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The time-varying impact of systematic risk factors on corporate bond spreads

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Non-technical summary

Research question

During the global financial crisis of 2007-09, stressed market conditions led to skyrocketing corporate bond spreads that could not be explained by conventional modeling approaches. This paper builds on this observation and sheds light on the way the relationship between corporate bond spreads and the underlying systematic risk factors varies between normal trading periods and times of crisis. Furthermore, we investigate whether the relationship between corporate bond spreads for different credit qualities and their underlying systematic risk factors changes simultaneously over time.

Contribution

Existing papers dealing with time variations in the interaction between corporate bond spreads and systematic risk factors exclusively analyze US markets. Unlike these papers, we are the first to consider the case of euro-denominated corporate bonds. As US firms rely, in comparison to their continental European counterparts, much more on bond funding than on bank loans, simply transferring the US results would seem doubtful. Another point that makes our study unique is that we choose risk factors in an objective way out of a universe of candidate variables using the so-called Bayesian model averaging (BMA) while former research simply selects the explanatory variables based on economic intuition.

Results

Our evidence suggests that systematic risk factors play a much more prominent role during stressed market conditions than during times of normal, uneventful trading. This implies that, during times of crisis, bond market investors resume rather fundamental-based pricing instead of relying on idiosyncratic characteristics. In particular, factors that are related to expectations about corporate earnings and, in turn, about default rates seem to have a much stronger impact on spread changes under stressed market conditions. Furthermore, our results indicate that bonds with a lower credit quality remain longer in the crisis state.

Nichttechnische Zusammenfassung

Fragestellung

Im Verlauf der Finanzmarktkrise 2007-2009 sind die Risikoaufschläge für Unternehmensanleihen stärker angestiegen, als es durch gängige Modelle hätte erklärt werden können. Dieses Forschungspapier wird durch diese Beobachtung motiviert und analysiert, wie sich der Einfluss von systematischen Risikofaktoren auf die Entwicklung der Risikoaufschläge zwischen normalen Perioden und Krisenphasen unterscheidet.

Beitrag

Die bestehende Literatur zur zeitlichen Entwicklung der Beziehung zwischen den Risikoaufschlägen für Unternehmensanleihen und den zugrundeliegenden Risikofaktoren analysiert ausschließlich Daten von US-Märkten. Dieser Artikel hingegen betrachtet den Markt für Euro-denominierte Unternehmensanleihen. Im Gegensatz zu US-Firmen finanzieren sich Unternehmen in Kontinentaleuropa traditioneller Weise stark über Bankkredite. Entsprechend lassen sich die Ergebnisse für die USA nicht einfach auf den Euroraum übertragen. Darüber hinaus hebt sich die vorliegende Studie von existierenden Untersuchungen ab, indem die Risikofaktoren über ein objektives Verfahren, das so genannte Bayesian model averaging (BMA), aus einer Sammlung von potenziellen Faktoren ausgewählt werden, anstatt sich auf subjektive ökonomische Intuition zu verlassen.

Ergebnisse

Dieses Forschungspapier stellt dar, dass der Einfluss systematischer Risikofaktoren auf die Risikoaufschläge für Euro-denominierte Unternehmensanleihen während Krisenzeiten deutlich höher ausfällt als unter normalen Marktbedingungen. Dies deutet darauf hin, dass Investoren ihre Anleihebewertungen in Phasen starker Marktturbulenzen verstärkt anhand von fundamentalen Einflüssgrößen vornehmen, anstatt sich auf idiosynkratische Faktoren zu verlassen. Vor allem scheinen Faktoren, die von Erwartungen bezüglich der Entwicklung von Unternehmensgewinnen und damit auch von Ausfallwahrscheinlichkeiten getrieben werden, während solcher Zeiträume einen deutlich stärkeren Enfluss auf die Entwicklung der Risikoaufschläge zu haben. Ein weiteres Ergebnis ist zudem, dass Anleihen mit einem schlechteren Rating länger im Krisenregime verharren.

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Abstract

During the global financial crisis, stressed market conditions led to skyrocketing corporate bond spreads that could not be explained by conventional modeling approaches. This paper builds on this observation and sheds light on time-variations in the relationship between systematic risk factors and corporate bond spreads. First, we apply Bayesian model averaging to a battery of candidate variables for determining meaningful systematic risk factors. Second, Markov switching techniques provide us with an endogenous separation of regimes accounting for times of stress, on the one hand, and for normal market conditions, on the other. Our evidence for market indices of euro-denominated bonds suggests that systematic risk factors play a much more prominent role during periods of market turmoil. Most important, expectations about default rates seem to be much more driven by systematic factors rather than idiosyncratic components during times of market stress.

Keywords: asset pricing, banking regulation, Bayesian model averaging, credit spreads, European bond market, Markov switching

JEL classification: G01, G10, G11, G12, G14, G15, G32

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1 Introduction

Spread-implied default rates have always been substantially higher than realized defaults of corporate bonds. For instance, Giesecke, Longstaff, Schaefer, and Strebulaev (2011) report that, over the course of 150 years of US history, corporate bond spreads were roughly twice the rate that would be required to compensate risk-neutral investors for taking credit risk. This pattern is dubbed the "credit spread puzzle". It materialized during the global financial crisis of 2007-09 when bond yields skyrocketed by far more than implied by the actual increase in default rates. Once this threat subsequently made it to the regulators' agenda, new regulatory requirements specifically accounting for this type of risk were introduced. The Basel Committee on Banking Supervision (BCBS) incorporated the incremental risk charge (IRC) for trading book instruments in 2009 (BCBS (2009)) and, afterwards, modified it to the default risk charge (DRC) in the revised standards for the trading book (BCBS (2016b)) which will come into force in 2022.[1] More recently, the BCBS published in April 2016 new standards for interest rate risk in the banking book explicitly mentioning credit spread risk which needs to be measured by banks as of 2018 under Pillar 2 (BCBS (2016a)).

A vast body of literature is targeted at identifying systematic risk factors contributing to the spreads of corporate bonds.[2] Thereby, the stability of the linkage between corporate bond spreads and these factors over time has also been discussed. Chun, Dionne, and François (2014a) reveal that corporate credit spreads can be explained much better by regime switching approaches than by simple constant parameter models. Interestingly, prior work on regime dependence in corporate bond spreads focuses exclusively on the US market (Davies (2004), Chun, Dionne, and François (2014b), Chun et al. (2014a), Pavlova, Hibbert, Barber, and Dandapani (2015)). Given different market characteristics[3] in distinct regions, it seems unreliable to simply transfer the results for the US to other markets. For instance, in continental Europe, bonds constitute traditionally a smaller part of the debt funding compared to the US. This motivates us to provide a detailed analysis of regime dependence in the relationship between corporate bond spreads and the underlying systematic risk factors for the European market.

Specifically, our analysis is carried out using broad market indices for AA- and BBB-rated euro-denominated bonds over the sample period 01/2003-02/2015. This provides us with an ideal setting to analyze regime dependence since it encompasses two severe crises, namely the global financial crisis and the subsequent European sovereign debt crisis, as well as periods of steady economic growth and low market volatility.

Furthermore, none of the existing papers does a systematic and objective selection of the variables used to explain spread changes. Instead, we rely on Bayesian model averaging (BMA) to avoid arbitrariness in the choice of systematic risk factors. Comparing the risk factors extracted based on this technique with those chosen by the authors in the above mentioned papers, the added value directly becomes apparent. Among our most significant variables are changes in the unemployment rate and in an index for economic

[1] However, the DRC does not capture credit spread risk, anymore.

[2] See, for example, Fama and French (1993), Elton, Gruber, Agrawal, and Mann (2001), Collin-Dufresne, Goldstein, and Martin (2001), and Giesecke et al. (2011).

[3] Markets can differ, for example, because of the degree of competition, the size of corporates and the access to the bond market.

sentiment, nothing of which is used in the previous literature on regime switching in corporate bond spreads. The other way around, industrial production and implied stock market volatility, which are employed by Davies (2004) and Pavlova et al. (2015), do not enter any of our specifications. Furthermore, our models have significantly higher explanatory power compared with these studies although we use a comparable number of exogenous variables. This also supports our assertion of a better selection of systematic risk factors.

