LUND UNIVERSITY
School of Economics and Management

Credit risk and stock return

An investigation of the credit risk premium

Master thesis
Department of Economics
Lund University School of Economics and Management
NEKN02
Authors: Axel Melander Norinder & Magnus Svensson
Supervisor: Thomas Fischer

Abstract

Several researchers have investigated the relationship between credit risk and stock returns, but their findings are ambiguous. While some have found the anomalous relationship that investors pay a negative risk premium when investing in high credit risk stocks, others have presented opposing results. This non-consensus and intriguing results motivated us to further investigate this relationship by examining the returns of approximately 8000 stocks in the U.S. during the period 2007-2017. To find if there is an anomalous relationship we used a multi-factor model incorporating market excess return and the firm-specific factors; size, value and credit ratings. Our results indicate that credit ratings can be used to explain stock return and that there is a positive relationship between the credit risk and stock return.

Key words: credit rating, credit risk, U.S. market, stock returns, risk premium, anomaly, multi-factor model

Acknowledgements

This master thesis was written during the spring of 2018 at Lund University School of Economics and Management. We would like to express our gratitude to our supervisor Thomas Fischer for his dedication and guidance throughout this period. Furthermore, we would also like to thank LINC and LUSEM for providing us with the tools necessary to conduct this research.

2018-05-28

Axel Melander Norinder Magnus Svensson

Table of Contents

List of Tables

1. Introduction

The market collapse in 2008 shook the world and took some of the largest firms in the world down with it. Firms that had previously been considered to be safe investments went from good to bad overnight. Lehman Brothers, one of the larger financial services providers in 2008, had an investment grade rating, but was downgraded one business day before its collapse. For decades investors have tried to understand and explain the dynamics of the markets for traded securities, but once again the market was caught off guard. Several models and theories have been developed to get a grip on the behavior of securities and they incorporate a variety of economic aspects. Some of the more acknowledged are the Capital Asset Pricing Model (CAPM) and the Fama and French factor models to name a few.

The Fama and French factor models are extensions to the Asset Pricing Model, which instead of only considering market excess return, also incorporate company specific features that have shown empirical evidence for explaining the excess stock returns. The original Fama and French three-factor model from 1992 incorporates size, value and market excess return as factors. In 2014, the model was extended to the five-factor model, which also considers profitability and investment patterns (Fama & French, 2014). In this paper we want to investigate if adding another factor to the model will increase our understanding of the stock market, for example credit risk.

There are opposing views on credit risks' effect on stock returns. Several studies have found the anomalous relationship that investors pay a negative risk premium when investing in high credit risk stocks (Avramov et al., 2009; Brooks & Godfrey, 2015; Chen et al., 2010; Griffin & Lemmon, 2002), while some have found the opposite and more rational relationship (Friewald et al., 2014; Anginer &Yildizhan, 2010; Nielsen, 2013). This ambiguity motivates further investigation of this relationship by using an alternative measure of credit risk, namely credit ratings.

Credit ratings provide information about the properties of a company and the underlying risk, which can have applications other than just assessing capability of meeting debt obligations.

When investigating credit ratings' effect on stock returns, it makes sense to conduct the research on the U.S. market as the market for corporate bonds has been pre-eminent and well established in the U.S. for a long time. Thus, credit ratings' effect on stock returns should be more apparent in the U.S. than for other geographical locations where credit ratings are not as instituted.

The Fama French factor models have previously proven to incorporate factors that have significant effects on the excess stock returns. Thus, their approach of constructing and measuring a factor to determine its effect, constitutes a great basis to conduct the research on credit ratings' relationship to excess stock returns. Using their approach we want to investigate if corporate credit ratings can be used to explain excess stock returns and if investors pay a negative risk premium for high credit risk stocks on the U.S. stock market.

The research question will be answered by investigating listed firms in the U.S. with a corporate credit rating during the period 2007 to 2017 and by adding an additional variable, corporate credit ratings, to Fama and French's (1992) three-factor model. Previous studies have come to the conclusion that adding more factors may result in other factors becoming redundant. This paper is therefore conducted by adding only one factor to the three-factor model instead of the more recent five-factor model. From our investigation we have found that credit ratings can be used to further explain excess stock returns and that the relationship between credit risk and stock return is positive.

Following the introduction we will, in the literature review, present basic concepts and fundamental theories needed to explain and interpret this paper's results. Furthermore, previous research will be reviewed and this study's dependent and independent variables will be introduced. Chapter three, Method, will focus on how this study is conducted. Choices and assumptions underlying the model will be presented and motivated. Methodology for gathering the data, precision of the model and test methodology will also be presented. We will also discuss the study's reliability and validity. The results of this study will be presented in chapter four. Finally, an analysis will be presented in chapter five, in which a discussion will be held concerning this study's results based on previous research and relevant theories leading to a final conclusion and suggestions for further research in chapter six.

2. Literature review

This chapter begins with an introduction of the underlying model used in this paper, known as the multi-factor model, followed by a review of relevant theories that will later be used to analyze the relationship between credit risk and stock return in chapter five. Thereafter follows a section in which we review the applied multi-factor model in more detail, through research conducted by Fama and French (1992, 2014). Lastly, this chapter will present the empirical findings of researchers who have investigated how stock returns are affected by credit risk.

2.1 Theories

Firstly, this section will present a general theoretical background to multi-factor models. Secondly, a number of theoretical frameworks will be presented and summarized, for which the underlying ideas are relevant to understand the relationship between credit risk and stock returns. The presented theories in this paper all propose a positive relationship between credit risk and stock return, implying that higher risk should result in higher return.

2.1.1 Multi-factor models

In a multi-factor model one can employ multiple factors when trying to explain or forecast asset prices. These models are applicable for explaining both individual assets or a portfolio of assets by comparing multiple factors and analyzing the relationship between variables and their performance. Generally, these models are extensions to the traditional CAPM where theoretical arguments suggest that more than one factor is required, since CAPM will only apply period by period under strong assumptions (Campbell et al., 2012; Schwabe, 1996). There are two main categories of approaches to multi-factor models. Firstly, one can specify macroeconomic and financial market variables that are thought to capture the systematic risks of the economy. Secondly, one can specify firm characteristics that are likely to explain the differential sensitivity to systematic risks by constructing portfolios of stocks that inhabit these characteristics (Campbell et al., 2012). Campbell et al. (2012) also state that there is no specification for the number of factors that should be included, but argues that for the model to be useful, the number of factors should be reasonably small.

2.1.2 Risk aversion and risk premium

The concept of risk aversion is one of the foundations of finance. Risk aversion is related to an agent's elementary utility curve. The shape of the individual curve decides whether the agent is risk avert, risk neutral or risk loving, where risk aversion is the most common behavior of humans. A risk avert agent prefers a certain strategy over a risky alternative if they have the same expected payoff. The agent may be willing to pay for insurance in order to get rid of the risk, called risk premium (Danthine and Donaldson, 2015). In the context of credit risk the theory proposes a positive relationship between credit risk and return, since a risk avert agent expects higher payoff for investing in a credit risky company.

2.1.3 Rational expectations theory

Rational expectations is a theoretical framework that explains the relationship between future expectations and outcomes. More specifically, the theory argues that outcomes can be explained by people's future expectations. Understanding how information is gathered and handled to estimate future conditions is key in order to fully understand the complexity of future expectations (Muth, 1961).

The model tries to explain the relationship by examining several factors such as how we, as people, interpret information, process it and make continuous adjustments based on the information we gather. Since the process is dynamic it is also extremely sensitive to external influences such as changes in the market (Muth, 1961). It is the dynamic process that separates the rational expectations theory from many other theories. The theory proposes that agents adapt themselves and adjust their expectations after shocks in the market, which in comparison to efficient capital markets, is often overlooked (Grossman, 1981). This rational behavior suggests that an investor only invests in a riskier firm if he or she expects to earn higher returns from that investment. Thus, the theory suggests a positive relationship between credit risk and return.

Previous research has criticized the theory for its unrealistic assumptions. One debated topic is the empirical validity of the research. Later studies suggest that the empirical evidence for the findings is lacking (Grossman, 1981). Others have argued that the assumed amount of

information possessed by an agent is unrealistic (Shiller, 1978; Feige & Pearce, 1976). Moreover, the assumption, presented by the theory, that individual expectations are similar to the prediction of relevant economic theory is also unlikely (Muth, 1961). Shiller (1978) also argues that it is unreasonable to assume that agents, who recently discovered the model, already knew it since it would also imply that they knew all the underlying parameters and variables.

2.1.4 Credit risk and capital structure

Unlike the optimal conditions and perfect markets often presented in financial theories, in reality factors such as taxation and transaction costs create imperfect markets (Berk & DeMarzo, 2014). The underlying factors to imperfect markets, such as taxation and transaction costs, create incentives for firms to increase their firm value by optimizing their level of debt. Increased leverage can be beneficial due to the benefits of the interest tax shield, but it is a trade-off since increased leverage also increases a firm's financial distress costs (Berk & DeMarzo, 2014). The Trade-off theory explain the downsides of the distress costs and increased risk of default and tries to weigh these costs with the benefits of increased leverage and maximizing the return on equity.

In the Credit Rating–Capital Structure hypothesis (CR-CS) developed by Kisgen (2006) the relationship between capital structure and credit risk is analyzed. His theory focuses on the connection between the traditional trade-off theory and credit ratings and their impact on the choice of capital structure. Kisgen (2006) argues that different credit ratings are associated with discrete costs and benefits, which influence managers' decision making concerning capital structure. The CR-CS raises criticism against the traditional trade-off theory implying that different credit ratings are related to different costs. More specifically, Kisgen (2006) argues that the costs and benefits associated with certain ratings needs to be balanced against the costs and benefits implied by the trade-off theory. While the traditional Trade-off theory focuses on general costs related to default and capital structure, Kisgen (2006) tries to nuance that debate by also arguing that firms close to a rating change face different specific costs that may outweigh the traditional costs and can affect a firm's ability to generate return on equity. Hence, the traditional Trade-off theory and the CR-CS hypothesis can therefore be seen as complements

when facing a credit rating decision. In the context of credit risk both the CR-CS hypothesis and the Trade-off theory support a positive relationship between risk and return.

The trade-off theory has been criticized for its simplicity (Myers, 1984). Berens and Cunny (1995) argue that the theory misses important factors such as future debt issues and that previous studies on capital structure has been misguided as a result. Hart and Moore (1995) put forward that actual corporate decisions cannot be explained by these simplified assumptions. Another argument directed at the trade-off theory is that debt financing has existed long before corporate taxes were implemented indicating that there are more reasons to debt financing than the corporate tax shield (Frank & Goyal, 2007).

