default risk was obtained using the structural Merton (1974) model for measuring credit risk. The authors applied the Fama and French (1993) portfolio formation procedure on the factors size and value, and included time series of aggregated default risk measurements. They were able to conclude that default risk was in fact being priced in equity returns. Furthermore Vassalou and Xing (2004) concluded that the Fama and French factors size and value are suitable proxies for default risk. Gharghori *et al.* (2009) utilized similar methods to determine whether default risk is systematic yet arrived at opposing results. The contradicting results, despite similar methodological approaches, were likely a result of the different investigated markets. As Gharghori *et al.* (2009) studied data from the Australian equity market, Vassalou and Xing (2004) derived the data from the U.S. equity market. The opposing results create a new question of whether the pricing of default risk in the equity market differs across different markets.

Garlappi and Hong (2008) attempted to address whether default risk influences equity returns by setting corporate leverage as a proxy for risk of default. The authors argue that the level of corporate leverage affects the dynamics of equity returns in a different manner compared to how it affects the dynamics of firms' asset returns. To address this, Garlappi and Hong extended the Fama and French (1993) model by incorporating default risk factor and taking shareholder recovery upon financial distress into account. The results suggest a relationship between default risk and equity return solely due to shareholder recovery upon financial distress.

Anginer and Yildizhan (2010) arrived at results contradicting many of the previous conclusions. The authors did not confirm the relationship between equity returns and default probability nor unusually high return on equity for distressed stocks as a result of investor compensation for taking on additional risk (Vassalou and Xing, 2004). On the contrary, Anginer and Yildizhan confirmed unusually low returns for distressed stocks. The authors discussed different models and methods to use as proxies for default risk and arrived at the conclusion that bond spreads account for the systematic element of default risk and therefore serve as an appropriate proxy for risk-adjusted probability of default. The authors mainly concluded that default risk is not priced in equity returns, although distressed stocks behaved abnormally based on leverage, volatility and profitability.

The above-mentioned studies tried to determine if a correlation between stock return and risk of default could be proven. Yet, inconclusive and contradicting results still leave the question un-answered.

2.5 CDS Spreads as Proxy for Default Risk

A CDS is a credit derivative instrument which is used in synthetic securitizations. A synthetic securitization constitutes a process, which allows a company to transfer risk to another party, i.e. the investor. The investor receives payments, the CDS spread, in order to be compensated for the obligation to pay the credit protection buyer in case the reference asset would default. The CDS spread is dependent on the reference asset. If the reference asset's expected return exceeds the risk-free interest rate, that difference should equal the CDS spread. (Culp, 2006)

The usage of CDS spreads as proxy for default risk is relatively intuitive. As the CDS contracts are constantly traded on the market, the prices are continuously updated. The risk imbedded in the contracts represents the riskiness of the underlying entity is thereby constantly priced and undated.

Byström (2005) brought the flaws of traditional risk of default proxies to attention. He expressed the lag characteristics of for example a credit rating from S&P or Moody's of not being representative of the actual creditworthiness of the company on a day-to-day basis. In the same manner, Byström criticized the usage of estimating default probabilities with the Merton (1974) model, one of the most common default estimation methodologies. As the Merton model requires an up-to-date balance sheet and historical data for stock volatility, he criticized the measurement for being too reliant on historical data instead of current market information. Rather than using traditional methods of estimating default probabilities, Byström put forward the use of CDS spreads. Advantages included the truly instantaneous characteristics of CDS spreads as a result of being updated daily and the spreads relying solely on readily available high-quality data. Furthermore, Byström suggested the superiority of CDS spreads over bond spreads as an estimate for default probability as they are insensitive to liquidity effects thus rendering them more pure indicators. This contradicts the conclusion presented by Anginer and Yildizhan (2010) and serves as a pillar in the structure of this study.

2.6 CDS Spread Efficiency and the Equity Market

Byström (2005) studied the relationship between the iTraxx sectoral indices and their corresponding sectoral stock indices, using the CDS spread as a proxy for determining the credit risk. Byström found significant correlation between iTraxx CDS spread changes and stock price returns, suggesting a link between the markets. He found that CDS spreads tend to widen when stock prices fall and vice versa. Furthermore, Byström was able to prove the existence of significant, positive autocorrelation in all studied iTraxx indices, suggesting inefficiencies in the iTraxx CDS market where changes in the index were predictable. Finally, Byström concluded significant correlation between the stock volatility and CDS spread.

Longstaff (2003) found that both the CDS market and stock market lead the corporate bond market, suggesting the bond market to be the least efficient of the three when taking new information into account. This can be seen as contradictory to Anginer and Yildizhan (2010) who determined bond spreads to be the most effective proxy of default risk and supportive of the conclusion reached by Byström (2005). The results suggest that CDS spreads could be a more appropriate proxy for default risk relative to bond spreads. Norden and Weber (2009) arrived at similar results when the authors studied the co-movement of CDS and bond spreads against equity price changes. They find empirical evidence that information first reaches the stock market, and causes changes in CDS and bond spreads thereafter. Furthermore, Norden and Weber found that the CDS spread changes cause changes in the bond spreads to a higher degree than vice versa, and that the CDS spreads are more easily affected by changes in the stock market.

To summarize, several studies have been conducted attempting to verify or disprove the systematic characteristic of default risk. The studies differ with respect to proxy employed, targeted market and applied method. Previous theory suggests the superiority of CDS spreads as opposed to other structural tools or marketable measurement as proxies for default risk. The inconclusive results in combination with the suitable characteristics of CDS spreads contribute to the purpose of this study.

3. Method and Data Collection

Section 3 will present the methods with which the study is carried out. The purpose of the chapter is to provide an adequate understanding of how the data has been collected, analysed and by which method it will be statistically processed.

3.1.1 Deductive Method

This study will be done by means of a deductive method. Initially, section 2 reviews current theories and literature from which the hypothesis is deduced, which in turn will be subject to empirical testing (Bryman and Bell, 2003). By compiling the available theories and studies in the field, one is able to identify an opportunity of testing if default probabilities have an impact on the corresponding companies' equity returns by utilizing CDS spreads as a proxy. This will be the first study attempting to bridge the gap between the default probability's impact on equity and correlations on the equity and CDS market. By following this linear process the study aims to confirm or discard the hypothesis by means of relevant, empirical testing methods and thorough interpretation of the acquired results. The alternative to a deductive method is the inductive method. The main characteristics of an inductive research method include the initial gathering of empirical data, which in turn is interpreted from the point of view of existing literature and theories. This method, however, increases the risk of choosing inappropriate testing methods and false interpretation of existing theories (Bryman and Bell, 2003).

3.1.2 Quantitative Data Analysis

The data analysis will be of quantitative nature as the intention of this thesis is to examine a significant amount of data from various companies over a large time span. Most important when dealing with quantitative data analysis is the choice of suitable testing methods before the data is collected. By determining how the data is to be analysed prior to the gathering of it, one minimizes the risk of choosing inappropriate data, thereby compromising the quality of the results (Bryman and Bell, 2003).

3.2 Collection of Data

The study will focus on the analysis of European companies. Previous research concerning the pricing of default risk on the stock market has mainly focused on the U.S. market, with some exceptions, as for example Gharghori *et al.* (2009), who examined the Australian equity market. The European stock market is relatively unexplored concerning research attributed to default risk pricing and the CDS market. This is the main reason for our selection of region.

The selected companies are those included in the European iTraxx, which consist of 100 non-financial companies and 25 financial companies, which are spread over Europe. The included companies are obtained from Markit Financial Information Services.

The firms are located in various countries around Europe. The countries in which most firms are situated for the sample include Great Britain and France with 29 and 21 firms, respectively[3].

[3] A complete list of the companies included can be reviewed in Appendix I

3.2.1 Collection of CDS Data

The CDS data is derived from Thomson Reuters DataStream which functions as a portal, compiling several instances of financial data for the sought after entity from various sources. This study will focus solely on the monthly spreads for 5-year CDS contracts in basis points[4]. Each time series of closing spreads is derived from the same source via DataStream and CMA in order to reduce the risk of various sources compromising the quality and reliability of the data set. The time span stretches from 2004-07-01 to 2010-10-01, after which Thomson Reuter's license to obtain CDS data from CMA was discontinued. Therefore the study was unable to acquire spreads for the following time period. During the stated period, however, a certain degree of data loss was experienced. Certain CDS contracts proved to be discontinued prematurely to the time span while others are contracts proved to be created post 2004-07-01 thus not having available data during the entirety of the selected time period. Of the original 125 companies on the European iTraxx, 101 remained after fall-off data was sorted out.

3.2.2 Collection of Equity Data

Monthly closing equity prices were utilized for each company. All equity prices of companies quoted on iTraxx were derived from Thomson Reuters DataStream with their listed stock exchanges as sources. In order to minimize the risk of compromising the data set by risk of converting to one common exchange rate, all companies are quoted in their respective currencies. This is evident as the data-set exhibits variances from i.e. EUR and GBP between different entities. The study will however examine effects on equity return, measured as relative values and is therefore not affected, nor susceptible to variations in currency. As the discontinuation of the CMA license to provide CDS data limited the time frame of the study, the length of the time period of monthly closing equity prices is set equal to equal that of the CDS data. As well as in acquiring the CDS data, the data set of equity prices suffered fall-off. While certain companies were not listed,

[4] Basis points will henceforth be referred to as bps.

others had de-listed over the course of the time period making them unsuitable for the requested time series. This fact might make the report sensible for survivorship bias.

When compiling the final data set, all companies, which did not have complete availability of both monthly closing CDS spreads as well as monthly closing equity prices, are rejected. Following these criteria, 101 companies have been included in the data set, compared to the original 125.

3.2.3 Collection of Market Capitalization and Book-to-Market Data

Each firm's market capitalization and book-to-market data was collected using DataStream. Monthly data was used and the period stretches from July 2004 to October 2010. The market capitalization data was expressed in EUR in order for the firms to be comparable.

3.3 Factor Estimation Methodology

In line with traditional methodology, this section will review the traditional Fama and French (1992) and the Fama and Macbeth (1973) methodologies by which the factors size, value, market risk, and default risk are estimated.

3.3.1 Portfolio Formation of Dependent Variable

For the original Fama and French (1993) three-factor model, four time series of portfolio returns have been constructed from the data set based on the size and value factors. Each factor has been divided at the 50th percentile into two respective groups, one high/low and one big/small. By allocating the returns of the respective firms by means of the split, four portfolios are constructed based on the characteristics of the included firms in accordance with the size and value factors. The portfolios will represent firms with the following characteristics: "Big

Size-High Value", "Big Size-Low Value", "Small Size-High Value" and "Small Size-Low Value".

After sorting the firms into their respective portfolios, their corresponding monthly excess equity returns are allocated accordingly. Next, the average portfolio return is calculated, producing four equally weighted portfolios with average monthly excess stock returns based on opposed corporate characteristics (with regard to above mentioned factors). This portfolio formation of sorting stock returns into different groups is consistent with the methodology used by Fama and French (1993) when constructing the original framework.

The four-factor model portfolio formation of dependent variable will follow the same methodology described. By adding one additional factor, probability of default, the intersectional splits will yield additional portfolios. The set will consist of eight portfolios with their corresponding eight time series of return on equity utilizing the three factors size, book-to-market and default probability.

Each of the three respective data sets (spread, value and size) will be split into two groups. By separating the sets at the 50^{th} percentile of the samples we will be left with a high/low or big/small value for each of the factors. The eight portfolios will be constructed at the intersections of the two sets (high and low) for each factor thus creating the spectrum: "Small Size – Low Value – High Spread", "Small Size – Low Value – Low Spread", "Small Size – High Value – High Spread", "Small Size – High Value – Low Spread", "Big Size – Low Value – High Spread", "Big Size – Low Value – Low Spread", "Big Size – High Value – High Spread", "Big Size – High Value – Low Spread".

By allocating stock returns to the above-mentioned portfolios in accordance with the three respective factors, the average returns can be calculated for each portfolio. In the same manner as for the three-factor model, this methodology will render eight equally weighted time series of excess stock returns with diametrically opposed corporate characteristics.

The three-factor portfolio set and the four-factor portfolio set will be separately exposed to different sets of regressions.

In line with the Fama and Macbeth (1973) two-step approach, the study will use cross-sectional regression on the estimated beta values in order to calculate the lambda values of the respective betas. It is thereafter possible to calculate the t-values of the risk factors in order to decide whether they are significant or not.

3.3.2. Mimicking Portfolio Formation, Independent Variables

Four different risk factors will make up the independent variables of this study, namely size factor, value factor, default risk factor and market risk factor. The market risk factor is common for both sets of regressions for both models and is constructed by deriving the return of the FTSEU300 index[5] on a monthly basis and subtracting the risk-free rate. As a risk-free proxy this study utilizes the monthly yield on the 12 month EURIBOR.

The factor mimicking portfolio formation technique is used to construct the remaining factors and is based on the methodology adopted by Fama and French (1993). Factor mimicking portfolios are constructed to the extent that the factors are mimicking portfolios of equity returns, thus mimicking the underlying risk factors. In order to achieve that the dependent portfolio and the mimicking portfolios contain similar underlying information, this method will need to be adopted separately for each set of regressions. The purpose of the method is to examine whether the mimicking portfolio and the dependent portfolio capture common risk factors in equity returns. If so, the factor in question is considered priced by the market and consequently being of systematic nature.

When constructing the mimicking portfolios for the three-factor model, the two data sets are split into groups similar to the methodology applied in the dependent variable portfolio formation. The value factor is split two times at the

[5] FTSEU300 is an index containing the 300 largest European firms in terms of market cap.

