A Study of Corporate Bond Returns

- using Sharpe-Lintner CAPM and Fama & French

The aim of this thesis was to better understand corporate bond returns. Regression analysis for a sample of 937 listed USD-denominated corporate bonds of both investment grade and non-investment grade was conducted using two models. The first model used was the Sharpe (1964) and Lintner (1965) CAPM, the second a multi-factor model of Fama & French (1993).

This study has broadened the research application of CAPM as previous use of the CAPM almost exclusively has focused on stock returns. We show that a large fraction of the variability of corporate bond returns can be captured using CAPM, but that Fama & French (1993) in comparison captures more of the variability.

Additionally, we find that a market risk factor exists for the pricing of corporate bonds. This suggests systematic influence on corporate bond prices. The conclusion was supported both by results of the CAPM and the Fama & French regressions. We further criticize the model specification of the Fama & French (1993) default risk factor, suggesting that it contradicts subsequent research and more intuitively would be renamed to a corporate bond market factor.

Keywords: CAPM, Fama & French, Corporate Bond, Return, Systematic Risk

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1. Introduction

In 1976, Ibbotson & Sinquefield evaluated 48 years of returns for different asset classes and came to the conclusion that stocks had yielded far superior results to government bonds and corporate bonds. More recently, holding stocks has not yielded returns close to those of the historical averages, with the broad stock market index S&P 500 having a negative return since the start of 2000 (Yahoo Finance, 2012)[1]. The recent poor performance of stocks compared to bonds has shifted the attention of many investors, from stocks to fixed income alternatives. In the research area, different researchers of corporate bonds have presented diverging arguments concerning the determinants of corporate bond prices.

We therefore believe that a study examining bond returns will cover a contemporary subject, and trying to improve the understanding of corporate bond returns[2] will be the intent of this study. The literature review will shed light over the debate whether there is systematic[3] risk affecting corporate bonds and introduce factors that have been found to have an impact on corporate bond returns. Time-series regression analysis has been conducted using two models. Firstly, the CAPM of Sharpe (1964) and Lintner (1965), and secondly the Fama & French (1993) model. These models have been used to answer our research question, which is:

> *Can the understanding of corporate bond returns be improved by using the Sharpe- (1964) and Lintner (1965) CAPM and the multi-factor model of Fama & French (1993), and if so, in what way?*

We have found that corporate bond returns can be captured both through the use of the Sharpe-Lintner CAPM and the Fama & French (1993) model. We present five conclusions that deepens the understanding of corporate bond returns. Doing so, we provide the reader with insights regarding specifications of the two models, limitations in the Fama & French (1993) model specification, and offer an argumentative case for systematic risk influencing corporate bond returns.

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[1] Since the first trading day in 2000 (3rd January) to December 3rd 2012, S&P 500 showed a return of -1,62%, according to data retrieved from Yahoo Finance.

[2] Throughout the paper, analysis will be performed describing corporate bond returns and corporate bond prices. As capturing the variability in prices of financial assets is the same thing as capturing the variability in the returns of the same financial assets, there is no difference between understanding corporate bond returns and corporate bond prices from a conceptual point of view.

[3] Systematic risk, in contrast to idiosyncratic risk, is risk that an investor cannot diversify away.

2. Literature Review

This section aims to describe what factors research to today's date has found to be of importance in explaining corporate bond returns. It will conclude by stating the research question and how this study will contribute to the current state of research in explaining corporate bonds returns.

The approach chosen by most researchers when studying corporate bond returns is to look at the spread between the yield on the corporate bond and the yield on a government bond of equal time to maturity. This spread, from here on referred to as the yield spread, is broken down in explaining factors capturing the variability in corporate bond returns. Most previous research favors the use of multiple explanatory factors to capture the variability in returns. Overall, multi-factor models have provided a good empirical fit with large and significant fractions of the variability in corporate bond returns being explained. The high explanatory power might be the reason that empirically developed multi-factor models have been preferred to the theoretically driven and developed CAPM when researchers study corporate bond returns. Among the factors that have been found to have explanatory power are default, liquidity, volatility, bond rating, and bond and stock market factors.

2.1 Systematic influence on corporate bond returns

Researchers debate whether there is a market factor influencing corporate bond returns. Existence of a market factor implies systematic influence as an investor cannot diversify away from market risk. Research of Fama & French (1993) found no evidence of a market risk factor for investment grade bonds, implying that there is no systematic risk in corporate bond returns. The notion that there are no systematic risk factors influencing corporate bond returns has been critiqued by later research (e.g. Elton et al., 2001; Geske & Delianedis, 2001; Collin-Dufresne et al., 2001; Huang & Huang, 2002). Considering that several researchers have found factors of systematic influence, there are indications that the research of Fama & French (1993) was inconclusive regarding how corporate bonds are effected by the market factor.

Of all studies that have examined and concluded systematic risk on corporate bond returns, Elton et al. (2001) have been credited to be the first study that provide empirical support for systematic risk affecting corporate bond returns. They argue that as compensation for risk changes over time in capital markets, both the equity and the bond markets will be affected, which in turn introduces a systematic influence on corporate bond returns. They deemed this finding to be controversial since it at the time contradicted the prevailing paradigm that there were no systematic influences on corporate bond returns. However, subsequent studies have come to the same conclusion (Geske & Delianedis, 2001; Huang & Huang, 2002).

2.2 Default risk

Collin-Dufresne et al. (2001) argue that the theoretical reason for the yield spread lie entirely in the spread coming from default risk. Fama & French (1993) make a similar assumption when studying the returns of American government and corporate bonds of all ratings. The bonds were listed at NYSE, Amex and Nasdaq and data from 1963 through 1991 was used. Fama & French (1993) assumes that default risk can be specified as the difference between the long-term government bond return and the long-term corporate bond return. Their default risk factor could, together with a factor capturing the interest rate change risk explain almost all of the variations in corporate bond returns, and they found no evidence for corporate bonds having a higher average return than government bonds long term.

Several studies subsequent to the Fama & French (1993) study argue that the impact of default risk is of less importance. Elton et al. studied the returns of investment grade corporate bonds and found that expected default can explain up to 25% of the yield spread, concluding this to be "surprisingly small" (2001, p. 247). These results were re-affirmed by Geske & Delianedis (2001), who found that the default spread was not a major component of the credit spread for investment grade corporate bonds. Thorsell summarizes the research status on the influence of default risk, by saying that "the credit spread 'puzzle' is the empirical finding that observed historical default rates are not sufficiently high to motivate the size of the yield spread" (2008, p. 15).

2.3 Liquidity risk

In a market with thin liquidity, a corporate bond trader might influence the price of the bond by trading. Illiquidity might also force a bond trader to trade outside the 'correct price' of the bond (Thorsell, 2008, p. 10). This makes liquidity or lack thereof a relevant explaining factor for the price of corporate bonds. Still, liquidity was until recently generally not considered as a factor for pricing corporate bonds (Elton et al., 2001). Recently, emphasis has changed and several studies have paid attention to liquidity as a factor in pricing corporate bonds (Elton et al., 2001; Geske & Delianedis, 2001; De Jong et al., 2007). The residual spread[4] between corporate and government bonds in addition to the default spread is reduced if liquidity in the underlying stock increases[5] (Geske & Delianedis, 2001). The fact that corporate bonds generally are less liquid than stocks and government bonds implies that liquidity risk should be comparatively more important as a pricing factor (Geske & Delianedis, 2001). De Jong et al. (2007) measured the pricing factor of liquidity for long term American corporate bonds and found that the investment grade liquidity risk premium was 0.6% per year and the liquidity risk premium for below investment grade was 1.5% per year. In addition, it has been found that improvements in bond liquidity results in a significant reduction of the yield spread and that illiquid bonds have a higher relative yield spread than liquid bonds (Chen et al. (2007).

2.4 Volatility risk

Firm specific equity volatility as well as systematic volatility was examined as explanatory factors for corporate bond returns by Campbell & Taksler (2003). They argue that increased idiosyncratic or systematic volatility will hurt the bond holder given an expected profit level. The reason for this is that holders of corporate bonds can be seen as holders of riskless bonds that have issued put options against the equity holders of the firm. As volatility increases, the value of the put option increases which implies a larger expected claim on the bond holder from the equity holder. Further, they conclude that firm specific equity volatility can capture as much as bond ratings when it comes to variations in yields. They suggest that the reason for this is that "equity volatility can reflect both continuous information that distinguishes bonds with the same credit rating, and recent information that may not yet be reflected in a bond's credit rating" (2003, p.11). The arguments of Campbell & Taksler (2003) are in line with the findings of Geske & Delianedis (2001) who found that the residual spread decreases when stock market volatility increases. They concluded that the reason was that the default spread grew in relative significance.

2.5 Bond rating

The importance of different explanatory variables for yield spreads have been shown to vary depending on the credit quality of the corporate bonds. There is a clear distinction regarding how high-grade and low-grade bonds behave. High-grade bonds have been found to behave more like Treasury bonds and low-grade bonds have been found to be more sensitive to stock market returns (Collin-Dufresne et al., 2001). That low-grade bonds behave more like stocks aligns with the claims of Thorsell (2008) who argues that a defaulted bond can be seen as an asset that will have the characteristics of a mix between bond and equity: As bonds default they "behave nothing like bonds and somewhat like shares" (2008, p. 15). An extension of this conclusion is that as a bond moves towards default, there is also a transition process where the bond becomes more like equity. Default spreads have been proved to be more important for

[4] The residual spread is the part of the yield spread not explained by default, hence the residual.

[5] The reason for the importance of liquidity in the firm's equity is that a significant fraction of the corporate bond holders use the underlying equity for hedging purposes against the corporate bond.

firms of lower rating classes compared to higher rating classes (Geske & Delianedis, 2001; Huang & Huang, 2002; Fama & French, 1993). Geske & Delianedis (2001) found that default spreads accounted for about 5% of the yield spread for AAA and AA corporate bonds whereas it explained 22% for BBB corporate bonds.

2.6 Stock and bond market factors

There is unison empirical evidence that corporate bonds below investment grade behave more like stocks than corporate bonds of higher rating. However, research has not provided unison answer whether stock market factors[6] have explanatory power for investment grade corporate bonds. Fama & French (1993) suggests that there is no overall influence of stock market factors on investment grade corporate bonds, whereas Elton et al. (2001) suggests that stock market factor influences corporate bonds.

Fama & French (1993) argue that if corporate bond and stock markets are integrated, a single model should be able to explain both bond returns and stock returns. They present a 5-factor-model of three stock market factors and two bond-market-factors and argue that the importance of the stock market factors disappear when introducing the bond market factors of default risk (DEF) and maturity risk (TERM).

Contrary to the findings of Fama & French (1993), Elton et al. (2001) argue that corporate bond spreads vary in a systematic way with the Fama & French (1993) stock market factors. Although Elton et al. (2001) in finding this conclusion did not test for the inclusion of the specific DEF and TERM factors as defined by Fama & French (1993), they did examine the impact of the default spread and found it to be of significance at the same time as the stock market factors bore significance. All in all, Elton et al. could explain "between 2/3 and 85 percent of the spread in corporate and government rates that is not explained by the difference between promised and expected payments and taxes" by using the Fama & French three factor model (2001, p. 272). Whether Elton et al. (2001) would have found the Fama & French (1993) stock market factors to be of significance if also including a variable capturing the term structure of corporate bonds remains unclear.

2.7 Research Question

Taking the previous research on bond returns into consideration, this study will make use of two models which consider different factors in order to explain the variability in returns. The first model is the Sharpe (1964) and Lintner (1965) CAPM and the second is a multifactor model of Fama & French (1993). CAPM is a theoretically developed model designed to hold for the pricing of all asset classes, whereas Fama & French (1993) is a model that empirically has explained the vast majority of variability in corporate bond returns. The choice of the models will be discussed in further detail in the method section where we will describe the specifications of the respective models. The research question of this study has been formulated as follows:

> *Can the understanding of corporate bond returns be improved by using the Sharpe- (1964) and Lintner (1965) CAPM and the multi-factor model of Fama & French (1993), and if so, in what way?*

2.7.1. Limitations of scope

The intention of this study is to understand corporate bond returns. In doing this, we will rely on the already established models CAPM and Fama & French. We are aware that some factors which in previous research have explained variability in corporate bond returns will not be included. These factors include but are not limited to the liquidity factor, volatility factor and two of the three Fama & French stock

[6] As known in the Fama & French (1992) 3-factor model, with a market factor, a firm size factor (SMB) and a factor of book-to-market value of equity (HML).

market factors (SMB and HML). Trying to create a new model that jointly considers all, most, or some of the empirically established determinants of the variability in corporate bond returns has been deemed too time consuming to justify the effort.

3. Data

This section will explain how we handled the data set in order to attain reliable data. It will describe how the data has been retrieved, what adjustments have been done and provide descriptive statistics to give a picture of the data used in the study.

3.1 Retrieving the data

Considerable effort has been taken to assure the quality of the data set. This effort includes careful consideration of the limiting search criteria under which the data set was retrieved. The data was retrieved through Thomson Datastream™ with the limiting search criteria specified below. The paragraphs directly ensuing will provide an overview of the data set, a discussion of the chosen limiting search criteria, and adjustments to the data set.

Issues Type:	Corporate bonds
Bond Type:	Straight
Currency:	United States Dollar (USD).
Issue Date Before:	2006/10/31.
Maturity Date After:	2012/03/01.
Exchange:	Frankfurt
Instrument Type:	Bond

As the intent of this study was to explain the returns on corporate bonds, it was natural to use corporate bonds as a limiting search criterion. Only corporate bonds with a straight interest rate were included for the data import, since mixing straight interest rate bonds with floating interest rate bonds or bonds with conversion and call options would decrease the comparability between bonds in the sample. To eliminate distorting effects based on currency movements, it was necessary to limit the search criteria to a single currency. USD was chosen since there were significantly more bonds issued in USD compared to other currencies. Significantly more bonds could be imported from the Frankfurt exchange compared to any other major exchange[7], making the Frankfurt Exchange the natural choice when limiting the search to one exchange to avoid double counting of dually listed bonds. Although the import was made from the Frankfurt exchange, a quick overview of the data sample suggests that most of the imported corporate bonds in the data sample are American.

Traditionally, transaction data on bonds has been hard to acquire as a major part of the trading was done interbank and thus never registered[8] (Thorsell, 2008). For time periods prior to 2002 very little corporate bond data was available in Thomson Datastream™ and from there on the availability of data got gradually better. As there is a greater risk of the results becoming time conditional if a shorter time period is chosen, the time period of examination needs to be carefully considered. The choice of studying the period 2007-01-01 to 2011-12-30 is a compromise made in good faith with regards to both the quality of data and risk of time conditionality in the results. In order to limit eventual distorting price influences that issuance or

[7] E.g. a search with the limiting search criteria at 30/11-2012 gave 352 listed corporate bonds for the New York Stock Exchange, and 1130 listed corporate bonds for the Frankfurt Exchange. We are puzzled as of why this is the case.

[8] Measures have been taken by regulators and market data collectors to address this issue. One example is the National Association of Securities Dealers that since 2002 has required its members to report all corporate bond trades in the TRACE system. Our reason for not using bond trades incorporated in the TRACE system was that we deemed the quality of our initial data set to be sufficient, and secondly that TRACE – although a great initiative – still lacks user friendliness.

maturity may have on the price of a corporate bond, the search was limited to corporate bonds issued before 2006/10/31 and maturing after 2012/03/01.

As the market price of a bond in a Thomson Datastream™ import can be either the gross or the clean price, we chose to retrieve the clean price of the corporate bond rather than the market price[9]. Prices were retrieved monthly, making possible a total of 60 data points per imported bond. All in all, 1006 corporate bonds were imported for our sample before screening the sample. After screening the sample for liquidity and availability of data points 937 corporate bonds remained in the sample. We will go through our data screening process in section 3.2.