2.1.5 The Merton model

The Merton model is currently the most well-known credit risk model and for this paper, the underlying ideas of the model are more relevant than its technical aspects. The model is structural, which implies that it relies on structural characteristics of the obligor. The model is based on the same principles as option pricing where if the total value of a firm's assets does not exceed the nominal value of debt at maturity, the firm defaults and vice versa. From this Merton (1974) derives explicit default formulas and the implied credit spread. The model assumes that the current stock price embodies the market's expectations of default for a firm similarly to the option price embodying expectations for the option to end up in the money (Merton, 1974; Nilsson, 2018). Since the returns on equity and debt securities depend on the assets of the firm, there is an interrelationship between the two. They both represent different types of claims on the firm, and consequently the estimate of one is relevant for the estimate of the other (Merton, 1974; SFG Consulting, 2014). Thus, since a less creditworthy firm needs to generate higher yields to its creditors, the same firm also has to generate higher returns for its equity holders. Therefore, a positive relationship between risk and return can be observed in the Merton model.

All the presented theories above propose a positive relationship between risk and returns. Consequently, when these are applied in the context of credit risk and stock returns, they suggest that firms with higher credit risk should generate higher returns on their stocks and vice versa.

These theories and their proposed relationships between credit risk and stock return are summarized in Table 1 below.

Table 1. Summary of theories related to to risk premium

Theory related to risk premium	**Underlying idea**	**Relationship to credit risk premium**
Risk aversion and risk premium	Agents prefer a certain strategy over a risky alternative if they have the same expected payoff. The agents may be willing to pay for insurance in order to get rid of the risk.	Positive
Rational expectations theory	Outcomes can be explained by people's future expectations.	Positive
Credit risk and capital structure	Different credit ratings are related to different costs. One has to weigh the benefits of increased leverage with the downsides of distress costs and increased risk of default.	Positive
The Merton model	Debt and equity claims on the same firm are interrelated and the compensation per unit of risk needs to be the same	Positive

2.2 Previous research

In the following section previous research related to the researched topic will be presented.

2.2.1 Fama and French factor models

Eugene F. Fama and Kenneth R. French published their paper *The Cross-Section of Expected Stock Returns* in 1992. The starting point of this paper was the authors' criticism of the Capital Asset Pricing Model of Sharpe (1964), Lintner (1965) and Black (1972) hereafter referred to as the CAPM. Fama and French (1992) state that there are several empirical contradictions to the CAPM, with the most prominent being size effects. Size effects refer to the empirical finding that the average returns on stocks with smaller market equity are too high given their beta, while average returns for large stocks are too low given their beta. Furthermore, they present the finding that the book-to-market ratio has a strong role in explaining stock returns, where high

book-to-market stocks outperform those with a low ratio. The goal of Fama and French's (1992) study was to evaluate the joint roles of market excess return and these factors, among others, in the cross-section of average stock returns in the U.S. for the period 1963-1990.

The results from their study suggest that, if priced rationally, stock risks are multidimensional. They propose that one dimension of risk is proxied by size and the another by the book value of equity to its market value. These two variables provide a simple and powerful characterization of the cross-section of average stock returns for the studied period. From these findings, Fama and French constructed the three-factor model for describing stock returns. This model equation is presented below, in equation 1, and consists of three explanatory variables (factors), namely: market excess return, the small minus big market capitalization portfolio (hereafter SMB) and the high minus low book-to-market portfolio (hereafter HML). The market excess return is measured by subtracting the risk-free rate from the return from an appropriate stock index. The two portfolios are constructed by taking a long position in the small market cap and high book-to-market stocks and taking a short position in large cap and low book-to-market stocks.

$$R_{it} - R_{Ft} = a_i + b_i\,(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad (1)$$

In equation 1, R_{it} represents the return on a security or portfolio i for period t, R_{Ft} is the risk free return. RM_t, SMB_t and HML_t are the factor-portfolios as stated above and e_{it} is a zero-mean residual (Fama & French. 2014).

In *A five-factor asset pricing model* Fama and French (2014) respond to some of the criticism they received for their paper written in 1992, *The Cross-Section of Expected Stock Returns.* The paper from 2014 proposes that there are also other factors, not captured by size and book-to-market ratio, that can help explain the variation in the average stock return, namely; profitability and investment (Fama and French, 2014). The evidence, presented by Novy-Marx (2013) and Titman et al. (2004), motivated the extended five-factor model:

$$R_{it} - R_{Ft} = a_i + b_i\,(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \qquad (2)$$

In equation 2 the added factor RMW_t represents the difference between the returns on a portfolio stocks with robust profitability and a portfolio of weak profitability. CMA_t represents the difference between the returns on a portfolio of stocks of low investments firms (conservative) and a portfolio of stocks of high investments firms (aggressive) (Fama & French. 2014).

Fama and French's (2014) results indicate that HML, one of the main variables in three-factor model, becomes redundant when adding the additional variables RMW and CMA. The empirical results show that the high average return is being captured by the other variables, mainly by RMW and CMA. This implies that a model with only four factors, dropping the HML-factor, will perform similarly to the five-factor model (Fama and French, 2014). Moreover, Fama and French (2014) were also able to disclose the importance of sorting, when constructing factors. Several methods were used and illustrated in their study, from the previously used 2x3 method in their study from 1992 to the 2x2 and 2x2x2x2 tested in the paper from 2014, see table 2. In conclusion, the 2x3 method is preferred since it performed as well as the other sortings and is generally more flexible (Fama and French, 2014). Table 2 gives a thorough explanation for how the factors, and their respective components, varies between different methods. More importantly, it shows a clear structure that can be adopted and applied to other models or used to recreate their results.

Table 2. Construction of Size, B/M, profitability and investment factors. Reprinted from "A five-factor asset pricing model" Fama. E. and French. K.. 2014. Journal of Financial Economics. 116. 6.

Sort	**Breakpoints**	**Factors and their components**
2×3 sorts on Size and B/M. or Size and OP. or Size and Inv	Size: NYSE median	$SMBB/M=(SH + SN + SL)/3 - (BH + BN + BL)/3$
		$SMBOP=(SR + SN + SW)/3 - (BR + BN + BW)/3$
		$SMBInv=(SC + SN + SA)/3 - (BC + BN + BA)/3$
		$SMB=(SMBB/M + SMBOP + SMBInv)/3$
	B/M: 30th and 70th NYSE percentiles	$HML=(SH + BH)/2 - (SL + BL)/2=[(SH - SL) + (BH - BL)]/2$

	OP: 30th and 70th NYSE percentiles	$RMW=(SR + BR)/2 - (SW + BW)/2=[(SR - SW) + (BR - BW)]/2$
	Inv: 30th and 70th NYSE percentiles	$CMA=(SC + BC)/2 - (SA + BA)/2=[(SC - SA) + (BC - BA)]/2$
2×2 sorts on *Size* and *B*/*M*. or *Size* and *OP*. or *Size* and *Inv*	*Size*: NYSE median	$SMB=(SH + SL + SR + SW + SC + SA)/6 - (BH + BL + BR + BW + BC + BA)/6$
	B/*M*: NYSE median	$HML=(SH + BH)/2 - (SL + BL)/2=[(SH - SL) + (BH - BL)]/2$
	OP: NYSE median	$RMW=(SR + BR)/2 - (SW + BW)/2=[(SR - SW) + (BR - BW)]/2$
	Inv: NYSE median	$CMA=(SC + BC)/2 - (SA + BA)/2=[(SC - SA) + (BC - BA)]/2$
2×2×2×2 sorts on *Size*. *B*/*M*. *OP*. and *Inv*	*Size*: NYSE median	SMB=(SHRC + SHRA + SHWC + SHWA + SLRC + SLRA + SLWC + SLWA)/8 − (BHRC + BHRA + BHWC + BHWA + BLRC + BLRA + BLWC + BLWA)/8
	B/*M*: NYSE median	HML=(SHRC + SHRA + SHWC + SHWA + BHRC + BHRA + BHWC + BHWA)/8 − (SLRC + SLRA + SLWC + SLWA + BLRC + BLRA + BLWC + BLWA)/8
	OP: NYSE median	RMW=(SHRC + SHRA + SLRC + SLRA + BHRC + BHRA + BLRC + BLRA)/8 − (SHWC + SHWA + SLWC + SLWA + BHWC + BHWA + BLWC + BLWA)/8
	Inv: NYSE median	CMA=(SHRC + SHWC + SLRC + SLWC + BHRC + BHWC + BLRC + BLWC)/8 − (SHRA + SHWA + SLRA + SLWA + BHRA + BHWA + BLRA + BLWA)/8

2.2.2 Support for the negative credit risk premium anomaly

Avramov et al. (2009) investigate the relationship between credit risk and stock return. Previous research has indicated that there is an anomalous pattern between credit risk and return and that investors seem to be paying a premium for taking on more risk (Avramov et al., 2009). Looking at the period between 1985 and 2007, using a total sample of 4.953 companies, Avramov et al. (2009) find that their research supports this puzzle, meaning that they find a negative relationship

between credit risk and return. Avramov et al. (2009) also argue that their results contribute to explain the cause of credit risk effects and that they do not find that the credit risk effect has a systematic component nor is dependent on business cycles. Differently put, although firms with higher credit risk experience tougher conditions and generally perform worse during downgrades in recessions, Avramov et al. (2009) do not find any evidence suggesting that credit risk effects are concentrated to certain periods in the business cycles. In conclusion, Avramov et al. (2009) point at mispricing as the main cause of the credit risk effect among high credit risk firms. Brooks and Godfrey (2015) also investigate the relationship between credit risk and average stock returns and the puzzle that high credit risk stocks earn lower returns than low credit risk stocks. In their paper, they provide evidence against the rational expectations explanations for the relationship through a model incorporating limits-to-arbitrage factors, which they believe can explain the anomaly. From their results, the negative pricing of high credit risk stocks is driven by underperforming stocks that have both high credit risk and have suffered recent relative underperformance. According to the authors their ongoing poor performance can be explained by four limits-to-arbitrage factors, namely idiosyncratic risk, turnover, illiquidity and bid-ask spreads. These factors collectively allow exploitation by arbitrageurs by impeding the correction of mispricing (Brooks & Godfrey, 2015). The authors chose to conduct their study on a sample of UK stocks as the UK bankruptcy regime is much more favorable to creditors than in the US regime. Their geographical choice is motivated, since they want evidence that the anomaly is not based on the rational expectations primary explanation, being that shareholders in low credit rating stocks in the U.S. rely on the process of strategically defaulting on their debt (Brooks & Godfrey, 2015).

