ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Master Specialisation Financial Economics

The missing puzzle piece in credit spreads:

An extensive analysis on historical tail risk and default dependence within European corporate bond markets

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Finish date: June 2018

PREFACE AND ACKNOWLEDGEMENTS

In an ambitious strive to possibly deliver a small contribution to the solution of the credit spread puzzle, I am satisfied with the results. I regret deeply not having more time to investigate further robustness of the results and having more time to perform in depth analysis on the main components of the models as well as the main components of the residuals. Nonetheless, this research has already gotten a little bit out of control, so perhaps it is best that this is left for further research anyways. I wholeheartedly thank supervisor Jan Lemmen for letting me freely chase whatever it was I was chasing for, and for the support in the process of writing the thesis. Especially remarks relating to the structure of the thesis have helped tremendously. Finally, we thank Carina van der Zee for the mental support during the writing of this research.

ABSTRACT

This research investigates the role of default dependence in credit spreads. We introduce several variables that proxy for default dependence. These variables introduced are the discrete default correlation, the time to default correlation and the yield correlation. After introducing these variables, they are tested one by one in a credit spread change factor model that strongly resembles that of Collin-Dufresne et al. (2001) and implements several unique as well as common factors. We find that of our introduced variables that proxy default dependence, yield correlation shows significant results for the extreme Spearman correlation and the tail dependence coefficient. From these results it becomes clear that the most extreme yield observations, that are those likely of firms in financial distress or recovering from financial distress, are a good proxy for default dependence. We report a high level of significance and large negative effect sizes for the former mentioned default dependence proxies. We provide strong evidence that the negative effect sizes are not attributable to multicollinearity but can possibly be explained through a result by Das et al. (2007); default intensity effects might outweigh default dependence effects. Although we do report a high level of significance for the former mentioned default proxies, they do not increase the explanatory power of the model as measured by the adjusted R^2. Concluding from these results, we have to answer indifferently to our research question; we do not offer conclusive evidence that historical default dependence structures are a missing puzzle piece in explaining the credit spread puzzle.

Keywords: Credit spreads, default dependence, factor model, Fama-MacBeth regression

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CHAPTER 1 Introduction

Under influence of unconventional monetary policy (UMP) by the European Central Bank (ECB) and the Federal Reserve Bank (FED) credit spreads have fluctuated substantially. Moreover, commonly known determinants of credit spreads such as the term structure and overall business climate have drastically changed since the US housing crisis and the Eurozone sovereign bond crisis in 2011. As credit spreads have fluctuated in size, there has not been an answer to why the credit spread premium is nearly always larger than the loss given default (LGD) of a given bond multiplied with its respective probability of default, which illustrates the credit-spread puzzle. This research focuses on discovering whether historical default dependence structures might be a missing puzzle piece in explaining European public corporate debt credit spread changes.

A credit spread is defined as the amount of yield basis points of a corporate bond over a government bond with equal original maturity. It is known to reflect the level of risk associated with fixed income instruments. Therefore, it is of the utmost importance for risk-averse institutional investors such as pension funds or insurance companies to understand what drives these credit spreads. In doing so, risk-averse institutional investors will be able to properly estimate the risk associated with their portfolio. Not only risk-averse investors benefit from properly understanding fixed income markets; as risk-premiums in fixed income markets increase/decrease, interest in substitution asset classes such as stocks is known to increase/decrease in opposite direction. Following this substitution effect, risk-seeking investors will be able to generate a higher risk-adjusted return by properly understanding fixed income markets. Finally, a proper understanding of credit spreads is essential for solid monetary policy. Monetary policy in Europe is solely aimed at price stability, i.e. inflation. Nonetheless, price stability should not supersede market efficiency, which will occur with inappropriate monetary policy.

Default dependence reflects the degree to which defaults can be expected to occur simultaneously. That is, if default dependence is high, one single default is expected to be followed by another default. In contrast, when default dependence is low, a single default is not likely to be followed by more defaults. It is argued here that there should be a default dependence premium because investors are exposed to a higher level of risk if default dependence is high. As such, if a portfolio of bonds is characterized by high default dependence, there is a considerable probability that multiple bonds default simultaneously, thus causing what can be seen as an extreme loss. To be compensated for the possibility of such extreme losses associated with high default dependence, investors would require a default dependence premium. It is expected that this premium is incorporated in the credit spread, because this additional risk cannot be diversified. This could be an important, currently unaccounted for, premium in the credit spread puzzle. This is the intuition to our general research question:

Are historical default dependence structures a significant missing puzzle piece in explaining the credit spread puzzle?

In addressing the role of historical default dependence in explaining variation within credit spread changes, we need to know what other factors influence credit spread changes. We therefore explore existing literature on the status of common and unique factors that influence credit spreads. Existing factor models explaining changes in credit spreads such as Collin-Dufresne, Goldstein, and Martin (2001) and Avramov, Jostova & Philipov (2007) cover a wide range of factors, but to this date there is no factor model with default dependence as individual factor. Nearly all literature relating to credit spreads and default dependence is focused on default correlation, which is a linear measure for co-moving default. Default, by definition, is an extreme event which means that these observations are in the tails of a probability distribution. Co-dependence in tail observations is not necessarily linear and we strive to address default dependence according to alternative non-linear structures as well. To this end, several dependence measures are discussed, ranging from linear to non-linear dependence measures. These measures are the Pearson correlation, the Spearman correlation, extreme variants of these measures, and the tail dependence coefficient. These measures are applied to three variables in approximating default between all pairs of credit instruments in our sample, leading to the discrete default correlation, the time to default correlation, and a derivative of standard asset correlation, the yield correlation. After having implemented the default dependence measures, the historical dependence structure is incorporated as a factor in a time-series factor model at every point in time for roughly 5000 individual public European corporate bonds from the 1st of January 2000 until the 1st of January 2016. Using the Fama-MacBeth (1973) two-step approach, these individual bond regression results are then aggregated, after which the explanatory power of historical default dependence in historical credit spreads is investigated.

We find that of our introduced variables that proxy default dependence, yield correlation shows significant results for the extreme Spearman correlation and the tail dependence coefficient. From these results it becomes clear that the most extreme yields observations, that are those likely of firms in financial distress or recovering from financial distress, are a good proxy for default dependence. We report a high level of significance and large negative effect sizes for the former mentioned default dependence proxies. We offer evidence of the unattributability of multicollinearity for the findings of negative effect sizes, but offer an alternative explanation through findings of Das et al. (2002), which might indicate that default intensity effects outweigh default dependence effects. Although we do report a high level of significance for the former mentioned default proxies, they do not increase the explanatory power of the model as measured by the adjusted R^2. Concluding from these results, we have to answer indifferently to our research question; we do not offer conclusive evidence that historical default dependence structures are a missing puzzle piece in explaining the credit spread puzzle.

This paper adds to existing literature in several ways. Firstly, we show the significance of historical default dependence in credit spread changes for several of the considered default dependence measures. To our knowledge, no premium on default dependence has been reported in credit spreads and we provide evidence on the existence of such a premium. Secondly, we consider a wide range of both linear and non-linearity measures for default dependence complementing the standard default correlation that is generally considered in the literature. These methods to assess default dependence closely resemble methods developed by Li (2000), which include the discrete default correlation, the time to default correlation, and a derivative of standard asset correlation, the yield correlation. Third, much research has been done on default dependence, but the only paper to our knowledge quantifying default dependence is that of Das, Freed, Geng & Kapadia (2002). This paper uses 7000 US firms' equity to determine default dependence through asset correlation, whereas this research focusses on quantifying default dependence by using European public corporate debt. Not only quantifying default dependence but also implementing such a structure in a time series-model as well as applying cross-section regression is to our knowledge a fully unexplored area of literature. The model most closely resembling the model used in this research is that of Collin-Dufresne, Goldstein and Martin (2001), which is according to literature, the most prominent model in estimating credit spread changes. Here the authors estimate credit spread changes using individual bond regressions by averaging coefficients and standard errors. In this paper we improve upon the method of aggregating results by implementing a two-step approach from Fama-MacBeth (1973), which is far more respected in scientific research than averaging individual regression coefficients and standard errors.

The rest of this paper is organized as follows. In chapter 2 we examine literature on the developments of factors and models explaining either credit spreads or credit spread changes, default correlation and non-linear default dependence structures and models. Chapter 3 offers theoretical insights in how default dependence can be measured and the construction of our default dependence measures. Finally, chapter 3 offers a small intuition on what the risk components of a default dependence premium might be. In chapter 4, a general model in explaining credit spread changes and a model including the default dependence factor is introduced and a description of the dataset is given. Chapter 5 will show results for both models mentioned in chapter 4. Finally, we conclude in chapter 6.

CHAPTER 2 Literature Review

The aim of this research is to investigate the impact of historical default dependence on credit spreads. Therefore, introducing a model in which the default dependence factor is tested is of great importance. Having a solid framework to introduce the default dependence factor will increase precision and significance. Furthermore, by creating an exhaustive factor model for credit spread changes, it will be possible to dissect where the variation in credit spread changes is actually stemming from. Nonetheless, the focus of this research is on establishing whether default dependence has a role in credit spreads and how this should be measured. Therefore, we will first discuss literature on default dependence. Thereafter, we will elaborately discuss literature on unique and common factors.

2.1 Default dependence literature

As mentioned in the introduction, the aim of this research is to investigate the effect of default dependence on the credit spread. Default dependence reflects the degree to which defaults co-occur. When there is high default dependence, defaults are likely to co-occur, and vice versa. Investors are likely to demand a compensation in carrying an increased level of default dependence risk. This is because the probability of an extreme portfolio loss increases substantially when default dependence is high and investors will require a default dependence premium to carry such an increased extreme loss risk. It is expected that this premium is incorporated in the credit spread and is part of the more general default risk premium. It is already known that the default risk premium consists of a multitude of premiums. Our argument is that there is no recognized premium (yet) for default dependence (see Figure 1). In order to better understand the possible effect of default dependence, this section covers existing literature on default dependence.

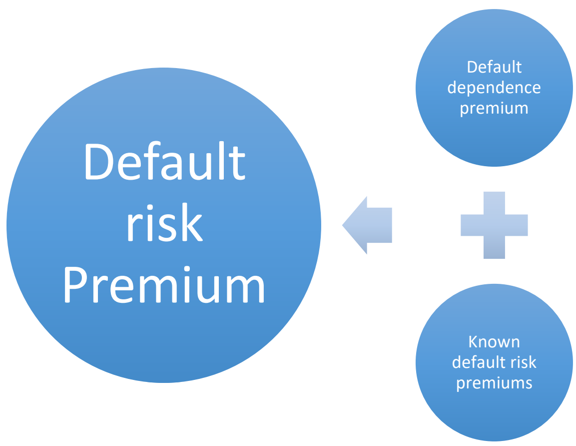


Figure 1: Possible structure of the default risk premium with default correlation included.

2.1.1 Developments in default dependence

Although default dependence has not been incorporated in a factor model to explain credit spreads, there exists a lot of research on the phenomenon of dependent defaults. Lucas (1995) is the first to mention and model default correlation. The author starts off by stating that default correlation is the event that a creditors' default triggers the default of its lender. This is an idiosyncratic risk view of looking at default dependence; a creditors' default triggers the default of the lender. This is a one-to-one firm relation, but has no relation to the rest of the market. However, Lucas (1995) then states that default correlation could also be triggered by a market-wide event, a so-called "aggregate shock". This implies not a relation between Firm A and Firm B, but a relation of firm A and firm B with the market-wide event, named here F. Market wide triggers for default are, e.g., financial recessions or a stock market collapse. In contrast, idiosyncratic risk factors are amongst others common geographical location and common production inputs. By looking at default correlation in a way where we differentiate between market-wide triggers for default and specific default triggers, we are basically dissecting the idiosyncratic and systematic risk component. Although one could argue that idiosyncratic risk should be equal to individual firm risk, Lucas (1995) approximates idiosyncratic risk factors as risk factors that are not inherent for the entire market but for so-called "niches". Therefore, one could argue that there is also a certain form of systemic risk in these idiosyncratic risk factors and therefore, also between these idiosyncratic risk factors. One example of this could be common production inputs: not all firms use steel as production input so it is an idiosyncratic risk. Nonetheless, if one firm in the steel industry defaults it might affect other firms in the steel industry, indicating systemic risk in this idiosyncratic risk factor. Finally, when several firms in the steel industry default, another idiosyncratic risk factor such as the production of Harley-Davidson's could be influenced. It is therefore argued that there is also systemic risk in and between idiosyncratic risk factors.

Although these risk components are similar to those of other financial products, default risk is a one-sided extremity. This means that in general, a portfolio of equities can be easily diversified because some equities will have extreme losses while others have extreme profits. With bonds this is not the case, as extreme profits are barely never the case, and all that remains are extreme losses. Because of this asymmetry, idiosyncratic default risk is just as systematic default risk, non-diversifiable. The non-diversifiable risk in such bond portfolios might carry a substantial premium, as the risk and size of extreme losses increases with the size of the portfolio. Lucas (1995) puts his theories to the test by investigating joint default probabilities and joint default correlation by looking at extremely safe debt, being letter of credit (LOC)-backed debt. This is also known as an irrevocable guarantee of an issuers debt by a creditworthy bank, thus minimizing counterparty credit risk. Lucas (1995) shows that historical default probabilities and default correlations are lower than default predicted by ratings would suggest. This in turn implies that investigating default probabilities and default correlation using an implied ratings-based approach will yield biased results.

Li (2000) provides a strong alternative for the abovementioned implied ratings-based approach to obtaining default probabilities and default correlation. The author suggests using a current market price implied approach rather than looking at historical default rates and their accompanied credit ratings. Using a contemporary market price based approach offers several advantages. First, current market prices are forward looking, i.e. prices are determined by the agreed upon perception of the future state of the market. Such future-implied prices imply much different current default rates then when implied from historical default rates. Second, ratings are given to firms by category. For example, firms within the healthcare industry are often labelled with a specific rating. A large drawback here however, is the fact that firm idiosyncratic risk is largely ignored in intra-category rating. Finally, default probabilities available from rating agencies are often the one-year default probability. Default probabilities, however, have not been shown to be necessarily stable over longer time periods.

Embrechts et al. (1999) show that there is a lot of misinterpretation about correlation. He points out that in finance and insurance, correlation is often used to cover any form of dependence, while correlation is only able to capture the dependence of linear relationships. There are however, many dependence structures that are fully or at least partially non-linear. Among those, as stated by Giesecke (2003), is also default "correlation". One could imagine that if there are 4 firms in the same industry, being firm A, B, C, D, that there would be a certain correlation to their defaults. This default correlation would change however when for example firm A would default, as the probability of firm B, C, D defaulting as a consequence of A's default increases. For obvious reasons, when firm B would default after the default of firm A, the probability of default that either firm C, D or both would default will see a stronger increase than when only firm A had defaulted, and so on. In short, there is non-linear dependence between defaults of multiple firms, not to mention the non-linear dependencies between factors linked to default such as recovery rates, hazard rates, and counterparty credit risk. Embrechts et al. (1999) show that observations stemming from the tail of a distribution have a non-linear dependence rather than a linear correlation. As default is an extremity and a very unlikely event, and therefore likely has a non-linear relation, we will from here on refer to default correlation as default dependence. Furthermore, Giesecke (2003) also shows how to model non-linear default correlation through the use of a so-called Copula function. This is however beyond the scope of this paper, but interesting for further research.

2.1.2 Empirical findings on default dependence related to credit spreads

Default dependence is the degree to which one default depends on another default. That is, if default dependence is high, one default is likely to be followed by another. Investors are likely to ask for a higher compensation of risk on their bonds when default dependence is high, as they carry an increased level of risk as opposed to when default dependence is low. A high level of default dependence strongly increases the probability of multiple defaults and increases the probability of an extreme loss, which will require compensation by investors. It is expected that this premium is incorporated in the credit spread. This premium might be of such a size, that it could provide an alternative explanation to the credit spread puzzle.

The credit spread puzzle is what is known as the gap between credit spreads and their associated expected default losses. For example, one would expect that if a credit spread were to exist purely to compensate for default, the credit spread be as large as the expected default loss. In practice, spreads are on average far larger than their associated default risk as in Amato & Remolona (2003), shown in Table 1:

Spreads and expected default losses[1]

Rating	Maturity							
	1–3 years		3–5 years		5–7 years		7–10 years	
	Spread	Expected loss	Spread	Expected loss	Spread	Expected loss	Spread	Expected loss
AAA	49.50	0.06	63.86	0.18	70.47	0.33	73.95	0.61
AA	58.97	1.24	71.22	1.44	82.36	1.86	88.57	2.70
A	88.82	1.12	102.91	2.78	110.71	4.71	117.52	7.32
BBB	168.99	12.48	170.89	20.12	185.34	27.17	179.63	34.56
BB	421.20	103.09	364.55	126.74	345.37	140.52	322.32	148.05
B	760.84	426.16	691.81	400.52	571.94	368.38	512.43	329.40

[1] In basis points. Spreads are averages over the period January 1997–August 2003 of Merrill Lynch option-adjusted spread indices for US corporate bonds. See text for details on computation of expected loss.

Sources: Altman and Kishore (1998); Bloomberg; Moody's Investors Service; authors' calculations. Table 1

Table 1: The Table shows that credit spreads have far exceeded their associated losses.

The solution to this puzzle is often sought in the codependence of possible defaults. Codependence of defaults could be a strong explanation for the gap between the maximum explained variation of the default component in credit spread changes as in Collin-Dufresne et al. (2001) and the theoretical size of the default components as in Longstaff et al. (2005). As mentioned before, several papers including Amato & Remolona (2003) have pointed out that default risk is a one-sided event, which yields substantial undiversifiable risk. With the suggestion that default risk cannot be diversified, also came the idea that systematic default risk cannot be diversified. Amato & Remolona (2003) argue that this undiversifiable systematic default risk might well be the largest part of the credit spread, as without full diversification, unexpected systemic losses will be priced in credit spreads. However, how clear the importance of default dependence seems to be, there is very few actual research because of its complexity.

Das, Freed, Geng, & Kapadia (2002) are the first to quantify default correlation. They use a sample of 7000 US firms over the period 1987-2000 to investigate joint default risk using firm-level default probabilities. Their research provides multiple interesting findings regarding joint default risk. Firstly, they show that individual default probabilities vary over time, mostly because of their associated links to business cycles. Secondly, they show that there are cross-sectional differences between rating classes; firms with higher credit quality have higher default correlations. This is intuitive; firms that are very unlikely to default will have large dependence on each other when one does default, Lehman Brothers as one of the most prominent examples. Third, default intensities also vary over time. This means that even if individual default probabilities would remain equal to their former values, it would not mean that their associated loss would also remain equal. Finally, it is shown that asset correlation varies over time and therefore so must default correlation.

Das, Duffie, Kapadia & Saita (2007) point out that the former four important results have implications for previous work on default risk in credit spreads; Credit spreads vary over time due to the fact that individual default probabilities vary over time with business cycles. Second, credit spreads may widen not because of an increase in default risk but due to an increase in default intensity. Finally, Das et al. (2007) show that during a downturn not only default probabilities increase but also default correlation.

Duffie, Saita & Wang (2007) use over 28000 individual firm quarterly observations of data for the period of 1971 to 2001 in the US industrial machinery and instrument sector to model conditional corporate bankruptcy probabilities. In accordance with work of Das et al. (2002) they show that hazard rates in the industrial machinery and instrument sector depend heavily on the overall state of the economy and the current leverage of the firm. They do point out that for some firms, the variation in distance to default has a greater relative effect than a change in the business-cycle. We like to note here that this can be explained through an idiosyncratic-risk way of thinking; some firms might have relatively short lifespans, not even passing a full business cycle.

Several other papers show the existence of a correlation of default probabilities, default intensity, and default correlation with business cycles. However, these are all based on the linear measure for dependence called "correlation". Fama (1965) is among the first to introduce that asset returns are non-normally distributed and Das, Freed, Geng, & Kapadia (2002) show that credit asset returns also behave non-normal. Moreover, credit asset returns also tend to show asymmetric dependence possibly due to the lack of extreme profits with credit assets.

Crook & Moreira (2011) introduce modelling default dependence through copulas on a portfolio of consumer loans of a large UK bank. The authors model ten different copula families to find the most representative dependence structure. Their results show that compared to traditional linear models the copula model outperforms. The model outperforms in a way that loan losses closer resemble reality than a linear model does, implying credit tail dependence does follow an asymmetric dependence structure rather than a linear one.

The default dependence factor is developed after arguments by Driessen (2002), Amato & Remolona (2003), and Collin-Dufresne et al. (2001) who argue that there is a missing puzzle piece in the credit-spread puzzle. This puzzle is disentangled into two parts largely recognized by literature, being the liquidity premium and the default risk premium. The liquidity premium has been addressed extensively and explaining more variation in credit spreads through liquidity premium adjustments will be exhaustive and of little added value, as past results have already been strong. The default risk premium nonetheless, has been less able to properly explain variation in credit spreads. Driessen (2002) argues that this is because default dependence risk might not be properly addressed and defaults might not be independent. Although much literature on credit-spreads disagrees with Driessen (2002) as to the attribution of the remaining puzzle piece to the financial health of a bond, no solid research has been done on the effect of dependence of defaults in credit spreads. Through a combination of demand from within literature on default dependence and in an attempt to solve or contribute to one of economics longest standing puzzles, the credit spread puzzle, it is argued that it would strongly add to literature to construct a default factor based on default dependence. This leads us to *hypothesis 1*:

The default dependence factor is significant in explaining a portion of the variation in a portfolio of European public corporate bonds' credit spread changes and a significant premium can be found for the historical default dependence structure

2.2 Common factor literature

Fama and French (1993) are one of the first to introduce the existence of certain "common" factors in bond and equity returns. Such common factors have a similar size for every individual bond or stock in a certain market or dataset. Because of this characteristic, it becomes very clear how a dependent variable can be explained. Fama and French (1993) argue that because of the linkage between stock market returns and bond market returns, there is not truly something called bond or equity-common factors. We will not only discuss developments on the factors themselves, but also on some of the cross-usage of factors between bond and equity markets.

Term and default

The first common factors are introduced in Fama and French (1993), who introduce the existence of certain "common" factors in bond and equity returns. Since their ground-breaking research, a lot of work has been done on equity factors. Less emphasis, however, has been put on the bond-factor perspective. Fama and French (1993) introduce two specific bond-market factors. They start off by introducing a factor labelled *TERM*, which is the difference between the mont1hly long term government bond return and one-month Treasury bill rate measured at the end of the previous month. Their intuition is that the Treasury rate should reflect the long term return on bonds, thus implying that the *TERM* factor will capture any unexpected deviation in the long term return due to changes in short term interest rates.

Trück, Laub & Rachev (2004) show that the term structure of bonds is a large determinant of its credit spread. The authors argue that the direction of the yield curve gives a good overview of the credit market as a whole in periods to come, which implicitly determines the value of the credit in the future. Furthermore, the authors show that different durations react differently to this term structure; The higher the duration, the lower the sensitivity of the bond to the term structure of yields, and the smaller the impact of the term structure on a given bonds' credit spread. Trück et al. (2004) conclude their research with a positive relation between maturity and credit spreads for investment grade debt, and are unable to draw any conclusions on their high-yield data sample regarding maturity and spreads.

The other factor introduced by Fama and French (1993) is a "default factor" labelled *DEF*. The factor is constructed through the difference between the return on a market portfolio of long term corporate bonds and the long term government bond return. The intuition here is that the difference as mentioned above, is a compensation for risks taken by selecting bonds that are not exactly similar to bonds that match the long term expected return. What is interesting here, is that Fama and French (1993) argue that this compensation, as measured my abovementioned difference, is purely for heightened default risk. It is argued here that there are a multitude of other risks that could be involved in this compensation. Therefore, the risk premium as mentioned above, measures *all* risks involved in taking on a bond or bond portfolio that does not exactly match the long term government bond return. To create a factor that solely captures a default premium, a different kind of approach would be necessary. Another important remark here is that, although long term government bonds are often regarded as the safest bonds, they are never default risk-free. This means that the part of the default risk in government bonds is not taken into account in the factor. One might argue that default rates of government bonds are low and negligible, but their rates do vary over time with the most recent example being sovereign government bonds from countries such as Greece, Italy, or Portugal. The government 10-year government bond yields for the Greece are shown in Figure 2.