3.2 Adjusting for patterns of illiquidity and bad data points

A problem when considering data from the corporate bond market is that the corporate bond market in general is less liquid than the equity market. The last reported transaction price can consequently represent an outdated transaction. In some cases, the reported corporate bond price does not even reflect an actual transaction price. This is because Thomson Datastream™, mainly source their corporate bond data from FT Interactive DATA (FTID), which uses market transaction prices but also *calculates* prices by using e.g. bid information in order to reflect the "good faith opinion for FTID as to what a buyer would pay for the bond in a current sale" Thorsell (2008, p. 82). Because of these considerations, it is evident that when using corporate bond data one needs to be extra cautious in adjusting for patterns of illiquidity and bad data points.

Starting with the initial sample of 1006 bonds, monthly returns were calculated for each bond over five years examined (hence, 60 data points for each listed corporate bond was available). The process of adjusting the data was then done through excluding corporate bonds that showed signs of illiquidity and excluding corporate bonds that had insufficient data points.

A corporate bond was deemed to show a pattern of illiquidity if it showed no price movement over five or more months throughout the data sample. Although it is possible for a liquid corporate bond to show a pattern of no price movement from time to time, having several (often consecutive) months of no price movements would be a statistical anomaly given that the bond was liquid. Doing the illiquidity exclusion, 61 corporate bonds were removed from the data sample.

A corporate bond was deemed to have an insufficient amount of data points if it had clean price data from 55 or less out of the 60 possible months. Doing this exclusion, a further 8 corporate bonds were excluded. No corporate bonds showed signs of illiquidity while at the same time having 55 or less data points.

Adjusting for patterns of illiquidity and bad data points	
Number of bonds in initial data set	1006
Bonds excluded due to risk of illiquidity	-61
Bonds excluded due to insufficient data points	-8
Final data-set	**937**

Table 3.1 – Excluded bonds due to signs of illiquidity or insufficient data

[9] The Thomson Datastream™ definition of clean price is "the price of an issue, less any accrued interest", whereas the market price definition is "the latest price obtained from the market, and it can be quoted as clean price or gross price".

Excluded bonds are included in Appendix B.1. A case of point will be provided in appendix B.1.1 considering two similar bonds issued by Alcatel Lucent where one was excluded since it showed signs of illiquidity.

As was outlined in the literature review, recent research has argued that liquidity is a factor for pricing of corporate bonds (Elton et al., 2001; Geske & Delianedis, 2001; De Jong et al., 2007). Since adjustments outlined in this segment have been made in order to reduce the effect that illiquidity has on corporate bond returns, it is likely that we have reduced the price effect of the liquidity factor for our data sample. However, it is still possible and reasonable that there is a liquidity factor for pricing the corporate bonds remaining in our data sample. Capturing the price effect of the liquidity factor is beyond the scope of this study. Exclusion of the more illiquid bonds can make the data sample less representative as a cross-section of the corporate bond market as it possibly introduces bias in our data sample.

3.1 Descriptive statistics

In table 3.2, we show in what industry the companies that issued the bonds operate. The majority of our sample is corporate bonds from the manufacturing sector and bonds from the transportation, communications, electric, gas and sanitary sector. Considering that some of the industry portfolios consist of very few underlying corporate bonds, we will analyze these portfolios with extra caution. As can be seen in table 3.3, the majority of the corporate bonds in the data sample are rated investment grade. Investment grade consists of all bonds with a rating of BB+ or above using the S&P rating scale (Standard and Poor's Rating Services n.d.). There are considerably more bonds of the BBB and A grade compared to the AA, AAA and below investment grade ratings.

Number of bonds in each industry and the equally weighted average industry return		
Industry	**Number of bonds**	**Average Returns**
Agriculture forestry and fishing	2	9,29%
Mining	71	16,40%
Construction	7	4,78%
Manufacturing	318	20,29%
Transportation, Communications, Electric, Gas, And Sanitary Services	355	16,86%
Wholesale trade	15	15,59%
Retail trade	77	11,66%
Finance, Insurance and Real Estate	33	14,46%
Services	45	22,65%
NA	14	16,51%
Total	**937**	

Table 3.2 – The table above shows how many in each industry and the equally weighted average return of that industry.

Number of bonds for each rating and their equally weighted average returns between 2007-01-01 and 2011-12-31		
Rating	**Number of Bonds**	**Average Returns**
AAA	10	16,28%
AA+	3	-4,17%
AA	14	18,55%
AA-	16	18,97%
A+	78	17,54%
A	141	17,63%
A-	88	17,39%
BBB+	104	14,76%
BBB	177	16,18%
BBB-	85	14,76%
BB+	19	9,70%
BB	29	10,14%
BB-	12	12,26%
B+	13	16,19%
B	2	-7,10%
B-	1	10,81%
CCC	0	N/A
DDD	0	N/A
DD	0	N/A
D	0	N/A
N/R	10	85,27%
No info	135	24,34%
Total	937	

Table 3.3 – The table above shows how many bonds that have a certain rating and the average return of that rating class.

4. Method, results and analysis

This study uses two models trying to capture the variability in corporate bond returns. The two models are the CAPM and Fama & French (1993). We have chosen to present the method, results and analysis one model at a time as we believe this approach will be the most intuitive for the reader. There are two reasons for this choice. Firstly, as the two models are very different to one another, presenting both the models prior to presenting the results could have the effect of confusing the reader. Secondly, it is entirely possible to consider and analyze the results of the CAPM and the Fama & French regressions separately since the regressions have been performed independently. Providing the results under a common headline would limit the potential of independent analysis.

We will first motivate the use of CAPM together with the model specifications and choice of market proxies. After this, the processes of forming portfolios is described. The results of the CAPM regressions will then be presented in combination with analysis based on the results. We will then turn to the Fama & French (1993) model. We will motivate the use of the model and explain our specifications of the model together with the process of portfolio formation. After this, the results of the Fama & French regressions will be presented and analyzed.

5a Method CAPM

To capture and find the explanatory variables of corporate bond returns, we have used the static[10] Sharpe-Lintner version of the CAPM. The reasons for choosing CAPM are twofold:

1) Applying CAPM to corporate bond returns is a largely unexplored area. We consider this remarkable since the model has been developed to price any capital asset. In previous research CAPM has mostly been applied to stocks. One possible reason for this is the availability of data for stocks. A large fraction of bond trading is performed over the counter and never registered. Stock trades are registered at a stock exchange and the trading has therefore been more transparent than bond trading (Thorsell, 2008). The lack of available data could consequently make it harder to estimate reliable betas for bonds compared to stocks, which might have led researchers to primarily focus on stocks.

2) CAPM is a widely used model for determining the cost of capital. Graham & Harvey (2002) conducted a study to establish what financial models North American CFOs used in their work. CAPM turned out to be the most commonly used tool among respondents, with 73,5% “always or almost always” using CAPM to estimate the cost of capital (p. 12, 2002). Jagannathan & Wang (1996) argue that the widespread use of the model is to a large extent motivated by its intuitive appealing characteristics.

5a.1 The Capital Asset Pricing Model

Application of CAPM on corporate bond returns is a surprisingly unexplored area as it is a theoretically intuitive and widely used model. CAPM can in theory estimate the cost of capital for all types of assets, although the model has mostly been used for predicting stock returns. The model originates from the work of Markowitz (1952) on diversification and Modern Portfolio Theory. It was later independently developed by Sharpe (1964) and Lintner (1965) to the Sharpe-Lintner CAPM. To capture corporate bond returns, we will use the Sharpe-Lintner CAPM. We will use the model specifications provided in Jensen (1972, p. 363).

[10] Static in this case means that the beta is held constant throughout the examined time period.

Where denotes the expected return, the risk free interest rate, (beta) the asset's sensitivity to expected excess market returns and E( ) is the expected market return.

5a.1.1 Estimating the risk free interest rate

The risk free rate used is in the CAPM model is based on the rates of Kenneth French, attained from French's (2012) homepage under Fama/French Factors[11]. The data retrieved was the year to year risk free rate on a monthly basis. This was converted to a monthly rate to fit our model specifications. As we use a constant risk free interest rate, we averaged the risk free interest rate of 2007 through 2011 to find that the average year to year risk free interest rate was 1.003%. This to the power of one twelfth corresponds to a month to month risk free interest rate of 0,083%. The choice of having a constant risk free interest rate is consistent with the choice of keeping the portfolios constant during the time period. This is true because changes in interest rates will affect bonds differently and aligns well with our purpose of testing whether the models can explain the variability in corporate bond returns.

will hereafter denote the constant month-to-month risk free rate that we calculated to average 0,083%.

5a.1.2 Choosing market portfolio proxy

Three different proxies for the market portfolio will be used in this study. These are MSCI World (MSCI World), Barclays Aggregate Global Corporate Bond Index (BAGG) and Barclay's Capital U.S. Long Index Corporate Bond (US Long).

The first market proxy used is the index MSCI World. The index includes 6000 stocks from various sectors in 24 developed countries. The index covers a wide range of securities including large, mid, small and micro-cap (MSCI 2012). By choosing the MSCI World index, we have intended to make use of very broad stock market index that is aimed to resemble the overall market portfolio. When Thorsell (2008) considered different indices to use as the market proxy, he found that differences in results between using S&P 500, Dow Jones Industrial Average, NASDAQ, Russel 300 and Wilshire 5 000 were unimportant. Thus, there is good reason to believe that the very broad MSCI World index should be a sufficiently good proxy for the market portfolio and that choosing another broad stock market index would not be likely to have any significant effect on the results.

When considering the results of MSCI World regressions, we saw that most of our examined corporate bond portfolios had low fractions of captured returns with insignificant and low beta values. By changing the market proxy to a broad bond market index, we hoped to capture additional variability in the returns of our corporate bond sample. Therefore, the second index used is Barclays Aggregate Global Corporate Bond Index. The index resembles a broad world bond index and is a global investment grade fixed-rate debt markets measure. The bonds included have at least one year until maturity. The index includes mainly treasuries, government-related bonds, corporate bonds and ABS:s denominated primarily in US Dollars, Euro, Pounds and Yen JPY. The domicile of the investments are spread over American, Pan-Europe and Asia (Barclays n.d.).

[11] The best explanation we have found from Kenneth French as of how the risk free rates were calculated is: "This file was created by CMPT_ME_BEME_RETS using the 201210 CRSP database. The 1-month TBill return is from Ibbotson and Associates, Inc.", from the file which we downloaded the risk free interest rate.

As can be seen in table 5.1 below, the risk free interest rate fell significantly throughout our sample period. It is intuitive that a significant change in the underlying interest rate will affect bonds of longer maturities more than bonds of shorter maturities. As our corporate bond sample consisted of USD denominated corporate bonds of relatively long maturities, we considered it likely that we could capture a larger fraction of the corproate bond returns if we changed our market proxy to a bond consisting of long term, USD denominated corporate bonds. Therefore we have included regression analysis using Barclays U.S. Long Corporate index as the market proxy. The index include dollar-denominated debt from industrial and utility companies in combination with financial institutions. The domicile for the included companies are US and non-US and the maturity is more than ten years (ETFdb n.d.).

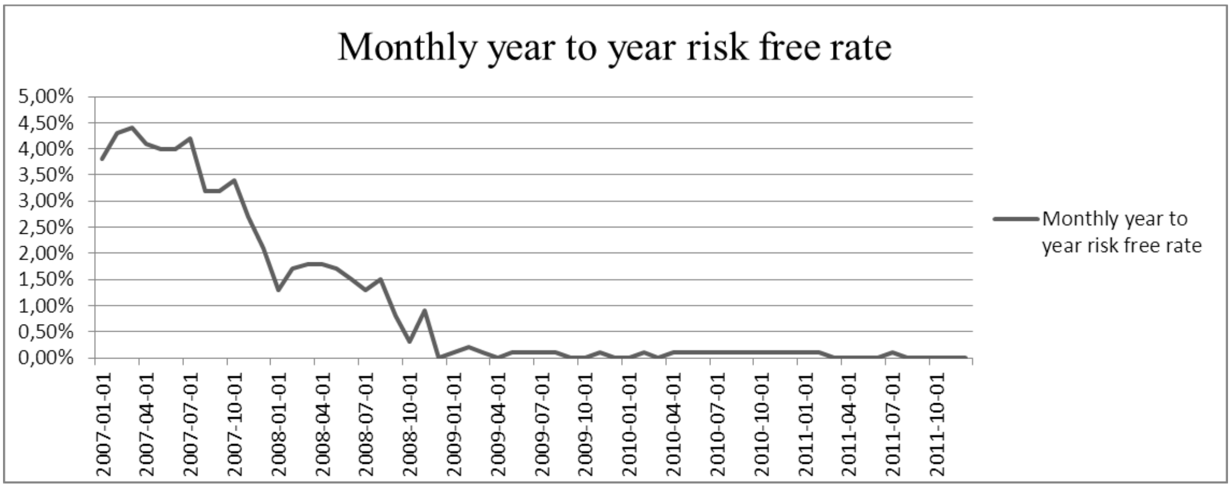


Table 5.1 – Above the monthly year to year risk free rate is shown. One should notice that the risk free rate fell drastically during the period.

5a.1.3 Estimating the beta

Beta is a measure of the co-variation between the return of a security and the return of the overall market. To proxy the overall market, a portfolio such as a broad stock index such is normally used, e.g. S&P 500 (Berk and De Marzo, 2007, p. 308). Thorsell (2008) uses S&P 500 as proxy, whereas Fama & French (1993) uses the return to common stocks for non-financials listed on NYSE and AMEX 1962-1990 and NASDAQ 1973-1990 as their market proxy. The process described in this section is the how we formed portfolios based on beta to regress against MSCI world, Barclays Aggregate Global Corporate Bond Index and Barclay's Capital U.S. Long Index Corporate Bond respectively. As the same process was conducted for each index, it will only be described once and use index return as a generic term to describe the returns of MSCI world or Barclays Aggregate Global Corporate Bond Index or Barclay's Capital U.S. Long Index Corporate Bond.

To form groups of bonds based on beta with our index, the first step was to regress each bond's monthly return against the monthly index return. This was done in order to attain the individual beta of each security with the index. The time series used to estimate the beta for each bond was the monthly returns of the bond from 2007-01-01 to 2011-12-31 and the corresponding index returns. The regression run to estimate the individual bond betas with the index can be specified as follows;

Where is the individual bond return, is the intercept, is the corporate bond sensitivity to the market return[12], is the market return and is an error term. Including a constant in the regression, such as the risk free interest rate, will not have any effect on the estimation. We assume that the error term has an expected value of zero for all performed regressions.

It should be noted that we use data from our examined time period to calculate the observed beta values. A bi-product of this is that the model as it has been specified, only can be constructed to capture historical bond returns and cannot be used for predicting future corporate bonds returns. For the purpose of answering our research question this is not a problem, since we are trying to understand historical corporate bond returns, rather than building a predictive model.

5a.1.4 Forming portfolios in the CAPM

As CAPM relies on estimates of beta, the estimation of these are of importance. Grouping the betas of the individual securities into ranked beta portfolios is a way of mitigating the potential shortcomings of extreme or misleading individual observations in a data sample (Fama & French, 2004). We will therefore form portfolios based on beta rankings, industry and rating. The industry and rating portfolios will be regressed against MSCI World, Barclays Aggregate Global Corporate Bond Index and Barclays U.S. Long Corporate Bond Index. Note that the beta ranked portfolios will be based on the beta regressions using the different market proxies. Consequently, the beta ranked portfolios of MSCI World are *not* comparable to the beta ranked portfolios of Barclays Aggregate Global Corporate Bond Index, and so on. The beta ranked portfolios will be regressed against the index which was used to calculate the respective beta values.