Chen et al. (2010) investigate the link between distress and idiosyncratic volatility and risk. From this relationship they investigate the puzzle of low returns for high distress risk stocks. In order to explain this, they use a simple, theoretical, single-beta CAPM model. According to their results, the credit risk puzzle can be explained by a rational theoretical model based on that of Ferguson and Shockley (2003). Their results indicate that stocks with high idiosyncratic volatility, in the highest and lowest distress risk quintile, have a much lower returns (Chen et al., 2010). Moreover, that the largest negative returns are always observed and statistically significant in the most distressed quintiles. Hence, they find credit risk to be negatively priced

for U.S. stocks. Their results also indicate that idiosyncratic volatility effects are related to distress risk (Chen et al., 2010). Similar research has been done by Griffin and Lemmon (2002) where they investigate the relationship between book-to-market equity, distress risk and stock returns. They use the accounting measure Ohlson's O-score, which is a multi-factor model for predicting bankruptcy, using publicly available financial ratios. They find that among the firms with the highest risk of distress, the difference in returns between stocks with high or low book-to-market ratio is more than twice as large as in groups sorted by other characteristics. This observation is partly explained by the authors' finding that firms with high distress risks have characteristics making them more likely to be mispriced by investors.

2.2.3 Disproof of the negative credit risk premium anomaly

In the paper of Friewald et al. (2014), they explore the link between stocks returns and credit risk. They point to the insight from the structural model of Merton (1974), which is saying that debt and equity claims on the same firm are interrelated and the compensation per unit of risk needs to be the same. The authors estimated credit risk from CDS spreads of a sample of 675 U.S. based obligors. In line with their presented theory they found that firms' stock returns increase with credit risk premia, thus a positive relationship between risk and realized returns is observed (Friewald et al., 2014). In Anginer and Yildizhan's (2010) paper the authors also investigate the relationship between credit risk and stock returns but for the period 1980-2008, for 1011 unique firms. They instead use corporate bond spreads to proxy default risk and argue that the spreads proxy for a risk-adjusted probability of default and thereby explicitly account for the systematic component of distress risk. By this, the authors state that this way of predicting default probability is better than previously used methods such as accounting variables, bond ratings, and structural model parameters. From their results they do not find default risk to be significantly priced in the cross-section of stock returns or that there would be any evidence of firms with high default risk having anomalously low returns (Anginer & Yildizhan, 2010).

Nielsen (2013) investigates if default risk is priced in equity returns. She does so by studying the market-revealed-credit-default-swap premiums for U.S. firms for the period 2004-2010. She also examines to what extent the effects from size and value stem from default risk by studying the SMB and HML portfolio in the Fama French three-factor model. Nielsen (2013) concludes from

portfolio grouping that there is a joint effect of size and value on default risk. Thus, she can provide evidence that part of the size or value effect on stock returns can be interpreted as a default-risk effect, especially for value effects. However, when studying each variable's exclusive effect Nielsen (2013) comes to the conclusion that both size and value contain more information about the cross-section of stock returns than default risk. In Nielsen's (2013) sample she obtains the result that size is priced with a negative risk premium and that value is priced with a positive risk premium. In other words, stocks with large market capitalization and value stocks generate higher returns than stocks with small market capitalization and growth stocks. As for default risk she finds that higher default risk generates higher stock returns. Thus, she does not find support for the negative risk premium anomaly for credit risk. Nielsen also finds that default risk cannot replace size and value effects, in explaining stock returns in the cross-section (Nielsen, 2013).

Table 3. Summary of previous research

Previous research	Conclusion	credit risk premium	Method
Avramov et al. (2009)	Mispricing is the main cause of the credit risk effect among high credit risk firms.	Negative	CAPM, Fama & French three-factor model, Fama & French three-factor model augmented by a momentum factor, characteristic-based model.
Brooks & Godfrey (2015)	Four limits-to-arbitrage factors cause mispricing in stocks.	Negative	Model incorporating limits-to-arbitrage factors.
Chen et al. (2010)	Firms with high or low distress risk have lower return.	Negative	Single beta CAPM model.
Griffin & Lemmon (2002)	Firms with high distress risk have characteristics making them more likely to be mispriced.	Negative	Ohlson's O-score.
Friewald et al. (2014)	Firms' stock returns increase with credit risk premia, indicating a positive relationship between risk and realised returns.	Positive	CDS spreads.
Anginer & Yildizhan (2010)	No evidence of firms with high default risk having anomalously low returns.	Positive	Corporate bond spreads.
Nielsen (2013)	Size is priced with a negative risk premium and value is priced with a positive risk premium. Higher default risk generates higher stock returns.	Positive	Fama & French three-factor model, market-revealed-credit-default-swap premiums.

2.3 Dependent and Independent variables

Following the discussion in section 2.2 it is clear that there are several approaches on how to calculate excess return or measure it. To begin with, Fama and French (1992, 2014) state that one can use either use portfolio returns as the dependent variable or individual stock returns. We

tried both methods but decided to use the individual stock return approach, which is discussed in the subsequent chapter. The calculations of the excess return for each individual stock were done in accordance with previous research and theory. In this study we used stock returns from the sample data minus the U.S. one-month treasury bill, which was used as risk-free rate, see equation 3.

$$R_{it} - R_{Ft} \qquad (3)$$

The independent variables have also been chosen based on previous research conducted within this field. As mentioned in section 2.2 some variables have a tendency to make others redundant when combined and in order to avoid this we used previous research as guidance. Moreover, Westerlund (2005) claims that this a reasonable approach in order avoid leaving out any significant independent variables. Thus, this study use the original Fama and French (1992) factors, namely; HML, SMB and Market excess return while adding an additional factor, credit rating, measured as high rated stocks (Good) minus low rated stocks (Bad), hereafter referred to as GMB. How these factors are calculated is presented in section 3.5.

To summarize, this study is using a multifactor model with excess stock return as a dependent variable and market excess return, HML, SMB and GMB as independent variables. The model used in this paper is presented in equation 4 below:

$$R_{it} - R_{Ft} = a_i + b_i\,(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + c_i GMB_t + e_{it} \quad (4)$$

3. Method

Firstly, this study's empirical approach will be presented followed by the choice of database, collection of data and methodology for corporate credit rating. Secondly, the selection of data, data processing, precision of the model and test methodology will be disclosed. Lastly, a discussion regarding this study's validity and reliability will be held.

3.1 Approach

Databases have been used to collect the necessary data, which motivates using a quantitative approach, according to Eriksson and Wiedersheim-Paul (2006). In addition, similar studies have also been conducted with a quantitative approach, which further motivated the choice of this approach.

3.2 Collection of data

The following sections disclose the data collection process used in this paper.

3.2.1 Choosing the right database

Bloomberg was used as the primary source for collecting data. Built-in functions in the Bloomberg terminal allowed us to download historical credit ratings as well as prices, market capitalization and price-to-book ratios. The credit ratings fetched from the Bloomberg terminal originates from Standard & Poor's, hereafter S&P. We are well aware that there are other actors providing financial data and credit ratings such as Thomson Reuters' Eikon, MSCI, Datastream, Moody´s and Fitch. What motivated the use of Bloomberg services was that the competing systems could not deliver all the necessary information by themselves, which is preferred. Other factors such as "tickers" (company identifiers) further complicated and hindered this study from using multiple sources.

3.2.2 Standard & Poor's

The credit ratings used in this paper were produced by S&P, which is one of the three largest credit rating agencies. S&P's (2018) credit ratings are generally updated or reviewed at least once a year in conjunction with annual/semi-annual/quarterly reports. A review may also be motivated by other factors such as changing market conditions or sudden change in company performance (S&P, 2018). The ratings are primarily used by financial investors as an indication of credit risk. The ratings are only available through subscriptions, this paper acquired the ratings through Bloomberg.

3.2.2.1 Methodology for credit rating

The general process of obtaining a credit rating is initiated by firms themselves. A corporate rating is not given to all public and non-public firms, but paid for in order to primarily attract investors to invest in their corporate bonds. The rating process is objective, although the rating agencies are paid for their services, meaning that the firm paying for the rating cannot interfere with the process and "choose" its own rating. As a result, less creditworthy firms have a tendency not to invest in a credit rating.

The rating process itself is generally not publicly disclosed by any rating agency and its transparency is therefore limited. However, firms are typically assessed by their communicated and projected financial information, benchmarked against their peers and evaluated by other qualitative factors such as their governance framework and the experience of the management team (S&P, 2018). The credit ratings are based on public as well as non-public information such as informal meetings with management, annual reports, news and general industry data (S&P, 2018).

The lack of transparency behind the rating process make comparisons between different rating institutes and their rating systems complicated and not necessarily accurate. One should therefore avoid a mixture of ratings in the dataset, if possible. An overview of the credit rating structure for three largest rating institutes is presented in table 4 below. The table shows how the different grades are translated between the different rating agencies. Moreover, it gives a brief explanation

of how one should interpret them and a categorization based on risk. The description can vary somewhat between the different rating agencies but it does provide a brief and general indication applicable to all.

Table 4. Credit rating table. From Czech national bank (2018). S&P (2009). Moody´s (n.d). FitchRatings (2018)

	Fitch	**S&P**	**Moody´s**	**Description (Moody's)**
Investment grade	AAA	AAA	Aaa	Minimal credit risk
	AA+	AA+	Aa1	Very low credit risk
	AA	AA	Aa2	
	AA-	AA-	Aa3	
	A+	A+	A1	Low credit risk
	A	A	A2	
	A-	A-	A3	
	BBB+	BBB+	Baa1	Moderate credit risk
	BBB	BBB	Baa2	
	BBB-	BBB-	Baa3	
Non-investment grade	BB+	BB+	Ba1	Substantial credit risk
	BB	BB	Ba2	
	BB-	BB-	Ba3	
	B+	B+	B1	High credit risk
	B	B	B2	
	B-	B-	B3	
	CCC+	CCC+	Caa1	Very high credit risk
	CCC	CCC	Caa2	
	CCC-	CCC-	Caa3	
	CC	CC	Ca	In or near default. with possibility of recovery
	C	C		
	RD	SD	c	In default. with little change of recovery
	D	D		

3.2.3 Bloomberg

Bloomberg offers a wide variety of financial services ranging from financial data to business chats, news and market/business analyses (Bloomberg, 2018). The financial data needed for this paper was collected using a Bloomberg terminal and their Excel extension, which allows further processing of data-sets. The Bloomberg subscription was provided by LINC via Lund University.

3.3 Selection

The studied time period for this paper is between 2007 and 2017. The portfolios used in this study are updated semi-annually, which limited the study to the calendar year 2017. Although it is possible to extend the historical time horizon, we chose to limit the time period to year 2007. This choice was motivated by the general shortage of data concerning credit ratings, where less than 70 firms were observed in the second period of 2006, which is not enough to make inferences from in our opinion.

