Herman Marelius Zahl

Predicting Distributions of Credit Spread Changes in the Era of Quantitative Easing

Master's thesis in Industrial Economics and Technology Management
Supervisor: Sjur Westgaard
June 2022

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Kunnskap for en bedre verden

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Abstract

Numerous models for predicting the future distribution of credit spread changes are specified and tested. Parsimonious factor models consisting of principal components of the risk-free and credit spread term structure are shown to significantly outperform other models. Additional market variables weaken the prediction performance, indicating that the information contained in the credit spread term structure and the risk-free term structure to a large degree span a sufficient set of information for credit spread predictions. One exception is the introduction of variables to account for unconventional monetary policies by the Fed in the time period. These variables are found to improve predictions for tails of the distributions of credit spread changes. The findings have implications for the modelling of credit spread changes and risk management, as the whole distribution is considered. Furthermore, earlier results in the literature are generalized to other quantiles of the distributions.

Sammendrag

Flere modeller for prediksjon av fremtidige fordelinger av kredittspread-endringer er spesifisert og testet. Modeller bestående av prinsipalkomponenter fra risikofri rentekurve og kredittspreadkurve viser seg å være signifikant bedre enn andre testede modeller. Å legge til andre variabler i prinsipalkomponent-modellene svekker prediksjonevnen, noe som indikerer at informasjonen i kurvenes prinsipalkomponenter er tilstrekkelig for å predikere kredittspreader. Et unntak fås ved å legge til variabler knyttet til den amerikanske sentralbankens ukonvensjonelle pengepolitikk i perioden. Disse variablene bedrer prediksjonen av halene til fordelingen. Funnene i oppgaven har implikasjoner for generell modellering av kredittspreader og risikostyring i foretak, ettersom hele fordelingen av kredittspreader er hensyntatt. Videre generaliseres tidligere funn i litteraturen til å gjelde andre kvantiler i fordelingene.

Preface

This Master's thesis marks the end of my studies at the Norwegian University of Science and Technology (NTNU). It has been an interesting journey, both academically and socially. I want to thank my supervisor, Sjur Westgaard, for his guidance and advice throughout the last two semesters. His ability to combine financial theory with practical financial in discussion has been inspiring. I further want to thank two of my friends, Kjartan Krange and Magnus Stray Schmidt, for valuable exchange of ideas on finance topics over these years. Lastly, I am grateful for the support of Britt Randi, Jon Erik, and Mie.

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1 Introduction

Ever since the classical corporate debt model of Merton (1974), the literature on credit spreads has mainly been centered on the explanation of predicting average credit spread changes (e.g. Collin-Dufresne et al. (2001); Krishnan et al. (2010)). For investors or companies with exposure to credit spreads, simple mean predictions, even accompanied by volatility estimates, may not be sufficient for evaluating an investor's utility function for undertaking an investment. It is well-documented that investors care about multiple traits of future returns beyond the classical mean-variance model assumption of Markowitz (1952) (see (Arditti (1967); Scott and Horvath, 1980); Fang and Lai, 1997), such as higher moments of relative price changes. From a risk-management perspective, more granular insights into future credit spread changes' distributions are valuable. Especially the tails of the distributions are of interest when considering risk metrics such as Value-at-Risk (VaR) or Conditional Value-at-Risk (CVaR). Credit spreads are important for market participants in numerous ways. First, they are, per se, a high-frequency indicator of investors' perception of risk as they are a bond's premium to the corresponding risk-free interest rate in the economy. Secondly, firms have intrinsic exposure to the changes in credit spread as they alter the firms' cost of capital, thus the firm value, ceteris paribus. Furthermore, as Flannery et al. (2012) found, credit spreads also comprise expectations of a firm's future capital structure. Additionally, changes in credit spreads pose a refinancing risk to companies looking to refinance debt to 'roll' their liabilities in the financial market (Brunnermeier and Yogo, 2009). For companies trying to match liabilities and asset cash flows, the bond market is a vital funding source with the credit spread a substantial funding cost. Banking and insurance are examples of industries in which the need to improve the matching of liabilities and assets is significant to limit the risk of liquidity issues (e.g. bank runs, see the classical Diamond and Dybvig (1987) work).

Since the great financial crisis (GCF) of 2007-08, the US Federal Reserve (the Fed) has implemented highly expansive monetary policies. As interest rates have been historically low, and the need for further stimulative action has been imminent in the eyes of central bankers, these policies have included extensive waves of asset purchases in the open market, commonly referred to as Quantitative Easing (QE). While Fed Chairman Ben Bernanke explicitly spoke of reducing the Fed's balance as early as 2009 [1], the programs are yet to be reserved. In total, the Fed's balance sheet has increased approximately tenfold since before the financial crisis to more than 8.9 trillion USD, as of May 2022.

[1] "Federal Reserve will be able to return to its traditional means of making monetary policy–namely, by setting a target for the federal funds rate", see https://www.federalreserve.gov/newsevents/speech/bernanke20090113a.htm

Research on the subject of interest rates and risk premiums has shown that such QE programs may lower both interest rates and premiums of credit risk in the economy (Krishnamurthy and Vissing-Jorgensen, 2011). Due to their unprecedented nature, the research on the effects of these QE programs has been facing obstacles. Prior to the Bank of Japan (BoJ) launching its QE program in 2001 in the wake of the 'lost decades', no modern large-scale QE program had ever been implemented [2]. Further, the US programs are different from that of BoJ's (See Shiratuksa, 2010). As Martin and Milas (2012) note, the QE policies are enacted as a response to extreme events, and, hence, are intrinsically covarying with other events that make the pure QE effects difficult to isolate. However, substantial academic literature has researched the effects of these programs. The research considering interest rates and credit spreads is of interest (e.g. Ugai, 2006; Gagnon et al., 2011; Gilchrist and Zakrajsek, 2013; Nozawa and Qiu, 2021). By categorizing the announcement of the Fed's QE policy changes, a dummy variable approach is taken for accounting for potential effects on credit spreads. However, the variables for announcements alone are not enough as the actual asset purchases indeed do increase investors' liquidity, which again leads to actual portfolio re-balancing effects. Although announcements may alter market expectations, the actual purchases and re-balancing effects could have implications for credit spreads as well. In my view, both of them are likely to change the demand for assets, and thus the price of the assets. To account for actual liquidity effects, a variable linked to the Fed's balance sheet is defined.

The fundamental motivations of the paper's modeling are the well-established factor analysis of the yield curve (Nelson and Siegel, (1987); Litterman and Scheinkman (1991); Diebold and Li (2006), and the similar applications to the credit spread term structure (Krishnan et al, 2010). In the academic literature, the amount of information contained in the yield curve factors (i.e principal components (PCs) of yield curve changes) is a debated topic. While Litterman and Scheinkman (1991) found bond returns to be explained by the three first PCs (PC1, PC2, PC3), later research found that additional factors improve the modeling of credit spreads beyond the parsimonious PC models (Cochrane and Piazezzi, 2005; Ludvigson and Ng, 2009; Joslin et al., 2014). In a thorough examination of the literature, Bauer and Hamilton (2018) refute much of the literature that claims to find further improvements in model specifications with additional variables than PC1, PC2 and PC3 of the yield curve. According to Bauer and Hamilton (2018), much of the literature that rejects the theory that current yield curve factors contain all needed for the prediction of future rates, named the spanning hypothesis, is weaker than formerly believed. This leaves more uncertainty as to whether additional variables than the term structure

[2]See Federal Reserve Bank of Francisco letter by Mark M. Spiegel https://www.frbsf.org/economic-research/publications/economic-letter/2006/october/did-quantitative-easing-by-the-bank-of-japan-work/.

factors are needed for predicting and explaining yields. Krishnan et al. (2010) test several models for credit spread predictions and find a model consisting of factors from the risk-free (RF) yield curve and the credit spread (CS) term structure to be superior to, among others, models extended with additional macroeconomic variables. These results may indicate that the information needed for predicting credit spreads is contained in these factors, similar to the spanning hypothesis of the yield curve.

In this paper, factor models are further developed for predicting credit spread changes. Importantly, the distribution of the credit spread changes is predicted in order to further analyze any heterogeneity in credit spreads and how the regressors influence the upper and lower parts of the distribution. Pires et al. (2015) illustrate the need of considering more than the mean of the distribution as heterogeneity is displayed across the distribution of credit spreads. Furthermore, given the widely recognized stylized fact in the academic studies that high-grade bonds tend to behave like treasuries, while lower-grade bonds tend to behave more similarly to equities (Fama and Bliss, 1987; Avramov et al.,2007), it seems reasonable to expect the drivers of credit spread changes to differ across the credit quality segments. Indeed, this paper's objective is to contribute to the literature by prudently testing factor models' predictive ability of credit spreads' distributions for a wide range of bond categories (credit qualities *and* maturities).

The thesis is divided into sections, which could be further divided into subsections. Firstly, the literature on credit spreads and how it relates to this thesis is presented (Section 2). Secondly, the data and the statistical methods are presented (Section 3 and 4). Thirdly, the term structure factors are interpreted and the model specifications are formulated in Section 5. Thereafter, the results are presented and discussed, with further in-depth analysis of the best-performing models. Lastly, a concluding section follows.

2 Literature review

In this section, the findings from the literature review are discussed. The determinants of credit spreads, in general, are discussed, before the literature considering the specifics of QE effects is presented. The credit spreads of interest here are the differences in yield between corporate debt and risk-free debt (see section 3.2) with a similar maturity. Thus, the literature covering sovereign credit spreads is not covered.

2.1 Classical Determinants of Credit Spreads

In the classical credit spread literature, structural models for predicting and explaining changes in credit spreads have been central. The seminal work of Merton (1974) established a framework for the pricing of risky debt, and hence, its implied credit spread. Following option pricing theory, equity is a long call position on a firm's assets with a strike equal to the firm's liabilities at maturity. The debt-holding position can be constructed with a long position on a firm's assets combined with a short call with a strike at the liabilities' value at maturity, which eliminates the further upside risk. Following non-arbitrage assumptions, this would deduct the value of risky debt.

The Merton (1974) model has the risk-free rate, the company's current capital structure, and the asset volatility as important input factors in the framework, and laid the ground for later formulation of structural models. While strong in theory, later empirical studies have shown the so-called Merton model to have a limited ability to correctly predict credit spreads, prompting the 'credit puzzle' phenomena (Jones et al., 1984; Amato and Remolona, 2003), where investors seemingly are compensated for more than credit risk, as wide gaps between expected losses and spreads have been observed. Further adjustments for taxation, illiquidity, and extra risk premia are shown by Amato and Remolona (2003) to not fully explain the observed credit spreads either. While the works supporting these findings are numerous, they have also been refuted (Feldhütter and Schaefer, 2018). Feldhütter and Schaefer (2018) find the modeled credit spreads to be in line with observed investment-grade bonds, while observed high-yield spreads are too high, partly due to illiquidity. Among the influential papers on determinants of credit spreads is Collin-Dufresne et al. (2001), which investigates the explanatory power of several categories of variables; among others, the structural model factors originated in Merton's (1974) work, which they find to have limited explanatory power (about 25%). Perhaps more interestingly, using principal component analysis (PCA), Collin-Dufresne et al. (2001) find credit spread changes to a large extent by driven by a single, unknown factor. This factor is nearly equally weighted across bins of bonds capturing different maturities and credit qualities. Eom et al. (2004) test a wide range of structural models on credit spreads on non-financial companies and find most of these to, on average, predict spreads that are too *high*, while the classical Merton (1974) predicts too low spreads, as expected. Furthermore, accuracy is still noted as a key obstacle in the models' performance.

The classical structural models focused on point estimates of actual changes in a single-regime period, and have yet to display strong predictive and explanatory power. Researchers thus extended the structural models to allow for regime changes. Hackbart et al. (2006) find that observed credit spreads can be generated by a two-regime model allowing for aggregate macroeconomic shocks (either 'boom' or 'recession'). Chen (2010) incorporates macroeconomic factors to account for the changing firm behavior over the business cycles as different macroeconomic environments lead to different financial decisions, and found risks related to the business cycle to be an additional explanation of the aforementioned 'credit spread puzzle'. Chun et al. (2014) tested regime-switching models with economic, monetary and credit-related regimes. The introduction of these regimes improves the explanatory power of market and liquidity variables. As such, Chun et al. (2014) also contribute to (at least partially) closing the credit spread puzzle gap. In sum, the classical structural models have seen improvements by the elimination of the single-regime modeling. Still, the classical factors for credit spread modeling, such as default risks, liquidity risks, and market-wide risks, show varying success in explaining observed credit spreads.

2.2 Factor Modelling and the Spanning Hypothesis

In this section, a brief introduction to factor modeling in finance is given. I then present the literature on yield curve modeling. Although these works mainly relate to the modeling and predictions of interest rates, they are seen as highly relevant, as I seek to build on this tradition, but now for *credit spreads*.

Financial factor modeling has been influential since the formalization of single-factor models for security returns by Sharpe (1964) and Lintner (1965), who, by building on Markowitz (1952) and Tobin (1958), proposed models for predicting risky assets' expected excess returns determined by one single factor. While intuitive and still widely taught in business schools around the globe, the empirical shortcomings are several (Fama and French, 2004). These original models later saw multiple improved extensions to account for other factors (Carhart 1997; Dittmar, 2002; Fama and French, 1993). For interest rates, several short-term models, in which the (stochastic) short-rate is typically developed through a binomial three, have been proposed (Hull and White, 1993). In yield curve modeling, Nelson and Siegel (1987) and Litterman and Scheinkman (1991) are pioneering works. Nelson and Siegel (1987) specified mathematical expressions where coefficients were able to fit what they defined as "monotonic", "humped" and "S shaped" characteristics in yield curves. Nelson and Siegel (1987) found a model to explain 96% of the variation in US T-bill yields in 1981-83. Litterman and Scheinkman (1991) found that three principal components explained more than 95% of US Treasury bond returns. They further provided interpretations of these factors as "level" (PC1), "steepness" (PC2), and "curvature" (PC3). These interpretations were supported by inspections of the factor loadings across bond maturities. Diebold and Li (2006) predict yield curve changes based on the Nelson-Siegel factors, and they provide similar interpretations of the factors as those attributed to the Litterman-Scheinkman factors. While the interpretations are similar, it is important to note that the Nelson-Siegel factors are restricted by the boundary conditions of the mathematical formulation and that the Litterman-Scheinkman factors are more unrestricted. Diebold and Li (2006) conclude that the performance of predictions made by the Nelson-Siegel yield curve factors on future yields substantially outperforms common benchmarks. Cochrane and Piazezzi (2005) regress future excess bond returns on combinations of forward interest rates, and find a single factor (a tent-shaped linear combination of the regressors) to predict excess bond returns. Furthermore, this factor is deemed unrelated to the level, slope, and curvature of the yield curve. As such, Cochrane and Piazezzi (2005) find these traditional factors to not fully explain future interest rates although they account for more than 99% of the yield change variability in the data set. Hence, the distinction is made between *explaining* yield curve changes and *predicting* them. Interestingly, the fourth factor of the yield curve changes (PC4) is found important in forecasting expected bond returns, while still negligible when purely explaining bond returns. Cochrane and Piazezzi (2009) revisit these tests and find the fifth factor (PC5) to significantly lift the predictive power of the models. Other researchers have noted that the yield curve factors are insufficient for yield curve predictions and that additional variables provide relevant information for improving predictions (For macroeconomic, see Ludvigson and Ng, (2009); for inflation and economic output, see Joslin et al., (2014)). The mentioned works are among the papers culminating in the debate on what Bauer and Hamilton (2018) name the spanning hypothesis. The spanning hypothesis holds that all relevant information for future yields and returns is spanned by the current yield curve (Bauer and Hamilton, 2018). Thus, the three most important PCs of the yield curve, the level, could be sufficient for predicting future yields. If correct, other additional variables are not needed for future predictions, and would possibly deteriorate predictions as more noise is added. Bauer and Hamilton (2018) argue that serial correlation in the prediction error terms non-reliable R^2 and standard error values in research that claims to reject the spanning hypothesis. Further, Bauer and Hamilton (2018) note that the violation of econometric exogeneity for small sample-sizes, combined with persistent regressor time series, leads to the risk of spurious null hypothesis-rejections. On the findings of Cochrane and Piazzi (2005), that PC4 of the yield curve is important for predictions, Hamilton and Bauer (2018) conclude that this is sample-dependent and provides no sufficient evidence for rejecting the spanning hypothesis. In sum, the evidence for so-called "unspanned" information (i.e. information not contained in the three common yield curve factors) is weaker than often argued. Following the substantial contribution of Bauer and Hamilton (2018) to the literature, the question of the spanning hypothesis seems less settled.

The literature concerning factor modelling of the credit spread term structure is certainly dwarfed by the extensive yield curve modeling covered in the previous paragraphs. Krishnan et al. (2010) provide a bridge from the yield curve modelling to credit spread predictions, and are thus highly motivating for this paper. Krishnan et al. (2010) extract three term factors for credit spreads and the risk-free yield curve, with a methodology inspired by Nelson and Siegel (1987) and Diebold and Li (2006). These three factors are shown to closely covary with the conventional definitions of the *level*, *slope*, and *curvature*, similar to the seminal Litterman-Scheinkmann factors. As such, Krishnan et al. (2010) do to the credit spread curve what numerous academics prior to them did to the yield curve. They find that, while CS factors are strong predictors of future credit spreads by themselves, performance is improved by adding RF factors. Perhaps more interesting is the finding of Krishnan et al. (2010) that further model extensions beyond the factors of the credit spread and risk-free yield curve cannot improve predictions, indicating that explicitly including macro variables as independent variables may result in disturbing noise. With the spanning hypothesis debate as a backdrop, this could indicate that the CS PCs alone do not span sufficient information for future credit spread curves but need to be supplemented with RF PCs. As much of the conventional methodology in the literature, Krishnan et al. (2010) apply linear regression on firm-specific credit spreads. By that, Krishnan et al. (2010) are narrowed in on the *mean point* prediction and do not cover the full distribution of credit spreads, which is this paper's objective. Nevertheless, such factor modelling of credit spreads represents a different line of research, given the earlier literature centered on market-wide and firm-specific variables. In fact, such prediction models represent one of the most parsimonious models in the field.

2.3 Distribution of Credit Spread changes

Since the aim of this paper is to predict distributions of future changes in credit spreads for a variety of both maturities and credit qualities, some further discussions of the literature concerning predictions of distributions is appropriate. As noted in the previous sections, the literature on (successful) predictions of credit spread changes is quite limited. Consequently, the literature on *distributions* of credit spread changes is even sparser. The tails of the distributions are naturally of interest in extreme risk modelling. The distributions of credit spreads, and thus credit risk-linked financial products, are widely known to be leptokurtic, characterized by fatter tails in the distribution (Pedrosa and Roll, 1998). This could lead to underperformance in classical risk models, which often assume standard statistical properties (e.g. i.i.d. and normal distributions) (Pownall and Huisman, 2002; Kuester et. al, 2006). Of particular pertinence to this paper is the work of Pires et al. (2015), who developed a quantile regression (QR) model for predicting future credit default swap (CDS) changes. Pires et al. (2015) regress CDS changes on a wide-ranging set of variables, many of them discussed in Section 2.1. Specifically on interest rates, they include the 10-year US treasury yield and the slope of the yield curve, which would correspond to the two most important factors in the yield curve if 10-year US treasury is to proxy the yield curve level. Pires et al. (2015) find these yield curve 'factors' to display heterogeneity for different quantiles. For example, these coefficients are only statistically significant for lower quantiles, and vary in size and sign. Somewhat interestingly, by benchmarking the QR model with an OLS model, it is found that the mean predictions are quite similar to the upper quantiles. As such, what may be perceived as an accurate reflection of the 'center' of the distribution is in fact not accurately represented by the modelling of average changes. Thus, Pires et al. (2015) illustrate the need for more granular modelling of credit spread changes' distribution. Hence, the findings of Pires et al. (2015) should spur distribution modelling of credit spreads – and this paper.

2.4 The QE effects on credit spreads

In this section, the academic literature regarding the effecs of quantiative easing (QE) programs on credit spreads is discussed. Firstly, I will briefly introduce the findings from the first large-scale QE program in modern economies - the BoJ's QE program in the period 2001-2006. Secondly, the more wide-ranging QE programs following the great financial crisis (GCF) and the related literature is discussed.

The first large-scale QE program was initied by Bank of Japan (BoJ) in March 2001, running over a 5-year period. The Japanese economy experienced low-to-negative price growth following the burst of the Japanese asset bubble, which, following 2001 and its dotcom market crash, had already led the BoJ to zero-rate policies. One of the program's pilars was that liquidity provisions should stay in place until the core inflation stabilized above zero percent (Ugai, 2006). Ugai's (2006) empirical analysis of BoJ's QE policies finds that the commitment to keep the program in place molded investor's expectations of continued low future interest rates, which again shifted the yield curve lower, especially for short-to-medium maturities. Kimura and Small (2006) study potential portfolio re-balancing effects, which are postulated to happen due to the increasing cash position as the central bank purchases securities. Kimura and Small (2006) find the BoJ's QE program to lower the risk premia for assets with counter-cyclical returns, such as governmental and investment grade bonds, while assets with pro-cyclical returns, such as high yield bonds and equities, experienced increased risk premia. Furthermore, they found the program to decrease the volatilies in equities and high-yield bonds. Thus, Kimura and Small (2006) represent an early discovery of the different implications for different financial assets (e.g. bonds of different ratings). Shiratsuka (2010) note the difference in credit spreads for financial institutions and non-financial companies, where the former see their credit spreads contract earlier compared to the non-financials' credit spreads which also contract but with some time lags.Shiratuksa (2010) further note some distinctions between the BoJ QE program and those of the Fed: while the BoJ concentrated on the liability side (specifically, the current account balances), the latter are deemed more asset-side focused. In this paper, as I am concerned with US credit spreads over the last decades, the sole data sampled for modelling purposes is the Fed balance sheet data and minutes of the Federal Open Market Committe's (FOMC) meetings. Martin and Milas (2012) argue that the effects of QE is difficult to evaluate as QE, at its core, is a response to extreme and unexpected economic shocks. The QE programs initiated by the Fed since 2008 (See Appendix, 8.4) have been in effect over long periods, with few and important announcement dates marking initiations and finalization of these programs. As such, any potential QE effects need to both be assessed by studying the effects of the policy announcements and the effects of implementation of these policies (e.g. purchases of assets). In particular, the initiations of these program covary with financial crises, and, hence, a wide range of other extreme economic observations. A 'what-would-have-happened' analysis of these policies are thus very difficult as Fed policies have multiple effects through different channels. The announcement-centered studies of QE focuses on the short-term effects as investors' expectations are altered over a short period of time due to Fed's public guidance and communication. Important events-studies include Gagnon et al. (2011), Cenesizoglu and Essid (2012), Gilchrist and Zakrajsek (2013), Javadi et al. (2017) and Nozawa and Qiu (2021). Gagnon et al. (2011) studies the general effects of announcements of QE programs on financial market and find that longer-term interest rates were reduced, primarily due to lower risk premiums and not due to generally reduced expectations of future interest rates. Cenesizoglu and Essid (2012) utilizes the futures market to decompose Fed's funds target rate policies into expected and unexpected policy changes. Due to the period of Cenesizoglu and Essid's (2012) interest, unconventional monetary policy (e.g. QE) is not relevant for study. The methodology is however, as it dealt with announcement of Fed policies and the issue related to market expectations ex ante and ex post. Interestingly, the Cenesizoglu and Essid (2012) find lower-rated bonds to be more sensitive to monetary shocks during recessions. Further, asymmetrical effects are discovered in how unexpected tightening and easing of monetary policy influence credit spreads. Hence, formulating models which allows for such asymmetrical effects seems necessary. Mamaysky (2018) studies the time horizon of price responses to QE announcements. Government bonds see quick price reactions, while equities' responses are delayed and spread out over several weeks. The paper defines a "maximal post-announcement response horizons" corresponding to the time horizon in which the observed effect is *least likely* to have occurred under the null-hypothesis that prices developed randomly. For US investment grade credit spreads, this time horizon is found to be three days compared to 10 days and 21 days for stock returns and implied volatility, respectively. Hence, the time window of QE events may be adjusted depending on the time series of interest. In this paper, weekly time series are sampled, which should be in line with the findings of Mamaysky (2018) as impacts on credit spreads are expected to be in effect. The most recent of the QE programs, QE4 (see Appendix, 8.4), was initiated in March 2020 as part of the monetary policy response to the Covid-19 pandemic and the associated restrictions on the economy. Nozawa and Qiu (2021) investigate the US corporate bond market in the first half of 2020. By applying a two-day event window, they find effects to be different across credit ratings, with investment grade spreads lowered and high-yield spreads lifted. These differences are attributed to the markets' expectations that the Fed would only purchase investment grade bonds. Further, they note that regulatory constraints on major bond investors may induce actual market segmentation in between credit ratings. Hence, different reactions to policy actions may be expected. These findings further motivate the differentiation made in this paper between different credit spread rating.