Another aspect differentiating our paper from existing studies is that we apply a Markov switching model with time-varying transition probabilities as proposed by Diebold, Lee, and Weinbach (1994) in order to shed light on the economic forces driving the shifts in regimes. Chun et al. (2014b) and Pavlova et al. (2015) use two-step approaches where they, first, extract regimes and, then, try to explain these regimes by economic variables. This is methodologically unsound and may bias the results as the inclusion of these variables in the estimation process may, of course, affect the determination of regimes. Moreover, we provide a joint modeling of corporate bond spreads of different rating categories in a bivariate Markov switching seemingly unrelated regressions (MSSUR) framework which takes into account correlations between bonds of higher and lower credit quality. This approach helps us understanding whether these bonds are governed by similar or by distinct regimes.

Besides the unemployment rate and an index for economic sentiment, the variables qualifying as risk factors in the BMA encompass stock market returns, term structure variables, and exchange rates, among others. Using these systematic risk factors in pricing spreads of AA and BBB corporate bond indices unveils two major findings. First, during times of high market volatility, systematic risk factors play a much stronger role in explaining these spreads than during normal market phases. In particular, coefficients tend to be larger in size and of increased statistical significance when a crisis regime prevails. Second, AA- and BBB-rated bonds are subject to different regimes. Specifically, crisis periods tend to be more extended for the lower-rated bonds.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. In Section 3, we describe the data employed in this study and argue why we focus on index data for euro-denominated bonds. In Section 4, we outline the BMA approach used in the selection of the systematic risk factors and describe the Markov switching approach applied to model a time-varying relation between systematic risk factors and credit spreads as well as the bivariate MSSUR extension, taking into account correlation between AA and BBB indices. Section 5 discusses the empirical results, while Section 6 briefly concludes.

2 Literature review

Research on the valuation of corporate debt traces back to Merton (1974). His approach builds upon option pricing theory using the notion that holding a corporate bond can be interpreted as being short in a put on that firm's asset value. In this setting, corporate bond spreads should be entirely explained by default risk.[4] Early empirical work can

[4]Generalized versions of such structural as well as so-called intensity (or reduced form) models (e.g. Jarrow and Turnbull (1995)) imply that the spread of a given corporate bond should be completely

be found in Fama and French (1993), who use two common factors to explain corporate bond returns: The term spread and the return difference between a market portfolio of long-term corporate bonds and long-term Treasury rates in order to capture default risk. These two factors have great explanatory power over bond returns.

The work of Elton et al. (2001) shows that default premia account for only a minor fraction of spreads across all rating categories. Furthermore, although considering taxes can significantly reduce the gap in the explanatory power, only the inclusion of the classical Fama and French (1993) stock market factors can produce satisfactory results. Collin-Dufresne et al. (2001) are the first to analyze the impact of fundamental macroeconomic and financial factors on individual corporate bond returns. First, they, confirm the finding of Elton et al. (2001) that factors suggested by traditional models of default probability are unable to achieve a sufficient fit. Second, the residuals from these regressions are highly correlated among bonds. Their attempts to explain the common factor in these residuals yield relatively poor results, with the exception of positive changes in implied stock market volatility. The latter is the main focus of Campbell and Taksler (2003). Using US data from the late 1990s, they provide evidence that a firm's equity volatility has as much explanatory power over the cross-section of bond yields as does its credit rating.

Driessen (2005) relies on an intensity-based model to estimate the default premium from returns of US corporate bonds. Intensity-based approaches model the default premium using jump processes. His evidence suggests that this premium provides an economically significant contribution to explaining corporate bond returns, although it lacks strong statistical significance. Moreover, he identifies tax and liquidity effects as well as a risk premium for market-wide movements in corporate bond spreads as major drivers. He also finds a very low market price of risk for firm-specific factors for the median firm. Huang and Huang (2012) apply a large number of different models and use 26 years of data to estimate the proportion of spreads that hinges on default risk. According to their results, default risk accounts for roughly 30% of observed spreads for Baa-rated bonds and for around 20% of higher-rated bonds.

The role of macroeconomic fundamentals, bank lending conditions, and financial variables in explaining default and rating cycles is the focus of Koopman, Kräussl, Lucas, and Monteiro (2009). Unlike similar papers, they do not only employ information from actual defaults but also take into account upgrades and downgrades. The study provides strong evidence for an unobserved systematic factor.

Giesecke et al. (2011) use a 150-year data history for non-financial US corporate bonds to examine the evolution of default rates. Their findings highlight some interesting features of corporate bond spreads. One striking fact is that past corporate bond spreads, unlike other financial and macroeconomic variables, appear to have only poor predictive power over default rates. Furthermore, current default rates lack explanatory power over credit spreads. Moreover, default losses explain only around half of the historical average spread of 153 basis points. The most outstanding aspect with respect to the scope of our study is that, according to their data set, changes in corporate bond spreads are not related to key macroeconomic variables. However, the authors confirm the impact of financial variables, namely stock market returns, changes in stock market volatility, and changes in the risk-free interest rate.

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determined by factors specific to the respective firm.

Davies (2004) is the first to consider different regimes in the relation between corporate bond spread dynamics and the underlying determinants making use of Markov switching vector error correction and of threshold autoregressive models. His most outstanding finding is that the determinants seem to exert a stronger impact on the spread during times of increased market volatility. Thereby, it is notable that the theory-implied negative relationship between the spread and the risk-free interest rate is borne out by the data only in a low volatility regime but disappears when a high volatility regime is governing.

Chun et al. (2014a) employ US data covering the period 1994-2011 and compare various model specifications. The authors adopt explanatory variables accounting for default, market, and credit risk. In line with other studies, the authors conclude that there are factors beyond default risk that should be taken into account as they have significant explanatory power over corporate bond spreads. Their most interesting result is that specifications based on endogenously determined switching regimes outperform linear models or those with states that were exogenously selected, for instance, based on NBER recessions, in terms of goodness of fit. Moreover, the paper confirms that the impact of key corporate bond spread determinants alters in time and can, for some variables, even change the direction.

Pavlova et al. (2015) also apply a regime switching model to US bond data. However, unlike Davies (2004), Chun et al. (2014a), and our paper, they analyze daily data which limits the explanatory variables to term structure variables, stock market returns, and measures of market volatility. It is notable that they include high-yield bonds in their study. Their results for investment-grade bonds suggest a permanent regime switch around the time of the failure of Lehman Brothers indicating a structural break. In the case of high-yield bonds, the market seems to return to the pre-crisis state after the end of 2009.

Chun et al. (2014b) apply descriptive regime switching techniques to analyze the behavior of the level and the volatility of US corporate bond spreads. According to their evidence, lower rating categories seem to be subject to more frequent shifts in regimes. Moreover, shifts tend to anticipate NBER recessions to a certain degree. Their evidence also suggests that periods of above-average spread levels often outlive NBER recessions. Volatility regimes appear to be shorter-lived than level regimes. The authors also analyze regime switches in the behavior of banks' credit standards and the federal funds rate in order to assess whether these variables share the same regime patterns. They conclude that regimes for these variables seem to be related to the ones for corporate bond spreads to some extent.

In a more recent paper, Dougal, Engelberg, Parsons, and van Wesep (2015) document a path dependence in the behavior of corporate bond spreads in firm loans that is not in line with rational pricing. In particular, the rate at which a loan is granted by banks is influenced by the rate the firm has received for its previous loan. Thus, two comparable firms have to pay different rates today if they have last borrowed at different points in time under different market conditions.

Some studies also zero in on the interaction between corporate bond spreads and the stock market. Chen, Collin-Dufresne, and Goldstein (2009) link the credit spread puzzle to the well-known equity premium puzzle. They provide a potential solution to these puzzles by allowing for correlations between default rates and Sharpe ratios. Han, Subrahmanyam, and Zhou (2015) make use of the term structure of default rates to make predictions about future default risk and profitability for stock trading.

A closely related body of literature deals with the determinants of credit default swaps (CDS). Of these papers, the work of Alexander and Kaeck (2008) is of particular relevance to our case. They analyze the impact of systematic risk factors on the iTraxx Europe and several subindices hereof using a regime switching approach. The evidence provided for the corporate subindex suggests that stock market returns and volatilities as well as changes in the interest rate level affect the corporate CDS market. During times of high volatility, most of the coefficients are larger in size but also of reduced statistical significance compared with coefficients in non-stress periods. Unfortunately, their data sample only covers the period from June 2004 to June 2007, which means excluding the major crises that global financial markets underwent since the beginning of the 2000s. This, in turn, reduces the added value of a regime switching approach.[5]

3 Data

We strive at identifying systematic risk factors driving the corporate bond market as a whole and, thus, we employ broad market indices rather than single bond data. This prevents us from choosing non-representative bonds, minimizes data quality issues immanent in single security time series and reduces arbitrariness from the gathering of data (e.g. the same bond might be traded on different stock exchanges). We choose the Merrill Lynch Euro Corporate one- to ten-year indices as they are available in good quality for a long data history. As different credit qualities might lead to diverging results, we use various credit qualities.