5a.1.5 Portfolio formation for the CAPM regressions based on beta

After the betas of the 937 individual corporate bonds were calculated as specified under 5a.1.3., the bonds were ranked based on their beta from low to high. The ranking enabled us to form ten equally weighted portfolios of bonds with the lowest decile of betas in the first portfolio and the highest decile of betas in the tenth portfolio. Regressions were performed on the excess returns of the respective portfolios as can be seen below.

We calculated the monthly return for each portfolio by averaging the monthly returns of the bonds included in the portfolio. After doing this we had ten data series of monthly portfolio returns comprised of 93-94 individual bonds for each portfolio. The regression run for each portfolio based on beta was:

Where is the calculated portfolio return, the applied constant risk free rate, is the intercept, is the portfolio's sensitivity to market returns, is the market (index) return and is an error term. We assume that the error term has an expected value of zero for all performed regressions. The procedure explained was conducted for each index creating three different sets of ten portfolios with monthly average returns based on the bonds included in the portfolio.

5a.1.6 Portfolio formation for the CAPM regressions based on rating

As previous research has found that corporate bonds of different ratings show different characteristics, where bonds of lower rating behave more similar stocks (e.g. Elton et al., 2001; Fama & French, 1993; Huang & Huang; 2002; Thorsell, 2008), we choose to form portfolios based on rating to perform Sharpe-Lintner CAPM regressions.

[12] Market return is the return of the market proxy used. In this case the return of MSCI world, Barclays Aggregate Global Corporate Bond Index or Barclay's Capital U.S. Long Index Corporate Bond

To construct portfolios based on rating, the rating of each specific bond was retrieved using Thomson Datastream™. Since no portfolio redistributions are done throughout the sample period, the rating the company had on 2007-01-01 was used. The S&P rating scale was used. For a full description of the distribution of rating scales, refer to table 3.2.

In similar fashion to Fama & French (1993), we disregarded the pluses and minuses in the ratings when forming the portfolios. It can be seen in table 3.2 that the sample contains very few observations for some of the rating classes. Considering this we grouped the first portfolio of AAA-rated corporate bonds and AA-rated corporate bonds to form the first portfolio. The second portfolio contained corporate bonds with A rating. The third portfolio contained corporate bonds with BBB rating. The fourth and last portfolio, named LG for low grade contains the corporate bonds below investment grade. Bonds on which we had no information or did not have any rating were excluded, look below at table 5.2 for details on number of corporate bonds in each portfolio and also aggregate average returns for the portfolios.

Number of bonds for each portfolio and the portfolio returns between 2007-01-01 and 2011-12-31		
Portfolio	**Number of Bonds**	**Return**
AAA & AA	43	17,01%
A	307	17,62%
BBB	366	15,52%
LG	76	11,67%
No info or rating	145	23,46%
Total	937	

Table 5.2 – The table above shows the portfolios based on rating, their returns and how many bonds there are in each portfolio

The average monthly return for each portfolio was calculated taking the average of the monthly return for each bond included in the portfolio. We performed a time series regression against the three indices MSCI World, BAGG and US Long using the following regression:

Where is the portfolio return, is the applied constant risk free rate, is the intercept, is the portfolio sensitivity to market returns, is the market (index) return and is the error term. We assume that the error term has an expected value of zero for all performed regressions.

5a.1.7 Portfolio formation for the CAPM regressions based on industry

It is intuitive that different industries will have different operational exposure to events that might threaten a firm's ability of meeting its credit obligations. Considering this, we chose to include and perform CAPM regression analysis on industry groups in similar fashion to Thorsell (2008).

To construct portfolios based on industry, the SIC Code of each specific bond was retrieved using Thomson Datastream™. The SIC code is a classification code for what industry a company operates in (Occupational Safety and Health Administration n.d.). The first level classification consists of nine different categories. Each bond was classified in accordance with the SIC classification system and the table 5.3 below shows the result.

Number of bonds in each industry portfolio	
Industry	**Number of bonds**
Agriculture forestry and fishing	2
Mining	71
Construction	7
Manufacturing	318
Transportation, Communications, Electric, Gas, And Sanitary Services	355
Wholesale trade	15
Retail trade	77
Finance, Insurance and Real Estate	33
Services	45
NA	14
Total	**937**

Table 5.3 – The table above shows the portfolios based on industry and how many bonds there are in each portfolio.

Each industry represents one portfolio. It can be noted that some of the industries are represented only by a few bonds. Whereas it was possible to merge rating portfolios "next to each other" in the continuous rating scale, it has not been possible to do a similar adjustment to merge industry portfolios. Instead, the results have to be interpreted bearing the different sizes of the portfolios in mind. This means that we will pay little emphasis to the Agriculture, forestry and fishing portfolio, the Construction portfolio, and the Wholesale trade portfolio. However, we have chosen to still perform and include the results of these regressions in our results segment. In the results segments, some of the industry names have been abbreviated. We introduce those abbreviations here. Ag, for fish is short for Agriculture, forestry and fishing. Fin, In, RE is short for Finance, Insurance and Real Estate. Transport, com... is the abbreviation used for Transportation, communications, electric, gas and sanitary services. Lastly, Wholes. Trade is short for Wholesale trade.

Similar to the approach used for beta and rating, the average monthly return for each portfolio was calculated taking the average of the monthly return for each bond included in the portfolio. These times series were regressed against the three indices MSCI World, BAGG and US Long using the following regression

Where is the portfolio return, is the risk free rate, is the intercept, is the portfolio sensitivity to market returns, is the market (index) return and is the error term. We assume that the error term has an expected value of zero for all performed regressions.

5b Results and analysis CAPM regressions

When performing statistical tests for heteroskedasticity and autocorrelation, we found that the results of the CAPM regressions showed signs of significant autocorrelation and heteroskedasticity. Therefore, we have adjusted the results for both autocorrelation and heteroskedasticity by using a Newey-West (1987) estimator. A more detailed specification as of how the estimator was used and the tests where we concluded significant autocorrelation and heteroskedasticity will be provided in the appendix, section A.

We will present the CAPM regression results in the following order:

1. Firstly, results of regressions with portfolios based on beta, rating and industry with MSCI World as market proxy will be presented.

2. Secondly, results of regressions with portfolios based on beta, rating and industry with Barclays Aggregate Global Corporate Bond Index as market proxy will be presented.

3. Lastly, regressions with portfolios based on beta, rating and industry with Barclays U.S. Long Index Corporate Bond as market proxy will be presented.

5b.1 Results of regressions with portfolios based on beta, rating and industry using MSCI World as the market proxy (MSCI World regressions)

5b.1.1 Tables with results MSCI World CAPM regressions

In the tables below, we present results from the CAPM regressions using MSCI World as the market proxy. α is the intercept of the portfolio, nwse(α) is the standard error of α using the Newey-West estimator, nwp(α) is the p-value for α using the Newey-West estimator. βMR is the portfolio sensitivity to the market risk factor, also known as the beta, nwse(β) is the standard error for β using the Newey-West estimator and nwp(β) is the p-value for β using the Newey-West estimator. Adj. R^2 is the fraction of the variability in the portfolio corporate bond return captured, measured as adjusted R^2.

CAPM regressions with portfolios based on beta using MSCI World as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
Portfolio 1	0,0023	0,0027	0,4034	-0,0317	0,0864	0,7151	-0,010
Portfolio 2	0,0019	0,0022	0,3953	0,0228	0,0786	0,7723	-0,012
Portfolio 3	0,0019	0,0024	0,4178	0,0484	0,0831	0,5626	0,005
Portfolio 4	0,0020	0,0025	0,4271	0,0713	0,0874	0,4180	0,027
Portfolio 5	0,0020	0,0027	0,4574	0,0998	0,1042	0,3426	0,051
Portfolio 6	0,0024	0,0030	0,4221	0,1301	0,1093	0,2388	0,079
Portfolio 7	0,0024	0,0032	0,4587	0,1661	0,1176	0,1632	0,122
Portfolio 8	0,0026	0,0034	0,4586	0,2294	0,1271	0,0763	0,202
Portfolio 9	0,0025	0,0036	0,4930	0,3378	0,1246	0,0088	0,375
Portfolio 10	0,0081	0,0082	0,3248	0,9824	0,1916	0,0000	0,621

Table 5.4 – Results of CAPM regressions with portfolios based on β using MSCI World as market proxy.

CAPM regressions with portfolios based on rating using MSCI World as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
AAA & AA	0,0021	0,0024	0,3903	0,0167	0,0706	0,8134	-0,015
A	0,0024	0,0029	0,4083	0,0924	0,1013	0,3653	0,034
BBB	0,0023	0,0030	0,4400	0,1567	0,1071	0,1488	0,133
LG	0,0026	0,0035	0,4643	0,3497	0,1174	0,0042	0,386

Table 5.5 – Results of CAPM regressions with portfolios based on rating using MSCI World as market proxy.

CAPM regressions with portfolios based on industry using MSCI World as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
Ag, For, Fish	0,0011	0,0018	0,5297	0,0795	0,0820	0,3361	0,030
Construction	0,0013	0,0036	0,7314	0,2953	0,0910	0,0020	0,320
Fin, In, RE	0,0029	0,0032	0,3763	0,3313	0,0800	0,0001	0,373
Manufacturing	0,0031	0,0032	0,3333	0,2000	0,1026	0,0560	0,212
Mining	0,0026	0,0029	0,3846	0,1905	0,1009	0,0641	0,191
Retail Trade	0,0023	0,0036	0,5130	0,2911	0,1293	0,0282	0,292
Services	0,0045	0,0047	0,3422	0,4178	0,1215	0,0011	0,398
Transport, com…	0,0025	0,0030	0,4056	0,1655	0,1039	0,1164	0,143
Wholes. trade	0,0022	0,0030	0,4685	0,0979	0,1141	0,3945	0,037

Table 5.6 – Results of CAPM regressions with portfolios based on industry using MSCI World as market proxy.

5b.1.2. Alpha

Using MSCI World as market proxy, the observed α-values were all very close to each other and also close to zero. All portfolio α-values are within one standard error from zero except for the manufacturing portfolio and the services portfolio. As all α-values are insignificant, it is not possible to refute the CAPM as it has been specified. The trend that the observed α-values are all very close to one another becomes especially evident when looking at the portfolios ranked by β-value. There, the α-values remain very close to 0,002 for portfolios 1 through 9 at the same time as the β-values range from -0,0317 to 0,3378. Overall, this suggests a good overall model fit of the CAPM. The argument for a good overall model fit is strengthened when considering that the Y-axis intercept is within one standard deviation from the origo for all portfolios except the manufacturing portfolio and the services portfolio.

One interesting trend is that even though all α-values are very close to zero, they are all positive and very close to each other. If our regression specification had included a slightly higher risk free interest rate, the α-values would consequently move closer to zero. It is possible that our assumption of a constant and arithmetic average of the interest rate yields a risk free interest rate which is too low. Since the risk free interest rate for the last three years of our examined time period was zero or very close to zero, it is also possible that this in itself is an underestimation of the correct risk free interest rate.

5b.1.3. Significant β-values, Explanatory Power and Systematic Risk

When performing MSCI World regressions, low explanatory power of the CAPM was found. Only seven portfolios of the total 23 portfolios had significant β-values on the 5% significance level. These seven portfolios were Portfolio 9 and Portfolio 10 from the β-ranked portfolios, Portfolio LG from the Rating-ranked portfolios and the Construction portfolio, Finance, Insurance and Real Estate portfolio, Retail Trade portfolio, and the Services portfolio from the sorted industry portfolios. The captured return measured as the adjusted R^2 of the seven portfolios with statistically significant β-values at the 5% level ranged between 0,292 and 0,621. Since β-values significant at the 5% level can be identified for several portfolios, the results suggest that – at least for some types of corporate bonds – corporate bond returns vary significantly with a market factor. This finding contradicts the findings of Fama & French (1993), but is in line with the findings of Elton et al., (2001) suggesting systematic risk in corporate bond returns.

5b.1.4. Other Trends in the Data Sample

One clear trend is that the portfolios with lower β-values also are the portfolios with the least significant results. Looking at the portfolios with the comparatively high β-values, it is noteworthy that these portfolios tend to be more significant. Doing a data check of the corporate bonds that were represented in the industry and β-ranked portolios, we could see that bonds from the LG-portfolio were overrepresented in the industry and β-portfolios with statistically significant β-values. All in all, in our sample corporate bonds of lower ratings behaved more like stocks compared to corporate bonds of higher rating, which is a re-affirmation of previous research (e.g. Fama & French, 1993; Elton et al., 2001; Thorsell, 2008). The average low explanatory power of the insignificant portfolios of lower β-value is intuitive, if one consider the equation

With the being kept constant, it is evident that as β_i approaches zero so must also and . Since the correlation coefficient R^2 is calculated as the , it is natural that low average β-value for a portfolio will cause the adjusted R^2 to approach zero.

In order to capture additional variability through CAPM regressions, a natural next step for us was to change the underlying market proxy to a portfolio that would more closely resemble a corporate bond market. The reasoning was that a market proxy more similar to our data sample would generate higher betas so that we could capture more of the variability as low betas makes this hard. This is the underlying intuition behind the regressions and portfolio analysis that will be conducted done in section 5b.2 below where we change the market proxy from MSCI World to Barclays Aggregate Corporate Bond Index.

5b.2. Results and analysis of regressions with portfolios based on beta, rating and industry using Barclays Aggregate Global Corporate Bond Index as the market proxy (BAGG-regressions)

5b.2.1. Tables with results BAGG CAPM Regressions

In the tables below, we present results from the CAPM regressions using Barclays Aggregate Global Corporate Bond Index as the market proxy. α is the intercept of the portfolio, nwse(α) is the standard error of α using the Newey-West estimator, nwp(α) is the p-value for α using the Newey-West estimator. βMR is the portfolio sensitivity to the market risk factor, also known as the beta, nwse(β) is the standard error for β using the Newey-West estimator and nwp(β) is the p-value for β using the Newey-West estimator. Adj. R^2 is the fraction of the variability in the portfolio corporate bond return captured, measured as adjusted R^2.

CAPM regressions with portfolios based on beta using BAGG as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
Portfolio 1	0,0009	0,0013	0,4860	0,3210	0,0850	0,0004	0,206
Portfolio 2	0,0010	0,0010	0,3308	0,6102	0,1159	0,0000	0,498
Portfolio 3	0,0014	0,0010	0,1938	0,7982	0,1633	0,0000	0,573
Portfolio 4	0,0017	0,0012	0,1479	0,9660	0,2003	0,0000	0,604
Portfolio 5	0,0019	0,0012	0,1201	1,1339	0,2390	0,0000	0,633
Portfolio 6	0,0023	0,0015	0,1479	1,2867	0,2739	0,0000	0,633
Portfolio 7	0,0026	0,0019	0,1737	1,4626	0,2964	0,0000	0,637
Portfolio 8	0,0025	0,0018	0,1643	1,6679	0,2839	0,0000	0,688
Portfolio 9	0,0029	0,0018	0,1026	1,9327	0,2720	0,0000	0,754
Portfolio 10	0,0063	0,0075	0,4059	3,0956	0,4810	0,0000	0,516

Table 5.7 – Results of CAPM regressions with portfolios based on beta using Barclays Aggregate Global Corporate Bond Index as market proxy.

CAPM regressions with portfolios based on rating using BAGG as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
AAA & AA	0,0021	0,0021	0,3192	0,8000	0,2359	0,0013	0,362
A	0,0023	0,0016	0,1565	1,1668	0,2413	0,0001	0,584
BBB	0,0020	0,0012	0,1094	1,2556	0,2046	0,0000	0,697
LG	0,0017	0,0028	0,5453	1,5486	0,2154	0,0000	0,570

Table 5.8 – Results of CAPM regressions with portfolios based on rating using Barclays Aggregate Global Corporate Bond Index as market proxy.