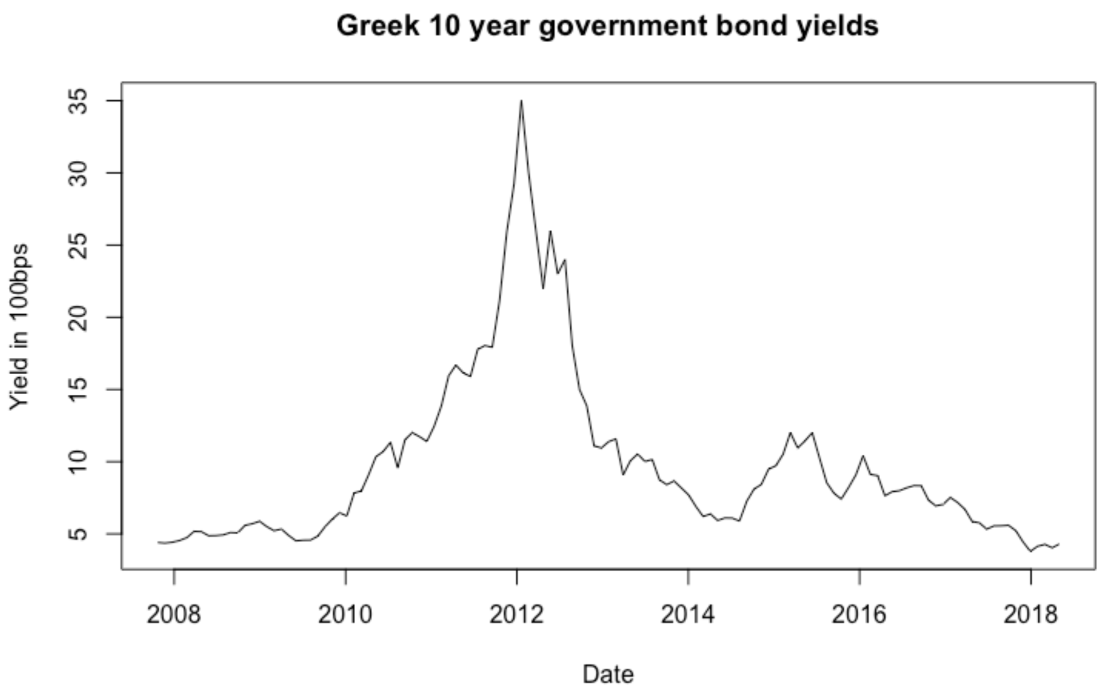


Figure 2: Development of Greek 10 year government bond yields. It is shown that government bonds are not always default risk-free

Momentum

Jostova, Nikolova, Philipov & Stahel (2013) show for the existence of the momentum bond return common factor. Jostova et al. (2013) document significant price momentum in US corporate bonds over 1973-2008. They show that the highest profits from momentum strategies stem from high risk bonds, i.e. bonds with a low credit rating. Although the authors specifically focus on momentum regarding prices, prices are strongly determined by yields. As the yield is the main component of the credit spread, it would be interesting to see what effect the momentum factor has on credit spreads. Although the momentum factor is listed in this section, it could also have been in the equity common factor section as Jegadeesh and Titman (1993) also document strong momentum in equity markets. There is in fact literature on spill-over effects of equity-market momentum to bond-market momentum. Due to the already large scope of this paper, we will not investigate what effects these spill-over effects have on the origin of momentum.

Value and size

Introduced originally in Fama and French (1992b), the *size and book-to-market equity* factors are some of the most well-known common factors in explaining stock returns. Both factors are related to the profitability of a firm. The *book-to-market* factor measures the value of book equity relative to the value of market value, or simply put BE/ME. Fama and French (1992b) show that firms with a high BE/ME tend to have low earnings on assets, while a low BE/ME provides exactly opposite results. The intuition here is that when a firm is overvalued it will underperform, and vice versa. This factor is known as the value factor, with the effect of this factor being the value effect.

Correia et al. (2012) test the existence of the value effect that has already been documented in equity markets, in bond markets. They look at the relative value of the credit spread towards a firms' risk measures such as leverage and credit ratings. It is shown that on foundations of accounting fundamentals it is often possible to predict what will happen to the credit spread. This predictive value is created by differentiating between the actual credit spread and implied credit spread based on best default forecast models and credit returns. These accounting fundamentals are referred to by literature as a "value" effect. The results of Correia et al. (2012) have also successfully been tested on robustness checks.

The *size* factor measures return relative to the size of assets of a firm. An interesting result here is that small firms seem to have a lower profitability (return/assets) than large firms. Intuitively this seems attributable to large firms having scale effects which they can use to increase their efficiency.

Market

Finally, the *market* factor captures the difference between the excess market return and the risk-free rate. The intuition here is that this factor should capture all risk related to taking on a portfolio of stocks. The risk here is basically measured as the compensation for taking on a portfolio of stocks, which is the difference between the excess market return and the risk-free rate. This factor closely resembles the *default* factor from the previous section, be it that the *market* factor captures equity market risk over the risk-free rate, while the *default* factor captures bond market risk over a close estimation of a bond risk-free rate, being the long term government bond yield.

Low risk

Houweling & Van Zundert (2017) show factor investing strategies related to bond and equity markets. They also show that investing on the factors such as value, momentum, and low risk in bond as well as in equity markets raises the amount of alpha in a multi-asset portfolio by 1%. Aside from the previously introduced factors, this paper strongly adds to the existing common bond-market factor literature. Houweling et al. (2017) introduces the *low risk* factor, following results from Ilmanen et al. (2004) about the existence of a "short-maturity" effect. The low risk factor is established on the basis of bond characteristics as opposed to the accounting fundamentals used in Correia et al. (2012). This implies that, firstly, the factor value is more imprecise to the actual factor value and secondly, it is constructed on lagged variables such as the credit rating and default probability. Although these assumptions don't make for the most solid methodological framework, the results are strongly significant. This in turn allows for some variation errors in its construction framework in our opinion. In approximating associated factor values, exact calculations based on accounting fundamentals will only yield more significant results. Finally, the authors show that low risk bonds have a higher risk-adjusted return. Here risk is measured by maturity, ratings, or default probability. The low risk factor is defined as the top decile of highest quality rated bonds minus the lowest decile of highest quality rated bonds with a secondary sorting on maturity, with short maturity being more preferable than a longer maturity.

VIX

Collin-Dufresne et al. (2001) not only show that the yield directly influences credit spreads in several ways, but also show that change in volatility is a strong determinant for credit spreads. Although the volatility measure as measured by the VIX is originally to measure volatility in North-American indices, it is argued here that because of the integration of US and EU bond markets, the VIX might also be an appropriate proxy for European fixed income market volatility. The reasoning behind volatility directly influencing credit spreads is intuitive; increased volatility increases potential risk of default, which in turn increases the default premium asked on bonds, thus widening credit spreads. Furthermore, Collin-Dufresne et al. (2001) also show that the state of equity markets directly influences credit spreads in two ways. First, when equity markets are rallying, more cash will be invested in equity markets, indirectly lowering liquidity in the bonds markets. Although less cash is invested in bond markets, the default probability of corporate bonds lowers due to an increase in safety in the equity market. Overall, there is a positive effect of rallying equity markets on corporate bonds as the decrease in default probability is larger than the decrease in liquidity. On government bonds, rallying equity tends to cause small negative effects as government bonds often have very save ratings and the decrease in default probability is close to null. With government bonds, we expect the liquidity decrease to be of larger impact than the decrease in default probability.

2.2.1 Unique factor literature

Yield factors

Starting off with Duffee (1995) who investigates whether there exists a relation between corporate bond yield spreads and treasury yield rates. Although Duffee (1995) finds that the 3-month treasury rate yield directly influences credit spreads, other works such as Collin-Dufresne et al. (2001), Litterman & Iben (1991), Helwege & Turner (1999) show that it is not only the short rate, but also the medium and long term rate that influences credit spreads. The intuition of this effect is that forward rates show which way spot rates will move. The forward rate can therefore be seen as a predictor for the spot rate and this is how the forward rate impacts the credit spread. Finally, Duffee (1995) points out that the degree in which the expected change in the yield curve affects the credit spread, depends on the initial quality of the intrinsic credit; Credit with for example a BBB rating is effected much more by changes in the yield curve than AAA rated credit. This is most likely caused by a non-linear increase/decrease in the default probability caused by an increase/decrease of the yield curve.

Collin-Dufresne et al. (2001) and Litterman and Scheinkman (1991) add to literature that it is not only the yield that directly influences the credit spread, but it is also the slope and level of the yield curve that influences credit spreads. These papers point out that changes in the slope of the yield curve will most likely change the short term interest rate, thus increasing/decreasing credit spreads through an increase/decrease of risk in the market.

Tax premium and liquidity premium

Elton, Gruber, Agrawal & Mann (2001) show that the difference between spot rates on corporate and government bonds comprises of more than just the influence of interest rates. Elton et al. (2001) show that risk compensation for corporate bonds over government bonds comprises out of three components. Firstly, the higher risk of default within corporate bonds over government bonds. Secondly, a compensation for state taxes because these are paid by corporate bond holders and not by government bond holders. Finally, a compensation for additional "systematic" risk in corporate bonds over government bonds. Important for literature is the introduction of the tax compensation in credit spreads reported here, since it is the first article to introduce the compensation of such an effect. Houweling et al. (2005) and Driessen (2002) show that there is a strong liquidity premium incorporated in bond returns. This means that there is a liquidity premium required for holding bonds, which also holds for credit spreads. Houweling et al. (2005) find that risk premiums of size 13 to 23 basis points are required in their corporate bond data sample. Houweling et al. (2005) also point out that due to government bonds being far more liquid than corporate bonds, liquidity premiums for such bonds should be lower than those observed for corporate bonds

In Elton et al. (2001) the tax premium is calculated as the difference between the estimated spot rate spread through incorporating only the expected losses due to default and the actual spot curve. The expected losses due to default are calculated through a risk-neutral valuation method. Nonetheless, Elton et al. (2001) also point out that even with their best finding of a tax premium in credit spreads, they are still unable to attribute variation in the spread to components as much as the total spread. The credit spread puzzle therefore, remains unsolved even though the addition of a tax premium brings us a step closer. Driessen (2002) confirms the existence of the tax premium within credit spreads, and a summary of the results of Elton et al. (2001) and Driessen (2002) can be found in Amato & Remolona (2003) as shown in Table 2:

Decomposing credit spreads							
Authors	Spread component	Attributed portion of spread (in percentages)					
		Rating					
		AA		A		BBB	
		Maturity					
		5	10	5	10	5	10
Elton et al (2001)	Expected loss	3.5	8.0	11.4	17.8	20.9	34.7
	Taxes	72.6	58.0	48.0	44.1	29.0	28.4
	Risk premium[1]	19.4	27.6	33.0	30.9	40.7	30.0
	Other[1]	4.5	6.4	7.7	7.2	9.4	7.0
Driessen (2003)	Taxes	57.1	55.0	50.8	48.5	37.4	34.0
	Risk premium	17.9	23.3	26.2	32.4	45.8	52.1
	Liquidity premium	25.0	21.7	23.0	19.1	16.9	13.8

[1] Approximation based on authors' calculations.

Sources: Driessen (2003); Elton et al (2001). Table 2

Table 2: Overview of premium sizes as in different papers. Large differences are shown in the size of the reported premiums

An interesting result that follows from Table 2 is that it shows that, according to Elton et al. (2001) and Driessen (2002), the tax premium is the most prominent premium within credit spreads. In both papers the tax premium is far larger than the liquidity premium and the default risk premium except for the riskiest category of debt for both maturities, five and ten years. This shows the relation argued in Elton et al. (2001) that the tax premium effect is larger within safer bonds than within riskier bonds. Nonetheless, we argue that these results do not mean that the tax premium is larger than the liquidity and default premium per se. It could well be possible that due to measurement errors or methodological errors that either the liquidity or the default premium could be understated. Following our methodology and reasoning we do in fact argue that the default premium is likely to be understated.

Geske & Delianedis (2003) is one of the few papers to argue that the credit spread is mainly attributable to taxes, liquidity and market risk factors. These results are acquired however, under the assumptions of a structural model. As Geske & Delianedis (2003) point out themselves, such models eliminate factors as costs of bankruptcy, tax effects, and liquidity effects. In our opinion these costs play such a large role that constructing such a model and the associated results are irrelevant. If one eliminates the role of bankruptcy costs, i.e. default intensity, one cannot properly attribute to the default premium in the credit spread. This might be elicited from the results of Geske & Delianedis (2003) who argue that the default premium is only 5% of the total credit spread. As this 5% is already without the implementation of abovementioned factors, these results seem extremely different from that of previous research.

Credit rating and default premium

A more recent paper from Longstaff, Mithal & Neis (2005) indeed shows that the default component in credit spreads plays an extremely large part. Longstaff et al. (2005) find that the default component represents 51% of AAA/AA-rated bonds, 71% for BBB-rated bonds, and 83% for BB-rated bonds. One might argue that these results are more accurate than former literary work such as Elton et al. (2001) as these components are deduced from credit default swap (CDS) spreads which tend to approximate default probabilities near perfect. Interesting here as well is that the authors define default just as Fama and French (1993) by stating that the default component can be defined as the yield on a corporate bond minus the yield on a riskless bond. No investigation into default correlation is however done in this paper and one could wonder how much of the abovementioned default component attribution in the credit spread is actually attributable to default correlation.

Collin-Dufresne et al. (2001) show that the credit rating of debt is the biggest determinant of the default premium included in credit spread changes. Intuitively, it is apparent that when debt becomes riskier the probability of default also increases. Collin-Dufresne et al. (2001) also show with regards to credit ratings that all factors from their model change when accounting for different rating groups. This in effect means that credit rating does not only directly influence credit spreads and the probability of default, but also indirectly influences the size of other determinants of credit spreads. Collin-Dufresne et al. (2001) show for example that their leverage factor, which is the level of debt to equity, is a far more important determinant of credit spreads for credit instruments with a lower credit rating. Another example is the effect of a lower rating on the VIX; The significance of the VIX factor on the credit spread of this specific low rated bond, becomes significant at the 1% level instead of hardly reaching the 5% level for a triple A rated bond.

Summary

In short, there is an abundance of common as well as unique factors influencing credit spread and credit spread changes directly or indirectly. Some might be strongly correlated, some might share characteristics, and some might share premiums. Nonetheless, no exhaustive model on common factors has been made on attribution of such factors in credit spreads. Some research such as Driessen (2002) focus on common factor variation attribution, but this is specifically for a certain type of bonds which are already hedged. Furthermore, they focus on risky bonds that form a relatively small part of the credit market. Driessen (2003) reports a yield variation attribution of ±96.5%. Although, the results of this paper are strong we point out that this is not a result which can be generalized to the entire bond market and although several factors have been included, there are far more factors known that influence credit spreads at this point in time. It would be interesting to see how their common factors and other common factors stemming from literature perform in credit spread change variation attribution. To maximize this level of attribution it would also be interesting to see how much added value some of the abovementioned unique factors have.

CHAPTER 3 Theory

This chapter covers theory on default dependence and dependence measures that is required to construct an appropriate default dependence factor. We will first discuss why and if our measures are suitable in proxying for default dependence. Hereafter, we introduce general statistical dependence measures that could accurately approximate the dependence between proxies for default. After this, we introduce each measure in a separate chapter. Finally, in assessing the existence of a default dependence premium, it is also important to discuss what the structure of such a premium could be. Moreover, which part of such a premium could be attributable to systematic risk and which part could be attributable to idiosyncratic risk. Furthermore, we argue that some part of the default dependence premium could possibly already be captured by the Fama and French (1993) default factor. We elaborate closely on this in the final section of this chapter.

3.1 Modelling default dependence

Default dependence is synonymous to the rate in which defaults are likely to coincide. When there is high default dependence, investors carry a higher degree of risk than when default dependence is low. This increased risk requires a premium from investors to be compensated for expected extreme losses on their portfolios due to a high default dependence. It is expected that this premium is incorporated in the credit spread. In order to incorporate default dependence in the factor model, we have to capture the default dependence structure. Intuitively, the current default dependence structure should closely resemble that of the default dependence structure a short period ago. It is argued that the closer by to the current time we measure the default dependence structure, the more likely it is that this "lagged" default dependence structure correctly reflects the current default dependence structure in the market. For the discrete default correlation and the time-to-default correlation we model the dependence structure of the period 1 year in advance to where we as measuring. For the yield correlation, this period is 6 months.

In more general terms default dependence refers to correlation of tail risk. Because this concerns the correlation of highly improbable events, accurate measurement is of equal importance as the construction of such a measure. Li (2000) calculates the joint probability of default by using discrete default correlation. One could establish the default correlation between given debt securities and their ratings in a certain time period. This default correlation would exist of the dependence of default events in a certain time period. The method of using discrete default correlation was introduced by Lucas (1995). This method however, has several drawbacks. The largest of these drawbacks is that discrete default probability correlation does not work when data is censored. This refers to the existence of "incomplete data", which with bonds is unfortunately a common practice.

An interesting alternative is also found in Li (2000). Li (2000) argues that for every debt security there is a given point at which the security has to default. The time until this occurs is called the time to default or simply put, the survival time. The problem is nearly always, that one cannot specify an exact point in time where a debt security will default, without it already having occurred. Therefore, the need to establish an alternative to post-ex examination of data is required. Li (2000) offers an interesting alternative by creating a random variable for this survival time. A key concept in survival analysis (Li, 2000) is the survival function which will be discussed in detail in upcoming sections.

Since defaults are rare events, it is challenging to accurately measure the dependence between defaults. This is a problem for both the discrete default correlation and the time to default correlation. Moreover, default dependence can also be present without the actual occurrence of defaults. Therefore, we consider the dependence between (extreme) corporate yields as a proxy for the dependence between defaults. An advantage of this method is that there are far more observations available for yields than for default events, making the measurements more reliable. As such, the final approach suggested by Li (2000) is asset correlation to calculate the joint probability of default.

We propose to use yield correlation as a form of asset correlation. This should deliver an unbiased correlation of debt instruments, which can be seen as a form of asset correlation. The idea here is that given Li (2000)'s intuition that there is a point in time in which every bond must default, we could observe how yields behave near their default. This we know from basic economics; when bond values go to zero, the yield will go to infinity. Therefore, the yield-correlation for extreme yields should offer a strong proxy for bonds that are near default. Nonetheless, it is in general interesting to see what the impact of all yield observations is, and not just for extreme yields. We will introduce several measures for dependence and the dependence between certain subsets of observations in the next section.

3.2 Summary measures for the dependence structure

The most common dependence measure in many fields of science is the correlation measure, or more specifically, the **Pearson correlation** measure. It can be estimated as follows for two random variables X and Y:

$$\rho = \frac{Cov\ (X,Y)}{\sqrt{Var(X)Var(Y)}} \qquad \text{with} \qquad Cov(X,Y) = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{N-1} \quad \text{and} \qquad Var(X) = Cov\ (X,X),$$

where $\bar{x}$ denotes the mean of the observations x_i, $i = 1, \dots, n$. The Pearson correlation only captures linear dependence between two variables X and Y. By using the covariance between X and Y, the measure becomes very sensitive to outliers as the covariance is skewed tremendously by extreme values. Furthermore, the Pearson correlation measure captures linear dependence between X and Y, but is also influenced by the marginal behaviour of variables X and Y. Although two variables may have a large linear dependence, two completely different marginal behaviours may strongly bias the Pearson correlation measure.

The **Spearman correlation**, also known as the rank correlation, as in Spearman (1904) can be defined as follows:

$$\rho_r(X,Y) = \rho(F_X(X), F_Y(Y)),$$

given that F_X and F_Y are the marginal cumulative distribution functions of random variables X and Y. Hence, it can be seen as the Pearson correlation of the ranked variables. The Spearman correlation as opposed to the Pearson correlation only captures the dependence structure between variables X and Y and is not influenced by their marginal behaviour. Furthermore, the Spearman correlation is insensitive to outliers because the variables are ranked. Both the Pearson and the Spearman correlation are dependence measures that capture the overall dependence between two random variables. However, as we are interested in default dependence, which is by nature an extreme event, we are interested in the dependence structure between the tails of the distributions.

Therefore, we move to a measure more appropriate to investigate the dependence structure of observations stemming from the tails of a distribution. To do so, we use extreme correlations as in Longin & Solnik (2001) who investigate the tails of the marginal distributions and the dependence structure of its associated observations in returns of international equity markets. The extreme correlation is defined as a conditional correlation between observations above a certain threshold. To adjust the Pearson correlation for values that only come from the tails of the distribution we adjust the estimators of the covariance and the variance to only include values above a certain value:

$$\text{"Threshold" } Cov(X_k, Y_k) = \frac{\sum_{i=0}^{k}(x_{n-i,n} - \bar{x}_{n-i,n})(y_{n-i,n} - \bar{y}_{n-i,n})}{N-1},$$

where the threshold value k determines how many tail observations are used from the observations ranking from the smallest observation to the largest one:

$$X_{1,n} \leq X_{2,n} \leq \cdots \leq X_{n-1,n} \leq X_{n,n}.$$

Obviously, this threshold also applies to the variance of both X and Y which gives:

$$Var(X_k) = (x_{n-i,n} - \bar{x}_{n-i,n}) \text{ and } Var(Y_k) = (y_{n-i,n} - \bar{y}_{n-i,n}).$$

We will refer to the threshold adjusted Pearson correlation as the **extreme Pearson correlation**, which can be defined as follows:

$$\rho_k = \frac{Cov\ (X_k, Y_k)}{\sqrt{Var(X_k)Var(Y_k)}}.$$

A similar definition holds for the **extreme Spearman correlation.** As the extreme correlations only includes values above a certain threshold, the number of values above this threshold is often very low. As few observations, especially with tail observations, tend to skew the variance and therefore the covariance, we need a measure that better suited for tail dependence. One often used measure for dependence measurement that complements the former mentioned extreme Pearson and Spearman correlation, is the tail dependence coefficient. The **Tail dependence coefficient (TDC)** can be defined as follows as in Geffroy (1958), given that random variables X and Y come from the same marginal distribution:

$$\chi = \lim_{z \to z^*} \Pr\ (Y > z | X > z),$$

where z^* is the right end boundary of the shared marginal distribution of X and Y. Note that the tail dependence coefficient represents a conditional probability instead of a correlation. It measures the likelihood of an extreme event Y which occurs when $Y > z$ given that extreme event X occurs, which happens when $X > z$. The tail dependence coefficient can be estimated as follows,

$$\hat{\chi} = \frac{1}{k} \sum_{i=1}^{n} 1\{X_i > X_{n-k}\ and\ Y_i > Y_{n-k}\},$$

where, similar as for the extreme correlations, k is a high threshold value and

$$X_{1,n} \leq\ X_{2,n}\ \leq \cdots \leq\ X_{n-1,n} \leq X_{n,n}$$

are the rank statistics of the observations.

Although we have defined several general dependence measures within the field of statistics, we have not yet defined the X and Y variables within these measures. Obviously, these X and Y variables cannot be arbitrary and need to be relevant to our proxy for default, as well as statistically comparable. As in Li (2000), we present several ways of constructing several suitable relations for default dependence measures in the next section.

3.3 Discrete default correlation

The discrete default correlation measures dependence between pairwise default events. This discrete default correlation, introduced in Lucas (1995), centres around the "survival" or "death" within a certain period, most commonly one year. Mathematically as in Li (2000), this can be defined as follows:

$$\rho = \frac{q_{AB} - q_A * q_B}{\sqrt{q_A(1-q_A)q_B(1-q_B)}},$$

with $q_A = Pr\{E_A\}$, $q_B = Pr\{E_B\}$, $q_{AB} = Pr\,\{E_A E_B\}$, and E_A and E_B are the default events of respectively securities A and B over 1 year. That is, E_A=1 if A defaults within 1 year, and E_A=0 if A does not default within 1 year. Hence, E_i can be seen as a Bernoulli variable with, e.g.

$$E_A \sim Ber\,(p),$$

where p is the success probability, in this case the probability of default. In the dataset as used in this research, E_A and E_B are defined as the default events within ratings classes. The probability of success can be approximated by counting the number of successes divided by the average:

$$\hat{P}_A = \frac{1}{n_A}\sum_{i=1}^{n_A} 1\{E_i^A = Succes\} \; and \; \hat{P}_B = \frac{1}{n_B}\sum_{i=1}^{n_B} 1\{E_i^B = Succes\}$$

and

$$\hat{P}_{AB} = \frac{1}{n_A+n_B}\sum_{i=1}^{n_A+n_B} 1\{E_i^A = Succes \; and \; E_i^B = Succes\}$$

This yields exactly the required measures for the Pearson correlation measure. Because of the fact that not all ratings and years have default observations for every class, we will compress ratings to a smaller group of default classes so that the observations between ratings become more accurate. Table 18 in the appendix shows the full observations of default per class and year, while table 18 also shows the compressed merged rating classes with the top ranked number of default years.

After having established the amount of defaults in our compressed ratings we are possibly interested in two things. Firstly, one could wonder what the correlation is between bonds of several different ratings, so for example the correlation between bonds rated A and bonds rated B. However, as in our factor model we will look at individual bonds from a certain rating category, we are more interested in how a certain rating category influences its individual bonds with the same rating. Therefore, we will investigate the correlation of bonds within the same rating class.

This is done following Lucas (1995), who starts off by showing the amount of possible combinations with two bonds, being A and B. Possible options between these bonds are: Only A defaults, only B defaults, both default, or neither default. When extended to three bonds, the amount of possible combinations counts up to eight, namely: Only A, B, or C defaults, A and B, A and C, or B and C default, and finally the simultaneous default of all three of the bonds. These are all possible combinations of possible outcomes of three bonds, but also of the utmost importance is the amount of combinations of possible pairs. Lucas (1995) shows that the total possible amount of given combinations of X defaulted bonds can be approximated with X(X-1)/2. The total amount of possible pairs of bonds that have defaulted is X(X-1)/2.

To find the probability that two bonds, bond A and bond B, who both stem from rating class A have defaulted, we have to divide the total possible amount of combinations of defaulted bonds in rating class A by the total possible amount of combinations of all bonds in rating class A. Mathematically this looks as follows:

$$\hat{P}_{DefAA} = \left(\frac{x_{DefA}(x_{DefA}-1)}{2}\right) / \left(\frac{x_{Total\,A}(x_{Total\,A}-1)}{2}\right),$$

where:

$\hat{P}_{DefAA}$= The probability of a simultaneous default of two random bonds from rating class A.

$\left(\frac{x_{DefA}(x_{DefA}-1)}{2}\right)$= The total number of combinations of defaulted bonds from rating class A.

$\left(\frac{x_{Total\,A}(x_{Total\,A}-1)}{2}\right)$= The total number of combinations of bonds from rating class A.

Obviously, similar expressions hold for the other two rating classes B and C. After determining the individual default probability of random bond A from rating class A, the simultaneous default probability of two random bonds, A and B from rating class A, and the covariance between the two random bonds from rating class A, we have all the components to determine the default correlation for bonds within rating class A, B, and C.