First, we take the index for BBB bonds as it is the lowest available credit quality for our desired index composition and considered maturities. Second, we include the index for AA bonds to capture bonds with very good credit quality as well. However, we do not include AAA indices due to the following two reasons. First, most AAA corporates are backed or (partially) controlled by the government and, therefore, barely differ from our proxy for risk-free investments. Second, the corporates therein are not representative for a broad market as only a very limited number of issuers is AAA-rated in the euro area. The average duration of both bond indices was between four and five years. Five-year bonds are generally known to be the most liquid ones and are used as key rates in many applications. Therefore, we calculate corporate bond spreads for AA and BBB bonds as the difference between the yield of the respective Merrill Lynch bond index and the German five-year Bobl yield, which serves as a proxy for the risk-free interest rate in the euro area.[6]

We use a wide range of 34 economic and financial variables as candidates for the systematic risk factors (see Table 1 at the end of this section). These candidate variables

[5]Other noteworthy papers dealing with determinants of CDS or their relationship with the corporate bond market include Blanco, Brennan, and Marsh (2005), Longstaff, Mithal, and Neis (2005), and Ericsson, Jacobs, and Oviedo (2009).

[6]In addition, as a robustness check, we match the exact duration of the AA/BBB bond index by a linear combination of German government zero yields. To do so, we use German government three-, four- and five-year yields and take the two yields with durations that are adjacent to the AA/BBB bond index's duration.

are the inputs for the BMA described in Section 4. They comprise, amongst many others, stock market returns and implied volatilities since these variables are known to contain information about future corporate earnings (Beaver, Lambert, and Morse (1980), Collins, Kothari, and Rayburn (1987), Brown (1993), Shroff (1999)). Earnings, in turn, exert a direct impact on a firm's default risk in a Merton-style model. In a more indirect way, the same holds true for indicators of economic activity and for commodity prices.

Following the implications of the theoretical work of Longstaff and Schwartz (1995), we also include the risk-free interest rate. Thereby, the same maturity that has been used to calculate the corporate bond spread should be adopted. According to the information on average durations of the spread data described above, the German five-year Bobl yield is used. In particular, higher risk-free interest rates increase the drift of the firm value process under the risk-neutral measure, thereby reducing the probability of default. In essence, this boils down to testing whether the spread is a relative or an absolute surcharge on top of the government bond yield. Put differently, including the corresponding risk-free interest rate is nothing more than a test of the notion that, in an equation for the corporate bond yield change, the coefficient for the change in the government bond yield is equal to one.

Furthermore, expectations about future interest rates matter as well. To account for this, we include the term spread. An additional reason to consider the term spread is that it contains expectations about future economic activity (Estrella and Hardouvelis (1991), Wheelock and Wohar (2009)). We define the term spread as the difference between the German ten- and one-year government yields.[7] We abstain from considering more interest rate variables so as to reduce multicollinearity issues.

In addition, we consider liquidity measures to account for spread changes induced by markets drying up. In line with Collin-Dufresne et al. (2001), we employ the swap-bond basis, the spread between the German five-year government swap rate and the German five-year Bobl yield, to account for liquidity discrepancies between the swap and the bond market (see, for example, Duffie (1999)). Additionally, we use the bid-ask spread of the German five-year government bond (see, for example, Boss and Scheicher (2002)).

We also incorporate a set of economic sentiment indicators such as indices for consumer and industrial confidence as well as composite measures providing a more comprehensive view. This holds particularly true for the "Economic Sentiment Index" calculated by the European commission (EUCOM) which encompasses industrial, service, consumer, construction, and retail trade indicators. Such an index composition can be expected to be a useful measure for future corporate earnings of the companies underlying the bond indices used in this study. First, a combination of industrial, service, and retail confidence appears suitable since the AA and BBB indices are not limited to certain business sectors. Second, Curtin (2007) provides a broad investigation of the predictive ability of consumer surveys for real macroeconomic variables based on 37 countries. His evidence suggests that, in the majority of countries, consumer sentiment has significant forecasting power for GDP, unemployment, personal consumption, and retail sales. Third, the economic sentiment index does not contain a financial market component. Financial

[7] If the only rationale for looking at the spread were expectations about the future path of the five-year rate, the spread should be defined as the slope between the five- and ten-year grid points of the curve. Nevertheless, the expected economic activity argument makes it reasonable to use the one- to ten-year spread.

market surveys such as analyst polls are more closely related to global financial trends and central banking then to the real economic activity.

When choosing the sample period to be considered, we face a trade-off between including as many relevant variables in the preselection process as possible, which is limited by the start date of the respective time series, and using a sample period that is as long as possible to include different economic periods to improve the additional value of the regime switching process. We decide to start in January 2003 and to end in February 2015. This allows us to consider 34 potential systematic risk factors (33 exogenous variables and one lagged dependent variable). We obtain data on a monthly basis to be able to include macroeconomic information that is usually not available for higher data frequencies.

Beforehand, we check candidate variables for unit roots using augmented Dickey-Fuller, Phillips-Perron, and Kwiatkowski-Phillips-Schmidt-Shin tests. We consider a variable to be stationary when the majority of tests suggest so. In the case of a unit root, we use log returns when the level of the variable is likely to increase exponentially over time. If non-stationary variables are bound, be it by definition or by economic intuition, we rely on first differences.

As expected, the corporate bond spreads for the AA as well as the BBB index turn out to be integrated of order one and first differencing appears to be the best way to remove the unit roots. Thus, in what follows, we analyze first differences of spreads. An analysis of the autocorrelation function including the corresponding t-values reveals that, for both rating categories, there is significant first order autocorrelation, while further lags are insignificant. To account for this, the first lag of the spread changes is part of our sample of candidate variables. The full list of the potential systematic risk factors is given in Table 1. The European Commission Employment Expectations Index and the Moody's Commodity Index are taken from Datastream, while the remaining variables are obtained from Bloomberg.

Table 1: Candidate variables for Bayesian model averaging

Variable	Definition	Stationarity method
Merrill Lynch AA Euro Corporate 1-10yr	Yield	First difference
Merrill Lynch BBB Euro Corporate 1-10yr	Yield	First difference
Merrill Lynch AA Euro Corporate 1-10yr (one-month lagged)	Yield, one-month lagged	First difference
Merrill Lynch BBB Euro Corporate 1-10yr (one-month lagged)	Yield, one-month lagged	First difference
Markit Eurozone Composite PMI	The index is constructed from queries on production, orders, inventories, etc.	Log return
Euro area Harmonised Inflation Index	Monthly growth rate represents inflation rate, MoM	Level
Reuters Commodity Index, international	Arithmetic average of commodity futures prices with monthly rebalancing. Currency base: USD	Log return
Unemployment rate	Euro area countries, %	First difference
Euro area export to non-euro area countries	EUR million (exports, nominal value)	Log return
Euro area import from non-euro area countries	EUR million (imports, nominal value)	Log return
EURO STOXX 50	Currency base: EUR	Log return
European Commission Economic Sentiment Index	Reflects industrial, service, consumer, construction, and retail trade confidence indicators	Log return
European Commission Industrial Confidence Index	Scope: 22,950 companies in the euro area, measured in absolute values	First difference
European Commission Consumer Confidence Index	Reflects a broad variety of measures for consumer confidence	First difference
European Commission Euro Area Business Climate Indicator	Indicator is calculated in order to receive a timely composite indicator for the manufacturing sector	First difference
M1 money supply	EUR billion, euro area	Log return
M3 money supply	EUR billion, euro area	Log return
Euro area HICP	Harmonised index of consumer prices, euro area	Log return
Euro area Producer Price Index (PPI), energy	Base year 2010=100	Log return
Industrial production excluding construction	MoM, %, euro area	Level
FX EUR / USD	FX rate	First difference
FX EUR / JPY	FX rate	First difference
FX EUR / GBP	FX rate	First difference
Eurostat Foreign Official Reserves	EUR million, euro area	Log return
CITI Terms of Trade Index	Base currency: USD. Measure of relative performance of commodity import and export prices, euro area	First difference
VSTOXX	EURO STOXX 50 Volatility Index	Level
Brent oil price	USD per barrel	Log return
Reserves-to-Import Ratio	Ratio of Eurostat Foreign Official Reserves and Imports from non-euro area countries	First difference
Rogers Commodity Index	Value of a basket of commodities consumed in the global economy	Log return
Bloomberg Commodity Index	USD, calculated based on excess return basis, reflects commodity futures price movements	Log return
RMI Value-Weighted Corporate Vulnerability Index	Weighted average of RMI PD for corporate entities domiciled in 17 member countries, euro area	First difference
European Commission Employment Expectations Index	Net balance, industry survey	First difference
Moody's Commodity Index	Currency base: USD	Log return
German government bond 5yr	Yield	First difference
Term spread 10yr over 1yr	Difference between the ten-year and one-year yield of German government bonds	First difference
Swap-bond basis 5yr	German government five-year swap rates minus German five-year government bond yields	Level
Bid-ask spread German government bond 5yr	Bid-ask spread taken from an index of a German government bond with a five-year maturity	Level