Firms were included or excluded from this study based on a few selection criteria, related to financial data. Only listed firms in the U.S. with available data for market capitalization, P/B ratio and stock prices, were included. Furthermore, a credit rating was also necessary for the firms included in the GMB portfolio.

3.3.1 Selection failure

Due to limitations of the Bloomberg terminal a number of firms whose financial data were not compliant with the selection criteria in section 3.3, were removed. The choice of removing these firms was motivated by the protection of the integrity and reliability of the dataset. The data loss could have been reduced by complementing the dataset using other financial services or by making the calculations ourselves. However, the calculations performed by Bloomberg are not disclosed in detail and a deviation from the original source could therefore jeopardize the integrity of the dataset.

The number of firms removed from this study is presented in appendix A, sorted by time period and portfolio to increase this study replicability. Since the firms were removed due to their lack of financial data our possibilities to investigate their impact on this study's result is limited.

3.4 Data processing

Initially, we made an assessment of the appropriate number of years to investigate based on the availability of data from Bloomberg for companies with credit ratings, where Bloomberg could

supply a sufficient amount of data for the period 2007-2017. Thereafter, lists were retrieved semi-annually for all U.S. companies for which Bloomberg could provide data regarding market capitalization, price-to-book ratio and credit ratings. From these lists we retrieved monthly stock prices for each respective company in the sample. Later, monthly returns were calculated from the retrieved stock prices in Excel. The frequency of monthly returns was chosen since use of more frequent return periods may lead to systematic biases (Koller et al., 2015). The returns were then recalculated to semi-annual returns in Excel in order to match the frequency of the rest of the data. These data points were then sorted and organized in Excel in accordance with the methodology of Fama and French (1992, 2014) to construct the portfolios that constitute the factors in the factor model. The factors were then exported to Eviews as explanatory variables and excess returns for individual stocks as the explained variables.

3.5 Portfolio construction

As previously mentioned, the independent variables are constructed as portfolios that recreate a long and short position in stocks with different characteristics. For our chosen independent variables the long positions are in small cap stocks, low price-to-book ratio stocks and good credit rating stocks and vice versa. Since Fama and French, in their most recent paper from 2014, argued that the 2x3 sorting of the portfolios is the preferred one, we chose to apply this method as well. Bloomberg provided this paper with the necessary calculations needed for market capitalization and price-to-book ratio, see equation 5 and 6. Price-to-book was needed for both the HML and SMB factor while market capitalization was used for three of the factors, namely; HML, SMB and GMB. The ratios were calculated as follows:

$$P/B = Last\ price/Book\ value\ per\ share \qquad (5)$$

$$Market\ Capitalization = Outstanding\ share * Price\ per\ share \qquad (6)$$

The SMB portfolio is constructed by firstly sorting the stocks into small and big stocks by dividing the sample into two subsets of stocks based on their market capitalization. Thereafter, each subset of small and big stocks are sorted again based on their price-to-book ratio (or book-to-market ratio). From this second sorting one obtains six subsets of stocks where value stocks

are the 30 lowest (highest) percentiles P/B ratio (B/M ratio), growth stocks are the 30 highest (lowest) percentiles P/B (B/M) and neutral stocks are the 40 percentiles in between. Lastly, these subsets of stocks are arranged like in equation 7 below, where their returns are compared. For this paper, the portfolios are updated semi-annually with each stock's return for the past six months. Thus, the samples are analyzed as a cross-section of the included stocks' past performance (Fama & French, 1992).

$$SMB = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth) \qquad (7)$$

The HML portfolio is constructed by using the same subsets of stocks as for SMB, for each period. However, for the HML portfolio the neutral stocks are not included in the last step of the calculation, which is demonstrated in equation 8 below. Similarly to the SMB portfolio the portfolio is updated semi-annually and the returns are collected from the prior six months.

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth) \qquad (8)$$

For our own introduced variable, the GMB portfolio, the sorting follows the same procedure as for the HML portfolio, where the sample is firstly divided into two subsets based on market capitalization. Then these two subsets of small and big stocks are sorted based on credit rating. The top 30 percentiles of the stocks with the highest credit ratings are considered as "good", the bottom 30 stocks with the worst ratings are considered "bad" and the 40 percentiles in between as "neutral". These are updated with the same frequency as the other portfolios and are lastly sorted as in equation 9 below.

$$GMB = \frac{1}{2}(Small\ Good + Big\ Good) - \frac{1}{2}(Small\ Bad + Big\ Bad) \qquad (9)$$

The last portfolio representing market excess return was constructed by taking the entire sample of stocks for each period and creating value-weighted portfolios. Thus, the assigned weight for each stock in the value-weighted portfolio was obtained by dividing each stock's market capitalization by the sum of the market capitalization for all the stocks in their respective period.

The portfolio excess returns were calculated by subtracting the weighted portfolio return with the risk-free rate, approximated by the one-month treasury bill, for each period.

In conclusion, for each semi-annual period one sub-portfolio was created for market excess return, six sub-portfolios for HML and SML combined and six sub-portfolios for GMB. These sub-portfolios combined formed four factor-portfolios for each semi-annual period. Thus, a total number of 336 portfolios were created, of which 252 were sub-portfolios and 84 factor-portfolios. Table 5 below illustrates how the different factor-portfolios are constructed and which breakpoints are used, in line with the methodology of Fama and French (2014), presented in table 2.

Table 5. Construction of factor-portfolios.

Factor-portfolio	**Breakpoints**	**Construction**
SMB	Size: Median P/B: 30th and 70th percentile	SMB=(SV+SN+SG)/3 – (BV+BN+BG)/3
HML	Size: Median P/B: 30th and 70th percentile	HML=(SV+BV)/2 – (SG+BG)/2
GMB	Size: Median Rating: 30th and 70th percentile	GMB=(SG+BG)/2 – (SB+BB)/2

3.6 Model precision

According to Gujarati and Porter (2010), testing a model is a necessary step to make sure that the model is correctly specified and that the results from our tests are not misleading. There are certain criteria that must be fulfilled and this section presents relevant tests that have been conducted and the results from those tests.

3.6.1 Testing the model

The final version of the model consists of four factors and is a cross-sectional regression. In order to test the model we have performed four tests related to the OLS assumptions required for the OLS to be the best linear unbiased estimator (BLUE) and to have the desirable properties; consistent, unbiased and efficient. The OLS assumptions are defined as follows (Brooks, 2014):

1. The errors have zero mean – $E(u_t) = 0$
2. The variance of the errors is constant and finite over all values of x_t – $var(u_t) = \sigma^2 < \infty$
3. The errors are linearly independent of one another – $cov(u_i, u_j) = 0$
4. There is no relationship between the error and corresponding x variate – $cov(u_i, x_j) = 0$

The developed model used in this paper is tested on individual stock return and the R^2 can therefore be misrepresentative and very low due to noisy data (Kelly, 2005; DeLong et al.,1989). Fama and French (1992, 2014) used value-weighted portfolios as the dependent variable, which reduces the disturbance of noisy data resulting in higher R^2. Although both approaches can be used it is important to understand the difference when testing the models and interpreting the results.

Ramsey RESET, which is a Regression Equation Specification Error Test, is performed in order to check if the model is correctly specified or not. A model that is considered to be correctly specified does not leave out any additional independent variables that has a significant impact. RESET has been criticized for providing little to no information if a model is rejected and it does not suggest a solution to correct the model, which is one of the downsides to using RESET (Gujarati and Porter, 2010). RESET is not always a necessity if the model is based on previous research, however if the new model deviates from the reference model it is encouraged. The results from the RESET are presented in appendix B. The p-value from the first test indicates that the null hypothesis is rejected. This implies that the model is miss-specified when all factors are included. When we removed the credit risk factor, GMB, the p-value increased and the null hypothesis could no longer be rejected, indicating that the model is correctly specified when GMB is excluded, see appendix B. To investigate why the null hypothesis is rejected when we add the GMB factor we proceeded with removing 72 outliers by trimming the top and bottom 0.3 percentiles of the observations. After removing 72 observations and performing the RESET again we observed that the p-value increased and the null hypothesis could no longer be rejected, implying that our OLS estimators are sensitive to the outliers. Since an incorrect exclusion of outliers may result in loss of integrity, reliability and incorrect inferences, other remedies were considered. The chosen remedy was robust least square, which is designed to be less sensitive to

outliers by giving them less weight in relation to the other observations (Eviews, 2017). Thus, all observations are still included in the regression. The downside of using robust least square is that we cannot perform the RESET using the method. However, the observed outputs from the different regressions using either robust least square or removing the outliers are very similar, see table 8 and appendix G. Hence, we draw the conclusion that using robust least square also solves the miss-specification issue.

To test the model for heteroscedasticity we used the White test which examines the variance of the errors (Brooks, 2014). If the variance of the errors is not constant it is referred to as heteroscedasticity, otherwise homoscedasticity, and a rejection of the null hypothesis implies a heteroscedasticity problem (Westerlund, 2005). The results from the White test is presented in appendix C and indicates that the null hypothesis of homoscedasticity is rejected. According to Gujarati and Porter (2010) heteroscedasticity can lead to incorrect inferences if not treated. One possible remedy is to use robust standard errors since they are both consistent and unbiased. Heteroscedasticity is a common problem for large samples and robust standard errors are therefore often used although the OLS will no longer be as efficient. However, given the large sample, inferences may still be made from the data (Gujarati & Porter, 2010).

Multicollinearity occurs when one or more independent variables are correlated with each other, which can result in skewed results and incorrect inferences. According to Westerlund (2005), the correlation should lie below 0.8 in absolute terms, if it is above it should be corrected. From the correlation matrix presented in appendix D it is evident that the correlation between the dependent variables are all below 0.4 in absolute terms and that no correction is needed. According to Gujarati and Porter (2010) one can also perform a Variance inflation factor test which is, simply speaking, a test for the amount of multicollinearity in a multiple regression. This test also rejects any suspicion of multicollinearity since none of the values were above the critical value of 10, see appendix E.

Finally, a Jarque-Bera test was performed to check for normal distribution. The residuals are tested for their skewness and kurtosis, which should be zero and three respectively (Gujarati & Porter, 2010). This test is not always performed since it is highly sensitive to outliers and one

often assumes that the Central limit theorem (CLT) and/or the Law of large numbers (LLN) holds (Brooks, 2014). The results indicate that the residuals are not normally distributed with a skewness and kurtosis of approximately 15 and 354 respectively, see appendix F. As previously discussed, when the number of observations is large enough one can neglect the violation under the assumption that either CLT and/or LLN holds (Brooks, 2014).