30th and 70th percentiles in accordance with the reasoning put forth by Fama and French (1993) while the size factor is split into two categories at the 50th percentile. From the intersections, six portfolios are constructed from the value-groups and size-groups. By allocating the respective monthly returns to destined portfolios, the average portfolio return is calculated. This will define the two factor mimicking portfolios on account of average returns in relation to the size and value factors. The factor mimicking portfolios high-minus-low (HmL) and small-minus-big (SmB) will represent the equally weighted monthly returns of the size and value factors.

The four-factor model will be constructed in a similar manner, yet with an additional variable. The data sets of the value factor and the size factor have each been split at the 50th percentile, respectively, splitting the two sets into four groups. As the default risk factor is expected to exhibit stronger characteristics of common risk factor, in relation to average monthly returns, relative to the size and value factors, it will be split at both the 30th and 70th percentiles in according with the reasoning put forth by Fama and French (1993). The data sets will thereby render twelve portfolios[6], constructed out of the intersections of the two size groups, two value groups and three default groups. The three respective factors are represented by equally weighted monthly returns on the "High-minus-Low" (HmL), "Small-minus-Big" (SmB) and the new "High Spread-minus-Low Spread" (HSmLS).

3.3.2.1 Mimicking Implications

The portfolio SmB (Small-minus-Big) is the difference on a monthly basis between the average of the returns of the six small stock portfolios and the average return of the six large portfolios. Therefore SmB is the difference between the returns on big and small stock portfolios with approximately the same weighted average value. Therefore the difference is expected to be free

[6] The constructed portfolios with corresponding weighted average returns can be reviewed in Appendix II

from the influence of the value factor, with pure focus on the different return characteristics between small and big stocks.

The portfolio HmL (High-minus-Low) is defined in a similar manner. HmL is the monthly difference between the average returns of the six high value portfolios and the six low value portfolios. The two components are return on high book-to-market equity and low book-to-market equity with approximately the same weighted average size. The difference is therefore expected to be free from influence from the size factor, focusing on the different return characteristics of high and low value stocks. The same reasoning goes for HSmLS (High Spread-minus-Low Spread).

3.4 Expected Output Data

The results are expected to be similar results as those produced by Fama and French (1993), which is a negative relationship between size factor and excess returns and a positive relationship between excess returns and value factor. However, with regards to the third, default factor, arguments can be made for both a positive and negative relationship with excess returns.

This paper has discussed empirical evidence supporting both a positive as well as a negative relationship between default risk and excess return (i.e. Vassalou and Xing (2004) and Gharghori *et al.* (2009)). Higher spread implies the contract owner requiring more compensation to be exposed to the default risk of the underlying entity thus higher risk and vice versa. Literature commonly reaches a consensus around the higher the risk taken on by the investor, the higher the required compensation, or expected return. This would imply a positive relationship between CDS spreads and excess returns. An increase in default risk (increase in CDS spreads) can also be perceived by investors as a worsening of the future outlook of the underlying entity (firm). This could lower expectations on future performance and/or creditworthiness thereby decreasing expected return rendering a negative relationship between spreads and returns.

It is also appropriate to discuss whether a positive or negative relationship is to be expected from a historic point of view. Investors in a firm, which on average display a low probability of default and limited volatility, are arguably likely to require more return in the event of an increase in default probability. This as the general stability and financial health of the underlying asset (firm) is less likely to be severely affected by an increase in default risk (moderate). In these firms, one could arguably assume a positive relationship between excess returns and CDS spreads. In the same manner investors in a firm with a higher average spread in combination with higher volatility will arguably exhibit a negative relationship between excess return and spread development. In the riskier firms, an increase in default probability may be interpreted by the market as a more potent threat of financial distress and lowering expectations of future performance.

Taking the arguments into account, a positive portfolio relationship is to be expected when creating a "High Spread-minus-Low Spread".

3.5 Empirical Testing and Statistical Approach

In order to measure the impact of the described factors against stock returns this study will apply the methodology introduced by Fama and French (1992) and Fama and Macbeth (1973). By regressing each asset against the factors, each asset will receive one beta value for each factor (HmL, SmB, HSmLS and Market-Rf). This will be done by utilizing the following regression with the excess return of each asset as dependent variable and utilizing the formerly calculated independent factors as independent variables according to the formula:

$$r_{it} - r_{ft} = \alpha_i + \beta_r\left(r_m - r_f\right) + \beta_s * SmB_t + \beta_v * HmL_t + \beta_d HSmLS_t + \varepsilon_i \quad (3)$$

Where,

$r_{it} - r_f$ = the excess return of asset *i* in month *t,*

r_m = the return on the market portfolio in month *t,*

β_r = the sensitivity of the asset's excess return to the return of the market portfolio,

β_s = the sensitivity of the asset's excess return to the return of the *SmB* portfolio,

β_v = the sensitivity of the asset's excess return to the return of the *HmL* portfolio,

β_d = the sensitivity of the asset's excess return to the return of the *HSmLS* portfolio,

SmB_t = the return of the *SmB* portfolio in month *t*,

HmL_t = the return of the *HmL* portfolio in month *t*,

$HSmLS_t$ = the return of the *HSmLS* portfolio in month *t*

The regression sets will produce four beta values per individual asset.

3.5.1 Cross-Sectional Regression Estimates

After having obtained the respective factor sensitivities above, the beta values are used in the OLS regression introduced as the second step in the Fama and Macbeth (1973) regression procedure according to the formula:

$$r_{it} - r_{ft} = \lambda_0 + \lambda_1 \widehat{\beta_\iota} + \lambda_2 \widehat{s_\iota} + \lambda_3 \hat{h}_i + \lambda_4 \widehat{d_\iota} + \mathcal{U}_{it} \quad (4)$$

In order to derive the coefficients from the cross-sectional regression stated above, the next step will be to take the average of each coefficient by the following calculation:

$$\hat{\lambda}_j = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_{jt} \quad (5)$$

To test whether the coefficients are significant, the respective t-statistics for each coefficient will be calculated:

$$w(\hat{\lambda}_j) = \frac{\hat{\lambda}_j}{\hat{\sigma}_{\lambda j}} \tag{6}$$

Where

$$\hat{\sigma}^2_{\lambda j} = \frac{1}{T(T-1)} \sum_{t=1}^{T} (\hat{\lambda}_{jt} - \hat{\lambda}_j)^2 \tag{7}$$

3.5.2 Errors-in-Variables

However, the Fama and Macbeth (1973) methodology includes an errors-in-variables problem when testing in this manner due to the fact that the various betas, i.e. the independent variables in the second step of the Fama and Macbeth approach, are estimated rather than observed. This issue can be addressed in two ways. Firstly, Shanken (1992) introduced the method of adjusting the variance of the final estimates by the formula:

$$\hat{\sigma}^{2*}_{\gamma j} = \hat{\sigma}^2_{\gamma j}(1 + \frac{(\hat{\mu}_m - \hat{\gamma}_0)^2}{\hat{\sigma}^2_m}) \tag{8}$$

The Shanken correction factor is expected to be very small and have minor impact on the test results as the observations are made on a monthly basis (Shanken, 1992).

The second way of escaping the errors-in-variables problem is to form portfolios, thus minimizing the beta values' estimation errors. The current study will utilize both the Shanken (1992) approach as well as the portfolio formation method.

3.5.3 Time Frame and Sub-Samples

In order for the study to adequately capture the pricing effects of default risk, the sample will be divided into two time periods. Via this method, the results will be three-fold; one compounded testing result for the entire sample-period and two results for each half of the time period namely 2004-07-01 to 2007-06-01 and 2007-07-01 to 2010-10-01. Due to the financial crisis, a single survey of the results for the total sample period runs the risk retaining an element of unreliability. By splitting the sample into pre-crisis and post-crisis period, the study can review how the pricing factors develop over times of different macroeconomic conditions.

3.5.3.1 Cross-Sectional Regressions on Portfolio Values

The Fama and Macbeth (1973) methodology will also be applied on the constructed 12 portfolios in accordance with the 2x2x3 portfolio split[7]. The statistical applications will be similar to those applied on the individual assets. The additional portfolio testing is expected to generate further explanatory variables to the study.

3.5.4 Hypothesis testing

The study is reviewing whether the risk of default is priced in the equity market[8].

The testing formula is as follows:

$$r_{it} - r_{ft} = \lambda_0 + \lambda_1 \widehat{\beta_i} + \lambda_2 \widehat{s_i} + \lambda_3 \hat{h}_i + \lambda_4 \widehat{d_i} + \mathcal{U}_{it} \tag{9}$$

[7] Further details of portfolio construction can be reviewed in section 3.3.1 and 3.3.2
[8] The possible testing outcomes are reviewed in Section 3.4 with respect to a positive or negative relationship

The lambda values will be tested against a two-sided t-test, therefore the testing hypothesis is as follows:

$$H_0: \lambda_4 = 0 \qquad H_A: \lambda_4 \neq 0 \tag{10}$$

3.6 Criticism of Sources

As the study relies on quantitative secondary data, one must bear in mind potential pitfalls when analysing the data. The following two sub-sections present potential criticism of the CDS and equity data and printed research used in this thesis.

3.6.1 Criticism of Data

The data is primarily collected from DataStream. The CDS data collected from DataStream stems from CMA, which is owned by The McGraw-Hill companies, and is a part of S&P Capital IQ. This data is thus highly reliable. However, as DataStream is a secondary source of information, certain risk of error in the data transaction between DataStream and CMA is present.

However, the agreement that DataStream had with CMA was discontinued from 1st of October 2010. The study only includes data that was available through DataStream, i.e. July 2004 until October 2010. This limits the scope of the study, as it would be of interest to analyse if CDS spreads could function as a proxy for default risk after 2010, i.e. when markets are not as volatile as they were from 2007-2010. The inclusion of the volatile period may render the results less applicable to current, less volatile, market circumstances.

The companies issuing CDS contracts need to command a certain level of financial stability and stock/bond liquidity in order for the CDS contracts to be demanded by investors. By this reasoning, it is fair to assume that the companies included in the European iTraxx in average have a larger size than that of the entire European corporate market. As the Fama and French (1993) model is based on a study of several thousand companies spanning more over the size spectrum, the effect of the SmB (Small-minus-Big) factor might play a less important role in this study. The same argument can be made for the HmL (High-minus-Low) factor. This risk is a consequence of the utilization of CDS spreads as a proxy for default.

Furthermore, collecting CDS and/or Equity data for all 125 companies that make up the European iTraxx index proved unsuccessful due to the availability through DataStream. If either the CDS data or the equity data for a firm was unavailable, we excluded this firm from the study.

As mentioned above, survivorship bias might further weaken the reliability of the thesis. As the study only includes data regarding firms that were included in the iTraxx index from July 2004 until October 2010, it excludes firms that might have gone bankrupt during that period. It would be interesting to examine the linkage between CDS spreads and equity returns of such firms when in financial distress, and this topic is recommended for future research.

3.6.2 Criticism of Literature and Articles

The literature used in this thesis stems from recognized authors with long history within financial research. All articles used are published in highly reliable journals.

4. Empirical Findings

This section will present the empirical findings and results of the study. The section will initially inspect the time series data followed by a presentation and discussion of the results. Finally, the outcome of the regression estimations and cross sectional results will be displayed.

4.1 Data Inspection

A survey of the data series, including both dependent variables and independent variables, shows a significant increase in volatility during 2007-2008, with significant fluctuations in all factors and portfolios. [9]

In order to avoid contaminating the results of the significance testing by the financial crisis, the time period is divided in to two, sub-sample periods, one pre-crisis and one post-crisis in addition to the tests for the entire sample period. This helps to observe whether any differences occurred between the boom preceding the recession and the volatile economy following the financial meltdown.

4.2 Regression Estimations

This section will review the regression estimation results from the two asset pricing models. First the conventional Fama and French (1993) three-factor model followed by the augmented four-factor model. The estimation results are arrived at using OLS regressions for the entire sample.

[9] Descriptive statistics for portfolio formations and calculated independent factors are available in Appendix III. The tables include skewness, kurtosis, mean, max, min, average, standard deviation and median values.

The results of the regression estimations for the three-factor model are summarized in *Table 4.3.1.* All factors except the size factor in "Big size-Low value" and the value factor in "Small size-Low value" are significant for all regressions[10]. Furthermore, one can see a high explanatory value (R^2) for all four regressions. "Small size-High value" exhibited a distinguishably high R^2 of 94.3%. "Big size-High value" is the only portfolio exhibiting theoretically expected factor values with a negative size factor in combination with a positive value factor [11]

Table 4.2.1.I Three-Factor Model Regression Estimation Results

	SL	SH	BL	BH
Intercept	**0,001**	**0,001**	**0,001**	**0,001**
Std. Error	0,003	0,002	0,002	0,003
T-stat	0,241	0,330	0,428	0,317
P-value	0,810	0,743	0,670	0,752
Value Factor	**-0,127**	**0,649**	**-0,414**	**0,810**
Std. Error	0,076	0,064	0,066	0,080
T-stat	-1,659	10,126	-6,306	10,091
P-value	0,101	0,000	0,000	0,000
Size Factor	**0,823**	**1,263**	**0,050**	**-0,389**
Std. Error	0,145	0,121	0,124	0,152
T-stat	5,692	10,416	0,406	-2,566
P-value	0,000	0,000	0,686	0,012
Market Risk Factor	**0,657**	**0,803**	**0,829**	**0,682**
Std. Error	0,072	0,061	0,062	0,076
T-stat	9,094	13,263	13,351	8,999
P-value	0,000	0,000	0,000	0,000
R2	**0,721**	**0,945**	**0,737**	**0,897**
R2 Adjusted	*0,709*	*0,943*	*0,725*	*0,892*
Sample Length		101 Observations		

Table 4.2.1.I depicts the results of the regression estimations for the three-factor model. "Small size-Low value" (SL), "Small size-High value" (SH), "Big size-Low value" (BL) and "Big size-High value" have been regressed against the independent variables market risk factor, value factor and size factor. Included in the table are standard error, t-statistics and P-value for each factor and R^2 for each regression. The period is from 2004-07-01 to 2010-10-01.