CAPM regressions with portfolios based on industry using BAGG as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
Ag, For, Fish	0,0009	0,0014	0,5070	0,6529	0,3074	0,0380	0,220
Construction	0,0005	0,0027	0,8466	1,3483	0,2468	0,0000	0,506
Fin, In, RE	0,0020	0,0020	0,3051	1,5956	0,1592	0,0000	0,655
Manufacturing	0,0027	0,0016	0,0921	1,2671	0,1661	0,0000	0,665
Mining	0,0021	0,0017	0,2034	1,2505	0,2153	0,0000	0,650
Retail Trade	0,0016	0,0025	0,5225	1,4622	0,2524	0,0000	0,562
Services	0,0035	0,0029	0,2448	1,7975	0,1954	0,0000	0,554
Transport, com…	0,0022	0,0012	0,0834	1,3170	0,2191	0,0000	0,739
Wholes. trade	0,0020	0,0019	0,3107	0,9370	0,2600	0,0007	0,353

Table 5.9 – Results of CAPM regressions with portfolios based on industry using Barclays Aggregate Global Corporate Bond Index as market proxy.

5b.2.2. Alpha

We notice that all α-values are close to zero and insignificant at the 5% level. After looking more closely at the α-values and the corresponding standard errors, we can see that they are much closer to being significant in the BAGG regressions compared to the MSCI World regressions. Seven of the portfolios ranked on β have a Newey West p-value of α (nwp(α)) in the 0,102 to 0,1938 range. The three portfolios having a higher nwp(α) than 0,1938 are on the extreme ends of the β-ranked portfolios (Portfolio 1, 2 and 10). We note that the two portfolio α-values that were closest to being significant were the industry portfolios with most listed corporate bonds: Manufacturing portfolio (nwp(α) = 0,0921, 318 corporate bonds) and the Transportation, communications, electric, gas and sanitary services portfolio (nwp(α) = 0,0834, 355 corporate bonds). We see two contradictory interpretations as of why we are closer to receive significant α-values when performing the BAGG regressions.

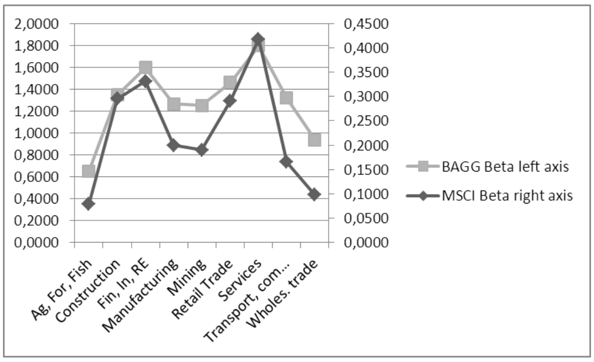
The first interpretation is that changing the underlying market proxy makes the model perform better and that it therefore becomes easier to conclude deviations from the model to be statistically significant. The other interpretation is that BAGG is less like the market portfolio compared to MSCI world, and that the lower nwp(α) values should be seen as indicators of the model performing worse. We believe that the first interpretation is the most reasonable due to two reasons. Firstly, higher adjusted R^2 values are captured in the BAGG regressions compared to the MSCI World regressions. Secondly, all α-values are generally even slightly closer to zero compared to the MSCI World regressions, and all α-values are within two standard deviations from zero. For 9 out of the 23 portfolios, the α-value is within one standard deviation from zero.

Similar to the MSCI World regressions, the BAGG regressions all showed positive α-values. The α-values were all relatively close to each other, although not as close as they were in the MSCI World regressions. Again, this indicates that a slightly higher risk free interest rate would have had the α-values closer to zero. It is possible that our assumption of a constant and arithmetic average of the interest rate yields a risk free interest rate which is too low. Since the risk free interest rate for the last three years of our examined time period was zero or very close to zero, it is also possible that this in itself is an underestimation of the correct risk free interest rate.

5b.2.3. Significant β-values, Explanatory Power and Systematic Risk

When performing CAPM regressions using Barclays Aggregate Global Corporate Bond Index (BAGG) as market proxy), significant betas with high explanatory power of the CAPM was found for all examined portfolios. The fraction of returns captured by the model varies between 0,206 and 0,754, measured as the adjusted R^2. Since the β-values are significant at the 5% level for all portfolios, the results suggest that corporate bond returns vary with a global bond market factor. This finding in itself is not enough to conclude that systematic risk is a factor that is priced in corporate bonds. It is possible (although in our opinion not realistic) that the effect of the global bond market factor can be diversified away.

When considering the results of the MSCI World regressions jointly with BAGG regressions we find some additional interesting trends to comment upon. Looking at the β-values of the portfolios that are directly comparable between the two regressions (the industry and the rating portfolios), we indicate a strong trend of the β-values co-varying between the two indices. As can be seen in the two tables below, portfolios with higher β-value from the MSCI World sample will also show the highest β-values when performing the BAGG regressions. The tendency is clear both for the industry and the rating portfolios, but especially in the industry portfolio.



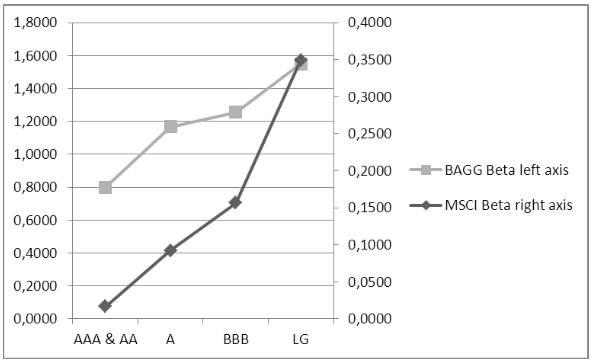
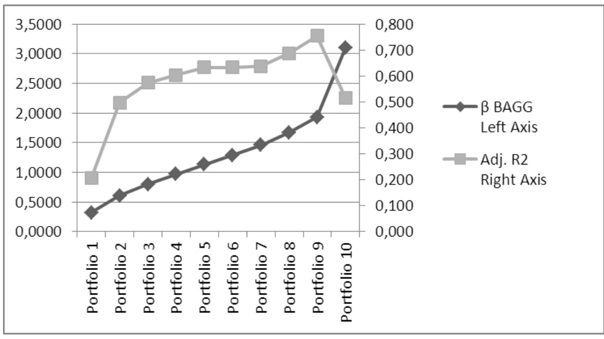


Table 5.10 and Table 5.11 In the above tables we can identify a strong trend that β-values co-vary between MSCI World and BAGG.

This is an indication that the global bond market factor and the global equity market factor to some extent capture the same underlying pricing factor, which we interpret as a clear indication of the existence of systematic risk affecting corporate bond prices. In short, the picture being painted by the regressions using BAGG as market proxy looks similar to the regressions using MSCI World as market proxy. The reason that additional variability could not be captured by MSCI World is likely due to corporate bonds having low β-values when regressions are performed against a global stock market index such as MSCI World. Consequently, the argument for systematic risk becomes stronger when jointly considering findings of the MSCI World regressions and the BAGG regressions.

5b.2.4. Other Trends in the Data Sample

Similar to the trend seen in the MSCI World regressions, we can see that higher β-values in general increase the proportion of the captured return measured as adjusted R^2. This trend is evident when looking at the β-ranked portfolios (Table 5.12). A clear exception to this rule is the results of β-ranked Portfolio 10 as it has a less fraction of captured return than portfolios 3 through 9. It is unclear why this is the case, but we note that researchers such as Fama & Macbeth (1973) suggest excluding the first and last portfolio of a β-ranked portfolio sample in order to show general results that are not influenced by extreme data points. If this is done, a smooth and intuitive trend of increasing adjusted R^2 values is experienced as the β-values increase through Portfolio 2 to Portfolio 9 (see Table 5.13). There is a clear link between the fraction of captured return and the portfolio β-value, where higher β-value gives higher explanatory power.



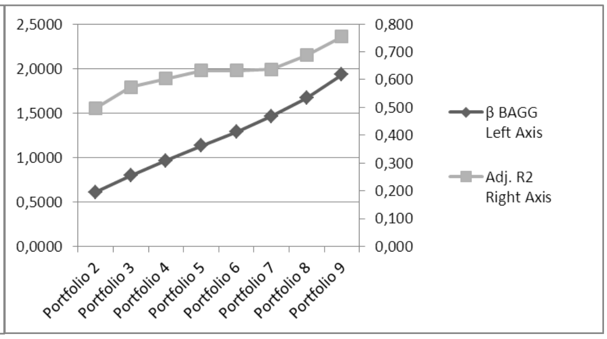


Table 5.12 and Table 5.13. The tables above shows the β from the BAGG regressions on the left axis and the adjusted R^2 on the right axis. There is an evident trend of higher β-value portfolios capturing higher fractions of the variability in corporate bond returns.

We used a CAPM specification with a constant risk free interest rate during the examined time period. Considering that the risk free interest rate dropped significantly during the examined time period, a natural next step was to consider the effect that an overall drop of the risk free interest rate might have on our corporate bond sample. Considering the limiting search criteria we used, we have reason to believe that our corporate bond sample consists of corporate bonds of longer maturities than Barclays Aggregate Corporate Bond Index (which includes bonds that has one year to maturity or more). We therefore chose to perform regressions and portfolio analysis with Barclays U.S. Long Index Corporate Bond (US Long) serving as the market proxy in the segment 5b.3 below. This index consists of long USD denominated corporate bonds with at least ten years to maturity, and we expect that the decline in the risk free interest rate will affect this index more than the Barclays Aggregate Corporate Bond Index.

5b.3 Results and analysis of regressions with portfolios based on beta, rating and industry using Barclays U.S. Long Index Corporate Bond as the market proxy (US Long regressions)

5b.3.1 Tables with results US Long CAPM regressions

In the tables below, we present results from the CAPM regressions using Barclays U.S. Long Index Corporate Bond as the market proxy. α is the intercept of the portfolio, nwse(α) is the standard error of α using the Newey-West estimator, nwp(α) is the p-value for α using the Newey-West estimator. βMR is the portfolio sensitivity to the market risk factor, also known as the beta, nwse(β) is the standard error for β using the Newey-West estimator and nwp(β) is the p-value for β using the Newey-West estimator. Adj. R^2 is the fraction of the variability in the portfolio corporate bond return captured, measured as adjusted R^2.

CAPM regressions with portfolios based on beta using US Long as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
Portfolio 1	0,0007	0,0023	0,7727	0,0775	0,1169	0,5102	0,022
Portfolio 2	0,0003	0,0015	0,8513	0,2318	0,0721	0,0021	0,361
Portfolio 3	0,0007	0,0016	0,6860	0,3351	0,0778	0,0001	0,536
Portfolio 4	0,0010	0,0018	0,5783	0,4270	0,0913	0,0000	0,574
Portfolio 5	0,0008	0,0020	0,6914	0,5107	0,0895	0,0000	0,675
Portfolio 6	0,0008	0,0019	0,6606	0,6044	0,1048	0,0000	0,689
Portfolio 7	0,0010	0,0016	0,5322	0,7192	0,0758	0,0000	0,800
Portfolio 8	0,0015	0,0017	0,3773	0,8319	0,0834	0,0000	0,792
Portfolio 9	0,0020	0,0020	0,3396	0,9284	0,0827	0,0000	0,845
Portfolio 10	0,0041	0,0056	0,4589	1,2547	0,1429	0,0000	0,649

Table 5.14 – Results of CAPM regressions with portfolios based on beta using Barclays U.S. Long Index Corporate Bond as market proxy.

CAPM regressions with portfolios based on rating using US Long as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
AAA & AA	0,0013	0,0015	0,4057	0,4559	0,0582	0,0000	0,603
A	0,0012	0,0010	0,2344	0,5988	0,0541	0,0000	0,780
BBB	0,0010	0,0017	0,5732	0,5704	0,0905	0,0000	0,725
LG	0,0006	0,0040	0,8721	0,5793	0,1503	0,0003	0,397

Table 5.15 – Results of CAPM regressions with portfolios based on rating using Barclays U.S. Long Index Corporate Bond as market proxy

CAPM regressions with portfolios based on industry using US Long as market proxy							
	α	nwse(α)	nwp(α)	βMR	nwse(β)	nwp(β)	Adj. R^2
Ag, For, Fish	0,0004	0,0016	0,8024	0,3049	0,1319	0,0244	0,244
Construction	-0,0005	0,0032	0,8783	0,5756	0,1082	0,0000	0,463
Fin, In, RE	0,0008	0,0028	0,7692	0,6836	0,0737	0,0000	0,604
Manufacturing	0,0017	0,0022	0,4577	0,5711	0,0843	0,0000	0,681
Mining	0,0011	0,0022	0,6078	0,5539	0,1072	0,0000	0,642
Retail Trade	0,0006	0,0037	0,8670	0,5672	0,1666	0,0012	0,422
Services	0,0021	0,0041	0,6082	0,7581	0,0916	0,0000	0,495
Transport, com…	0,0011	0,0015	0,4589	0,6058	0,0774	0,0000	0,788
Wholes. trade	0,0012	0,0023	0,5941	0,4360	0,1067	0,0001	0,387

Table 5.16 – Results of CAPM regressions with portfolios based on industry using Barclays U.S. Long Index Corporate Bond as market proxy

5b.3.2. Alpha

We once more notice that all α-values are close to zero and insignificant at the 5% level. The trend in the portfolios is that the α-values are consistently similar and close to zero. For the US Long regressions, α-values for all portfolios are within one standard deviation of zero. The Newey-West p-value of α (nwp(α)) is consistently much higher compared to the values from the BAGG regressions, and also higher than the nwp(α) values from the MSCI World regressions. The reason to why the nwp(α) values are lower in the other two regressions is unclear, although we to some extent have discussed this matter in 5b.2.2. We note that no significant α-values could be found at the 5% level for any portfolios, no matter if the proxy for the market portfolio is MSCI World, BAGG or US Long.

Another interesting trend is that only one out of 23 portfolios showed a negative α-value. As this was the Construction portfolio, with only seven bonds included in the portfolio, we feel confident to conclude that the general trend of having positive α-values holds also for the US Long regressions. In addition to seeing this trend already in the MSCI World regressions and the BAGG regressions, we can once more conclude that a slightly higher risk free interest rate would have had the α-values move closer to zero. It is possible that our assumption of a constant and arithmetic average of the interest rate yields a risk free interest rate which is too low. Since the risk free interest rate for the last three years of our examined time period was zero or very close to zero, it is also possible that this in itself is an underestimation of the correct risk free interest rate.

5b.3.3. Significant β-values, Explanatory Power and Systematic Risk

When performing CAPM regressions using Barclays U.S. Long Index Corporate Bond (US Long), significant results with high explanatory power of the CAPM was found for all examined portfolios except for β-ranked portfolio 1. The β-ranked portfolio 1 has the β-value closest to 0, making it reasonable that it also experiences the lowest fraction of captured return and it being the β-value of least significance similar to the results of the MSCI World and BAGG regressions.

As previously outlined, our primary reason for including regressions against US Long was that we intended to capture additional variability in returns that was caused by the risk free interest rate declining under the examined time period. Considering that the captured variability measured as the adjusted R^2 showed a slight decrease throughout the US Long regressions compared to the BAGG regressions, it is clear that our intention of increasing the variability in return captured was unsuccessful. We have identified two distinct reasons as of why this might be, outlined separately in the two below paragraphs.

Firstly, conducting regressions against US Long gives lower β-values compared to doing the regressions against BAGG. A possible explanation for the US Long portfolios having lower β-values compared to BAGG is that the US Long consists of bonds with comparatively longer time to maturity and therefore is more sensitive to interest rate changes. As interest rates change, prices will be affected more in the US Long index compared to BAGG. Since our sample consists of long maturity bonds, we will experience lower β-values when doing the regressions against the US Long index. Throughout the MSCI World and the BAGG CAPM regressions, we have seen a trend that portfolios of higher β-values in general captures larger fraction of the variability in the return, and it is therefore in line with our previous findings that we experience a similar trend when conducting the US Long regressions.