3.7 Method discussion

In this section, the chosen methodology will be critically discussed and reviewed.

3.7.1 General criticism

From an objective point of view, there are several decisions that have been made in this paper that can be criticized. Firstly, one of the main problems for any paper is how one should choose the dependent and independent variables. The choice of dependent variable is limited due to the objective of the research and comparability to relevant studies. This study used individual stock returns for the different periods instead of portfolio returns as many other studies have done. The chosen approach was motivated by the number of observations and the results from our preliminary testing, which showed that more data improved our results. More interesting is the choice of independent variables where a number of studies have shown how different variables impact stock return. Generally speaking, a model is considered to be better with less explanatory variables. At this point HML, SMB and market excess return have all been proven to explain stock return and adding more variables has also been proven to be difficult due to redundancy and correlation. This motivated the choice of using the original three variables above, as well as adding only one additional variable. Other variables could also have been included, however given that many have already been researched and proven to make HML redundant, we decided not to include them.

Arguably the result is very dependent on how the different portfolios for the independent variables are constructed. As previously mentioned in section 3.5, we chose not to use the 2x2 or the 2x2x2x2 method in favor of the 2x3 method. Nearly 40 % of all the observations are lost for the GMB and HML variables when using the 2x3 method instead of the 2x2, which is difficult to

motivate. However, previous research has shown that the performance of the different methods are fairly similar. Moreover, the separation of the effects from high and low ratings is more distinct when using the 2x3 method which is important for this paper.

Finally, it is also worth discussing the choice of updating the portfolios semi-annually and the use of cross-sectional data instead of panel data. The choice of updating the portfolios semi-annually is simply related to having more observations and to how often ratings are updated. This study used cross-sectional data instead of panel data since a lot of firms do not necessarily have a credit rating over long periods of time and the number of observed firms would therefore drop significantly. Furthermore, according to Brooks (2014), cross-sectional data is a suitable choice when studying stock returns. It is also the most common approach among the studies referenced in this paper.

3.7.2 Limitations to the selection

As mentioned in section 3.2.1 all data was collected using services provided by Bloomberg. By restricting the paper to only use one source the paper is exposed to certain limitations and shortfalls that could have been prevented by using complementary sources. One example of an evident shortfall is the observed number of rated firms during the first period in 2007, which only amounted to 77 firms. Given the size of the sample there is a risk that the sample is not representative for the entire population, which in this case is public firms with a credit rating in the U.S.. Several attempts were made in order to try to improve the result, such as using several rating agencies (Moody's and Fitch). It, however, only marginally increased the sample data for certain periods. Following the discussion in section 3.2.2.1 we therefore chose not to add these firms. Other limitations to the Bloomberg Excel add-in was its inability to pick up prices for illiquid stocks. If a firm's stock had not been traded during certain periods, we were unable to retrieve a stock price for those periods. Reasonably the stock price should have been the same as the period before, but given the amount of data we were not able to cross check all those firms and therefore chose to not include them. This choice was also motivated from a reliability perspective.

3.7.3 Reliability and Validity

It is important to make sure that there are no random errors that could skew the presented results. To ensure reliability for this paper, we applied the well-established three factor-model of Fama and French (1992). This model and methodology is a widely used and accepted method to assess the impact of a certain factor on stock returns. However, as discussed in the theory chapter there is a variety of other possible ways this investigation could be conducted.

Validity is another important component when judging the quality of research and is divided into external and internal validity. External validity concerns whether the sample of the study is representative for the general population and internal validity concerns the extent to which conclusions can be made based on the measures used (Lundahl & Skärvad, 2016). The external validity is somewhat reliant on the ability of Bloomberg to supply a representative sample and as discussed the samples obtained for the initial years may be too small. However, in large the sample obtained should be considered as extensive. The internal validity was considered by applying the widely accepted and practiced methodology of Fama and French (1992, 2014).

3.7.4 Source criticism

This paper relies heavily on secondary data, which is data not collected by yourself directly from the original source (Bryman & Bell, 2015). Since the data is created by others it is important to scrutinize it and be critical since it may be misrepresentative, false or easily misinterpreted (Bryman & Bell, 2015). This study was primarily conducted using the sources mentioned in section 3.2. Complementary sources included research papers and literature related to finance or econometrics. Although the research papers have been chosen with care, one can debate whether they are reliable or not. To be as objective and transparent as possible we have presented available criticism throughout the paper and also used the original source when possible.

4. Results

In the following section the obtained results from the conducted regressions will be presented and interpreted.

4.1 Results

Table 6. Average return for the sub-portfolios

	SMB & HML sub-portfolio average	
	Small (MCAP)	**Big (MCAP)**
Value (Low P/B)	8.39%	5.75%
Neutral	2.67%	4.66%
Growth (High P/B)	0.19%	5.37%

	GMB sub-portfolio average	
	Small (MCAP)	**Big (MCAP)**
Bad (Rating)	32.79%	15.08%
Neutral	5.61%	6.55%
Good (Rating)	4.62%	4.93%

Market excess return average
4.79%

Table 6 above summarizes the average return, for the entire period, for each respective sub-portfolio. Referring to the SMB/HML sub-portfolio averages, there is a consistent pattern for the stocks categorized as small, where the sample stocks generate higher returns the lower the P/B ratio. This pattern is not present for the stocks categorized as big since the returns for these stocks differ inconsistently between different categories of the P/B ratio. When comparing small and big stocks there is also inconsistency in what returns they generate. Small value stocks generate higher returns than big value stocks, while big neutral and growth stocks generate higher returns than the corresponding small stocks.

Referring to the GMB sub-portfolios, the average returns for the entire period indicate that small firms with bad credit ratings have higher returns than firms with good credit ratings.

Furthermore, the results also show that firms in the neutral group have higher returns than the firms with a good credit rating. Similar results can be observed when comparing big firms. Big firms with bad credit ratings show higher returns than the neutral group and firms in the good rating group. Comparing small firms to big firms it is noticeable that smaller firms with a bad credit rating have higher returns than larger firms with a difference of approximately 18%. The neutral group as well as the group consisting of firms with a good credit rating show that big firms generally have higher returns than small firms. The average market excess return for the for the period 2007 to 2017, presented in table 6 above, amounted to 4,79 %.

Table 7. Average return on factor-portfolios

Period	**SMB**	**HML**	**GMB**	**Rm-Rf**
2017-12-31	-7.9%	-1.9%	-6.2%	0.1%
2017-06-30	-12.2%	1.3%	-28.7%	0.0%
2016-12-31	-16.8%	-3.8%	-28.8%	9.2%
2016-06-30	-9.1%	10.6%	-42.8%	8.4%
2015-12-31	-0.7%	8.0%	5.2%	4.6%
2015-06-30	-7.4%	4.4%	10.3%	7.8%
2014-12-31	-0.3%	-5.0%	-4.9%	5.3%
2014-06-30	-8.2%	3.8%	3.7%	7.0%
2013-12-31	2.2%	-4.4%	-4.9%	4.6%
2013-06-30	8.0%	-0.4%	-20.4%	16.2%
2012-12-31	1.7%	-2.0%	-3.7%	16.7%
2012-06-30	-4.0%	4.5%	-0.8%	6.1%
2011-12-31	3.9%	3.7%	-10.4%	8.0%
2011-06-03	-7.4%	5.1%	0.2%	-4.1%
2010-12-31	6.6%	-1.9%	-23.4%	8.2%
2010-06-30	1.7%	-2.5%	-12.5%	16.5%
2009-12-31	14.0%	10.1%	-29.9%	-0.8%
2009-06-30	10.4%	17.8%	-36.4%	18.3%
2008-12-31	55.4%	24.3%	-123.3%	5.9%
2008-06-30	5.0%	13.6%	0.2%	-34.9%
2007-12-31	6.6%	4.9%	-44.7%	-3.3%
Average:	2.0%	4.3%	-19.2%	4.8%

In table 7 the returns from the factor-portfolios are presented for each of the observed periods as well as an average for the entire period. The SMB factor-portfolio had an average return of 2.0

%, indicating that the average return of a small firm exceeds the return of a big firm. The average return for the HML factor-portfolio was 4.3 %. This implies that value stocks outperform growth stocks during the studied period. The results from the GMB factor-portfolio indicate that a firm with a bad credit rating generated greater returns than those with a good credit rating, where the average return for the entire period was -19.2 %. Lastly, as presented above, the average market excess market return was 4.8 %.

Regression equations 10 and 11 were used to retrieve the regression outputs presented in table 8 and 9 respectively.

$$R_{it} - R_{Ft} = a_i + b_i\,(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + \; c_i GMB_t + e_{it} \quad (10)$$

$$R_{it} - R_{Ft} = a_i + b_i\,(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad (11)$$

Table 8. Regression output including GMB

Regression output

Variables	R_{it} -R_F Coefficient	P-value
Constant	-0.0051	[0.0713]
R_M-R_F	0.6545	[0.0000]**
HML	0.1024	[0.0019]**
SMB	-0.0866	[0.0000]**
GMB	-0.0340	[0.0002]**
R^2	0.0469	
Adjusted R^2	0.0464	

* = Significant on five-percent level
** = Significant on one-percent level

In table 8 above the output of the first regression is presented. This regression is run with robust least squares, White's robust standard errors to account for heteroscedasticity and includes the variable GMB. The output shows that all independent variables, except for the intercept C, are significant at one-percent level, from looking at the P-values. The intercept shows a coefficient

very close to zero and is not significant at a five-percent level. This implies that the alpha is not significantly different from zero, which is necessary for a model of this kind to be valid. The coefficients for RM_RF and HML are positive with the rounded values of 0.65 and 0.10 respectively. This implies that these variables have a positive impact on the dependent variable, excess stock return. The two other variables, SMB and GMB, have negative coefficients implying that they have a negative impact on excess returns. From the output one can also see that the obtained R^2 is low with a rounded value of 0.06. We ran a similar regression where we removed 72 outliers, but without robust least squares. Similar relationships were observed and the output from that regression is presented in appendix G.

Table 9. Regression output excluding GMB

Regression output

Variables	R_{it} -R_F Coefficient	P-value
Constant	-0.0014	[0.5841]
R_M-R_F	0.6655	[0.0000]**
HML	0.1341	[0.0000]**
SMB	-0.0819	[0.0000]**
R^2	0.0457	
Adjusted R^2	0.0454	

* = Significant on five-percent level
** = Significant on one-percent level

The regression presented in table 9 was run under similar conditions as the regression presented in table 8 with robust least squares and White's robust standard errors, but without the GMB variable. From the output one can see that there are only slight changes to the independent variables' coefficients and that they are still significant. The P-value for the intercept C becomes bigger as compared to the first regression, and is not significant at a five-percent level. There is also a minor decrease in the R^2 when the GMB variable is removed.