If observations for the calculation of the individual default probabilities and of the joint default probabilities are taken from one and the same period, multiplying $\hat{P}_B$ with $\hat{P}_A$ will give a value very close to, but slightly larger than $\hat{P}_{AB}$ which would indicate that $\hat{P}_B$ and $\hat{P}_A$ are uncorrelated or slightly negatively correlated. Although this could be an outcome of our research, the problem lies in the mathematical calculation. As we multiply $\hat{P}_B$ with $\hat{P}_A$ it shows that we are basically taking the pairs that are used to calculate $\hat{P}_{AB}$ individually. This will make these ratios cancel each other out and skew the probabilities. Therefore, it is necessary to implement a multi-period default probability, so that the ratios do not cancel each other out and we don’t necessarily get a negative correlation. This is done by taking an average of default probabilities in every period. Mathematically this looks as follows, with for example five periods:

$$\widehat{P}_A = \frac{1}{5}\left(\frac{\#_1 DefA}{\#_1 A} + \frac{\#_2 DefA}{\#_2 A} + \frac{\#_3 DefA}{\#_3 A} + \frac{\#_4 DefA}{\#_4 A} + \frac{\#_5 DefA}{\#_5 A}\right),$$

$$\widehat{P}_B = \frac{1}{5}\left(\frac{\#_1 DefB}{\#_1 B} + \frac{\#_2 DefB}{\#_2 B} + \frac{\#_3 DefB}{\#_3 B} + \frac{\#_4 DefB}{\#_4 B} + \frac{\#_5 DefB}{\#_5 B}\right),$$

$$\widehat{P}_{AB} = \left(\frac{\#_1 DefA * \frac{\#_1 DefA-1}{2}}{\frac{\#_1 A(\#_1 A-1)}{2}} + \frac{\#_2 DefA * \frac{\#2DefA-1}{2}}{\frac{\#_2 A(\#_2 A-1)}{2}} + \frac{\#_3 DefA * \frac{\#_3 DefA-1}{2}}{\frac{\#_3 A(\#_3 A-1)}{2}} + \frac{\#_4 DefA * \frac{\#4DefA-1}{2}}{\frac{\#_4 A(\#_4 A-1)}{2}} + \frac{\#_5 DefA * \frac{\#_5 DefA-1}{2}}{\frac{\#_5 A(\#_5 A-1)}{2}}\right),$$

where $\#_{\mathrm{i}} DefA$ denotes the number of defaulted bonds of rating A in period $i, i = 1, \dots, 5$. Similarly, $\#_{\mathrm{i}} A$ denoted the total number of bonds of rating A that were 'alive' in period $i, i = 1, \dots, 5$. In doing so, $\widehat{\mathrm{P}}_{\mathrm{A}} * \widehat{\mathrm{P}}_{\mathrm{B}}$ does not equal $\widehat{\mathrm{P}}_{\mathrm{AB}}$. Note that we can use any amount of periods to investigate the discrete default correlation. Whether these are months, weeks, or days doesn't really matter for the calculation, as long as it is multi period. This does provide the opportunity to look very far and very close back in time to the dependence structure of defaults. For example, the dependence structure of defaults of the past five weeks could be implemented but also that of the past five years. Such an approach would be possible with the dataset used in this research. However, the dataset spans sixteen years and one can wonder how likely it is that bonds that have defaulted, defaulted exactly in the one-year period after the previous one-year period of default. Therefore, as Li (2000) also argues, the time horizon is a large issue with discrete default correlation. One could argue that increasing the time horizon would be a suitable solution, but then an issue arises about the actual effect of bond A's default influencing bond B's default, e.g. five years later. Furthermore, by solely focusing on a relevant time horizon the individual bonds' characteristics are being neglected. Bond characteristics such as rating, duration, and country of issue are widely known to influence the probability of default. Therefore, a comparison based on solely the time horizon seems inappropriate, but it could show some interesting initial results.

3.4 Correlation time to default

Another way of looking at default correlation, as well introduced in Li (2000), is not by looking at the correlation between defaults, but rather by looking at the correlation between the time bonds have ran until default. According to Li (2000) and general survival analysis theorem, we need *three* things to determine the time to default. *Firstly*, we need a defined time origin and defined time end. *Secondly*, a time scale for measuring the passage of time, and *finally* a clear definition of default. As the time origin, we use a different approach than Li (2000) who uses *current time*. Li (2000) argues that current market information can be used to build credit curves if the current time is the time origin. However, we are not so much interested in current market information as we observe default probabilities from our dataset, which are more accurate than those of credit ratings or implied in the current market. Our defined time origin beginning of each period and the defined end time is the end of the period or the moment of default. The *time scale is in days* in continuous models so it is also in ours. Finally, default is defined as bonds having a default date. This implies that default is not per se defined by a certain credit rating.

Finally, close to default data on ratings is often incomplete so its most recent rating might not reflect an accurate measure for default.

As discussed in section 3.1, the time-until-default can also be defined as the survival time of a bond, with function:

$$S(t) = 1 - F(t) = \Pr(T > t), t \geq 0$$

The concept of the survival time function is common in papers used in survival analysis, yet from there on things become more ambiguous as several different definitions of hazard rate functions, definitions of default, and rating censoring are given. This problem arises from the fact that survival analysis assumes that everything dies, sometime. Yet determining non post-ex when a bond will exactly default is difficult and literature such as Bellotti & Crook (2009) use censoring to determine an event date for bonds yet "alive". In the case of possible default there are two options that require censoring. Firstly, right censoring is required if the event has not occurred within the observed timeframe. In this research, that would mean that no default before the 1st of January 18 would require censoring. Right censoring is seen as "non-informative" censoring because the censoring does not provide extra information about the results, since in reality it is unknown when exactly default will occur, if it occurs. This is also referred to administrative censoring. Secondly, informative censoring happens when an observation for some alternative reason leaves the sample. This might be due to the subject being lost or leaving the investigation for some reason. Alternative events in the dataset included here is that of a bond maturing, or being paid in full before maturity. Therefore, these bonds also require censoring. These bonds will be censored in the same way as the non-informative censored observations, yet they will be marked differently as these informative censored bonds will also be treated as a separate variable.

Right censoring effectively means that we set either the maturity date, if matured within the sample, or the ultimate sample date while "alive" as the defined end time for censorable observations. The censored observations then also give their individual survival time, just as the non-censored bonds. The censored bonds are then taken into account in the Kaplan-Meier estimator as a separate variable so that they are accounted for in the sample, but do not have a similar weight as non-censored observations. The most common way of estimating the survival time function is by using the Kaplan-Meier estimator. This estimator is defined as follows:

$$\hat{S}(t) = \prod_{i:t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

Where,

d_i: Number of defaults at time t_i

n_i: Number of bonds that have survived or have been censored at time t_i

t_i: A time where at least one default occurred

This estimator is commonly used in medical research where studies of survival of patients given a certain disease is modelled. Nonetheless, it can be extended to nearly any survival analysis framework. The estimator basically gives the ratio of events to non-events for each individual time interval $t - t_i$.

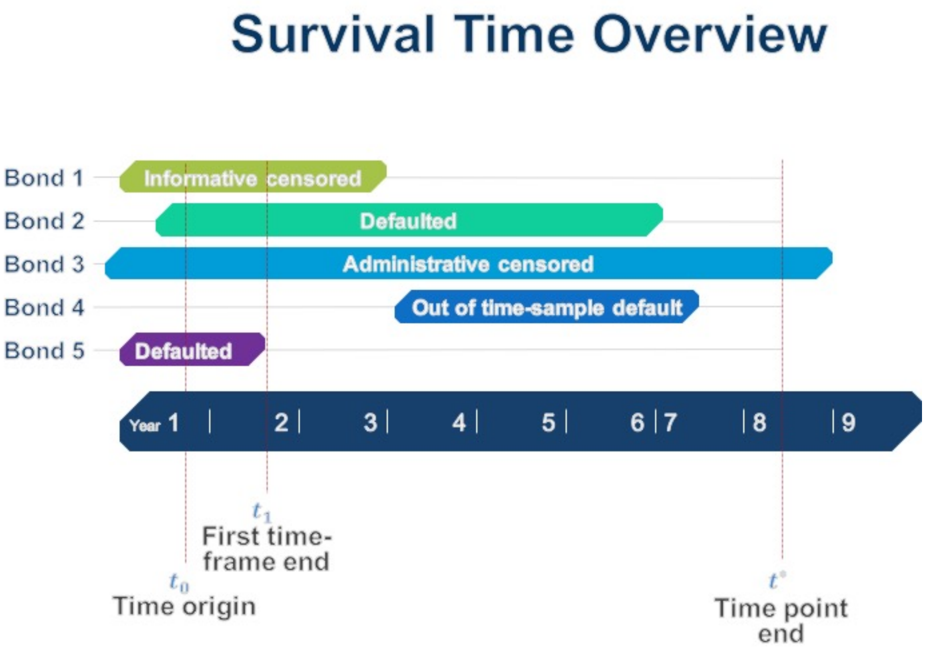


Figure 3: Survival time situations; Event, censoring, elimination

As shown in Figure 3, the approximation of the Kaplan-Meier estimator requires a careful estimation through treating many observations very differently. The time period in which observations are counted is set to one year in Figure 3. However, in increasing precision of the survival time correlation, one might shorten the timeframe wherein is counted to a month, a week, or even a day. After estimating the survival time functions for the individual bonds, the survival time correlation according to Li (2000) can be estimated as follows:

$$\rho_{AB} = \frac{Cov(T_A, T_B)}{\sqrt{Var(T_A)Var(T_B)}}$$

Where,

ρ_{AB}: The correlation between the survival times of entity A and entity B

$Cov(T_A, T_B)$: The covariance between the survival times of entity A and entity B

$Var(T_A)Var(T_B)$: Respectively, the variance of the survival time of entity A and entity B

Following Li (2000), moving from the survival time correlation to the discrete default correlation is done as follows. If we define $E_1 = [T_A < 1]$ and $E_2 = [T_B < 1]$ then using the Pearson correlation, the discrete default correlation over a one year period is defined as:

$$q_{12} = \Pr[E_1 E_2] = \int_0^1 \int_0^1 f(s,t) ds dt$$

with,

$$q_1 = \int_0^1 f_A(s) ds \qquad \text{and} \qquad q_2 = \int_0^1 f_B(s) ds$$

Yet transforming the survival time correlation to discrete default correlation eliminates the purpose of the survival time correlation, as it is an alternative dependence measure of default dependence. Therefore, the deduced discrete default correlation as mentioned above might be used as a control for the default correlation established in 3.4, but it is nothing more than that. The other dependence measures as in 3.3 can be estimated similarly by taking $X = T_A$ and $Y = T_B$.

3.5 Yield correlation

We want to calculate a dependence measure between two variables. Therefore, we need to form pairs again, which makes it extremely important to make a correct dataframe of possible pairs. As opposed to the discrete default correlation and the survival time correlation, pairs formed in the yield correlation must be matched by date. Whereas the discrete default correlation only calculated a correlation between defaulted or not, which did not account for dates specifically, and the survival time correlation only calculated the correlation between the amount of days "survived" in a given period, pairs formed in the yield correlation must be formed by measuring the correlation between the movements of yields of two different credit instruments on exactly the same date. If dates are not matched, the correlation between two yields would give skewed results as a change in yield on two different dates could have different underlying drivers/events. Graphically this looks as follows as can be seen in Figure 4:

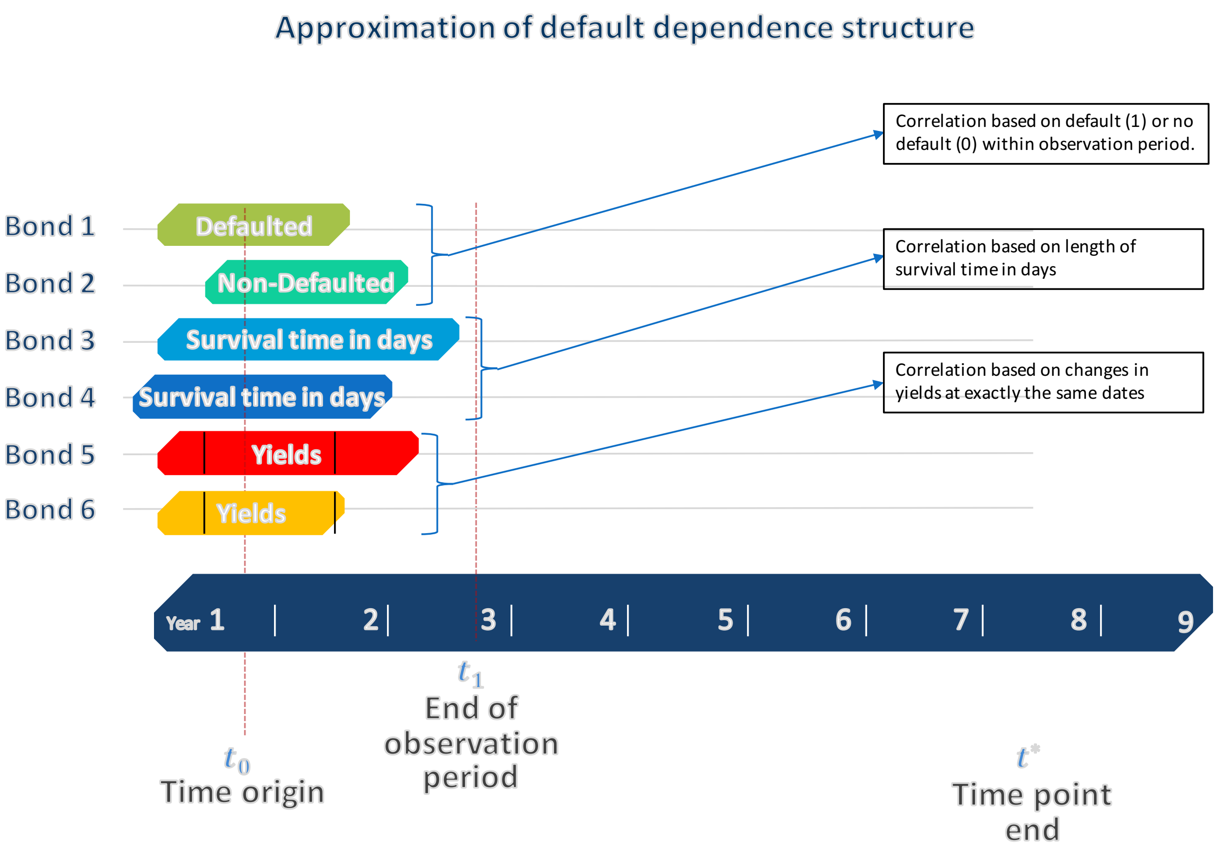


Figure 4: Different timeframes for different default dependence structures

The method in establishing the yield correlation is a follows. Firstly, we select all bonds that lived 6 months before the day we want to calculate the correlation on. From those yields, we form all possible pairs, where a pair is 2 yield observations from 2 different bonds at the same day. From these yields we calculate the dependence measures again with:

$$\rho_{AB} = \frac{Cov(Y_A, Y_B)}{\sqrt{Var(Y_A)Var(Y_B)}}$$

Where:

ρ_{AB}: The correlation between yields of entity A and entity B
$Cov(Y_A, Y_B)$: The covariance between the yields of entity A and entity B
$Var(Y_A)Var(Y_B)$: Respectively, the variance of the yields of entity A and entity B

The other dependence measures are calculated as in 3.3, but by replacing relevant variables by yields as shown above. This process is then repeated for all credit ratings, and all days in the regression timeframe.

3.6 The default dependence premium

As described in the literature review, the Fama and French (1993) default factor is defined as the difference between the yield on a market portfolio of long term corporate bonds and the long term government bond yield. Basically, the linear regression coefficient associated with the default factor can be seen as the CAPM Beta for a bond model; the default factor reflects how individual bond yields relate to market yields. This can be shown as follows:

$$(y_i - rf) = \alpha + \beta(y_m - rf) + \varepsilon_i$$

Where:

$y_i - rf$: Excess yield of bond i over the risk-free rate

y_m: Market yield of a long term corporate bond portfolio

rf: Long term government bond yield which can be seen as the risk-free rate

Fama and French's intuition here is that when market yields soar, a higher premium for default should be reflected in individual bond yields. Nonetheless, this only holds if individual bond yields have a positive exposure to the default factor. Fama and French (1993) argue that their default factor is solely a compensation for default risk. However, it is argued here that this default premium might capture far more premia than solely a default premium. Furthermore, as indicated in Figure 2, the long term government bond yield is not always completely riskless, and there might still be a default risk premium hidden in government bonds. Hence, it might be that the default factor of Fama and French (1993) only partly captures default risk and contains other risks. In this case, their default factor would not accurately measure the premium required for default as it might be augmented through the implementation of several other premia. Moreover, their factor could also already capture a premium for default dependence. We argue that our approach separates the default dependence premium from other possible premiums in the Fama and French (1993) default factor, and possibly captures the remainder of default dependence premium not captured by the Fama and French (1993) default factor. In doing so, our factor captures purely the default dependence premium. Default risk in literature is often defined as follows:

$$T_i = pF + \sqrt{(1 - p^2)} * Z_i$$

Where:

T_i:	Risk of default for firm i
pF:	Probability of default due to systematic risk
$\sqrt{(1 - p^2)} * Z_i$:	Probability of default due to idiosyncratic risk factors

From this formula it becomes strongly clear that if the Fama and French (1993) default factor does indeed correctly capture the default risk premium, which part it captures. The systematic risk component of default risk is intuitively largely attributable to a market factor, which in this case would be the Fama and French (1993) default factor. As systematic risk is mostly determined by the overall state of the economy, differences between corporate and long term government yields are a strong proxy for this. If a default dependence premium would be captured by the Fama and French (1993) default factor, it would likely be the premium for systematic default dependence risk. Therefore, if the systematic default dependence premium is a large part of the Fama and French (1993) default factor, the factor should perform poorly in times of upswing economies as there is little systematic default risk. However, as the Fama and French (1993) default factor could be a good proxy for the systematic default risk premium, it does definitely not proxy idiosyncratic default risk well.

As mentioned in Lucas (1995) in the literature review, most idiosyncratic risk factors are not truly idiosyncratic. They are more often niche-specific risk factors such as similar production inputs or similar geographical dispersion. Because of the fact that in an upswing market default risk mainly hinges on idiosyncratic risk, firms with similar idiosyncratic risk components are exposed to simultaneous defaults. Because of the relation between the state of the economy and the importance of the idiosyncratic risk component, it is argued that the idiosyncratic default dependence premium becomes more important in upswing economies due to its ability to forecast other defaults between firms with similar idiosyncratic risk components. Moreover, idiosyncratic risk might have a systemic component as well. Imagine as follows, a niche sector specific idiosyncratic risk factor; the steel industry and car components. Both companies operate in different sectors and do not share the same idiosyncratic risk sector factor, but it is evident that these two depend on each other; when there is less steel, car components become more expensive and the risk of default for car components increases etc.

Although we do not provide any explanation for the size of the systematic default risk premium component and the idiosyncratic risk premium component, we argue that in upstate economies the systematic default risk component is close to zero as there is little systematic market risk. Therefore, we predict that in upstate economies default risk, and therefore default dependence, is nearly fully attributable to idiosyncratic default risk and compensated by the idiosyncratic default risk premium. As pointed out in the former example and intuitively from Lucas (1995), idiosyncratic default dependence is large in upswing economies. Evidence for such a statement could be found in a higher default dependence in upswing economies than in downturn economies.

CHAPTER 4 Data & Methodology

As this research is mainly done to investigate the significance of the herein established default dependence variables, we tend to stick to the most prominent models in explaining credit variations of Collin-Dufresne et al. (2001) and Avramov, Jostova & Philipov (2007). We do not want to investigate the effect of a multitude of other factors on credit spread changes. Therefore, we do not implement all of the factors mentioned in the literature review. Factors not included in the models are the low risk factor, the market factor, or any factor that possibly proxies for tax effects. We do add some, in our opinion, evident factors that closely resemble the factors in abovementioned works but were excluded from those. Finally, the two factors that we really add ourselves are the inflation and the Fama and French (1993) default factor. This is due to, in our opinion, the obvious effect of inflation which should not be excluded. Finally, the Fama and French (1993) default factor is included due to the possible overlap and ability to provide a good comparison between our default dependence variables.

4.1 General model

As mentioned in the introduction changes in bond credit spreads are to be estimated through the use of a bond factor model. Although estimating changes in bond credit spreads is not the same as estimating effects of the credit spreads itself, Collin-Dufresne et al. (2001) argue that explaining a difference with differences should yield similar results when a stationary spread is explained through stationary variables. Credit spreads cannot be estimated directly as these series and the implemented factors are non-normal and violate assumptions inherent to the model. Using such series could yield biased results. Following Collin-Dufresne et al. (2001) and Avramov et al. (2007) who also estimate changes in credit spreads through first difference factors, changes in credit spreads are estimated. All factors used in our model are tested in either or both abovementioned works with the exception of the inflation, the Eurostoxx50, and the Fama and French (1993) default factor. All regressions are ran for the entire sample and for subgroups of the sample based on credit rating and maturity. We estimate monthly credit spread changes with daily data with the following equation:

$$\begin{aligned}\Delta CS_t^i = \alpha + \ & \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t \\ & + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t \\ & + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \epsilon_t^i\end{aligned}$$

where

- ESTOXX50: Monthly returns on EU stock markets as measured by the Eurostoxx50.
- SP: Monthly returns on US stock markets as measured by the S&P500.
- $\Delta Y3m$: The difference in the 3-month short term spot rate as measured by EU treasury 3-month treasury bills.

- $\Delta Y12m$: The difference in the 12-month medium term spot rate as measured by the interest rate on 1-year EU bonds.
- $\Delta Y120m$: The difference in the 10-year spot rate as measured by the interest rate on 10-year EU bonds.
- $\Delta INFL$: Change in monthly inflation as measured by the historic harmonised inflation prices (HICP).
- $\Delta TERM$: Change in the term structure as measured by the difference between the 10-year interest rate and the 1-month treasury bill rate.
- $\Delta FFDEFAULT$: The change in the Fama and French (1993) default factor. For high quality bonds this is measured through the FTSE Euro Broad Investment-Grade bond index minus the 30-year spot rate on EU government bonds. For low quality bonds, this is measured through the Bank of America Merril Lynch Euro high yield index minus the 30-year spot rate on EU government bonds.
- $\Delta MOMENTUM, \Delta VALUE, \Delta SIZE$: Change in momentum factor, change in value factor, and change in size factor as measured through the values reported on Ken French' website.
- ΔVIX: Change in the monthly volatility in US equity markets measured by the VIX index.

More information on the factors can be found below.

Opposed to Collin-Dufresne et al. (2001) and Avramov et al. (2007) who run monthly regressions with at least twenty-five yield debt quotes as a minimum for their bonds, we run daily regressions for all individual bonds. We do so, because it is argued that yields for firms in financial distress are extremely volatile and that measuring on a monthly basis will not accurately capture the actual movements of such yields. We further increase precision and significance by only running regressions for firms that have at least one full year of trading quotes, that is 12 times 21 trading days in quotes. Avramov et al. (2007) eliminate all data that has observations more than 5 standard deviations from the mean of their data, due to the fact that these observations are likely those of near default bonds Furthermore, both the work of Collin-Dufresne et al. (2001) and Avramov et al. (2007) use a methodology of averaging coefficients and standard errors from every individual bond regression. We argue that such an approach is fairly trivial in describing such large data sets, but due to the elimination of extreme observations such a method could possibly yield representative results, although this is strongly doubted upon. In this research we opt to use a more respected way in working with multiple regressions. Here a method from Fama & MacBeth (1973) is followed. In this paper a two-step approach is utilized. Firstly, individual asset betas are calculated by regressing them against their risk factors. Secondly, these asset betas are held fixed and they are regressed on asset returns to calculate the associated risk premiums. The cross-section of credit spreads is in this way explained with the cross-section of the coefficients of the time-series for the factors used as input. Formally these steps look as follows:

$$R_{1,t} = \alpha_1 + \beta_{1,F1}F_{1,t} + \beta_{1,F2}F_{2,t} + \cdots + \beta_{1,Fm}F_{m,t} + \epsilon_{1,t}$$
$$R_{2,t} = \alpha_2 + \beta_{2,F1}F_{1,t} + \beta_{2,F2}F_{2,t} + \cdots + \beta_{2,Fm}F_{m,t} + \epsilon_{2,t}$$
$$\vdots$$
$$R_{n,t} = \alpha_n + \beta_{n,F1}F_{1,t} + \beta_{n,F2}F_{2,t} + \cdots + \beta_{n,Fm}F_{m,t} + \epsilon_{n,t}$$

Where in our case:

$R_{1,t}$: Credit spread on the first bond of the dataset at time t

$\beta_{1,F1}F_{1,t}$: Factor exposure of the first bond to the Eurostoxx50 at time t

The second step is to hold time constant and only do a cross-sectional analysis with the betas that were found in step 1, over time. This can be shown as follows:

$$R_{i,1} = \gamma_{1,0} + \gamma_{1,1}\hat{\beta}_{i,F_1} + \gamma_{1,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{1,m}\hat{\beta}_{i,F_m} + \epsilon_{i,1}$$
$$R_{i,1} = \gamma_{2,0} + \gamma_{2,1}\hat{\beta}_{i,F_1} + \gamma_{2,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{2,m}\hat{\beta}_{i,F_m} + \epsilon_{i,2}$$
$$\vdots$$
$$R_{i,T} = \gamma_{T,0} + \gamma_{n,1}\hat{\beta}_{i,F_1} + \gamma_{n,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{n,m}\hat{\beta}_{i,F_m} + \epsilon_{i,T}$$

With:

$R_{i,1}$: The same credit spread as in step 1 on the first bond of the dataset

γ: The betas calculated in step 1.