4 Methodology

Our approach explains corporate bond spread dynamics by systematic risk factors, which need to be selected in a first step. In order to limit arbitrariness when selecting these factors to the greatest extent possible, we apply BMA to a universe of candidate variables (see Section 3). This can be motivated by simulation studies revealing that model averaging leads to models with a better forecast ability than other techniques (see, for example, Raftery, Madigan, and Hoeting (1997), Hayden, Stomper, and Westerkamp (2014)). Given that the sample of candidate variables contains, among other things, all the financial and macroeconomic factors that have a significant impact on corporate bond spreads, the BMA should provide us with a tailor-made set of explanatory variables.

The idea of the BMA is to calculate for a given number of K candidate systematic risk factors - in our case 34 variables as shown in Table 1 - all linear models $M_l, l \in \{1, ..., 2^{34}\}$, consisting of subsets of the systematic risk factors. Instead of including all candidate factors, only those that are deemed to be relevant will be part of the final model. The criterion for including a systematic risk factor is the posterior inclusion probability (PIP), which is given for any component β_h of the parameter vector $\boldsymbol{\beta_{BMA}}$ containing all variables as a weighted sum of each parameter's conditional probabilities over all models

$$PIP := Pr(\beta_h|\boldsymbol{\Delta S}) = \sum_{l=1}^{2^{34}} Pr(\beta_h|M_l) \cdot Pr(M_l|\boldsymbol{\Delta S}), \tag{1}$$

where $\boldsymbol{\Delta S} := [\Delta S_1 \dots \Delta S_T]'$ denotes the vector of credit spread changes that are to be explained by systematic risk factors. We follow the proposal of Raftery (1995) and include only systematic risk factors with a PIP of at least 50%. Obtaining a systematic risk factor's conditional inclusion probability $Pr(\beta_h|M_l)$ is straightforward as this can be done once the corresponding model has been calculated. It is noteworthy that the conditional marginal likelihood $Pr(M_l|\boldsymbol{\Delta S})$ takes into account the goodness of fit as well as the model size (see, for instance, Sala-i-Martin, Doppelhofer, and Miller (2004)).

As at the beginning, a distribution assumption for the regression parameter vector $\boldsymbol{\beta}$ is required, g-priors (see Zellner (1986)) are commonly assumed,

$$\boldsymbol{\beta}|g = N\Big(\mathbf{0}, \Big(\frac{1}{g}\boldsymbol{\Lambda}'\boldsymbol{\Lambda}\Big)^{-1}\Big), \tag{2}$$

where the matrix $\boldsymbol{\Lambda} \in \mathbb{R}^{T \times K}$ contains all T historical observations for the K candidate systematic risk factors. The parameter g makes it possible to consider the degree of a priori certainty, i.e. a smaller value of the parameter implies a lower variance.

In order to set the parameter g, we apply the unit information prior (UIP), which sets $g = T$, and the so-called BRIC,[8] which specifies $g = \max\{T, K^2\}$ (see Fernández, Ley, and Steel (2001), Feldkircher and Zeugner (2009)). Moreover, the Bayesian inference procedure requires assumptions concerning the initial model probabilities $Pr(M_l), l \in \{1, ..., 2^{34}\}$. For this purpose, we run a specification with a uniform and a beta-binomial (random) distribution of the model size. This sums up to four specifications for each rating

[8]This criterion is named BRIC because it combines elements of the Bayesian (BIC) and the residual (RIC) information criterion for selecting a model.

category. Evaluating all models $Pr(M_l|\boldsymbol{\Delta S}), l \in \{1,..,2^{34}\}$, which would mean having to conduct more than 17 billion regressions, proves to be too intricate in computational terms. In order to overcome this issue, we employ the Markov chain Monte Carlo sampler (see, for example, Madigan and York (1995)).

Next, the factor combinations that turned out to be most meaningful based on the BMA are used as explanatory variables for changes in corporate bond spreads. In order to allow for regime dependence, all parameters are subject to Markov switching between two regimes $V_t \in \{1, 2\}$ indicating the state the process is in at time t. The number of states is set equal to two since we want to analyze how the impact of systematic risk factors on corporate bond spread dynamics changes during periods of crisis with high volatility compared to times of routine trading with low volatility. For each model specification with $i \in \{AA, BBB\}$ denoting rating classes, we explain the first difference of the corporate bond spread $\Delta S_{i,t}$ by a vector of parameters $\boldsymbol{\beta_{i,V_t}} := [\beta_{1,V_t} \dots \beta_{N_i,V_t}]'$ related to the N_i (stationary) risk factors $\boldsymbol{X_{i,t}} := [x_{1,t} \dots x_{N_i,t}]'$

$$\Delta S_{i,t} = \alpha_{i,V_t} + \boldsymbol{\beta'_{i,V_t}} \boldsymbol{X_{i,t}} + \epsilon_{i,t}. \tag{3}$$

The variable α_{i,V_t} denotes the regime specific constant. The errors, ϵ_t, are normally distributed with mean zero and state dependent standard deviation, σ_{i,V_t}. Inference about the regime $m \in \{1, 2\}$ in which the process is in at time t, $V_t \in \{1, 2\}$, can be obtained from either the ex-ante probabilities $Pr\,(V_t = m|\Gamma_t)$ based on information available at t, i.e. Γ_t, or from the smoothed probabilities $Pr\,(V_t = m|\Gamma_T)$ exploiting all information up to the end of the sample period T, i.e. Γ_T. The smoothed probability can be regarded as an estimate for a dummy variable indicating the prevailing regime. Put differently, $Pr\,(V_t = m|\Gamma_T)$ corresponds to the probability that the parameter set m applies at time t using the information contained in the entire sample. A measure of the persistence of a regime is given by the transition probabilities $p_{i,11} = Pr\,(V_{t+1} = 1|V_t = 1)$ and $p_{i,22} = Pr\,(V_{t+1} = 2|V_t = 2)$.

For both rating categories, Equation 3 is estimated for the systematic risk factor combinations obtained using the four specifications of the Bayesian model averaging, namely for the UIP and for the BRIC priors, each with a normal (abbreviated as “uni”) and a beta-binomial (random) distribution (abbreviated as “rnd”). In addition to different optimality criteria for the model averaging, we also want to check for robustness with respect to the specification of the Markov switching model. So far, we have used transition probabilities that are constant over time, e.g. $p_{i,11} = Pr\,(V_{t+1} = 1|V_t = 1)$ for state number 1. However, the probability of switching into or staying in a certain regime might change over the sample period depending on financial and macroeconomic conditions. Diebold et al. (1994) derive a version of Markov switching models allowing for time-varying transition probabilities. In their approach, certain exogenous variables govern these probabilities. The relation between these variables and the transition probabilities is modeled using a logistic function,

$$Pr_{i,t}\,(V_{t+1} = m|V_t = m) = \frac{exp\,(\boldsymbol{\kappa_{i,V_t} Z_{i,t}})}{1 + exp\,(\boldsymbol{\kappa_{i,V_t} Z_{i,t}})}, \tag{4}$$

where $\boldsymbol{Z_{i,t}}$ is the matrix of exogenous variables and $\boldsymbol{\kappa_{i,V_t}}$ contains the corresponding parameters. Thus, instead of two constants, p_{11} and p_{22}, there are now two time series, or rather two functions of exogenous variables, $p_{11,t}$ and $p_{22,t}$. Beyond a constant term, we apply the following three explanatory variables. First, changes in the respective corporate bond spread are included since the dynamics of the spread may contain information about changes in the regime in the next period. For instance, a severe widening of the spread may increase the likelihood of switching to a crisis regime. Second, the first difference of the two-year German government bond yield serves as a proxy for monetary policy. We abstain from using shorter maturities because these are related to the money market, which has been subject to structural breaks due to non-standard monetary policy measures over the course of the recent years. Third, we take into account changes in the euro area industrial production as a macroeconomic indicator.