2.5 The contributions of this paper

In sum, this paper is motivated by a variety of literature. Of the most motivating papers are Krishnan et al. (2010), with the factor modelling of credit spreads. The need for QR models, as opposed to simpler OLS models, is highlighted by the findings of Pires et al. (2015) that there are heterogeneity across the quantiles and that factors have different significance and effects on different parts of the distribution.

Furthermore, the Spanning hypotehsis debate makes it tempting to parsimoniously specify pure term structure factor models. However, while motivated by the works mentioned above, this paper differentiates itself from the credit spread literature in numerous ways:i) contrary to Krishnan et al. (2010), the factor extraction from the term structures is by PCA, both for CS and RF term structures, ii) more models are tested on a variety of credit qualities and maturities to investigate the prediction power different bond categories, iii) the models are tested for different time horizons (i.e. 1 week, 2 weeks and 4 weeks ahead), iv) motivated by the findings of Pires et al. (2015), a more granular analysis of the whole credit spread change distribution is performed, v) the spanning hypothesis motivates the model specifications, as both pure term structure factor models and macro-extended models are tested for predictions, vi) lastly, attempts are made to improve models by accounting for unconventional Fed policies, both in terms of actual purchases and policy change announcements.

3 Data

In this section, the data considered in this paper is presented. The four categories of data are i) the credit spread indices, ii) the risk-free rates and iii) the macroeconomic data, iv) Federal Reserve data . Descriptive statistics are organized in tables for each category, followed by brief discussions.

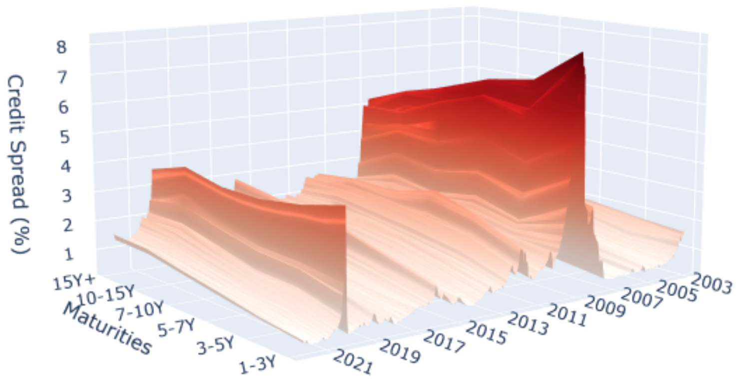
3.1 Credit Spread Data

The credit spread indices are the ICE BofA option adjusted credit spread indices, all sourced from Federal Reserve Economic Data (FRED) in February 2022. The indices are the well-established and have been quoted daily since the late 90s. While initially constructed by Bank of America's fixed income research division, the indices have been under Intercontinental Exchange's (ICE) ownership since 2017. The data frequency is a weekly basis, with the Friday's close as reference point. In order to more accurately reflect vanilla bonds' credit spreads at any point, the bonds in each with certain embedded options are adjusted by ICE. The data set complies of 998 weeks, starting at the end of 2002 and ending in February of 2022.

As this paper aims to present quite granular results for the prediction models, both varying along maturity and credit quality, the credit data set consists of the investment grade indices for intervals of constant maturities, as well as the basket indices for different ratings. To limit the scope of the paper, only the investment grade bonds data comprises different maturities. The shape of the term structure in the investment grade credit spread should substantially overlap with any pure AAA and BBB, as they are components in the investment grade class. From a more practical view, they will often be covered by similar risk weights in bank's regulatory framework and often be covered by the same investment mandates. The high-yield and even lower rated bonds, CCC&Lower, are thought to have somewhat different credit spread determinants as found in the literature review. The pure credit rating indices are consists of AAA, investment grade, BBB, high-yield and CCC&Lower rated bonds. These credit ratings indices are constructed by ICE to reflect the markets pricing of all dollar-denominated bonds with the relevant rating, subject to option adjustments. As such, the changes in credit spreads index is interpreted as the change in the market's total basket of bonds with a specific rating.

The use of indices comes with certain pros and cons, some of which I find appropriate to elaborate on further. One advantage concerns the issue of time-varying data for firm-specific bonds. Since the time until maturity for each bond varies in the period, credit spreads are not directly comparably just as yields on different maturities are not directly comparable. As both the credit spread curve (Bedendo et al., 2007; Helwege and Turner, 1997; Merton, 1973) and risk-free yield (Campbell and Shiller, 1991; Fama and Bliss, 1987) curve are tend to display slopes (either negative or positive) due to term premiums. By collecting the credit spread indices, which are constructed to be comparable over time, this issue is avoided. Indices in general have inherent survivor effects, as its components often are removed before complete deterioration. In this specific example, this could suggest that bonds are removed from indices as a default events nears. Bhanot (2005) investigates the mean reverting tendency in bond indices and find survival effects and ratings based classifications to contribute substantially to mean reversion. The implications of these findings are manifold, with one of them being that this paper's findings may not be naively extrapolated to a single bond's credit spread.

Figure 3.1: Surface plot of the credit spread data set



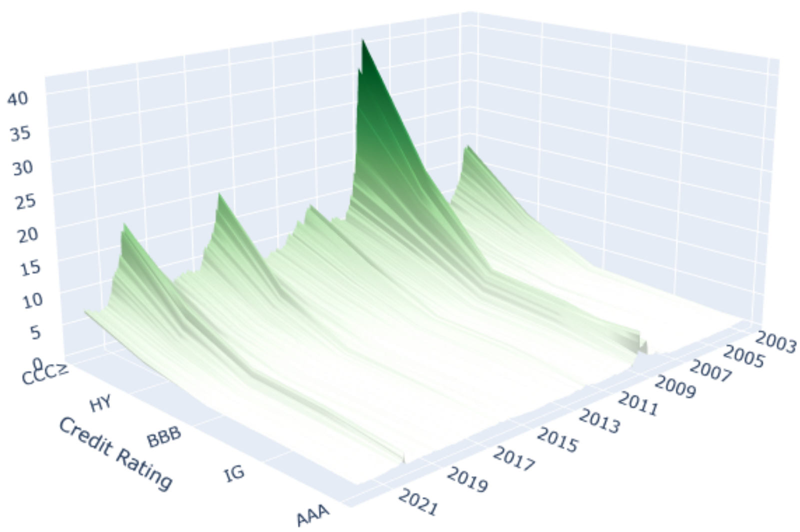
In the classical Merton (1974) framework, the expected credit term structure depends on the credit quality of the debt. For high-quality debt, an upward slope is expected. For low-quality debt, however, a downward slope is expected. The conclusions are perhaps less intuitive for the low-quality debt. The reason, however, is that low quality debt is the debt of companies near their default-boundary. As time goes, without the company defaulting on its liabilities, the probability of defaults conditioned upon survival increases, as the company increases its chances of a improved financial position. In Figure 3.1, a surface plot of the investment grade spreads for different maturities is shown. As expected, the term structure is mostly upward-sloping in the maturity dimension. During the most volatile markets of the GFC, however, the term structure is inverted to higher spreads for shorter-term bonds rather than longer-term. Following the reasoning of Merton (1974), this should imply a market expectation of an even larger share of investment grade companies to be near their default boundaries.

Table 3.1: Credit spread statistics for ICE BofA Investment Grade indices (%)

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15+Y
Average	1.22	1.39	1.63	1.70	1.84	1.88
Median	0.79	1.03	1.29	1.49	1.75	1.74
1st Quartile	0.59	0.8	1.01	1.12	1.27	1.43
3rd Quartile	1.25	1.55	1.84	1.89	2.1	2.08
Min	0.38	0.59	0.74	0.77	0.87	1.15
Max	8.13	6.98	6.74	6.22	5.80	5.23
Std.Dev	1.29	1.04	1.02	0.89	0.80	0.66

In Table 3.1, descriptive statistics of the investment grade indices are presented. As expected, the average spreads are rising in maturities. The larger standard deviation in the shorter-maturity spreads can partly be attributed to the rapid inversions during the GFC and the onset of the Covid-19 pandemic in the US. Another characteristic is that all medians are below the corresponding average, which indicates a positive skewness. Not that surprising considering the practical lower-bound of spreads to zero (at least adjusted for liquidity and transaction costs, see Bhanot and Guo (2011)), while no such upper-bound exists.

Figure 3.2: Surface plot of the Investment grade credit spread data set



In Table 3.2, the credit spread data for the different ratings are summarized. The investment grade spreads are strikingly close to a 40%-60% weighted sum of the AAA and BBB. High-yield and CCC&Lower are by many means a totally different investment regime, with high-yield almost yielding an US equity risk premium above Treasuries, while CCC&Lower almost yields it twofold.

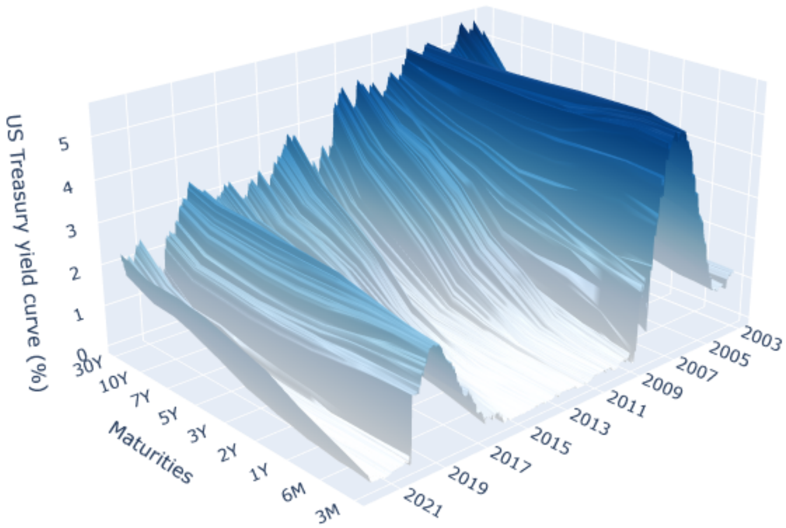
Table 3.2: Credit spread statistics for different credit ratings (%)

	AAA	IG	BBB	High-yield	CCC&Lower
Average	0.82	1.59	2.03	5.32	10.28
Median	0.65	1.33	1.76	4.54	8.94
1st Quartile	0.59	1.01	1.34	3.68	7.57
3rd Quartile	0.78	1.71	2.26	6.14	11.45
Min	0.44	0.79	1.07	2.41	4.16
Max	6.03	6.56	8.01	21.30	41.20
Std.Dev	0.59	0.94	1.12	2.71	4.81

3.2 Risk-Free Interest Data

The risk-free interest data consists of US Treasuries with a maturity in the range of 3 months to 30 years, as sourced from the FRED database. Figure 3.3 displays a surface plot of the interest rates, which serve as proxies for the hypothetical risk-free rates. The notion that governmental debt is without risk of default has been proving wrong on multiple occasions during the relevant period for this paper, with the Greek debt restructuring and effective short-term default on IMF debt being an example (Reinhart and Trebesch, 2015). Fisher (2013) lists several distinct risk-factors inherent in sovereign debt (e.g. inflation, shape risk and possibly currency risk). Since a liability in domestic currency on the government, the government could pay of its debts by 'printing money', thus putting the borrower at risk of receiving substantially less in coupons and principal due to inflationary effects. The practical implications of such behavior would, however, be significantly reduced trust in the central bank, which could result in higher risk-premiums (Stella, 2005).

Figure 3.3: Surface plot of US Treasuries in sampled data set



The US sovereign debt has historically been the safe haven for investors during market volatility with a significant convenience yield for the investors (Hager, 2017; Krishnamurthy and Vissing-Jorgensen (2012)). Krishnamurthy and Vissing-Jorgensen (2012) found that two attributes high-liquidity and low-risk, in US Treasuries significantly lowered their yields - more than 70 basis points in the 82-year period studied. This translates to a negative relationship between the supply of US Treasuries and the equilibrium pricing of these two attributes. As the supply of US Treasuries increases, measured by the Debt/GDP ratio, the premium pricing of safety and liquidity decreases. Nevertheless, the findings bring substantial support to the common notion that investors recognize large values in US Treasuries and their minor default risk, thus providing a good proxy for risk-free interest rates.

Table 3.3: US Treasury yield statistics (Dec 2002- Feb 2022) (%)

	3M	6M	1Y	2Y	3Y	5Y	7Y	10Y	30Y
Average	1.18	1.29	1.38	1.59	1.80	2.23	2.58	2.91	3.59
Median	0.30	0.46	0.65	1.03	1.43	1.90	2.30	2.74	3.40
1st quartile	0.07	0.12	0.18	0.45	0.79	1.35	1.67	1.99	2.82
3rd quartile	1.86	2.01	2.13	2.46	2.6	3.05	3.49	3.96	4.58
Min	0.00	0.02	0.04	0.09	0.11	0.21	0.39	0.55	1.17
Max	5.18	5.28	5.27	5.27	5.23	5.21	5.21	5.23	5.59
Std.Dev	1.51	1.54	1.51	1.42	1.35	1.24	1.17	1.14	1.09

Table 3.3 summarizes the US Treasury data in the sample. The averages are increasing in maturity, as one would expect form a normal (i.e. non-inverted) yield

curve. All medians are below the the averages.

3.3 Macroeconomic data

The macroeconomic data in this paper is summarized in the table below. All but the TED spread are collected from Eikon datastream as of March 2022. The TED spread is, like the risk-free yield curve and credit spread data, sourced from the FRED database. The returns are simple returns. To address the issue of mulitcollineraity in the model, a correlation matrix can also be found in the Appendix. None of the macroeconomic data series are highly correlated, with the correlation between VIX_Diff and S&P500_R spread being the highest in absolute terms (-0.54). As such, the risk of multicollinearity in macroeconomic data seems negligible. Furthermore, as the aims of this thesis are related to predictive power of the model, rather than explanatory powers, the issue itself is less of a problem.

Table 3.4: Macroeconomic data: Simple returns for WTI, Gold and S&P500 index. Non-differenced time series for the VIX index and the TED spread

	WTI_{return}	Gold_{return}	$\text{S\&P500}_{return}$	VIX	TED spread
Average	0.26%	0.20%	0.19%	18.94	0.41%
Median	0.48%	0.35%	0.28%	16.45	0.29%
1st quartile	-2.52%	-1.10%	-0.83 %	13.21	0.21%
3rd quartile	3.15%	1.64%	1.41%	21.59	0.43%
Min	-29.31%	-8.64%	-18.20%	9.14	0.06%
Max	31.75%	14.11%	12.10%	79.13	4.58%
Std.Dev	5.34%	2.36%	2.38%	8.86	0.42%

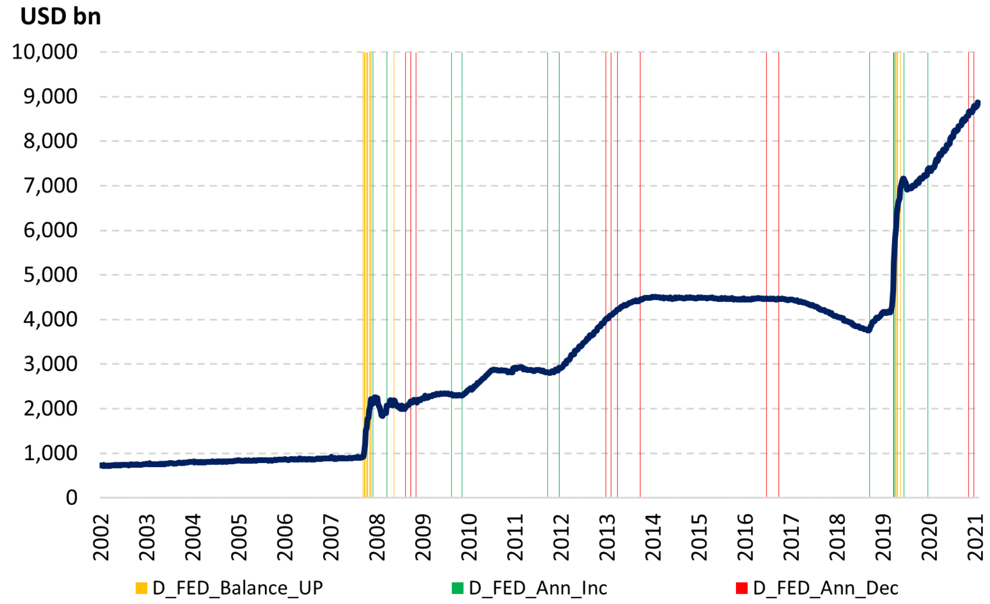
3.4 Federal Reserve data

The quantitative easing data collected consists of the Fed's total balance sheet, as reported weekly, from the FRED database. The balance sheet has grown substantially, from sub 1 billion USD prior to the first round of quantitative easing (QE1), to almost 9 billion in February 2022. In total, there have been four rounds of large-scale asset purchases by the Fed, often referred to as QE1-QE4. Throughout the period, there have been several policy changes, as decided by the Federal Open Market Committee (FOMC). To account for these changes, the announcement dates for what I deem the most important announcements are collected and visually represented in Figure 3.4. Announcements of monetary policy changes are important as they potentially alter bond investors' expectations of the future. As presented in the literature review, event studies centered on policy announcement dates are crucial for taking into account the effects of the policies. At the same time, the actual purchases of assets from the Fed's Trading Desk will ceteris paribus increase bank's liquidity, which further encourages increased lending, leading to monetary growth. As such, I see it as essential to have variables for both changing expectations due to policy changes *and* the actual asset purchases. Some studies simply use the Fed's balance sheet as a proxy for the QE effects; typically by calculating relative changes in the balance sheet over time. While ensuring stationarity, such an exercise would potentially equate a 5% increase in the balance sheet in Dec 2004 with a 5% increase in the balance sheet in Dec 2021, which would represent a ten-fold increase in purchases. I argue that the amount purchased on a weekly basis is indeed relative - but relative to what? It could be argued that the size of the purchases should be viewed relative to total outstanding the asset in focus (e.g. US Treasuries, MBSs and investment grade bonds). The aforementioned effects on bank's lending behavior a specific example of more broad portfolio re-balancing effects. If we consider the outstanding debt in the market as the full set of feasible credit investments, the necessary size of an asset purchase program to have equal effects on spreads and yields, should be linked to the total debt market in some way, as the additional provided liquidity is spanned across a wider set of financial assets in a larger credit market. In our considered time period, both the Fed's balance sheet and the US bond market grew considerably. Looking at the Fed's balance sheet development in Figure 3.4, the growth stems - by and large - from a few periods of of aggressive purchases over time periods. In order to capture the information contained in these purchases, I introduce a variable, D_Fed_Balance_UP, that takes the value of the relative weekly change in the Fed's balance sheet, given that it is larger than the 0.975 quantile of relative weekly balance sheet expansions in an expanding window, starting in December 2002 and expanding from mid-2008. The window is expanding to ensure no information spillover from the future to our prediction model. The weeks that have a non-zero value for D_Fed_Balance_UP are highlighted in yellow in Figure 3.4. D_Fed_Balance_UP is mathematically defined as follows:

$$D\_Fed\_Balance\_UP_t = \begin{cases} Balance\_r_t & \text{if } Balance\_r_t > Q^{0.975}_{[0,t]} \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

where $Balance\_r_t$ is the relative change in the Fed's balance sheet in time t, and $Q^{0.975}_{t,0}$ is the 0.975-quantile in the window from the first week (week 0) to week t.

Figure 3.4: Federal Reserve Balance sheet and events. See Appendix, Subsection 8.4 for detailed description of the selected events



In addition to the D_Fed_Balance_UP variable that accounts for significant liquidity effects, selected FOMC meetings are categorized to capture potential effects on spreads from changing market pricing of risk due to Fed policy changes. An included event is either categorized as D_FED_Ann_Dec, which represents a FOMC meeting indicating a slow-down of purchases or tapering, or D_FED_Ann_Inc, which represents announced acceleration of QE or increased commitment to credit markets (e.g. a stated 'whatever-it-takes' approach). The selection of which FOMC announcements to include are naturally subject to the author's personal opinion and possibly biases or other shortcomings. The expected impact from Fed announcements is also a question of what the ex ante market expectations were, and the potential gap between Fed's announcement policies and the expected policies. In the Appendix, Subsection 8.4, a more thorough overview of the events and, for events we find it necessary, an associated comment on the why the event is attached to either D_FED_Ann_Dec and D_FED_Ann_Inc.

4 Statistical Methods for Distribution Prediction

4.1 Quantile Regression

The desire to estimate quantiles of a data sample dates at least back to the 18th century (e.g. Boscovich and later Laplace), then centered on the median regression (Koenker, 2017). Quantile regression in modern academia was pioneered by Koenker and Bassett (1978). Contrary to ordinary least square (OLS) regression, the quantile regression developed by Koenker and Bassett (1978) does not specifically assume errors to be normally distributed. This provides more flexibility with respect to the data set. The quantile regression model has proved to significantly out-perform least square estimates for non-Gaussian error distributions. Further, conditional mean regression analysis is much more prone to destabilization due to data outliers, as it equally weighs the error squares. Quantile regression, however, weights the absolute errors differently depending on whether an observation is above or below the specified quantile (see Equation 4.2).

The mathematical formulae for quantile regression, as proposed by Koenker and Bassett (1978), are as follows:

$$Y_q = \beta_{0,\,q} + \sum_{i=1}^{n} \beta_{i,\,q} X_{i,\,q} + \epsilon_q \tag{4.1}$$

The regression coefficients are estimated as the solution to the minimization problem:

$$\min_{\beta \in \mathbb{R}} \left[\sum_{t \in t:\, y_t \geq x_t b} \theta \left| y_t - x_t b \right| \; + \sum_{t \in t:\, y_t < x_t b} (1-\theta) \left| y_t - x_t b \right| \right] \tag{4.2}$$

The weight, θ, takes the value equal to the quantile level to be estimated, e.g. 0.05, 0.95. x_t is a vector containing the independent variables and b is the vector with the quantiles' regression coefficients. Consequently, $\theta = 0.5$ represents a special case that yields the solution to the least absolute error problem, i.e. the median regression.

Quantile regression proves to be superior to OLS in presence of heterogeneous relationships between explanatory variables and response variables. Such differences in relationships are at risk of being neglected by an OLS apporach. Furthermore, extrapolating results from OLS to the full distribution may lead to severely incorrect conclusions, as the significance and contributions in the different variables may change considerably, dependent upon the quantiles in consideration.

While the mean predictions provided by OLS may be interesting in a variety of disciplines (including finance), the mean serves as a poor metric for assessing financial risks companies or investors are exposed to. For the investor being long a portfolio, the lower quantiles (e.g. 1% or 10%) may be of interest, for example, due to leverage control or liabilities coming due. Another example is a bond-funded bank, which may want to control refinancing risk and study the drivers of higher quantiles in credit spread changes' distribution.

4.2 Backtesting of Quantiles

Accuracy tests for quantile regression models deviate from the prediction models utilizing OLS. On a fundamental level, the quantile regression does not seek to establish point estimates of observed values but rather point estimates of where θ% of the observed values will be lower. For a simple OLS prediction of $\hat{y}_t = 2.00$ and the corresponding observed value of $y_t = 1.90$, there are a number of clearly defined errors measures such as Mean Absolute Deviation, (0.10) or Mean Absolute Percentage Error (5.3%). For the quantiles regression, however, these measures are not applicable, as the actual quantiles at each point in time are unknown. Building on the OLS example, let $y_t = 1.90$ once again. The quantile regression model yields a prediciton of $\hat{y}_{t,q=0.05} = -1.05$. The accuracy of such estimates is difficult to empirically test based solely on a few observations. This is why sufficient backtesting of the model is a necessity.