The regression estimation results for the augmented four-factor model are presented in *Table 4.3.2*. The regression estimations for "Big size-Low value-Low default risk" resulted in no significant factors apart from the market risk factor. For "Small size-High value-

[10] Statistical significance at the 95% condidence level is confirmed when *P-value < 0,05* or T-statistics >1,96 / <-1,96.
[11] See section 3.4

Low default risk", the default risk is not significant, in the same manner that the size factor is not significant for "Big size-High value-High default risk". No regressions are in line with expected outcomes and theoretically supported.[12][13]

Table 4.2.1.II Four-Factor Model Regression Estimation Results

	SLL	SLH	SHL	SHH	BLL	BLH	BHL	BHH
Intercept	**0,003**	**-0,001**	**-0,002**	**0,001**	**-0,002**	**0,006**	**0,003**	**-0,004**
Std. Error	0,004	0,003	0,004	0,003	0,003	0,005	0,003	0,005
T-stat	0,725	-0,160	-0,505	0,393	-0,612	1,226	0,978	-0,873
P-value	0,471	0,874	0,615	0,695	0,542	0,224	0,332	0,386
Value Factor	**-0,888**	**-0,332**	**0,386**	**0,275**	**-0,233**	**-1,020**	**0,319**	**0,662**
Std. Error	0,213	0,157	0,217	0,125	0,142	0,235	0,160	0,226
T-stat	-4,160	-2,111	1,783	2,199	-1,643	-4,343	1,991	2,933
P-value	0,000	0,038	0,079	0,031	0,105	0,000	0,050	0,005
Size Factor	**1,007**	**1,151**	**0,872**	**0,960**	**0,111**	**-0,792**	**-0,426**	**0,247**
Std. Error	0,230	0,170	0,234	0,135	0,153	0,254	0,173	0,244
T-stat	4,372	6,771	3,732	7,117	0,729	-3,123	-2,465	1,012
P-value	0,000	0,000	0,000	0,000	0,468	0,003	0,016	0,315
Default Factor	**-0,361**	**0,666**	**-0,193**	**0,773**	**-0,064**	**0,877**	**-0,336**	**0,730**
Std. Error	0,165	0,121	0,167	0,096	0,109	0,181	0,123	0,174
T-stat	-2,189	5,483	-1,153	8,022	-0,588	4,837	-2,721	4,194
P-value	0,032	0,000	0,253	0,000	0,559	0,000	0,008	0,000
Market Risk Factor	**0,924**	**0,722**	**0,801**	**0,800**	**0,623**	**0,888**	**0,822**	**0,761**
Std. Error	0,112	0,083	0,114	0,066	0,074	0,123	0,084	0,118
T-stat	8,242	8,740	7,052	12,192	8,388	7,202	9,787	6,421
P-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
R2	**0,616**	**0,772**	**0,712**	**0,909**	**0,759**	**0,527**	**0,738**	**0,759**
R2 Adjusted	*0,594*	*0,759*	*0,696*	*0,903*	*0,745*	*0,500*	*0,723*	*0,745*
Sample Length				101 Observations				

Table 4.2.1.II depicts the results of the regression estimations for the Four-factor model. "Small size-Low value-Low default risk" (SLL), "Small size-Low value-High default risk" (SLH) "Small size-High value-Low default risk" (SHL), "Small size-High value-High default risk" (SHH), "Big size-Low value-Low default risk" (BLL), "Big size-Low value-High default risk" (BLH), "Big size-High value-Low default risk" (BHL) and "Big size-High value-High default risk" (BHH) have been regressed against the independent variables Market risk factor, Value factor and size factor. Included in the table is Standard error, t-statistics and P-value for factor and a R^2 for each regression. The period is from 2004-07-01 to 2010-10-01.

[12] The expected relationship arguments can be viewed in section 3.4
[13] The estimation results for each firm can be reviewed in Appendix I

4.3 Fama and Macbeth Regression Results

After estimating the beta values for each factor, the study applies cross-sectional regression using excess return as dependent variable and the beta values as independent variables. The regression was made for each month during the period examined and the results, which are presented below, were aggregated. The individual firms' lambda values were corrected to avoid the errors-in-variables problem.

4.3.1 Lambda Values of Individual Firms

The results of the second step of the Fama and Macbeth (1973) methodology are presented below.

Table 4.3.1.I Four-Factor Model Regression Estimation Results

2004.06-2010.10				
	Value β	**Size β**	**Default risk β**	**Market β**
λ	-0,004369181	0,000630616	-0,001396334	0,006271739
T-stat	-0,11897083	0,022543482	-0,036816403	0,106594449
2004.06-2007.06				
	Value β	**Size β**	**Default risk β**	**Market β**
λ	-0,00220833	0,001399727	-0,003815229	0,014980737
T-stat	-0,223524092	0,107051046	-0,180322154	0,447115946
2007.07-2010.10				
	Value β	**Size β**	**Default risk β**	**Market β**
λ	-0,006259925	-4,23563E-05	0,0007202	-0,001348635
T-stat	-0,126088726	-0,001170944	0,019554657	-0,017736372

Table 4.3.1.I shows the lambda values and t-statistics of our four explanatory variables calculated by examining each individual firm. The whole period examined is presented on the top of the table, and this period is later split into one pre-crisis and one post-crisis period.

The findings for the whole period show negative lambda values for the value and default risk factors. The size and market risk factors have positive lambda values. However, all lambda values are close to zero.

The pre-crisis period shows similar results as the whole period, while in the post-crisis period, negative lambda values are attributable to the size factor and market risk factor. The default risk factor's lambda decreased and was negative during the post-crisis period.

As presented in table 4.3.1.I, the risk proxy employed explains excess return on a level that is comparable with Fama and French's (1993) original three factors. In the period following the financial meltdown the default risk factor's t-statistic even exceeds the market beta, meaning that the null-hypothesis cannot be rejected[14]. However, the t-statistics do not exceed 1.96 in either of the factors or periods examined. While not being able to show any significant effect of default risk on equity returns, one must bear in mind that neither of the tested factors were proved to be significant.

4.3.1.1 Shanken Corrections

As illustrated in the table 4.3.1.1.I, the corresponding Shanken (1992) correction factors are presented for each t-statistic[15].

Table 4.3.1.1.I Shanken-Coefficients

	HmL	SmB	HSMLS	Market-rf
2004.06-2010.10	0,036724806	0,027973308	0,03792694	0,058837385
2004.06-2007.06	0,009879608	0,01307532	0,021157847	0,033505263
2007.07-2010.10	0,049646981	0,036172746	0,036830083	0,076037831

Table 4.3.1.1.I presents the different respective Shanken-correction coefficients distributed over the entire time period as well as for the sub-samples.

As expected, the Shanken correction coefficients are very small and have little impact on the statistical significance of the factor premiums.

[14] Testing on the 95% confidence level results in a rejection of the null hypothesis providing t-statistic <-1,96 or >1,96.
[15] In line with theory discussed in Section 3.5.2

4.3.2 Lambda Values of Portfolios

Table 4.3.2.I Four-Factor Model Regression Estimation Results

2004.06-2010.10				
	Value β	**Size β**	**Default risk β**	**Market β**
λ	0,0009312	0,003586	0,004623616	0,022771131
T-stat	0,0289828	0,158634	0,148891494	0,19537885
2004.06-2007.06				
	Value β	**Size β**	**Default risk β**	**Market β**
λ	0,001515	0,004411	-0,000214179	0,026756119
T-stat	0,100833	0,32583	-0,00850502	0,219016285
2007.07-2010.10				
	Value β	**Size β**	**Default risk β**	**Market β**
λ	0,0004205	0,002863	0,008856687	0,019284267
T-stat	0,010019	0,100701	0,251766813	0,170875956

Table 4.3.2.I shows the lambda values and t-statistics of the four explanatory variables from the 12 portfolios. The whole period examined is presented on the top of the table, and this period is later split into one pre-crisis and one post-crisis period. The lambda values are also referred to as factor premiums.

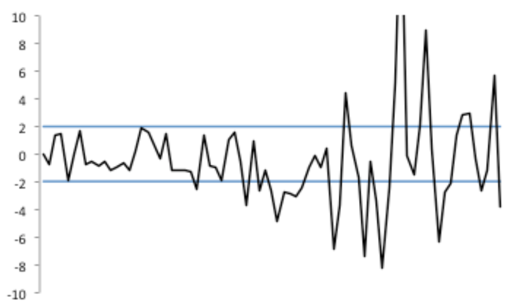
The lambda values of the portfolios' factors are different from the findings of the factors attributable to individual firms. All lambda values are close to zero, but only the default risk factor in the pre-crisis period had a negative lambda value. The market risk factor has slightly higher lambda values than the other factors in all three periods examined.

4.4 Factor Significance Inspection for Individual Firms

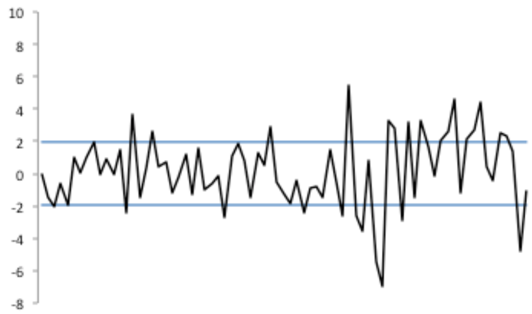
A further time series inspection of the respective lambda values' t-statistics depict how the fluctuations of the positive/negative values render the results insignificant on account of the consolidation according to:

$$\hat{\lambda}_j = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{jt} \qquad \textbf{(11)}$$

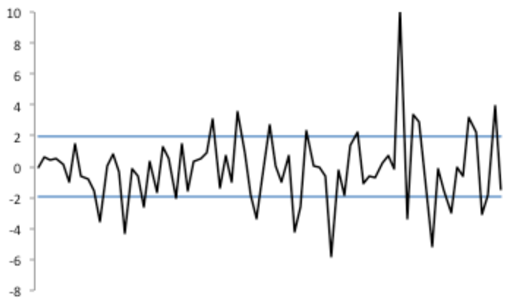
Table 4.4.I T-Statistic development over time for λ_s, λ_v, λ_d, and λ_β for individual firms



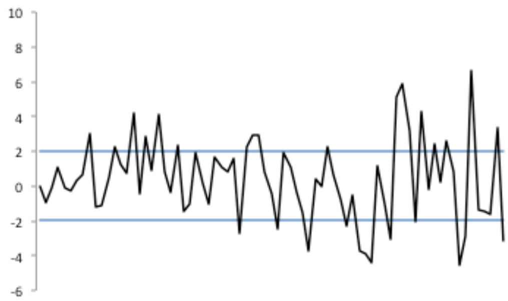
λ_v, HmL



λ_s, SmB



λ_d, HSmLS



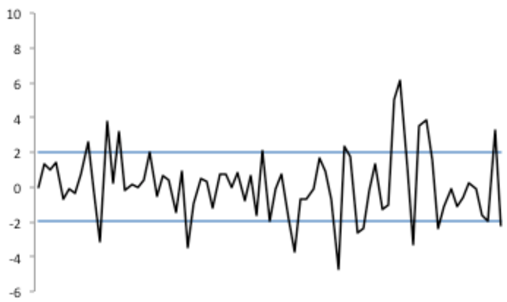
λ_β, Mkt-rf

Table 4.4.I illustrates the variation in t-statistics for the cross-sectional regression coefficient for HmL, SmB, HSmLS and market beta over time for individual firms. The two horizontal blue lines represent the point at which the null is rejected: t >1.96 and t < -1.96.

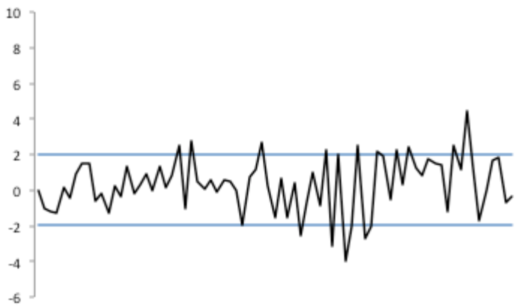
Although the consolidated lambda value for the value factor of individual firms is insignificant, the variable proved significant on 29 out of the 75 observations. The fluctuation between positive and negative relationships, however, still points to a statistically insignificant result. The lambda for the size factor proved significant in 28 out of the 75 observations. Also here, the oscillating properties between negative and positive values render the factor statistically insignificant. As for the previous factors, the same properties are retained in the default risk factor derived from CDS spreads. In 24 out of the 75 observations the factor did exhibit statistical significance. Finally, the market beta displayed significant results in 31 out of the 75 observations and is thereby the factor which in total proved to be most significant. The default risk factor proved to be the least. Common for all tested lambdas is a significant oscillation between positive and negative values, which despite instances of t-statistics > 1.96 and < -1.96 proved insignificant.