Below we list more information on the variables used in the regression.

Unique factors

$\boldsymbol{ESTOXX50_t}$: ESTOXX50 captures the effect of the Eurostoxx 50 index, which represents the largest 50 companies by market capitalization in Europe. This variable is included because it captures how stock markets in Europe have moved versus European corporate bond markets. It is expected that when stock markets perform better (move upwards), credit spreads will tighten as liquidity risk and default risk will decline. **(-)**

$\boldsymbol{SP_t}$: The returns on the Standards&Poor 500 (S&P500) at time t. In determining credit spreads we have to account for the level of equity returns at time t, as the status of the economy will determine the riskiness of a country's debt. This will be reflected in a higher yield, which in turn causes a larger spread.

We use both equity returns from the US and the EU because the international state as well as the national state can reflect a better overall picture of the state of economy and the availability of capital. It is expected that when stock markets perform better (move upwards), credit spreads will tighten as liquidity risk and default risk will decline. As European and American stock markets are in general strongly correlated, the same effect of the S&P as that of the Eurostoxx50 is expected on credit spread changes. **(-)**

$\boldsymbol{Y3m_t}$: This variable represents the 3-month interest short rate. Interesting here is that according to Morris, Neal & Rolph (1998) an increase in the short term treasury rate leads to a tightening of credit spreads and Longstaff and Schwartz (1995) argues that increased spot rates lead to higher firm value whilst lowering risk of default, thus tightening credit spreads. **(-)**

$\boldsymbol{Y12m_t}$: This variable represents the 12-month interest medium term rate. Following Litterman and Scheinkman (1991), it is strongly expected that there is an ancipatory effect of future bond rates on current bond purchasing and spreads. Therefore, it is examined what the effect of the expected change in medium term interest rate is on the credit spread. Expected is that an increase in the treasury rate by x% will have to be compensated in the corporate bond market by an increase of >x%, due to the nature of risk in the corporate bond market. **(+)**

$\boldsymbol{Y120m_t}$: This variable represents the 10-year long term interest rate and is also known as the yield curve slope. Collin-Dufresne et al. (2001) argue that an increase in the slope of the yield curve leads to an increase in the short rate, which in turn leads to a decrease in credit spreads. **(-)**

$\boldsymbol{INFL_t}$: Following Kang and Pflueger (2012) it is argued that investors are scared of debt deflation and in their consideration of debt purchase account for inflation. As such, we will investigate the explanatory power of inflation in credit spreads. As inflation decreases the value of future cash flows, investors will require a higher yield to compensate for this loss in cash flows. Therefore, when inflation increase, it is expected that yields increase as well. **(+)**

Common factors

$\boldsymbol{Term_t}$: The difference between the monthly long term government bond return and one-month Treasury bill rate measured at the end of the previous month. According to Fama and French (1989), an increase in the term structure factor leads to higher spot rates, which in turn tighten credit spreads. **(-)**

$\boldsymbol{FFDefault_t}$: The difference between the return on a market portfolio of long term corporate bonds and the long term government bond return. An increase in the default factor would imply an increase on the return of the market portfolio of long term corporate bonds, which in turn means that this higher return is a larger compensation for larger market risk. This means credit spreads widen. **(+)**

$\boldsymbol{Momentum_t}$: Defined as the difference between the return of the top 10% performing bonds and the worst 10%. The strategy here is to go long in the top 10% performing bonds compared on returns of the last 6 months, and to short the worst performing 10% compared on returns of the past 12 months. It is argued by Avramov et al. (2007) that higher momentum leads to higher firm valuation, and in turn lowers probability of default. **(-)**

$\boldsymbol{Value_t}$: Difference between buying the top 10% of stocks based on book-to-market ratio and shorting the worst 10% based on book-to market ratio. If the value factor increases, the difference between the top performing stocks based on returns and the worst performing becomes larger. This implies a higher volatility in the market or/and higher risk, which in turn increases credit spreads. **(+)**

$\boldsymbol{Size_t}$: The size factor is defined as the return of a bond divided by the total assets of a firm. Although the dataset does not contain equity values of the firms included this will be difficult. Nonetheless, a comparable measure is constructed by dividing bonds return by the amount issued. As only bonds with a minimum amount issued of one hundred and sixty million and higher are included in the dataset, this should provide a qualitative standardized measure. The top 10% smallest firms' returns are subtracted of those of the top 10% largest firms to create this factor. Finally, a larger size effect could indicate larger volatility or increased risk which leads to the need for a higher compensation, which should be reflected in credit spreads. **(+)**

$\boldsymbol{VIX_t}$: This variable represents the volatility in the market, which following literature, can be seen as a measure for global risk-aversion. Although VIX is originally measured on US indices, the high correlation of US and EU volatility make it a suitable measure for risk aversion in the EU. When the volatility in the market increases, so does risk. An increase in the VIX is therefore associated with higher liquidity and default risk which in effect means a larger credit spread. **(+)**

The expected sign of impact of the common and unique factors are summarized in Table 3. Sign of impact of common and unique factors on changes in the credit spread:

Factor	ESTOXX50	SP	Y3m	Y12m	Y120m	INFL
Sign	-	-	-	+	-	+
Factor	TERM	FFDEFAULT	MOMENTUM	VALUE	SIZE	VIX
Sign	-	+	-	+	+	+

Table 3: Effect signs of factors on changes in credit spreads

4.1.1 General model with default dependence factor

After testing the general model as described above, our default dependence factor is added to the model in order to investigate the effect of default dependence on the credit spread. The default dependence factor comes in three forms as introduced in chapter three. Firstly, a general discrete default correlation variable is implemented in the model. This variable generates a correlation based on all possible pairs of observed default events in a certain period. Secondly, a survival time correlation is modelled to observe the effect of survival time correlation on the credit spread. The idea here is that when bonds "survive" shorter, market circumstances are such, that for some reasons bonds tend to default faster than they do on average. Finally, a yield correlation approach is used to indirectly approximate default; defaults are not observed here, but it is argued that the correlation of extreme yields is a good proxy for the correlation between defaults. Each variable will be implemented one by one into the general model, i.e. not all three the variables are implemented at once.

As with the general model, we estimate credit spreads changes including our default dependence factor following Collin-Dufresne et al. (2001) and Avramov et al. (2007) with:

$$\Delta CS_t^i = \alpha + \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta Default - Dependence_t + \epsilon_t^i$$

where

- ESTOXX50: Monthly returns on EU stock markets as measured by the Eurostoxx50.
- SP: Monthly returns on US stock markets as measured by the S&P500.
- $\Delta Y3m$: The difference in the 3-month short term spot rate as measured by EU treasury 3-month treasury bills.
- $\Delta Y12m$: The difference in the 12-month medium term spot rate as measured by the interest rate on 1-year EU bonds.
- $\Delta Y120m$: The difference in the 10-year spot rate as measured by the interest rate on 10-year EU bonds.
- $\Delta INFL$: Change in monthly inflation as measured by the historic harmonised inflation prices (HICP).
- $\Delta TERM$: Change in the term structure as measured by the difference between the 10-year interest rate and the 1-month treasury bill rate.
- $\Delta FFDEFAULT$: The change in the Fama and French (1993) default factor. For high quality bonds this is measured through the FTSE Euro Broad Investment-Grade bond index minus the 30-year spot rate on EU government bonds. For low quality bonds, this is measured through the Bank of America Merril Lynch Euro high yield index minus the 30-year spot rate on EU government bonds.
- $\Delta MOMENTUM, \Delta VALUE, \Delta SIZE$: Change in momentum factor, change in value factor, and change in size factor as measured through the values reported on Ken French' website.
- ΔVIX: Change in the monthly volatility in US equity markets measured by the VIX index.
- $\boldsymbol{\Delta Default - Dependence}$: One of our default dependence factors measured through the difference in the default-dependence measure as introduced in chapter 3.

The expected sign of impact of the common and unique factors are summarized in Table 4:

Factor	ESTOXX50	SP	Y3m	Y12m	Y120m	INFL	
Sign	-	-	-	+	-	+	
Factor	TERM	FFDEFAULT	MOMENTUM	VALUE	SIZE	VIX	DEFAULT-DEPENDENCE
Sign	-	+	-	+	+	+	+

Table 4: Effect signs of factors on changes in credit spreads, including the default dependence factor

4.2 Data description

This research on the effect of default dependence on credit spreads is performed with a dataset spanning approximately 5000 non-defaulted bonds and approximately 500 defaulted exchange-traded bonds running from the 1st of January 2000 until the 1st of January 2016, as shown in Appendix A, Table 18. Data is obtained from Bloomberg. This research specifically uses European exchange traded corporate bonds because firstly, these are all trading on European exchanges which standardizes the dataset and secondly because exchange traded bonds are in general far more liquid than over-the-counter (OTC) bonds. Finally, OTC data is difficult to come by while the exchange-traded bond dataset provides a clear overview of yield developments over time. On both the defaulted and the non-defaulted bonds several filters are applied. Firstly, a ratings filter is applied that only retrieves bonds that have an initial rating from either Fitch, Moody's, or S&P above D. The second filter requires that bonds also have a present pre-default rating by one of the three abovementioned rating firms as to make the dataset more comparable. In doing so, one can observe the change in its initial rating to its default rating. Secondly, as in Collin-Dufresne et al. (2001) and Avramov, Chordia, Jostova & Philipov (2007), we also implement a minimum of debt quotes for bonds to be included in our dataset. In their research the minimum of quotes is 25 monthly observations, whereas ours is 21 trading days times 12, which is a full year of trading days. As in both abovementioned papers, we also do not filter for maturity or adjust for duration. As in Avramov, Chordia, Jostova & Philipov (2007), but opposed to Collin-Dufresne et al. (2001) we do not filter for sectors. Except for the amount issued filter, the remainder of the filters are standard practice in corporate bond literature according to Avramov, Chordia, Jostova & Philipov (2007). After these filters have been applied, the ratings are standardized to one general rating as per Jewell & Livingston (1999). This process is shown in Appendix B, Tables 19-21.

The following sections provide summary statistics on the data required for the factor model. We first describe the properties of the corporate bonds data, next we describe the data retrieved for the common and unique factors, and finally we show our results on the default dependence measures. All results and data descriptions are our own and created with the statistics program R. If results are not ours this will be mentioned in the source of the table or figure these results are in.

4.2.1 Bond Coupons

As expected and is shown in Table 5, the average coupon and the standard deviation of the coupon of defaulted bonds are larger than those of non-defaulted bonds. Coupons are largely known to reflect the level of risk associated with the bonds. One could expect that the average risk of defaulted bonds is higher than that of non-defaulted bonds. Interestingly, coupons are determined at the issue of a bond and given an equal average rating of both the defaulted bonds and the non-defaulted bonds one could conclude that at issue some defaulted bonds already seem to bear a higher risk than non-defaulted bonds while no differentiation is made here by the market. Another expected result is that the standard deviation of defaulted bonds is higher than that of non-defaulted bonds. This might be attributable to the fact that the defaulted bond dataset is significantly smaller than that of the non-defaulted bonds set or, in our opinion more likely, another example of an unattributed part of risk not included in a general bond rating.

All Bonds			Def Bonds			Non-Def Bonds	
	Coupon			Coupon			Coupon
Mean	4.69		Mean	4.89		Mean	4.671
Std Dev	2.55		Std Dev	4.86		Std Dev	2.218
Median	4.50		Median	4.38		Median	4.5
Minimum	0.00		Minimum	0.00		Minimum	0
Maximum	27.13		Maximum	16.00		Maximum	27.125
N	5464		N	465		N	4999

Table 5: Bond coupon descriptive statistics

4.2.2 Bond amount issued

Also expected and as is shown in Table 6, in agreement with literature and as mentioned in the introduction, increasing the amount issued decreases the probability of default. From Table 6 it shows that the mean amount issued of defaulted bonds is about 6 times as small as that of the amount issued of the non-defaulted bonds. The standard deviation of the defaulted bonds provides an even more solid result; on average, the amount issued of defaulted bonds including the standard deviation is a smaller distribution of observations which makes for a narrower distribution. This means that there is stronger evidence for the relation between the amount issued and default probability.

All Bonds			Def Bonds			Non-Def Bonds	
	Amount Issued			Amount Issued			Amount Issued
Mean	856.411.656		Mean	133.687.167		Mean	856.411.656
Std Dev	793.257.189		Std Dev	196.545.323		Std Dev	793.257.189
Median	643.445.250		Median	50.000.000		Median	643.445.250
Minimum	200.000		Minimum	200.000		Minimum	200.000
Maximum	10.241.987.602		Maximum	1.222.250.000		Maximum	10.241.987.602
N	5461		N	492		N	4969

Table 6: Bond amount issued descriptive statistics

4.2.3 Bond three-month default probabilities

Table 7 shows the three-month default probability given the bonds initial rating. As expected, the mean default probability for defaulted bonds is far larger than that of non-defaulted bonds. On average, defaulted bonds have a default probability of approximately one hundred times as large as that of non-defaulted bonds. This means that ratings do, to a certain degree, a good job in explaining expected defaults based on their ratings as the default probabilities for defaulted bonds are far higher than those of non-defaulted bonds.

All Bonds			Def Bonds			Non-Def Bonds	
	3-monthdfprob			3-monthdfprob			3-monthdfprob
Mean	0.01		Mean	0.1080		Mean	0.00167
Std Dev	0.03		Std Dev	0.0396		Std Dev	0.00777
Median	1.93		Median	0.1240		Median	0.0105
Minimum	0		Minimum	0.0000		Minimum	0.00
Maximum	0.13		Maximum	0.1251		Maximum	0.09846063
N	4893		N	320		N	4573

Table 7: Bond three-month default probabilities descriptive statistics

4.2.4 Bond five-year default probabilities

In Table 8, data seem to be as expected with the average five-year default probability of defaulted bonds being approximately ten times as large as that of the non-defaulted bonds. Interesting here is that for a change in time horizon of three-months to five-years the defaulted bond probabilities change by a factor 2.9 while for the non-defaulted bonds it changes with a factor 16.3. One might argue that this large difference in increase might be attributable to the relative large initial size of the three-month default probability of 0.1080. Nonetheless, the time horizon here changes by a factor twenty and one might argue to expect a larger increase in the five-year default probability for the defaulted bonds. From these results it shows that relative safe non-defaulted bonds show on average a far stronger increase in default probabilities, but never cross 2.73%. Therefore, bonds stemming from the defaulted bonds set on average default one in three, while bonds stemming from the non-defaulted bond set default on average one in thirty. This again shows the strength in explanatory power of initial bond ratings.

All Bonds			Def Bonds			Non-Def Bonds	
	5-yeardfprob			5-yeardfprob			5-yeardfprob
Mean	0.05		Mean	0.29		Mean	0.0273
Std Dev	0.08		Std Dev	0.10		Std Dev	0.043
Median	0.02		Median	0.31		Median	0.0169
Minimum	0.00		Minimum	0.00		Minimum	0.0000478
Maximum	0.56		Maximum	0.63		Maximum	0.53444
N	4893		N	320		N	4573

Table 8: Bond five-year default probabilities descriptive statistics

4.2.5 Bond maturities

From the results in Table 9 it shows there is a strong relation between maturity and default. On average, non-defaulted bonds have a longer maturity and larger standard deviation than defaulted bonds.

All Bonds			Def Bonds			Non-Def Bonds	
	Maturity			Maturity			Maturity
Mean	11.32		Mean	8.52		Mean	11.62
Std Dev	29.32		Std Dev	5.67		Std Dev	30.8
Median	8.05		Median	8.00		Median	8.082
Minimum	0.23		Minimum	0.97		Minimum	0.229
Maximum	1000.48		Maximum	40.00		Maximum	1000.48
N	5053		N	496		N	4557

Table 9: Bond maturities descriptive statistics

4.3 Non-differenced factors

As shown in Figure 5 when credit spreads would be estimated without differencing the factors used to calculate the factor exposures, non-normal series would be used. It can be observed clearly that the histograms shown below show non-normality in non-differencing series for the four yields implemented in our factor model.

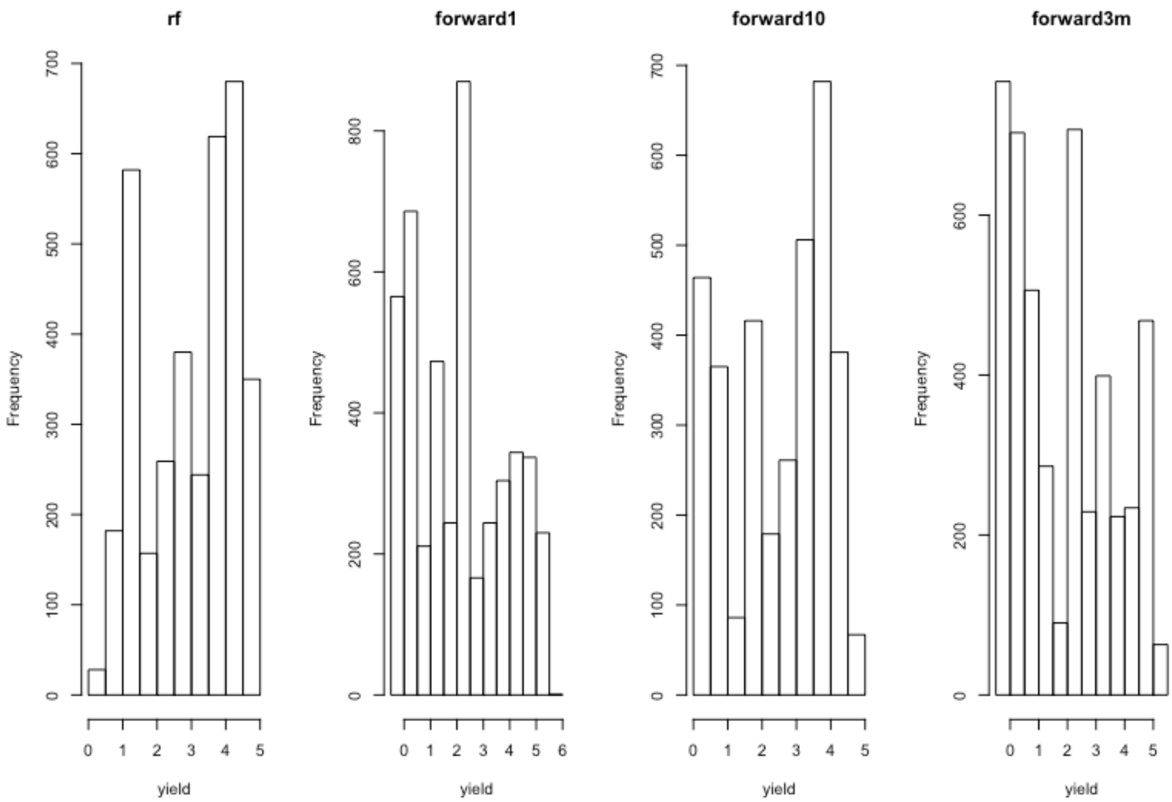


Figure 5: Yield frequencies when no differencing is applied

Although non-differenced factors are non-normal and are therefore by definition poor to be used as factors in the factor model, they do show trends. Such trends are very undesirable in regression analysis as it biases the results. Nonetheless, graphically strong relations can be deducted from such trends. We graphically list the most important ones below.

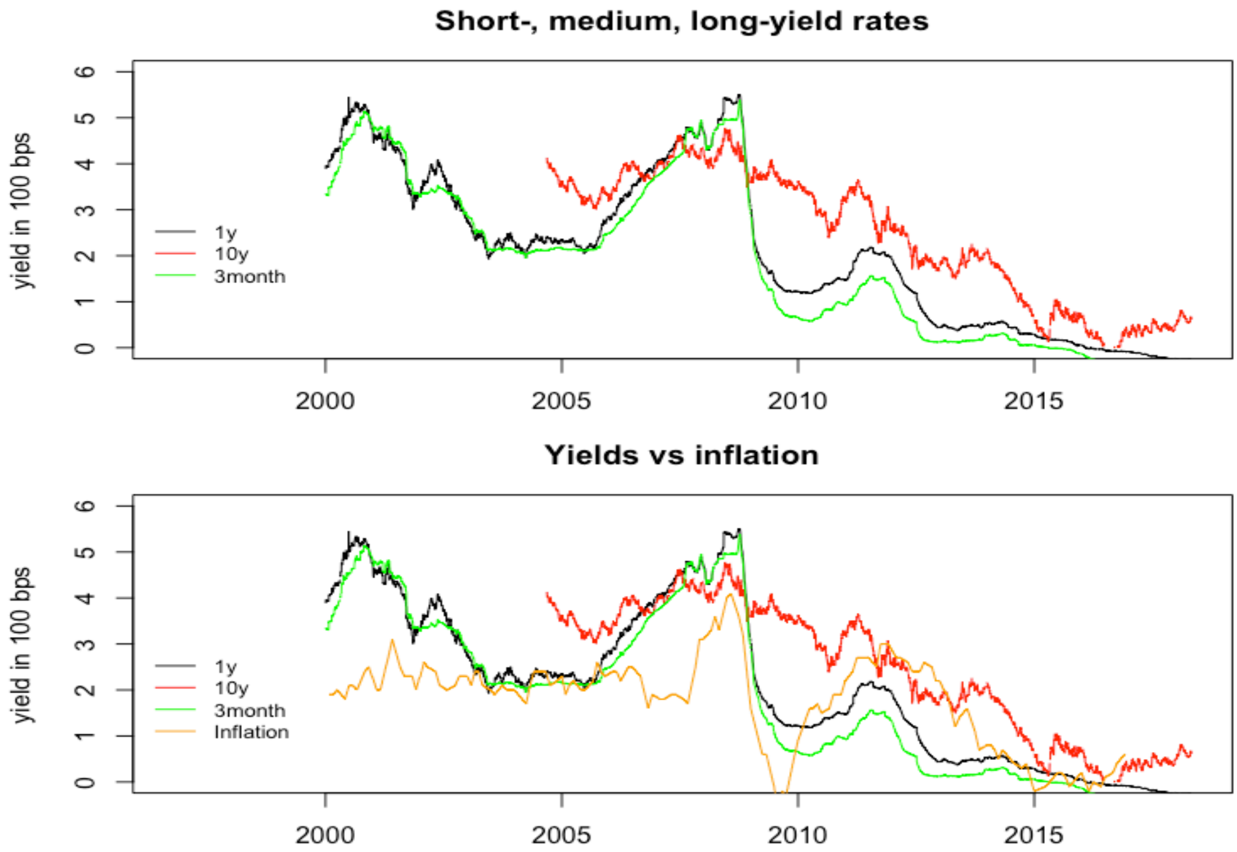


Figure 6: Yields over time and yields vs inflation

Figure 6 clearly shows the level of risk represented by each yield curve. The longer maturity curve shows a higher yield, which means a higher risk. This is in accordance with economic theory, which argues that longer maturity yields are more sensitive than shorter maturity bonds. Furthermore, the inflation curve tends to follow yields largely. This could possibly be explained due to the result stated in David (2008) and Kang & Pflueger (2012), who argued that investors require compensation for a lower value of discounted cash flows when there is inflation. Yet this will have to show in the regression analysis.

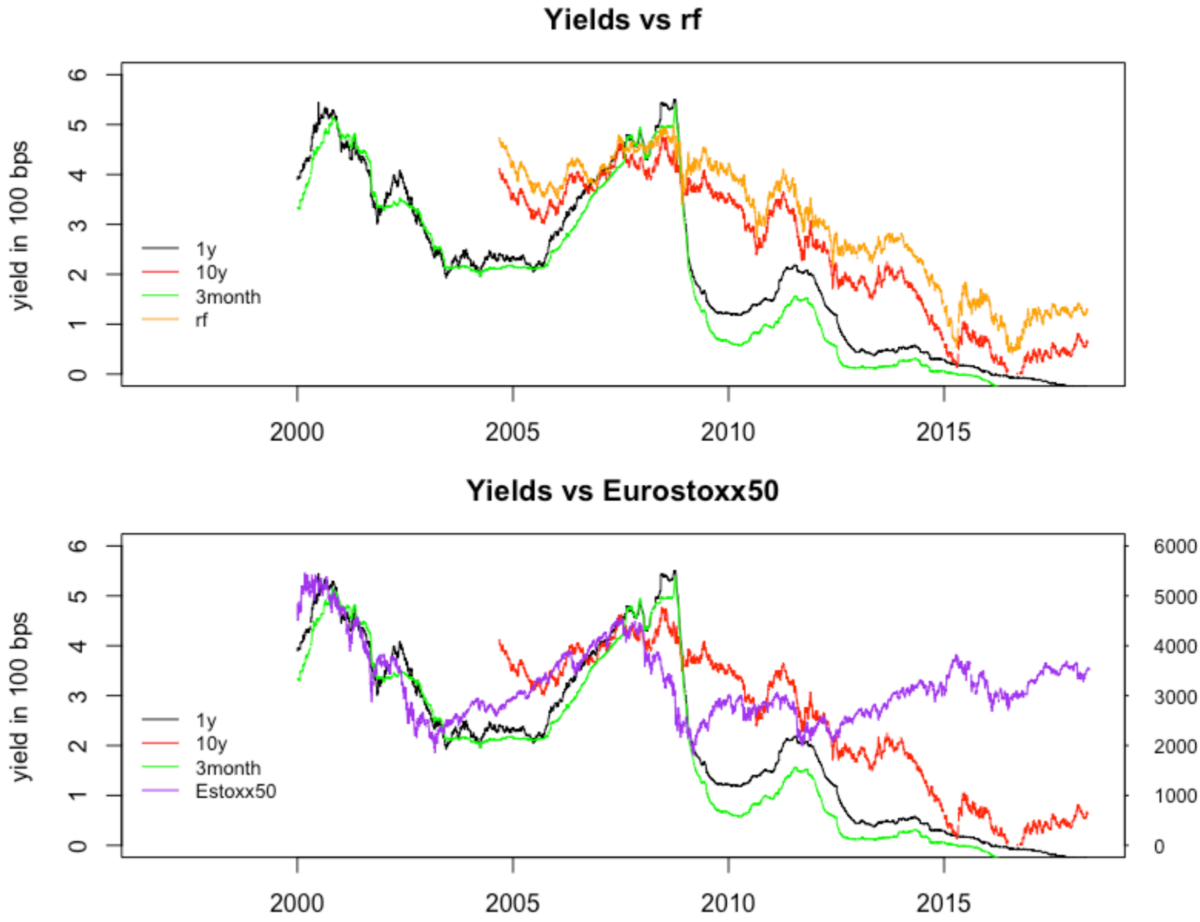


Figure 7: Yields over time vs the risk-free rate and yields vs the Eurostoxx50

Figure 7 clearly shows that the risk-free rate, as measured by the 30-year long term Eurozone AAA rated government bonds, is higher than the three yield curves. Nonetheless, it is also the least sensitive curve to risk inherent in the market. This is obviously why the curve is called the risk-free rate; it should not contain any risk, a risk-free investment. We see that since 2000 the Eurostoxx50 has largely followed yield curves until about 2012, where we see that yields drastically decrease while the Eurostoxx50 soars. This might be caused by the introduction of unconventional monetary policy (UMP) by the European Central Bank (ECB).