Secondly, it might be that the global and broader BAGG simply is a better proxy for the market portfolio from the point of examining corporate bond prices and returns compared to US Long. What is captured when doing the US Long regressions is on all merits significantly better than what is captured when doing the MSCI World regressions and are by those comparative means not unsatisfactory. However, it might be so that the regressions done against the broader BAGG provides a better overall market factor for the pricing of corporate bonds making the US Long regressions lose importance.

All in all, we do not see the results from the regressions against US Long either strengthening or weakening the argument for the existence of systematic risk factors in corporate bond returns compared to the argument based on the joint MSCI World and BAGG regression analysis.

5b.3.4. Other Trends in the Data Sample

The US Long regressions paint a similar picture to the BAGG regressions. They have portfolios of higher relative β-values that are able to capture an increased fraction of the variability in the return of a corporate bond, measured as the adjusted R^2 (Table 5.17). Also, in a similar fashion to the BAGG regressions, the US Long regressions present a smoother and more intuitive trend of the adjusted R^2 increasing as β increases if portfolios on the extreme ends are excluded, as is suggested by Fama & Macbeth (1973) (Table 5.18).

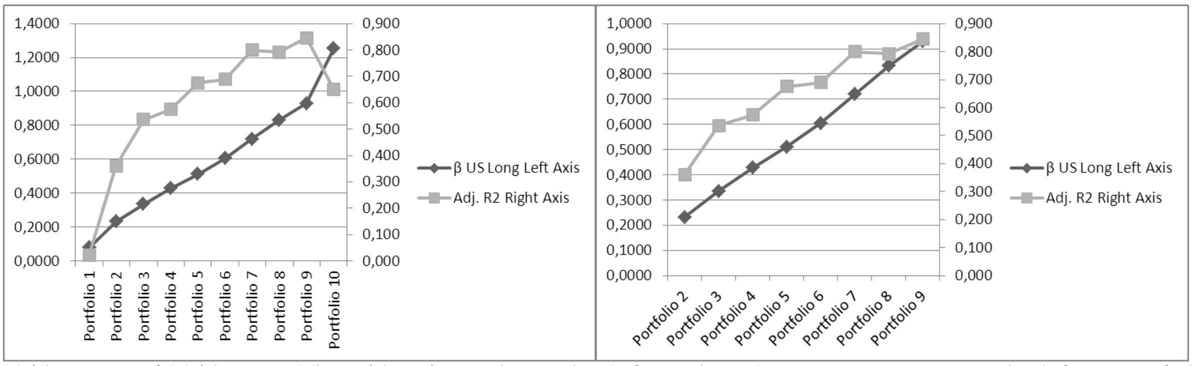


Table 5.17 and Table 5.18. The tables above shows the β from the US Long regressions on the left axis and the adjusted R^2 on the right axis. There is an evident trend of higher β-value portfolios capturing higher fractions of the variability in corporate bond returns.

6a. Method Fama & French factor model

In order to further deepen our understanding of corporate bond returns, we take inspiration from the framework of Fama & French (1993). In their study, Fama & French developed a model for capturing corporate bond returns that showed results superior to those of CAPM. The study originates from the widely cited Fama & French (1992) paper, where the Fama & French 3-factor model was introduced. We include the Fama & French factor model for two reasons:

1) The first reason is that the model has generated superior empirical results than CAPM. Fama & French (1993) showed that their factors for default risk (DEF) and interest rate change risk (TERM) could capture almost all of the variability in corporate bond returns.

2) The second reason for using the method of Fama & French (1993) is that by using both CAPM and the Fama & French factor model we will be able to capture, compare and contrast corporate bond returns using the two methods. As far as we have seen, no such comparison has previously been conducted.

6a.1. Multi-factor approach of Fama & French (1993)

In their study from 1993, Fama & French identified five common risk factors influencing the returns of stocks and bonds. These consist of three factors for the stock market (stock market factors) and two for the bond market (bond-market factors). The stock market factors are an overall market factor, a firm size factor and a factor of book-to-market value of equity. The bond-market factors consist of one interest rate change risk factor (TERM) and a default risk factor (DEF). In full, their model was specified as below:

Fama & French (1993) evaluated seven bond portfolios to test their defined stock and bond market factors on bond returns. The seven portfolios consisted of two government bond portfolios covering maturities of 1 to 5 years and 6 to 10 years, and five corporate bond portfolios containing the rating groups Aaa, Aa, A, Baa and Low-Grade. Their conclusion was that their factor for default risk (DEF) and their factor for interest rate change risk (TERM) could explain almost all of the variability in returns. Explanatory power of stock-market factors disappeared for all but the low grade corporate bonds when the two bond-market factors were included in the bond regressions. It would therefore be a natural step to exclude the stock-market factors when using the Fama & French (1993) model on corporate bond returns. However, subsequent research to Fama & French has argued for systematic risk factors affecting corporate bond prices (e.g. Elton et al., 2001). In addition we see strong indications of systematic risk in our CAPM regressions which led us to include the market risk factor in our application of the Fama & French (1993) model. Our application of the Fama & French (1993) is specified as follows.

Where denotes the return of the portfolio, is the varying risk free rate, is the intercept, captures the impact of market risk, captures the impact of default risk, captures the impact of interest rate change risk and is the error term. We assume that the error term has an expected value of zero for all performed regressions. The specifications of the different factors and the used in our regression analysis will be explained in the segments below, and have been constructed to as closely as possible resemble the factors that Fama & French (1993) used for their regressions. We have no reason to believe that our results as a result of the slightly different specifications will differ in any meaningful way to those of Fama & French (1993). We will run regressions on portfolios based on bond ratings. The ratings used are the ratings from the beginning of 2007. Moreover, we will also perform regressions based on industry sorted portfolios similar to those of our CAPM regressions.

6a.1.1. Estimating the risk free interest rate

In the Fama & French regressions, we have chosen to let the risk free interest rate vary throughout the examined time period rather than keeping it constant as in the CAPM regressions. The reason for applying a varying interest rate rather than a constant one is that doing so replicates the way Fama & French (1993) are specifying their model. The rates applied are again the rates of Kenneth French, attained from French's (2012) homepage. The data retrieved was the year to year risk free rate on a monthly basis which was converted to monthly rate to fit our model specifications. The risk free interest rate used is shown in Table 6.1 below. We are denoting this varying risk free interest rate as .

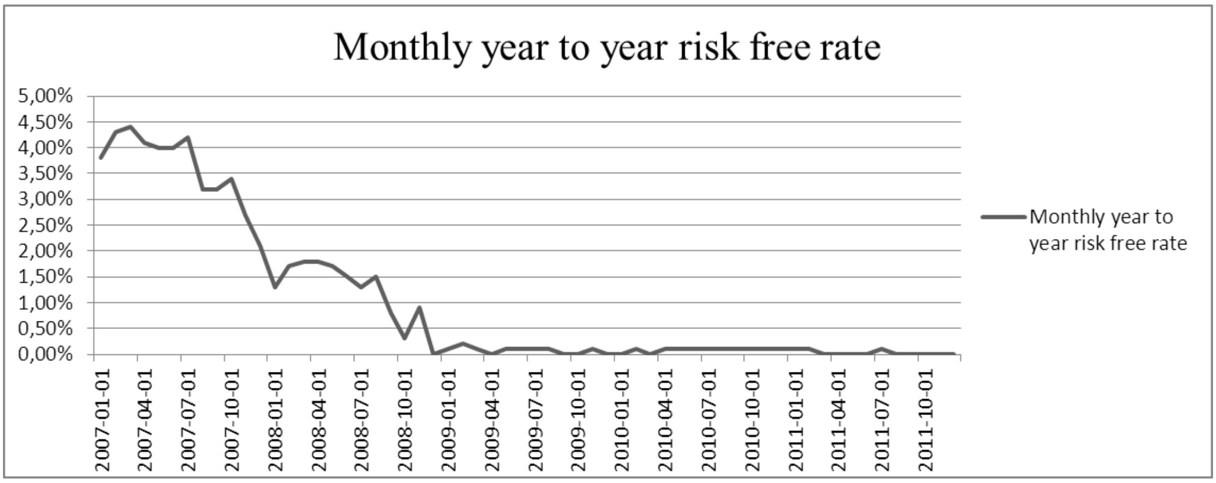


Table 6.1 – Above the monthly year to year risk free rate is shown. One should notice that the risk free rate fell drastically during the period.

6a.1.2 The TERM factor

Relying on the argument that changes in interest rates is a common risk in bond returns, Fama & French (1993) introduce a proxy for this factor which they name TERM. They specify the TERM factor as "the difference between monthly long-term government bond return (…) and the one-month Treasury bill rate measured at the end of the previous month"(1993 p.7).

Our specification of the TERM factor will be the difference between the long-term government bond return collected from CRSP (Center for Research in Security Prices) named "CRSP Monthly Treasury - Fama Bond Portfolio Returns (12 Mos.)", and the one-month Treasury bill rate also retrieved from CRSP. The "CRSP Monthly Treasury - Fama Bond Portfolio Returns (12 Mos.)" are the monthly returns of treasuries with a maturity longer than 120 months. Below we will first specify what TERM intends to capture, and then provide the exact replica of our specification:

6a.1.3 The DEF factor

Fama & French introduce a factor named DEF to capture the default risk on corporate bonds. They define DEF as "the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return" (1993, p.7). We have used the monthly return on Barclays

U.S. Long Corporate index as our proxy for the return of a market portfolio of long-term corporate bonds. The same proxy for the long-term government bond return as we used when defining TERM, namely the "CRSP Monthly Treasury - Fama Bond Portfolio Returns (12 Mos.)" was used. Below we will first specify what DEF intends to capture, and then provide the exact replica of our specification:

6a.1.4 The Market Risk factor

To include stock market factors into the model, a market risk factor is also included. Fama & French (1993) define their market risk factor as the excess market return of the value-weighted portfolio of stocks used in their study, with the risk free rate being the one month Treasury bill rate. We will use the monthly returns of MSCI World to proxy the market returns and use the monthly variable risk-free interest rate retrieved from Kenneth French's homepage as the risk free interest rate ( ). Below we will first specify what our Market Risk (MR) factor intends to capture, and then give the exact replica of our specification:

6a.1.5 Portfolio formation for the modified Fama & French model based on rating

The portfolios based on rating used for the Fama & French regressions are equal to those used for the CAPM regressions. In order to not be repetitive, we refer to chapter 5a.1.7. "Portfolio formation for the CAPM regressions based on rating" which in detail outlines how we have constructed the portfolios.

6a.1.6 Portfolio formation for the modified Fama & French model based on industry

The portfolios based on industry used for the Fama & French regressions are equal to those used for the CAPM regressions. In order to not be repetitive, we refer to chapter 5a.1.7. "Portfolio formation for the CAPM regressions based on industry" which in detail outlines how we have constructed the portfolios.

6b Results and analysis of Fama & French regressions

When performing statistical tests for heteroskedasticity and autocorrelation, we found that the results of the Fama & French regressions showed signs of significant autocorrelation and heteroskedasticity. Therefore, we have adjusted the results for both autocorrelation and heteroskedasticity by using a Newey-West (1987) estimator. A more detailed specification as of how the estimator was used and the tests where we concluded significant autocorrelation and heteroskedasticity will be provided in the appendix, section A. Since Fama & French (1993) is a multi-factor model, we have also tested for multicollinearity.

Results of industry and rating regressions and analysis of the results from the regressions will be presented jointly in the section below. As Fama & French is a multi-factor model, we will present and analyze the individual factors one at a time, but also conduct joint analysis on the overall performance of the multi-factor model.

6b.1 Results and analysis of Fama & French regressions

6b.1.1. Tables with results Fama & French Regressions

In the tables below, we present results from the Fama & French regressions. α is the intercept of the portfolio, nwse(α) is the standard error of α using the Newey-West estimator, nwp(α) is the p-value for α using the Newey-West estimator. β_1MR is the sensitivity of the portfolio to the market risk factor, nwse(β_1) is the standard error of β_1 using the Newey-West estimator, nwp(β_1) is the p-value for β_1 using the Newey-West estimator. β_2DEF is the sensitivity of the portfolio to the default risk factor, nwse(β_2) is the standard error of β_2 using the Newey-West estimator, nwp(β_2) is the p-value for β_2 using the Newey-West estimator. β_3TERM is the sensitivity of the portfolio to the interest rate change risk factor, nwse(β_3) is the standard error of β_3 using the Newey-West estimator, nwp(β_3) is the p-value for β_3 using the Newey-West estimator. Adj. R^2 is the fraction of the variability in the portfolio corporate bond return captured, measured as adjusted R^2.

Fama & French regressions with portfolios based on rating													
	α	nwse(α)	nwp(α)	β_1MR	nwse(β_1)	nwp(β_1)	β_2DEF	nwse(β_2)	nwp(β_2)	β_3TERM	nwse(β_3)	nwp(β_3)	Adj. R^2
AAA & AA	-0,0013	0,0008	0,1197	-0,0042	0,0322	0,8978	0,2845	0,0565	0,0000	0,6410	0,0365	0,0000	0,893
A	-0,0004	0,0013	0,7397	-0,0014	0,0436	0,9750	0,4827	0,0646	0,0000	0,7211	0,0534	0,0000	0,874
BBB	0,0007	0,0020	0,7301	0,0252	0,0663	0,7057	0,5208	0,0797	0,0000	0,5864	0,0907	0,0000	0,724
LG	0,0045	0,0030	0,1407	0,0664	0,0972	0,4976	0,7658	0,1310	0,0000	0,2947	0,1164	0,0142	0,665

Table 6.2 – Results of Fama & French regressions based on rating.

Fama & French regressions with portfolios based on industry													
	α	nwse(α)	nwp(α)	β_1MR	nwse(β_1)	nwp(β_1)	β_2DEF	nwse(β_2)	nwp(β_2)	β_3TERM	nwse(β_3)	nwp(β_3)	Adj. R^2
Ag, For, Fish	-0,0012	0,0021	0,5868	0,0920	0,0764	0,2334	0,1096	0,0627	0,0862	0,3761	0,1372	0,0082	0,319
Construction	0,0016	0,0030	0,5973	0,0920	0,0966	0,3451	0,6215	0,1425	0,0001	0,4025	0,1078	0,0004	0,578
Fin, In, RE	0,0029	0,0022	0,1820	0,1059	0,0435	0,0181	0,7092	0,1200	0,0000	0,5045	0,0645	0,0000	0,716
Manufacturing	0,0009	0,0023	0,7018	0,1212	0,0514	0,0219	0,3961	0,0880	0,0000	0,5764	0,0969	0,0000	0,720
Mining	0,0009	0,0022	0,6967	0,0834	0,0661	0,2123	0,4481	0,1101	0,0002	0,5425	0,0992	0,0000	0,654
Retail Trade	0,0024	0,0035	0,4917	0,1095	0,1017	0,2864	0,5718	0,1168	0,0000	0,4069	0,1518	0,0096	0,512
Services	0,0022	0,0036	0,5472	0,3312	0,1502	0,0316	0,4292	0,1873	0,0257	0,6134	0,0788	0,0000	0,632
Transport, com…	0,0011	0,0018	0,5503	0,0114	0,0580	0,8455	0,5834	0,0762	0,0000	0,6139	0,0754	0,0000	0,785
Wholes. trade	-0,0006	0,0026	0,8300	0,0792	0,0894	0,3793	0,2385	0,0721	0,0017	0,5281	0,1133	0,0000	0,459

Table 6.3 – Results of Fama & French regressions based on industry

6b.1.2. Alpha

All α-values are close to zero and insignificant at the 5% level. This means that we cannot refute the Fama & French (1993) model as it has been specified. The trend in the portfolios is that the α-values are consistently similar and close to zero. The α-values of all portfolios are within two standard deviations of zero when performing the Fama & French regressions, and in 10 out of 13 portfolios the α-value is within one standard deviation from zero. All in all, this suggests a good overall fit of the Fama & French (1993) model.