5. Analysis

In this section we will analyze the results presented in chapter four and compare it to previous research and relevant theories presented in chapter two. Initially, a general discussion will be held related to the tested model and its accuracy followed by a comparison to the theories and previous research.

The model used in this study originates from the traditional Fama and French three-factor model from 1992 and is further developed based on the results presented in their later study from 2014 and the previous research presented in section 2.2. As previously discussed it has become clear that one can extend the three-factor model to better explain stock returns. Looking at the results presented in chapter four it is evident that the R^2 is very low with or without the added GMB factor. This implies that the model might be defect or miss-specified. The results are quite surprising given that it is a widely used and tested multifactor model and the fact that it is based on previous research where high explanatory power normally is observed. An analysis of this study's results, solely based on the explanatory power, may therefore be misleading and needs to be addressed.

To explain the low R^2 we performed several tests including Ramsey RESET which is a test for miss-specification. The test result indicates that the null hypothesis of a correctly specified model cannot be rejected when all factors but GMB are included. This result is in line with previous research and tells us that the original three-factor model holds. When adding the GMB factor the null hypothesis is initially rejected, but later remedied by either using robust least squares or by removing 72 extreme outliers. The interpretation is that the extended model is highly sensitive to extreme outliers in the sample data, but rejects any suspicions related to miss-specification. Similar conclusions can be drawn when testing for normality using the Jarque-Bera test. Although the data does not become normally distributed when removing the same 72 outliers, a significant change can still be observed, see appendix F. From section 2.1.1 it is evident that one can use either individual stock returns or portfolio returns as the dependent variable when using a multifactor model. As briefly mentioned in section 2.3 we also tested the portfolio approach while later deciding to use individual stock returns. The initial tests showed, when using the

portfolio approach, an R^2 of approximately 75 to 80 %. These results indicate that the regression output is affected by noise, often apparent when using individual stock returns. One of the benefits of using portfolio return is diversification, which usually solves noise related issues.

In conclusion, when analyzing the information provided by the different tests and the final results from this study´s regressions it becomes apparent that the low R^2 is mainly related to noise. The interpretation of the variables in the regression outputs will however be the same and the p-values are still representative. Lastly, we observed that the results are similar if the outliers are excluded or not, see appendix G and table 8, which is why section 4.1 only discloses the results that include the entire sample.

When comparing the results of this paper to those obtained in the original Fama and French factor models (1992, 2014), there are some apparent differences. Firstly, Fama and French (1992) found, in their study for the three-factor model, that the size factor is the most prominent factor, thus having the biggest impact on excess stock returns. This is not the case for the sample of this study where the SMB factor obtained a coefficient of -0.087 while the value factor HML obtained a coefficient of 0.102, when the GMB factor is included in the regression. This implies that for the studied sample of this paper the most prominent factor is the value factor, which also holds when the GMB factor is excluded from the regression. Another interesting finding in this study, compared to what Fama and French (1992, 2014) found, is that the size effects seem to have the reverse relationship to stock returns according to the sign of the coefficient, which is negative in our regression output. This implies that for our sample, firms with bigger market capitalization generate higher returns than those with small market capitalization. This reverse relationship is rather surprising to us, both due to results of previous empirical research and because table 7 in section 4.1 showed that the SMB factor-portfolio on average generated positive returns for the entire period. Worth mentioning however, is that the SMB variable received a positive sign before robust least squares were applied to the regression, which gives less weight to extreme outliers. If we disregard this remedy then our results would entirely be in line with what Fama and French (1992, 2014) found.

In chapter four we presented one regression output including the introduced variable GMB and one without it. Fama and French (2014) found that when they expanded the three-factor model to include the two additional factors profitability and investment, the value factor becomes redundant to the model for explaining stock returns. The regression outputs of this paper do not demonstrate the same situation since SMB and HML are still significant at the one-percent level after adding the additional variable GMB, with only a slight increase in p-value. One explanation to this could be that GMB is not explained by or correlated with the other variables and thus contributes to the regression. Furthermore, when running the regressions with and without the additional variable GMB the coefficients are very similar, only differing on the third decimal. Also, the p-values tell us that the intercepts are not significantly different from zero, in both cases, which implies that the model is still valid after adding the additional variable GMB.

In general, one could observe the change in explanatory power to assess whether additional variables contribute to better explain the dependent variable. The R^2 only improves slightly in our case but due to the noise effects from using individual stocks as the dependent variable as discussed above, this figure is not particularly useful to draw conclusions from for this paper. However, since the GMB variable is highly significant and because adding variables to a model usually captures some of the noise from the error term, one can assume that the GMB variable improves the Fama and French (1992) three-factor model.

The output in table 8 shows that the additional variable GMB has a significant negative relationship to the dependent variable excess stock return with a coefficient of -0.034. The implication of this, due to the nature of the portfolio construction, is that higher credit risk generates higher stock returns. This result is in line with the foundational theoretical arguments of risk aversion and risk premium. Thus, a less risk avert agent is compensated by higher returns on his investment when investing in high credit risk stocks and subsequently pays a risk premium when investing in low credit risk stocks. Furthermore, the results are also in line with the rational expectations theory. As stated in section 2.1.3 this theory argues that outcomes can to some extent be explained by people's future expectations and that people are informed enough to act on these expectations. Higher credit risk in a firm directly means that one should expect a

higher risk of default of that same firm. In accordance with the model of rational expectations an investor of such a firm should reasonably be compensated for taking on greater risk.

In table 6 and 8, presented in section 4.1, there is an evident pattern for the GMB sub-portfolios that returns become higher the lower the credit rating. This pattern finds support in the Trade-off theory and the CR-CS hypothesis. These theoretical frameworks discuss the benefits of increased leverage and weigh them to the downsides of distress costs and increased risk of default. Thus, one has to assess the balance between greater yield and the risks it comes with. From this discussion it is evident that these frameworks assume the same relationship between credit risk and stock returns as we have found. The relationship found in the outputs from the regressions is also supported by Merton's theoretical model for credit risk. The underlying idea of the model is that there is an interrelationship between debt and equity claims on a firm. Since less creditworthy firms need to generate higher returns to its creditors they consequently have to generate higher returns to their equity holders for the model to hold. This relationship holds for the sample of stocks investigated in this study, since firms with bad credit ratings generated higher returns than firms with good credit ratings.

To summarize, the relationship found in this study between credit risk and stock returns is in line with theory. However, this result is not empirically observed by Avramov et al. (2009) who find the puzzling result of a negative relationship between risk and return and that investors pay a premium to invest in credit riskier stocks. Also, they do not find any evidence that the relationship is concentrated in particular stages of the business cycle. Looking at table 7, this finding seems to hold also for the results in our study as it consistently exhibit negative returns for the GMB factor-portfolio with only five exceptions on random occasions throughout the business cycle. However, we find the opposite relationship between credit risk and stock returns. Avramov et al. (2009) points at mispricing as the main cause of credit risk effects among high credit risk firms. Since this study does not find the same relationship as Avramov et al. (2009), we consequently do not find support for their explanation. Brooks and Godfrey (2015) also find the negative relationship between credit risk and stock return. Similarly to this paper they use the rational expectations theory as a theoretical perspective but aim to find an alternative explanation. They do so by pointing at four limits-to-arbitrage factors, exploited by arbitrageurs,

as the explanation to the underperformance of high credit risk stocks. Thus, Brooks and Godfrey (2015) also find mispricing as the cause of the underperformance of credit risky stocks. Since we find a positive relationship between credit risk and stock returns, their explanations and conclusions are not supported by this paper. In contrast to this paper, Brooks and Godfrey (2015) refer to the rational expectations theory as a theory providing an explanation to why investors pay a negative credit risk premium when investing in credit risky stocks. The explanation provided by this theory is that shareholders rely on the process of strategically defaulting on their debt. Therefore, they emphasize their geographical choice to study the UK market since the UK has a much more favorable bankruptcy regime to creditors than in the U.S. Thus, it is possible that Brooks and Godfrey (2015) obtained different results than this study due to having studied another financial market.

Chen et al. (2010) argue that the negative credit risk and return relationship can be explained by a rational theoretical model. Their results indicate that returns in the highest and lowest quintiles of distress risk are much lower and always statistically significant. The results of this study do not support the findings of Chen et al. (2010) nor the results presented by Griffin and Lemmon (2002), which point to firm specific characteristics for high distress risk stocks, making them more likely to be mispriced by investors.

Similarly to this paper, Friewald et al. (2014) also approached the topic with the theoretical background of Merton's model for credit risk saying that debt and equity claims on the same firm are interrelated and the compensation per unit of risk needs to be the same. They found this relationship to be true when studying credit spreads as a proxy for credit risk on the U.S. market, thus concluding that there is a positive relationship between credit risk and stock returns. Anginer and Yildizhan (2010) came to the same conclusion in a similar empirical study when studying corporate bonds as proxies for credit risk. Consequently, both studies provide empirical findings in line with those of this study.

Lastly, Nielsen (2013) investigates whether default risk is priced in equity returns and to what extent size and value effects stem from default risk. Nielsen (2013) concludes that default risk is priced in equity returns and finds the same relationship between credit risk and stock returns as

we do. As for the second research question, Nielsen (2013) concludes that both the SMB and HML factor contain information about default risk, but that default risk cannot replace the two factors in explaining stock returns in the cross-section. This finding opens up for questioning the importance of the additional factor GMB in this study, if the effects of default risk are already captured in the existing factors SMB and HML. Due to the issue of noisy data from individual stock observations, this question is hard to evaluate since the R^2 is not particularly useful to interpret in this paper, as discussed above. Similarly to this paper, Nielsen (2013) finds the opposite relationship between size effects and stock return from what Fama and French (1992, 2014) found, that size is priced with a negative risk premium. Thus, her findings support the findings of this paper for another period of study.

6. Conclusion

In conclusion, we have found significant relationships between each of the studied factors and stock returns. The value factor has a positive relationship to stock returns while the size and credit risk factor have negative relationships to stock returns. In other words, stocks inhabiting low P/B ratios, large market capitalization and lower credit ratings generate higher returns and vice versa, according to the performed regressions. The results for the size variable are somewhat surprising since the majority of previous empirical evidence suggest the opposite. However, one could argue that the tables 6, 7, 8 and 9 in chapter four may provide an inconsistent indication of how size really affects stock returns.