Since the 1990s, the applications of Value-at-Risk-like calculations became more widespread, although sometimes under different names (e.g. 'Dollars-at-Risk', 'Capital-at-Risk', 'Value-at-Risk) (Holton, 2002). Among the early advanced proprietary VaR calculations was JP Morgan's 'RiskMetrics', which was developed at the wish of Chairman Sir Dennis Weatherford's desire to have a simple and sufficient risk calculation to cover the spectrum of risks the bank faced in the coming 24 hours (Adamko et al., 2015). In financial institutions' regulatory framework, the backtesting of quantile predictions and VaR calculations have become closely linked in the academic literature (Gaglianone et al. 2011; Holton, 2002; Kuester et al., 2006). More specifically, the 1996-amendments to the Basel I accords stated that banks were, at a minimum, required to calculate daily Value-at-Risk, with a corresponding backtesting by both external and internal supervisory [3]. In this paper, the backtesting procedure combines two of the earlier tests for VaR backtesting: i) the Kupiec (1995) unconditional coverage test and, ii) the Christoffersen (1998) conditional coverage test. In addition to being widely used, both tests are intuitive and

[3]See Bank for International Settlements' *Amendment to the capital accord to incorporate market risks*, https://www.bis.org/publ/bcbs24.htm

quite simplistic in their application, which are the main rationales for selecting them in this paper.

The unconditional coverage test proposed by Kupiec (1995) is of the earliest back-testing procedures for testing the accuracy of loss distribution predictions. The Kupiec (1995) test applies a proportion of failure (PoF) methodology, where the predicted share of exceedances is compared to the expected share of exceedances. An exceedance is defined an event in which the predicted value, $\hat{y}_{t,q}$, exceedes the observed value, y_t. After running the model, all events of exceedances are counted and divided by the number of events. For example, considering the 1% quantile one-week-ahead predictions for a period of 1,000 weeks, the expected number of observed exceedances is 10. As such, we expect the model to only predict credit spread changes above the observed change in 10 of the 1,000 weeks. The null hypothesis is that the share of exceedances predicted by the model is equal to the quantile of interest. Mathematically, such a exceedance function can be formulated:

$$I_{t,q} = \begin{cases} 1 & \text{if } \hat{y}_{t,q} > y_t \\ 0 & \text{Otherwise} \end{cases} \tag{4.3}$$

where $\hat{y}_{t,q}$ is the predicted quantile for the observation at time t, and y_t is the observed value at time t. Given such a function, the observed share of exceedances for a quantile, $\hat{p}_q$ becomes:

$$\hat{p}_q = \frac{1}{T} \sum_{t=1}^{T} I_{t,q} \tag{4.4}$$

where the predictions are made on the time interval [1, T].

The Kupiec (1995) test relates to the the unconditional prediction power of a quantile prediction model, which test whether the observed share of exceedances,$\hat{p}_q$, deviates from the quantile. However, such a property would not alone be sufficent to ensure the desired prediction properties. As Christoffersen (1998) points out, such models' predictions must also be independent of each other. For illustration of the independence property's importance, consider the following example: If the model's exceedance events are fully clustered in a subsequent order of four, there may be indications that the predictions are not independent. If three exceedances have occured in the recent three intervals, and given the fully clustered exceedances modelled, there is no true probability distribution to estimate, as the next event is known to be an exceedance as well. Such model behavior would distort the notion of quantile predictions for the next interval since it would lead to wrongfully assigning probability estimates to a deterministic event. This illustrates the need to test the independence of the predictions. Christoffersen (1998) proposed a test for such conditional properties. The Christoffersen (1998) conditional coverage test is formulated with the null hypothesis that the model's prediction exceedances are randomly distributed, indicating no systematic clustering.

4.3 Principal Component Analysis

Another important statistical method in the modelling is Principal Component Analysis (PCA). PCA is a widely applied dimensionality reduction method, with applications in a diversity of disciplines. The aim is the extract important features for a set of covarying data sets and find the factors explaining a sufficient share of their variance. With more-than-ever amounts of data available to researchers, the need of dimensionality reduction techniques may rise, in order to combat the 'curse of dimensionality', and, potentially, reduced explainability and accuracy in models (Verleysen and François, 2005). Especially for time series, such as yield and spread changes, whose changes are highly correlated, PCA substantially reduces the number of calculations needed to explain close to all variability in the data set (See Section 5.1). High correlations among series could be due to shared impacts, or 'common factors', that each contribute to changes in the multivariate system. Mathematically, the eigenvectors of the covariance (or correlation) matrix form a new orthogonal basis. In the academic literature concerning factor modelling of bonds, the aforementioned Litterman and Scheinkman (1991) is seminal, with the famous interpretation of the three most important factors as *level*, *slope*, and *curvature*, following inspection of the principal components' loadings across the yield curve.

5 Empirical Methodology

In this section, a brief introduction to the extraction of the term structure factors, both for the risk-free (RF) term structure and the credit spread (CS) term structure, is given. Firstly, details on the extraction of term structure factors are presented, and the eigenvectors of the correlation matrix are interpreted and visualized. Secondly, the model specifications to be tested is formulated and discussed.

5.1 Extracting Term Structure Factors

With the objective of capturing information contained in the CS term structure and RF term structure, the aforementioned method of PCA is applied. The method is applied across the investment grade credit spread term structure (Table 3.1, Figure 3.1) and the risk-free yield curve (Table 3.3, Figure 3.2). The transformation to a lower dimension is as follows:

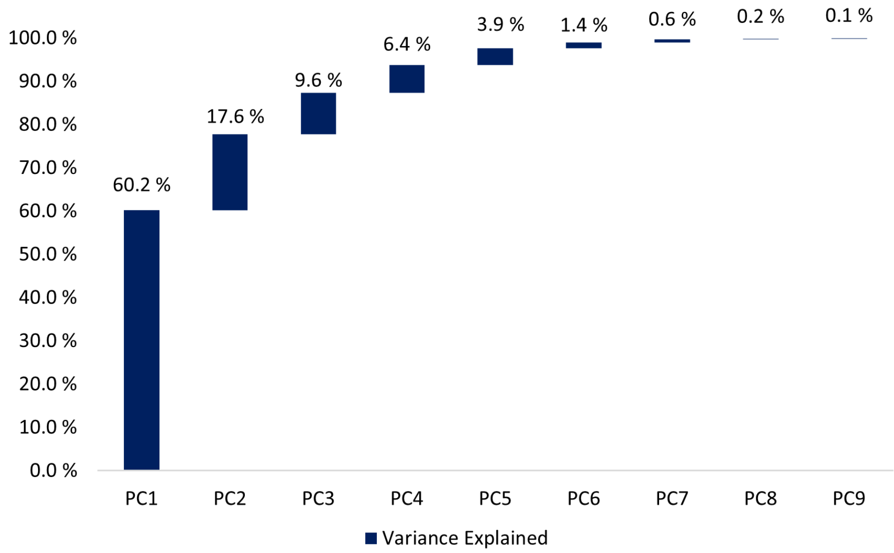
$$X_1, ..., X_n \implies Y_1, ..., Y_m \tag{5.1}$$

Where $X_i, i \in (1, n)$ is ith maturity credit spread and risk-free yield time series. n is the number of different maturities considered in total, and m (¡n) the number of PCs to be extracted. The correlation matrices for the two PCAs consists of the *simple relative changes* for both the risk-free (RF) term structure and the credit spread (CS) term structure. This is common practice in yield curve modelling to ensure stationarity (ADF stationary tests of regressors in the appendix). In order to decide on the number of principal component to extract, I study each component's proportion of variance explained, which is calculated as follows:

$$\text{Variance explained by } PC_i = \frac{\lambda_i}{\sum_{i=1}^{m} \lambda_i} \tag{5.2}$$

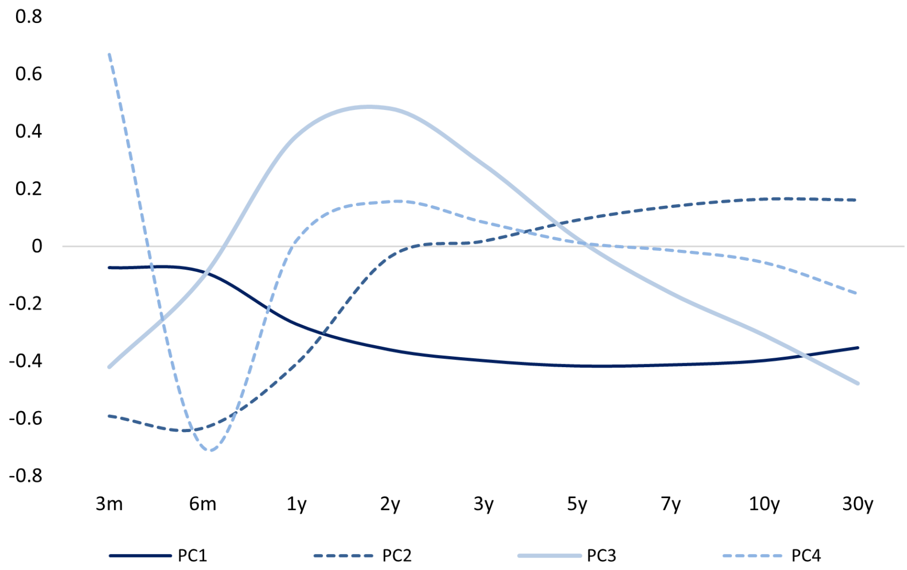
Where λ_i is the eigenvalue of the eigenvector that calculates the ith PC.

Figure 5.1: PCs of the risk-free yield: Variance explained by the PCs



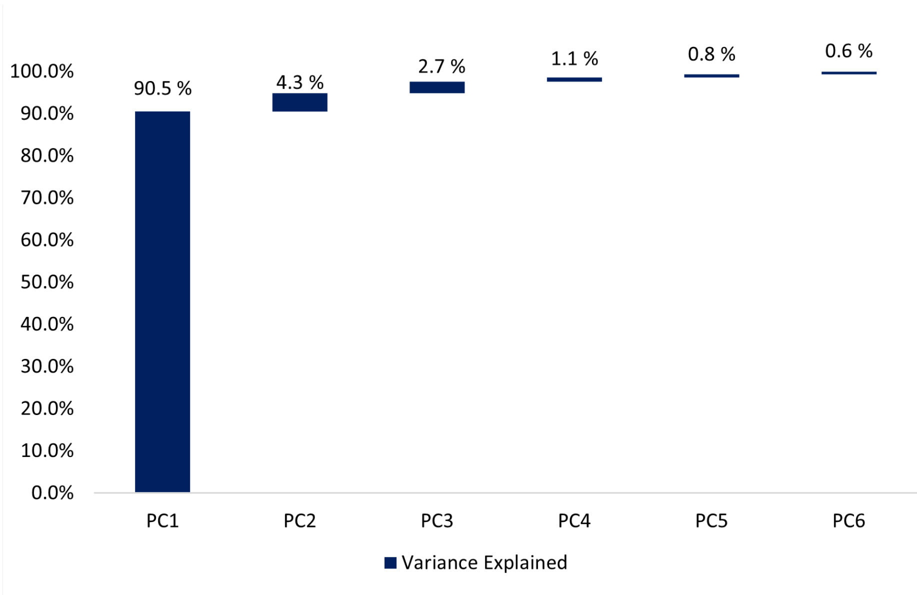
In Figure 5.1 and 5.3, the distributions of variance explained by the PCs of the data sets are displayed. For table form, reference is made to the appendix. The changes in the credit spread term have a dominant PC1 that explains more than 90% of the variance. Cumulatively, PC1, PC2, and PC3 explain more than 97% of the variance, which is in the higher range of variance explained by three PCs in the academic literature concerning *interest rates*. On the back of this, the three first PCs of the CS term structure may encompass predictive power on CS changes alone. For the RF interest rates, however, PC1 only explain 60.2% of the variance. This is substantially lower than for other periods researched (Barber and Cooper, 1996; Litterman and Scheinkman, 1991). Driessen et al. (2003) investigate an international factor-model using both currency- hedged and unhedged returns for Japanese and German, and US bond returns. With the interpretation of the PC1 in the multi-country model as a worldwide level, PC1 is found to explain 60-20% of the variance in international bond returns. For comparison, single-country factor models were constructed as well, with the PC1 explaining 96-89%. As such, the PC1 in this paper's US Treasury data interestingly explains as much variance as the *worldwide* interest rate level did in the period of 1990-1999, but nowhere near the findings in the classical factor modelling of yield curve changes. One stark trend in interest rates over the periods discussed here is the downward trend in US Treasusy yield levels, proxied by the 10-year Treasury yield, which peaked at above 15% in September 1981, more than 2 years after Paul Volcker took helm at the Fed. The generally lower interest levels in the period may have reduced the importance of the PC1 compared to that of other PCs.

Figure 5.2: PC loadings for RF PCs



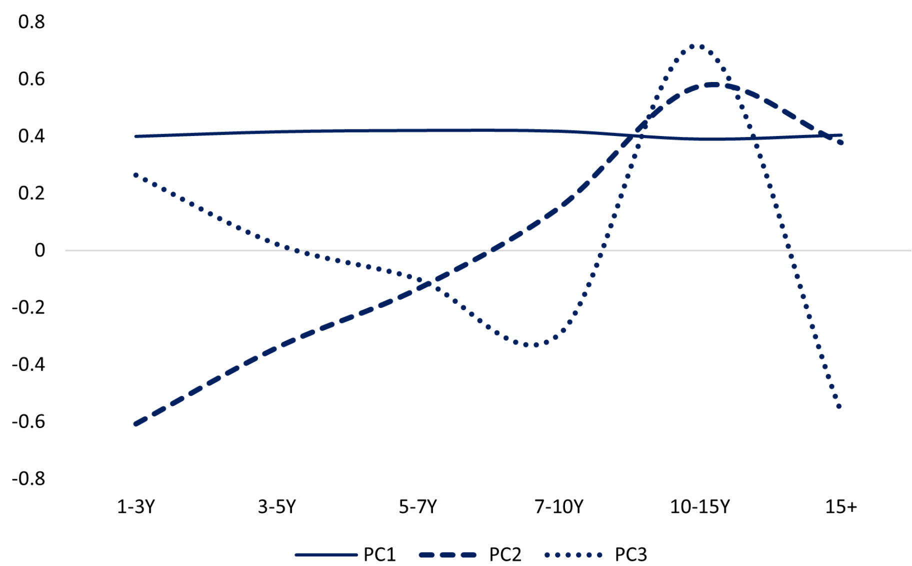
In Figure 5.2, the principal components are plotted across the maturities. The principal components, or the *eigenvectors*, of the yield changes' correlation matrix, which represent the impacts the factors have at different maturities. The eigenvectors scaled by the corresponding eigenvalues are equal to the so-called 'loadings'. As such, since the eigenvalues differ substantially for different the different PCs, the pure eigenvectors are helpful for visual inspections of the impacts. The RF PC1 display somewhat constant impact across all maturities but for the shortest rates (3m and 6m). This supports the interpretation of PC1 as a *level* factor with similar impacts across the yield curve. The risks related to RF PC1 is thus approximately parallel shifts in the yield curve. Such risks can be quantified by the classical Macaulay (1938) duration metric. Further, PC2 has increasing impact for increasing maturity, with close-to-neutral impact at mid-maturities. These findings are in alignment with the classical interpretation of RF PC2 as the slope of the curve (longer term yields less shorter term yields). RF PC3 display highest impact for the 3m, 30y and 2y interest rates. That is, the shortest term yields, the longest term yields, and at some point in-between. Noteworthy is the changing sign for the mid-term yields. This is supportive of the curvature interpretation of PC3, as it has a similar impact in the yield curve 'tails' but opposite in the center. Due to the numerous examples of PCA applications of PCs explaining 95+% of yield changes, the fourth PC, PC4, is also included. PC4 has high impacts for the shorter-term yields, while a muted, but downward trend for 2y-plus maturities. On the 3m-1y interval, PC4 resembles a form of curvature relationship between these short-term yields but in the opposite direction of what PC3 displays on the whole curve. Thus, PC4 may represent some relative changes in the short-term Treasury market that contributes to overall variance in the yield curve changes.

Figure 5.3: PC loadings for Credit spread PCs



In Figure 5.3, the variances explained by each CS PC are presented. In general, fewer decomposition and interpretations of the PCs in the *credit spread* term structure have been done in the literature.The first PC clearly dominates with an explained variance above 90%. Cumulatively, PC1 and PC2 explain close to 95% of the credit spread changes in the data set. Important to note is that the dimension in which the PCA is applied to is maturity, and not credit ratings which Chun et al. (2014) did. As I i) am building on the findings of Krishnan et al. (2010) by using factors of the credit term structure, ii) want to analyze and compare the CS PCs and the RF PCs in meaningful ways, I find the PCA of CS term structure more suited than PCA in the credit rating dimension (See Chun et al. (2014) for such PCA).

Figure 5.4: PC loadings for Credit spread PCs



In Figure 5.4, the normalized loading vector for the different credit spread maturities can be seen. PC1 has a steady impact for all maturities, even more than the RF PC1. Hence, CS PC1 is interpreted. PC2 trends upwards in maturity, arguably like a slope component of the term structure. Contrary to the US Treasury data, the credit spread data set does not contain any of the short-term maturities (¡1y). For PC3 a curvature-like impact change can be seen from 1y-15y. For the longest-maturity credit spreads however, there is a high-impact change from the 10-15y loading, which differs from the usual curvature impacts.

5.2 Prediction Model Validation

In this section, the rationales for the thesis' modelling and validation are presented. In order to understand the rationales, it seems fruitful return to the objective of this paper. The most fundamental objective is to test whether the information contained in the CS PCs have prediction power on a wide distribution of credit spread changes. Further, the findings of Krishnan et al. (2010), that the RF factors contains additional information that substantially improves point prediction abilities, are to be investigated for the whole distribution. Thirdly, by building on these preceding and more parsimonious models, the models are expanded in a hierarchical fashion to include other relevant macroeconomic variables, all common for prediction and explanatory models in the literature. More specifically, the defined variables related to the Fed are added to the parsimonious pure PC models in order to investigate their prediction powers. Although the aims of the paper is related to prediction ability of the models, the explanatory power of the variables in successful models is considered interesting too. As such, these are investigated for the most successful models.

Since I have manifold modelling desires, I find it useful to expand the models in a hierarchical fashion. As the models are for future predictions and for practitioners to apply (or build on), I emphasize the importance of out-of-sample testing of all models. There is broad agreement in the empirical finance literature that strong in-sample performance does not guarantee satisfactory out-of-sample performance. The in-sample predictions are thus secondary. This also has implications for whether variables should omitted due to high correlation, or a non-linear relationship, with other independent variables, to avoid multicollineary-like issues, which can improve explainability without necessarily improving predictive power (Alin, 2010; Mason and Perreaul (1991)). Still, as Inoue and Killian (2005) note, the out-of-sample tests may results in lower test powers, leading to higher changes of falsely accepting prediction models (Type I error, with rejection of null hypothesis). Furthermore, the risk of data mining, which could lead to us conclude positively on prediction models which really are built on spurious relationships. As several model specifications are tested, the risk of data mining is indeed prevalent. Hence, I find it appropriate to both report in-sample and out-of-sample results. The prediction models are not only measured against each other but also benchmarked against the highly common quantile prediction method Historical Simulation (HS), based on a rolling window of equal size as the other prediction models.

In total, there are six model specifications to formulate. These are all tested for 1-week, 2-weeks, and 4-weeks ahead predictions for different credit qualities (AAA, investment grade, BBB and CCC&Lower) and different maturities (1-15Y, and only for investment grade rating). For each model, a **name** is assigned, which will be consequently be referred to in **bold** in the rest of the thesis. The first model only regresses on the two CS PC scores that explain the most of the variation. The model is named **2xCS model**, since it encompasses only two CS PCs:

$$\Delta Spread_q\,(t+h) = \beta_{0,\,q} + \beta_{1,\,q}, CS\_PC_1\,(t) + \beta_{2,\,q}\,CS\_PC_2\,(t), + \epsilon_{\,t+h} \tag{5.3}$$

with $h = [1, 2, 4]$ week(s), and $CS\_PC_i(t)$ is the CS PC *score* of the ith most dominant principal component with respect to variance explained. The CS PC scores are the values along the new coordinate system, in which the PCs form the basis, at each point in time. That is to say, if we fully assume CS PC1 to represent the credit spread level (See Section 5.1), the CS PC1 score is the change in the yield curve along the spread level axis. As earlier noted, these two PCs, CS PC1 and CS PC2, explain approximately 95% of the variance in the yield curve (See Table 8.2 in the appendix). The rationale to start with such a parsimonious specification are the desires to model with simplicity and to potentially find highly applicable models. Furthermore, $\Delta Spread_q$ is the conditional quantile of the credit spread change (bps) from time t to time $t + h$ for the relevant credit spread index (i.e AAA, Investment grade, BBB, CCC&Lower, and Investment grade with constant maturity in 1-15Y). The quantiles of interest are $q = [0.01, 0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95, 0.99]$, which should allow for more granularity in the tails of the distribution as all 0.01, 0.05, 0.95, 0.99 are included. These are arguably the most interesting from an extreme risk viewpoint and portfolio stress testing. The second model is a simple extension of the **2xCS model** to the **3xCS model**, which, as implied by its name, also has the third most dominating CS PC as a regressor as a explanatory variable. The CS PCs are still the only regressors in the model.

$$\Delta Spread_q\,(t+h) = \beta_{0,\,q} + \sum_{i=1}^{3} \beta_{i,\,q}\,CS\_PC_i(t) + \epsilon_{\,t+h} \tag{5.4}$$

with the similar notations as in Equation 5.3. The rationale for the specification in Equation 5.4 is to test whether we could leave out the CS PC3 which explaines nearly 3% of the variation in the credit spread variation at minor costs. The next model is the first model which includes the RF PCs as well. Inspired by the modelling in Krishnan et al. (2010), the pure CS PC models, **2xCS model** and **3xCS model**, are expanded with RF PCs too, as we seek to account for any additional predictive power contained in the RF yield-curve. Two RF extended models are made specified: i) The **2xCS+3xRF model**, which builds on the **2xCS model**, and ii) the **3xCS+4xRF model**, which builds on the **3xCS model**.

$$\Delta Spread_q\,(t+h) = \beta_{0,\,q} + \sum_{i=1}^{2} \beta_{i,\,q}\, CS\_PC_i(t) + \sum_{i=1}^{3} \beta_{i,\,q}\, RF\_PC_i(t) + \epsilon_{\,t+h} \tag{5.5}$$

$$\Delta Spread_q\,(t+h) = \beta_{0,\,q} + \sum_{i=1}^{3} \beta_{i,\,q}\, CS\_PC_i(t) + \sum_{i=1}^{4} \beta_{i,\,q}\, RF\_PC_i(t) + \epsilon_{\,t+h} \tag{5.6}$$

The latter model, formulated in Equation 5.6, is the model specification with the most principal component variables in the paper and has variables that capture more than 97% and 93% of the variance in the CS and RF term structure explained, respectively.