4.5 Factor Significance Inspection for Portfolios

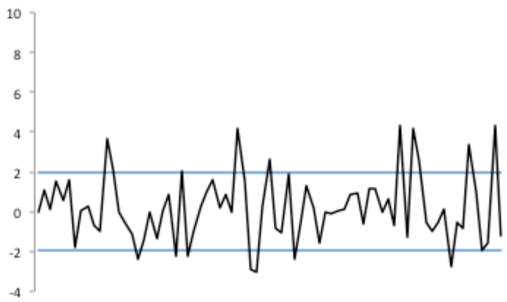
Table 4.5.I. T-Statistic development over time for λ_s, λ_v, λ_d, and λ_β. Portfolios



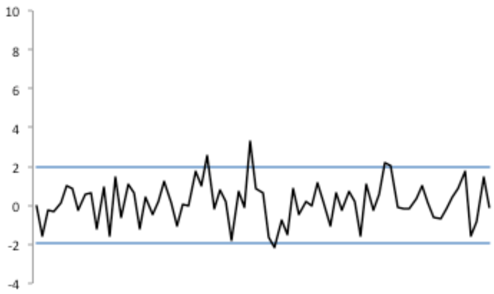
λ_v, HmL



λ_s, SmB



λ_d, HSmLS



λ_β, Mkt-rf

Table 4.5.I illustrates the variation in t-statistics for the cross-sectional regression coefficient for HmL, SmB, HSmLS and market beta over time for portfolios. The two horizontal blue lines represent the point at which the null is rejected: t >1.96 and t < -1.96.

Relative to the significance inspection of the lambda values of the individual firms, the portfolio lambdas display slightly less volatility and in total generated less statistically significant results during the time period. HmL displayed 21 significant results (t-statistics > 1,96 and < -1,96), SmB displayed 18, HSmLS displayed 19 and the market beta interestingly proved to be the least significant with a mere 5 significant observations out of the total sample of 75.

5. Analysis

This section will discuss the implications and interpretations of the results by analyzing them from a theoretical point of view with respect to the working hypothesis.

The study has examined whether default risk is a systematically priced factor in equity returns by adding an additional default risk factor to the Fama and French (1993) three-factor model. The study has been applied on the European market, using iTraxx as a reference index between 2004 and 2010 with monthly observations. The results have not been able to present figures that show a significant impact of default risk on equity returns during the period July 2004 to October 2010.

After deriving the beta estimations, the results show poor characteristics relative to expected outcome based on outstanding theory. When analysing the beta estimations for the three-factor model, only one portfolio displayed the expected beta values, namely “Big Size-High Value”. The expected beta values are based on the discussions put forth by Fama and French (1993), concluding a negative size beta and a positive value beta.

When analysing the results of the regression estimations of the augmented four-factor model, the results show that “Big size-High Value-Low default risk” exhibits expected beta values for size and value, however not for default risk. In line with the reasoning presented[16], the argument was made for both a negative as well as a positive relationship between expected return and CDS spread. Yet, considering the size and stability of the sample firms, a positive beta value was expected rendering the augmented four-factor model with no relevant outcomes.

Four out of the eight portfolios tested as dependent variables exhibited positive default betas, a result that further invites to the discussion of under what

[16] See section 3.4

circumstances a positive relationship versus a negative is to be expected. This study can neither confirm the conclusion of a positive relationship between default risk and return arrived at by Vassalou and Xing (2004), nor a negative relationship as confirmed by Gharghori *et al.* (2009). The variations of the results can been seen as proof for a non-linear relationship between default risk and expected return based on several input factors, both external and internal. Garlappi and Hong (2008) found this to be true in their paper, depicting the relationship of expected return as a function of default risk as a positive parabolic curve where firms with a very low default risk experienced an increase in expected return when the risk increased until a certain point $(y' = 0)$, after which the relationship turned negative.

When applying the Fama and Macbeth (1973) procedure by means of a cross-sectional regression on the beta values, the obtained lambda values were all close to zero. Similar results were arrived at both when applying the Shanken (1992) correction factors to the individual firms and when regressing the portfolios. All four factors exhibited low t-statistics and were unable to be statistically confirmed.

As for the default factor not being systematic could be a result of the proxy employed. While Vassalou and Xing (2004) and Gharghori *et al.* (2009) arrived at the similar conclusion, namely that default risk is priced, yet opposing values, Anginer and Yildizhan (2010) found that there is no statistical support for default risk being priced in equity returns. Unlike Vassalou and Xing (2004) and Gharghori *et al.* (2009), Anginer and Yildizhan (2010) applied a marketable proxy while the former utilized structural modelling to measure default risk. This study applied a marketable proxy as well, which could also suggest them being inferior to the structural modelling approaches.

Similar results were arrived at for the size factor and value factor, which displayed unexpectedly low t-statistics. This study failed to statistically confirm the systematic element of the two factors, which is unexpected. Although the systematic characteristics of default risk is and has been debated and tested, size and value have been repeatedly confirmed to retain an element of systematic risk and in fact be priced by the market, albeit the reason for this is still debated. The results arrived at concerning these two factors are inconclusive both from the perspective of statistical insignificance and also on account of the variation between positive and negative beta values. The size factor has on several occasions been concluded to have a negative relationship with equity earnings (Fama and French, 1993 and Fama and Macbeth, 1973) while the value factor has been proved to have a positive relationship. Although the two factors tend to show significance in equity returns, the reason behind this relationship is widely debated.

Fama and Macbeth (1973) did not confirm that market beta explains stock variation, despite having a high correlation. This might be a reason as to why the factor was not included in the study performed by Fama and French (1995). Fama and French came to the conclusion that the relationship between market beta and return on equity diminishes when controlling for size is included. One possible explanation to this phenomenon is that the size factor to a certain extent captures the explanatory power of the market beta. This result may provide an explanation as to why the results proved insignificant in this study

A possible explanation to the outcome of the study can be based on the quality and size of the sample. As mentioned in data criticisms, the companies included in the iTraxx index are similar in certain aspects including size, stability and volatility. In the original study by Fama and French (1992), several thousand companies were included in the regressions and models over a wide spectrum of the U.S. market. It is therefore likely that the scope of their study captured the variations and effects of the different factors more adequately relative to this study. Furthermore, an unsteady time period was used due to the limitations of available data. The sample period includes an economic boom following 2001 and a period of severe financial complications in the world's markets following the financial crisis preluding in 2007. Although the study attempts to separate the data sample to avoid contamination, both sub sample time series exhibited insignificant results. The sample employed is therefore not suitable as an adequate representation of the entire market during normal market conditions and based on this the study cannot refute nor confirm the validity of CDS spreads as a suitable proxy for default risk and thus confirm that default risk is systematic. However, due to the fact that CDS contracts are a relatively new product of the financial market in combination with the limited percentage of companies able to uphold stability and standards necessary to support them, employing them as proxies for similar empirical studies may futile. Despite arguing the superiority of CDS spreads as a proxy relative to structural models or other marketable proxies, the limited history and homogeneity of the companies who uphold them suggest they may be inappropriate in empirical studies.

For further research, an increased sample size and time scope could render different results. While this study was conducted on the European market, further research could try to apply similar methodology to the U.S. market. Despite the inconclusive results of this study, the debate remains whether CDS spreads could be considered a suitable proxy for default risk. We invite future researchers to continue to pursue the area with more a more extensive sample size and time frame.

6. Conclusion

This section summarizes the findings concluded by analyzing the results and methodology of the study.

This study has applied the Fama and Macbeth (1973) cross-sectional regressions and further applied by Fama and French (1992) to test the pricing of European stocks. Excess stock return has been tested as dependent variable against three independent variables apart from market beta, all with monthly observations from July 2004 to October 2010. The variables used are size, value and default risk. The study has utilized both classical mimicking portfolio formation as well as Shanken (1992) correction to approach the errors-in-variables issue. As a proxy for default risk, the study employed CDS spreads derived from Markit through Thomson Reuters DataStream.

The regression estimations produced inconclusive beta values and all three independent variables vary between positive and negative relationships with equity returns contrary to expectations. These results were achieved through both the three-factor model and the augmented four-factor model with the regression models applied on both individual firms and constructed portfolios in line with the Fama and French (1992) methodology.

The cross-sectional analysis of the factors, provide statistically insignificant results during both the divided time frame and throughout the scope of the entire time frame. The insignificance of default risk resulting in it not being priced by the market and hence not being a systematic risk, is in line with certain theory and previous studies. However, the study was unable to confirm the systematic element of size and value, a result that has been disproved on several occasions in many studies. The study is unable to confirm any statistically significant systematic aspect of default risk.

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Appendix I

I.1 – Sample List

Table I.1 - The firms included in this study and their respective beta values

Sector	Firm	Headquartered	HmL	SmB	HSMLS	Market-rf
Financial	UBS AG	CH	0,8375583	-0,63756	0,230174	1,214702
Financial	Royal Bank of Scotland	GB	2,2983766	1,079353	1,208845	0,605017
Financial	Swiss Re	CH	1,3944943	0,61068	0,138564	1,072473
Financial	Societe GERnerale	FR	1,429457	-1,09974	0,196408	1,359658
Financial	Lloyds	GB	1,5439932	0,109149	0,727496	0,977371
Financial	Intesa	IT	0,6354324	-0,84967	0,206058	1,060863
Financial	ING Bank	NE	0,6101764	1,099799	-0,14095	1,128224
Financial	HSBC	GB	1,1469708	-0,12546	-0,22144	0,377154
Financial	Hannover Rueckversicherung	GER	-0,1826258	0,710435	0,33547	0,499843
Financial	Deutsche Bank	GER	1,505128	0,036721	-0,45088	1,179515
Financial	Credit Suisse Group	CH	0,7016669	-0,62083	-0,00761	0,948511
Financial	Credit Agricole	FR	0,9342543	-0,90614	0,346671	1,098
Financial	Commerzbank	GER	2,1056956	0,17799	-1,18666	1,435374
Financial	BNP Paribas	FR	1,0435544	-1,03294	-0,3886	1,049804
Financial	Barclays	GB	3,1983168	0,274099	0,579228	0,645024
Financial	Banco Santander	SP	0,2611207	-0,20343	0,473457	1,245181
Financial	AXA	FR	1,4715316	-0,0393	0,184023	1,040804
Financial	AVIVA	GB	1,0936303	1,165907	0,437715	0,299151
Financial	ASSICURA	IT	0,614961	-0,22941	0,102421	0,762832
Financial	Allianz	GER	0,9263214	0,150883	-0,17883	0,815769
Financial	Aegon	NE	0,2381248	1,28297	0,972334	1,197981
TMT	WPP 2005	GB	0,3074901	0,573681	0,39115	0,758894
TMT	Wolter Kluwer	NE	-0,6247153	0,483036	-0,04783	0,92761
TMT	Vodafone	GB	-0,1847555	0,225604	0,112871	0,45583
TMT	Vivendi	FR	0,1451249	0,114539	0,032815	0,593027
TMT	TeliaSonera	SW	-0,14267	-0,12451	0,416826	0,604518
TMT	Telenor	NO	-0,6465722	0,548422	0,2355	1,531985
TMT	Telekom Austria	AU	-0,4797911	0,351787	0,106497	0,735182
TMT	Telefonica	SP	-0,4393306	0,079737	0,473238	0,552134
TMT	Telefonaktiebolaget Ericsson	SW	-0,4826155	0,892601	0,414779	0,449492
TMT	Telecom Italia	IT	-0,1353015	0,388197	0,491701	0,394824
TMT	STMicroelectronics	CH	0,7509263	0,64317	0,027384	0,98408
TMT	Publicis	FR	0,4382454	0,696984	0,483112	0,464064
TMT	Pearson	GB	-0,4043156	0,34454	0,26502	0,649849
TMT	Koninlklijke KPN	NE	-0,3101962	-0,24897	-0,20476	0,38636
TMT	France Telecom	FR	-0,1641775	-0,25961	0,186199	0,45179
TMT	Deutsche Telekom	GER	-0,0291815	-0,87224	-0,05526	0,412649
TMT	British Telecommunications	GB	-0,3714751	1,251664	1,326862	0,624943
TMT	British Sky Broadcast	GB	-0,5382789	1,381416	0,641795	0,394681