The conducted research provides additional evidence to the ambiguous discussion on how credit risk affects stock returns. We do not find support for the anomalous empirical finding of other researchers that investors pay a negative credit risk premium when investing in credit risky stocks. In our case, the opposite is true: investors pay a positive risk premium when investing in credit risky stocks, which is in line with what one could expect from a rational and theoretical perspective. Thus, due to the different empirical findings and methodology of this paper, it should provide a new perspective to the topic. Lastly, we, like many others, believe that the original three-factor model by Fama and French (1992) can be improved by adding additional variables, which our results also indicate.

From this research, it is apparent that this field of study generates interesting results that motivate further research. A suggestion, related to the topic of this study, could be to investigate if firms with a certain credit rating on average outperform firms in other rating groups. Thus, locating the optimal rating group to invest in. Moreover, it could be interesting to follow up on Kisgen's (2006) research presented in section 2.1.4, in which he examines how different grades are associated with different costs and capital structure, but to perform this investigation in the context of stock returns.

Regarding the studied time period, it could be of interest to also investigate the period before the financial crisis to better capture and analyze the effect of business cycles. Although the downfall

is captured by this research, a more insightful result could perhaps have been achieved with a longer time horizon. However, due to shortage in credit rating data provided by Bloomberg, and the limited availability of other sources, an extended time period was not possible to make reliable inferences from. Finally, it is worth mentioning that a similar study can be done for other markets or countries, but the availability of credit ratings may be an obstacle for conducting a proper statistical study.

References:

Anginer, D. & Yildizhan, C. (2010). Is there a Distress Risk Anomaly? Corporate Bond Spread as a Proxy for Default Risk, working paper. SSRN Electronic Journal, 1.

Avramov, D., Chordia, T., Jostova, G. & Philipov, A. (2009). Credit Ratings and the Cross-Section of Stock Returns. *SSRN Electronic Journal*, vol. 12, no. 3, pp.469-499.

Berens, J. & Cuny, C. (1995). The Capital Structure Puzzle Revisited, *Review of Financial Studies*, vol. 8, no. 4, pp.1185-1208.

Berk, J. & DeMarzo, P. (2014). Corporate finance. 1st ed. Boston: Pearson/Addison Wesley.

Bloomberg L.P. (2018). Bloomberg L.P. | About, Products, Contacts. [online] Available at: https://www.bloomberg.com/company/ [Accessed 17 Apr. 2018].

Brooks, C. (2014). Introductory Econometrics for Finance. Cambridge: Cambridge University Press.

Bryman, A. & Bell, E. (2015). Business Research methods. 4th ed. Oxford: Oxford University Press.

Campbell, J., Lo, A. & MacKinlay, A. (2012). Econometrics of Financial Markets. New Jersey: Princeton University Press.

Chen, J., Chollete, L. & Ray, R. (2010). Financial distress and idiosyncratic volatility: An empirical investigation, *Journal of Financial Markets*, vol.13, no. 2, pp.249-267.

Cnb.cz. (2011). The credit rating of the Czech Republic - Czech National Bank. [online] Available at:

https://www.cnb.cz/en/monetary_policy/inflation_reports/2011/2011_IV/boxes_and_annexes/zoi_2011_IV_box_2.html [Accessed 2 May 2018].

De Long, J., Shleifer, A., Summers, L. & Waldmann, R. (1989). The Size and Incidence of the Losses from Noise Trading. *The Journal of Finance*, vol. 44, no. 3, pp.681-696.

Fama, E. & French, K. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, vol. 47, no. 2, pp.427-465.

Fama, E. & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, vol. 116, no. 1, pp.1-22.

FitchRatings (2018). Rating Definitions. [PDF] FitchRatings. Available at: https://www.fitchratings.com/site/definitions [Accessed 8 May 2018].

Frank, M. & Goyal, V. (2007). Trade-Off and Pecking Order Theories of Debt. *Handbooks of Finance*, vol. 2, pp.20-61.

Friewald, N., Wagner, C. & Zechner, J. (2014). The Cross-Section of Credit Risk Premia and Equity Returns. *The Journal of Finance*, vol. 69, no. 6, pp.2419-2469.

Feige, E. and Pearce, D. (1976). Economically Rational Expectations: Are Innovations in the Rate of Inflation Independent of Innovations in Measures of Monetary and Fiscal Policy?. *Journal of Political Economy*, vol. 84, no. 3, pp.499-522.

Godfrey, C. and Brooks, C. (2015). The Negative Credit Risk Premium Puzzle: A Limits to Arbitrage Story. *SSRN Electronic Journal*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2661232 [Accessed 8 Apr. 2018].

Griffin, J. and Lemmon, M. (2002). Book-to-Market Equity, Distress Risk, and Stock Returns. *The Journal of Finance*, vol. 57, no. 5, pp.2317-2336.

Grossman, S. (1981). An Introduction to the Theory of Rational Expectations Under Asymmetric Information. *The Review of Economic Studies*, vol. 48, no. 4, p.541.

Gujarati, D.N., & Porter, D.C. (2010). Essentials of Econometrics. 4th ed. International edition. McGraw-Hill Companies: United States of America.

Hart, O. and Moore, J. (1995). Debt and Seniority: An Analysis of the Role of Hard Claims in Constraining Management. *The American Economic Review*, vol. 85, no. 3, pp.567-585.

Myers, S. (1984). The Capital Structure Puzzle. *The Journal of Finance*, vol. 39, no. 3, pp.575-592.

Kelly, P. (2005). Information Efficiency and Firm-Specific Return Variation. *SSRN Electronic Journal*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=676636 [Accessed 4 May 2018].

Kisgen, D. (2006). Credit Ratings and Capital Structure. *The Journal of Finance*, vol. 61, no. 3, pp.1035-1072.

Koller, T., Goedhart, M. and Wessels, D. (2015). Valuation. 6th ed. Hoboken, NJ: Wiley.

Danthine, J. and Donaldson, J. (2015). Intermediate financial theory. 3rd ed. Amsterdam: Elsevier Academic Press.

Moody's (n.d.). Rating Scale and Definitions. [PDF] Moody's. Available at: https://www.moodys.com/sites/products/ProductAttachments/AP075378_1_1408_KI.pdf [Accessed 8 May 2018].

Muth, J. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica*, vol. 29, no. 3, pp.315-335.

Nielsen, C. (2013). Is Default Risk Priced in Equity Returns? *SSRN Electronic Journal. Available* at: https://www.lusem.lu.se/media/kwc/working-papers/2013/kwc-wp-2013-2.pdf [Accessed 4 May 2018].

Nilsson, B. (2018). Financial Risk Analysis, LUSEM Lund, Mars 2018.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, vol. 108, no. 1, pp.1-28.

Schwabe, R. (1996). Optimum designs for multi-factor models. New York: Springer.

SFG Consulting (2014). The relationship between the required return on debt and equity. [online] Brisbane: SFG Consulting. Available at: https://www.erawa.com.au/cproot/13293/2/Submission%2012%20-%20Appendix%20L%20-%20Merton%20and%20the%20Consistency%20Between%20Debt%20and%20Equity.PDF [Accessed 6 May 2018].

Shiller, R. (1978). Rational expectations and the dynamic structure of macroeconomic models. *Journal of Monetary Economics*, vol. 4, no, 1, pp.1-44.

Skärvad, P-H. & Lundahl, U., (2016). Utredningsmetodik. 4 ed. Lund: Studentlitteratur.

Standard and Poor's (2009). Understanding Standard & Poor's Rating Definitions. [ebook] New York: McGraw Hill. Available at: https://www.spratings.com/documents/20184/774196/Understanding+Standard+%26+Poor%27s+Rating+Definitions/b2ca0e9d-1162-4a0f-ae1b-03847c9fba37 [Accessed 3 May 2018].

Standard & Poor's. (2018). General Description of the Credit Rating Process. 1st ed. [ebook]. Available at:

https://www.standardandpoors.com/en_US/delegate/getPDF?articleId=2017770&type=COMMENTS&subType=REGULATORY [Accessed 17 Apr. 2018].

Titman, S., Wei, K. and Xie, F. (2004). Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis*, vol. 39, no. 04, pp.677-700.

Westerlund, J. (2005). Introduktion till ekonometri. Lund: Studentlitteratur

Appendix

Appendix A - Disclosure of data loss

	Number	In percent (%)
Total number of firms	**76336**	**100**
Loss in data due to MCAP		
2007-12-31	542	0.71%
2008-06-30	556	0.73%
2008-12-31	480	0.63%
2009-06-30	576	0.75%
2009-12-31	382	0.50%
2010-06-30	30	0.04%
2010-12-31	30	0.04%
2011-06-03	32	0.04%
2011-12-31	30	0.04%
2012-06-30	25	0.03%
2012-12-31	23	0.03%
2013-06-30	21	0.03%
2013-12-31	16	0.02%
2014-06-30	14	0.02%
2014-12-31	22	0.03%
2015-06-30	25	0.03%
2015-12-31	18	0.02%
2016-06-30	20	0.03%
2016-12-31	18	0.02%
2017-06-30	12	0.02%
2017-12-31	4	0.01%
Sum:	2876	3.77%
Number of firms recovered:	**73460**	**96.23%**

Data loss due to unobservable MCAP.

	Number	In percent (%)
Total number of firms	**73460**	**100**
Loss in data due to stock price		
2007-12-31	335	0.46%
2008-06-30	344	0.47%
2008-12-31	401	0.55%
2009-06-30	226	0.31%
2009-12-31	350	0.48%
2010-06-30	644	0.88%
2010-12-31	577	0.79%
2011-06-03	628	0.85%
2011-12-31	621	0.85%
2012-06-30	650	0.88%
2012-12-31	577	0.79%
2013-06-30	614	0.84%
2013-12-31	518	0.71%
2014-06-30	560	0.76%
2014-12-31	532	0.72%
2015-06-30	573	0.78%
2015-12-31	520	0.71%
2016-06-30	491	0.67%
2016-12-31	433	0.59%
2017-06-30	439	0.60%
2017-12-31	255	0.35%
Sum:	10288	14.0%
Number of firms recovered:	**63172**	**86.00%**

Data loss due to unobservable stock price.

	Number	In percent (%)
Total number of firms	**8122**	**100**
Loss in data due to credit rating		
2007-12-31	0	0.00%
2008-06-30	1	0.01%
2008-12-31	0	0.00%
2009-06-30	3	0.04%
2009-12-31	3	0.04%
2010-06-30	4	0.05%
2010-12-31	4	0.05%
2011-06-03	7	0.09%
2011-12-31	3	0.04%
2012-06-30	5	0.06%
2012-12-31	6	0.07%
2013-06-30	8	0.10%
2013-12-31	5	0.06%
2014-06-30	5	0.06%
2014-12-31	10	0.12%
2015-06-30	13	0.16%
2015-12-31	16	0.20%
2016-06-30	22	0.27%
2016-12-31	22	0.27%
2017-06-30	23	0.28%
2017-12-31	22	0.27%
Sum:	182	2.24%
Number of firms recovered:	**7940**	**97.76%**

Data loss due to unobservable credit rating.