To gather insights into the interaction between the markets for AA and BBB bonds, we also estimate bivariate MSSUR models. From this type of model, two things about the relationship between the two market segments can be inferred. First, it allows us to be mindful of (regime-specific) correlations in the error terms of AA- and BBB-rated bonds. Second, in this setting, both AA and BBB indices are subject to the same regime. Comparing the persistence and time sequence of these regimes with the ones from the univariate models allows us to draw conclusions about the existence of common or distinct regimes for the two credit qualities. Notably, finding that the bivariate approach yields regimes which are significantly less stable than those obtained from the univariate model would lend support to a separate modeling, i.e. distinct regimes for AA and BBB bonds. The bivariate MSSUR model is given by:

$$\Delta S_{AA,t} = \alpha_{AA,V_t} + \boldsymbol{\beta'_{AA,V_t}} \boldsymbol{X_{AA,t}} + \nu_{AA,t} \tag{5}$$

$$\Delta S_{BBB,t} = \alpha_{BBB,V_t} + \boldsymbol{\beta'_{BBB,V_t}} \boldsymbol{X_{BBB,t}} + \nu_{BBB,t} \ . \tag{6}$$

The vector $\boldsymbol{\nu_t} := [\nu_{AA,t} \ \nu_{BBB,t}]'$ follows a bivariate normal distribution,

$$\boldsymbol{\nu_t} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{AA,V_t} & \rho_{V_t} \\ \rho_{V_t} & \sigma^2_{BBB,V_t} \end{bmatrix} \right), \tag{7}$$

where ρ_{V_t} is the regime-dependent correlation coefficient between the idiosyncratic risk of AA and BBB bonds. Analogously to the univariate case, the MSSUR model is estimated using the results of the four specifications as obtained from Bayesian model averaging. Transition probabilities between the states are assumed to be constant, again.

To estimate the univariate and bivariate Markov switching models, we apply the expectation maximization (EM) algorithm (Dempster, Laird, and Rubin (1977), Hamilton (1990)). In the estimation procedure, we use ordinary least squares (OLS) in the case of the univariate models while, for the MSSUR models, the iterative generalized least squares (GLS) procedure (feasible GLS) enables us to take correlations between the AA and BBB indices into account. Closed-form solutions for the estimation step for the logit parameters gathered in $\boldsymbol{\kappa_{i,V_t}}$ of the model with time-varying transition probabilities are provided in Diebold et al. (1994). Although the EM algorithm is extremely robust to the selection of starting values, we try different vectors of initial values to be on the safer side. These are obtained as follows: For each specification, the single-state version is estimated using ordinary least squares. Then, random normal numbers are generated using the means and standard errors of the respective OLS parameter estimates.

5 Empirical results

We start this section with a short overview of the variables included according to different BMA criteria. Next, we present the results of the univariate and bivariate Markov switching models. Finally, we explore the significance of our results in a discussion.

5.1 Model selection

To begin with, we consider the results of the BMA showing us the systematic risk factors that shall explain the AA and BBB corporate bond spreads. As stated above, we include all systematic risk factors that are associated with a posterior inclusion probability of at least 50%.

In the case of the AA spread, this leaves us with two different specifications since the $BRIC_{uni}$, the UIP_{rnd}, and the $BRIC_{rnd}$ criteria yield similar results. The specifications contain the EURO STOXX 50, the unemployment rate, the five-year German Bobl rate, and the term spread. Moreover, the UIP_{uni} adds the "Economic Sentiment Index" from the EUCOM.

For the BBB spread, we end up with three specifications since the $BRIC_{uni}$ and the UIP_{rnd} criteria find the same variable set to be significant. The EURO STOXX 50, the unemployment rate, the exchange rate with the USD, and the "Economic Sentiment Index" from the European Commission are included in all specifications for BBB bonds. The five-year German Bobl rate, the term spread, and the exchange rate with the GBP are in addition included in $BRIC_{uni}$ and UIP_{rnd}. Finally, the lagged BBB spread feeds, in addition to the former seven variables, into the UIP_{uni} specification. Table 2 summarizes the variables included according to the individual BMA specifications.[9]

[9]For assessing the robustness of the variable selection process via BMA, we conduct the forward stepwise regression as well. Out of the 34 candidate variables as shown in Table 1, we include in each step the variable with the highest absolute t-value. We proceed with the inclusion of variables as long as all of these variables remain significant at the 5% level. For AA-rated bonds, the first four included variables correspond to those selected via BMA (EURO STOXX 50, unemployment rate, German government bond 5yr, term spread 10yr over 1yr). In addition, this approach suggests taking into account Moody's Commodity Index and euro area imports from non-euro area countries. However, as the first four variables are identical and as an improvement can only be achieved by increasing the number of selected variables, we deem our variable selection to be robust. In the case of BBB-rated bonds, the stepwise regression leads to the inclusion of EURO STOXX 50, Moody's Commodity Index, lagged BBB spread, unemployment rate and the European Commission's Economic Sentiment Index. Besides Moody' Commodity Index, all variables are included using BMA as well. As the exchange rate of the euro with the USD is assumed to capture - similarly to Moody's Commodity Index - increasing costs, we conclude our variable selection for BBB-rated bonds to be robust. The application of the forward stepwise regression by maximizing the R^2 (instead of the criterion based on the t-value) leads to the same selected variables for AA- and BBB-rated bonds as do the ones based on the t-value.

Table 2: Overview of included explanatory variables

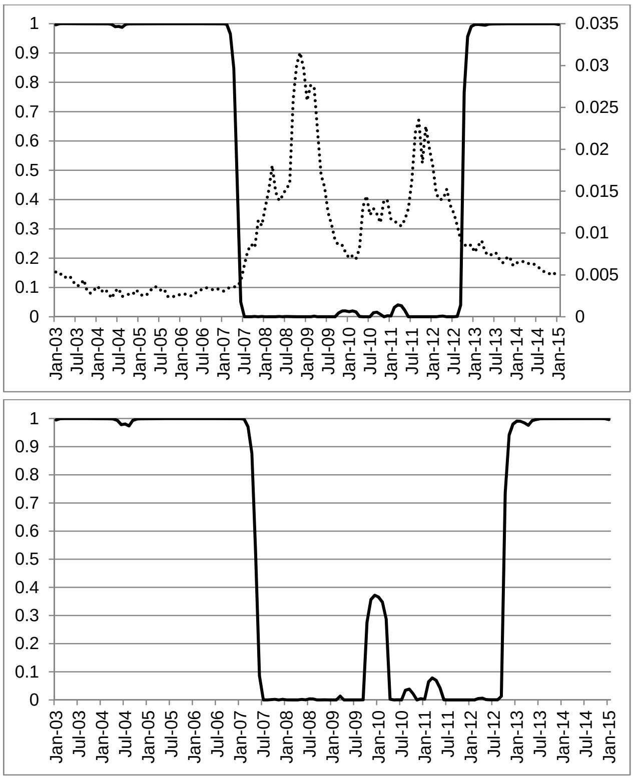
Rating category	UIP_{uni}	$BRIC_{uni}$, UIP_{rnd}, $BRIC_{rnd}$	
AA	EURO STOXX 50	EURO STOXX 50	
	Unemployment rate	Unemployment rate	
	German government bond 5yr	German government bond 5yr	
	Term spread 10yr over 1yr	Term spread 10yr over 1yr	
	EUCOM EcoSent Index		
	UIP_{uni}	$BRIC_{uni}$, UIP_{rnd}	$BRIC_{rnd}$
BBB	EURO STOXX 50	EURO STOXX 50	EURO STOXX 50
	Unemployment rate	Unemployment rate	Unemployment rate
	FX USD / EUR	FX USD / EUR	FX USD / EUR
	EUCOM EcoSent Index	EUCOM EcoSent Index	EUCOM EcoSent Index
	German government bond 5yr	German government bond 5yr	
	Term spread 10yr over 1yr	Term spread 10yr over 1yr	
	FX GBP / EUR	FX GBP / EUR	
	Lagged BBB spread		

Notes: The table shows the variables included according to various BMA criteria.