The next model specifications is the first move away from formulations purely based on PCs (either CS or RF). Following the quite extensive research seeking to explain and predict credit spread changes with market or macroeconomic variables, a macro-extended model is specified, the **2xCS + Macro model**:

$$\begin{aligned}\Delta Spread_q\,(t+h) = \beta_{0,\,q} + \sum_{i=1}^{2} \beta_{i,\,q}\, CS\_PC_i(t) + \beta_{3,\,q}\, WTI_{Return}\,(t) + \beta_{4,\,q}\, GOLD_{Return}\,(t) + \\ \beta_{5,\,q}\, S\&P500_{Return}\,(t) + \beta_{6,\,q}\, \Delta VIX\,(t) + \beta_{7,\,q}\, \Delta TEDRATE\,(t) + \epsilon_{\,t+h}\end{aligned} \tag{5.7}$$

Lastly, the aims of taking Federal Reserve actions into account are addressed with the specification of the **2xCS + FED model**, which represent a quite neat formulation, given the inclusion of three Fed related variables:

$$\begin{aligned}\Delta Spread_q\,(t+h) = \beta_{0,\,q} + \sum_{i=1}^{2} \beta_{i,\,q}\, CS\_PC_i(t) + +\beta_{3,\,q}\, D\_FED\_Balance\_UP\,(t) \\ +\beta_{4,\,q}\, D\_FED\_Ann\_Inc\,(t) + \beta_{5,\,q}\, D\_FED\_Ann\_Dec\,(t) + \epsilon_{\,t+h}\end{aligned} \tag{5.8}$$

, where, as defined in Section 3.4, D_FED_Balance_UP is a variable, starting in second quarter of 2008, and taking the value of the week-over-week expansion if the balance sheet expansion is higher than a expanding window of 2.5% percentiles for historical increases. As large parts of the weekly changes are considered noise and that today's USD 9 tn is primarily due to short periods of highly aggressive QE purchases, only a few of the weekly increases are considered important, hence the percentile threshold. The other two variables, D_FED_Ann_Inc and is a dummy variables taking the value 1 in weeks where FOMC announces acceleration or increases, hence "Inc", in purchases, or 0 else. The D_FED_Ann_Inc, however, takes the value 1 in weeks where FMOC announces slowdown or *decreases*, hence "Dec", in purchases.

In sum, a wide range of model specifications are presented, all to be tested rigorously for 1-week, 2-week, and 4-week ahead predictions for a variety of credit spreads (both ratings and maturities), as I seek highlighting potential heterogeneity across different credit spread categories.

6 Results and Discussion

6.1 Out-Of-Sample Results

In this subsection, the out-of-sample prediction results are presented. In total, I have tested six model specifications for quantile predictions for one week, two weeks and four weeks ahead. The credit spread changes are for five different maturities, and for four different credit maturities (all investment grade). With 13 quantiles, the total number of quantile prediction results is therefore more than 700. The MAD (mean average deviation) is calculated for each quantile and the averages are summarized in the following subsections. Nevertheless, MAD, which is commonly used when predicting mean point estimates, is less suited for ranking predictions of distributions. For illustration, consider a model which is specified to predict the 0.5 quantile. After testing the model, the exceedance frequency is 51%, which corresponds to a MAD of 0.01. Now, consider the hypothetical model's prediction ability for the 0.01, and a corresponding exceedance frequency of 0%. That is, the model never overshoots the quantile. This would too yield a MAD of 0.01. Only considering the deviation from the respective quantile, we would conclude that the model specification is equally (un)successful at predicting the 0.5 quantile and the 0.01, which may prove to be a poor conclusion. A model specification setting the 0.01 quantile prediction to a artificially negative number would of course results in MAD of 0.01 as well. At the same time, this would be an awful model specification without any theoretically anchored formulation. Hence, the results are differentiated as to whether results are in the center or tails of the distribution. I define the tails of the distribution as q = [0.01, 0.05, 0.10, 0.90, 0.95, 0.99] quantiles. The center quantiles are defined as q = [0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8]. For benchmarking purposes, a historical simulation is performed based on a rolling window consisting of 350 weeks for each quantile. From a regulatory perspective, the prediction of quantiles are highly relevant for Value-at-Risk calculations, in which historical simulation is often applied by financial institutions. For reference, Pérignon and Smith (2010) studied financial institutions disclosure of VaR caclulations and found historical simulation to be the most popular method.

After presenting the average absolute deviations of the different model specifications, the best performing models are then backtested with the Kupiec (1995) and Christoffersen (1998) tests, to test prediction ability and potential clustering of prediction errors, respectively.

6.1.1 One-week ahead predictions

In Figure 6.1, the average absolute deviations for the one-week ahead distribution are presented.

Figure 6.1: Average MAD - One-week ahead prediction results

1 Week, Full distribution	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS+Fed	Historical Sim.
IG	0.78 %	0.84 %	0.77 %	1.01 %	1.54 %	0.78 %	2.22 %
AAA	0.97 %	1.01 %	1.13 %	1.31 %	0.90 %	0.84 %	3.68 %
BBB	0.93 %	0.86 %	0.86 %	1.02 %	1.62 %	0.85 %	1.06 %
CCC-	0.77 %	1.00 %	1.08 %	1.22 %	1.38 %	0.70 %	1.10 %
IG 1-3Y	1.22 %	1.40 %	1.34 %	0.77 %	1.98 %	0.99 %	3.21 %
IG 3-5Y	0.94 %	1.19 %	1.01 %	1.17 %	1.62 %	0.99 %	2.25 %
IG 5-7Y	1.26 %	1.06 %	1.19 %	0.96 %	1.36 %	1.23 %	1.88 %
IG 7-10Y	0.97 %	1.16 %	1.21 %	1.22 %	1.23 %	1.22 %	1.04 %
IG 10-15Y	0.98 %	1.10 %	0.97 %	1.07 %	1.73 %	1.09 %	0.96 %
Average	**0.98 %**	**1.07 %**	**1.06 %**	**1.08 %**	**1.48 %**	**0.97 %**	**1.93 %**

1 Week, q=<10%,90%>	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS + Fed	Historical Sim.
IG	1.10 %	1.01 %	0.99 %	1.14 %	2.04 %	1.26 %	3.12 %
AAA	1.26 %	1.21 %	1.43 %	1.34 %	0.93 %	1.36 %	5.90 %
BBB	1.15 %	0.90 %	1.01 %	1.15 %	2.37 %	1.25 %	1.02 %
CCC-	0.57 %	0.80 %	1.09 %	1.25 %	1.52 %	0.89 %	1.32 %
IG 1-3Y	1.18 %	1.31 %	1.59 %	0.57 %	1.98 %	0.96 %	4.36 %
IG 3-5Y	1.20 %	1.30 %	1.18 %	1.16 %	1.98 %	1.34 %	3.08 %
IG 5-7Y	2.12 %	1.70 %	1.90 %	1.37 %	2.09 %	1.92 %	2.68 %
IG 7-10Y	1.45 %	1.59 %	1.54 %	1.65 %	1.76 %	1.94 %	1.23 %
IG 10-15Y	1.40 %	1.58 %	1.31 %	1.37 %	2.64 %	1.69 %	1.48 %
Average	**1.27 %**	**1.27 %**	**1.34 %**	**1.22 %**	**1.92 %**	**1.40 %**	**2.69 %**

1 Week, q=[1% , 5%, 10% ,90%, 95%, 99%]	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS + Fed	Historical Sim.
IG	0.41 %	0.65 %	0.52 %	0.85 %	0.95 %	0.23 %	1.18 %
AAA	0.65 %	0.77 %	0.77 %	1.26 %	0.88 %	0.24 %	1.08 %
BBB	0.67 %	0.83 %	0.70 %	0.88 %	0.75 %	0.39 %	1.10 %
CCC-	1.01 %	1.24 %	1.06 %	1.19 %	1.22 %	0.47 %	0.85 %
IG 1-3Y	1.26 %	1.50 %	1.06 %	1.01 %	1.98 %	1.03 %	1.88 %
IG 3-5Y	0.65 %	1.06 %	0.80 %	1.19 %	1.21 %	0.57 %	1.28 %
IG 5-7Y	0.25 %	0.32 %	0.36 %	0.48 %	0.52 %	0.44 %	0.95 %
IG 7-10Y	0.40 %	0.66 %	0.82 %	0.72 %	0.62 %	0.38 %	0.82 %
IG 10-15Y	0.48 %	0.53 %	0.57 %	0.72 %	0.66 %	0.39 %	0.36 %
Average	**0.64 %**	**0.84 %**	**0.74 %**	**0.92 %**	**0.98 %**	**0.46 %**	**1.06 %**

The average absolute deviation is defined as:

$$Average(MAD) = \frac{1}{Q}\sum_{q=1}^{Q}|\pi_{exp,q} - \pi_{pred,q}| \tag{6.1}$$

, where Q is the number of quantiles and $\pi_{exp,q}$ is the expected exceedance frequency, e.g. 1%, 5%, and $\pi_{exp,q}$ is the observed share of exceedances for the model specification.

As indicated by the color map, the introduction of our macroeconomic variables in the model specification does not improve the prediction power. Interestingly, the parsimonious **2xCS model**, consisting only of the first and second principal components extracted from the credit spread term curve, represents one of the most successful models for one-week predictions. The two PCs in the **2xCS model** explain nearly 95% of the variance in the credit spread time series (see Table 8.2 in the Appendix). Contrary to the findings of Krishnan et al. (2010), I do not find the risk-free factors to improve prediction ability for all spreads. While Krishnan et al. (2010) predict point estimates for actual changes and not the expected distribution, I would expect the prediction of the center quantiles to be improved as risk-free factors were introduced. This is not the case for the **2xCS+3xRF model**, with some investment grade spreads as exceptions. The **2xCS+3xRF model** specification improves the predictions in the center quantiles, as defined above. More notably, the introduction of the Fed variables contribute to a substantially better prediction of the tail quantiles. Hence, practitioners may apply the **2xCS model**, the **2xCS+3xRF model**, or the **3xCS+4xRF model** for the center of the distribution and the **2xCS + FED model** estimate the credit spread distribution next week. The **2xCS+3xRF model**, the **2xCS model**, and the **2xCS + Fed model** are deemed the best performing models for further investigations. In the credit quality dimension, the tails of the lowest rated bonds proves hard to predict. In the maturity dimension, the lower maturity spreads are harder to predict for the best performing models. While the **2xCS + Fed** model is more accurate in the tails of the distribution, the middle quantiles are less successfully predicting compared to the parsimonious **2xCS model** or the **2xCS+3xRF model**. The model with macroeconomic variables, **2xCS+Macro model** and the CS PCs are worst of the specified models but still perform better than the **Historical Simulation**.

6.1.2 Two-weeks ahead predictions

In Figure 6.2 the average absolute deviations for the two-weeks ahead distribution are presented.

Figure 6.2: Average MAD - Two weeks prediction results

	2 Weeks, Full distribution						
	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS+Fed	Historical Sim.
IG	1.22 %	1.41 %	1.11 %	1.33 %	2.04 %	1.30 %	1.48 %
AAA	0.74 %	0.88 %	0.63 %	0.64 %	0.93 %	0.81 %	1.70 %
BBB	1.02 %	1.22 %	0.89 %	1.04 %	2.35 %	1.03 %	1.24 %
CCC-	0.67 %	0.78 %	0.53 %	0.67 %	1.50 %	0.47 %	1.22 %
IG 1-3Y	1.12 %	1.29 %	1.00 %	1.14 %	1.97 %	1.09 %	2.18 %
IG 3-5Y	1.23 %	1.46 %	1.38 %	1.32 %	1.97 %	1.18 %	1.56 %
IG 5-7Y	0.98 %	1.20 %	1.12 %	1.20 %	1.78 %	1.01 %	1.28 %
IG 7-10Y	1.22 %	1.40 %	1.21 %	1.51 %	1.71 %	1.46 %	1.45 %
IG 10-15Y	1.24 %	1.17 %	1.19 %	1.25 %	2.43 %	1.17 %	1.16 %
Average	**1.05 %**	**1.20 %**	**1.01 %**	**1.12 %**	**1.85 %**	**1.06 %**	**1.47 %**

	2 Weeks, q=<10%,90%>						
	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS + Fed	Historical Sim.
IG	1.67 %	1.68 %	1.50 %	1.49 %	2.64 %	1.85 %	1.46 %
AAA	0.86 %	0.90 %	0.62 %	0.57 %	0.76 %	1.21 %	2.40 %
BBB	1.18 %	1.18 %	1.05 %	0.98 %	2.93 %	1.49 %	1.09 %
CCC-	0.61 %	0.59 %	0.53 %	0.62 %	1.51 %	0.32 %	1.12 %
IG 1-3Y	1.13 %	1.27 %	1.01 %	1.08 %	2.17 %	1.40 %	2.42 %
IG 3-5Y	1.34 %	1.54 %	1.67 %	1.42 %	2.26 %	1.51 %	1.53 %
IG 5-7Y	1.43 %	1.54 %	1.81 %	1.81 %	2.35 %	1.65 %	1.28 %
IG 7-10Y	1.76 %	1.76 %	1.71 %	1.90 %	2.31 %	2.16 %	1.27 %
IG 10-15Y	1.84 %	1.69 %	1.46 %	1.53 %	3.54 %	1.95 %	1.40 %
Average	**1.31 %**	**1.35 %**	**1.26 %**	**1.27 %**	**2.27 %**	**1.51 %**	**1.55 %**

	2 Weeks, q=[1% , 5%, 10% ,90%, 95%, 99%]						
	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS + Fed	Historical Sim.
IG	0.70 %	1.08 %	0.66 %	1.13 %	1.34 %	0.66 %	1.50 %
AAA	0.59 %	0.85 %	0.65 %	0.72 %	1.13 %	0.34 %	0.88 %
BBB	0.83 %	1.26 %	0.70 %	1.11 %	1.68 %	0.49 %	1.42 %
CCC-	0.74 %	1.01 %	0.53 %	0.72 %	1.50 %	0.64 %	1.34 %
IG 1-3Y	1.11 %	1.31 %	0.98 %	1.21 %	1.73 %	0.72 %	1.91 %
IG 3-5Y	1.11 %	1.37 %	1.03 %	1.21 %	1.62 %	0.80 %	1.60 %
IG 5-7Y	0.45 %	0.80 %	0.31 %	0.48 %	1.11 %	0.26 %	1.29 %
IG 7-10Y	0.58 %	0.98 %	0.63 %	1.05 %	1.01 %	0.64 %	1.57 %
IG 10-15Y	0.53 %	0.57 %	0.87 %	0.93 %	1.13 %	0.25 %	0.88 %
Average	**0.74 %**	**1.03 %**	**0.71 %**	**0.95 %**	**1.36 %**	**0.53 %**	**1.38 %**

On average, the deviations are larger for all model specifications but for the **2xCS+3xRF model** and the **Historical Simulation** model. CCC&Lower credit spreads proves to the credit rating for which predicting powers are strongest. Akin to the one-week ahead predictions, the **2xCS + Fed model** displays superiority to the other specifications in the tails of the distribution. In the center of the distribution, however, the models combining the CS PCs and the RF PCs are the most accurate. In the maturity dimension, the best performing models are more or less constant in the center of the distribution, while substantially better for increasing maturity in the tails of the distribution.

6.1.3 Four-weeks ahead predictions

In Figure 6.3 the average absolute deviations for the four-weeks ahead distribution are presented. The four-weeks ahead predictions distinguish from the one and two-weeks predictions as the average MADs have increased significantly for the **2xCS model**, the **2xCS+3xRF model**, and the **2xCS+Fed model**. Especially, for the center of the distribution the deviations are now close to 2% for all models. The lowest rated bonds (CCCLower ratings) remain the exception, especially in the center of the distribution. The **2xCS + Fed model** once again performs better than the other specifications. For the first time, the **Historical Simulation** predicts better in the center of the distribution than all models purely based on PCs.

While the prediction ability **Historical Simulation** is quite constant as the models are tested for one-week to four-week predictions, the factor models' performance deteriorates quite dramatically.

Figure 6.3: Average MAD - Four weeks prediction results

	4 Weeks, Full distribution						
	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS+Fed	Historical Sim.
IG	1.56 %	1.64 %	1.68 %	1.77 %	2.16 %	1.64 %	1.48 %
AAA	1.25 %	1.38 %	1.38 %	1.40 %	1.16 %	1.45 %	1.11 %
BBB	1.49 %	1.73 %	1.38 %	1.43 %	2.37 %	1.51 %	2.18 %
CCC-	0.68 %	0.81 %	0.85 %	1.02 %	1.40 %	0.44 %	1.57 %
IG 1-3Y	1.46 %	1.64 %	1.34 %	1.56 %	2.12 %	1.61 %	1.83 %
IG 3-5Y	1.61 %	1.79 %	1.63 %	1.68 %	2.06 %	1.62 %	1.68 %
IG 5-7Y	1.32 %	1.53 %	1.35 %	1.22 %	1.91 %	1.24 %	1.63 %
IG 7-10Y	1.37 %	1.38 %	1.38 %	1.55 %	1.96 %	1.52 %	1.59 %
IG 10-15Y	1.84 %	1.82 %	1.78 %	1.86 %	2.14 %	2.06 %	1.65 %
Average	**1.40 %**	**1.52 %**	**1.42 %**	**1.50 %**	**1.92 %**	**1.45 %**	**1.64 %**

	4 Weeks, q=<10%,90%>						
	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS + Fed	Historical Sim.
IG	2.13 %	1.93 %	2.29 %	2.06 %	2.79 %	2.52 %	1.35 %
AAA	1.50 %	1.50 %	1.59 %	1.54 %	1.04 %	2.10 %	0.91 %
BBB	1.82 %	2.11 %	1.57 %	1.67 %	2.92 %	2.11 %	2.28 %
CCC-	0.34 %	0.34 %	0.50 %	0.67 %	1.37 %	0.21 %	1.55 %
IG 1-3Y	1.84 %	1.91 %	1.72 %	1.62 %	2.55 %	2.42 %	1.75 %
IG 3-5Y	1.93 %	2.06 %	2.08 %	1.95 %	2.55 %	2.20 %	1.71 %
IG 5-7Y	1.82 %	1.88 %	1.84 %	1.46 %	2.59 %	1.91 %	1.64 %
IG 7-10Y	1.68 %	1.63 %	1.72 %	1.87 %	2.46 %	2.22 %	1.45 %
IG 10-15Y	2.79 %	2.57 %	2.59 %	2.50 %	3.01 %	3.30 %	2.24 %
Average	**1.76 %**	**1.77 %**	**1.77 %**	**1.71 %**	**2.37 %**	**2.11 %**	**1.65 %**

	4 Weeks, q=[1% , 5%, 10% ,90%, 95%, 99%]						
	2xCS	3xCS	2xCS + 3xRF	3xCS +4xRF	2xCS+Macro	2xCS + Fed	Historical Sim.
IG	0.90 %	1.29 %	0.98 %	1.42 %	1.42 %	0.61 %	1.62 %
AAA	0.95 %	1.24 %	1.13 %	1.23 %	1.29 %	0.69 %	1.34 %
BBB	1.11 %	1.29 %	1.15 %	1.15 %	1.73 %	0.80 %	2.06 %
CCC-	1.08 %	1.37 %	1.26 %	1.42 %	1.44 %	0.71 %	1.60 %
IG 1-3Y	1.01 %	1.31 %	0.90 %	1.50 %	1.62 %	0.66 %	1.93 %
IG 3-5Y	1.24 %	1.47 %	1.11 %	1.37 %	1.50 %	0.95 %	1.65 %
IG 5-7Y	0.75 %	1.11 %	0.76 %	0.93 %	1.11 %	0.45 %	1.63 %
IG 7-10Y	1.01 %	1.08 %	0.98 %	1.19 %	1.37 %	0.71 %	1.75 %
IG 10-15Y	0.74 %	0.94 %	0.83 %	1.11 %	1.13 %	0.61 %	0.96 %
Average	**0.98 %**	**1.23 %**	**1.01 %**	**1.26 %**	**1.40 %**	**0.69 %**	**1.62 %**

6.1.4 Prediction plots

In the figures below, the plotted predictions for the best performing models overall can be seen.

Figure 6.4: The 2xCS model: 1-Week ahead predicted tail quantiles and actual credit spread changes (bps)

The 2xCS model

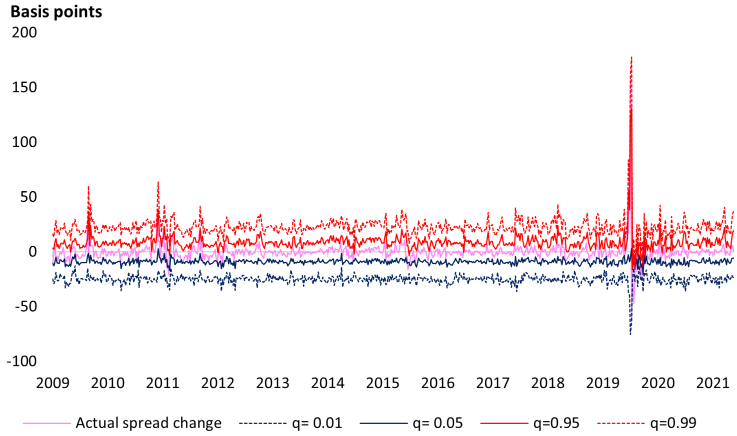


Figure 6.5: The 2xCS+3xRF model: 1-week ahead redicted tail quantiles and actual credit spread changes (bps)

The 2xCS+3xRF model

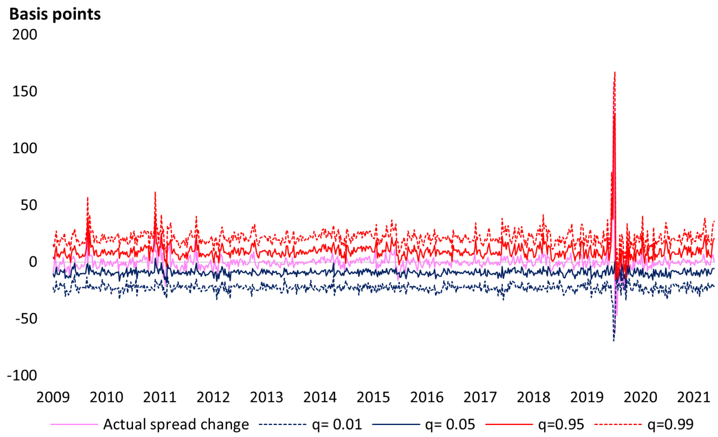
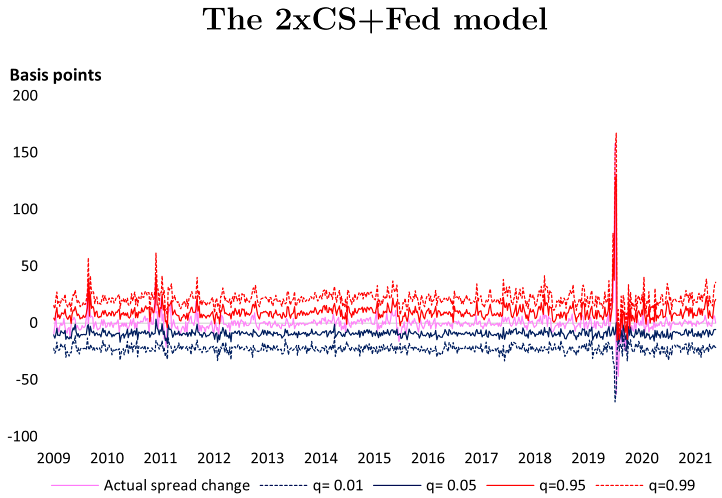


Figure 6.6: The 2xCS+Fed model: 1-week ahead predicted tail quantiles and actual credit spread changes (bps)



6.2 Backtesting the Out-of-Sample results

In this subsection, the results from the Kupiec (1995) and Christoffersen (1998) tests are presented. Only the best performing model specifications, the **2xCS model**, **2xCS+3xRF model** and the **2xCS+Fed model** are presented with their full distribution, as the other model specifications are now considered of less interest. The Kupiec (1995) test ensures that similar absolute deviations in the tail quantiles (e.g. 1% and 5%) are harder punished than the deviations in the center quantiles. As argued in the discussion of the MAD tables, this is a critical feature of statistical tests for a predicted distribution. Further, another valued feature of predicting models, beyond the difference between predicted and expected value, is the model's tendency to adapt to newly received information, and, thus, avoids clusters of errors (Campbell, 2005). Christoffersen (1998) formulated these conditions as two distinct properties, namely; i) the unconditional coverage property, and ii) the independence property (Christoffersen (1998); Campbell (2005)). The first property is tested with the Kupiec (1995) test, while the latter is tested with the Christoffersen (1998) test. In this paper, both tests are required to pass in order for a series of predictions to be deemed 'successful'.