Looking at the rating portfolios we can see that we have two negative and two positive α-values. The Low Grade portfolio has the α-value furthest away from zero when doing the Fama & French regressions. A plausible explanation for this could be that corporate bonds below investment grade behave differently than bonds of investment grade (e.g. Fama & French, 1993; Geske & Delianedis, 2001; Huang & Huang, 2002). As we did not see a similar pattern from our CAPM regressions this conclusion is a speculative one. Considering that the α-value of the Low Grade rating portfolio was much higher compared to other rating portfolios, the effect of the higher α-values is likely to be "spread out" throughout the industry portfolios. This can explain why the industry portfolios in general show positive α-values.

One interpretation of the better general fit of α-values when using the Fama & French (1993) model is that the model in itself provides a better empirical understanding of corporate bond returns. This interpretation is supported by our finding that the Fama & French (1993) model can capture more than CAPM of the variability in corporate bond returns, measured as adjusted R^2. An alternative interpretation is that implementing a varying risk free interest rate is better than using a constant interest rate (as was done in the CAPM regressions).

6b.1.3. Analyzing the β_2DEF factor

B_2DEF was significant at the 5% level for all portfolios of meaningful size (the Agriculture, Forestry and Fishing portfolio consisted only of two bonds). We can therefore conclude that the β_2DEF factor is a significant pricing factor for corporate bonds. It is intuitive that a default risk should be a significant pricing factor for corporate bonds, and finding it significant is in line with previous research (Fama & French, 1993; Elton et al., 2001; Geske & Delianedis, 2001). In our sample, default risk was more important for corporate bonds of lower credit rating. This finding is intuitive as bonds of lower credit rating is expected to default more often, and the finding is also in line with previous research (Fama & French, 1993; Geske & Delianedis, 2001; Huang & Huang, 2002). Default risk was in addition to being the most important pricing factor for the Low-Grade portfolio, also the most important pricing factor for the Construction portfolio, the Financial, Insurance and Real Estate portfolio, and the Retail Trade portfolio. The trend of default risk being the most important pricing factor for these three industry portfolios is not nearly as strong as the trend is for the Low-Grade portfolio. Thus, our results indicate that rating is more important than industry for the default risk factor. This is reasonable since the intention of credit ratings is to capture short-term and long-term default risk.

The variable DEF is defined as the difference between the return of a long term corporate bond index of investment grade and the return of a long term government bond portfolio. Considering this, it is not strange that we have attained higher explanatory power for the investment grade rating categories compared to the bonds below investment grade. If the DEF variable instead was defined as the difference between the return of a portfolio of long maturity corporate bonds *below* investment grade and the return of a long maturity government bond portfolio, we would intuitively expect a higher fraction of the variability in the corporate bond return to be captured in the *low grade* portfolio.

6b.1.4. Analyzing the β_3TERM factor

As previously outlined, TERM is a proxy to capture interest rate change risk or maturity risk. In our sample β_3TERM was significant for all sample portfolios on the 5% level. B_3TERM was comparatively the most important for portfolio consisting of AAA and AA bonds, the A portfolio, the Manufacturing portfolio, the Services portfolio, the Wholesale trade portfolio and the Agriculture, Forestry and Fishing portfolio. Since the Agriculture, Forestry and Fishing portfolio only consists of two listed bonds, and the

Wholesale trade portfolio only consists of 15 listed bonds additional the results of these portfolios are to be analyzed with caution.

Among the portfolios of adequate size, β_3TERM was of greatest significance in the AAA & AA-rated portfolio. As the default risk factor becomes less important for companies of better credit rating, it is intuitive that other factors should grow in relative significance. We therefore find it reasonable that the impact of interest rate changes should grow in significance for corporate bonds of higher ratings. However, when considering the results of the Services portfolio and the Manufacturing portfolio we have found no intuitive answer as of why interest rate change risk these cases are more important compared to other industry sectors of our sample.

6b.1.5. Analyzing the β_1MR factor and Systematic Risk

On the 5% significance level, a β_1MR factor was found for three portfolios: the Financial, Insurance and Real Estate portfolio, the Manufacturing portfolio and the Services portfolio. The Manufacturing portfolio consisted of vastly more listed corporate bonds (318) compared to the Finance, Insurance and Real Estate portfolio (33) and the services portfolio (45). Identifying a significant β_1MR factor for three separate industry portfolios is a strong indication of existence of systematic risk in corporate bonds, although the market risk factor was comparatively small to the default risk factor and the interest change risk factor. There is an intuitive possibility that the β_2DEF and β_3TERM factors overlap with the β_1MR factor, and this intuition is re-affirmed when performing statistical tests for multicollinearity. Multicollinearity measures the correlation between two or more explaining variables in a regression model (Edlund 1997). When performing the multicollinearity test, it can be seen that the β_1MR factor is highly correlated to the β_2DEF factor (-0,685, see table 6.4) suggesting that the specified default risk factor and market risk factor to a high extent capture the same thing. Having the β_1MR factor be significant for some portfolios when the β_2DEF factor is present is therefore a strong argument for the existence of systematic risk on its own merit as it will be harder to show significance in the β_1MR factor as long as the β_2DEF factor is present. Performing regressions using only the β_1MR factor and β_3TERM factors confirm this analysis, but as these regressions were performed during the editing stages of this paper and consist of an additional modification to the Fama & French (1993) model, they will not be presented.

Considering that our data sample shows high negative correlation between the β_2DEF factor and the β_1MR factor, the argument for systematic risk becomes stronger. Finding a strong link between the proxied market risk factor and the proxied default risk factor for capturing the variability in corporate bond returns is a strong indication of there being systematic risk in corporate bond returns, and we find that this argument is contradictory to Fama & French (1993).

Coefficient correlations for the explanatory variables in the modified Fama & French regressions			
	β_3TERM	β_1MR	β_2DEF
β_3TERM	1,000	-0,143	0,455
β_1MR	-0,143	1,000	-0,685
β_2DEF	0,455	-0,685	1,000

Table 6.4 The correlation between β_2DEF and β_1MR of -0,685 show clear signs that there is an overlap between the market risk and default risk as specified.

6b.1.6. Explanatory Factors and their Explanatory Power

In similar fashion to the results of Fama & French (1993), we found that β_2DEF and β_3TERM were the two most important factors for the pricing of corporate bonds. The captured variation of the corporate bond return measured as the adjusted R^2 value was very high throughout the Fama & French regressions compared to the CAPM regressions. The fraction of the captured return for the rating portfolios decreased as the rating of the corporate bond portfolio decreased. At the same time as the fraction of the captured return decreased for bond portfolios of lower credit rating, the importance of default risk increased and the importance of interest rate change risk decreased. The same trend can be seen in the findings of Fama & French (1993, p. 34), although the trend for their data sample is not as strong as in our data sample.

It is intuitive that corporate bonds should behave more like stocks when credit quality of the corporate bond decreases, and this intuition is also supported by research (Elton et al., 2001; Thorsell, 2008; Fama & French, 1993; Geske & Delianedis, 2001; Huang & Huang, 2002). The findings of Elton et al., (2001, p. 271-272) suggest that the Fama & French stock market factors can be used to explain a significant fraction of the spread between corporate and government bonds, and that these stock market factors become increasingly important as the credit rating of the examined corporate bond decreases. We have only examined one of the stock market factors of Fama & French (1993), the market risk factor β_1MR, and in the Fama & French regressions we could not see that the importance of it being significant or indicative for any of the rating portfolios.

6b.1.7. Questioning the specification of the DEF variable

After considering the high correlation between the default risk factor β_2DEF and the market risk factor β_1MR when performing the Fama & French regressions, we paid specific attention to how the Fama & French (1993) model was specified and how the input variables of our data sample changed throughout the sample period. When looking at the default risk variable DEF we saw an interesting pattern. On average, the default risk variable, being the difference between the return on a long term corporate bond index (US Long) and the return of a long term government bond portfolio, was -0,00677. The development of the DEF-variable can be seen in table 6.5 below.

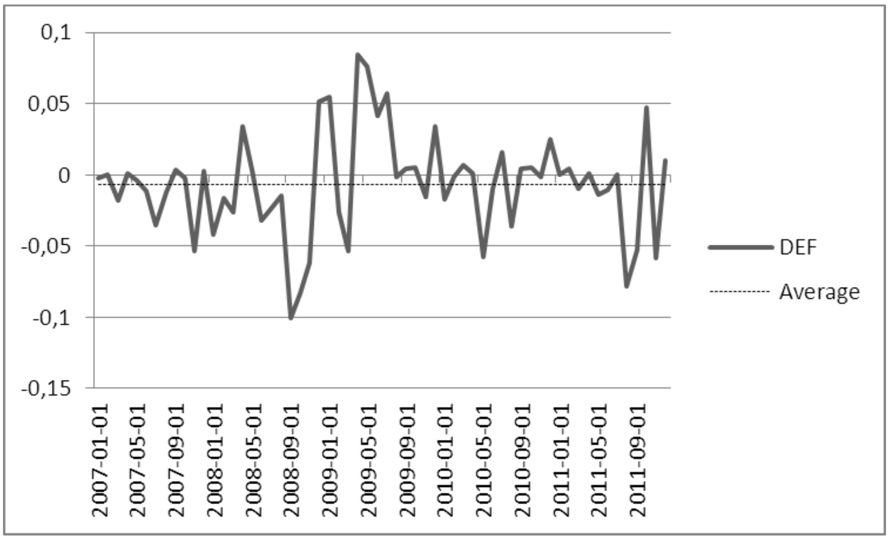


Table 6.5 The default risk factor is on average -0,00677 throughout our sample period.

We have identified three separate ways of interpreting this finding. The first possibility is that the implied default rate for the American government is higher than the American corporate bonds in US Long. The second possibility is that our examined time period is too short and/or extreme to base conclusions upon. The third possibility is that the DEF factor has not been specified to measure default risk in the best way.

Although we are aware (and consider it intriguing) that some American companies such as Berkshire Hathaway had its debt traded at yields below corresponding US government debt during some parts of our examined time period (Kruger and Keogh, 2010), we deem the first possibility to be an unreasonable conclusion.

The second possibility is a more plausible reason, considering that the examined time period covers a severe financial crisis. However, as the Fama & French model consistently shows high explanatory values, and general tendencies of a good model fit, we believe that the second possibility falls short upon explaining the negative DEF variable in an intuitive manner.

The third possibility offers the most realistic explanation as of why we have experienced a negative DEF variable value. Adopting the model specification at the DEF variable from Fama & French (1993), this variable was defined as the difference between the return on a corporate bond module of long maturities and the long-term government bond return.

The implicit assumption in this case, is that the spread difference between the long term corporate bond index (US Long) and the government bond index is equal to the default risk. This is in line with the argument provided by Collin-Dufresne et al., (2001) who argue that the theoretical reason for the yield spread will entirely be in the default spread. However, if default risk is not the only factor that explains the price difference between government and corporate bonds of equal maturities, the Fama & French default variable DEF is not specified in a way that covers default risk in an appropriate way but should rather be seen as a corporate bond market factor.

As has been made clear in the literature review, research subsequent to Fama & French (1993) have critiqued the assumption of default risk being the only factor that prices the difference in yield between government and corporate bonds (e.g. Elton et al., 2001; Geske & Delianedis, 2001). We therefore feel confident to say that what Fama & French have done is not to proxy the default risk, but instead proxied a bond market factor consisting of the excess return of a long maturity corporate bond portfolio over a government bond portfolio. In our view, it would be more transparent to rename the DEF variable to more closely reflect that it is indeed a corporate bond market factor that is captured, and not a factor of default risk. We believe that the DEF variable as specified by Fama & French (1993), in the light of subsequent research of e.g. Elton et al. (2001) and Geske & Delianedis (2001) and the results of our Fama & French regressions, does not capture default risk in a meaningful way.

It is plausible that one effect of the financial crisis is that long term government bonds have overperformed long term corporate bonds, making the DEF variable negative. As a consequence of investors seeking less risk, the price of government bonds have been pushed up relative to the price of corporate bonds during the financial crisis. The consequence is that the DEF variable became negative for the examined period. It is noteworthy that the trend curve for DEF throughout the examined period consists of a slightly positive slope. A plausible explanation for this is that the immediate effects of the financial crisis have ebbed out during later stages of the examined time period.

6b.1.8. Overall Fama & French Model Performance

Looking at the overall performance of the Fama & French (1993) model in terms of capturing the variability in corporate bond returns, it does an overall better job than the Sharpe-Lintner CAPM. Considering the arguments we provided under 6b.1.7., it is indeed intuitive that corporate bond prices should vary with changes in interest rates and a bond market factor (originally specified to capture default risk).

Even after considering the lacking transparency in the model specification of the DEF variable, we have respect for the high fractions of corporate bond returns that Fama & French (1993) provides. Overall the Fama & French model performs superior to CAPM in capturing the variability in returns, even when bond market indices are used as the market proxy when performing the CAPM regressions.

Compared to CAPM, the Fama & French (1993) model showed a limitation in its ability to capture the β_1MR factor. We believe the reason for this to be that the DEF variable is specified in a way that makes β_2DEF overlap the β_1MR factor, which is showed by the high correlation between β_2DEF and β_1MR. This has the consequence that it is hard to capture the systematic β_1MR factor using the Fama & French (1993) model.

All in all, the Fama & French regressions could only provide limited support for the argument of systematic risk in corporate bond returns. It was only after performing statistical test for multicollinearity that the link between the β_1MR factor and the β_2DEF factor was evident, in turn suggesting a strong indication of systematic risk factors being present in the pricing of corporate bond returns. The finding of systematic risk is in line with previous research of e.g. Elton et al., (2001) and Geske & Delianedis, (2001).

7. Conclusion

We have used the Sharpe-Lintner CAPM and the Fama & French (1993) model to understand corporate bond returns. We present five main contributions from this study. These conclusions are based on the analysis performed on the CAPM and Fama & French regressions while answering the following research question:

> *Can the understanding of corporate bond returns be improved by using the Sharpe- (1964) and Lintner (1965) CAPM and the multi-factor model of Fama & French (1993), and if so, in what way?*

1) Our first contribution is the finding that CAPM regressions on corporate bond returns can be improved and understood better by introducing bond market indices to work as the market portfolio proxy. The explanatory power of CAPM applied to corporate bonds was low when doing the regressions the conventional way using the broad stock market index MSCI World as proxy for the market portfolio. When introducing corporate bond market indices as the market portfolio proxy in the CAPM regressions we found similar trends to those we saw in the CAPM regressions using MSCI World as the market portfolio proxy. However, the results and trends that were captured by the CAPM regressions using the bond market indices were more significant and had better explanatory power, and this was especially evident when using Barclays Aggregate Global Corporate Bond Index. We believe that the major reason for the difficulty in applying a broad stock market index (such as MSCI World) as the proxy for the market portfolio when applying CAPM regressions to study corporate bond returns is that doing so will yield β-values that are too close to zero. This in turn will lead to a higher possibility of insignificant regression results and the model capturing a very low fraction of the variability in the corporate bond returns.

2) We find that the model of Fama & French (1993) does a better job in capturing the variability of corporate bond returns than CAPM. When applying CAPM regressions and Fama & French regressions to both the industry and the rating portfolios, the Fama & French model consistently captured more of the variability in corporate bond returns compared to CAPM.