5.2 Univariate models

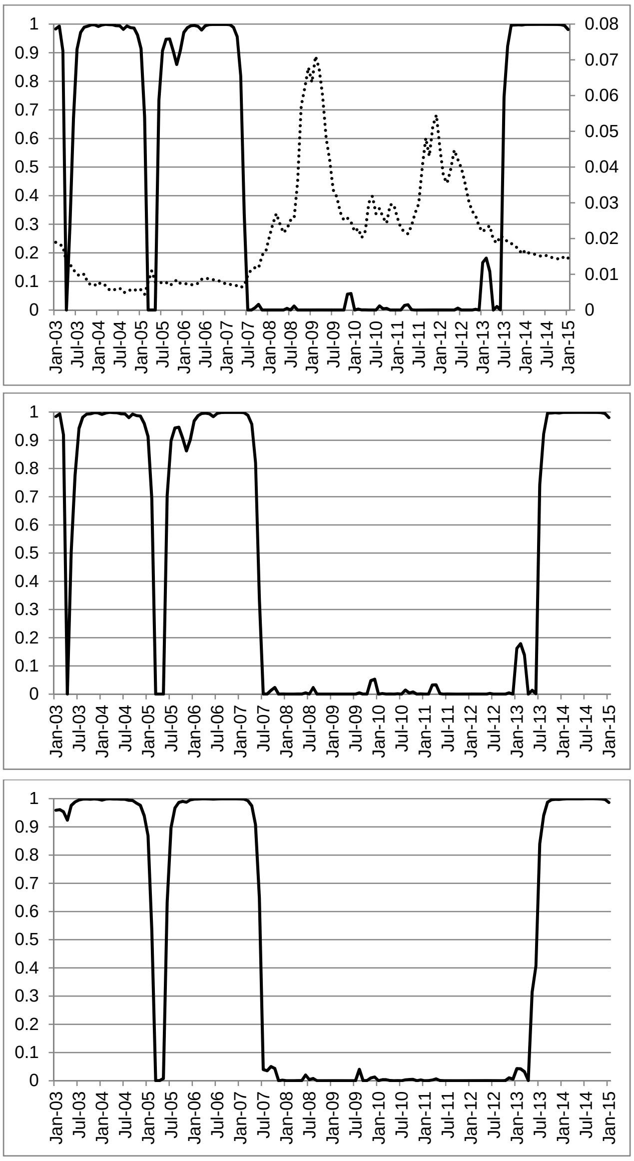
Now, we use the extracted systematic risk factors as explanatory variables for the univariate Markov switching models laid out in Equation 3. Figure 1 (for AA bonds) and Figure 2 (for BBB bonds) depict the development of smoothed probabilities $Pr\left(V_t = 1|\Gamma_T\right)$ over time for the first state which, by definition, always refers to the state with the lower estimate for the standard deviation of error terms, $\sigma_{i,V_t=1}$. Additionally, the first graphs for AA and BBB smoothed probabilities also include the level of the respective spread (right-hand side axis) for comparative purposes.

Figure 1: Smoothed probabilities for the Markov switching models based on the UIP_{uni} (upper figure) and the $BRIC_{uni}/UIP_{rnd}/BRIC_{rnd}$ (lower figure) criteria for the AA spread



The solid line shows the smoothed probabilities for being in the first state calculated as proposed by Kim (1994). The first state refers to the one with the lower estimate for the standard deviation of error terms. The dotted line in the upper figure is the level of the AA spread (right-hand side axis).

Figure 2: Smoothed probabilities for the Markov switching models based on the UIP_{uni} (upper figure), the $BRIC_{uni}/UIP_{rnd}$ (middle figure) and $BRIC_{rnd}$ (lower figure) criteria for the BBB spread



The solid line shows the smoothed probabilities for being in the first state calculated as proposed by Kim (1994). The first state refers to the one with the lower estimate for the standard deviation of error terms. The dotted line in the upper figure is the level of the BBB spread (right-hand side axis).

We find clearly separated regimes for both rating classes. In the case of the AA bonds, the crisis regime - characterized by a significantly higher spread level and volatility - seems to dominate from May 2007 until September 2012, covering the global financial crisis and the European sovereign debt crisis. Mario Draghi's so-called "Whatever it takes" speech on 26 July 2012 seems to be a major turning point here. Before and after that time span, a state with lower volatility prevails.

For BBB-rated bonds, the probabilities indicate that the crisis state is predominant from mid-2007 until mid-2013, thus, it lasts almost one year longer than for better-rated bonds. Unlike for the AA index, there appears to be a short switch to the crisis regime in spring 2005 for the BBB index. This finding is in line with results for US data in Chun et al. (2014b), who also detect more regime shifts for lower rating categories. That time span coincides with a period of political uncertainty in the European Union. First, in March 2005, the Stability and Growth Pact aimed at restricting budget deficits was amended. Second, this period also covers the time of the run-up to and the actual days of election when French and Dutch voters rejected the proposal for the European constitution. It is noteworthy that the regimes extracted by our model are much more stable than the ones in Pavlova et al. (2015) although both samples cover periods before, during, and after the global financial crisis. This may be a consequence of our more sophisticated variable selection process.

We now turn to the analysis of the parameter estimates which are tabulated in Table 3 and Table 4. As expected, the volatility of BBB bonds in a respective high or low volatility regime is always higher than the one for AA-rated bonds, given the same type of regime. As measured by means of statistical significance, the EURO STOXX 50 log return seems to be among the most relevant systematic risk factors. Its impact only lacks significance in the case of the AA bonds when volatility is low. According to the absolute size of parameters and t-values, the stock market generally has a stronger influence when markets are in turmoil. As predicted by theory, signs are always negative, implying that positive returns are related to expectation about higher corporate earnings in the future, which in turn, reduce default probabilities. This is a crucial result suggesting that the systematic component of default risk plays a more important role during times of crisis relative to the idiosyncratic part. By contrast, the findings in Davies (2004) and Pavlova et al. (2015) for the US suggest that the stock market has a significant impact only for parts of the analyzed portfolios and during some regimes.

Table 3: Parameter estimates for the univariate Markov switching models for the AA spread

Rating category	**AA**			
BMA criterion	UIP_{uni}		$BRIC_{uni}/UIP_{rnd}/BRIC_{rnd}$	
	Coeff.	t-value	Coeff.	t-value
$V_t = 1$				
$\hat{\alpha}$	$-1.233 \cdot 10^{-4***}$	(-2.652)	$-1.026 \cdot 10^{-4**}$	(-2.363)
$\hat{\beta}_{EUROSTX}$	-0.001	(-0.818)	-0.001	(-0.715)
$\hat{\beta}_{UNEMPL}$	-0.175^{***}	(-3.084)	-0.176^{***}	(-3.063)
$\hat{\beta}_{GOV_{5yr}}$	-0.153^{***}	(-5.164)	-0.142^{***}	(-4.782)
$\hat{\beta}_{TERM_{10-1yr}}$	-0.016	(-0.356)	-0.016	(-0.355)
$\hat{\beta}_{ECON\_SENT}$	0.006	(1.641)		
$\hat{\sigma}$	$3.485 \cdot 10^{-4}$		$3.568 \cdot 10^{-4}$	
$\hat{p}_{11}$	0.986		0.980	
$V_t = 2$				
$\hat{\alpha}$	$3.130\ 10^{-4}$	(1.431)	$3.031\ 10^{-4}$	(1.320)
$\hat{\beta}_{EUROSTX}$	-0.021^{***}	(-5.507)	-0.024^{***}	(-6.332)
$\hat{\beta}_{UNEMPL}$	-1.119^{***}	(-5.834)	-1.042^{***}	(-5.380)
$\hat{\beta}_{GOV_{5yr}}$	-0.291^{***}	(-3.174)	-0.324^{***}	(-3.481)
$\hat{\beta}_{TERM_{10-1yr}}$	0.244^{***}	(3.211)	0.242^{***}	(3.073)
$\hat{\beta}_{ECON\_SENT}$	-0.017^{*}	(-1.915)		
$\hat{\sigma}$	$1.486 \cdot 10^{-3}$		$1.533 \cdot 10^{-3}$	
$\hat{p}_{22}$	0.983		0.974	
R^2	0.672		0.665	
No. of obs.	145		145	

Notes: t-values are provided in brackets. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. In the EM algorithm, the transition probabilities p_{11} and p_{22} are calculated as a biproduct of the smoothed probabilities. Therefore, no standard errors and, thus, no t-values are available for these parameters. R^2 is regression R squared. R^2 is displayed for descriptive purposes only since our approach does not directly maximize R^2.