Sector	Firm	Headquartered	HmL	SmB	HSMLS	Market-rf
Energy	Veolia	FR	0,0514281	1,596078	0,7596	0,930152
Energy	United Utilities	GB	-0,0788066	-0,05653	-0,21839	0,549579
Energy	Total SA	FR	-0,1968489	-0,12492	-0,13078	0,674124
Energy	Technip	FR	0,039223	0,643623	0,887444	0,924182
Energy	RWE	GER	-0,1091288	0,066483	-0,25833	0,695219
Energy	Royal Dutch Shell	NE	-0,4937572	0,191432	-0,0675	0,764635
Energy	National Grid	GB	-0,091611	-0,03314	0,000699	0,415916
Energy	Iberdrola	SP	-0,2016519	0,530452	0,363196	0,878771
Energy	Gas Natural SDG	SP	-0,3377285	0,472931	0,131646	0,804948
Energy	Fortum Oyj	FI	-0,2698205	0,34582	-0,26868	0,883777
Energy	ENI SPA	IT	-0,1665744	0,286761	-0,03381	0,625513
Energy	ENEL SPA	IT	0,0620483	0,301613	0,205542	0,619963
Energy	Energie Baden-Wuertemberg	GER	-0,1979347	0,733949	-0,26615	0,567817
Energy	E.ON	GER	0,3120952	0,048897	-0,18488	0,883173
Energy	Centrica PLC	GB	0,0037653	-0,10266	-0,19903	0,320683
Energy	BP PLC	GB	-0,2821131	-0,52312	0,422382	0,861569
Consumer	Unilever	GB	-0,3492236	0,337169	0,035158	0,590823
Consumer	Tesco	GB	-0,4762832	-0,40823	0,254877	0,87159
Consumer	Tate & Lyle	GB	0,010142	0,391057	0,401151	0,48151
Consumer	SCA	SW	0,0782301	1,15448	0,522251	0,546867
Consumer	SODEXO	FR	0,1223365	0,498109	-0,05495	0,438652
Consumer	Sabmiller PLC	GB	-0,4351192	0,568567	0,327209	0,939547
Consumer	PPR	FR	-0,2658088	1,939649	0,681845	0,963063
Consumer	Nestle SA	CH	-0,2505977	0,16441	-0,17218	0,439583
Consumer	Metro AG	GER	-0,4544444	0,989305	0,877368	1,173076
Consumer	Marks and Spencer PLC	GB	-1,0835049	1,4052	0,773904	0,728726
Consumer	LVMH	FR	0,2578717	0,5685	0,12204	0,779734
Consumer	Koninklijke Philips Electronics	NE	-0,2299577	0,904195	0,322985	0,949735
Consumer	Koninklijke Ahold NV	NE	-0,9186626	0,999991	0,372032	0,558057
Consumer	Kingfisher PLC	GB	0,0219702	0,849336	1,227514	0,491478
Consumer	Imperial Tobacco Group PLC	GB	-0,5269903	0,091592	0,002988	0,557524
Consumer	Henkel AG	GER	-0,3961588	0,645975	-0,34521	0,87357
Consumer	DiaGERo PLC	GB	-0,5385833	0,181672	0,226422	0,621474
Consumer	Danone	FR	0,0464851	0,275168	-0,15702	0,409389
Consumer	Compass Group	GB	-0,8877829	1,201574	0,302072	0,582866
Consumer	Carrefour	FR	-0,2854041	0,343391	0,366855	0,598605
Consumer	British American Tobacco PLC	GB	-0,2821851	0,176705	-0,11091	0,446239
Consumer	Anheuser	BE	-0,5092435	0,763208	0,239432	0,868101
Consumer	Electrolux	SW	0,2524623	1,211274	1,296081	0,466511
Consumer	ACCOR	FR	0,4173835	0,90753	0,383607	0,600643
Autos & In	XSTRATA	CH	0,0888208	0,990381	0,817716	1,173802
Autos & In	VolkswaGERn AG	GER	-1,4289119	-2,28069	0,682246	0,872547
Autos & In	VINCI	FR	-0,0302643	1,300065	0,572854	0,765288
Autos & In	VALEO	FR	0,0279439	1,431967	1,28306	1,363022
Autos & In	Siemens AG	GER	0,4600326	-0,05659	-0,06067	0,887325
Autos & In	SANOFI	FR	0,0568889	-0,33711	-0,44545	0,548337
Autos & In	Rolls-Royce	GB	-0,1002517	0,261896	0,341069	0,904365
Autos & In	Rentokil Initial PLC	GB	-0,497002	2,508638	1,015531	0,924989
Autos & In	Linde AG	GER	0,1486351	0,407859	0,181873	0,715301
Autos & In	Koninklijke DSM NV	NE	0,1806369	0,536837	0,195429	1,06144
Autos & In	Holcim Ltd	CH	0,4091667	0,864825	0,446604	0,977144
Autos & In	EADS NV	NE	0,3088148	0,571978	0,228581	0,53417
Autos & In	BOUYGUES	FR	0,3697242	0,375752	-0,08672	0,851399
Autos & In	BMW AG	GER	-0,4650601	1,272744	0,833494	0,911072
Autos & In	Bayer AG	GER	-0,428144	0,181642	-0,2794	0,92457
Autos & In	BASF AG	GER	0,0874186	0,701966	0,434156	0,92728
Autos & In	BAE Systems	GB	-0,4631045	0,711966	0,47654	0,519749
Autos & In	Astra Zeneca	GB	0,298047	-0,45561	-0,5956	0,396785
Autos & In	Anglo American PLC	GB	-0,2117367	0,326822	0,307622	1,450893
Autos & In	ALSTOM	FR	-0,0312282	1,617033	0,258006	0,895521
Autos & In	Akzo Nobel NV	NE	-0,4501909	1,043466	0,224531	1,094777
Autos & In	Volvo AB	SW	0,1711831	1,26003	0,609381	0,929666

In this table the firms are presented as well as the sectors to which they belong. Each firm has one value beta, one size beta, one default risk beta and one market risk beta. All beta values are estimated. Autos & In. stands for autos and industrials.

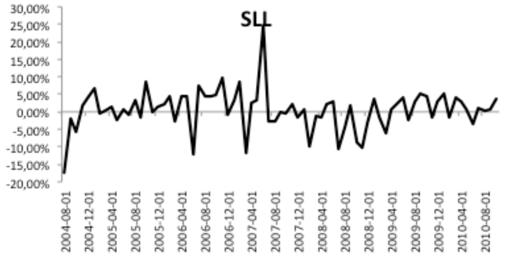
Appendix II

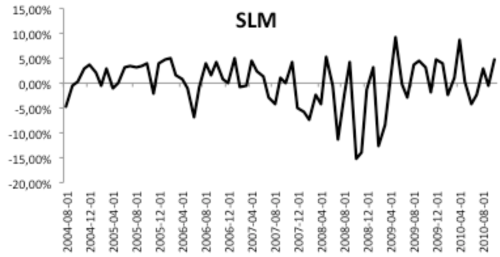
II.1.a – 2x2x3 Portfolio Formation Including Factors