4.3.1 Differenced factors

Shown below in Figure 8 are the differenced factors for the four yields shown above and the other factors that are implemented in the model. It can be observed clearly that these series all follow an approximate normal distribution and are far more appropriate than their non-differenced counterparts. All series are absolute differences except for the S&P500 and the Eurostoxx50, which following Collin-Dufresne, Goldstein & Martin (2001), are used as relative differences which are the returns on the indexes.

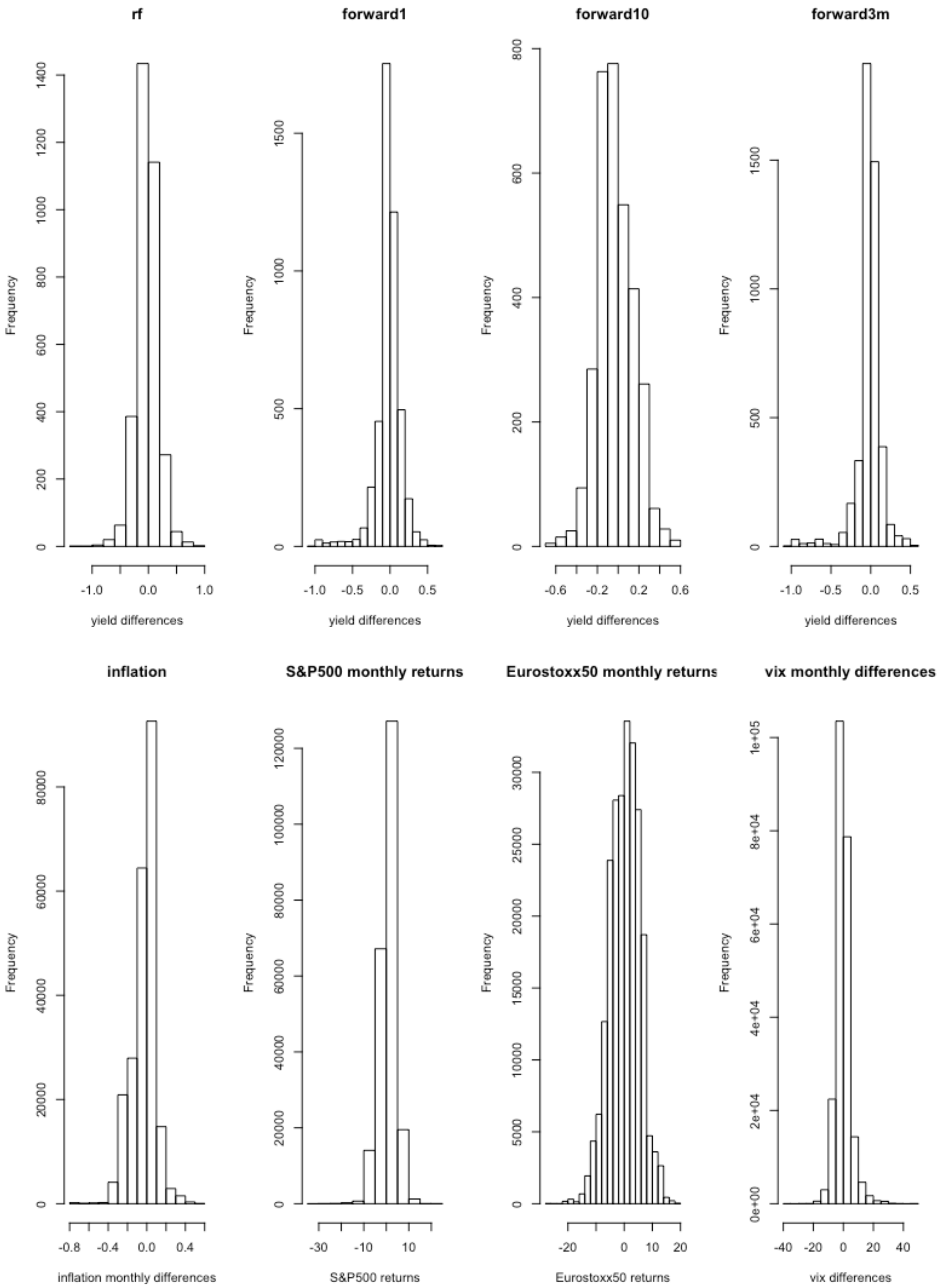


Figure 8: Frequency and associated values when differencing is applied

Below in Figure 9 is graphically shown how the differences of the yields relate to the differences of the Fama and French (1993) factors. 99% of all observations are between a difference of -3 to +4. Due to the fact that daily differences are used, the picture shows a lot of noise. Nonetheless, the initial data looks promising as the yields and the factors show similar difference patterns and are all normally distributed.

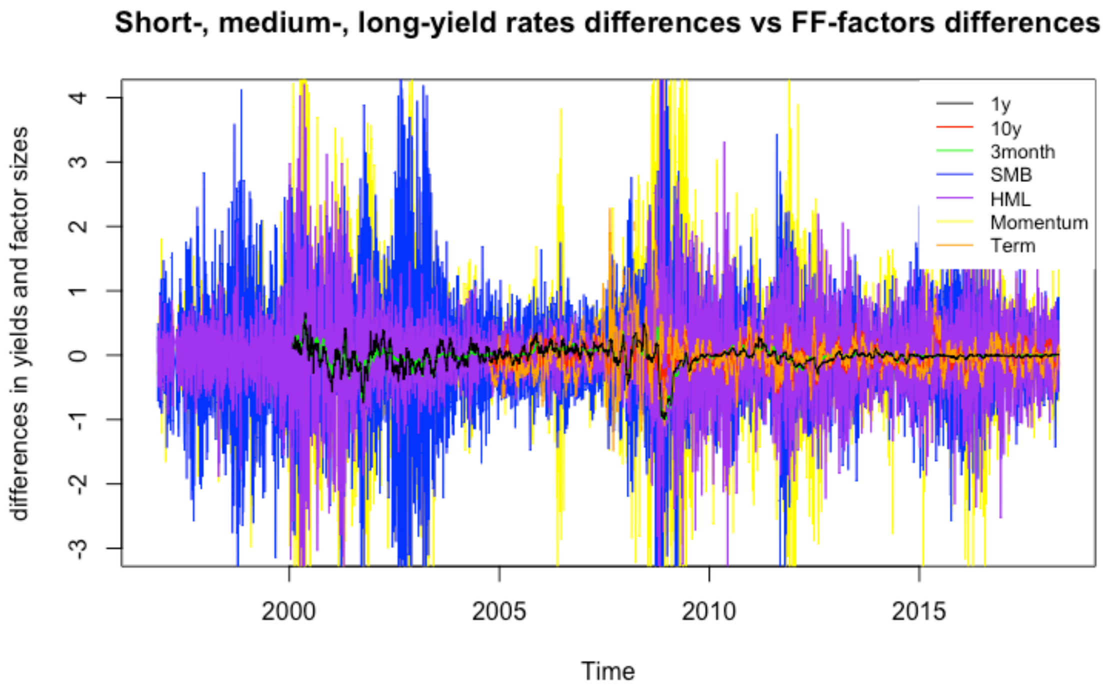


Figure 9: Differenced model factors with mean around 0

As can be shown from Table 10, nearly all variables have very small or no outliers. Notable exceptions are the credit spread, the S&P500 and the Eurostoxx50. These relatively large minima and maxima are due to the unit of observation. For the Eurostoxx50 and the S&P500 this is and index. For the credit spread changes, some points in time show extremely large values for bonds in the data sample. This is most likely due to sudden financial distress of the firm and/or a sudden market collapse. We still study yields in the next section.

Table 10: Descriptive statistics for differenced factors

	RF			Forward1			SMB
Mean	-0.04		Mean	-0.02		Mean	0.00
Std Dev	0.22		Std Dev	0.06		Std Dev	0.72
Median	-0.05		Median	-0.01		Median	0.01
Minimum	-1.23		Minimum	-1.00		Minimum	-5.33
Maximum	0.86		Maximum	0.49		Maximum	5.78
	CS			**Forward10**			**HML**
Mean	-0.13		Mean	-0.04		Mean	0.00
Std Dev	32446		Std Dev	0.17		Std Dev	0.64
Median	0.04		Median	-0.07		Median	0.01
Minimum	-523830		Minimum	-0.69		Minimum	-4.31
Maximum	458585		Maximum	0.59		Maximum	4.45
	Infl			**Forward3m**			**Momentum**
Mean	-0.02		Mean	-0.02		Mean	-0.01
Std Dev	0.13		Std Dev	0.06		Std Dev	0.90
Median	0.00		Median	-0.05		Median	-0.02
Minimum	-0.78		Minimum	-1.03		Minimum	-7.52
Maximum	0.57		Maximum	0.50		Maximum	7.68
	S&P500			**Eurostoxx50**			**Term**
Mean	0.74		Mean	0.23		Mean	-0.05
Std Dev	3.58		Std Dev	5.31		Std Dev	0.23
Median	1.06		Median	0.38		Median	-0.06
Minimum	-30.03		Minimum	-27.34		Minimum	-1.49
Maximum	23.43		Maximum	19.92		Maximum	2.28
	VIX			**RF**			
Mean	-0.14		Mean	-0.04			
Std Dev	4.88		Std Dev	0.22			
Median	-0.36		Median	-0.05			
Minimum	-35.93		Minimum	-1.23			
Maximum	46.31		Maximum	0.86			

4.4 Data sample yields and credit spread changes per rating class

As mentioned before, ratings are compressed into three group, as in Appendix B Tables 19-21. Average yields for the compressed ratings classes "A", "B", and "C" are shown below in Figure 10. For the points in time where no yields are shown our data sample did not have any available yields. Some noticeable large changes in the yield curves are shown. For rating classes A and B these are fairly similar, with 2008 being the US housing crisis. The small peak in 2011 for class A and B might be attributable to the US elections, where yields soared as it became clear that Donald Trump would win the elections. The 2014 yield hikes occurred possibly because of the devaluation of the Swiss Franck. This result holds for all three rating classes. The peaks for classes A and B after 2016 might be attributable to volatility around the Brexit referendum and its actual occurrence.

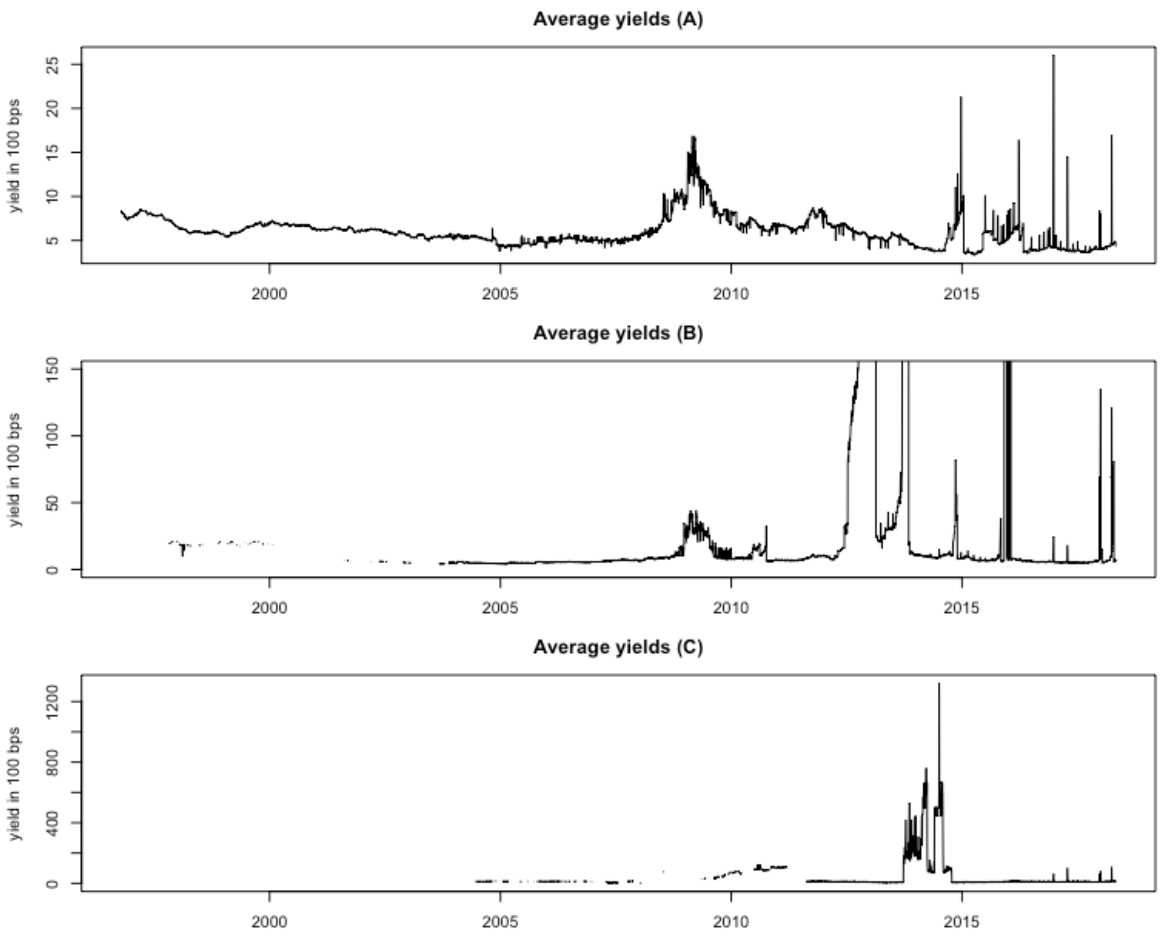


Figure 10: Average yields per rating class over time for observed yields in the dataset

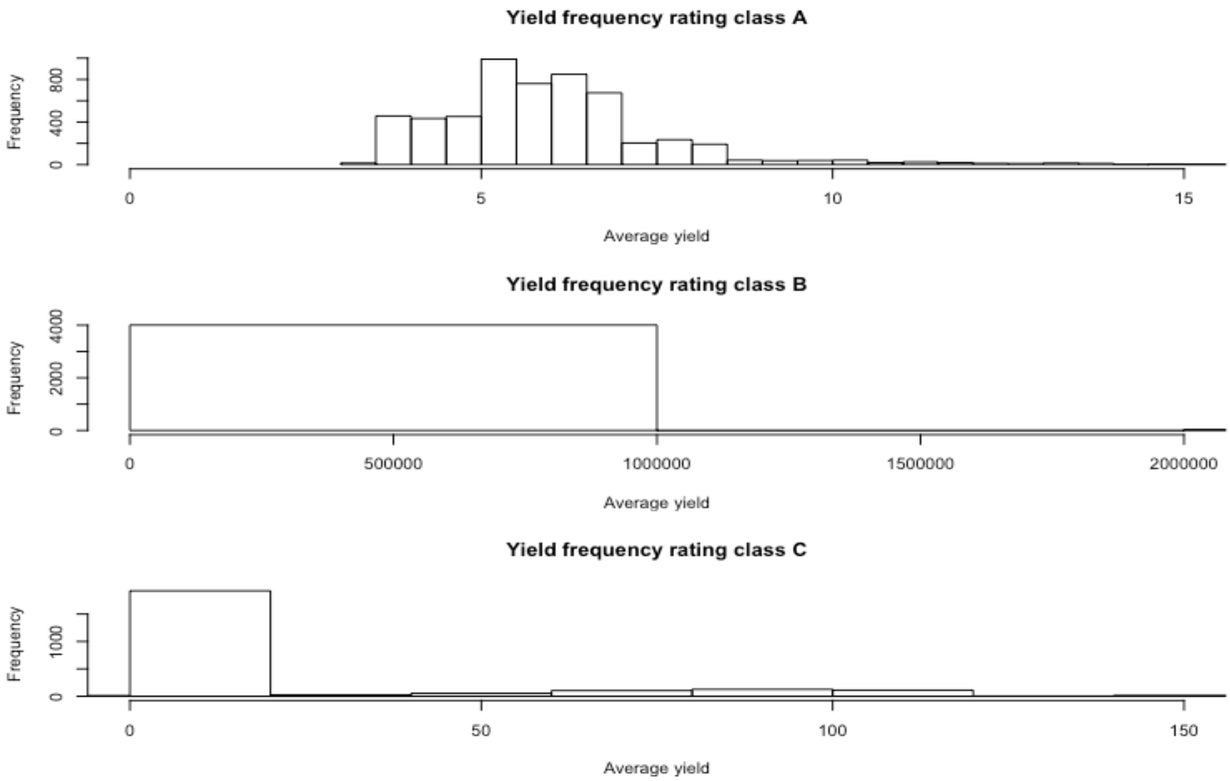
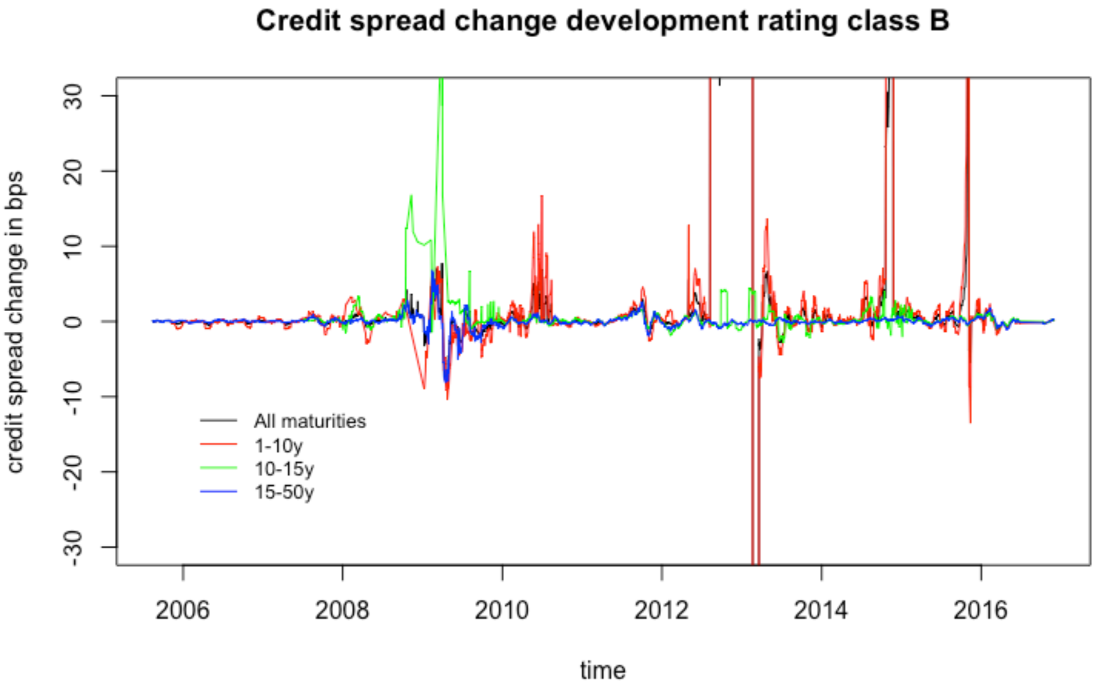


Figure 11: Average yield frequency per rating class over time for observed yields in the dataset

Figures 10 and 11 show the average yields and their frequency per date for the three rating classes “A”, “B”, and “C”. The yields for rating class “A” are fairly consistent with the yields that are expected with high quality credit. Yields between five to ten percent is normal for such quality credit. For the B rated yields, interesting data is shown. B rated yields have a very high yield. This is possibly due to the fact that when a bond default and the value of the bond becomes zero, the yields go towards infinity. Therefore, such large values are not data errors or outliers, but consistent with theory. C rated yields also show interesting data. This is most likely due to a lack in quantity of C rated issued bonds, where our data sample does not have many C rated bonds at issue. Therefore, the yields for C rated bonds at issue might not be representative. Due to such a lack of data, no regressions will be done for rating class C as the results would most likely be biased and do not meet our criteria of using at least 1 month of trading quotes.

As shown from Figure 12, rating class A has approximately normally distributed credit spread changes with a mean around 0. For rating class B, the mean is also around 0, but especially the lower maturities show a high deviation from the mean. A plausible explanation for this would be that default is centred in this rating class around these maturities; default implies a yield going to infinity with bond values falling to 0. As mentioned before, rating class C did unfortunately not have enough data to construct reliable credit spread changes.



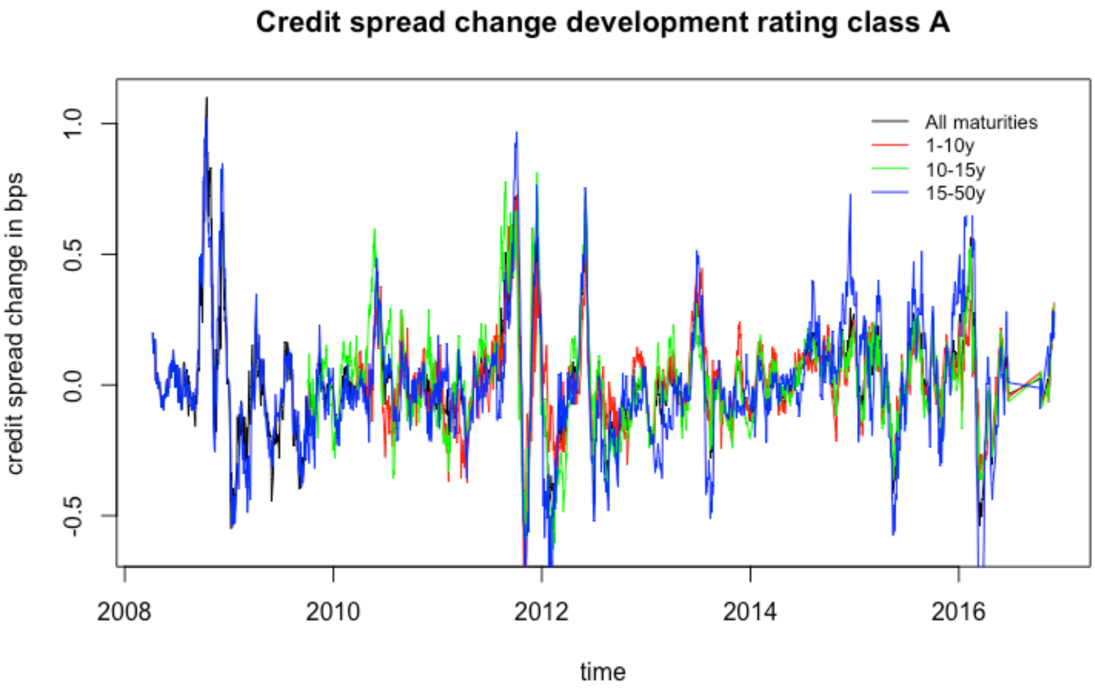


Figure 12: Credit spread differences over time per rating class and maturity

4.4.1 Yield correlations over time

The correlations between yields are calculated on basis of 6-month periods. This means that our approximation of the historical default dependence structure is implemented with a 6-month lag, meaning that the current market default dependence used in our factor model is that of 6 months ago. This is the best estimation for a close-to-current market default dependence as possible, as mentioned in section 3.3, multiple periods are necessary to calculate a correlation. The correlation measure that shows in the upcoming graphics as such is the average of 6 monthly yield correlations.

In general, we can observe from all our measures that 2000 to 2008 shows a very high yield dependence for rating class A. This might be well possible due to the likeliness that the yield correlations follow yields; yields were above 5% in this period and the likelihood of default in this upswing period was low. As in Das, Freed, Geng, & Kapadia (2002) it is argued here that our data shows that high quality credit in an upswing economy also show a very high default dependence, proxied by the yield correlations. This result is strengthened from rating classes B and C; these lower credit rating classes show a substantial lower yield correlation. Furthermore, overall, we see a lowering of yield correlation with rating class A after the initiation of the US housing crisis; 2008 shows a strong reversal of yield correlation within rating class A. From there on, default becomes more random and of a higher occurrence and we observe that the yield correlation even after the end of the US housing crisis does not pick up again. This might be explained through the initiation of large-scale UMPs by the ECB which have drastically lowered yields and thereby the likelihood of default (Borgdorff 2016).