3) The third contribution is the finding that grouping bonds on rating rather than industry captures a higher variability in returns when performing regression analysis. Higher explanatory power was found for Fama & French rating portfolio regressions compared to the Fama & French industry portfolio regressions. A similar trend could not be observed when performing the CAPM regressions.

4) Our fourth contribution is that a significant amount of the market risk factor when performing Fama & French (1993) regressions will likely be hidden in the default factor. Fama & French has specified the default factor to be the difference in return between a long term corporate bond portfolio and a long term government bond portfolio. The Fama & French (1993) specification implicitly assumes that default risk is the sole factor explaining the yield spread between corporate and government bonds, and this notion has been critiqued both intuitively and empirically by subsequent research (e.g. Elton et al., 2001[13]; Geske & Delianedis, 2001; Huang & Huang, 2002).

5) The last finding is that systematic risk is a factor for the pricing of corporate bonds. We base this conclusion on the findings from our CAPM regressions and Fama & French regressions. From the CAPM regressions that were conducted using MSCI World as the market proxy, it was concluded that several of

[13] Elton et al., 2001 argues the most deliberate and outspoken criticism of default risk being the only factor for the difference in pricing between corporate and government bonds.

the examined portfolios were priced with a market factor. A similar but much stronger trend for the importance of the market factor was found when performing the CAPM regressions after changing the market proxy to Barclays Aggregate Global Corporate Bond Index. When performing the Fama & French regressions, a significant market factor was found for several portfolios. We found that there was a large overlap between the market risk factor and the default risk factor when performing the Fama & French regressions. This suggests that the systematic market risk factor is "hidden" within the default risk factor when performing the regressions according to the Fama & French (1993) specifications.

One trend that was noted in our regression but requires further study for better understanding is that the α-values given by the CAPM regressions were consistently positive and similar. A similar trend was not found for the Fama & French regressions. Since a constant risk free interest rate was used for the CAPM regressions, and a varying risk free interest rate was used for the Fama & French regressions, introducing a varying risk free interest rate for the CAPM regressions would be a natural next step for the inquiring researcher. Doing so would lead to an overall better assessment of the general fit of the CAPM, and would also increase the comparability between the CAPM and Fama & French regressions.

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APPENDIX

A. Statistical tests conducted

A.1 Statistical tests and adjustments for the CAPM regressions

The CAPM regressions were tested for autocorrelation and for heteroskedasticity. As significant autocorrelation and heteroskedasticity was indicated, the regression results have been adjusted in accordance with the Newey & West (1987) estimator. Below, we will show how the tests for autocorrelation and heteroskedasticity were performed and how we adjusted for it.

A.1.1. Autocorrelation

Autocorrelation is a statistical problem that can arise if observations of a variable are significantly related to other observations in the same time series (Edlund, 1997). As significant autocorrelation might be a problem in times series data we retrieved the Durbin-Watson statistic for each regression run using SPSS. The statistic computed is a value between zero and four. The Durbin Watson statistic is compared to a range given by limits which depend on the number of explaining variables and observations in the data sample.

With n = 60, one explaining variable and a five percent significance level, the critical Durbin Watson lower limit was 1,549, and the critical Durbin Watson upper limit was 1,616. As Edlund (1997, p. 125) specifies, we can reject the hypothesis that there is no autocorrelation in the sample if either our observed Durbin Watson statistic is less than the Durbin Watson upper limit = 1,616 or if our observed Durbin Watson statistic is greater than (4 – Durbin Watson upper limit) = 4 – 1,616 = 2,384.

Durbin Watson statistic for CAPM regressions based on beta with MSCI World as market proxy		
	Durbin watson	**Autocorrelation**
Portfolio 1	2,031	NO
Portfolio 2	1,958	NO
Portfolio 3	1,929	NO
Portfolio 4	1,790	NO
Portfolio 5	1,852	NO
Portfolio 6	1,796	NO
Portfolio 7	1,749	NO
Portfolio 8	1,706	NO
Portfolio 9	1,578	YES
Portfolio 10	1,432	YES

Table A.1 The Durbin Watson statistic for CAPM regressions based on beta with MSCI World as market proxy shows significant autocorrelation at the 5% significance level for Portfolio 9 and Portfolio 10.

Durbin Watson statistic for CAPM regressions based on beta with BAGG as market proxy		
	Durbin watson	**Autocorrelation**
Portfolio 1	1,902	NO
Portfolio 2	2,405	YES
Portfolio 3	2,550	YES
Portfolio 4	2,563	YES
Portfolio 5	2,716	YES
Portfolio 6	2,489	YES
Portfolio 7	2,367	NO
Portfolio 8	2,562	YES
Portfolio 9	2,464	YES
Portfolio 10	1,449	YES

Table A.2 The Durbin Watson statistic for CAPM regressions based on beta with BAGG as market proxy shows significant autocorrelation at the 5% significance level for all portfolios except Portfolio 1 and Portfolio 7.

Durbin Watson statistic for CAPM regressions based on beta with US Long as market proxy		
	Durbin watson	**Autocorrelation**
Portfolio 1	1,534	YES
Portfolio 2	2,122	NO
Portfolio 3	1,971	NO
Portfolio 4	2,051	NO
Portfolio 5	1,825	NO
Portfolio 6	2,035	NO
Portfolio 7	2,310	NO
Portfolio 8	2,463	YES
Portfolio 9	2,074	NO
Portfolio 10	1,249	YES

Table A.3 The Durbin Watson statistic for CAPM regressions based on beta with US Long as market proxy shows significant autocorrelation at the 5% significance level for Portfolio 1, Portfolio 8 and Portfolio 10.

Durbin Watson statistic for CAPM regressions based on rating with MSCI World as market proxy		
	Durbin watson	**Autocorrelation**
AAA & AA	1,959	NO
A	1,862	NO
BBB	1,796	NO
LG	1,588	YES

Table A.4 The Durbin Watson statistic for CAPM regressions based on rating with MSCI World as market proxy shows significant autocorrelation at the 5% significance level for the Low Grade portfolio.

Durbin Watson statistic for CAPM regressions based on rating with BAGG as market proxy		
	Durbin watson	**Autocorrelation**
AAA & AA	2,110	NO
A	2,478	YES
BBB	2,642	YES
LG	1,631	NO

Table A.5 The Durbin Watson statistic for CAPM regressions based on rating with BAGG as market proxy shows significant autocorrelation at the 5% significance level for the A portfolio and the BBB portfolio.

Durbin Watson statistic for CAPM regressions based on rating with US Long as market proxy		
	Durbin watson	**Autocorrelation**
AAA & AA	2,116	NO
A	2,690	YES
BBB	2,177	NO
LG	1,429	YES

Table A.6 The Durbin Watson statistic for CAPM regressions based on rating with US Long as market proxy shows significant autocorrelation at the 5% significance level for the A portfolio and the Low Grade portfolio.

Durbin Watson statistic for CAPM regressions based on industry with MSCI World as market proxy		
	Durbin watson	**Autocorrelation**
Agriculture, forestry, fishing	2,681	YES
Construction	1,692	NO
Finance, Insurance, Real Estate	1,843	NO
Manufacturing	1,803	NO
Mining	1,761	NO
Retail Trade	1,986	NO
Services	1,795	NO
Transportation, communications, electric, gas and sanitary services	1,662	NO
Wholesale trade	2,154	NO

Table A.7 The Durbin Watson statistic for CAPM regressions based on rating with MSCI World as market proxy shows significant autocorrelation at the 5% significance level for the Agriculture, forestry and fishing portfolio.

Durbin Watson statistic for CAPM regressions based on industry with BAGG as market proxy		
	Durbin watson	Autocorrelation
Agriculture, forestry, fishing	2,911	YES
Construction	2,031	NO
Finance, Insurance, Real Estate	2,361	YES
Manufacturing	2,452	YES
Mining	2,317	NO
Retail Trade	2,157	NO
Services	2,221	NO
Transportation, communications, electric, gas and sanitary services	2,447	YES
Wholesale trade	2,651	YES

Table A.8 The Durbin Watson statistic for CAPM regressions based on rating with BAGG as market proxy shows significant autocorrelation at the 5% significance level for the Agriculture, forestry and fishing portfolio, the Finance, Insurance, Real Estate portfolio, the Manufacturing, the Transportation, communications, electric, gas and sanitary services portfolio and the Wholesale trade portfolio.

Durbin Watson statistic for CAPM regressions based on industry with US Long as market proxy		
	Durbin watson	Autocorrelation
Agriculture, forestry, fishing	2,824	YES
Construction	1,759	NO
Finance, Insurance, Real Estate	1,713	NO
Manufacturing	1,668	NO
Mining	1,826	NO
Retail Trade	1,731	NO
Services	1,765	NO
Transportation, communications, electric, gas and sanitary services	2,225	NO
Wholesale trade	2,465	YES

Table A.9 The Durbin Watson statistic for CAPM regressions based on rating with US Long as market proxy shows significant autocorrelation at the 5% significance level for the Agriculture, forestry and fishing portfolio and the Wholesale trade portfolio.

A.1.2. Heteroskedasticity

One of the underlying assumptions when running a regression is that the error term is constant and independent of the value of the explanatory variables (Edlund, 1997). If this assumption does not hold, the error term is said to be heteroskedastic. Heteroskedasticity might generate misleading results and was therefore tested for running White's general heteroskedasticity test in accordance with Edlund (1997, p.112.) For each CAPM regression conducted, the following regression was run:

Where is the square of the unstandardized residual of the original portfolio regression, is the intercept, is the market risk factor for the different indices and its coefficient and is the market risk factor squared for the different indices squared.

The R^2 value derived when running the regression above was multiplied with the number of observations of 60. The number computed was compared to the critical value of 5,99 which was retrieved from a $\chi 2$-table using two degrees of freedom and 60 observations. Below, the results and calculations are shown.

White's general test for heteroskedasticity on CAPM regressions based on beta with MSCI World as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Portfolio 1	0,369	22,14	5,99	YES
Portfolio 2	0,424	25,44	5,99	YES
Portfolio 3	0,493	29,58	5,99	YES
Portfolio 4	0,468	28,08	5,99	YES
Portfolio 5	0,563	33,78	5,99	YES
Portfolio 6	0,488	29,28	5,99	YES
Portfolio 7	0,576	34,56	5,99	YES
Portfolio 8	0,607	36,42	5,99	YES
Portfolio 9	0,618	37,08	5,99	YES
Portfolio 10	0,311	18,66	5,99	YES

Table A.10 White's general test for heteroskedasticity on CAPM regressions based on beta with MSCI World as market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios.

White's general test for heteroskedasticity on CAPM regressions based on beta with BAGG as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Portfolio 1	0,032	1,92	5,99	NO
Portfolio 2	0,274	16,44	5,99	YES
Portfolio 3	0,341	20,46	5,99	YES
Portfolio 4	0,343	20,58	5,99	YES
Portfolio 5	0,356	21,36	5,99	YES
Portfolio 6	0,327	19,62	5,99	YES
Portfolio 7	0,259	15,54	5,99	YES
Portfolio 8	0,339	20,34	5,99	YES
Portfolio 9	0,244	14,64	5,99	YES
Portfolio 10	0,046	2,76	5,99	NO

Table A.11 White's general test for heteroskedasticity on CAPM regressions based on beta with BAGG as market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios except Portfolio 1 and Portfolio 10.

White's general test for heteroskedasticity on CAPM regressions based on beta with US Long as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Portfolio 1	0,743	44,58	5,99	YES
Portfolio 2	0,538	32,28	5,99	YES
Portfolio 3	0,552	33,12	5,99	YES
Portfolio 4	0,529	31,74	5,99	YES
Portfolio 5	0,536	32,16	5,99	YES
Portfolio 6	0,536	32,16	5,99	YES
Portfolio 7	0,432	25,92	5,99	YES
Portfolio 8	0,236	14,16	5,99	YES
Portfolio 9	0,421	25,26	5,99	YES
Portfolio 10	0,027	1,62	5,99	NO

Table A.12 White's general test for heteroskedasticity on CAPM regressions based on beta with US Long as market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios except Portfolio 10.

White's general test for heteroskedasticity on CAPM regressions based on rating with MSCI as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
AAA & AA	0,141	8,46	5,99	YES
A	0,389	23,34	5,99	YES
BBB	0,592	35,52	5,99	YES
LG	0,373	22,38	5,99	YES

Table A.13 White's general test for heteroskedasticity on CAPM regressions based on rating with MSCI World as market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios.

White's general test for heteroskedasticity on CAPM regressions based on rating with BAGG as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
AAA & AA	0,150	9,00	5,99	YES
A	0,167	10,02	5,99	YES
BBB	0,359	21,54	5,99	YES
LG	0,139	8,34	5,99	YES

Table A.14 White's general test for heteroskedasticity on CAPM regressions based on rating with BAGG as market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios.

White's general test for heteroskedasticity on CAPM regressions based on rating with USL as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
AAA & AA	0,014	0,84	5,99	NO
A	0,095	5,70	5,99	NO
BBB	0,588	35,28	5,99	YES
LG	0,180	10,80	5,99	YES

Table A.15 White's general test for heteroskedasticity on CAPM regressions based on rating with US Long as market proxy indicates significant heteroskedasticity on the 5% significance level for the BBB portfolio and the Low Grade portfolio.

White's general test for heteroskedasticity on CAPM regressions based on industry with MSCI as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Agriculture, forestry and fishing	0,441	26,46	5,99	YES
Construction	0,501	30,06	5,99	YES
Finance, Insurance and Real Estate	0,043	2,58	5,99	NO
Manufacturing	0,571	34,26	5,99	YES
Mining	0,575	34,50	5,99	YES
Retail Trade	0,676	40,56	5,99	YES
Services	0,149	8,94	5,99	YES
Transportation, Communications, Electric, Gas, And Sanitary Services	0,498	29,88	5,99	YES
Wholesale trade	0,518	31,08	5,99	YES

Table A.16 White's general test for heteroskedasticity on CAPM regressions based on industry with MSCI World as market proxy indicates heteroskedasticity on the 5% significance level for all portfolios except the Finance, Insurance and Real Estate portfolio.

White's general test for heteroskedasticity on CAPM regressions based on industry with BAGG as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Agriculture, forestry and fishing	0,207	12,42	5,99	YES
Construction	0,433	25,98	5,99	YES
Finance, Insurance and Real Estate	0,138	8,28	5,99	YES
Manufacturing	0,362	21,72	5,99	YES
Mining	0,193	11,58	5,99	YES
Retail Trade	0,378	22,68	5,99	YES
Services	0,001	0,06	5,99	NO
Transportation, Communications, Electric, Gas, And Sanitary Services	0,312	18,72	5,99	YES
Wholesale trade	0,262	15,72	5,99	YES

Table A.17 White's general test for heteroskedasticity on CAPM regressions based on industry with BAGG market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios except the services portfolio.

White's general test for heteroskedasticity on CAPM regressions based on industry with US Long as market proxy				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Agriculture, forestry and fishing	0,366	21,96	5,99	YES
Construction	0,354	21,24	5,99	YES
Finance, Insurance and Real Estate	0,060	3,60	5,99	NO
Manufacturing	0,526	31,56	5,99	YES
Mining	0,470	28,20	5,99	YES
Retail Trade	0,463	27,78	5,99	YES
Services	0,001	0,06	5,99	NO
Transportation, Communications, Electric, Gas, And Sanitary Services	0,438	26,28	5,99	YES
Wholesale trade	0,307	18,42	5,99	YES

Table A.18 White's general test for heteroskedasticity on CAPM regressions based on industry with US Long as market proxy indicates significant heteroskedasticity on the 5% significance level for all portfolios except the Finance, Insurance and Real Estate portfolio and the Services portfolio.