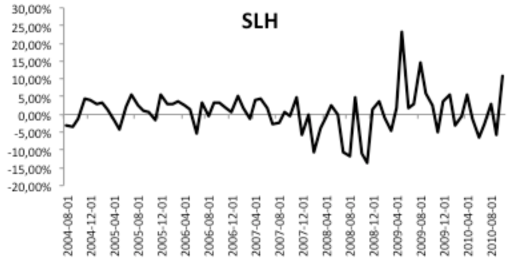
2x2x3

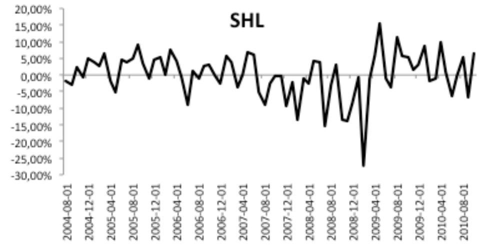
Small Size						Big Size									
SLL		SLH	SHL		SHH	BLL		BLH	BHL		BHH	HmL	SmB	HSMLS	Market-rf
Low Value-Low Spread	*Low Value-Med Spread*	*Low Value-High Spread*	*High Value-Low Spread*	*High Value-med Spread*	*High Value-High Spread*	*Low Value-Low Spread*	*Low Value-Mid spread*	*Low Value-High Spread*	*High Value-Low Spread*	*High Value-Mid Spread*	*High Value-High Spread*				
-17,27%	-4,54%	-2,96%	-1,49%	-0,37%	-0,91%	-0,88%	-2,87%	-3,52%	-4,30%	-1,28%	-6,66%	**2,84%**	**-1,34%**	**2,47%**	**-1,63%**
-1,96%	-0,37%	-3,20%	-2,78%	-0,89%	-0,79%	-0,27%	-0,88%	-1,77%	1,26%	-2,50%	2,73%	**0,92%**	**-1,43%**	**0,18%**	**-0,25%**
-5,51%	0,47%	-0,91%	2,37%	1,87%	5,41%	1,41%	0,35%	2,95%	2,50%	0,17%	1,04%	**2,44%**	**-0,79%**	**1,93%**	**2,69%**
2,06%	3,08%	4,55%	-0,33%	1,45%	2,91%	0,59%	2,24%	2,27%	4,11%	1,38%	1,09%	**-0,69%**	**0,34%**	**1,10%**	**0,10%**
4,36%	3,86%	4,12%	5,30%	2,83%	3,07%	1,55%	1,07%	7,94%	2,65%	4,13%	6,66%	**0,29%**	**-0,08%**	**1,98%**	**2,81%**
6,78%	2,24%	3,22%	3,92%	4,80%	-0,57%	2,30%	2,73%	1,69%	4,30%	0,15%	3,03%	**-0,56%**	**1,03%**	**-2,48%**	**1,09%**
-0,18%	-0,29%	3,66%	2,96%	2,22%	2,49%	1,58%	3,88%	-1,28%	0,96%	0,46%	0,97%	**0,45%**	**0,72%**	**0,13%**	**2,03%**
0,40%	3,14%	1,60%	6,67%	4,95%	8,11%	1,34%	1,21%	-0,27%	2,80%	4,00%	1,93%	**3,51%**	**2,31%**	**0,04%**	**2,84%**
1,53%	-0,88%	-1,25%	-1,73%	-0,11%	-2,38%	-0,30%	1,04%	0,05%	-1,12%	1,08%	0,28%	**-0,69%**	**-0,97%**	**-0,42%**	**-0,80%**
-2,19%	0,24%	-4,01%	-4,89%	-3,96%	-6,57%	-2,39%	-2,56%	-1,56%	-4,94%	-5,63%	-6,91%	**-3,40%**	**0,44%**	**-1,16%**	**-1,83%**
0,85%	3,45%	2,28%	4,58%	8,09%	5,89%	2,96%	3,25%	6,14%	2,95%	4,84%	9,56%	**2,83%**	**-0,76%**	**3,13%**	**5,92%**
-0,71%	3,46%	5,59%	4,03%	2,83%	3,98%	3,10%	2,60%	3,25%	2,90%	1,49%	3,86%	**0,30%**	**0,33%**	**1,84%**	**2,67%**
3,62%	3,46%	2,69%	5,19%	6,54%	5,95%	3,45%	3,13%	4,00%	5,18%	6,15%	3,82%	**2,08%**	**0,29%**	**-0,25%**	**2,52%**
-1,55%	3,55%	1,37%	9,45%	-2,65%	0,74%	-0,06%	-4,19%	-2,50%	-2,45%	-1,57%	-2,18%	**0,79%**	**3,98%**	**-1,99%**	**0,58%**
8,83%	4,14%	1,04%	3,49%	4,10%	4,05%	3,79%	0,93%	4,31%	6,08%	4,54%	5,10%	**0,72%**	**0,15%**	**-1,92%**	**4,39%**
0,07%	-1,94%	-1,45%	-0,97%	-3,68%	-6,14%	-3,76%	-0,59%	-4,32%	-1,17%	0,01%	-3,11%	**-0,51%**	**-0,20%**	**-2,30%**	**-3,18%**
1,59%	4,21%	5,93%	4,83%	4,87%	3,95%	4,14%	1,52%	-0,66%	5,51%	4,60%	-1,83%	**0,87%**	**2,02%**	**-2,17%**	**4,61%**
2,27%	4,86%	3,17%	5,54%	4,99%	3,85%	2,87%	5,40%	3,27%	3,39%	5,33%	4,04%	**0,88%**	**0,06%**	**0,06%**	**1,85%**
4,85%	5,26%	3,11%	0,50%	4,95%	3,90%	2,93%	1,49%	-0,84%	3,98%	1,99%	-3,15%	**-0,77%**	**2,69%**	**-2,31%**	**3,83%**
-2,40%	1,70%	3,96%	7,88%	7,40%	0,75%	0,06%	3,33%	3,15%	4,61%	-2,59%	0,04%	**1,38%**	**1,79%**	**-0,56%**	**1,61%**
4,86%	1,05%	2,71%	4,64%	2,13%	5,79%	2,40%	2,00%	3,92%	0,60%	5,68%	3,97%	**0,98%**	**0,43%**	**0,97%**	**1,96%**
4,80%	-0,67%	1,85%	-0,50%	-2,15%	-0,55%	0,40%	-0,20%	-3,55%	-0,12%	0,22%	-0,98%	**-1,12%**	**1,17%**	**-1,95%**	**-0,07%**
-11,83%	-6,61%	-5,10%	-8,60%	-6,24%	-3,05%	-5,56%	-3,71%	-6,23%	-5,81%	-5,99%	-5,36%	**0,66%**	**-1,46%**	**3,01%**	**-4,30%**
7,74%	-0,38%	3,40%	1,49%	-3,01%	2,01%	3,32%	1,17%	-1,05%	0,78%	-1,73%	-1,70%	**-2,73%**	**1,74%**	**-2,67%**	**0,68%**
4,58%	4,15%	-0,21%	-0,66%	1,15%	4,14%	2,70%	3,59%	0,87%	0,93%	3,60%	-3,15%	**-1,62%**	**0,77%**	**-1,48%**	**0,37%**
4,73%	1,89%	3,54%	2,82%	4,50%	2,71%	0,25%	1,49%	4,85%	3,11%	5,79%	1,41%	**0,60%**	**0,55%**	**0,40%**	**3,83%**
5,25%	4,47%	3,50%	3,38%	5,35%	2,36%	1,83%	3,40%	4,55%	2,35%	2,75%	6,58%	**-0,04%**	**0,47%**	**1,05%**	**1,10%**
10,15%	0,98%	2,12%	0,08%	3,07%	5,26%	0,79%	4,28%	9,82%	3,46%	-1,11%	7,75%	**-1,60%**	**-0,55%**	**2,62%**	**3,61%**
-0,47%	0,42%	0,95%	-2,39%	3,22%	0,18%	-1,06%	-0,66%	-1,62%	-1,12%	3,05%	-2,42%	**0,49%**	**0,96%**	**0,53%**	**-2,06%**
3,78%	5,33%	5,48%	6,10%	5,31%	3,70%	0,86%	1,19%	5,46%	3,78%	5,46%	4,20%	**1,07%**	**1,46%**	**1,08%**	**4,08%**
8,72%	-0,41%	1,97%	4,24%	1,67%	2,83%	1,08%	2,50%	1,68%	1,78%	3,27%	2,46%	**0,12%**	**1,04%**	**-1,72%**	**2,90%**
-11,50%	-0,21%	-0,94%	-3,34%	-0,66%	2,35%	-0,66%	-0,22%	2,48%	-3,19%	-2,51%	0,65%	**0,73%**	**-1,81%**	**5,81%**	**-4,23%**
2,84%	4,89%	4,48%	0,42%	5,39%	8,11%	-0,08%	3,26%	6,98%	1,04%	2,15%	-2,86%	**-1,35%**	**2,61%**	**3,12%**	**3,60%**
3,76%	2,68%	4,87%	7,26%	3,38%	1,76%	3,19%	3,90%	-0,25%	5,17%	5,01%	-0,18%	**0,71%**	**1,15%**	**-3,30%**	**3,39%**
25,00%	1,74%	2,09%	6,29%	-0,67%	1,76%	-0,36%	7,24%	0,58%	2,74%	5,18%	1,75%	**-3,21%**	**3,18%**	**-6,87%**	**4,16%**
-2,30%	-2,42%	-2,42%	-4,71%	3,25%	-2,88%	-4,72%	-1,55%	-4,20%	-1,11%	-1,53%	-0,86%	**1,63%**	**0,41%**	**0,62%**	**-1,73%**
-2,18%	-3,71%	-1,84%	-8,49%	-4,89%	-1,79%	-4,44%	-5,54%	3,45%	-3,93%	-1,61%	-3,90%	**-1,72%**	**-1,16%**	**3,74%**	**-4,84%**
0,30%	1,38%	1,05%	-2,31%	1,49%	-2,60%	1,11%	0,27%	-3,08%	-1,47%	1,22%	0,15%	**-0,76%**	**0,19%**	**-0,53%**	**0,69%**
0,00%	0,37%	-0,09%	0,03%	0,67%	1,73%	3,83%	-0,27%	-0,22%	1,99%	2,40%	1,18%	**0,73%**	**-1,03%**	**-0,82%**	**1,22%**
2,46%	4,60%	5,26%	0,17%	2,61%	3,28%	2,57%	4,50%	4,50%	0,36%	3,86%	1,75%	**-1,98%**	**0,14%**	**2,31%**	**0,20%**
-1,21%	-4,55%	-5,40%	-8,87%	-6,55%	-9,47%	-0,21%	-3,11%	-2,21%	-2,49%	-6,08%	-6,32%	**-3,85%**	**-2,61%**	**-2,65%**	**-3,36%**
0,94%	-5,47%	0,33%	-1,93%	-1,18%	-1,82%	-0,06%	1,11%	0,40%	0,54%	-0,37%	-2,64%	**-0,77%**	**-1,35%**	**-0,81%**	**-1,28%**
-9,46%	-6,95%	-10,22%	-13,19%	-15,10%	-5,58%	-10,79%	-13,29%	-11,62%	-13,42%	-11,31%	-7,00%	**-0,55%**	**1,15%**	**3,11%**	**-10,39%**
-0,68%	-2,02%	-3,50%	-0,76%	3,25%	-4,92%	-1,12%	-6,48%	3,86%	-1,07%	-3,21%	-1,31%	**0,32%**	**0,11%**	**-0,56%**	**-4,30%**
-1,29%	-3,88%	-0,42%	-2,35%	-2,21%	-1,75%	-3,64%	-2,91%	-10,47%	-2,64%	1,41%	-3,83%	**1,87%**	**1,70%**	**-1,63%**	**0,35%**
2,66%	5,69%	2,82%	4,59%	8,64%	0,25%	1,97%	4,95%	12,33%	12,08%	5,99%	5,30%	**1,07%**	**-3,00%**	**-0,15%**	**3,18%**
3,39%	-0,07%	0,26%	4,11%	3,01%	1,88%	0,82%	-2,93%	-0,42%	-2,16%	-7,33%	-1,61%	**-0,53%**	**4,37%**	**-1,51%**	**-0,73%**
-10,15%	-10,86%	-9,99%	-14,90%	-16,42%	-17,37%	-8,94%	-9,63%	-3,82%	-9,71%	-12,92%	-10,79%	**-4,79%**	**-3,98%**	**0,43%**	**-11,13%**
-3,78%	-1,56%	-11,17%	-2,56%	2,37%	-1,50%	-1,77%	-3,48%	0,17%	-1,63%	3,68%	1,91%	**3,97%**	**-2,85%**	**-0,22%**	**-1,32%**
2,35%	4,75%	5,23%	3,61%	4,24%	10,95%	2,06%	0,73%	-5,06%	3,60%	0,50%	8,19%	**3,50%**	**3,52%**	**1,92%**	**2,04%**
-8,19%	-14,75%	-10,58%	-13,20%	-18,29%	-7,66%	-7,47%	-10,08%	1,18%	-7,50%	-8,99%	-12,51%	**-3,04%**	**-4,55%**	**1,70%**	**-10,14%**
-9,79%	-13,63%	-13,39%	-13,59%	-14,45%	-21,58%	-9,19%	-14,77%	12,90%	-1,16%	-20,65%	-32,19%	**-9,29%**	**-3,56%**	**-5,13%**	**-13,25%**
-2,73%	-0,98%	1,83%	-8,24%	-2,65%	-6,51%	-3,08%	-10,59%	-12,26%	-16,20%	-4,14%	3,68%	**-1,04%**	**3,88%**	**4,25%**	**-13,17%**
3,75%	3,38%	3,94%	-0,31%	5,56%	3,87%	-1,90%	5,84%	-1,47%	-1,46%	4,29%	5,38%	**0,63%**	**1,58%**	**2,91%**	**2,52%**
-1,58%	-12,39%	-0,78%	-27,09%	-9,00%	-7,55%	-4,27%	-8,09%	-3,60%	-2,97%	-3,53%	-19,81%	**-6,54%**	**-2,69%**	**1,04%**	**-6,58%**
-5,81%	-8,34%	-4,49%	-1,05%	-8,28%	-4,88%	-8,17%	-2,57%	-7,57%	-13,68%	-14,38%	-7,87%	**-2,20%**	**3,57%**	**0,98%**	**-12,08%**
0,71%	0,71%	2,10%	5,86%	12,24%	3,79%	-2,45%	3,40%	-1,41%	8,03%	6,98%	2,93%	**6,13%**	**1,32%**	**-1,19%**	**9,39%**
2,32%	9,36%	23,31%	15,82%	37,92%	32,45%	-0,32%	10,25%	7,56%	13,55%	22,37%	23,91%	**15,59%**	**7,31%**	**13,97%**	**12,19%**
4,28%	-0,12%	2,00%	-1,00%	3,27%	3,41%	3,03%	4,72%	-6,73%	2,93%	3,68%	2,38%	**1,25%**	**0,30%**	**-2,05%**	**7,95%**
-2,16%	-2,75%	3,21%	-3,69%	-2,13%	0,34%	-1,46%	0,82%	3,08%	-4,41%	-5,14%	-1,62%	**-2,90%**	**0,26%**	**4,18%**	**-2,14%**
2,95%	3,91%	14,61%	11,63%	19,42%	17,11%	9,76%	10,01%	4,68%	7,59%	10,51%	14,88%	**5,87%**	**2,03%**	**4,84%**	**8,82%**
5,25%	4,66%	5,97%	5,88%	9,61%	6,54%	2,46%	4,38%	-6,86%	6,32%	12,25%	13,50%	**6,37%**	**0,98%**	**-0,19%**	**1,43%**
4,68%	3,18%	2,65%	5,61%	10,83%	3,59%	1,75%	6,11%	0,52%	3,02%	4,40%	0,29%	**1,48%**	**2,41%**	**-2,00%**	**2,87%**
-1,57%	-1,73%	-4,93%	1,82%	-13,03%	-5,53%	-1,08%	0,81%	4,87%	-3,93%	-4,93%	-4,90%	**-4,48%**	**-2,63%**	**-1,43%**	**-0,18%**
3,01%	4,82%	3,82%	3,31%	0,42%	3,34%	1,50%	1,72%	0,69%	1,51%	0,75%	2,61%	**-0,60%**	**1,66%**	**0,28%**	**3,38%**
5,30%	4,12%	5,85%	8,64%	5,84%	4,47%	6,81%	5,06%	1,23%	7,65%	2,76%	0,29%	**0,21%**	**1,74%**	**-4,14%**	**3,43%**
-1,29%	-2,20%	-3,02%	-1,69%	-3,85%	-0,06%	-3,01%	-3,39%	-6,55%	-5,91%	-6,14%	-5,19%	**-0,56%**	**3,01%**	**-0,73%**	**-2,67%**
4,23%	1,18%	-0,47%	-0,96%	-1,86%	0,30%	-0,07%	-0,41%	-2,14%	-0,31%	-0,27%	2,11%	**-0,55%**	**0,59%**	**-0,77%**	**0,25%**
3,20%	8,74%	5,73%	9,98%	9,19%	9,46%	5,30%	6,59%	20,80%	4,49%	6,25%	15,70%	**0,78%**	**-2,14%**	**7,18%**	**7,60%**
0,70%	0,23%	-1,20%	1,09%	0,36%	-1,28%	-4,40%	1,11%	3,37%	0,32%	-5,69%	2,77%	**-0,37%**	**0,40%**	**1,49%**	**-2,25%**
-3,29%	-4,18%	-6,39%	-6,30%	-3,49%	-6,77%	-2,66%	-6,35%	-8,46%	-8,43%	-6,83%	-10,98%	**-1,91%**	**2,21%**	**-2,98%**	**-4,86%**
1,30%	-2,23%	-2,44%	-0,24%	-2,70%	-1,24%	2,06%	0,64%	-3,93%	-4,98%	-4,40%	-4,08%	**-2,17%**	**1,19%**	**-2,46%**	**-3,24%**
0,47%	3,02%	3,23%	5,40%	7,99%	9,34%	1,13%	2,47%	8,58%	1,86%	6,88%	16,31%	**4,81%**	**-1,30%**	**7,15%**	**10,52%**
0,61%	-0,37%	-5,60%	-6,61%	-5,79%	-3,68%	-2,00%	-1,29%	-2,63%	-3,06%	-4,06%	-4,30%	**-2,70%**	**-0,68%**	**-1,29%**	**-1,32%**
3,69%	4,77%	11,05%	6,75%	4,23%	6,60%	5,45%	3,54%	11,49%	-1,15%	5,00%	4,25%	**-2,39%**	**1,42%**	**4,66%**	**0,16%**

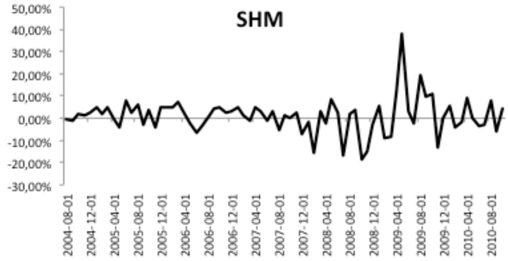
II.1.b – 2x2x3 Excess Return of Portfolio Formations