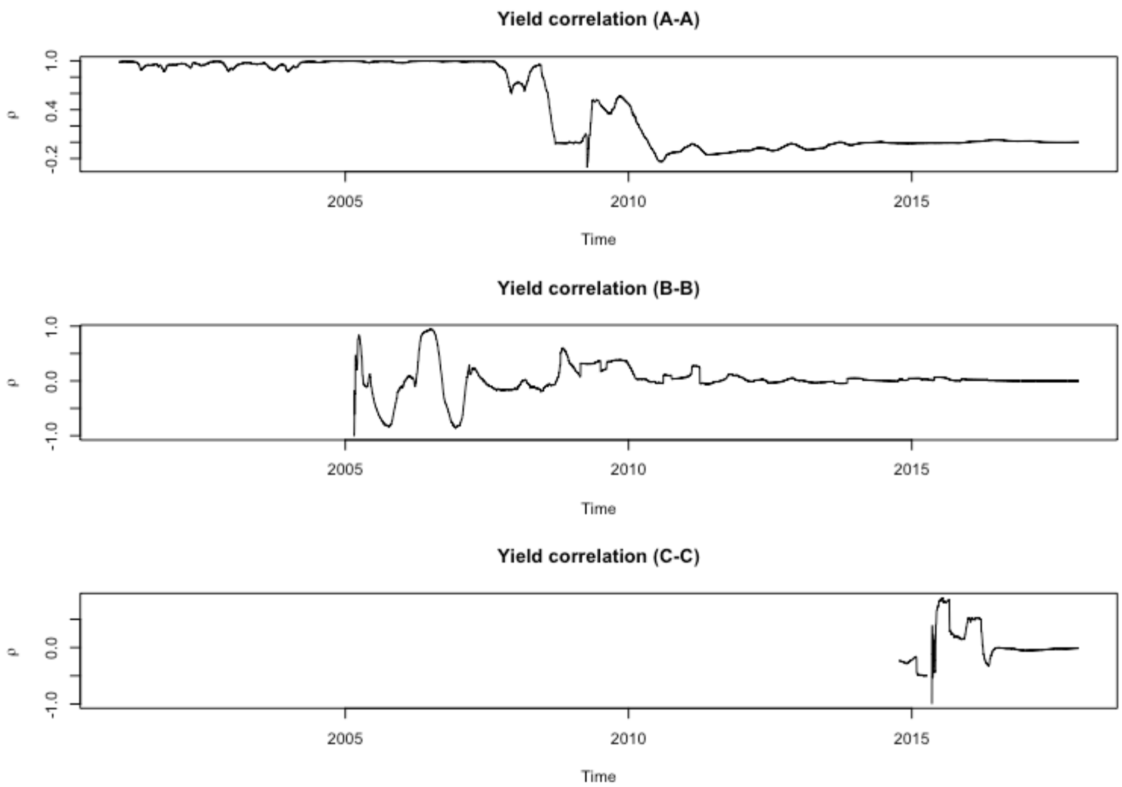


Figure 13: Pearson default-correlation over time

The Pearson correlation, as in Figure 13, captures the marginal behaviour as well as the dependence structure, while the Spearman correlation, as in Figure 14, only captures the dependence structure and not the marginal behaviour. Although these two measures behave quite similarly, the slight discrepancies indicate some non-linearity in the dependence structure between yields.

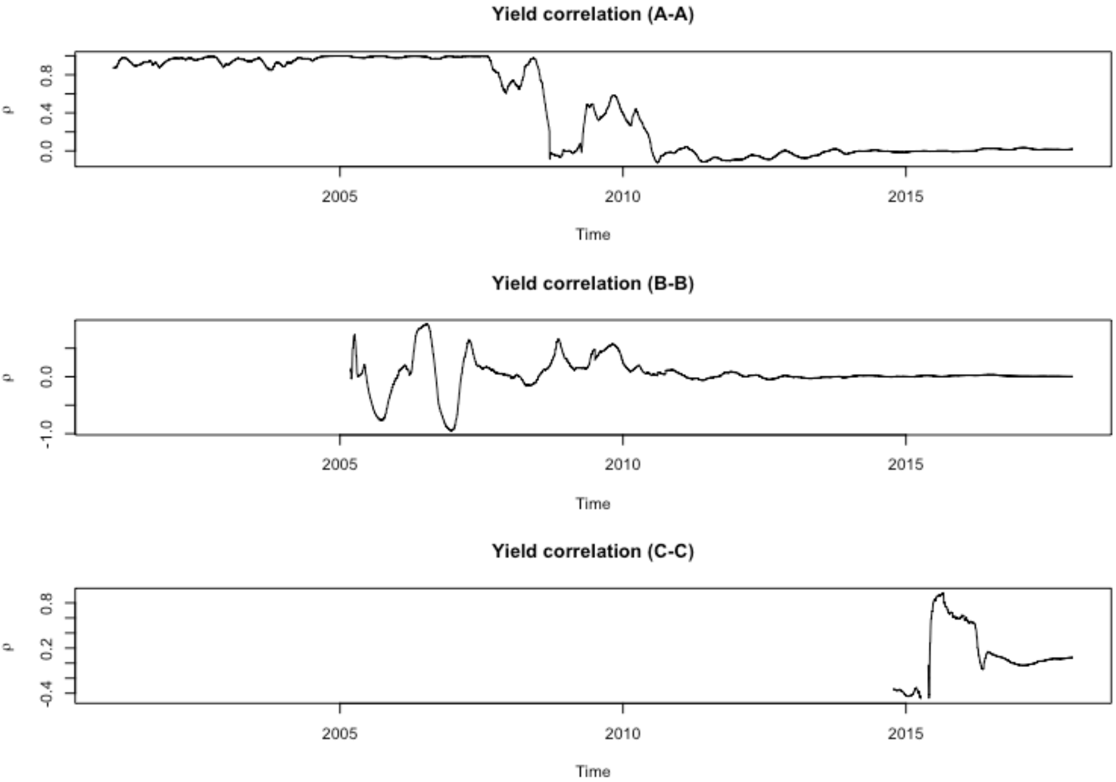


Figure 14: Spearman default-correlation over time

Opposed to the general Pearson and Spearman yield correlation we see far more variation in the extreme yield correlations, pictured in Figure 15 and Figure 16 respectively, in all three rating classes. This is likely due to the higher sensitivity of extreme observations to changes in market circumstances and possible financial distress.

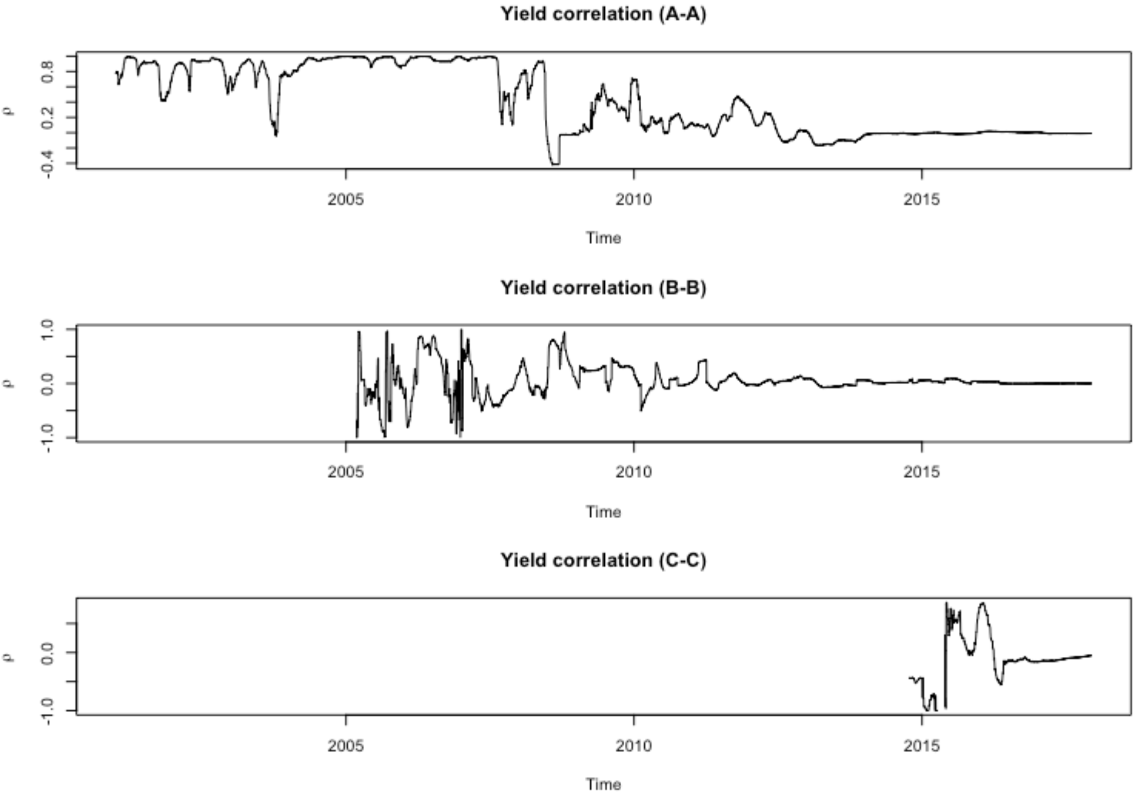


Figure 15: Extreme Pearson default-correlation over time

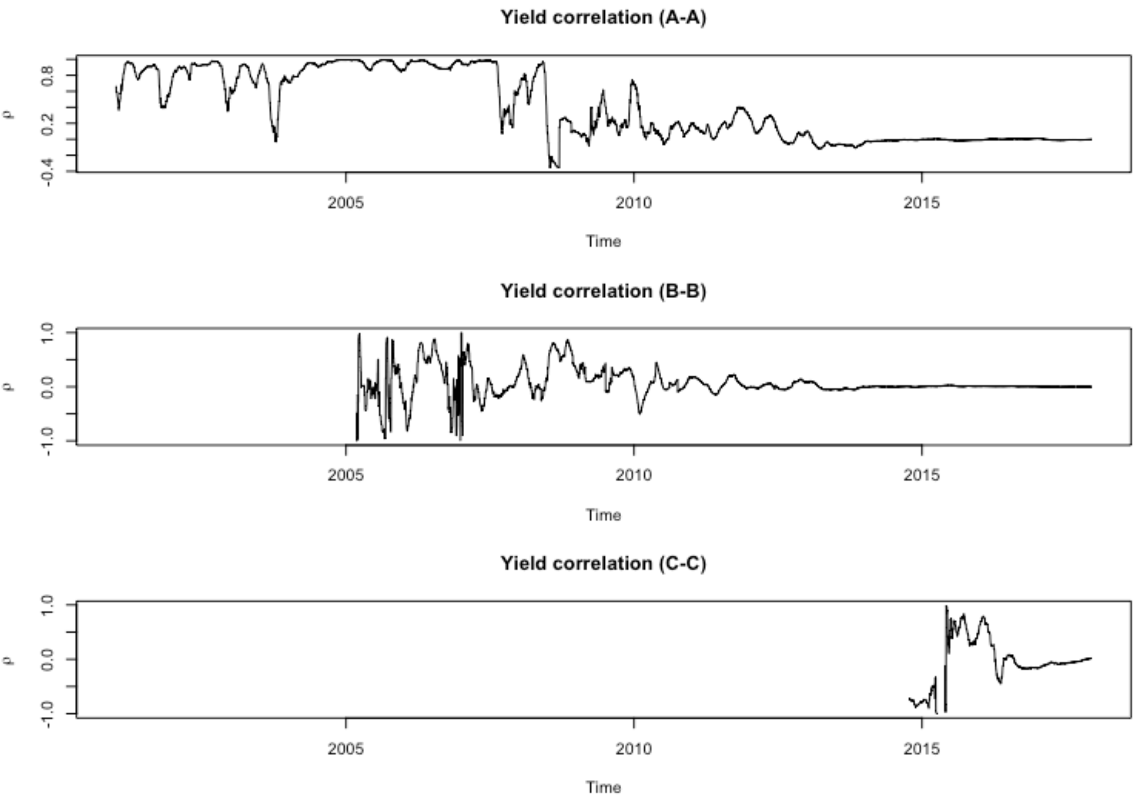


Figure 16: Extreme Spearman default-correlation over time

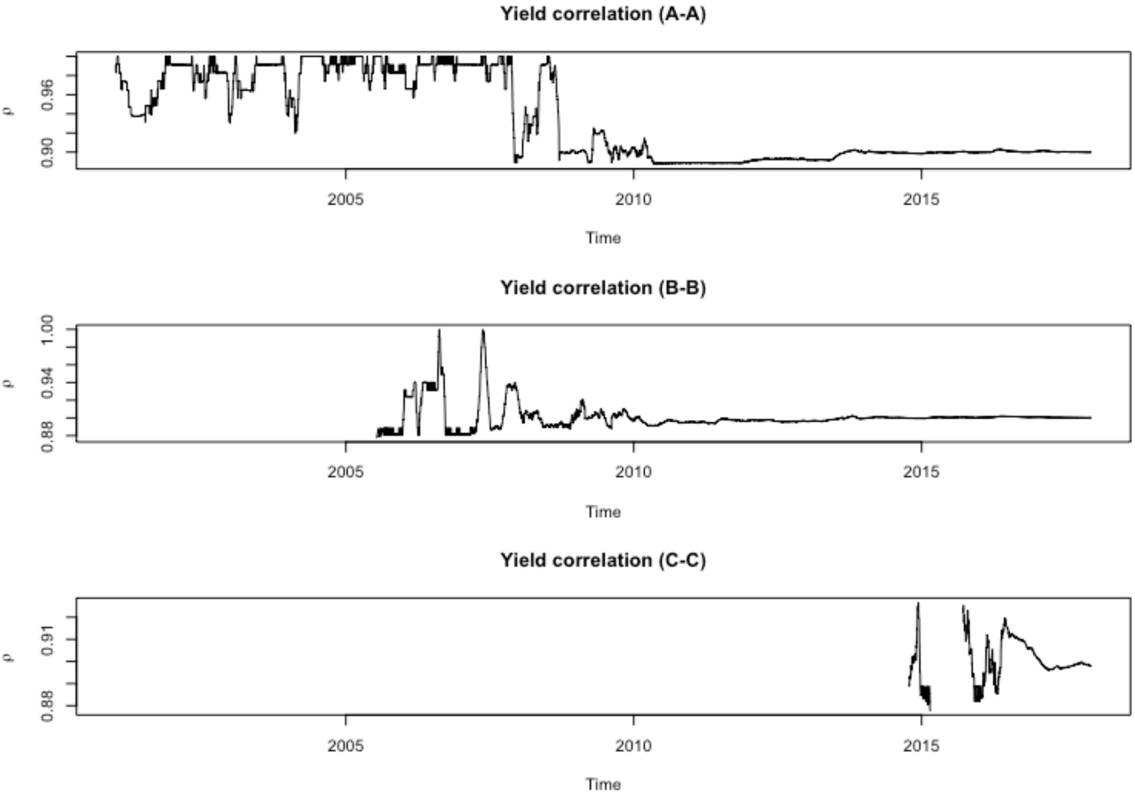


Figure 17: Tail dependence-coefficient over time

The tail dependence coefficient, as in Figure 17, shows a far different graphic than the other four measures do; the yield correlation tail dependence coefficient (TDC) is between 0.88 and 1 over the entirety of the data, time, and rating classes, indicating that the extreme (top 5%) yields are tail dependent.

4.5 Discrete default correlation

The discrete default correlation, as shown in Figure 18, based on the previous 12 months shows that the discrete default correlation for class A has nearly always been close to zero except for 2008 until 2013. This implies that before the crisis of latter mentioned period, very few to none correlated defaults took place in rating class A. Rating class B shows a very different result. This rating class shows strongly correlated defaults mainly before the crisis, and shows little to none default correlation from the initiation of the crisis. Rating class C shows a very short interval of correlation from just after 2015 and onwards. Notable here is that, although 2016 can be regarded as an upswing economy with low yields and thus low defaults, there is still a default correlation of 0.2. This might be due to the fact that C rated bonds have a low probability of non-default and have all defaulted since their issue.

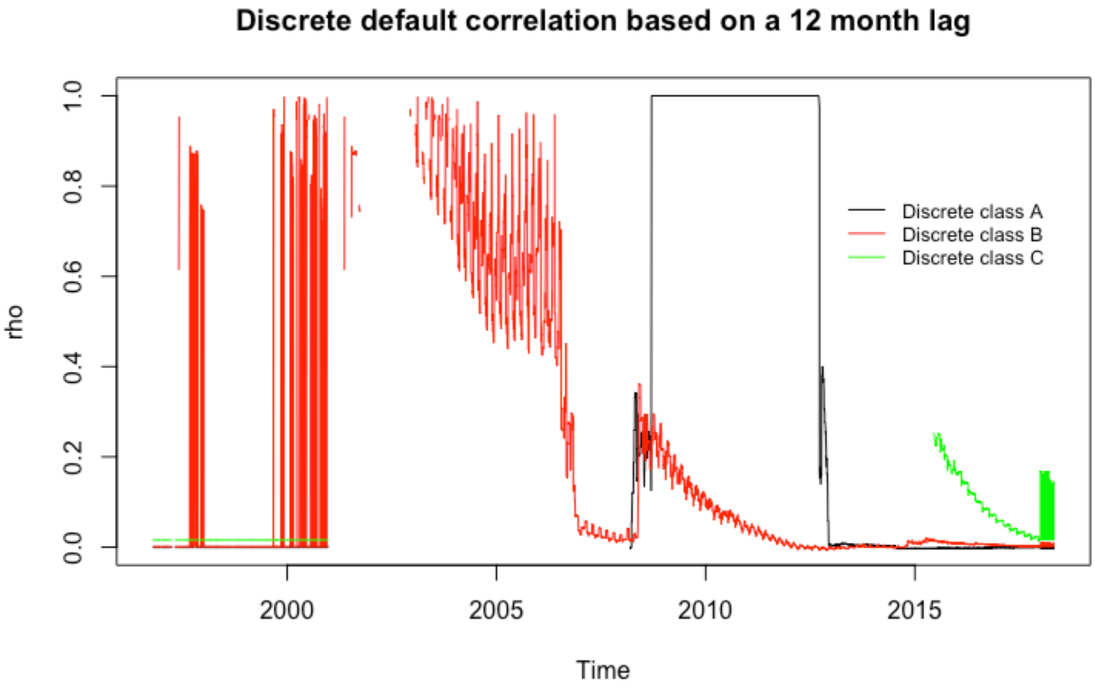


Figure 18: Discrete default correlation over time

4.6 Survival times and time to default correlation

Below is graphically depicted what the frequency of survival times per rating class is.

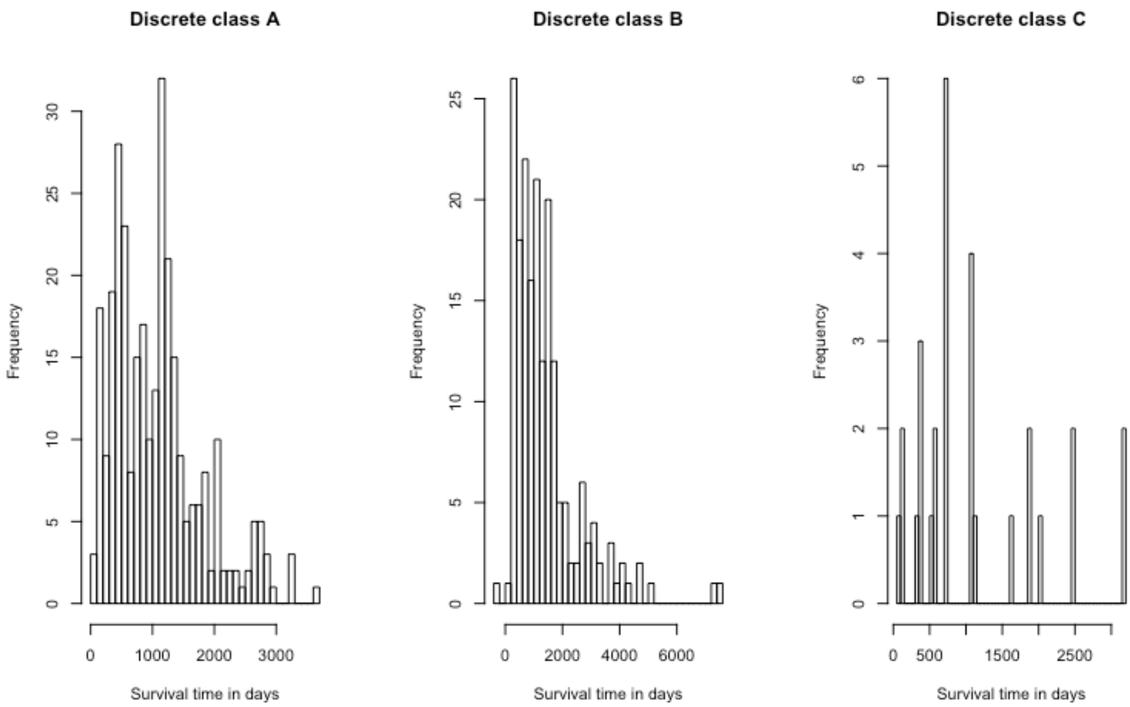


Figure 19: Frequency of survival times in days per rating class

Interesting from Figure 19 is that it shows that the average of survival time for rating class A is shorter than that of rating class B. One could argue that due to the fact that rating class B bonds carry far more default risk, it would be expected that they have a shorter lifespan than rating class A bonds. Nonetheless it shows that rating class B bonds do in fact tend to have a longer lifespan than rating A bonds, on average. Rating class C bonds do show the expected description of their data; their lifespan in survival days is on average far lower than that of rating class A and rating class B rated bonds. We do point out here, that not much data is available on rating class C bonds and that results might be biased.

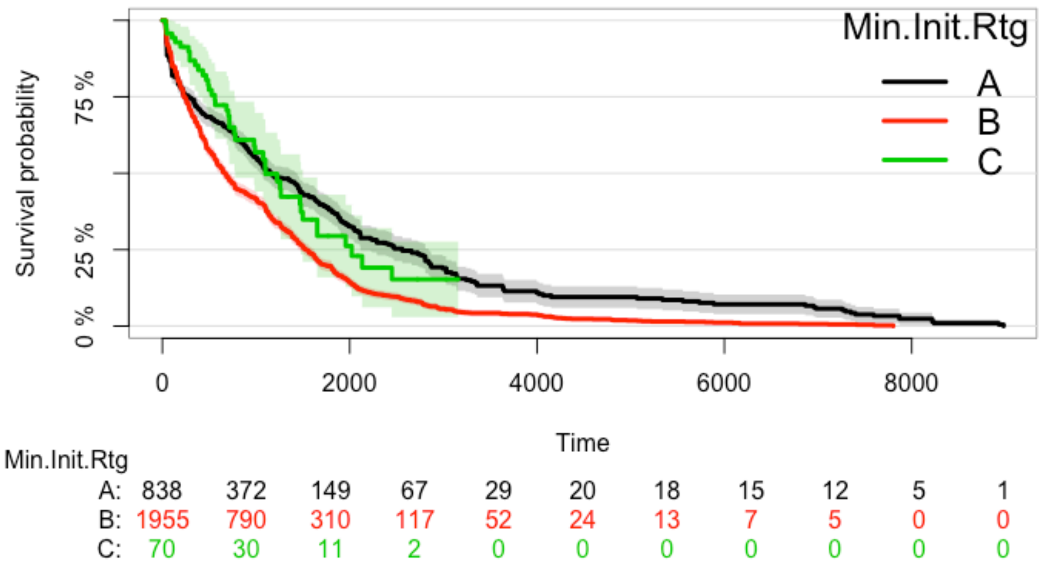


Figure 20: Survival times per rating class with the number of observations per rating class listed below the figure

Figure 20 shows the survival time in days given a certain survival probability. What shows from this Figure is that the survival probability of B rated bonds decreases very quickly, whereas the survival probability of A decreases more linearly. This means that on average rating class A rated bonds have a higher survival probability given a certain survival time than rating class B rated bonds. Rating class C shows a somewhat puzzling result; one would have expected that the survival probability of these bonds would decrease fastest of the three rating classes, as these bonds have the shortest survival time following Figure 22. The result again might be caused due to a lack of data for C rated bonds, which might cause inaccuracy in the results. This lack of data in general is why it was not possible to run regressions for the time to default correlation.