A.1.3. Applying the Newey-West (1987) estimator

The Newey & West (1987) estimator is a common way of adjusting when there is evidence of significant autocorrelation and heteroskedasticity in a data sample. As we had evidence of both significant autocorrelation and/or heteroskedasticity on the 5% significance level for most of the CAPM portfolios, we chose to incorporate a syntax that made the Newey-West adjustments when performing the regressions in SPSS. The syntax we used was written by Associate Professor at the Center for Economic Statistics at the Stockholm School of Economics Per-Olov Edlund.

A.2 Statistical tests for the modified Fama & French factor model regressions

For the Fama & French regressions, tests were conducted for autocorrelation and heteroskedasticity. Since the Fama & French regressions included three variables, there was also risk for multicollinearity between the explanatory variables. Therefore, tests for multicollinearity were conducted. In similar fashion to the adjustments made for the CAPM regressions, all results were adjusted with the Newey-West (1987) estimator using a syntax attained from Edlund.

A.2.1 Autocorrelation

Autocorrelation is a statistical problem that can arise if observations of a variable are significantly related to other observations in the same time series (Edlund, 1997). As significant autocorrelation might be a problem in times series data we retrieved the Durbin-Watson statistic for each regression run using SPSS. The statistic computed is a value between zero and four. The Durbin Watson statistic is compared to a range given by limits which depend on the number of explaining variables and observations in the data sample.

With n = 60, three explaining variables and a five percent significance level, the critical Durbin Watson lower limit was 1,480, and the critical Durbin Watson upper limit was 1,689. As Edlund (1997, p. 125) specifies, we can reject the hypothesis that there is no autocorrelation in the sample if either our observed Durbin Watson statistic is less than the Durbin Watson upper limit = 1,689 or if our observed Durbin Watson statistic is greater than (4 – Durbin Watson upper limit) = 4 – 1,689 = 2,311.

Durbin watson statistic for Fama & French regressions based on rating		
	Durbin watson	**Autocorrelation**
AAA & AA	2,316	YES
A	2,115	NO
BBB	2,044	NO
LG	1,971	NO

Table A.19 The Durbin Watson statistic for Fama & French regressions based on rating shows significant autocorrelation at the 5% significance level for the AAA & AA portfolio.

Durbin watson statistic for Fama & French regressions based on industry		
	Durbin watson	**Autocorrelation**
Agriculture, forestry, fishing	2,790	YES
Construction	2,129	NO
Finance, Insurance, Real Estate	2,212	NO
Manufacturing	1,572	YES
Mining	1,903	NO
Retail Trade	2,251	NO
Services	1,858	NO
Transportation, communications, electric, gas and sanitary services	2,146	NO
Wholesale trade	2,035	NO

Table A.20 The Durbin Watson statistic for Fama & French regressions based on industry shows significant autocorrelation at the 5% significance level for the Agriculture, forestry, fishing portfolio.

A.2.2. Heteroskedasticity

One of the underlying assumptions when running a regression is that the error term is constant and independent of the value of the explanatory variables (Edlund, 1997). If this assumption does not hold, the error term is said to be heteroskedastic. Heteroskedasticity might generate misleading results and was therefore tested for running White's general heteroskedasticity test in accordance with Edlund (1997, p.112.) For each Fama & French regression conducted, the following regression was run:

Where is the square of the unstandardized residual of the original portfolio regression, is the intercept, is the market risk factor, is the default risk factor, is the interest rate change risk factor, is the market risk factor squared, is the default risk factor squared, is the interest rate change risk factor squared, is DEF and TERM multiplied, is DEF and MR multiplied and which is MR and TERM multiplied.

The R^2 value derived when running the regression above was multiplied with the number of observations of 60. The number computed was compared to the critical value of 16,92 which was retrieved from a χ2-table using nine degrees of freedom and 60 observations. Below, the results and calculations are shown.

White's general test for heteroskedasticity on Fama & French regression based on rating				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
AAA & AA	0,119	7,14	16,92	NO
A	0,670	40,20	16,92	YES
BBB	0,826	49,56	16,92	YES
LG	0,816	48,96	16,92	YES

Table A.21 White's general test for heteroskedasticity on Fama & French regression based on rating shows significant indications of heteroskedasticity at the 5% significance level for all portfolios except for the AAA & AA portfolio.

White's general test for heteroskedasticity on Fama & French regression based on industry				
	R^2	χ^2 Obs ($n*R^2$)	χ^2 Critical 5%	Heteroskedasticity
Agriculture, forestry and fishing	0,708	42,48	16,92	YES
Construction	0,713	42,78	16,92	YES
Finance, Insurance and Real Estate	0,245	14,70	16,92	NO
Manufacturing	0,824	49,44	16,92	YES
Mining	0,541	32,46	16,92	YES
Retail Trade	0,787	47,22	16,92	YES
Services	0,729	43,74	16,92	YES
Transportation, Communications, Electric, Gas, And Sanitary Services	0,810	48,60	16,92	YES
Wholesale trade	0,551	33,06	16,92	YES

Table A.22 White's general test for heteroskedasticity on Fama & French regression based on industry shows significant indications of heteroskedasticity at the 5% significance level for all portfolios except for the Finance, Insurance and Real Estate portfolio.

A.2.3. Applying the Newey-West (1987) estimator

The Newey & West (1987) estimator is a common way of adjusting when there is evidence of significant autocorrelation and heteroskedasticity in a data sample. As we had evidence of both significant autocorrelation and/or heteroskedasticity on the 5% significance level for most of the Fama & French portfolios, we chose to incorporate a syntax that made the Newey-West adjustments when performing the regressions in SPSS. The syntax we used was written by Associate Professor at the Center for Economic Statistics at the Stockholm School of Economics Per-Olov Edlund.

A.2.4. Tests for multicollinearity

In order to assure that the variables don't capture the same effect on the dependent variable the model was tested for multicollinearity. We do this in two ways. First we look for a high R^2 and none or few significant variables and secondly we look at the correlations between the explanatory variables.

Edlund (1997, p.84) says that there is risk for multicollinearity if the model has a R^2 above 0,8 in combination with few or no significant variables. This is not the case of any of our Fama & French regressions which can be seen in the tables below. We can therefore not indicate significant multicollinearity in our industry or rating sample.

Value of R^2 for modified Fama & French regressions based on industry				
Portfolio	R^2	nwp(β_1MR)	nwp(β_2DEF)	nwp(β_3TERM)
Agriculture, forestry and fishing	0,354	0,2334	0,0862	0,0082
Construction	0,599	0,3451	0,0001	0,0004
Finance, Insurance and Real Estate	0,731	0,0181	0,0000	0,0000
Manufacturing	0,734	0,0219	0,0000	0,0000
Mining	0,672	0,2123	0,0002	0,0000
Retail Trade	0,537	0,2864	0,0000	0,0096
Services	0,651	0,0316	0,0257	0,0000
Transportation, Communications, Electric, Gas, And Sanitary Services	0,795	0,8455	0,0000	0,0000
Wholesale trade	0,487	0,3793	0,0017	0,0000

Table A. 23 Value of R^2 for modified Fama & French regressions based on industry does not indicate significant multicollinearity.

Value of R^2 for modified Fama & French regressions based on rating				
Portfolio	R^2	nwp(β_1MR)	nwp(β_2DEF)	nwp(β_3TERM)
AAA & AA	0,898	0,8978	0,0000	0,0000
A	0,88	0,9750	0,0000	0,0000
BBB	0,738	0,7057	0,0000	0,0000
LG	0,682	0,4976	0,0000	0,0142

Table A. 23 Value of R^2 for modified Fama & French regressions based on rating does not indicate significant multicollinearity.

In addition to investigate for multicollinearity by looking at the R^2 and the number of significant variables, we look at the correlations between the explanatory variables. Edlund (1997, p. 85) say that one correlation of at least 0,8, or several values over 0,5 indicate multicollinearity. We have no values over 0,8 and only one over 0,5. Consequently, there is no reason to assume multicollinearity.

Coefficient correlations for the explanatory variables in the modified Fama & French regressions			
	β_3TERM	β_1MR	β_2DEF
β_3TERM	1,000	-0,143	0,455
β_1MR	-0,143	1,000	-0,685
β_2DEF	0,455	-0,685	1,000

Table A. 24 Coefficient correlations for the explanatory variables in the modified Fama & French regressions does not indicate significant multicollinearity.

B Adjustments

B.1 Excluded bonds

Bonds excluded due to risk of illiquidity	
AES CHIVOR 2004 9 3/4% 30/12/14 REG.S	ENCANA CORP. 2003 4 3/4% 15/10/13 S
AES GENER 2005 7 1/2% 25/03/14 S-B	FORD MOTOR COMPANY 1998 6 5/8% 01/10/28 S
ALCATEL LCT.USA INC 1999 6.45% 15/03/29 S	FORD MOTOR COMPANY 1999 6 3/8% 01/02/29 S
AMGEN INCO. 2005 4.85% 18/11/14 S-B	HP ENTERPRISE SVS. 1999 7.45% 15/10/29 S
ANIXTER INCO. 2005 5.95% 01/03/15 S	KELLOGG 2001 7.45% 01/04/31 S-B
ASTRAZENECA 2004 5.4% 01/06/14 S	KELLWOOD 1997 7 5/8% 15/10/17 S
BARRICK GOLD FIN. 2004 5.8% 15/11/34 S	KIMBERLY CLARK CORP 2005 4 7/8% 15/08/15 S
BELO CORPORATION 1997 7 1/4% 15/09/27 S	MACYS RET.HDG.INCO. 1998 7% 15/02/28 S
BELO CORPORATION 1997 7 3/4% 01/06/27 S	MASCO CORP. 1998 6 5/8% 15/04/18 S
BLYTH INCORPORATED 2003 5 1/2% 01/11/13 S	NEW ALBERTSONS INCO 1998 6.57% 23/02/28 S-C
BOTTLING GROUP LLC 2003 4 5/8% 15/11/12 S-B	PITNEY BOWES INCO. 2003 3 7/8% 15/06/13 S
BRUNSWICK CORP. 1993 7 3/8% 01/09/23 S	QANTAS AIRWAYS LTD. 2003 5 1/8% 20/06/13 S
BRUNSWICK CORP. 1997 7 1/8% 01/08/27 S	QANTAS AIRWAYS LTD. 2006 6.05% 15/04/16 REG.S
CANADIAN NAT.RY. 2001 7 3/8% 15/10/31 S	RITE AID CORP. 1996 7.7% 15/02/27 S
CBS CORP. 2000 7 7/8% 30/07/30 S	RITE AID CORP. 2003 9 1/4% 01/06/13 S
CBS CORP. 2003 5 1/2% 15/05/33 S	ROYAL CRBN.CRUISES 2006 7 1/4% 15/06/16 S
CDN.NTRL.RES.LTD. 2002 7.2% 15/01/32 S	SIX FLAGS ENTM. 2003 9 3/4% 15/04/13 DEFAULT
CELL C PTY.LTD. 2005 11% 01/07/15 REG.S	SIX FLAGS ENTM. 2004 9 5/8% 01/06/14 DEFAULT
CHESAPEAKE ENERGY 2006 7 5/8% 15/07/13 S	TENET HEALTHCARE 2002 6 7/8% 15/11/31 S-B
COMPANHIA BRASL. 2003 8 3/4% 15/09/13 REG.S	TENET HEALTHCARE 2003 7 3/8% 01/02/13 S
CONOCOPHILLIPS CO. 1999 6.95% 15/04/29 S	TENET HEALTHCARE 2005 9 7/8% 01/07/14 S-B
CONSUMERS ENERGY CO 2005 5.8% 15/09/35 S	THOMSON REUTERS 2003 5 1/4% 15/08/13 S
CORNING INCO. 1993 6 3/4% 15/09/13 S	TYSON FOODS INCO. 1998 7% 15/01/28 S
CROWN HDG.INCO. 1996 7 1/2% 15/12/96 S	UNION PAC.RAILROAD 1955 5% 01/01/45
DENBURY RES.INCO. 2004 6 1/4% 15/04/14 S	VERIZON NEW YORK 2002 7 3/8% 01/04/32 S-B
DENBURY RES.INCO. 2005 6% 15/07/15 S-B	VERIZON VIRGINIA 2003 4 5/8% 15/03/13 S
DENBURY RES.INCO. 2005 7 1/4% 01/12/17 S	VODAFONE GROUP 2002 6 1/4% 30/11/32 S
DOMTAR INCORPORATED 2003 5 3/8% 01/12/13 S	WALT DISNEY 2002 7% 01/03/32 S-B
EASTMAN CHM.CO. 1994 7 5/8% 15/06/24 P06/06	WALT DISNEY 2006 5 5/8% 15/09/16 S-C
ELI LILLY 2003 4 1/2% 15/03/18 S	WOOLWORTHS LTD. 2005 5.55% 15/11/15 REG.S
EMBRAER OVERSEAS 2006 6 3/8% 24/01/17 REG.S	

Bonds excluded due to insufficient data points
CENTURYLINK INCO. 2005 5% 15/02/15 S-M
EMBRAER OVERSEAS 2007 6 3/8% 24/01/17 S
HYUNDAI MOTOR MANUF 2005 5.68% 25/04/15 REG.S
LOMA NEGRA CIA.ARGN 2006 7 1/4% 15/03/13 REG.S
MACYS RET.HDG.INCO. 1997 7.45% 15/07/17 S
OKLAHOMA GS.&.ELEC. 2006 5 3/4% 15/01/36 S
OKLAHOMA GS.&.ELEC. 2006 5.15% 15/01/16 S
SUNCOR ENERGY INCO. 2005 5.95% 15/05/35 S

Table B.1 A list of bonds that were excluded from the data sample when performing regressions.

B.1.1 Case of point bond excluded for signs of illiquidity

Consider the below example of two similar corporate bonds of the same underlying company. With a gap of slightly more than one year, Alcatel Lucent issued bonds with 30 years to maturity with only a 0,05% difference in coupon. Consequently, one would expect very small price differences between the two bonds. This is also seen when looking at the price of the two bonds between 2007-08-31 and 2008-04-30.

	2007-08-31	2007-09-28	2007-10-31	2007-11-30	2007-12-31	2008-01-31	2008-02-29	2008-03-31	2008-04-30
ALCATEL LCT.USA INC 1998 6 1/2% 15/01/28 S	84	83	83,5	80,5	82,625	80,5	75	71,5	75
ALCATEL LCT.USA INC 1999 6.45% 15/03/29 S	84,05	84,05	83,5	83,5	83,5	83,5	83,5	83,5	74,87

Table B.2 A table showing the prices of the two very similar Alcatel Lucent bonds from 2007-08-31 to 2008-04-30 suggest small price differences.

When considering for the same two bonds for the nine directly subsequent months however, a different trend can be seen. From 2008-05-30 to 2009-01-30, the overall price difference grows significantly as the price of the Alcatel Lucent bond issued in 1998 drops sharply at the same time as the one issued in 1999 does not change. Finally, in January 2009 a very sharp decline is recorded in the bond issued in 1999. We deem it self-evident that it is more likely that the 1999 bond was not traded for several months before a trade in January finally moved the price, rather than the months of no price movements reflecting actual transaction prices. This pattern is a clear sign of illiquidity in the underlying bond, and the 1999 bond has therefore been excluded from our data sample.

	2008-05-30	2008-06-30	2008-07-31	2008-08-29	2008-09-30	2008-10-31	2008-11-28	2008-12-31	2009-01-30
ALCATEL LCT.USA INC 1998 6 1/2% 15/01/28 S	76	76,5	70,5	69,5	61	49	40	39	33,5
ALCATEL LCT.USA INC 1999 6.45% 15/03/29 S	77	77	77	77	77	77	77	77	42,8099

Table B.3 A table showing the prices of the two very similar Alcatel Lucent bonds from 2008-05-30 to 2009-01-30, the increasing price difference movements between the two bonds suggest an evident pattern of illiquidity.