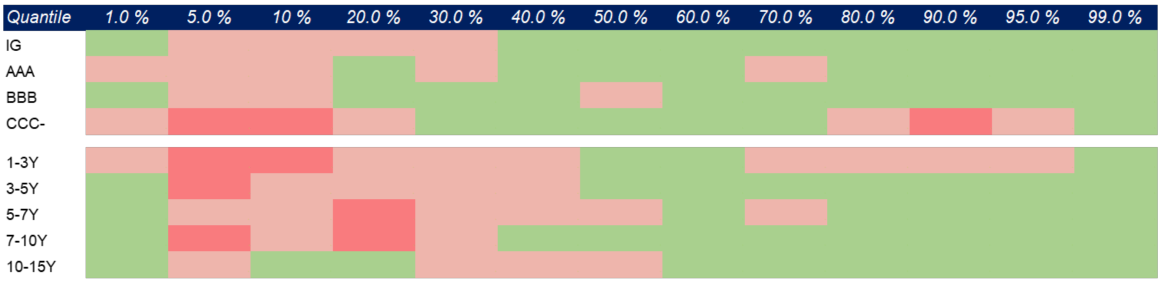


Figure 6.7: The 2xCS model: Backtesting results with Kupiec (1995) and Christoffersen (1998) at 5% significance level. Two tests passed=**green**, one test passed=**pink**, none passed=**red**

As seen in Figure 6.7, the quantile predictions in the lower part of the distribution (5%-30%) are more prone to failing one of the tests than other parts of the distribution. The introduction of the RF PCs as variables to the model does not improve the test performance but rather further exacerbates it in these quantiles.

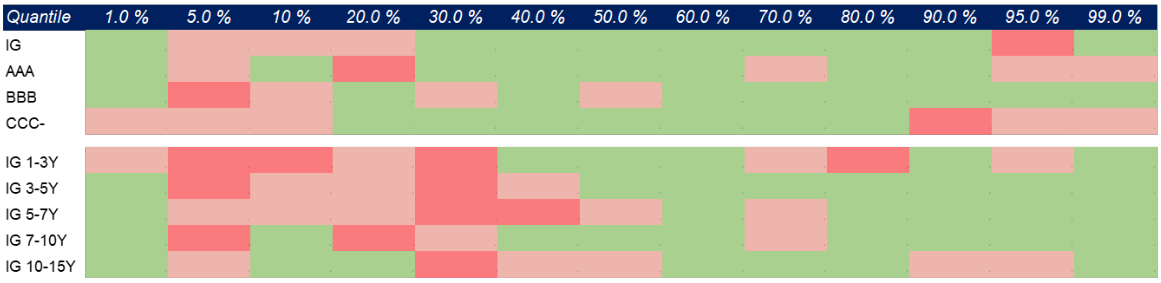


Figure 6.8: The 2xCS+3xRF model: Backtesting results with Kupiec (1995) and Christoffersen (1998) at 5% significance level. Two tests passed=**green**, one test passed=**pink**, none passed=**red**

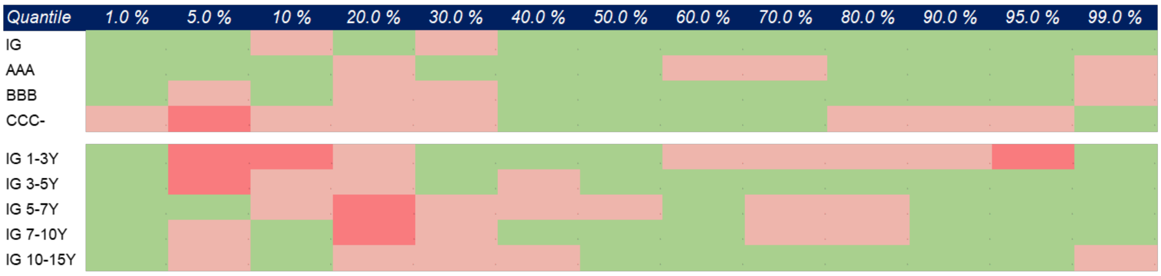


Figure 6.9: The 2xCS+Fed model: Backtesting results with Kupiec (1995) and Christoffersen (1998) at 5% significance level. Two tests passed=**green**, one test passed=**pink**, none passed=**red**

In Figure 6.9, the **2xCS+Fed model** results are illustrated. It displays the improvements made by introducing the variables accounting for Federal Reserves' most rapid balance sheet expansions and its announcements of policy changes. The 5% quantile predictions are improved for the higher rated bonds. The models are more successful in predicting the upper quantiles of the distribution, suggesting that i) the RF PCS and CS PCs contain information about future credit spread changes, while more variables are needed for explaining the lower quantiles. These findings are in-line with the findings of Pires et al. (2010) which indicated that the center-to-upper Credit spread quantiles were driven by the same factors. With respect to the credit spread dimension, the lowest rated bonds are not as successful as the higher quality bonds.

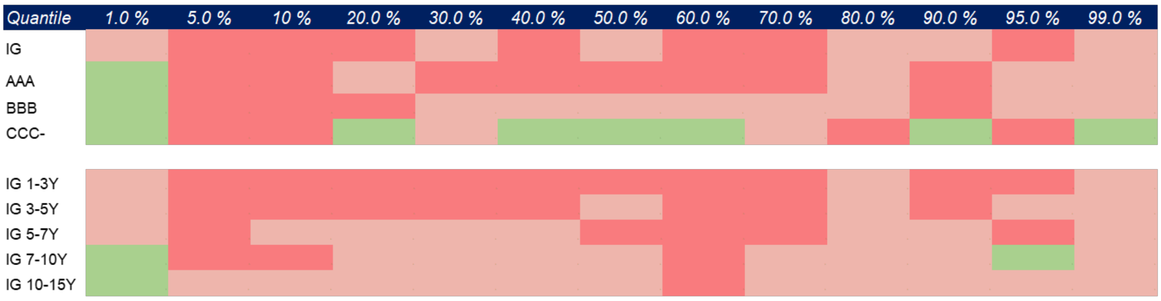


Figure 6.10: Historical Simulation: Backtesting results with Kupiec (1995) and Christoffersen (1998) at 5% significance level. Two tests passed=**green**, one test passed=**pink**, none passed=**red**

To further illustrate the model's performance, the backtesting results of the **Historical Simulation** is presented as well.

6.3 In-sample Results

In this section, the regression coefficients of the most successful predictions models are discussed. Quantile regressions are run on the whole data set for the **2xCS model**, **2xCS+3CS model**, and **2xCS + FED model** with the purpose of further analyzing potential relationships between the the different credit spread changes (independent variables) and the variables used for prediction.

Dep. Var	Quantile	1.0 %	5.0 %	10.0 %	20.0 %	30.0 %	40.0 %	50.0 %	60.0 %	70.0 %	80.0 %	90.0 %	95.0 %	99.0 %
Investment grade	$\beta_{0,q}$	-25.11***	-8.694***	-5.282***	-2.866***	-1.651***	-0.8725***	-0.195*	0.4967***	1.415***	2.714***	4.562***	7.648***	29.72***
	Std.Err	*1.984*	*0.5427*	*0.4104*	*0.1775*	*0.1327*	*0.1162*	*0.1129*	*0.1203*	*0.1426*	*0.1811*	*0.2555*	*0.7225*	*2.442*
	$\beta_{CS\_PC1,q}$	-2.435	10.84*	11.55***	14.37***	14.73***	15.04***	15.54***	16.66***	19.66***	22.25***	22.91***	26.87***	54.65
	Std.Err	*38.42*	*6.335*	*3.897*	*1.312*	*0.8249*	*0.6451*	*0.5947*	*0.6387*	*0.8084*	*1.205*	*2.121*	*8.252*	*53.75*
	$\beta_{CS\_PC2,q}$	-27.94	1.578	-8.665	-13.57***	-13.05***	-10.02***	-11.06***	-9.119***	-6.977**	-6.03	-2.06	9.854	99.07
	Std.Err	*127.5*	*21.69*	*12.88*	*4.443*	*2.942*	*2.377*	*2.267*	*2.499*	*3.240*	*4.812*	*8.917*	*28.62*	*144*
CCC&Lower	$\beta_{0,q}$	-153.0***	-63.97***	-44.47***	-27.20***	-16.96***	-9.162***	-2.609**	4.354***	11.63***	22.06***	43.82***	78.18***	173.5***
	Std.Err	*22.43*	*3.396*	*3.002*	*1.450*	*1.225*	*1.110*	*1.064*	*1.119*	*1.254*	*1.689*	*2.774*	*5.626*	*10.75*
	$\beta_{CS\_PC1,q}$	-19.29	34.55	32.56	40.07***	40.97***	47.09***	54.45***	65.44***	67.41***	76.11***	94.85***	63.38	128.8
	Std.Err	*412.4*	*37.13*	*26.75*	*10.18*	*7.270*	*6.021*	*5.607*	*6.053*	*7.422*	*11.71*	*24.84*	*64.62*	*212.8*
	$\beta_{CS\_PC2,q}$	-139.6	-159.7	-148.2	-89.25**	-67.49**	-30.75	-4.747	-16.67	28.21	39.78	67.04	43.17	317.4
	Std.Err	*1143*	*135.3*	*94.69*	*35.46*	*26.17*	*22.3*	*21.38*	*23.69*	*29.63*	*47.62*	*103.8*	*268.4*	*925.4*

Figure 6.11: In-sample **2xCS model**: QR coefficients for different credit ratings (bps). *** p<0.01, ** p<0.05, * p<0.10

For illustration, the investment grade spreads and CCC&Lower spreads are presented. In the maturity dimension, the 1-3Y bonds and 10-15Y bonds are presented. The $\beta_{CS\_PC\_1,q}$ is significant across all but the tails of the distribution, with a positive value for all significant coefficients. This implies that an increase in the *level* factor (See Section 5.1) lifts the estimated distribution of next week's credit spreads (10.84-26.87 bps for an incremental increase in the CS PC1). The $\beta_{CS\_PC\_2,q}$, the curvature factor for CS, is significant for mid-quantiles (70-20%) in investment grade spreads, while less significant in the CCC&Lower credit spreads.

Dep. Var	Quantile	1.0 %	5.0 %	10.0 %	20.0 %	30.0 %	40.0 %	50.0 %	60.0 %	70.0 %	80.0 %	90.0 %	95.0 %	99.0 %
Investment grade	$\beta_{0,q}$	-23.94***	-8.516***	-5.342***	-2.787***	-1.672***	-0.8995***	-0.2453**	0.5164***	1.452***	2.759***	4.621***	8.113***	31.49***
	Std.Err	*1.471*	*0.5941*	*0.3104*	*0.1749*	*0.1278*	*0.1151*	*0.1132*	*0.1231*	*0.1440*	*0.1849*	*0.2517*	*0.5955*	*1.707*
	$\beta_{CS\_PC1,q}$	-0.2323	11.43	12.8***	15.19***	15.49***	16.52***	16.02***	18.47***	20.27***	22.08***	23.25***	26.05***	53.22
	Std.Err	*29.23*	*7.065*	*2.974*	*1.301*	*0.8306*	*0.6787*	*0.6434*	*0.7144*	*0.9052*	*1.357*	*2.420*	*7.699*	*38.86*
	$\beta_{CS\_PC2,q}$	10.12	-0.4607	-10.43	-11.40**	-12.51***	-9.567***	-9.161***	-8.764***	-6.445*	-6.138	-0.8097	8.833	98.40
	Std.Err	*93.35*	*23.67*	*10.26*	*4.547*	*3.015*	*2.520*	*2.445*	*2.752*	*3.520*	*5.290*	*9.678*	*24.88*	*95.86*
	$\beta_{RF\_PC1,q}$	6.580	-2.920	-4.156	-2.594*	-2.452**	-2.401***	-1.188	-2.446**	-1.602	-0.3995	-1.541	-1.625	-24.36
	Std.Err	*26.22*	*6.612*	*2.940*	*1.495*	*1.033*	*0.8806*	*0.8519*	*0.9572*	*1.214*	*1.708*	*2.843*	*8.383*	*46.89*
	$\beta_{RF\_PC2,q}$	-7.951	3.013	3.157	0.7745	1.211	0.8501	0.6601	1.378*	1.461*	0.8617	1.935	5.684	28.91
	Std.Err	*42.54*	*8.056*	*3.263*	*1.385*	*0.8712*	*0.7052*	*0.6538*	*0.7059*	*0.8653*	*1.167*	*1.956*	*5.641*	*51.25*
	$\beta_{RF\_PC3,q}$	44.1	3.572	1.663	-0.1223	-0.1964	0.1018	0.2969	-1.636	-1.803	-0.6226	-1.607	-5.821	-43.39
	Std.Err	*55.17*	*10.26*	*4.43*	*2.047*	*1.335*	*1.156*	*1.109*	*1.235*	*1.542*	*2.117*	*3.605*	*8.252*	*64.85*
CCC&Lower	$\beta_{0,q}$	-173.9***	-65.18***	-44.48***	-26.76***	-17.78***	-9.392***	-2.975***	3.875***	12.06***	21.73***	45.18***	79.66***	177.5***
	Std.Err	*9.646*	*2.938*	*2.814*	*1.340*	*1.167*	*1.123*	*1.065*	*1.118*	*1.269*	*1.690*	*2.675*	*4.741*	*12.38*
	$\beta_{CS\_PC1,q}$	43.93	49.72	47.44*	56.26***	53.31***	65.32***	79.7***	73.84***	80.55***	79.08***	88.27***	59.69	108.3
	Std.Err	*176.8*	*32.86*	*25.31*	*9.655*	*7.266*	*6.470*	*6.054*	*6.599*	*8.268*	*13.10*	*27.18*	*64.11*	*201.8*
	$\beta_{CS\_PC2,q}$	-22.24	-108.7	-77.19	-20.99	-8.770	14.63	4.086	9.424	52.17	39.52	55.97	39.72	160.4
	Std.Err	*661.5*	*121.5*	*89.91*	*34.55*	*26.7*	*24.16*	*23.01*	*25.39*	*32.17*	*51.15*	*108.0*	*251.5*	*763.6*
	$\beta_{RF\_PC1,q}$	-245.8	-72.05**	-40.14	-37.26***	-41.84***	-26.16***	-25.21***	-6.386	-12.17	1.409	15.53	37.57	55.66
	Std.Err	*179.6*	*33.28*	*27.13*	*12.03*	*9.701*	*8.651*	*8.016*	*8.507*	*10.08*	*14.89*	*29.48*	*64.40*	*258.3*
	$\beta_{RF\_PC2,q}$	28.83	14.71	18.04	11.83	20.42**	10.01	5.263	-5.095	-4.078	-11.52	8.022	32.14	85.70
	Std.Err	*271.6*	*40.48*	*28.75*	*10.62*	*8.204*	*6.977*	*6.152*	*6.245*	*7.151*	*9.998*	*19.14*	*44.43*	*350.7*
	$\beta_{RF\_PC3,q}$	-17.77	13.21	-1.185	-10.07	-17.88	-9.889	-7.385	7.084	6.827	9.490	-11.89	-65.33	-122.1
	Std.Err	*348.6*	*51.78*	*37.91*	*14.88*	*13.28*	*11.57*	*10.43*	*10.56*	*12.00*	*16.74*	*30.14*	*77.48*	*462.3*

Figure 6.12: In-sample **2xCS+3xRF model**: QR coefficients for different credit ratings (bps). *** p<0.01, ** p<0.05, * p<0.10

The coefficients in the **2xCS+3xRF model** includes the three RF PCs. $\beta_{RF\_PC\_1,q}$ is significant for all but the tail quantiles, with a negative value for most quantiles in investment grade spreads. Increasing RF levels are thus significantly explaining the lowering of next week's credit spread distribution.

Dep. Var	Quantile	1.0 %	5.0 %	10.0 %	20.0 %	30.0 %	40.0 %	50.0 %	60.0 %	70.0 %	80.0 %	90.0 %	95.0 %	99.0 %
Investment grade	$\beta_{0,q}$	-18.68***	-7.479***	-5.217***	-2.797***	-1.662***	-0.8638***	-0.2092*	0.4650***	1.304***	2.637***	4.475***	7.206***	24.80***
	Std.Err	*0.8660*	*0.5110*	*0.3628*	*0.1733*	*0.1341*	*0.1178*	*0.1145*	*0.1205*	*0.1386*	*0.1779*	*0.2384*	*0.4969*	*1.446*
	$\beta_{CS\_PC1,q}$	20.89	13.19**	12.21***	13.8***	14.25***	15.37***	15.5***	16.59***	18.55***	21.15***	21.32***	25.39***	32.51
	Std.Err	*17.54*	*5.661*	*3.197*	*1.206*	*0.8190*	*0.6548*	*0.6046*	*0.6394*	*0.7606*	*1.100*	*1.852*	*5.020*	*26.36*
	$\beta_{CS\_PC2,q}$	-8.531	-17.17	-9.638	-14.1***	-11.97***	-13.18***	-10.14***	-5.376**	-1.003	1.558	0.7947	-4.617	-54.44
	Std.Err	*57.00*	*17.79*	*10.32*	*4.121*	*2.931*	*2.392*	*2.264*	*2.417*	*2.731*	*3.738*	*6.020*	*15.09*	*58.33*
	$\beta_{\_D\_FED\_Balance\_UP,q}$	-396.9***	-399.2***	-331.6***	-261.3***	-153.6***	50.50***	53.33***	74.97***	150.2***	289.1***	281.3***	634.2***	1010***
	Std.Err	*58.56*	*19.08*	*15.290*	*10.03*	*8.568*	*7.974*	*8.437*	*9.319*	*11.37*	*16.43*	*30.64*	*31.50*	*103.9*
	$\beta_{\_D\_FED\_Ann\_Inc,q}$	-99.27***	-87.69***	-9.125***	-0.5764	-0.6127	-1.416	-0.1029	0.1213	-0.5794	-1.012	-1.272	2.590	-18.24
	Std.Err	*18.73*	*5.279*	*2.852*	*1.533*	*1.236*	*1.099*	*1.101*	*1.192*	*1.451*	*1.725*	*2.366*	*6.528*	*39.93*
	$\beta_{\_D\_FED\_Ann\_Dec,q}$	15.14	3.295	2.981	1.318	0.2430	-0.3601	0.5616	-0.09162	0.1261	1.440	-0.3039	1.886	-13.81
	Std.Err	*22.22*	*6.288*	*3.279*	*1.844*	*1.234*	*1.136*	*1.079*	*1.160*	*1.271*	*1.885*	*2.147*	*6.237*	*38.12*
CCC&Lower	$\beta_{0,q}$	-124.0***	-62.37***	-43.27***	-27.07***	-17.23***	-9.722***	-3.417***	3.757***	11.67***	21.07***	40.75***	69.96***	153.0***
	Std.Err	*8.368*	*3.262*	*2.490*	*1.419*	*1.212*	*1.100*	*1.067*	*1.122*	*1.258*	*1.566*	*2.371*	*4.980*	*10.03*
	$\beta_{CS\_PC1,q}$	89.99	35.17	35.31*	42.57***	35.65***	37.64***	43.61***	55.17***	57.76***	61.96***	77.58***	63.18	118.5
	Std.Err	*151.5*	*33.19*	*19.99*	*9.380*	*7.100*	*5.954*	*5.631*	*6.052*	*7.230*	*10.26*	*19.71*	*53.16*	*195.5*
	$\beta_{CS\_PC2,q}$	-70.86	-112.4	-65.27	-95.74***	-52.78**	-30.13	33.92	83.26***	111.8***	127.6***	143.3**	173.1	122.3
	Std.Err	*371.4*	*111.2*	*69.81*	*33.23*	*25.49*	*22.00*	*21.09*	*22.61*	*27.53*	*34.99*	*63.40*	*154.4*	*498.0*
	$\beta_{\_D\_FED\_Balance\_UP,q}$	-632.5	-1656***	-874.9***	-929.5***	333.2***	1016***	1434***	1571***	1691***	1630***	1487***	1401***	4156***
	Std.Err	*796.4*	*161.1*	*102.6*	*88.35*	*76.02*	*74.84*	*78.58*	*85.33*	*101.2*	*146.4*	*310.8*	*308.70*	*1252*
	$\beta_{\_D\_FED\_Ann\_Inc,q}$	-342.0*	-141.7***	-98.29***	-7.892	14.72	14.90	12.11	7.863	0.9052	-7.625	-4.963	340.4***	246.50
	Std.Err	*180.0*	*33.92*	*19.31*	*14.33*	*11.95*	*10.27*	*10.26*	*11.08*	*13.17*	*17.66*	*23.49*	*64.44*	*273.8*
	$\beta_{\_D\_FED\_Ann\_Dec,q}$	92.57	33.58	32.28	18.04	10.54	5.211	0.6981	-0.6725	4.131	-2.727	18.99	15.03	-66.78
	Std.Err	*215.0*	*40.24*	*22.42*	*15.04*	*12.09*	*10.60*	*10.05*	*10.80*	*12.53*	*14.24*	*29.07*	*61.62*	*261.6*

Figure 6.13: In-sample **2xCS+Fed model**: QR coefficients for different credit ratings (bps). *** p<0.01, ** p<0.05, * p<0.10

An interesting finding in the **2xCS + Fed model** is the significance of D_FED_Balance_UP and D_FED_Ann_Inc. The variable for actual (extreme) purchases is positive for most quantiles but negative for the lowest quantiles. This suggest the subsequent widening of the credit spread change interval. The coefficient is not to say that asset purchases increases spreads but rather that expansions of the amounts is expected after aggressive asset purchases (more than 2.5%-percentile of historical purchases). As such, the asset purchases, which is a monetary policy question, will tend to co-vary with other extreme events. As such, the inclusion of these variables account for important information. However, a weak point in modelling of policy actions for prediction matters is that the validness of a model may be dependent upon the political leadership (here: Fed leadership). Policy actions coming as a response to changing conditions (e.g. Covid-19 or GFC) are assumed to occur during similar conditions in the future. If the Fed's political leadership were to change dramatically in the future, the Fed data and their historical implications for credit spreads may be incorrect. The D_FED_Ann_Inc is significant for the lower tail of the investment grade distribution, all with negative sign (expect 95%). The D_FED_Ann_Dec, however, is not significant which could imply that the effects of the events in the period are priced in or expected.

7 Conclusion

In this paper, several quantile regression models for predicting the future distribution of US credit spread changes are presented and tested out-of-sample. Parsimonious models consisting only of term structure factors significantly outperform models containing additional market-wide variables. As such, the amount of information contained in these term factors are found to be sufficient for successfully predicting a quite granular 1-week ahead distribution of credit spreads. For 2-weeks and 4-weeks ahead predictions, exceedances are clustered and therefore represent a violation of the much-desired independence property of quantile prediction models (See Section 4.2). Further, variables to account for announcements Fed policy behavior related to the QE programs improve the out-of-sample predictions, especially for the tails of the distributions. The categorization of these events could be subject to criticism as no further decomposition related to the expected and unexpected policies are made (See 8.7 for events included and categories). Purely based on a MAD metric of predictions, the inclusion of risk-free yield factors improves the prediction of the middle of the distribution compared to the pure credit spread factor models. Backtesting of the models with conditional and unconditional coverage tests indicates that the models based on credit spread principal components are most successful, while the inclusion of the risk-free factors lead to a weaker model, overall. As such, I do not find support for general improved predictions by adding the risk-free yield curve factors to the models, which is contrary to Krishnan et al. (2010). For predictions of 4-weeks ahead credit spread changes, historical simulation performs as well as my proposed models. Thus, they have limited use for prediction horizons over many weeks.

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8 Appendix

8.1 The Kupiec (1995) test

$$LR_{Kupiec} = -2ln\left[\frac{p^{n_1}(1-p^{n_0})}{\hat{p}^{n_1}(1-\hat{p}^{n_0})}\right] \sim \chi_1^2 \tag{8.1}$$

, with n_1 being the number of exceedances when backtesting in the out-of-sample. n_0 is the number of non-exceedances. Thus, the total number of events is $n_0 + n_1$. p and $\hat{p}$ are the expected share and the observed share of exceedances, respectively. That is: $p = q$ and $\hat{p} = \frac{n_1}{n_1+n_0}$ for the quantile, q.