Table 4: Parameter estimates for the univariate Markov switching models for the BBB spread

Rating category	**BBB**					
BMA criterion	UIP_{uni}		$BRIC_{uni}/UIP_{rnd}$		$BRIC_{rnd}$	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
$V_t = 1$						
$\hat{\alpha}$	$-2.846 \cdot 10^{-4***}$	(-3.129)	$-2.640 \cdot 10^{-4***}$	(-3.116)	$-1.393 \cdot 10^{-4}$	(-1.375)
$\hat{\beta}_{EUROSTX}$	-0.006**	(-2.469)	-0.006***	(-2.654)	-0.013***	(-5.149)
$\hat{\beta}_{UNEMPL}$	-0.164	(-1.624)	-0.162	(-1.605)	-0.215*	(-1.767)
$\hat{\beta}_{EUR\_USD}$	$-2.230 \cdot 10^{-4}$	(-0.080)	$-2.092 \cdot 10^{-4}$	(-0.075)	-0.001	(-0.253)
$\hat{\beta}_{GOV_{5yr}}$	-0.100*	(-1.812)	-0.100*	(-1.819)		
$\hat{\beta}_{TERM_{10-1yr}}$	-0.163*	(-1.965)	-0.153*	(-1.876)		
$\hat{\beta}_{ECON\_SENT}$	-0.003	(-0.413)	-0.002	(-0.273)	-0.014*	(-1.728)
$\hat{\beta}_{EUR\_GBP}$	-0.004	(-0.531)	-0.004	(-0.513)		
$\hat{\beta}_{\Delta s_{BBB,t-1}}$	-0.068	(-0.803)				
$\hat{\sigma}$	$5.423 \cdot 10^{-4}$		0.001		$6.980 \cdot 10^{-4}$	
$\hat{p}_{11}$	0.944		0.944		0.966	
$V_t = 2$						
$\hat{\alpha}$	$2.167 \cdot 10^{-4}$	(0.711)	$2.238 \cdot 10^{-4}$	(0.724)	$3.808 \cdot 10^{-4}$	(1.057)
$\hat{\beta}_{EUROSTX}$	-0.037***	(-6.413)	-0.035***	(-6.204)	-0.038***	(-5.925)
$\hat{\beta}_{UNEMPL}$	-1.337***	(-4.702)	-1.377***	(-4.801)	-1.249***	(-3.796)
$\hat{\beta}_{EUR\_USD}$	-0.034***	(-4.220)	-0.036***	(-4.399)	-0.025***	(-3.513)
$\hat{\beta}_{GOV_{5yr}}$	-0.365***	(-2.720)	-0.375***	(-2.754)		
$\hat{\beta}_{TERM_{10-1yr}}$	0.325***	(2.769)	0.332***	(2.800)		
$\hat{\beta}_{ECON\_SENT}$	-0.050***	(-3.010)	-0.060***	(-4.112)	-0.093***	(-6.259)
$\hat{\beta}_{EUR\_GBP}$	0.055***	(3.505)	0.056***	(3.548)		
$\hat{\beta}_{\Delta s_{BBB,t-1}}$	0.083	(1.279)				
$\hat{\sigma}$	0.002		0.002		0.003	
$\hat{p}_{22}$	0.955		0.954		0.970	
R^2	0.786		0.782		0.712	
No. of obs.	145		145		145	

Notes: t-values are provided in brackets. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. In the EM algorithm, the transition probabilities p_{11} and p_{22} are calculated as a biproduct of the smoothed probabilities. Therefore, no standard errors and, thus, no t-values are available for theses parameters. R^2 is regression R squared. R^2 is displayed for descriptive purposes only since our approach does not directly maximize R^2.

Changes in the unemployment rate always exert a negative impact on spreads and prove to be significant except for two specifications of BBB bonds during the low volatility state. It holds always true that the corresponding parameter is larger in absolute terms and more significant during times of crisis. The negative impact of the unemployment rate on corporate bond spreads is in line with other studies (see, for example, Goldberg and Leonard (2003)). However, this result is not intuitive at first glance as one would expect better economic conditions (and, thus, a decrease in the unemployment rate) to go along with a higher demand for risky bonds and, therefore, a decrease in the corporate bond spread. Nevertheless, as the unemployment rate usually reacts delayed to the economy, the observed negative impact is possible. An explanation for the negative association could be a short-term positive market reaction following corporate redundancies. Financial markets tend to relate the cost saving through the cut-off in wages with increases in future earnings implying an improvement in the firm's value alongside with a reduction of its default probability.

Changes in the five-year German government yield are always significant when they are included in a model. It happens only in the case of the specification for BBB bonds based on the $BRIC_{rnd}$ criterion that this variable is not part of the model. Otherwise, the estimates for the coefficients are always larger in absolute terms during the volatile state but they differ with respect to whether statistical significance is higher during the volatile or the tranquil state. The sign is always found to be negative, which implies that rising interest rates reduce the spread. This notion is consistent with the implications of the theoretical model put forward by Longstaff and Schwartz (1995) and the empirical findings therein, as well as with Duffee (1998), Collin-Dufresne et al. (2001), Alexander and Kaeck (2008), and Giesecke et al. (2011).

The impact of the term spread turns out to be significantly positive for AA and BBB bonds when the market is in stressed condition. When volatility is low, however, the coefficient for the term spread gets slightly negative and loses its significance in the case of the AA index and is markedly less significant for BBB bonds. Obviously, investors seem to drag more information out of this spread when the going gets tough. The studies on the impact of this variable for the US market come to inconclusive or different results. Pavlova et al. (2015) indicate a consistently inverse relationship between the slope of the term structure and corporate bond spreads, whereas Chun et al. (2014a) report a positive relation. Collin-Dufresne et al. (2001) find the impact of the term spread to be insignificant, and Davies (2004) documents a significant (and negative) effect only for high volatility regimes.

Of the determinants of BBB spread changes, exchange rates seem to play a material role. All specifications for this rating category contain at least the exchange rate with the USD; some also include the GBP exchange rate. These rates are highly significant during periods of crisis, while they completely lack statistical significance when volatility is low. In the case of the USD, a stronger euro is always accompanied by reduced spreads for bonds with a BBB rating when there is stress in the market. Conversely, an appreciation against the GBP during times of high volatility has a positive effect on BBB spreads. These opposing directions of action might be explained as follows. The underlying firms are corporates. Unlike financial firms, many of them are engaged in both merchandize export and import of commodities. Commodities constitute costs and are usually settled in USD. Therefore, a rising USD is associated with increasing costs, on the one hand. On the other hand, however, a stronger USD improves the competitiveness of goods manufactured in the euro area due to the price effect. If the former relation dominates, a USD appreciation increases the default probability of the corporate issuers resulting in a negative estimate for β_{EUR_USD}. In the case of the GBP, the only factor at play is the price impact on merchandize exports and imports which justifies the positive coefficient value.

Several specifications include the Economic Sentiment Indicator of the EUCOM[10] which is an index for economic confidence building itself upon surveys. As argued in Section 3, similar to the EURO STOXX 50, economic confidence can also be considered as an indicator for future corporate earnings. During times of high volatility, the corre-

[10]The indicator is abbreviated with $ECON\_SENT$ in Table 3 to Table 7.

sponding parameters always indicate significantly negative effects, implying that spreads are reduced when investors and economists are in high spirits. When, however, the low volatility state prevails, significance is reduced or eliminated. This outcome corroborates the remark made for the case of the stock market with respect to a more important role of systematic influences on perceived default risk. In some of the specifications for the BBB index, the first lag of the spread change is also included. However, it always lacks significance.