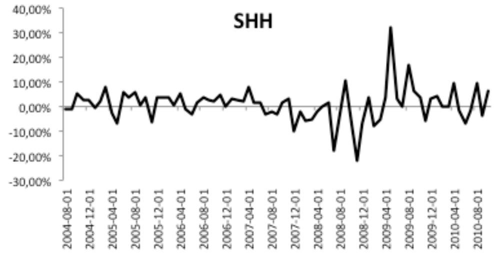


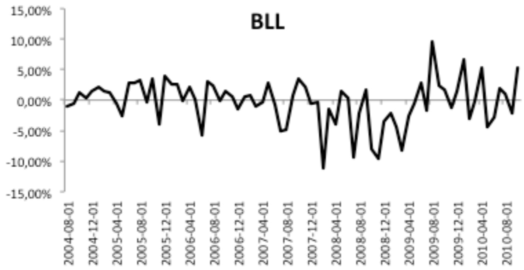


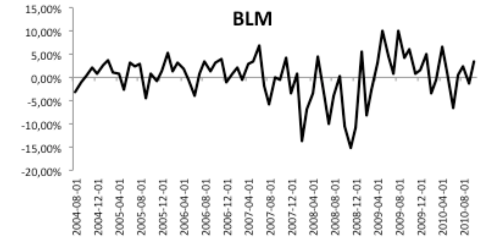


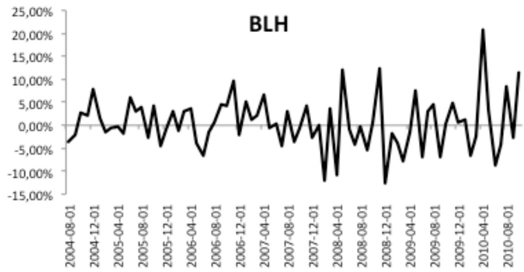


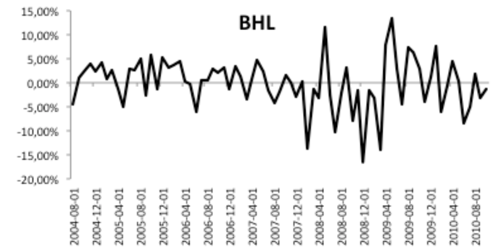


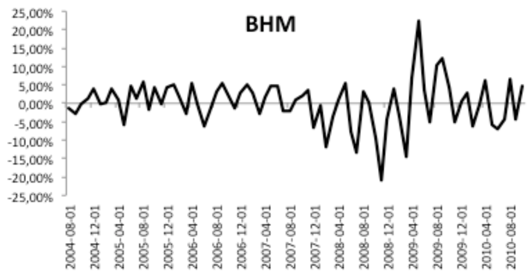


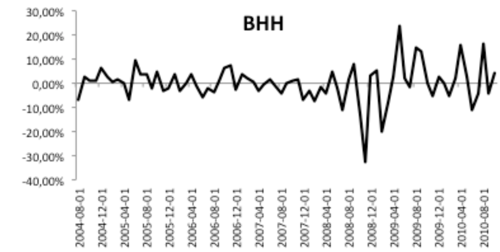








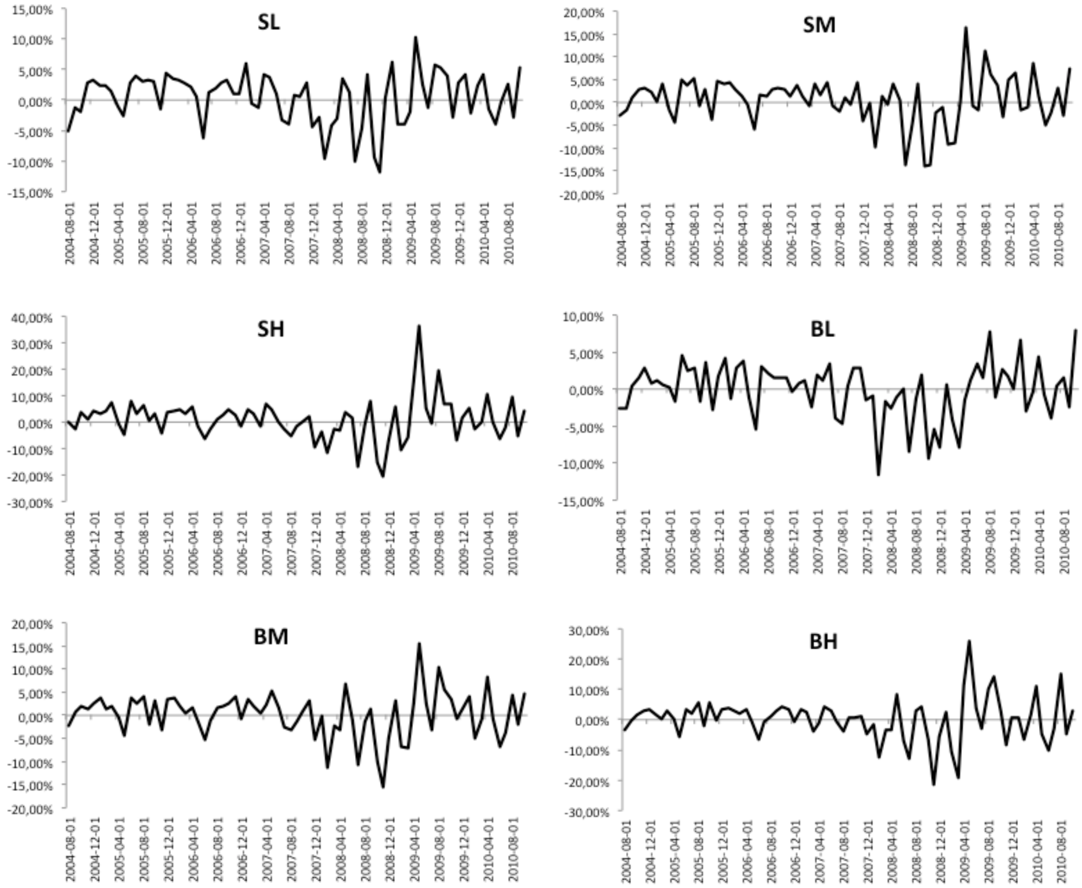




II.2.a – 2x3 Portfolio Formation including Factors.

	2x3								
	Small Size			Big Size					
	SL		**SH**	**BL**		**BH**			
	low	*medium*	*high*	*low*	*medium*	*high*	***HmL***	***SmB***	***Mkt-RF***
	-4,99%	-2,96%	-0,03%	-2,67%	-2,14%	-3,60%	**2,01%**	**0,14%**	**-1,63%**
	-1,19%	-1,77%	-2,67%	-2,51%	0,73%	-0,28%	**0,38%**	**-1,19%**	**-0,25%**
	-1,90%	1,18%	3,86%	0,45%	1,81%	1,46%	**3,39%**	**-0,20%**	**2,69%**
	2,93%	2,90%	1,04%	1,52%	1,24%	2,81%	**-0,30%**	**0,43%**	**0,10%**
	3,32%	3,29%	4,13%	2,92%	2,59%	3,40%	**0,65%**	**0,61%**	**2,81%**
	2,40%	2,15%	3,06%	0,76%	3,91%	1,76%	**0,83%**	**0,40%**	**1,09%**
	2,47%	0,10%	4,11%	1,19%	1,47%	0,24%	**0,34%**	**1,26%**	**2,03%**
	1,44%	3,95%	7,13%	0,60%	1,94%	2,74%	**3,91%**	**2,41%**	**2,84%**
	-0,91%	-1,68%	-0,73%	0,25%	-0,54%	0,32%	**0,13%**	**-1,11%**	**-0,80%**
	-2,55%	-4,45%	-4,87%	-1,59%	-4,37%	-5,79%	**-3,26%**	**-0,04%**	**-1,83%**
	2,71%	5,09%	7,86%	4,46%	3,72%	3,38%	**2,04%**	**1,37%**	**5,92%**
	3,85%	3,90%	3,23%	2,55%	2,60%	1,94%	**-0,61%**	**1,29%**	**2,67%**
	3,04%	5,25%	6,21%	2,78%	4,13%	5,75%	**3,07%**	**0,61%**	**2,52%**
	3,31%	-0,64%	0,70%	-1,73%	-1,84%	-1,95%	**-1,42%**	**2,96%**	**0,58%**
	3,06%	2,86%	3,00%	3,59%	3,19%	5,43%	**0,89%**	**-1,09%**	**4,39%**
	-1,55%	-3,79%	-4,14%	-2,81%	-3,27%	-0,32%	**-0,05%**	**-1,02%**	**-3,18%**
	4,34%	4,81%	3,87%	1,75%	3,35%	3,52%	**0,65%**	**1,47%**	**4,61%**
	3,41%	4,16%	4,11%	4,19%	3,80%	3,72%	**0,11%**	**-0,01%**	**1,85%**
	3,22%	4,34%	4,91%	-1,25%	1,86%	2,94%	**2,94%**	**2,97%**	**3,83%**
	2,82%	2,74%	3,33%	2,78%	0,46%	2,00%	**-0,13%**	**1,21%**	**1,61%**
	2,05%	1,24%	5,63%	3,89%	1,56%	3,20%	**1,45%**	**0,09%**	**1,96%**
	0,60%	-0,35%	-1,47%	-1,12%	-1,21%	-0,50%	**-0,72%**	**0,54%**	**-0,07%**
	-6,20%	-5,83%	-6,37%	-5,40%	-5,17%	-6,75%	**-0,76%**	**-0,36%**	**-4,30%**
	1,20%	1,76%	-2,41%	2,95%	-0,91%	-0,73%	**-3,65%**	**-0,25%**	**0,68%**
	1,87%	1,47%	0,91%	2,18%	1,73%	0,98%	**-1,08%**	**-0,21%**	**0,37%**
	2,80%	2,99%	2,89%	1,53%	1,96%	2,84%	**0,70%**	**0,78%**	**3,83%**
	3,35%	3,04%	4,74%	1,47%	2,63%	4,26%	**2,09%**	**0,92%**	**1,10%**
	1,11%	2,81%	2,61%	1,58%	4,01%	3,34%	**1,63%**	**-0,80%**	**3,61%**
	0,98%	1,42%	-1,81%	-0,34%	-0,72%	-0,82%	**-1,63%**	**0,82%**	**-2,06%**
	5,95%	3,85%	4,62%	0,74%	3,54%	3,59%	**0,76%**	**2,18%**	**4,08%**
	-0,49%	1,49%	3,10%	1,09%	1,92%	2,27%	**2,38%**	**-0,39%**	**2,90%**
	-1,34%	-0,65%	-1,66%	-2,43%	0,40%	-3,97%	**-0,93%**	**0,78%**	**-4,23%**
	4,21%	4,10%	6,78%	1,88%	2,36%	-0,95%	**-0,13%**	**3,93%**	**3,60%**
	3,77%	1,75%	4,49%	1,10%	5,21%	4,16%	**1,89%**	**-0,16%**	**3,39%**
	0,93%	4,40%	0,11%	3,35%	1,74%	3,15%	**-0,51%**	**-0,93%**	**4,16%**
	-3,37%	-0,82%	-2,41%	-3,83%	-2,42%	-0,75%	**2,02%**	**0,13%**	**-1,73%**
	-3,88%	-1,93%	-5,23%	-4,72%	-3,20%	-3,79%	**-0,21%**	**0,22%**	**-4,84%**
	0,83%	1,12%	-1,75%	0,50%	-1,44%	0,60%	**-1,24%**	**0,18%**	**0,69%**
	0,56%	-0,56%	-0,03%	2,92%	0,67%	0,57%	**-1,47%**	**-1,40%**	**1,22%**
	2,89%	4,26%	2,35%	2,95%	3,01%	1,13%	**-1,18%**	**0,80%**	**0,20%**
	-4,35%	-4,06%	-9,26%	-1,50%	-5,17%	-4,85%	**-4,13%**	**-2,05%**	**-3,36%**
	-2,85%	-0,25%	-3,46%	-0,97%	-0,27%	-1,76%	**-0,70%**	**-1,19%**	**-1,28%**
	-9,58%	-9,88%	-11,57%	-11,56%	-11,15%	-12,42%	**-1,42%**	**1,37%**	**-10,39%**
	-4,21%	1,22%	-2,78%	-1,58%	-2,26%	-3,61%	**-0,30%**	**0,56%**	**-4,30%**
	-2,95%	-0,36%	-3,41%	-2,53%	-3,04%	-3,40%	**-0,66%**	**0,75%**	**0,35%**
	3,60%	4,16%	3,72%	-1,17%	6,62%	8,37%	**4,83%**	**-0,78%**	**3,18%**
	1,28%	0,52%	1,64%	0,13%	-1,13%	-7,18%	**-3,48%**	**3,88%**	**-0,73%**
	-10,14%	-13,77%	-17,02%	-8,34%	-10,60%	-12,68%	**-5,61%**	**-3,10%**	**-11,13%**
	-4,61%	-4,69%	-0,99%	-1,30%	-1,45%	2,99%	**3,95%**	**-3,51%**	**-1,32%**
	4,22%	3,97%	8,11%	1,98%	1,38%	4,17%	**3,04%**	**2,93%**	**2,04%**
	-9,39%	-13,95%	-15,19%	-9,31%	-10,02%	-6,68%	**-1,59%**	**-4,18%**	**-10,14%**
	-11,80%	-13,73%	-20,70%	-5,33%	-15,61%	-21,66%	**-12,61%**	**-1,21%**	**-13,25%**
	0,39%	-2,19%	-7,21%	-7,91%	-4,87%	-5,71%	**-2,70%**	**3,16%**	**-13,17%**
	6,09%	-1,14%	5,74%	0,64%	3,09%	2,39%	**0,70%**	**1,52%**	**2,52%**
	-4,03%	-9,18%	-10,51%	-4,02%	-6,90%	-10,70%	**-6,58%**	**-0,70%**	**-6,58%**
	-3,89%	-8,80%	-5,86%	-7,92%	-7,00%	-19,31%	**-6,68%**	**5,22%**	**-12,08%**
	-1,87%	0,04%	14,69%	-1,46%	2,46%	11,34%	**14,68%**	**0,17%**	**9,39%**
	10,31%	16,49%	36,41%	1,16%	15,40%	26,06%	**25,50%**	**6,86%**	**12,19%**
	2,58%	-0,80%	5,11%	3,37%	2,51%	3,97%	**1,57%**	**-0,99%**	**7,95%**
	-1,21%	-1,74%	-0,32%	1,47%	-3,14%	-2,74%	**-1,66%**	**0,38%**	**-2,14%**
	5,82%	11,19%	19,21%	7,78%	10,42%	10,13%	**7,88%**	**2,63%**	**8,82%**
	5,31%	6,16%	6,94%	-1,09%	5,61%	14,37%	**8,54%**	**-0,16%**	**1,43%**
	3,99%	3,89%	7,08%	2,70%	3,52%	2,77%	**1,58%**	**1,99%**	**2,87%**
	-2,90%	-3,23%	-6,73%	1,81%	-0,85%	-8,40%	**-7,01%**	**-1,81%**	**-0,18%**
	2,87%	4,81%	1,81%	0,04%	1,27%	0,48%	**-0,31%**	**2,57%**	**3,38%**
	4,08%	6,42%	5,04%	6,56%	4,06%	0,79%	**-2,40%**	**1,37%**	**3,43%**
	-2,26%	-1,59%	-2,86%	-2,98%	-4,96%	-6,73%	**-2,18%**	**2,65%**	**-2,67%**
	2,34%	-1,07%	-0,15%	-0,40%	-0,68%	1,51%	**-0,29%**	**0,23%**	**0,25%**
	4,25%	8,59%	10,62%	4,36%	8,24%	10,86%	**6,43%**	**0,00%**	**7,60%**
	-1,58%	1,36%	0,06%	-0,64%	-0,64%	-4,55%	**-1,14%**	**1,89%**	**-2,25%**
	-4,00%	-5,09%	-6,26%	-3,86%	-6,79%	-10,03%	**-4,22%**	**1,77%**	**-4,86%**
	-0,29%	-2,31%	-1,90%	0,48%	-3,68%	-2,95%	**-2,52%**	**0,55%**	**-3,24%**
	2,64%	3,17%	9,65%	1,56%	4,29%	15,19%	**10,31%**	**-1,86%**	**10,52%**
	-2,83%	-2,89%	-5,18%	-2,35%	-1,82%	-4,79%	**-2,39%**	**-0,65%**	**-1,32%**
	5,34%	7,24%	4,46%	7,88%	4,59%	3,02%	**-2,87%**	**0,52%**	**0,16%**
#									
Average	16	19	14	16	19	16			
	0,37%	0,47%	0,96%	-0,09%	0,16%	0,13%			

II.2.b – 2x3 Excess Return of Portfolio Formations



Tables II.1.a through II.2.b present the excess return patterns for the augmented Four-factor portfolio set-up according to the 2x2x3 portfolio split and the three-factor set-up according to the 2x3 portfolio split. The return developments are illustrated graphically for the entirety of the period from 2004-06-01 to 2010-10-01. The respective factors are derived form these portfolio formations.