8.2 The Christoffersen (1998) test

$$LR_{Chr.} = -2ln\left[\frac{(1-p)^{n_0}\, p^{n_1}}{(1-p_{01})^{n_{00}}\, p_{01}^{n_{01}}\, (1-p_{11})^{n_{10}}\, p_{11}^{n_{11}}}\right] \sim \chi_2^2$$

Here p is the expected share of exceedances. n_{00} is the number of events in which two consecutive non-exceedances is observed. n_{01} is the number of events with a non-exceedance followed by an exceedance, n_{10} the number of events wit an exceedance followed by a non-exceedance. n_{11} notes the number of two consequtive exceedances. Furthermore, the two proportions, p_{01} and p_{11}, are defined as follows:

$$p_{01} = \frac{n_{01}}{n_{01} + n_{00}}$$

$$p_{11} = \frac{n_{11}}{n_{10} + n_{11}}$$

8.3 Principal Component Analysis

Table 8.1: Explained variance by credit spread term structure principal components

	PC1	*PC2*	*PC3*	*PC4*	*PC5*	*PC6*
(%) Var. explained	90.5%	4.3%	2.7%	1.1%	0.8%	0.6%
Cumulative explained	90.5%	94.8%	97.6%	98.6%	99.4%	100%

Table 8.2: Explained variance by risk-free term structure principal components

	PC1	*PC2*	*PC3*	*PC4*	*PC5*	*PC6*	*PC7*	*PC8*	*PC9*
(%) Var. explained	60.2%	17.6 %	9.6%	6.4%	3.9%	1.4%	0.6%	0.2%	0.1%
Cumulative explained	60.2%	77.8%	87.4%	93.7%	97.7%	99.0%	99.7%	99.9%	100%

Figure 8.1: CS PC1 score time series

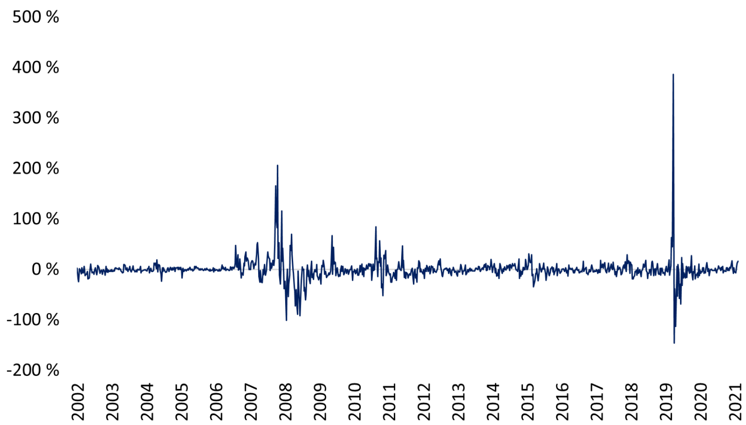


Figure 8.2: CS PC2 score time series

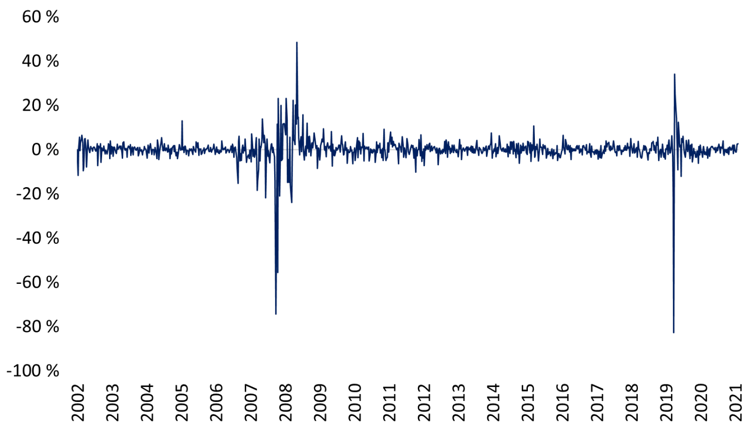


Figure 8.3: CS PC3 score time series

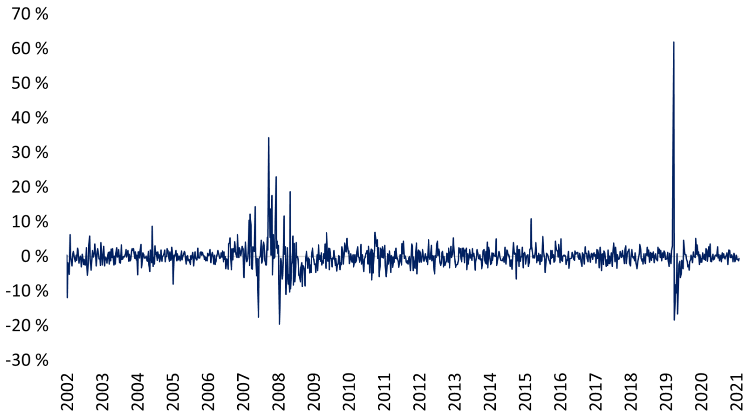


Figure 8.4: RF PC1 score time series

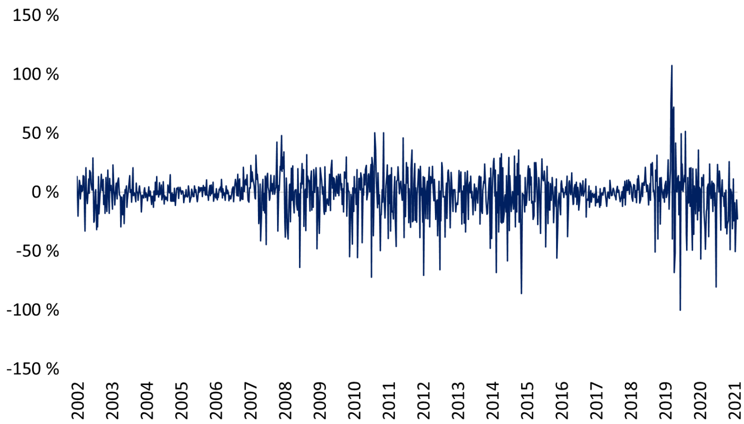
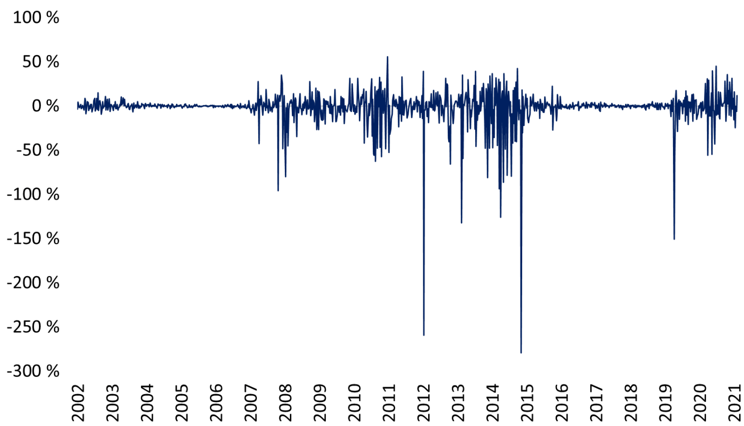
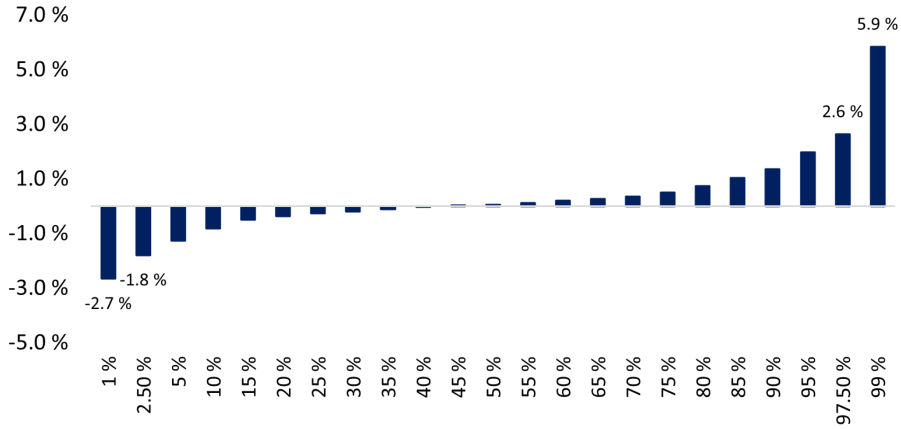


Figure 8.5: RF PC3 score time series



8.4 More on Fed data

Figure 8.6: Percentiles of weekly changes in Fed's balance sheet



Fed Events - Descripton and comments *Color codes: D_FED_Ann_Inc, D_FED_Ann_Dec, None*	
25.11.2008	FOMC announces program to purchase USD 100 bn of agency debt securities and USD 500 bn of mortgage-backed securities (MBS). Marks the start of QE1
18.03.2008	Announces expansion of its asset purchasing program. Now USD 1.2 tn of MBS and USD 200 bn of agency debt. Purchases of long-term Treasuries also introduced. Purchases to be done by year-end.
12.08.2009	Announces gradual slowdown of Treasury purchases and anticipates completion by October 2009. Categorized as D_FED_Ann_Dec since it represents a slowdown and guidance of the program's completion.
23.09.2009	Reiterates its intention to complete Treasury purchases by October-end. Also anticipates slowdown of MBS and agency debt purchases
04.11.2009	Announces a USD 25 bn reduction in agency debt-target. Included, altough somewhat in-line with guided policy, as it represents the first numerical specifics with respect to the slowdown
10.08.2010	Announces its intention to reinvest principal payments on its current holdings
03.11.2010	Announces plan to expand balance sheet by purchasing long-term Treasuries, USD 600 bn by end of Q2'11
22.06.2011	Announces end of QE2 and plan to reinvest payments to be received. No variable attached to the event as Fed sticks to guiding and reinvesting security recievables already was a well-established policy tool following QE1
21.09.2011	Announces the so-called 'Operation Swift', which was undetaken to increase the average maturity of the Fed's holdings. Buying 400 USD bn in 6-year-plus securities and selling 3-year-less securities for an equal amount. Operation Swift does neither represent a slowdown nor acceleration of purchases.Hence, the event is not deemed suited for any of the categories
20.06.2012	Announces that it anticipates the completion of 'Operation Swift' by the year-end
13.09.2012	Announces increasing purchases of MBS (up 40 USD bn per month). Also hints at additional purchases if labor market does not improve. Marks the beginning of QE3
12.12.2012	Announces the continuation of the MBS program and launches purchase program of long-term Treasuries, wanting to see improved labor market outlook. Fits the category as the event includes both continued purchases, and, more importantly, expansion to Treasuries
18.12.2013	Announces plan to slow down pace of asset purchases. The Committe still stresses that the course of purchases is not preset. Announcement of slowdown, as labor market conditions had improved. However, not widely unexpected announcement. Still, included in the catogory as it represents a policy shift
29.01.2014	Announces a 5 USD bn per month reduction in purchases of MBS and Treasuries. Further slowdown - once again USD 5 bn
19.03.2014	Announces another reduction in purchases of MBS and Treasuries. The last of these reductions to be included in the category as a clear USD 5 bn per meeting-pattern is established. Indeed, the FOMC continued to decrease purchases by USD 5 bn for every meeting in Jan-Sept 2014. The last of these reductions to be included in the category as a clear USD 5 bn per meeting-pattern is established
17.09.2014	Publishes plan to normalize balance sheet ('Policy Normalization Principles and Plans'). A key feature in the plans is to cease the reinvestments of securities' principal payments. Regarding the MBS held, it is stated that any sales will be limited. The last event included from QE3.
14.06.2017	Announces that it expects the normaliziation program to begin within year-end, contingent upon anticipated deveolopments. The event is the first clear signal of balance sheet normalization
20.09.2017	Announces the normalization to begin in October. While guided, and partially expected by market participants, the event is important as it represents the first specific policy change to include balance sheet reduction
11.09.2019	Announces purchases of Treasury bills at least into Q2'20, following the repo market turmoil in Sept. 2019. The purchases of USD 60 bn per month is signifcant, and thus included. However, I do not consider this the start of QE4
15.03.2020	Announces its intention of buying USD 500 bn Treasuries and USD 200 bn in MBS in the coming months, amid the global Covid-19 outbreak. The event is the beginning of an unprecedented balance sheet expansion
23.03.2020	Announces a signifcant expansion of the asset purchasing program. The program is expanded to several other asset classes as well, e.g , primary and secondary markets for corporate bonds and ABS. The Fed promises to use 'its full range of tools' to support the flow of credit and other objectives
10.06.2020	FOMC directs the Desk to continue purchasing 'at least' at current pace, resulting in USD 80 bn Treasuries per month and USD 40 bn of MBS. Categorized as D_FED_Ann_Inc since the FOMC established the current pace as a lower-bound going forward and directs the Trading Desk to be prepared in order to adjust as 'needed to sustain the smooth functioning' of credit markets
16.12.2020	Announces its intention of slowing down purchases but not 'until substantial further progress has been made toward the Committee's maximum employment and price stability goals. ' The purchasing volumes of Treasuries and MBS were both held at approx. USD 80 bn and USD 40 bn, respectively. Although these are one of the first hints of slowing-down purchases, I have categorized it as D_FED_Ann_Inc since the conditions needed for normalizations illustrates Fed's committement to continued support in the markets. The tone from the Committe is still to use 'its full range of tools to support the U.S. economy.'
03.11.2021	Announces its first reductions in purchasing volumes, USD 10 bn for Treasuries and USD 5 bn for MBS. Note the relative reduction is equal. Tapering of purchases starts
15.12.2021	Announces further acceleration of tapering in both Treasuries and MBS. FMOC sees more rapid tapering as necessary as inflation remains elevated (no longer the 'transitory'-wording) and labor markets have improved

SOURCES: NEW YORK FED, BROOKINGS INSTITUTION

Figure 8.7: Selected Fed events related to QE programs, and their dummy category

8.5 More on the data

	CS_PC1	CS_PC2	CS_PC3	RF_PC1	RF_PC2	RF_PC3	RF_PC4	WTI_R	GOLD_R	SP500_R	VIX_DIFF	TEDRATE
CS_PC1	1.00	-0.59	0.54	0.27	0.16	0.04	-0.03	-0.27	-0.03	-0.53	0.10	0.40
CS_PC2	-0.59	1.00	-0.45	0.06	-0.16	-0.09	0.01	0.03	-0.03	0.16	0.04	-0.43
CS_PC3	0.54	-0.45	1.00	0.00	0.12	0.07	0.02	-0.14	-0.09	-0.13	-0.03	0.24
RF_PC1	0.27	0.06	0.00	1.00	0.44	0.12	-0.19	-0.22	0.25	-0.30	0.19	0.17
RF_PC2	0.16	-0.16	0.12	0.44	1.00	0.82	-0.46	-0.13	0.08	-0.07	0.08	0.26
RF_PC3	0.04	-0.09	0.07	0.12	0.82	1.00	-0.69	-0.06	0.00	-0.03	0.06	0.19
RF_PC4	-0.03	0.01	0.02	-0.19	-0.46	-0.69	1.00	-0.06	-0.04	0.07	-0.02	-0.16
WTI_R	-0.27	0.03	-0.14	-0.22	-0.13	-0.06	-0.06	1.00	0.20	0.27	-0.19	-0.05
GOLD_R	-0.03	-0.03	-0.09	0.25	0.08	0.00	-0.04	0.20	1.00	0.05	0.00	0.07
SP500_R	-0.53	0.16	-0.13	-0.30	-0.07	-0.03	0.07	0.27	0.05	1.00	-0.54	-0.17
VIX_DIFF	0.10	0.04	-0.03	0.19	0.08	0.06	-0.02	-0.19	0.00	-0.54	1.00	0.07
TEDRATE	0.40	-0.43	0.24	0.17	0.26	0.19	-0.16	-0.05	0.07	-0.17	0.07	1.00

Figure 8.8: Regressor data correlation matrix

Figure 8.9: Augmented Dickey Fuller test statistics for regressors

CS_PC1	CS_PC2	CS_PC3	RF_PC1	RF_PC2	RF_PC3	RF_PC4	WTI_R	S&P500_R	Vix_Diff	TEDRATE
-8.00	-7.12	-26.49	-9.86	-13.02	-22.84	-23.29	-9.95	-17.22	-12.16	-9.50

All statistics are significant, clearly indicating stationarity in all regressor time series. The ADF tests are conducted using the number of lags that minimizes the Akaike information criterion

Figure 8.10: S&P500 - weekly returns in sample period

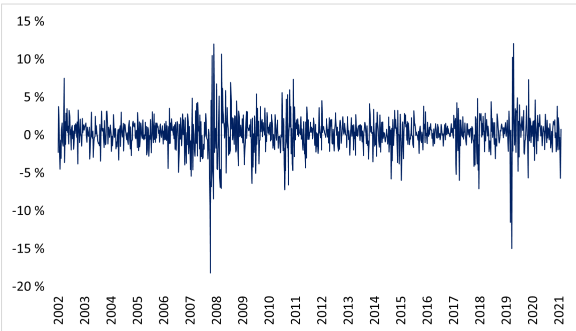


Figure 8.11: Oil (WTI) - weekly returns in sample period

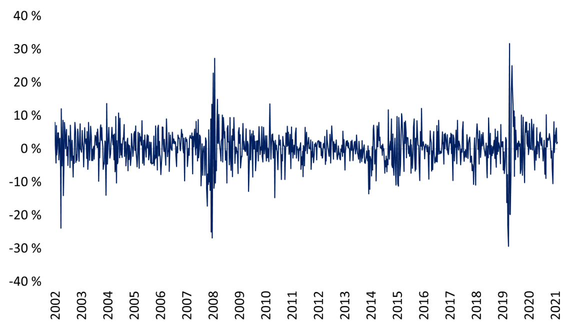


Figure 8.12: Gold price - weekly returns in sample period

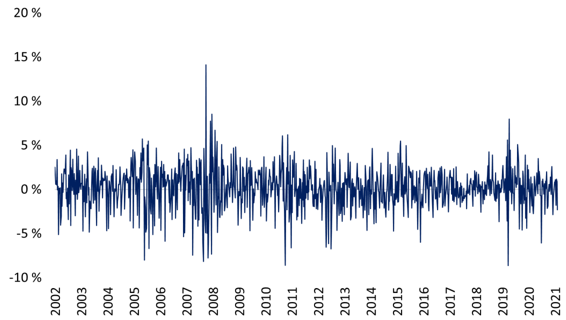


Figure 8.13: VIX index - weekly changes in sample period

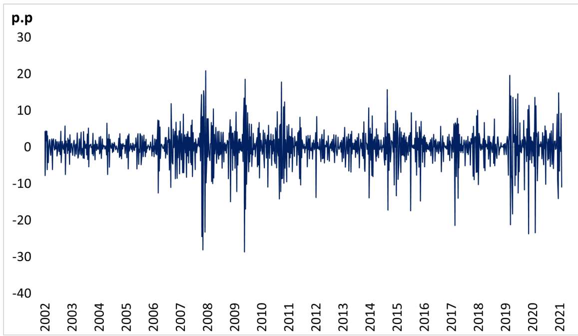
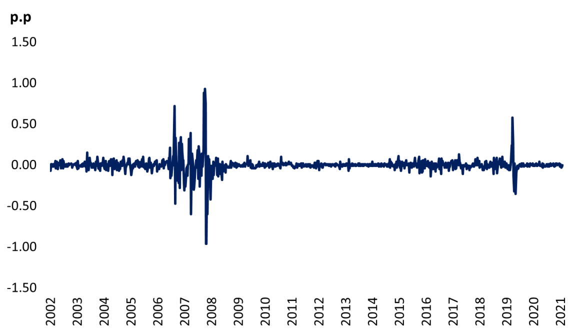


Figure 8.14: TED spread- weekly changes in sample period



8.6 In-Sample QR results for best prediction models

Figure 8.15: In-sample: QR coefficients of the 1-week **2xCS model** on different investment grade maturities (bps). *** p<0.01, ** p<0.05, * p<0.10

Dep. Var	*Quantile*	*1.0 %*	*5.0 %*	*10.0 %*	*20.0 %*	*30.0 %*	*40.0 %*	*50.0 %*	*60.0 %*	*70.0 %*	*80.0 %*	*90.0 %*	*95.0 %*	*99.0 %*
1-3Y IG	$\beta_{0,q}$	-24.41***	-8.653***	-4.861***	-2.545***	-1.578***	-0.8876***	-0.2463**	0.3862***	1.222***	2.142***	4.110***	8.104***	34.51***
	Std.Err	*1.476*	*1.032*	*0.3287*	*0.1656*	*0.1121*	*0.1031*	*0.1023*	*0.1091*	*0.121*	*0.1387*	*0.3155*	*0.7799*	*2.445*
	$\beta_{CS\_PC1,q}$	0.6942	12.38	14.12***	15.95***	16.59***	17.74***	18.14***	18.44***	20.52***	21.60***	24.84***	31.25***	63.17
	Std.Err	*30.30*	*12.17*	*3.268*	*1.226*	*0.6988*	*0.5716*	*0.539*	*0.5812*	*0.6942*	*0.9153*	*2.834*	*9.236*	*53.00*
	$\beta_{CS\_PC2,q}$	-35.94	-24.34	-29.76**	-27.02***	-27.10***	-27.45***	-27.36***	-25.34***	-18.87***	-16.67***	-17.24	-14.52	65.79
	Std.Err	*103.0*	*44.30*	*11.65*	*4.387*	*2.529*	*2.129*	*2.055*	*2.234*	*2.765*	*3.576*	*11.06*	*36.29*	*143.2*
10-15Y IG	$\beta_{0,q}$	-28.07***	-8.063***	-5.263***	-3.053***	-1.827***	-0.9195***	-0.213*	0.5253***	1.587***	2.857***	5.276***	8.249***	27.01***
	Std.Err	*1.415*	*0.5153*	*0.3592*	*0.1869*	*0.1405*	*0.1241*	*0.1238*	*0.1295*	*0.1585*	*0.2009*	*0.3367*	*0.6377*	*1.960*
	$\beta_{CS\_PC1,q}$	-7.116	13.37**	12.14***	11.30***	11.43***	11.58***	12.63***	13.6***	12.82***	14.10***	16.59***	16.59**	26.50
	Std.Err	*28.27*	*5.370*	*3.196*	*1.264*	*0.8278*	*0.6751*	*0.6524*	*0.6985*	*0.9098*	*1.291*	*2.869*	*6.917*	*34.63*
	$\beta_{CS\_PC2,q}$	-13.96	-2.630	-3.191	-10.37**	-7.680**	-5.482**	-2.923	-1.938	3.601	4.666	19.31*	18.7	22.17
	Std.Err	*90.94*	*22.51*	*12.34*	*4.899*	*3.216*	*2.597*	*2.487*	*2.614*	*3.349*	*4.548*	*10.01*	*24.04*	*108.6*

Figure 8.16: In-sample: QR coefficients of the **2xCS + 3xRF model** for different maturities (bps). *** p<0.01, ** p<0.05, * p<0.10