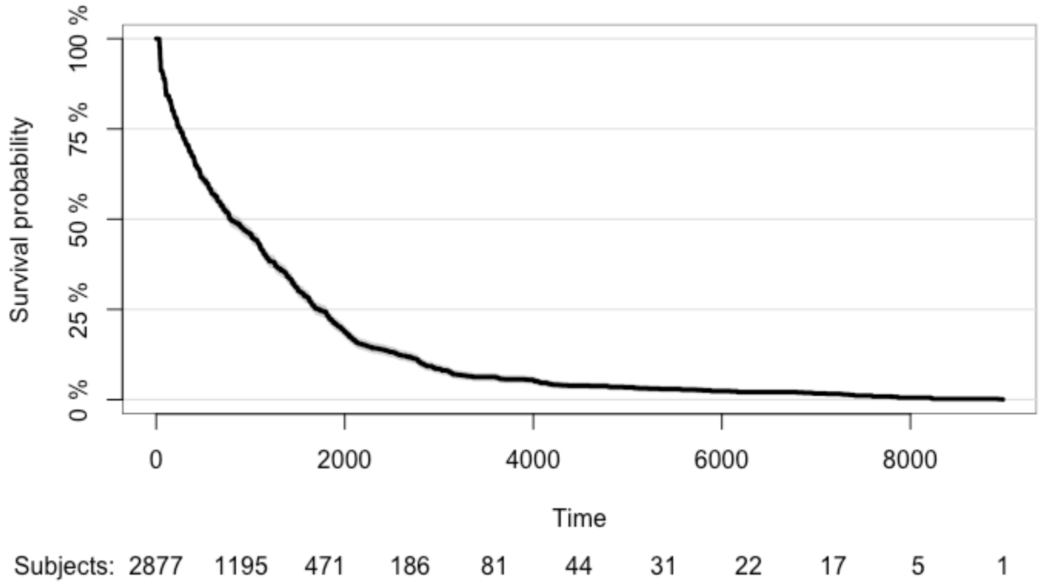


Figure 21: Cumulative survival probability of all rating classes

Figure 21 shows the cumulative survival probability of all rating classes. It shows from the Figure that after in the first year after issuance, bonds survival probability tends to fall from 100% to 75%. This relation also holds for the second year, where we see a decrease of survival probability from 75% to 50%. This means that given that the bonds has survived for 2 years, it has only a 50% chance of surviving, according to our data. The lower bound of survival probability tends to lie around 2000 days, which is equal to around 5-6 years. From there on the survival probability flattens, implying that bonds older than 2000 days until 4000 days have sort of the same survival probability as those of 5-6 years. This Figure furthermore means for investors that if they want to minimize risk of default, they would do wise to buy bonds that have just been issued. This finding might have some overlap with the short maturity effect found in Ilmanen et al. (2004), who finds that shorter maturity bonds carry a premium over long maturity bonds.

CHAPTER 5 Results

This chapter presents results on the implementation of the Fama-Macbeth regression models to explain credit spread changes. We first report results on the general model, that is, the regression model without our default dependence factor. Next, we report results on the models with the different variants of the default dependence factor, as discussed in section 4.1.1. For each regression we state the F-statistic, the R^2 and the adjusted R^2 indicating the significance and explanatory power of the model. Based on these statistics it is possible to compare the different models. As mentioned in the methodology chapter, all regressions are run for the entire sample and for subgroups of the sample based on credit rating and maturity. All results are retrieved from our analysis in R. We do not comment much on the adjusted R^2 and the F-statistic, as due to the large number of observations our adjusted R^2 is close to the general R^2 and the F-statistic is extremely significant in all our results.

5.1 General model results

The general model, as reported in the methodology, is estimated. Results are shown in Table 11. The regression looks as follows:

$$\begin{aligned}\Delta CS_t^i = \alpha + \ & \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t \\ & + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t \\ & + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \epsilon_t^i\end{aligned}$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.01	1.89	0.01	4.14	0.01	0.17	0.02	0.03
Z-score	3.33	2.13	2.29	2.07	1.10	1.52	2.08	2.10
ESTOXX50	-0.01	-10.74	0.00	-24.42	-0.01	-0.04	-0.02	-0.04
	-5.17	-1.08	-2.39	-1.08	-3.12	-2.71	-3.67	-3.99
SP	0.00	9.89	0.00	22.55	0.00	-0.02	-0.01	-0.04
	-1.32	1.12	0.11	1.12	-0.65	-0.97	-1.78	-3.45
Y3m	3.00	-394.01	1.29	-906.40	3.13	8.54	6.67	5.05
	6.19	-1.01	2.78	-1.02	5.45	3.04	3.73	3.13
Y12m	-3.75	221.50	-2.07	514.95	-3.74	-9.18	-7.73	-7.12
	-7.01	0.95	-4.51	0.97	-5.76	-2.64	-3.83	-3.79
Y120m	0.45	773.90	0.27	1760.94	0.30	1.49	1.12	1.41
	5.56	1.02	3.30	1.02	2.53	3.33	4.40	2.44
INFL	-0.27	-123.55	-0.18	-280.54	-0.22	-0.67	-0.61	-0.68
	-4.36	-1.02	-5.25	-1.02	-4.30	-4.03	-2.12	-1.83
TERM	-0.56	-546.83	-0.34	-1242.90	-0.48	-2.26	-1.18	-1.80
	-10.51	-1.03	-7.70	-1.03	-8.65	-2.93	-6.30	-3.75
FFDEFAULT	0.02	47.44	0.02	108.06	0.00	0.02	0.04	-0.05
	4.61	1.09	3.95	1.09	0.27	0.27	4.96	-1.32
MOMENTUM	-0.01	18.18	-0.01	41.47	-0.01	-0.06	-0.02	-0.03
	-6.42	0.95	-3.11	0.95	-6.12	-2.85	-2.79	-2.28
VALUE	-0.01	13.62	-0.01	31.02	-0.01	-0.01	0.00	0.01
	-2.99	0.98	-2.13	0.98	-3.39	-0.75	0.18	1.24
SIZE	0.00	38.21	0.00	87.11	-0.01	-0.07	-0.02	-0.02
	-2.31	0.98	1.31	0.98	-2.07	-2.08	-3.15	-2.83
VIX	0.00	-10.85	0.00	-24.70	-0.01	0.00	0.00	-0.03
	-1.77	-1.08	-1.53	-1.08	-1.76	0.15	-0.53	-2.35
R^2	0.37	0.10	0.27	0.10	0.37	0.16	0.40	0.32
Adjusted R^2	0.37	0.10	0.27	0.10	0.37	0.16	0.40	0.32
F-Statistic	3836.32	1958.03	873.27	808.75	1339.03	1133.03	1126.49	1694.51
N	71139	180064	24736	74381	24505	64101	18376	39151

Table 11: General model coefficients and Z-statistics following the two-step Fama-MacBeth (1973) approach. Green marked values are significant at the 5% confidence level or lower. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

<u>*Unique factors*</u>

$\boldsymbol{ESTOXX50_t}$ $\boldsymbol{and}$ $\boldsymbol{SP_t}$: Our results show that changes in the returns of the Eurostoxx50 are strongly significant in explaining changes in credit spreads in European public corporate bonds. These results are near equivalent to those of Collin-Dufresne et al. (2001) who find that for US debt the S&P500 is strongly significant. Our sample finds very little significance for the changes in the returns of the S&P500 in explaining changes in European public credit spreads. This might be due to a non-correlation somewhere in the interlinkage between European and US stock markets. Overall, these stock markets are known to exhibit great correlation so these results are somewhat puzzling.

$\boldsymbol{\Delta Y3m_t}$: We report strong significance of changes in the 3-month short term interest rate on changes in credit spreads. For higher quality credit (A), the factor shows to be significant in all maturities. Even for lower quality credit, the factor seems of great significance, with notable exception the 1-10 year maturity bucket. This maturity seems to be biased in such a way, that it also skews the “all-maturities” bucket. A possible explanation for the bias in the 1-10 year maturity bucket and therefore in the “all maturities” bucket, is that we noticed in section 4.4 how large the credit spread changes were for this rating class and maturity. We pointed out here that it was likely that defaults in our full sample are centred around the lower quality credit class B with 1-10 year maturity. Finally, we do not confirm findings of Morris, Neal & Rolph (1998) who argue that an increase in the short term treasury rate leads to a tightening of credit spreads. We also do not confirm findings of Longstaff and Schwartz (1995) who argued that a higher spot rate leads to increased firm values, which lowers risk of default and subsequently tightens credit spreads. We offer a different perspective. Former mentioned research investigates a data sample pre the year 2000, whereas this paper investigates changes in credit spreads from 2000 and onwards. One might argue that historical yield levels, from around 10% in the 90's, have drastically declined and so has the size of the credit spread. We argue here that the positive change in the 3-month spot rate is accompanied by a smaller positive change in the yield on a government bond, thus widening credit spreads on average.

$\Delta \boldsymbol{Y12m_t}$: Following and Litterman and Scheinkman (1991), we report strong significance of changes in the 1-year medium term interest rate on changes in credit spreads. For higher quality credit (A), the factor shows to be significant in all maturities. Even for lower quality credit, the factor seems of great significance, with notable exception the 1-10 year maturity. This maturity seems to be biased in such a way, that it also skews the "all-maturities" bucket. A possible explanation for the bias in the 1-10 year maturity bucket and therefore in the "all maturities" bucket, is that we noticed in section 4.4 how large the credit spread changes were for this rating class and maturity. We pointed out here that it was likely that defaults in our full sample are centred around the lower quality credit class B with 1-10 year maturity bucket.

$\Delta \boldsymbol{Y120m_t}$: Following Collin-Dufresne et al. (2001), we report strong significance of changes in the 10-year long term interest rate on changes in credit spreads. For higher quality credit (A), the factor shows to be significant in all maturities. Even for lower quality credit, the factor seems of great significance, with notable exception the 1-10 year maturity. This maturity seems to be biased in such a way, that it also skews the "all-maturities" bucket. A possible explanation for the bias in the 1-10 year maturity bucket and therefore in the "all maturities" bucket, is that we noticed in section 4.4 how large the credit spread changes were for this rating class and maturity. We pointed out here that it was likely that defaults in our full sample are centred around the lower quality credit class B with 1-10 year maturity bucket. Strangely though, Collin-Dufresne et al. (2001) reports that an increase in the 10-year yield, which can according to them be seen as the risk-free rate, tightens credit spreads. We report that an increase in the 10-year yield curve actually widens credit spreads. To us this seems intuitively correct; if government bond yields increase, then so will corporate yields. Intuitively also, we argue that due to a higher risk of default, corporate yields should increase by more than the increase on government bond yields thus explaining a widening of credit spreads.

$\Delta \boldsymbol{INFL_t}$: Following Kang and Pflueger (2012) we provide evidence on the positive effect of changes in inflation on credit spreads. We show that the change in inflation is statistically significant in explaining changes in credit spreads. Kang and Pflueger (2012) argued that investors require compensation for the lower value of discounted cash flows stemming from periodical bond payments which seems consistent with our findings

Common factors

$\Delta \boldsymbol{Term_t}$: We infer to confirm findings of Trück, Laub & Rachev (2004) who find that the term structure is a significant factor in explaining credit spreads. We argue that our finding of term structure differences significantly explaining credit spread differences is basically equivalent. Opposite to the findings of Trück, Laub & Rachev (2004), we find an increasing sensitivity of high quality credit (A) to the term structure with an increase in maturity. This is opposite to the result of Trück, Laub & Rachev (2004) who find that a higher maturity means a lower sensitivity to the term structure factor. Complementary to their results, we also report significant results for lower quality credit (B); for maturities 10-15 years and 15-50 years we report a significant role of the term structure factor. For the low maturity subset (1-10 years), there is no significant role for the term structure factor.

$\Delta \boldsymbol{FFDefault_t}$: The Fama French (1993) default factor shows significance for all high quality credit maturities except for that of the 10-15 year maturity subset. It has no significance for low quality credit, not even for one maturity bucket. We point out that the effect size of the Fama French (1993) default factor overall seems to be low. It is strongly argued here as well as in the construction of hypothesis 2, that the Fama French (1993) default factor does not accurately capture the default premium.

$\Delta \boldsymbol{Momentum_t}$: In accordance with Jostova, Nikolova, Philipov & Stahel (2013) who confirm the existence of momentum in US corporate bond markets, this paper confirms the existence of momentum in European corporate bond markets. Also, in accordance with Jostova, Nikolova, Philipov & Stahel (2013) we confirm that the largest effect size for momentum is that of lower quality credit in the 10-15 year maturity bucket and the 15-50 year maturity bucket. We point out here, that although the relative effect size increases by a factor 3-6 relative to high quality credit, the absolute effect size is still close to zero.

$\Delta \boldsymbol{Value_t}$ **and** $\Delta \boldsymbol{Size_t}$: To our knowledge, this paper is the first to confirm that changes in the size and value factor, as measured respectively by the SMB and the HML factors, are significant factors in explaining changes in credit spreads. Our results are closest to that of van Houweling (2017) who shows that the SMB and HML factors are both significant in explaining bond returns. Although our results are strongly significant in nearly all maturities, we point out that the effect sizes are very small and moreover, close to zero.

$\Delta \boldsymbol{VIX_t}$: Opposed to Collin-Dufresne, Goldstein and Martin (2001) we do not find any significance in the VIX factor. This might be due to the fact that US stock market volatility might in the end not be a good enough proxy for stock market volatility in European stock markets. Nonetheless, the question here remains that if an appropriate proxy was used, would it have been significant. Although Collin-Dufresne, Goldstein and Martin (2001) find some significance for the VIX factor, we do point out that their results only show significance for most of the shorter maturities and only one of the longer maturities. Furthermore, as with our results, the effect size of the VIX is both in theirs as in our research close to 0.

5.2 General model with discrete default correlation

In this section, the discrete default correlation factor is added to the general model. Results are shown in Table 12. The following regression equation is fitted:

$$\begin{aligned}\Delta CS_t^i = \alpha + \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t \\ + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t \\ + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta Discrete\_Def_t + \epsilon_t^i\end{aligned}$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.01	0.13	0.01	0.14	0.01	0.17	0.02	0.02
Z-score	2.92	0.49	2.19	0.24	0.67	1.47	1.98	1.81
ESTOXX50	-0.01	-10.35	0.00	-23.53	-0.01	-0.04	-0.02	-0.03
	-5.13	-1.05	-2.30	-1.05	-3.13	-2.96	-3.66	-3.94
SP	0.00	9.82	0.00	22.40	0.00	-0.02	-0.01	-0.05
	-1.33	1.13	0.03	1.13	-0.61	-0.85	-1.78	-3.57
Y3m	5.63	1.00	3.37	1.00	2.49	3.36	4.53	2.47
	2.99	-363.03	1.28	-835.76	3.10	8.58	6.73	4.79
Y12m	-3.77	209.63	-2.06	487.88	-3.79	-9.18	-7.79	-7.07
	-7.08	0.95	-4.54	0.97	-5.83	-2.64	-3.89	-3.81
Y120m	0.44	747.99	0.27	1701.93	0.30	1.48	1.12	1.43
	5.56	1.02	3.30	1.02	2.53	3.33	4.40	2.44
INFL	-0.27	-123.66	-0.19	-280.79	-0.22	-0.66	-0.61	-0.69
	-4.40	-1.01	-5.45	-1.01	-4.31	-3.92	-2.13	-1.85
TERM	-0.56	-546.83	-0.34	-1242.90	-0.48	-2.26	-1.18	-1.80
	-10.51	-1.03	-7.70	-1.03	-8.65	-2.93	-6.30	-3.75
FFDEFAULT	0.02	52.29	0.02	119.11	0.00	0.02	0.04	-0.06
	4.55	1.11	4.08	1.11	0.29	0.19	4.78	-1.38
MOMENTUM	-0.01	19.02	-0.01	43.39	-0.01	-0.06	-0.02	-0.03
	-6.52	0.97	-3.30	0.97	-6.53	-2.83	-2.69	-2.37
VALUE	-0.01	13.32	-0.01	30.35	-0.01	-0.01	0.00	0.01
	-2.92	1.01	-2.15	1.01	-3.45	-0.67	0.38	0.96
SIZE	0.00	38.14	0.00	86.95	-0.01	-0.07	-0.02	-0.02
	-2.36	0.98	1.35	0.98	-2.18	-2.08	-3.10	-2.69
VIX	0.00	-11.12	0.00	-25.33	-0.01	0.00	0.00	-0.03
	-1.84	-1.05	-1.72	-1.05	-1.74	0.19	-0.54	-2.36
Discrete_Def	3.18	3042.46	-3.69	6929.31	10.42	-0.02	4.78	2.35
	0.75	1.65	-1.20	1.66	1.08	0.00	0.45	0.78
R^2	0.37	0.10	0.28	0.10	0.37	0.16	0.41	0.32
Adjusted R^2	0.37	0.10	0.28	0.10	0.37	0.16	0.40	0.32
F-Statistic	3597.91	1806.50	814.51	746.16	1245.36	1069.06	1062.44	1586.73
N	71139	180064	24736	74381	24505	64101	18376	39151

Table 12: General model including discrete default correlation coefficients and Z-Statistics following the two-step Fama-MacBeth (1973) approach. Green market values are significant at the 5% confidence level or lower. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

The model with discrete default correlation shows that the factor discrete default correlation changes has no significant effect on credit spread changes. It shows no significance for any quality credit or maturity, except for the all maturities bucket and 1-10 year maturity bucket where the factor is significant at the 10% level. This is an interesting result as it shows that, for the bucket and quality credit where defaults are centred around as we pointed out in section 4.4 rating class B, some form of significance can be found. However, this correlation measure does not extend to different buckets, credit quality, and arguably, different time periods. Furthermore, the coefficients of the other factors remain largely the same with no notable exceptions.

5.3 General model with Pearson yield correlation

In this section, the Pearson yield correlation factor is added to the general model. Results are shown in Table 13. The following regression equation is fitted:

$$\Delta CS_t^i = \alpha + \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta Pearson\_yield\_corr_t + \epsilon_t^i$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.02	-0.91	0.01	-2.22	0.01	0.17	0.03	0.03
Z-score	3.91	-0.33	2.67	-0.36	1.52	1.55	2.30	2.42
ESTOXX50	-0.01	-8.96	0.00	-20.36	-0.01	-0.04	-0.02	-0.03
	-5.12	-1.11	-2.30	-1.11	-3.13	-2.79	-3.62	-4.03
SP	-0.01	9.46	0.00	21.57	0.00	-0.02	-0.02	-0.05
	-1.66	1.14	0.09	1.14	-0.89	-0.79	-2.28	-3.38
Y3m	2.86	-718.27	1.33	-1645.25	2.93	8.87	6.23	4.97
	5.84	-0.97	2.94	-0.97	5.21	3.12	3.32	3.04
Y12m	-3.64	521.62	-2.11	1198.63	-3.60	-9.37	-7.35	-6.96
	-6.62	0.93	-4.70	0.94	-5.60	-2.69	-3.39	-3.64
Y120m	0.44	764.73	0.26	1740.05	0.31	1.52	1.10	1.40
	5.43	1.03	3.16	1.02	2.60	3.21	4.20	2.43
INFL	-0.27	-167.82	-0.18	-381.38	-0.21	-0.65	-0.59	-0.72
	-4.42	-1.01	-5.32	-1.00	-4.44	-3.85	-2.13	-1.87
TERM	-0.56	-550.10	-0.33	-1250.33	-0.48	-2.29	-1.18	-1.79
	-10.34	-1.03	-7.80	-1.02	-8.59	-2.91	-6.09	-3.74
FFDEFAULT	0.02	36.79	0.02	83.80	0.00	0.03	0.04	-0.05
	4.58	1.12	3.62	1.12	0.34	0.30	4.90	-1.28
MOMENTUM	-0.01	17.95	-0.01	40.95	-0.01	-0.06	-0.02	-0.03
	-6.69	0.95	-3.11	0.95	-6.21	-2.80	-2.95	-2.35
VALUE	-0.01	14.23	-0.01	32.41	-0.01	-0.01	0.00	0.01
	-3.30	0.98	-2.55	0.98	-3.61	-0.66	0.35	1.24
SIZE	-0.01	40.73	0.00	92.85	-0.01	-0.07	-0.02	-0.02
	-2.41	0.98	1.26	0.98	-2.07	-2.10	-3.23	-2.86
VIX	0.00	-9.98	0.00	-22.72	-0.01	0.00	0.00	-0.03
	-2.07	-1.09	-1.36	-1.09	-1.98	0.23	-0.72	-2.33
Pearson_yield_corr	-1.58	918.14	0.01	2091.52	-2.35	-0.86	-3.67	1.04
	-1.64	0.96	0.00	0.96	-1.86	-0.78	-1.02	1.45
R^2	0.37	0.11	0.28	0.11	0.37	0.16	0.41	0.32
Adjusted R^2	0.37	0.11	0.28	0.11	0.37	0.16	0.41	0.32
F-Statistic	3623.41	1957.08	837.50	808.35	1248.40	1052.14	1067.09	1581.82
N	71139	180064	24736	74381	24505	64101	18376	39151

Table 13: General model with Pearson yield correlation coefficient and Z-statistics following the two-step Fama-MacBeth (1973) approach. Green marked values are significant at the 5% confidence level or lower.. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

The Pearson yield correlation shows significance at the 10% level for the all maturity bucket and 10-15 year maturity bucket for high quality credit. More interesting in our opinion, is the effect of the Pearson yield correlation on VIX. The VIX shows significance in 3 buckets after the implementation of the Pearson yield correlation factor. We offer no plausible explanation for this finding. It follows from this result that the Pearson yield correlation is not a measure that best describes the structure of default dependence, possibly through also measuring marginal behaviour in the default dependence factor.

5.3.1 General model with Spearman yield correlation

In this section, the Spearman yield correlation factor is added to the general model. Results are shown in Table 14. The following regression equation is fitted:

$$\Delta CS_t^i = \alpha + \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta Spearman\_yield\_corr_t + \epsilon_t^i$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.02	-8.31	0.02	-19.08	0.01	0.17	0.03	0.03
Z-score	4.07	-0.86	2.76	-0.87	1.04	1.51	2.84	2.05
ESTOXX50	-0.01	-11.75	0.00	-26.73	-0.01	-0.04	-0.02	-0.04
	-5.17	-1.09	-2.50	-1.09	-3.09	-2.56	-3.55	-3.97
SP	0.00	13.57	0.00	30.95	0.00	-0.02	-0.02	-0.04
	-1.47	1.08	0.20	1.08	-0.77	-0.78	-2.06	-3.48
Y3m	2.92	-826.71	1.26	-1891.87	3.02	8.43	6.34	5.07
	6.13	-0.99	2.81	-0.99	5.48	3.04	3.53	3.20
Y12m	-3.65	540.08	-2.02	1240.86	-3.78	-8.92	-7.34	-7.15
	-6.92	0.94	-4.70	0.95	-5.77	-2.57	-3.58	-3.91
Y120m	0.44	713.57	0.25	1623.42	0.32	1.42	1.11	1.42
	5.46	1.03	3.07	1.03	2.55	3.30	4.38	2.45
INFL	-0.26	-185.27	-0.17	-421.09	-0.23	-0.68	-0.58	-0.69
	-4.25	-1.03	-5.01	-1.03	-4.50	-3.63	-2.05	-1.86
TERM	-0.56	-498.30	-0.33	-1132.27	-0.50	-2.22	-1.19	-1.79
	-10.40	-1.03	-7.44	-1.03	-8.04	-2.98	-6.30	-3.74
FFDEFAULT	0.02	49.10	0.02	111.83	0.00	0.00	0.04	-0.05
	4.74	1.11	3.76	1.11	0.13	0.05	5.28	-1.26
MOMENTUM	-0.01	16.01	-0.01	36.52	-0.01	-0.06	-0.02	-0.03
	-6.50	0.94	-3.06	0.94	-5.88	-2.77	-2.87	-2.29
VALUE	-0.01	17.27	-0.01	39.33	-0.01	-0.01	0.00	0.01
	-3.42	0.99	-2.59	0.99	-3.40	-0.86	0.03	1.24
SIZE	0.00	40.47	0.00	92.25	-0.01	-0.07	-0.02	-0.02
	-2.31	0.98	1.30	0.98	-2.23	-2.12	-3.05	-2.92
VIX	0.00	-8.61	0.00	-19.61	-0.01	0.00	0.00	-0.03
	-1.87	-1.12	-1.31	-1.12	-1.84	0.27	-0.63	-2.32
Spearman_yield_corr	-1.83	3114.98	-0.33	7097.12	-1.46	0.48	-5.97	-0.06
	-2.19	1.05	-0.25	1.05	-1.88	0.50	-2.43	-0.03
R^2	0.38	0.12	0.29	0.12	0.37	0.16	0.41	0.33
Adjusted R^2	0.38	0.12	0.29	0.12	0.37	0.16	0.40	0.33
F-Statistic	3639.44	2126.50	855.25	878.33	1263.52	1169.06	1062.53	1657.94
N	71139	180064	24736	74381	24505	64101	18376	39151
N	130	369	54	162	47	136	26	64

Table 14: General model with Spearman yield correlation coefficients and Z-statistics following the two-step Fama-MacBeth (1973) approach. Green marked values are significant at the 5% level or lower.. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

The Spearman yield correlation measure does show some significance with strong effect sizes. For high quality rated credit in the all maturities bucket and the 15-50 year bucket we show a 5% level significance for the Spearman yield correlation factor. This means that changes in the Spearman yield correlation have a significant effect on credit spread changes. This result might be explained through the definition of the Spearman correlation, which solely measures the dependence-structure between yields and does not also measure the marginal behaviour of the yields. We point out that the significant effect sizes of -1.83 and -5.97 are substantial and have somewhat similar effect sizes as that of the forward rates. Since these have been largely known to drive credit spreads, we argue that the Spearman yield correlation measure in approximating might be an important missing puzzle piece in the credit spread puzzle. We would also like to point out the slight increase of 1% in the R^2 for the significant maturity buckets. Although this is not a huge increase in explanatory power, we refer to the general model where we argued that due to our methodology with the two-step approach, the R^2 might be biased.