Appendix III

III.1 – Results of Portfolio Beta Regression Estimations

Table 1 4-Factor beta regression results for Portfolios

	HmL	SmB	HSmLS	Market-rf
SLL	-0,89401	1,017159	-0,35585	0,931512
SLM	-0,17171	0,671725	0,188797	0,716125
SLH	-0,33828	1,160331	0,67074	0,730173
SHL	0,380292	0,881984	-0,1878	0,809446
SHM	0,878951	0,753096	0,338895	0,764025
SHH	0,268959	0,969742	0,778249	0,807659
BLL	-0,23851	0,121125	-0,05946	0,631359
BLM	-0,20713	0,265975	0,107313	0,853701
BLH	-1,02616	-0,78228	0,881497	0,896069
BHL	0,312742	-0,41624	-0,33133	0,830185
BHM	0,627267	0,00922	0,099943	0,779023
BHH	0,65599	0,256234	0,735076	0,768602

Table III.1 presents the results of the portfolio regressions. SLL (small size-low Value-Low spread) through BHH (Big size-High value-High spread) for the 12 portfolio formations with respect to a 2x2x3 split. The regressed factors can be viewed in Appendix II.1.

III.2.a – Descriptive Statistics of Portfolios

Table 2.a 2x3 Portfolio formation statistical characteristics

	SL	SH	BL	BH	HmL	SmB	Mkt-RF
Average	0,00	0,01	- 0,00	0,00	0,00	0,01	0,00
Median	0,01	0,01	0,00	0,01	- 0,00	0,00	0,01
Max	0,10	0,36	0,08	0,26	0,25	0,07	0,12
Min	- 0,12	- 0,21	- 0,12	- 0,22	- 0,13	- 0,04	- 0,13
Std. Dev.	0,04	0,08	0,04	0,07	0,05	0,02	0,05
Skewness	- 0,74	0,86	- 0,71	0,07	2,09	0,51	- 0,62
Kurtosis	0,73	5,82	1,17	3,06	10,23	1,75	1,16

Table III.2.a presents the descriptive statistics for the 2x3 portfolios created for the three-factor model. Including the average, median, maximum value, minimum value, standard deviation, skewness and kurtosis for each time series.

III.2.b – Descriptive Statistics Portfolio formation 2x2x3

Table 2.b 2x2x3 Portfolio formation statistical characteristics

	SLL	SLM	SLH	SHL	SHM	SHH	BLL	BLM	BLH	BHL	BHM	BHH	HmL	SmB	HSmLS	Mkt-RF
Average	0,01	0,00	0,01	0,00	0,01	0,01	-0,00	0,00	0,00	-0,00	0,00	0,00	0,00	0,00	0,00	0,00
Median	0,01	0,01	0,02	0,00	0,02	0,01	0,00	0,01	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,01
Max	0,25	0,09	0,23	0,16	0,38	0,32	0,10	0,10	0,21	0,13	0,22	0,24	0,16	0,07	0,14	0,12
Min	-0,17	-0,15	-0,14	-0,27	- 0,19	-0,22	-0,11	-0,15	-0,13	-0,17	-0,21	-0,33	-0,09	-0,05	-0,07	-0,13
Std. Dev.	0,06	0,05	0,05	0,07	0,08	0,07	0,04	0,05	0,06	0,05	0,06	0,08	0,03	0,02	0,03	0,05
Skewness	0,16	-1,15	0,42	-1,13	0,92	0,62	-0,65	-0,95	0,49	-0,59	-0,24	-0,63	1,31	0,13	1,28	-0,62
Kurtosis	4,44	1,76	3,69	3,00	6,38	6,52	1,24	1,45	1,56	1,56	2,80	4,91	7,52	1,00	4,38	1,16

Table III.2.b presents the descriptive statistics for the 2x2x3 portfolios created for the three-factor model. Including the average, median, maximum value, minimum value, standard deviation, skewness and kurtosis for each time series.

Appendix IV

IV.1 – Lambda Values

Table IV.1 - The respective lambda values for each time period

Date	Konstant	Value beta	Size beta	Default risk beta	Market beta
2004-08-01	-0,010817091	-0,005378636	-0,012088903	0,008558552	-0,016914873
2004-09-01	-0,006800002	0,010196169	-0,016332844	0,006255864	-0,002157426
2004-10-01	-0,006734946	0,011732031	-0,005780797	0,007012257	0,021648775
2004-11-01	0,028864454	-0,012073693	-0,013307775	0,001837139	-0,002142617
2004-12-01	0,036046161	-8,34905E-05	0,007791978	-0,011967857	-0,005324788
2005-01-01	0,013860081	0,010651981	0,00017986	0,016561806	0,004307133
2005-02-01	0,005341571	-0,00536775	0,008473139	-0,008808969	0,011588514
2005-03-01	-0,011991551	-0,003654217	0,014804504	-0,009934404	0,049796315
2005-04-01	0,008555939	-0,004144041	-0,000464787	-0,013525236	-0,013993544
2005-05-01	-0,017177248	-0,003338126	0,006441924	-0,042151408	-0,018881526
2005-06-01	0,038851486	-0,00746641	-0,000585833	0,000238334	0,007760042
2005-07-01	0,003098803	-0,005329073	0,00918851	0,008587134	0,030448041
2005-08-01	0,038813459	-0,004305038	-0,019259419	-0,004810002	0,021576333
2005-09-01	-0,009459064	-0,007025164	0,026199187	-0,049957529	0,010981
2005-10-01	-0,021807108	0,001455871	-0,012575389	-0,002374923	0,081960404
2005-11-01	-0,02049734	0,0130525	0,00285138	-0,007641987	-0,007959856
2005-12-01	-0,000598591	0,011148333	0,021049247	-0,033790331	0,049902234
2006-01-01	0,025754768	0,00316117	0,002635121	0,003708673	0,012626411
2006-02-01	-0,030327148	-0,002607735	0,006411045	-0,023687228	0,079790084
2006-03-01	0,006538199	0,012121017	-0,010501734	0,01940022	0,016702616
2006-04-01	0,030786153	-0,008137789	-0,001441689	0,006536407	-0,006349881
2006-05-01	-0,027094318	-0,00703687	0,00754996	-0,021900878	0,034491007
2006-06-01	-0,040753547	-0,007503825	-0,009277259	0,017023494	-0,023145273
2006-07-01	0,01702629	-0,008505542	0,01171835	-0,019105125	-0,01674295
2006-08-01	-0,002239878	-0,014222	-0,006521583	0,003494742	0,027233378
2006-09-01	0,023049528	0,008286961	-0,003837504	0,005645711	0,001633849
2006-10-01	0,042828526	-0,005317429	-0,000699249	0,01097009	-0,017292489
2006-11-01	0,005914526	-0,00650669	-0,020412441	0,037296349	0,028034751
2006-12-01	-0,012719867	-0,01286529	0,008082189	-0,01678298	0,017872343
2007-01-01	0,021460659	0,006215229	0,012798803	0,008079138	0,012010019
2007-02-01	-0,00939917	0,012084888	0,007422333	-0,01437086	0,031113583
2007-03-01	0,015051266	-0,003633575	-0,01103798	0,044963603	-0,046394794
2007-04-01	-0,007442509	-0,028238223	0,010619173	0,011932126	0,043201627
2007-05-01	-0,000654892	0,006199306	0,003868564	-0,023289581	0,049646951
2007-06-01	-0,017612072	-0,020856414	0,025030352	-0,047535341	0,057300411
2007-07-01	-0,027075351	-0,008466437	-0,004487632	-0,008659168	0,014223598
2007-08-01	-0,033841265	-0,01589027	-0,008880953	0,029830086	-0,007326768
2007-09-01	0,036723011	-0,031043539	-0,013108112	0,000786627	-0,039378689
2007-10-01	-0,017622234	-0,022234284	-0,003899968	-0,014340546	0,039122847
2007-11-01	0,019122091	-0,025092499	-0,023716656	0,01100972	0,022618259
2007-12-01	-0,021292337	-0,026162728	-0,008079586	-0,064727748	-0,007689561

Date	Konstant	Value beta	Size beta	Default risk beta	Market beta
2008-01-01	0,01754264	-0,016465723	-0,006192654	-0,032110746	-0,026260894
2008-02-01	-0,052366022	-0,008139136	-0,013613261	0,035062294	-0,075600145
2008-03-01	-0,038828345	-0,001058044	0,017103585	0,000587008	0,01103264
2008-04-01	-0,025938853	-0,010682056	-0,006422266	-0,0007935	0,000569425
2008-05-01	0,017873487	0,004206533	-0,030779323	-0,010870119	0,057647787
2008-06-01	-0,013409722	-0,051489773	0,046110736	-0,07910318	0,011920455
2008-07-01	-0,089837096	-0,03333375	-0,026740206	-0,003759996	-0,018442285
2008-08-01	0,046578328	0,043534122	-0,039764532	-0,033048236	-0,057062394
2008-09-01	0,037724264	0,006028288	0,009039941	0,024925633	-0,013377366
2008-10-01	0,007899563	-0,021883483	-0,079401108	0,051992541	-0,121849207
2008-11-01	0,043569757	-0,116488368	-0,124180787	-0,032088946	-0,155464788
2008-12-01	0,059633154	-0,007229606	0,054292865	-0,017071376	-0,159857345
2009-01-01	-0,01332523	-0,049162866	0,046058749	-0,019573354	0,041494745
2009-02-01	-0,01935174	-0,110627786	-0,042991904	0,00664263	-0,03519497
2009-03-01	-0,012754169	-0,037824859	0,055391073	0,019242668	-0,118746165
2009-04-01	-0,105466474	0,07618801	-0,024719395	-0,0025369	0,187755279
2009-05-01	-0,023001789	0,18671561	0,036285701	0,182966483	0,145469995
2009-06-01	-0,032685426	-0,00104177	0,020659612	-0,068373892	0,090257256
2009-07-01	0,007957102	-0,013849819	-0,001484814	0,056212518	-0,045663073
2009-08-01	-0,009346191	0,023277678	0,02524134	0,056757071	0,117298067
2009-09-01	0,053984191	0,08895984	0,029050359	-0,027445067	-0,005088976
2009-10-01	0,004403691	0,003075642	0,040489797	-0,072874002	0,046464708
2009-11-01	-0,025354029	-0,055263619	-0,011287348	-0,001449023	0,004397033
2009-12-01	-0,032075046	-0,026156009	0,023263195	-0,026819995	0,063376136
2010-01-01	0,035493989	-0,018866237	0,027003625	-0,047989687	0,018215838
2010-02-01	0,008235976	0,009021409	0,03323165	-9,97159E-07	-0,075167715
2010-03-01	0,042953934	0,021822138	0,003719148	-0,0082707	-0,055586589
2010-04-01	-0,023255449	0,020954091	-0,003250973	0,040536295	0,116373819
2010-05-01	-0,006118087	-0,003306264	0,025892281	0,036714421	-0,031181296
2010-06-01	-0,037086746	-0,017572232	0,017922224	-0,037628812	-0,024996118
2010-07-01	0,013715856	-0,01039589	0,01430033	-0,030327007	-0,037075939
2010-08-01	0,001987023	0,049252384	-0,046705642	0,062099908	0,071956583
2010-09-01	0,01782393	-0,02518534	-0,008095953	-0,017826149	-0,052251873
2010-10-01	-0,001273864	-0,018520343	0,001052612	0,07113123	0,049122275

Table IV.1 display the results from the cross-sectional regressions. Each beta-value receives one lambda value for each observation in the sample period.

Default Risk in Equity Returns

During the past two decades, several studies have attempted to measure if default risk is priced in equity returns. The pursuit of understanding the systematic aspect of default risk has resulted in a vast amount of empirical studies in the area, arriving at inconclusive or contradicting results. In an attempt to contribute to the field, the authors Hagander and Egervall employ credit-default swap spreads as a proxy for default risk and augment the traditional Fama and French Three-Factor model by adding a fourth default risk factor.

Previous studies have brought attention to the shortcomings of the traditional proxies employed for default risk. As the structural models i.e. the Merton model or credit ratings are based on up to date balance sheet data, thus lacking in update frequency, marketable measurements such as bond spreads have been employed as well. However recent studies have suggested bond spreads to be inferior to CDS spreads in terms of efficiency in reacting to information, hence the purpose of the study. The data sample includes 101 firms listed on the European iTraxx index from July 2004 to October 2010. Hagander and Egervall have applied factor mimicking portfolio technique to construct the original factors employed by the Three-factor model (size, value and market risk) and additionally a default risk factor, based on monthly closing prices.

The study subjects both the individual firms as well as the constructed portfolios to regressions against both the three, original factors and the augmented four factors as independent variables. The results suggest that augmenting the original asset pricing model with default risk does not improve its performance and the authors found that the four-factor model exhibited less explanatory power in terms of equity return relative to the three-factor model.

As a second step, the study employs the cross-sectional regression methodology, developed by Fama and MacBeth to statistically verify the significance of the factors. Hagander and Egervall correct for the errors in variables problem by applying the Shanken correction coefficient to the data sample of individual firms, in addition to running the regressions on the constructed portfolios. In order to avoid contaminating the results with volatile market conditions following the financial meltdown in 2007, the data sample is split into two. The first sub-sample captures the market from July 2004 to July 2007, the second from August 2007 to October 2010, in addition, the results are individually compared to the results on the entire sub sample for both the portfolios and individual firms.

The results from the cross-sectional regressions proved statistically insignificant for both the individual firms and constructed portfolios for all four factors. Thereby the study does not verify the systematic risk property for default risk or any of the other three factors.

Hagander and Egervall suggest further research within the field in combination with the application of CDS spreads. Increasing the data sample to include more firms in addition to increasing the tested time frame may hopefully aid in the strive towards finally determining whether default risk indeed is systematic or idiosyncratic.