Dep. Var	*Quantile*	*1.0 %*	*5.0 %*	*10.0 %*	*20.0 %*	*30.0 %*	*40.0 %*	*50.0 %*	*60.0 %*	*70.0 %*	*80.0 %*	*90.0 %*	*95.0 %*	*99.0 %*
1-3Y IG	$\beta_{0,q}$	-24.49***	-8.939***	-4.664***	-2.601***	-1.578***	-0.9043***	-0.2823***	0.3642***	1.159***	2.188***	4.018***	8.777***	34.87***
	Std.Err	*1.739*	*0.9514*	*0.3201*	*0.1504*	*0.1114*	*0.1042*	*0.1023*	*0.1095*	*0.1206*	*0.1387*	*0.2742*	*0.725*	*1.931*
	$\beta_{CS\_PC1,q}$	3.293	14.63	16.36***	17.33***	16.96***	17.96***	19.08***	19.08***	21.20***	21.81***	26.05***	30.93***	67.05
	Std.Err	*34.50*	*12.18*	*3.137*	*1.161*	*0.7268*	*0.6153*	*0.5815*	*0.6330*	*0.7539*	*1.005*	*2.704*	*9.507*	*42.27*
	$\beta_{CS\_PC2,q}$	-19.14	-11.49	-28.08**	-17.97***	-23.11***	-24.44***	-25.52***	-24.08***	-17.49***	-15.06***	-15.55	-20.12	90.72
	Std.Err	*107.4*	*40.74*	*11.73*	*4.237*	*2.675*	*2.303*	*2.210*	*2.410*	*2.957*	*3.844*	*10.27*	*35.57*	*150.0*
	$\beta_{RF\_PC1,q}$	1.481	-6.195	-3.030	-3.750***	-2.398***	-1.794**	-1.432*	-1.125	-0.9658	-1.034	-2.172	3.060	-25.35
	Std.Err	*33.68*	*11.03*	*3.185*	*1.336*	*0.8788*	*0.7913*	*0.77*	*0.8381*	*0.9918*	*1.277*	*3.019*	*10.02*	*52.61*
	$\beta_{RF\_PC2,q}$	-6.426	4.607	1.404	1.008	0.3248	0.7474	-0.08744	-0.09009	0.2513	0.8541	2.387	2.460	30.78
	Std.Err	*49.62*	*13.01*	*3.318*	*1.193*	*0.7477*	*0.6380*	*0.5910*	*0.6226*	*0.7124*	*0.8683*	*2.223*	*7.466*	*56.95*
	$\beta_{RF\_PC3,q}$	43.16	9.563	3.531	-0.05785	0.3189	-0.3707	1.097	0.3418	-0.1903	-0.7077	-3.095	-3.309	-43.92
	Std.Err	*65.86*	*16.73*	*4.479*	*1.712*	*1.141*	*1.047*	*1.002*	*1.092*	*1.275*	*1.589*	*3.585*	*11.68*	*72.05*
10-15Y IG	$\beta_{0,q}$	-23.88***	-8.236***	-5.458***	-3.098***	-1.887***	-0.9493***	-0.2595**	0.4906***	1.506***	2.798***	5.286***	9.156***	29.00***
	Std.Err	*1.312*	*0.5283*	*0.3243*	*0.1758*	*0.1406*	*0.1235*	*0.1223*	*0.1286*	*0.1538*	*0.1980*	*0.3436*	*0.7889*	*1.691*
	$\beta_{CS\_PC1,q}$	4.388	13.95**	13.04***	13.81***	12.23***	13.49***	14.24***	13.81***	14.26***	14.40***	16.53***	17.05*	34.39
	Std.Err	*26.11*	*5.958*	*2.903*	*1.251*	*0.8796*	*0.7167*	*0.6951*	*0.7589*	*0.9806*	*1.426*	*3.269*	*10.05*	*34.57*
	$\beta_{CS\_PC2,q}$	33.89	0.5863	1.182	-0.7519	-6.173*	-2.931	-1.084	-0.9111	3.337	6.845	18.94*	28.91	47.93
	Std.Err	*86.42*	*25.08*	*11.59*	*4.931*	*3.423*	*2.768*	*2.642*	*2.818*	*3.578*	*4.879*	*10.78*	*32.48*	*97.25*
	$\beta_{RF\_PC1,q}$	-10.81	-6.971	-5.657*	-4.830***	-3.274***	-1.514	-2.582***	-1.507	-2.181*	-1.497	-0.4354	-2.553	-10.96
	Std.Err	*24.61*	*6.621*	*3.323*	*1.520*	*1.098*	*0.9262*	*0.9204*	*1.010*	*1.299*	*1.833*	*3.832*	*11.34*	*48.13*
	$\beta_{RF\_PC2,q}$	-1.990	3.073	1.236	0.6317	0.2694	-0.8519	-0.2744	0.3963	1.385	1.117	1.294	5.403	15.81
	Std.Err	*37.03*	*7.537*	*3.523*	*1.455*	*0.9739*	*0.7615*	*0.7065*	*0.7262*	*0.8827*	*1.207*	*2.602*	*7.882*	*49.43*
	$\beta_{RF\_PC3,q}$	24.96	6.505	4.176	0.3793	0.7341	1.560	-0.03726	-1.237	-2.162	-1.521	-1.647	-5.510	-12.46
	Std.Err	*44.36*	*9.671*	*4.807*	*2.131*	*1.542*	*1.251*	*1.198*	*1.265*	*1.582*	*2.213*	*4.930*	*15.09*	*65.97*

Figure 8.17: In-sample: QR coefficients of the **2xCS + FED model** for different credit ratings (bps). *** p<0.01, ** p<0.05, * p<0.10

Dep. Var	Quantile	1.0 %	5.0 %	10.0 %	20.0 %	30.0 %	40.0 %	50.0 %	60.0 %	70.0 %	80.0 %	90.0 %	95.0 %	99.0 %
1-3Y IG	$\beta_{0,q}$	-21.51***	-7.596***	-4.538***	-2.498***	-1.514***	-0.8648***	-0.2741***	0.3992***	1.205***	2.105***	3.941***	7.144***	25.55***
	Std.Err	*0.9866*	*0.5126*	*0.2587*	*0.1563*	*0.1094*	*0.1033*	*0.1024*	*0.1112*	*0.1221*	*0.1362*	*0.2762*	*0.6122*	*1.086*
	$\beta_{CS\_PC1,q}$	29.03	16.78***	14.16***	14.45***	15.48***	17.63***	18.14***	19.61***	21.57***	21.44***	23.96***	27.47***	43.97**
	Std.Err	*20.06*	*5.836*	*2.320*	*1.102*	*0.6742*	*0.5720*	*0.5405*	*0.5931*	*0.6828*	*0.8529*	*2.299*	*6.675*	*21.08*
	$\beta_{CS\_PC2,q}$	-16.03	-22.46	-18.94**	-23.8***	-24.52***	-26.26***	-25.57***	-27.63***	-23.47***	-15.31***	-18.36**	-23.41	-30.97
	Std.Err	*65.25*	*19.45*	*8.247*	*3.872*	*2.404*	*2.101*	*2.025*	*2.235*	*2.599*	*2.905*	*7.612*	*20.14*	*47.53*
	$\beta_{\_D\_FED\_Balance\_UP,q}$	-862.7***	-729.4***	-655.7***	-343.70***	-203.6***	-44.92***	3.944	20.65**	191.4***	464.4***	449.6***	692.0***	3789***
	Std.Err	*66.89*	*20.00*	*10.73*	*9.159*	*7.183*	*7.058*	*7.543*	*8.597*	*9.621*	*12.38*	*35.64*	*38.69*	*72.65*
	$\beta_{\_D\_FED\_Ann\_Inc,q}$	-128.6***	-111.5***	-10.78***	-2.146	-3.018***	-3.439***	-0.07678	0.002308	-0.6687	-1.081	-0.683	3.530	-16.97
	Std.Err	*21.33*	*5.410*	*3.046*	*1.652*	*1.102*	*1.003*	*0.9846*	*1.099*	*1.175*	*1.531*	*3.668*	*7.890*	*29.55*
	$\beta_{\_D\_FED\_Ann\_Dec,q}$	17.87	4.495	2.131	0.3475	-0.4760	-1.036	-1.527	-0.9026	0.1522	0.1626	-1.070	-1.968	-19.25
	Std.Err	*25.33*	*6.379*	*2.350*	*1.666*	*1.005*	*0.9953*	*0.9648*	*1.070*	*1.119*	*1.441*	*3.390*	*7.499*	*27.87*
10-15Y IG	$\beta_{0,q}$	-20.15***	-7.901***	-5.079***	-3.017***	-1.836***	-0.9096***	-0.2187*	0.5206***	1.494***	2.751***	5.055***	7.919***	21.19***
	Std.Err	*1.231*	*0.4441*	*0.3256*	*0.1777*	*0.1419*	*0.1256*	*0.1249*	*0.1303*	*0.1561*	*0.1912*	*0.301*	*0.5175*	*1.340*
	$\beta_{CS\_PC1,q}$	25.76	15.01***	13.06***	12.66***	12.51***	12.19***	13.09***	13.70***	13.30***	12.87***	16.53***	16.61***	19.66
	Std.Err	*23.32*	*4.907*	*2.716*	*1.140*	*0.8266*	*0.6820*	*0.6591*	*0.6905*	*0.8749*	*1.140*	*2.368*	*5.018*	*24.06*
	$\beta_{CS\_PC2,q}$	15.78	-6.693	-10.85	-17.22***	-8.881***	-5.885**	-3.183	-1.898	1.746	3.004	15.12**	7.978	-36.02
	Std.Err	*72.26*	*14.83*	*8.578*	*4.507*	*3.140*	*2.594*	*2.469*	*2.534*	*3.117*	*3.832*	*6.968*	*14.13*	*58.85*
	$\beta_{\_D\_FED\_Balance\_UP,q}$	-602.1***	-402.7***	-218.5***	-196.3***	-49.49***	-25.65***	134.6***	131.0***	150.6***	146.3***	227.9***	477.8***	411.7**
	Std.Err	*75.90*	*16.33*	*13.13*	*11.080*	*8.949*	*8.588*	*9.197*	*9.779*	*12.96*	*12.43*	*19.33*	*32.16*	*165.9*
	$\beta_{\_D\_FED\_Ann\_Inc,q}$	-60.55**	-66.35***	-8.398**	-1.442	1.490	0.3952	-0.5342	-0.001760	0.1113	-1.108	-1.707	26.79***	11.19
	Std.Err	*26.32*	*4.642*	*3.796*	*1.573*	*1.429*	*1.221*	*1.200*	*1.252*	*1.508*	*1.828*	*3.898*	*6.688*	*36.57*
	$\beta_{\_D\_FED\_Ann\_Dec,q}$	16.12	3.606	1.942	0.9657	0.3450	0.2068	0.4040	-0.06441	0.4613	-0.4979	-2.151	-3.891	-14.58
	Std.Err	*31.62*	*5.534*	*4.018*	*1.888*	*1.304*	*1.211*	*1.176*	*1.209*	*1.556*	*2.034*	*3.712*	*6.393*	*34.77*

8.7 Out-of-Sample Exceedance-% for all models

Table 8.3: The **2xCS** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	0.77%	4.33%	9.89%	21.33%	32.15%	41.58%	51.0%	59.81%	69.09%	79.44%	90.88%	95.52%	98.92%
AAA	0.62%	3.40%	9.43%	21.79%	30.60%	40.19%	51.16%	58.42%	67.54%	78.98%	90.26%	95.83%	99.23%
BBB	0.93%	4.17%	8.81%	20.87%	31.84 %	41.89%	52.09%	60.59%	69.86%	80.68%	90.88%	95.83%	99.23%
CCC&Lower	0.31%	3.55%	8.66%	20.40%	29.98%	39.41%	48.68%	59.35%	70.02%	80.99%	91.81%	95.52%	99.32%
IG 1-3Y	0.62%	3.25%	7.57%	18.86%	29.37%	40.80%	51.62%	60.59%	71.56%	81.92%	91.65%	96.14%	99.23%
IG 3-5Y	0.77%	3.71%	9.12%	20.87%	32.15%	42.50%	51.00%	61.05%	69.40%	80.22%	90.88%	95.52%	98.92%
IG 5-7Y	0.77%	4.95%	10.82%	22.10%	33.38%	43.12%	51.00%	59.04%	67.08%	78.67%	90.11%	95.21%	98.92%
IG 7-10Y	0.77%	4.02%	10.05%	22.26%	32.46%	42.04%	50.85%	60.12%	68.16%	79.44%	90.57%	95.52%	98.92%
IG 10-15Y	0.77%	4.64%	10.36%	21.33%	32.92%	42.66%	51.78%	60.43%	69.55%	79.75%	91.04%	95.67%	99.23%
2-weeks ahead													
IG	0.62%	3.55%	9.58%	21.33%	32.92%	43.28%	52.70%	59.97%	68.93%	80.37%	91.04%	95.52%	99.38%
AAA	0.46%	3.71%	9.89%	21.02%	31.38%	40.19%	49.77%	59.04%	68.47%	79.29%	90.11%	95.98%	99.54%
BBB	0.77%	3.55%	8.81%	21.17%	31.38 %	42.66%	51.16%	60.90%	70.02%	80.99%	91.04%	95.67%	99.38%
CCC&Lower	0.46%	3.55%	8.81%	20.87%	29.68%	40.65%	50.85%	60.59%	70.48%	80.53%	89.80%	95.83%	99.23%
IG 1-3Y	0.62%	3.25%	8.19%	19.94%	31.68%	41.42%	51.78%	61.05%	71.10%	80.83%	91.34%	95.98%	99.38%
IG 3-5Y	0.62%	3.09%	8.19%	21.33%	32.77%	43.12%	51.47%	59.81%	69.86%	80.37%	91.19%	95.98%	99.38%
IG 5-7Y	0.62%	4.33%	10.05%	21.48%	32.46%	43.28%	51.47%	59.51%	69.24%	80.06%	90.73%	95.52%	99.38%
IG 7-10Y	0.62%	3.71%	10.05%	22.41%	34.00%	43.28%	51.62%	59.97%	69.24%	79.75%	90.73%	95.67%	99.38%
IG 10-15Y	0.77%	4.33%	10.36%	22.57%	33.54%	43.12%	52.09%	60.74%	70.02%	80.83%	90.88%	95.98%	99.07%
4-weeks ahead													
IG	0.62%	3.55%	9.74%	22.10%	33.54%	44.20%	53.01%	60.59%	68.78%	80.22%	91.96%	95.98%	99.38%
AAA	0.31%	3.55%	9.74%	21.48%	32.30%	41.73%	50.39%	58.42%	67.39%	79.60%	91.65%	96.29%	99.38%
BBB	0.62%	3.25%	8.96%	20.40%	32.46%	43.89%	53.01%	61.51%	70.48%	80.99%	91.96%	96.14%	99.38%
CCC&Lower	0.15%	3.09%	8.66%	20.09%	29.83%	39.57%	49.92%	60.28%	70.79%	80.53%	90.88%	95.98%	99.54%
IG 1-3Y	0.46%	3.86%	9.27%	20.56%	31.99%	44.51%	53.01%	62.44%	70.17%	80.22%	92.12%	96.14%	99.38%
IG 3-5Y	0.46%	3.25%	8.50%	21.02%	32.92%	44.05%	53.17%	61.05%	69.71%	80.99%	92.27%	95.98%	99.38%
IG 5-7Y	0.62%	3.55%	9.58%	21.64%	33.23%	43.59%	52.55%	60.90%	69.71%	80.53%	91.19%	95.83%	99.23%
IG 7-10Y	0.46%	3.09%	9.74%	22.41%	34.00%	43.12%	51.47%	60.12%	69.71%	80.37%	91.81%	96.14%	99.38%
IG 10-15Y	0.46%	3.86%	10.20%	22.34%	35.55%	44.98%	53.32%	60.74%	68.62%	80.22%	91.65%	95.83%	99.07%

Table 8.4: The **2xCS + 3xRF** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	0.77%	4.33%	9.89%	21.64%	30.91%	41.73%	50.39%	59.35%	68.78%	79.60%	90.42%	96.29%	98.61%
AAA	0.77%	3.86%	9.43%	22.87%	30.14%	40.65%	51.78%	58.27%	67.23%	80.06%	90.57%	96.45%	99.69%
BBB	0.77%	3.71%	9.12%	20.87%	32.61%	41.89%	51.16%	60.43%	70.02%	79.91%	90.88%	95.83%	99.07%
CCC&Lower	0.31%	4.02%	8.66%	21.02%	29.06%	38.18%	48.07%	58.58%	69.71%	80.22%	92.12%	95.83%	99.38%
IG 1-3Y	0.93%	2.78%	8.04%	18.24%	27.36%	40.65%	51.62%	59.81%	71.87%	82.38%	90.73%	95.98%	99.38%
IG 3-5Y	0.77%	3.09%	8.81%	21.02%	32.15%	42.35%	50.70%	60.43%	70.32%	81.30%	90.57%	95.83%	99.07%
IG 5-7Y	0.62%	5.41%	9.58%	21.17%	33.38%	43.74%	49.61%	58.89%	67.70%	78.83%	89.34%	95.21%	99.07%
IG 7-10Y	0.77%	3.25%	10.97%	22.72%	32.77%	41.58%	50.23%	59.04%	67.85%	79.60%	90.88%	95.83%	98.76%
IG 10-15Y	0.77%	4.95%	9.74%	21.17%	32.30%	42.35%	51.31%	60.59%	69.40%	79.13%	91.65%	95.98%	98.76%
2-weeks ahead													
IG	0.77%	4.17%	10.05%	20.87%	33.08%	43.28%	52.55%	59.97%	69.71%	79.60%	91.50%	95.67%	99.69%
AAA	0.46%	3.55%	9.89%	21.17%	30.14%	40.34%	49.92%	59.51%	68.32%	79.60%	90.26%	96.14%	99.38%
BBB	0.77%	4.17%	9.27%	20.87%	31.53%	42.35%	51.31%	60.43%	70.48%	80.37%	90.88%	95.98%	99.54%
CCC&Lower	0.62%	3.86%	9.89%	20.71%	31.22%	39.88%	50.39%	60.59%	70.17%	80.53%	89.80%	95.98%	99.38%
IG 1-3Y	0.62%	3.71%	8.19%	20.40%	30.45%	42.04%	52.70%	60.90%	70.02%	79.44%	91.04%	95.67%	99.69%
IG 3-5Y	0.77%	3.25%	8.66%	22.41%	33.23%	42.19%	51.31%	59.51%	68.78%	80.83%	91.34%	95.83%	99.69%
IG 5-7Y	0.77%	4.48%	9.89%	22.26%	33.85%	44.05%	50.70%	58.89%	70.17%	79.44%	90.11%	95.21%	99.69%
IG 7-10Y	0.77%	4.33%	10.36%	21.95%	33.69%	43.74%	50.54%	60.59%	69.09%	79.44%	91.04%	95.67%	99.85%
IG 10-15Y	0.62%	4.02%	10.51%	21.64%	31.99%	42.19%	52.09%	60.74%	69.24%	80.83%	91.19%	96.45%	99.69%
4-weeks ahead													
IG	0.46%	3.71%	9.74%	21.48%	34.93%	44.05%	53.01%	60.59%	68.78%	79.29%	92.12%	96.29%	99.38%
AAA	0.31%	3.25%	9.27%	21.48%	31.53%	41.11%	51.16%	57.96%	67.23%	78.98%	91.65%	96.45%	99.54%
BBB	0.46%	3.40%	10.97%	19.63%	31.84%	43.89%	52.55%	61.82%	70.48%	80.06%	91.96%	96.29%	99.54%
CCC&Lower	0.31%	2.94%	8.04%	19.94%	29.37%	39.57%	49.30%	59.97%	70.79%	80.83%	91.04%	96.29%	99.54%
IG 1-3Y	0.46%	3.86%	9.27%	20.56%	31.99%	44.51%	53.01%	62.44%	70.17%	80.22%	92.12%	96.14%	99.38%
IG 3-5Y	0.62%	3.25%	8.96%	20.56%	32.92%	43.89%	53.32%	60.74%	68.78%	81.92%	91.96%	96.14%	99.38%
IG 5-7Y	0.62%	4.02%	10.20%	20.71%	33.69%	43.43%	52.40%	60.43%	69.24%	78.52%	91.19%	96.29%	99.54%
IG 7-10Y	0.46%	3.71%	9.43%	21.64%	34.62%	43.59%	51.47%	59.97%	69.55%	79.75%	91.65%	96.29%	99.54%
IG 10-15Y	0.62%	3.86%	9.89%	23.18%	35.86%	43.89%	52.40%	60.90%	68.16%	79.91%	91.81%	96.14%	99.38%

Table 8.5: The **2xCS + Fed** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	1.08%	4.64%	10.05%	21.48%	32.46%	41.11%	49.61%	59.51%	68.47%	78.67%	90.26%	95.21%	98.61%
AAA	0.77%	4.33%	10.05%	21.95%	31.07%	39.88%	50.08%	57.50%	67.70%	78.52%	89.95%	95.36%	99.07%
BBB	1.24%	4.33%	9.89%	21.95%	32.30%	42.19%	51.00%	60.12%	69.24%	79.60%	90.26%	95.52%	98.45%
CCC&Lower	0.46%	3.86%	9.12%	20.56%	29.21%	39.10%	47.76%	59.20%	69.09%	80.06%	90.11%	94.90%	99.07%
IG 1-3Y	0.93%	2.78%	8.04%	18.24%	27.36%	40.65%	51.62%	59.81%	71.87%	82.38%	90.73%	95.98%	99.38%
IG 3-5Y	0.62%	3.86%	8.66%	19.32%	30.29%	40.96%	51.62%	60.43%	71.25%	81.45%	92.12%	96.14%	98.92%
IG 5-7Y	1.24%	3.86%	9.12%	21.33%	31.99%	42.04%	51.31%	59.66%	68.47%	79.13%	90.42%	95.36%	98.61%
IG 7-10Y	1.24%	5.10%	10.66%	22.10%	32.77%	42.97%	50.39 %	59.20%	67.70%	77.90%	89.64%	95.36%	98.76%
IG 10-15Y	0.93%	5.26%	11.28%	22.10%	33.54%	42.50%	51.31%	60.28%	68.62%	79.29%	90.11%	95.05%	98.45%
2-weeks ahead													
IG	0.77%	4.17%	10.82%	21.95%	32.92%	43.89%	52.70%	59.66%	68.93%	79.91%	91.19%	95.67%	99.23%
AAA	0.77%	4.79%	10.97%	21.95%	31.68%	41.11%	50.23%	58.89%	68.62%	78.98%	89.80%	95.36%	99.07%
BBB	0.62%	3.86%	9.74%	21.64%	32.30%	43.12%	51.31%	60.90%	70.32%	80.83%	90.42%	95.36%	98.61%
CCC&Lower	0.77%	3.86%	8.50%	20.56%	29.37%	40.19%	50.08%	60.28%	69.55%	79.91%	89.18%	94.90%	98.92%
IG 1-3Y	0.62%	4.33%	9.74%	21.02%	32.61%	42.19%	51.78%	60.90%	70.63%	80.68%	91.50%	95.98%	99.54%
IG 3-5Y	0.46%	3.71%	8.96%	21.64%	33.23%	43.43%	51.47%	60.12%	69.55%	79.75%	91.19%	95.52%	99.23%
IG 5-7Y	0.77%	4.79%	10.51%	21.95%	32.92%	43.43%	51.47%	59.51%	68.93%	79.75%	90.42%	94.90%	98.92%
IG 7-10Y	0.62%	4.17%	10.82%	22.87%	34.47%	43.74%	52.09%	59.51%	69.09%	79.44%	90.88%	95.83%	98.92%
IG 10-15Y	0.62%	4.95%	10.05%	23.03%	33.85%	42.97%	52.09%	61.05%	69.86%	80.53%	90.57%	95.21%	98.76%
4-weeks ahead													
IG	0.62%	4.48%	10.20%	22.41%	34.47%	45.13%	53.48%	61.05%	69.09%	80.22%	91.65%	95.67%	99.23%
AAA	0.46%	4.79%	10.97%	22.41%	33.23%	43.12%	51.47%	58.58%	67.85%	79.13%	91.34%	95.83%	99.23%
BBB	0.62%	3.86%	9.43%	21.17%	32.77%	44.67%	53.48%	61.51%	70.63%	80.53%	91.65%	95.98%	98.92%
CCC&Lower	0.31%	3.40%	8.50%	19.94%	29.68%	39.57%	49.77%	59.81%	70.17%	79.91%	89.95%	95.36%	99.07%
IG 1-3Y	0.62%	4.95%	10.05%	21.33%	33.23%	44.82%	53.94%	62.75%	70.32%	80.53%	92.27%	95.83%	99.38%
IG 3-5Y	0.62%	4.02%	9.27%	21.17%	34.00%	44.67%	53.32%	61.82%	70.02%	80.37%	92.27%	96.14%	99.23%
IG 5-7Y	0.77%	4.48%	10.20%	22.10%	33.54%	43.74%	52.40%	60.90%	69.86%	80.53%	91.19%	95.52%	99.07%
IG 7-10Y	0.62%	4.48%	10.82%	23.18%	34.62%	44.36%	52.24%	60.74%	69.71%	79.91%	91.65%	95.83%	99.07%
IG 10-15Y	0.77%	4.48%	10.66%	24.27%	36.79%	45.44%	53.94%	60.90%	68.47%	79.75%	91.34%	95.67%	98.76%