5.3.2 General model with extreme Pearson yield correlation

In this section, the extreme Pearson yield correlation factor is added to the general model. Results are shown in Table 15. The following regression equation is fitted:

$$\Delta CS_t^i = \alpha + \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t \\ + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t \\ + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta Extreme\_Pearson\_yield\_corr_t + \epsilon_t^i$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.01	-11.18	0.01	-25.61	0.01	0.17	0.02	0.03
Z-score	3.59	-0.83	2.65	-0.84	1.04	1.51	2.28	2.39
ESTOXX50	-0.01	-9.07	0.00	-20.62	-0.01	-0.04	-0.02	-0.03
	-5.06	-1.13	-2.30	-1.12	-3.09	-2.56	-3.56	-4.04
SP	0.00	15.89	0.00	36.22	0.00	-0.02	-0.01	-0.04
	-1.26	1.07	0.16	1.07	-0.77	-0.78	-1.51	-3.41
Y3m	3.02	-771.54	1.39	-1766.25	3.02	8.43	6.76	5.03
	6.17	-0.93	2.91	-0.94	5.48	3.04	3.71	3.12
Y12m	-3.73	621.69	-2.08	1426.22	-3.78	-8.92	-7.56	-7.04
	-6.93	0.89	-4.57	0.90	-5.77	-2.57	-3.68	-3.70
Y120m	0.43	668.51	0.25	1520.97	0.32	1.42	1.04	1.41
	5.32	1.03	3.16	1.03	2.55	3.30	4.03	2.46
INFL	-0.28	-224.43	-0.19	-510.31	-0.23	-0.68	-0.59	-0.72
	-4.67	-1.01	-5.49	-1.01	-4.50	-3.63	-2.19	-1.82
TERM	-0.55	-522.53	-0.32	-1187.58	-0.50	-2.22	-1.10	-1.79
	-10.34	-1.03	-7.65	-1.02	-8.04	-2.98	-5.92	-3.78
FFDEFAULT	0.02	23.70	0.02	54.01	0.00	0.00	0.04	-0.05
	4.38	1.20	3.90	1.20	0.13	0.05	4.60	-1.30
MOMENTUM	-0.01	15.66	-0.01	35.72	-0.01	-0.06	-0.02	-0.03
	-6.61	0.94	-3.39	0.94	-5.88	-2.77	-2.86	-2.34
VALUE	-0.01	13.17	-0.01	30.00	-0.01	-0.01	0.00	0.01
	-3.47	0.98	-2.68	0.98	-3.40	-0.86	-0.03	1.18
SIZE	0.00	42.27	0.00	96.34	-0.01	-0.07	-0.02	-0.02
	-2.38	0.97	1.37	0.97	-2.23	-2.12	-2.99	-2.87
VIX	0.00	-6.33	0.00	-14.41	-0.01	0.00	0.00	-0.03
	-1.64	-1.15	-1.29	-1.15	-1.84	0.27	-0.38	-2.27
Extreme_Pearson_yield_corr	0.90	1524.58	0.93	3471.98	-1.46	0.48	5.17	0.46
	1.36	0.96	1.10	0.96	-1.88	0.50	2.35	0.77
R^2	0.38	0.16	0.29	0.16	0.37	0.16	0.42	0.32
Adjusted R^2	0.38	0.16	0.29	0.16	0.37	0.16	0.42	0.32
F-Statistic	3736.41	2883.33	872.10	1190.93	1250.37	1066.84	1114.83	1587.91
N	71139	180064	24736	74381	24505	64101	18376	39151

Table 15: General model with extreme Pearson yield correlation coefficients and Z-statistics following the two-step Fama-MacBeth (1973) approach. Green marked values are significant at the 5% confidence level or lower.. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

As with the Pearson yield correlation, the extreme Pearson yield correlation measures the marginal behaviour of yields as well as the dependence of the yields, but then for extreme observations. This means that this measure only takes into consideration the 50% highest yield observations. Nonetheless, as with the Pearson yield correlation we see very little significance of the extreme Pearson yield correlation. One notable exception is the significance for the high quality 15-50 year maturity bucket. In fact, this result shows a very large size effect as well as significance around the 1% level. Yet we also note an increase in the R^2 to 0.42. This means that extreme Pearson yield correlation changes measure does have some explanatory power in explaining credit spread changes.

5.3.3 General model with extreme Spearman yield correlation

In this section, the Extreme Spearman yield correlation factor is added to the general model. Results are shown in Table 16 The following regression equation is fitted:

$$\Delta CS_t^i = \alpha + \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t$$
$$+ \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t$$
$$+ \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta Extreme\_Spearman\_yield\_corr_t + \epsilon_t^i$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.01	-13.21	0.01	-30.24	0.00	0.16	0.02	0.03
Z-score	2.79	-0.84	2.30	-0.84	0.33	1.39	2.26	2.03
ESTOXX50	-0.01	-8.06	0.00	-18.31	-0.01	-0.03	-0.02	-0.04
	-5.12	-1.15	-2.35	-1.15	-3.10	-2.24	-3.63	-4.00
SP	0.00	20.95	0.00	47.75	0.00	-0.01	-0.01	-0.04
	-1.04	1.04	0.28	1.04	-0.40	-0.35	-1.73	-3.51
Y3m	2.84	-1410.00	1.29	-3220.02	2.84	7.56	6.39	5.57
	6.01	-0.96	2.84	-0.96	5.00	3.21	3.68	3.42
Y12m	-3.73	1361.96	-2.08	3112.31	-3.78	-8.39	-7.54	-7.82
	-7.02	0.94	-4.55	0.95	-5.81	-2.69	-3.76	-3.80
Y120m	0.44	479.08	0.26	1089.78	0.33	1.02	1.07	1.47
	5.39	1.06	3.16	1.06	2.61	2.48	4.09	2.43
INFL	-0.30	-211.73	-0.20	-481.29	-0.25	-0.79	-0.65	-0.71
	-4.75	-1.02	-5.68	-1.02	-4.66	-4.31	-2.28	-1.83
TERM	-0.59	-405.98	-0.35	-922.36	-0.52	-1.93	-1.20	-1.79
	-10.26	-1.04	-7.60	-1.04	-8.31	-3.07	-5.89	-3.74
FFDEFAULT	0.01	24.02	0.01	54.76	0.00	-0.02	0.03	-0.06
	4.03	1.24	3.72	1.24	0.06	-0.33	4.24	-1.32
MOMENTUM	-0.01	15.59	-0.01	35.56	-0.01	-0.06	-0.02	-0.03
	-6.40	0.94	-2.90	0.94	-5.75	-3.04	-2.97	-2.31
VALUE	-0.01	19.04	0.00	43.38	-0.01	-0.02	0.00	0.01
	-2.82	0.98	-1.85	0.98	-3.16	-1.48	0.23	0.51
SIZE	0.00	46.48	0.00	105.94	-0.01	-0.07	-0.02	-0.02
	-2.27	0.98	1.44	0.98	-2.29	-2.06	-3.09	-3.16
VIX	0.00	-1.22	0.00	-2.78	-0.01	0.01	0.00	-0.03
	-1.64	-1.51	-1.30	-1.51	-1.64	0.63	-0.52	-2.36
Extreme_Spearman_yield_corr	-3.98	2256.41	-2.74	5146.02	-4.77	-4.38	-5.61	-5.92
	-4.89	0.91	-2.40	0.91	-4.03	-1.11	-2.22	-2.24
R^2	0.38	0.19	0.28	0.19	0.38	0.18	0.42	0.33
Adjusted R^2	0.38	0.19	0.28	0.19	0.38	0.18	0.42	0.33
F-Statistic	3720.90	3562.95	849.68	1471.64	1260.44	1186.61	1110.95	1606.96
N	71139	180064	24736	74381	24505	64101	18376	39151

Table 16: General model with extreme Spearman yield correlation coefficients and Z-statistics following the two-step Fama-MacBeth (1973) approach. Green marked values are significant at the 5% confidence level or lower.. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

The extreme Spearman yield correlation captures solely the dependence structure of the 50% highest yield observations. It shows from Table 16 that this dependence-measure is strongly significant for all high quality credit maturity buckets. Furthermore, large effect sizes can be observed ranging from -5.61 to -2.74. We point out that these effects have a larger size than that of the short term forward rate. Interesting here is that, a lower default dependence is followed by a positive change in credit spreads, given that the measure is correct. It was expected that a positive credit spread change, which means a higher risk in the market, would be accompanied by a higher default correlation. This in turn because a higher risk in the market, which means a higher yield on corporate bonds in the market, would mean a higher rate of default. The results tend to strongly disagree with this reasoning nonetheless. We do however, offer a potential alternative explanation. Das et al. (2007) suggested that credit spreads are more heavily affected by the default intensity than the probability of default. This could offer an explanation to our negative effect sizes; although a high default dependence leads to a higher expected number of default for investors, thus increasing risk, high default dependence is mainly observed during economic upswing periods. In such periods recovery rates are usually higher than in bear markets, because more firm value is recovered through a higher amount of buy-outs in case of default. This would cause the credit spread to tighten. If the recovery rate effects outweigh the default dependence effects, this would explain the negative effect sizes for some of our, most significant, default dependence factors. Further research has to be conducted to disentangle these two effects.

Furthermore, we show that there is little significance of the Extreme Spearman yield correlation for the lower quality credit, with notable exception the 15-50 year maturity bucket. The effect size for this coefficient is extremely large with a value of -5.92. This value is larger than that of the medium term forward rate and the long term forward rate used in this model. This would mean that this factor has a greater effect than the medium and long term forward rate. Furthermore, we point out once again the small increase in R^2.

5.3.4 General model with tail dependence coefficient

In this section, the tail dependence coefficient factor is added to the general model. Results are shown in Table 17. The following regression equation is fitted:

$$\begin{aligned}\Delta CS_t^i = \alpha + \ & \beta_1^i ESTOXX50_t + \beta_2^i SP_t + \beta_3^i \Delta Y3m_t + \beta_4^i \Delta Y12m_t + \beta_5^i \Delta Y120m_t + \beta_6^i \Delta INFL_t \\ & + \beta_7^i \Delta TERM_t + \beta_8^i \Delta FFDEFAULT_t + \beta_9^i \Delta MOMENTUM_t + \beta_{10}^i \Delta VALUE_t \\ & + \beta_{11}^i \Delta SIZE_t + \beta_{12}^i \Delta VIX_t + \beta_{13}^i \Delta TDC\_Yield_t + \epsilon_t^i\end{aligned}$$

	Rating groups		Rating groups		Rating groups		Rating groups	
	A	B	A	B	A	B	A	B
	All maturities		1-10 year maturities		10-15 year maturities		15-50 year maturities	
(Intercept)	0.02	-0.39	0.02	-1.09	0.01	0.20	0.03	0.06
Z-score	4.05	-0.20	2.78	-0.24	1.50	1.74	2.49	3.81
ESTOXX50	-0.01	-12.14	0.00	-27.61	-0.01	-0.03	-0.02	-0.03
	-5.09	-1.06	-2.43	-1.05	-2.99	-2.24	-3.59	-4.63
SP	-0.01	10.37	0.00	23.66	-0.01	-0.02	-0.02	-0.05
	-1.81	1.12	0.10	1.13	-1.07	-1.25	-2.37	-3.19
Y3m	2.78	-374.36	1.08	-860.94	2.95	7.77	6.29	4.90
	5.84	-1.10	2.42	-1.11	5.55	2.76	3.50	2.93
Y12m	-3.56	156.38	-1.87	365.10	-3.62	-7.83	-7.43	-6.26
	-6.66	1.18	-4.16	1.21	-5.75	-2.24	-3.60	-3.47
Y120m	0.40	750.92	0.21	1708.69	0.27	1.39	1.08	1.41
	5.19	1.03	2.75	1.03	2.30	2.98	4.44	2.36
INFL	-0.26	-110.59	-0.16	-250.97	-0.21	-0.71	-0.59	-0.71
	-4.08	-1.03	-4.23	-1.02	-4.07	-4.08	-2.08	-1.82
TERM	-0.53	-510.45	-0.30	-1160.00	-0.45	-2.27	-1.15	-1.85
	-10.28	-1.04	-7.11	-1.04	-8.71	-2.76	-6.46	-3.60
FFDEFAULT	0.02	51.89	0.02	118.20	0.01	0.03	0.05	-0.05
	5.72	1.07	4.23	1.07	1.25	0.32	5.14	-1.22
MOMENTUM	-0.01	18.76	-0.01	42.80	-0.02	-0.06	-0.02	-0.03
	-6.41	0.95	-3.02	0.95	-6.21	-2.97	-2.83	-2.39
VALUE	-0.01	15.33	-0.01	34.93	-0.01	-0.02	0.00	0.00
	-3.78	0.98	-3.03	0.98	-3.74	-1.71	-0.23	0.25
SIZE	0.00	37.67	0.00	85.88	-0.01	-0.07	-0.02	-0.02
	-2.29	0.98	1.25	0.98	-1.93	-2.00	-3.12	-2.30
VIX	0.00	-11.16	0.00	-25.41	-0.01	0.00	-0.01	-0.03
	-2.13	-1.07	-1.37	-1.07	-1.97	0.08	-0.80	-2.20
TDC_Yield	-23.08	17127.81	-4.02	39293.85	-31.19	-211.38	-51.47	-241.96
	-2.57	0.92	-0.23	0.93	-3.50	-2.31	-2.41	-1.84
R^2	0.38	0.11	0.31	0.10	0.38	0.16	0.41	0.36
Adjusted R^2	0.38	0.11	0.31	0.10	0.38	0.16	0.41	0.36
F-Statistic	3757.90	1865.00	945.99	770.32	1288.34	1074.22	1080.23	1843.17
N	71139	180064	24736	74381	24505	64101	18376	39151

Table 17: General model with tail dependence coefficient coefficients and Z-statistics following the two-step Fama-MacBeth (1973) approach. Green marked values are significant at the 5% confidence level or lower. Below the factors included in the model are shown respectively, the R^2, the adjusted R^2, and the F-Statistic.

The tail dependence coefficient measures solely the dependence structure for the tails of the distribution of yields. Since default is a one sided-extremity, the dependence between the 5% largest yield observations as measured by the tail dependence coefficient should reflect the impact of near defaulted observations best. As can be observed from Table 17, the tail dependence coefficient is significant for all high quality credit maturities except for the 1-10 year maturity. The size of the effects of these coefficients ranges from -51.47 to 23.08. Such values are extremely large compared to the other effects such as the yields, thus indicating the possible huge impact of this result. However, the sign is the opposite of what was expected by our reasoning. We refer to the same alternative explanation offered as with the negative effect sizes of the extreme Spearman correlation; default intensity effects might possibly outweigh default dependence effects, thus explaining the negative effect sizes for the tail dependence coefficient as well. Finally, it could also be that the effect sizes are negative due to a positive relation between multiple variables and indicating that our default dependence factor is a suppressor variable. We test for correlation between the variables used in our models, but do not find any problematic correlation as such. These results are unreported. Nonetheless, we test and report results for multicollinearity in Appendix C, Table 22. The first model tested is the general model from the methodology chapter with only all control variables included. In the second model, we exclude the 1-

year spot rate as measured by the Y12m variable. The final test is ran on the general model, excluding again the 1-year spot rate as measured by the Y12m variable, but including our default dependence factor. Six tests for multicollinearity are used for all three model tests. We find that three out of the six tests indicate multicollinearity for the general model including the 1-year spot rate, as measured by the Y12m variable. For the remaining two tests, we only report two out of six tests indicating for multicollinearity, while the 4 remaining tests indicate that there is no multicollinearity. We argue that there is sufficient evidence to say that the negative effect size results found for the extreme Spearman correlation and for the tail dependence coefficient are not attributable to multicollinearity.

CHAPTER 6 CONCLUSION

We investigate the effect of default dependence on changes in credit spreads with Fama-MacBeth regressions for a bond factor model with common and unique control factors. Overall, we find that changes in the short term, the medium term, and the long term yields are the most important factors in explaining changes in credit spreads. We argue these are the most important due to a combination of their effect sizes as well as their overall significance. We find that the overall business climate, as measured through the Eurostoxx50, the term structure, and the inflation are the most important factors after the abovementioned period yields.

The model with discrete default correlation shows that the factor discrete default correlation changes has no significant effect on credit spread changes. It shows no significance for any quality credit or maturity, except for the all maturities bucket and 1-10 year maturity bucket for low quality credit (B) where the factor is significant at the 10% level. This is an interesting result as defaults in our sample have mainly occurred in this credit class and these maturity buckets. With regards to the time-to-default measure, we unfortunately had to conclude that there was insufficient data to run reliable regressions. Nonetheless, we did show that on average, lower credit quality (B) bonds tend to have a shorter lifespan than higher credit-quality (A). Furthermore, we also reported a cumulative loss of life in our data sample of 75% in the first 2000 days. This might be an equivalent to the short-maturity effect found by Ilmanen et al. (2004).

The two default dependence measures that measure the dependence between all yield observations, the Pearson correlation and the Spearman correlation, show no significance in explaining changes in credit spread. It is argued that the correlation between all yields seems to be an unsuitable proxy for default dependence as it does not accurately reflect the dependence between firms that are near default. On the other hand, after introducing the measures that measure only the upper 50% of yield observations, being the extreme Pearson correlation and the extreme Spearman correlation, we report strong significance. Especially the extreme Spearman correlation seems to appropriately capture the dependence structure between these yield observations, implying the extreme Spearman correlation might be a good proxy for default dependence. This result mainly holds for high quality credit (A). After introducing the tail dependence coefficient which measures the conditional probability on the default of firm B conditionally on the default of A for only the top 5% of yield observations, we report high significance and large effect sizes ranging from -51.47 to 23.08. Considering the effect sizes and significance of our default-dependence measures, we find that the tail dependence coefficient is the most important measure. Theoretically this also seems correct; the top 5% most extreme yields are likely those of firms that have extreme movements in yields. In general, these firms are in financial distress, or recovering from financial distress. Therefore, default is likely, and dependence between extreme yields seem to be a good proxy for default dependence. Assuming that extreme yield correlation is a good proxy for default dependence, a large default dependence premium can be observed in credit spread changes as measured by the effect size of the betas of the tail dependence coefficient. We showed that our results regarding the default dependence measures are not attributable to multicollinearity, but can in our opinion likely be explained through a result of Das et al. (2007). Das et al. (2007) find that credit spreads can widen not only due to an increase in default probability but also through an increase in default intensity. This could offer an explanation to our negative effect sizes; although a high default dependence leads to a higher expected number of defaults for investors, thus increasing risk, high default dependence is mainly observed during economic upswing periods. In such periods recovery rates are usually higher than in downturn economies, as more firm value can be recovered through a higher amount of buy-outs in case of default. This would cause the credit spread to tighten. It is likely that default intensity effects seem to outweigh default dependence effect, therefore causing negative effect sizes for some of our default dependence factors.

Furthermore, assuming that extreme yield correlation is a good proxy for default dependence, we confirm findings of Das, Freed, Geng, & Kapadia (2002) who argued that default dependence is time-varying because asset-correlations are time varying and that high quality credit (A) has a higher default correlation than lower quality credit (B). Another insight from this paper is that the historical default dependence structure, as measured by the extreme yield dependencies of the past 6 months, seems to be a good approximation of the current default dependence structure in the market. Two more final insights can be deduced from the results of this paper. Firstly, the Fama and French (1993) default factor does not capture our default dependence premium. Secondly, our prediction that default dependence would be higher in times of an upswing economy is also confirmed.

Although we report high significance of the extreme Spearman correlation and the tail dependence coefficient, we do not observe a large increase in explanatory power in the models. We argue that this is possibly due to the two-step approach by Fama-MacBeth (1973) implemented in the model. Finally, in addressing whether default dependence might be the missing puzzle piece in the credit spread puzzle, we answer ambiguously; we do report a substantial and significant premium, but do not observe a large increase in explanatory power. Thus, this paper suggests further work should be done on other possible default dependence structures, possibly through the use of copulas, and alternative methodologies in estimating credit spread changes. One interesting complementary research to ours' would be to see how default dependence measures perform in CDS spreads. We also potentially found results that indicate that default intensity might be of large importance in explaining credit spread changes. As such, we suggest further research be done on the role of default intensity in credit spread change models.

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APPENDIX A: Defaults per rating and year

Default per rating	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	
AAA	0	0	0	0	0	0	0	11	0	1	0	0	0	0	0	0	0	0	12
AA+	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
AA	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	2
AA-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A+	0	0	0	0	0	0	0	167	2	0	1	2	0	0	0	0	0	0	172
A	0	0	0	0	0	0	0	110	3	1	0	0	2	1	1	0	0	0	118
A-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BBB+	0	0	0	0	0	0	0	0	2	0	0	1	0	0	2	0	0	0	5
BBB	1	7	0	1	0	0	0	4	4	0	0	0	4	1	1	4	0	3	30
BBB-	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	3	0	4	9
BB+	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	3
BB	0	9	0	1	0	0	0	0	0	0	1	0	1	0	0	3	0	0	15
BB-	0	0	1	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	4
B+	0	0	0	0	0	0	0	3	2	0	0	0	0	5	2	0	1	1	14
B	7	10	0	0	0	3	0	13	3	4	0	0	2	1	16	1	2	1	63
B-	10	19	0	0	0	0	1	0	0	3	0	0	0	1	5	0	1	1	41
CCC+	9	5	0	0	0	1	0	1	7	0	0	0	0	1	2	0	0	1	27
CCC	0	5	0	0	0	0	0	3	0	0	0	0	0	4	1	0	0	5	18
CCC-	1	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	4
CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
C	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	4
D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	28	58	1	2	0	4	1	316	26	10	2	6	9	15	32	12	4	17	543

Default per rating	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	
A	0	0	0	0	0	0	0	289	5	3	1	3	2	1	1	0	0	0	305
B	18	46	1	2	0	3	1	22	13	7	1	3	7	8	26	12	4	10	184
C	10	12	0	0	0	1	0	5	8	0	0	0	0	6	5	0	0	7	54
	28	58	1	2	0	4	1	316	26	10	2	6	9	15	32	12	4	17	543

Table 18: Defaults per rating and year

APPENDIX B: Standardization of multiple bond ratings

A Comparison of Bond Ratings from Moody's S&P and Fitch IBCA 7

Code	Moody's	Fitch IBCA and S&P	Interpretation
1	Aaa	AAA	
2	Aa1	AA+	
3	Aa2	AA	High Quality
4	Aa3	AA−	
5	A1	A+	Strong Payment
6	A2	A	Capacity
7	A3	A−	
8	Baa1	BBB+	Adequate Payment
9	Baa2	BBB	Capacity
10	Baa3	BBB−	
11	Ba1	BB+	Likely to fulfill
12	Ba2	BB	obligations; ongoing
13	Ba3	BB−	uncertainty
14	B1	B+	
15	B2	B	High Risk Obligations
16	B3	B−	
17		CCC+	Current vulnerability
18	Caa	CCC	to default
19		CCC−	
20	Ca	CC	In bankruptcy or
21	C	C	default or other
22	D	D	marked shortcomings

Table 19: Bond rating numerical code convserions to letters. Source: Jewell & Livingston (1999)

After this standardization we find that although one rating standard is applied, multiple different ratings have been given to bonds. Therefore, ratings are counted on a basis of most risky rating, as this rating is likely to capture best the unexplained risk within other ratings. Again, we opt here for a higher safety level by taking the lowest rating instead of the highest rating. After eliminating multiple ratings on the same bond, we end up with the following results:

Code	Initial Rating	Fitch Moody’s and S&P	Interpretation
1	107	AAA	
2	57	AA+	
3	140	AA	High Quality
4	0	AA−	
5	365	A+	Strong Payment
6	735	A	Capacity
7	0	A−	
8	337	BBB+	Adequate Payment
9	1067	BBB	Capacity
10	511	BBB−	
11	376	BB+	Likely to fulfill
12	439	BB	obligations; ongoing
13	215	BB−	uncertainty
14	353	B+	
15	386	B	High Risk Obligations
16	189	B−	
17	140	CCC+	Current vulnerability
18	63	CCC	to default
19	14	CCC−	
20	4	CC	In bankruptcy or
21	10	C	default or other
22	1	D	marked shortcomings

Table 20: Initial rating observations as in the dataset per rating class

Code	Current Rating	Fitch Moody’s and S&P	Interpretation
1	85	AAA	
2	50	AA+	
3	103	AA	High Quality
4	0	AA−	
5	156	A+	Strong Payment
6	539	A	Capacity
7	0	A−	
8	543	BBB+	Adequate Payment
9	563	BBB	Capacity
10	651	BBB−	
11	379	BB+	Likely to fulfill
12	404	BB	obligations; ongoing
13	357	BB−	uncertainty
14	267	B+	
15	259	B	High Risk Obligations
16	283	B−	
17	156	CCC+	Current vulnerability
18	73	CCC	to default
19	32	CCC−	
20	20	CC	In bankruptcy or
21	471	C	default or other
22	43	D	marked shortcomings

Table 21: Current rating observations as in the dataset per rating

APPENDIX C: Multi-collinearity test results

Overall Multicollinearity Diagnostics					
Full general model including Y12m					
Determinant |X'X|:	0.0014	1			
Farrar Chi-Square:	1653323	1			
Red Indicator:	0.2734	0			
Sum of Lambda Inverse:	41.0966	0			
Theil's Method:	6.7397	1			
Condition Number:	7.0776	0			
Overall Multicollinearity Diagnostics					
Full general model excluding Y12m					
Determinant |X'X|:	1.04E-02	0			
Farrar Chi-Square:	1.15E+06	1			
Red Indicator:	2.68E-01	0			
Sum of Lambda Inverse:	2.66E+01	0			
Theil's Method:	5.01E+00	1			
Condition Number:	4.83E+00	0			
Overall Multicollinearity Diagnostics					
Full general model including tail dependence coefficient					
Determinant |X'X|:	0.0101	0			
Farrar Chi-Square:	1153097	1			
Red Indicator:	0.245	0			
Sum of Lambda Inverse:	27.7574	0			
Theil's Method:	5.0423	1			
Condition Number:	4.8807	0			
1 --> COLLINEARITY is detected by the test					
0 --> COLLINEARITY is not detected by the test					

Table 22: Multicollinearity results. It shows that the general model including the 1 year spot rate (Y12m) shows multi-collinearity in 3 out of 6 tests. The general model without the 1 year spot rate (Y12m) shows multicollinearity in 2 out of 6 tests.