	Value	**df**	**Probability**
t-statistics	0.197194	7930	0.8437
F-statistics	0.038886	(1, 7930)	0.8437
Likelihood ratio	0.038910	1	0.8436

Ramsey RESET excluding GMB.

	Value	**df**	**Probability**
t-statistics	5.487766	7930	0.0000
F-statistics	30.11558	(1, 7930)	0.0000
Likelihood ratio	30.08128	1	0.0000

Ramsey RESET including GMB

	Value	**df**	**Probability**
t-statistics	0.318818	7930	0.7499
F-statistics	0.101645	(1, 7930)	0.7499
Likelihood ratio	0.101722	1	0.7499

Ramsey RESET including GMB, no outliers.

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

F-statistic	3.854639	Prob. F(14,7920)	0.0000
Obs*R-squared	53.70124	Prob. Chi-Square(14)	0.0000
Scaled explained SS	9468.660	Prob. Chi-Square(14)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/26/18 Time: 15:48
Sample: 1 7935
Included observations: 7935

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.110459	0.207806	-0.531548	0.5951
RM_RF^2	2.465246	7.931905	0.310801	0.7560
RM_RF*SMB	-4.960825	11.25050	-0.440943	0.6593
RM_RF*HML	5.229816	28.24880	0.185134	0.8531
RM_RF*GMB	0.646455	6.297810	0.102648	0.9182
RM_RF	0.265554	1.884583	0.140909	0.8879
SMB^2	-3.752087	14.79965	-0.253525	0.7999
SMB*HML	-14.41158	22.12967	-0.651233	0.5149
SMB*GMB	-13.62079	7.123748	-1.912026	0.0559
SMB	-1.304697	2.615806	-0.498774	0.6180
HML^2	14.96847	33.21398	0.450668	0.6522
HML*GMB	12.02765	7.104753	1.692902	0.0905
HML	1.115489	1.789716	0.623277	0.5331
GMB^2	-3.440149	2.921787	-1.177412	0.2391
GMB	-3.040049	1.406110	-2.162028	0.0306

R-squared	0.006768	Mean dependent var	0.130769
Adjusted R-squared	0.005012	S.D. dependent var	2.457380
S.E. of regression	2.451215	Akaike info criterion	4.632933
Sum squared resid	47586.95	Schwarz criterion	4.646126
Log likelihood	-18366.16	Hannan-Quinn criter.	4.637451
F-statistic	3.854639	Durbin-Watson stat	1.600541
Prob(F-statistic)	0.000001		

Appendix D - Correlation & covariance matrix

Covariance	GMB	HML	RM_RF	SMB
GMB	0.040475	-	-	-
HML	-0.004119	0.003412	-	-
RM_RF	-0.001467	-0.000343	004476	-
SMB	-0.004922	0.002346	0.000662	0.009713

Correlation	GMB	HML	RM_RF	SMB
GMB	1.000000	0.100347	-0.087845	-0.109032
HML	0.100347	1.000000	0.407571	-0.248226
RM_RF	-0.087845	0.407571	1.000000	-0.350464
SMB	-0.109032	-0.248226	-0.350464	1.000000

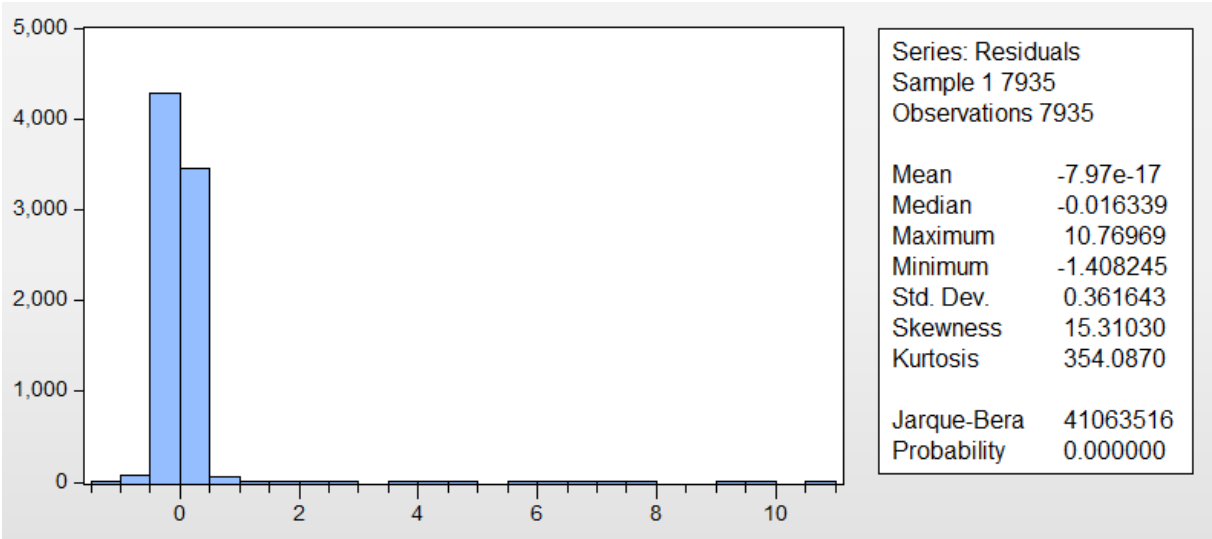
Appendix E - Variance Inflation factor test

Variance Inflation Factor

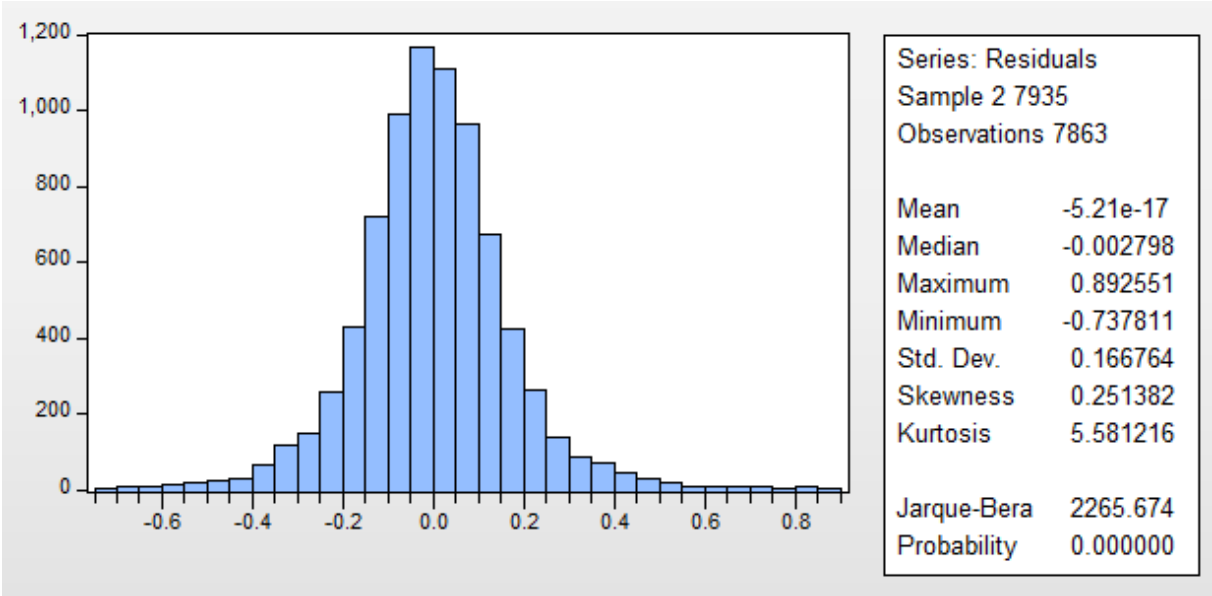
Sample: 7935

Included observations: 7935

Variable	Coefficient variance	Uncentered VIF	Centered VIF
C	4.68E-05	2.838931	NA
$R_m\_R_F$	0.003868	1.698525	1.049703
SMB	0.002105	1.501270	1.239865
HML	0.006492	1.520729	1.343329
GMB	0.000480	1.836653	1.178747



Jarque-Bera test including outlier.



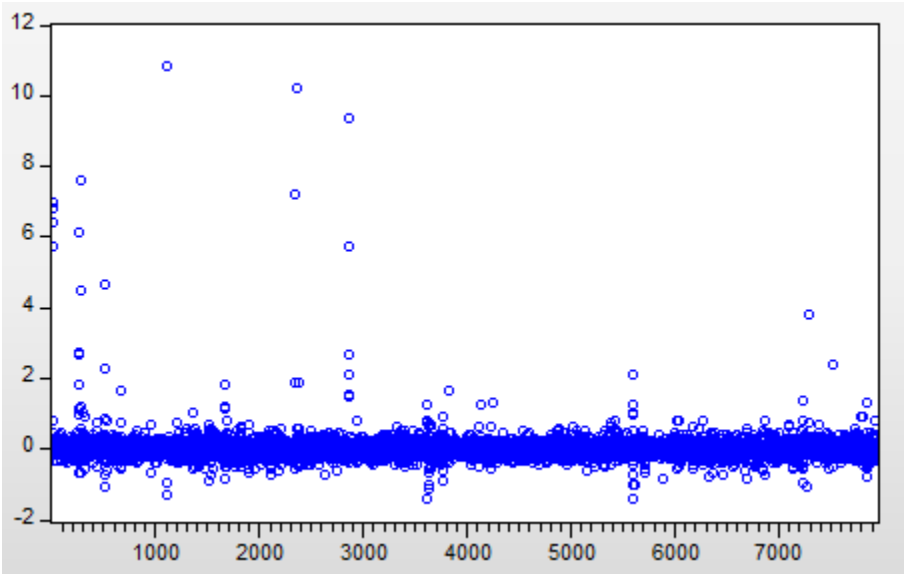
Jarque-Bera test excluding outliers.

Regression output

Variables	R_{it} -R_F Coefficient	P-value
Constant	-0.0008	[0.8106]
R_M-R_F	0.5882	[0.0000]**
HML	0.1450	[0.0001]**
SMB	-0.0611	[0.0145]*
GMB	-0.0533	[0.0000]**
R^2	0.0469	
Adjusted R^2	0.0464	

* = Significant on five-percent level
** = Significant on one-percent level

Regression output including GMB, no outliers.



Residual distribution including outliers.