Table 8.6: The **2xCS** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	0.77%	4.33%	9.89%	21.33%	32.15%	41.58%	51.0%	59.81%	69.09%	79.44%	90.88%	95.52%	98.92%
AAA	0.62%	3.40%	9.43%	21.79%	30.60%	40.19%	51.16%	58.42%	67.54%	78.98%	90.26%	95.83%	99.23%
BBB	0.93%	4.17%	8.81%	20.87%	31.84 %	41.89%	52.09%	60.59%	69.86%	80.68%	90.88%	95.83%	99.23%
CCC&Lower	0.31%	3.55%	8.66%	20.40%	29.98%	39.41%	48.68%	59.35%	70.02%	80.99%	91.81%	95.52%	99.32%
IG 1-3Y	0.62%	3.25%	7.57%	18.86%	29.37%	40.80%	51.62%	60.59%	71.56%	81.92%	91.65%	96.14%	99.23%
IG 3-5Y	0.77%	3.71%	9.12%	20.87%	32.15%	42.50%	51.00%	61.05%	69.40%	80.22%	90.88%	95.52%	98.92%
IG 5-7Y	0.77%	4.95%	10.82%	22.10%	33.38%	43.12%	51.00%	59.04%	67.08%	78.67%	90.11%	95.21%	98.92%
IG 7-10Y	0.77%	4.02%	10.05%	22.26%	32.46%	42.04%	50.85%	60.12%	68.16%	79.44%	90.57%	95.52%	98.92%
IG 10-15Y	0.77%	4.64%	10.36%	21.33%	32.92%	42.66%	51.78%	60.43%	69.55%	79.75%	91.04%	95.67%	99.23%
2-weeks ahead													
IG	0.62%	3.55%	9.58%	21.33%	32.92%	43.28%	52.70%	59.97%	68.93%	80.37%	91.04%	95.52%	99.38%
AAA	0.46%	3.71%	9.89%	21.02%	31.38%	40.19%	49.77%	59.04%	68.47%	79.29%	90.11%	95.98%	99.54%
BBB	0.77%	3.55%	8.81%	21.17%	31.38 %	42.66%	51.16%	60.90%	70.02%	80.99%	91.04%	95.67%	99.38%
CCC&Lower	0.46%	3.55%	8.81%	20.87%	29.68%	40.65%	50.85%	60.59%	70.48%	80.53%	89.80%	95.83%	99.23%
IG 1-3Y	0.62%	3.25%	8.19%	19.94%	31.68%	41.42%	51.78%	61.05%	71.10%	80.83%	91.34%	95.98%	99.38%
IG 3-5Y	0.62%	3.09%	8.19%	21.33%	32.77%	43.12%	51.47%	59.81%	69.86%	80.37%	91.19%	95.98%	99.38%
IG 5-7Y	0.62%	4.33%	10.05%	21.48%	32.46%	43.28%	51.47%	59.51%	69.24%	80.06%	90.73%	95.52%	99.38%
IG 7-10Y	0.62%	3.71%	10.05%	22.41%	34.00%	43.28%	51.62%	59.97%	69.24%	79.75%	90.73%	95.67%	99.38%
IG 10-15Y	0.77%	4.33%	10.36%	22.57%	33.54%	43.12%	52.09%	60.74%	70.02%	80.83%	90.88%	95.98%	99.07%
4-weeks ahead													
IG	0.62%	3.55%	9.74%	22.10%	33.54%	44.20%	53.01%	60.59%	68.78%	80.22%	91.96%	95.98%	99.38%
AAA	0.31%	3.55%	9.74%	21.48%	32.30%	41.73%	50.39%	58.42%	67.39%	79.60%	91.65%	96.29%	99.38%
BBB	0.62%	3.25%	8.96%	20.40%	32.46%	43.89%	53.01%	61.51%	70.48%	80.99%	91.96%	96.14%	99.38%
CCC&Lower	0.15%	3.09%	8.66%	20.09%	29.83%	39.57%	49.92%	60.28%	70.79%	80.53%	90.88%	95.98%	99.54%
IG 1-3Y	0.46%	3.86%	9.27%	20.56%	31.99%	44.51%	53.01%	62.44%	70.17%	80.22%	92.12%	96.14%	99.38%
IG 3-5Y	0.46%	3.25%	8.50%	21.02%	32.92%	44.05%	53.17%	61.05%	69.71%	80.99%	92.27%	95.98%	99.38%
IG 5-7Y	0.62%	3.55%	9.58%	21.64%	33.23%	43.59%	52.55%	60.90%	69.71%	80.53%	91.19%	95.83%	99.23%
IG 7-10Y	0.46%	3.09%	9.74%	22.41%	34.00%	43.12%	51.47%	60.12%	69.71%	80.37%	91.81%	96.14%	99.38%
IG 10-15Y	0.46%	3.86%	10.20%	22.34%	35.55%	44.98%	53.32%	60.74%	68.62%	80.22%	91.65%	95.83%	99.07%

Table 8.7: The **3xCS** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	0.31%	4.02%	9.58%	21.02%	32.15%	41.11%	49.92%	59.04%	68.93%	79.29%	91.04%	95.67%	98.92%
AAA	0.31%	3.09%	9.89%	20.87%	30.29%	40.19%	51.31%	57.34%	68.32%	78.52%	90.26%	96.29%	99.38%
BBB	0.62%	4.02%	8.96%	21.79%	31.84%	41.89%	50.54%	59.97%	69.86%	80.06%	91.50%	95.83%	99.23%
CCC&Lower	0.15%	3.25%	8.66%	20.56%	30.14%	38.95%	48.53%	58.89%	69.55%	80.83%	91.50%	96.29%	99.69%
IG 1-3Y	0.46%	2.94%	7.88%	18.24%	29.37%	41.11%	51.93%	60.43%	71.41%	81.92%	92.12%	96.75%	99.38%
IG 3-5Y	0.46%	2.47%	8.50%	21.02%	31.68%	42.50%	51.31%	59.51%	68.32%	79.60%	90.88%	95.67%	98.76%
IG 5-7Y	0.46%	4.33%	10.20%	21.48%	32.77%	43.12%	50.85%	59.66%	68.01%	78.67%	89.80%	94.74%	99.07%
IG 7-10Y	0.62%	2.94%	10.66%	22.72%	32.46%	41.58%	50.39%	59.51%	68.16%	78.36%	90.42%	95.36%	98.92%
IG 10-15Y	0.62%	4.02%	10.36%	21.33%	33.23%	42.50%	51.93%	60.12%	68.78%	79.29%	90.73%	95.52%	99.23%
2-weeks ahead													
IG	0.46%	3.25%	8.35%	21.64%	32.77%	43.12%	52.70%	60.12%	69.09%	80.53%	91.04%	95.98%	99.54%
AAA	0.46%	3.55%	9.58%	21.02%	31.53%	40.49%	49.77%	59.04%	68.32%	79.60%	90.88%	96.29%	99.54%
BBB	0.46%	3.40%	7.88%	20.87%	31.53%	42.97%	51.00%	60.59%	70.02%	81.30%	91.96%	95.98%	99.38%
CCC&Lower	0.31%	3.55%	7.88%	20.56%	29.68%	40.80%	50.85%	60.59%	70.48%	80.53%	90.42%	95.52%	99.85%
IG 1-3Y	0.46%	3.25%	7.73%	20.09%	31.68%	41.58%	51.93%	61.67%	71.25%	80.68%	90.88%	96.91%	99.54%
IG 3-5Y	0.46%	2.63%	8.04%	21.48%	32.61%	42.97%	51.47%	59.66%	70.02%	81.92%	91.50%	96.29%	99.54%
IG 5-7Y	0.31%	4.17%	9.12%	21.48%	32.15%	43.59%	51.47%	59.51%	68.78%	80.37%	90.88%	95.98%	99.54%
IG 7-10Y	0.31%	2.78%	9.12%	22.26%	34.00%	43.59%	51.00%	59.81%	68.93%	79.75%	91.04%	95.52%	99.54%
IG 10-15Y	0.46%	4.17%	9.89%	22.57%	32.77%	42.50%	52.24%	60.90%	70.02%	80.83%	90.57%	95.83%	99.54%
4-weeks ahead													
IG	0.31%	3.09%	9.12%	21.48%	33.08%	44.36%	53.01%	60.74%	69.24%	79.91%	92.12%	96.75%	99.38%
AAA	0.15%	2.78%	9.27%	20.09%	32.30%	41.73%	50.70%	58.27%	67.54%	78.52%	92.12%	96.29%	99.23%
BBB	0.46%	2.94%	8.81%	20.56%	32.46%	44.20%	52.70%	61.21%	71.87%	81.76%	92.12%	96.45%	99.38%
CCC&Lower	0.31%	2.16%	8.04%	19.94%	30.29%	40.03%	49.61%	60.28%	70.63%	80.68%	91.19%	95.98%	99.54%
IG 1-3Y	0.31%	3.40%	9.74%	20.40%	31.84%	44.82%	53.01%	61.98%	70.17%	81.14%	93.04%	96.91%	99.38%
IG 3-5Y	0.62%	2.63%	8.19%	20.71%	32.61%	43.89%	52.86%	61.05%	69.40%	82.69%	92.58%	96.14%	99.38%
IG 5-7Y	0.46%	3.09%	8.81%	22.10%	33.38%	43.43%	52.55%	60.74%	69.86%	80.83%	91.65%	95.98%	99.38%
IG 7-10Y	0.62%	2.63%	9.43%	22.26%	33.38%	42.97%	51.16%	60.12%	71.25%	79.75%	91.65%	96.14%	99.38%
IG 10-15Y	0.31%	3.25%	10.05%	22.26%	35.24%	45.13%	52.86%	60.59%	68.62%	80.53%	91.81%	96.14%	99.23%

Table 8.8: The**3xCS + 4xRF** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	0.46%	3.55%	9.27%	21.02%	32.46%	40.96%	49.46%	59.20%	68.32%	80.53%	91.65%	95.52%	99.23%
AAA	0.46%	2.78%	8.81%	21.64%	30.45%	40.65%	51.31%	57.34%	68.47%	78.83%	91.19%	96.91%	99.54%
BBB	0.77%	3.71%	9.12%	20.40%	32.30%	42.66%	50.54%	59.51%	68.93%	79.44%	91.50%	95.98%	99.38%
CCC&Lower	0.31%	3.40%	8.81%	20.25%	28.44%	38.49%	47.60%	58.58%	69.40%	80.99%	92.12%	96.14%	99.38%
IG 1-3Y	0.31%	3.55%	8.66%	20.40%	29.98%	39.41%	48.69%	59.35%	70.02%	80.99%	91.81%	95.52%	99.23%
IG 3-5Y	0.46%	2.63%	8.19%	20.25%	30.29%	42.35%	51.62%	58.73%	68.32%	80.68%	91.04%	96.29%	99.07%
IG 5-7Y	0.62%	4.17%	9.27%	21.48%	32.61%	43.12%	50.08%	59.66%	68.93%	79.13%	89.49%	95.36%	99.07%
IG 7-10Y	0.77%	2.94%	9.89%	22.57%	32.77%	41.27%	50.54%	59.20%	68.16%	78.21%	90.88%	95.83%	99.23%
IG 10-15Y	0.77%	4.02%	9.43%	21.17%	32.61%	42.35%	50.39%	59.51%	68.78%	78.67%	90.88%	96.45%	99.23%
2-weeks ahead													
IG	0.46%	3.25%	8.04%	20.71%	32.92%	43.43%	52.24%	59.97%	69.55%	80.68%	91.19%	95.83%	99.54%
AAA	0.46%	3.55%	9.74%	20.87%	30.14%	40.03%	50.54%	59.20%	68.62%	79.75%	90.42%	96.29%	99.38%
BBB	0.62%	3.55%	7.73%	20.71%	31.38%	42.35%	51.16%	60.59%	69.86%	80.53%	90.73%	95.98%	99.85%
CCC&Lower	0.62%	3.86%	8.66%	21.17%	30.45%	39.72%	49.77%	60.90%	69.86%	81.14%	90.11%	95.98%	99.38%
IG 1-3Y	0.62%	3.25%	7.42%	20.25%	30.76%	42.19%	52.55%	60.43%	70.94%	79.60%	90.88%	96.29%	99.38%
IG 3-5Y	0.62%	2.78%	7.73%	21.64%	32.92%	42.35%	51.31%	60.43%	69.71%	80.99%	90.57%	96.29%	99.54%
IG 5-7Y	0.93%	3.86%	9.89%	22.87%	33.23%	43.74%	50.85%	58.89%	70.32%	79.44%	89.95%	96.14%	99.38%
IG 7-10Y	0.77%	3.25%	8.20%	22.14%	34.37%	43.65%	50.46%	60.53%	68.42%	79.41%	90.56%	96.13%	99.85%
IG 10-15Y	0.31%	3.71%	9.43%	21.17%	32.46%	42.35%	52.40%	60.90%	69.40%	80.83%	91.19%	96.29%	99.54%
4-weeks ahead													
IG	0.46%	2.94%	9.12%	21.17%	33.54%	44.05%	53.01%	60.74%	68.93%	79.13%	92.58%	96.91%	99.54%
AAA	0.31%	2.63%	10.05%	20.71%	31.99%	41.27%	50.85%	58.11%	67.70%	78.21%	92.12%	96.45%	99.69%
BBB	0.46%	3.25%	10.20%	20.09%	32.30%	43.74%	52.55%	61.36%	71.25%	80.37%	92.58%	96.60%	99.23%
CCC&Lower	0.46%	2.47%	7.88%	19.47%	29.37%	38.95%	49.46%	59.51%	70.63%	80.83%	91.81%	95.98%	99.54%
IG 1-3Y	0.46%	2.47%	8.81%	20.40%	31.53%	43.89%	52.86%	61.82%	69.24%	80.06%	92.43%	96.91%	99.38%
IG 3-5Y	0.46%	2.16%	8.96%	19.94%	32.30%	44.05%	53.01%	60.59%	68.32%	81.92%	92.12%	96.29%	99.38%
IG 5-7Y	0.62%	3.55%	9.12%	20.87%	32.46%	42.97%	52.70%	60.28%	69.55%	80.53%	91.34%	96.29%	99.23%
IG 7-10Y	0.46%	2.63%	9.12%	21.33%	34.62%	43.74%	51.31%	60.43%	70.79%	79.13%	91.50%	96.29%	99.54%
IG 10-15Y	0.62%	3.25%	8.96%	23.03%	35.55%	43.43%	53.01%	60.74%	68.32%	80.06%	92.27%	95.98%	99.23%

Table 8.9: The**3xCS + Macro** model:Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*	*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead													
IG	0.62%	4.33%	9.43%	22.41%	32.61%	41.11%	51.16%	62.75%	72.49%	81.76%	92.74%	95.98%	99.38%
AAA	0.77%	3.71%	9.27%	22.87%	30.29%	40.96%	51.62%	59.97%	69.55%	79.75%	91.04%	96.29%	99.69%
BBB	0.62%	3.86%	9.43%	20.87%	33.38%	42.81%	51.93%	62.91%	72.64%	82.07%	90.73%	96.14%	98.45%
CCC&Lower	0.31%	3.40%	8.19%	20.40%	29.83%	40.49%	50.54%	61.51%	73.42%	84.08%	92.58%	94.90%	99.54%
IG 1-3Y	0.46%	3.40%	7.26%	18.86%	29.68%	41.58%	51.78%	62.44%	72.95%	83.62%	93.66%	97.68%	99.69%
IG 3-5Y	0.62%	3.25%	8.96%	20.25%	33.23%	42.35%	52.09%	62.75%	71.87%	81.30%	92.27%	96.45%	99.38%
IG 5-7Y	0.46%	4.79%	9.27%	21.48%	33.69%	44.20%	52.55%	61.05%	71.56%	80.06%	91.04%	95.36%	99.23%
IG 7-10Y	0.46%	4.02%	9.89%	22.57%	33.08%	43.89%	50.54%	61.36%	70.32%	80.53%	91.19%	95.83%	99.07%
IG 10-15Y	0.77%	4.02%	10.51%	22.87%	34.47%	44.05%	53.48%	62.44%	70.94%	80.22%	91.34%	95.52%	98.61%
2-weeks ahead													
IG	0.46%	3.40%	9.58%	21.95%	34.31%	44.98%	53.01%	61.21%	70.79%	82.23%	92.58%	97.06%	99.85%
AAA	0.62%	3.25%	8.81%	21.02%	31.99%	41.42%	50.39%	60.28%	69.86%	80.06%	91.19%	96.91%	99.38%
BBB	0.62%	2.94%	8.50%	21.79%	32.15%	44.36%	53.48%	63.06%	72.95%	82.69%	94.13%	96.14%	99.85%
CCC&Lower	0.15%	2.94%	6.80%	21.33%	30.45%	41.89%	51.93%	61.67%	71.25%	82.07%	90.73%	96.60%	99.54%
IG 1-3Y	0.31%	2.94%	8.50%	20.25%	32.46%	43.28%	52.70%	61.51%	71.72%	83.31%	93.20%	97.22%	99.69%
IG 3-5Y	0.62%	2.94%	7.42%	20.25%	32.15%	42.35%	53.48%	62.91%	72.18%	82.53%	92.27%	96.60%	99.85%
IG 5-7Y	0.62%	4.02%	8.81%	23.34%	33.23%	44.20%	51.16%	61.05%	71.56%	81.92%	91.65%	96.75%	99.69%
IG 7-10Y	0.46%	3.40%	9.89%	21.02%	34.16%	45.13%	52.86%	61.98%	70.63%	80.37%	91.81%	96.29%	99.69%
IG 10-15Y	0.77%	3.40%	9.58%	24.27%	35.55%	43.59%	53.79%	62.75%	71.72%	83.15%	92.74%	96.45%	99.38%
4-weeks ahead													
IG	0.46%	3.86%	8.96%	21.33%	33.69%	45.13%	55.18%	62.13%	71.10%	80.99%	93.35%	97.06%	99.38%
AAA	0.77%	3.55%	8.96%	21.17%	32.61%	42.04%	50.54%	60.43%	69.71%	80.22%	92.43%	96.91%	99.69%
BBB	0.46%	3.25%	7.73%	19.94%	32.61%	44.98%	55.02%	62.91%	72.80%	82.07%	93.51%	96.91%	99.38%
CCC&Lower	0.15%	2.78%	7.88%	19.47%	29.37%	39.41%	51.00%	62.29%	72.49%	82.07%	91.96%	95.67%	99.85%
IG 1-3Y	0.46%	3.55%	9.12%	19.94%	31.68%	44.36%	54.25%	63.99%	72.02%	81.45%	93.82%	97.68%	99.38%
IG 3-5Y	0.31%	3.09%	8.81%	19.94%	32.46%	43.59%	55.18%	62.44%	71.72%	82.38%	93.04%	96.91%	99.23%
IG 5-7Y	0.46%	3.55%	9.74%	22.10%	33.08%	44.67%	53.01%	61.98%	71.72%	81.61%	92.58%	96.60%	99.23%
IG 7-10Y	0.46%	3.25%	9.74%	21.02%	35.09%	43.89%	53.01%	61.05%	71.25%	81.92%	93.20%	97.22%	99.23%
IG 10-15Y	0.62%	4.02%	9.27%	23.18%	35.55%	45.13%	54.40%	60.90%	69.24%	81.14%	92.89%	96.45%	99.38%

Table 8.10: The**Historical Simulation** model: Out-of-sample exceedances-% for each estimated quantile level

Quantile	*1%*	*5%*	*10%*	*20%*	*30%*		*40%*	*50%*	*60%*	*70%*	*80%*	*90%*	*95%*	*99%*
1-week ahead														
IG	1.08%	3.10%	7.12%	17.18%	28.64%		36.84%	47.83%	53.25%	65.33%	79.10%	90.87%	96.13%	99.23%
AAA	1.08%	3.25%	7.74%	18.89%	25.85%		33.90%	43.34%	44.27%	64.71%	77.71%	87.93%	95.05%	98.76%
BBB	1.08%	3.72%	7.89%	17.96%	29.41%		40.09%	50.00%	57.89%	71.05%	81.27%	91.95%	95.82%	99.38%
CCC&Lower	1.08%	4.02%	8.05%	19.20%	28.64%		38.85%	49.54%	60.68%	71.36%	83.44%	91.02%	95.98%	99.07%
IG 1-3Y	0.77%	3.10%	5.11%	14.40%	24.77%		33.90%	47.52%	52.32%	67.34%	79.26%	92.72%	96.13%	99.38%
IG 3-5Y	1.08%	3.10%	6.97%	18.11%	24.92%		35.91%	49.23%	53.87%	67.18%	80.80%	91.64%	95.82%	99.23%
IG 5-7Y	1.08%	3.25%	8.82%	18.27%	28.17%		38.54%	45.67%	53.41%	67.65%	80.50%	91.02%	96.44%	99.23%
IG 7-10Y	1.08%	3.10%	8.36%	19.04%	29.26%		38.24%	48.92%	57.43%	69.35%	80.80%	90.25%	95.82%	99.23%
IG 10-15Y	0.93%	4.18%	10.06%	19.81%	30.65%		37.93%	49.07%	55.11%	69.35%	80.96%	90.87%	94.89%	99.23%
2-weeks ahead														
IG	1.08%	3.40%	6.18%	17.77%	30.60%		39.57%	46.68%	58.73%	70.63%	81.76%	92.43%	95.83%	99.23%
AAA	1.08%	3.25%	8.35%	19.17%	29.98%		35.09%	45.75%	57.50%	67.70%	78.05%	90.57%	96.14%	98.92%
BBB	0.93%	3.09%	7.42%	18.39%	30.76%		40.49%	49.30%	60.74%	71.10%	82.23%	92.27%	96.45%	99.23%
CCC&Lower	1.08%	3.55%	7.88%	18.70%	30.14%		39.41%	49.92%	60.43%	72.02%	83.31%	93.20%	96.14%	99.07%
IG 1-3Y	0.93%	2.78%	6.03%	15.92%	26.89%		38.02%	47.45%	56.26%	71.10%	80.37%	93.04%	96.91%	99.23%
IG 3-5Y	1.24%	2.78%	6.65%	17.62%	29.83%		39.26%	48.38%	58.42%	71.72%	82.53%	92.58%	96.14%	99.07%
IG 5-7Y	1.08%	2.94%	8.04%	19.94%	28.59%		39.26%	48.38%	57.81%	70.94%	81.92%	91.81%	96.75%	99.07%
IG 7-10Y	0.77%	3.25%	6.49%	19.94%	27.98%		41.73%	49.15%	60.74%	72.02%	81.92%	92.12%	96.60%	99.23%
IG 10-15Y	1.08%	3.86%	8.66%	21.33%	31.22%		40.19%	50.85%	62.60%	71.56%	82.07%	91.65%	95.83%	99.23%
4-weeks ahead														
IG	0.93%	3.09%	6.18%	18.55%	31.38%		41.42%	49.61%	60.43%	70.48%	83.93%	92.43%	96.45%	99.07%
AAA	1.08%	3.71%	6.65%	18.86%	30.91%		39.72%	47.60%	59.81%	69.09%	80.53%	91.96%	96.29%	98.92%
BBB	1.39%	2.94%	5.72%	17.77%	31.68%		41.42%	51.31%	61.51%	72.95%	84.85%	93.51%	97.06%	98.92%
CCC&Lower	1.08%	3.55%	7.57%	18.24%	30.76%	40.65%	50.39%	61.51%	72.02%	83.77%	93.35%	97.06%	98.76%	
IG 1-3Y	0.93%	2.94%	5.87%	15.61%	29.21%		39.10%	49.46%	61.05%	70.79%	83.77%	92.74 %	97.53%	99.07%
IG 3-5Y	1.08%	3.25%	6.34%	18.39%	29.37%		40.80%	50.39%	61.67%	72.02%	84.85%	93.04%	96.29%	99.07%
IG 5-7Y	1.08%	2.94%	6.96%	18.08%	29.68%		39.88%	50.39%	62.60%	72.18%	83.93%	92.89%	96.60%	99.07%
IG 7-10Y	0.93%	2.94%	6.80%	19.47%	29.06%		41.27%	51.16%	61.36%	72.33%	82.53%	93.35%	96.75%	99.07%
IG 10-15Y	1.08%	3.40%	8.35%	22.72%	33.54%		41.42%	51.47%	61.36%	71.87%	83.31%	91.50%	95.83%	99.07%

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