Surprisingly, the set of variables selected by means of BMA does not include any liquidity measures. As a robustness check, we raised the liquidity measures to higher power (up to four) to account for non-linearities.[11] Nevertheless, the employed liquidity measures still prove to be not meaningful enough or, more likely, their impact has already been taken into account by another systematic risk factor.[12]

According to our estimates, the specifications for AA indices are related to a lower R^2 ranging between 66.5% and 67.2% compared with 71.2% and 78.6% for BBB spreads. Compared to the Markov switching models used by Davies (2004) and Pavlova et al. (2015) for the US, our specifications provide a better fit - probably through the more elaborated algorithm for including variables that is also optimizing the coefficient of determination - although we include a comparable number of exogenous variables.

As laid out in Section 3, we perform a robustness check in which we use a linear combination of German government yields exactly matching the bond indices' durations. The obtained results confirm qualitatively and quantitatively our previous findings. In particular, the economic interpretation of the variables' coefficients in both states and the development of regime probabilities over time are corroborated.

The results for the model with time-varying transition probabilities as given in Equation 4 very much confirm the findings from our baseline specifications with fixed transition probabilities. The estimates for both the smoothed probabilities and the parameters belonging to the corresponding regimes essentially mirror those for the models with constant transition probabilities. Chun et al. (2014b) and Pavlova et al. (2015) also try to model the economic determinants of regime switches but do so by analyzing estimated state probabilities in a second step. Such an approach may be misleading as the extracted regimes can be biased when constant transition probabilities are assumed when the true model is governed by time-varying probabilities (Diebold et al. (1994)). We, however, proceed methodologically in a sounder way by incorporating the variables used to explain the switches between regimes within the model.[13]

5.3 Multivariate models

Smoothed probabilities for the bivariate MSSUR model are given in Figure 3 and Figure 4. In this setting, AA and BBB bonds are jointly modeled. The plots show that the smoothed probabilities are fluctuating much more strongly than in the case of the univariate models. In line with that, the estimates for the transition probabilities p_{11} and p_{22} are smaller.

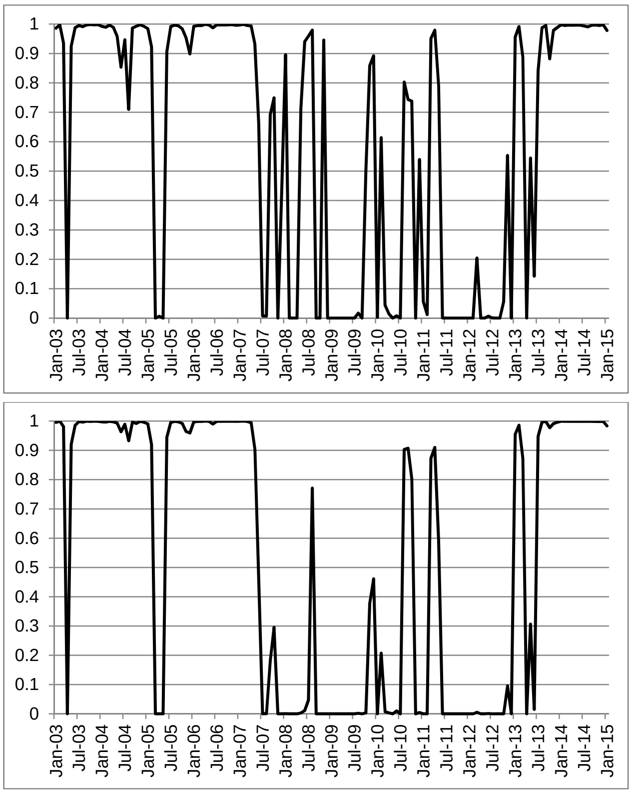
[11] That means that, for a given liquidity proxy x_t (i.e. the five-year swap-bond basis and the bid-ask spread of the five-year German government bond yield), we include not only x_t but also x_t^2, x_t^3, and x_t^4 as candidate variables in the BMA.

[12] Pavlova et al. (2015) use the spread between three-month Treasury and Eurodollar rates as a proxy for aggregate bond market liquidity and find it to be significant in particular for investment-grade bonds.

[13] Detailed results are available on request.

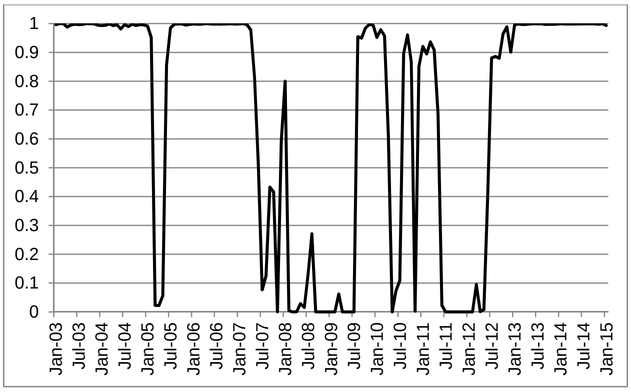
Thus, the states separated using the bivariate MSSUR model seem to be less persistent and clear than the ones obtained from the univariate approaches. This result parallels the above finding that the crisis regimes for AA and BBB bonds in the univariate models (see Figure 1 and Figure 2) are partly distinct from each other. In particular, periods of stress appear to be extended for BBB bonds. In summary, these facts favor separate univariate modeling specifications for different rating categories over of bivariate or multivariate regime switching approaches.

Figure 3: Smoothed probabilities for the bivariate Markov switching model based on the UIP_{uni} (upper figure) and the $BRIC_{uni}/UIP_{rnd}$ (lower figure) criteria for AA and BBB bonds



The solid line shows the smoothed probabilities for being in the first state calculated as proposed by Kim (1994). The first state refers to the one with the lower estimate for the standard deviation of error terms.

Figure 4: Smoothed probabilities for the bivariate Markov switching model based on the $BRIC_{rnd}$ criterion for AA and BBB bonds



The solid line shows the smoothed probabilities for being in the first state calculated as proposed by Kim (1994). The first state refers to the one with the lower estimate for the standard deviation of error terms.

The parameter estimates in Table 5 to Table 7 suggest a picture that is similar to the one painted by the univariate models. In general, systematic risk factors are found to be statistically more significant and coefficients are larger in size during times of increased volatility.[14] The error correlation between AA and BBB indices, ρ_{V_t}, is significantly higher when the low variance regime prevails. This indicates a flight-to-quality behavior. During normal periods, investors seem to consider, to some degree, AA- and BBB-rated bonds as substitutes to each other. Times of crisis then reveal the risky nature of lower-rated bonds, reducing the synchronization with higher-quality debt.[15]

[14]The only exception is the coefficient of the lagged BBB index change, which is more significant during the tranquil state in the case of UIP_{uni}.

[15]Research on differences in the asset correlation between crises and normal periods can be found, for example, in Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005).

Table 5: Parameter estimates for the bivariate Markov switching models for the UIP_{uni} criterion

Rating category	**AA**		**BBB**	
BMA criterion	UIP_{uni}			
	Coeff.	t-value	Coeff.	t-value
$V_t = 1$				
$\hat{\alpha}$	$-9.311 \cdot 10^{-6}$	(-0.217)	$-3.548 \cdot 10^{-5}$	(-0.457)
$\hat{\beta}_{EUROSTX}$	-0.004^{***}	(-3.195)	-0.011^{***}	(-5.031)
$\hat{\beta}_{UNEMPL}$	-0.1414^{**}	(-2.489)	-0.188^{*}	(-1.840)
$\hat{\beta}_{EUR\_USD}$			-0.004^{**}	(-2.319)
$\hat{\beta}_{GOV_{5yr}}$	-0.147^{***}	(-6.094)	-0.207^{***}	(-4.737)
$\hat{\beta}_{TERM_{10-1yr}}$	$2.438 \cdot 10^{-4}$	(0.007)	-0.046	(-0.691)
$\hat{\beta}_{ECON\_SENT}$	-0.007	(- 2.168)	-0.008	(-1.269)
$\hat{\beta}_{EUR\_GBP}$			0.005	(1.073)
$\hat{\beta}_{\Delta S_{BBB,t-1}}$			0.137^{***}	(5.668)
$\hat{\sigma}$	$3.687\ 10^{-4}$		$6.608\ 10^{-4}$	
ρ_{V_t}	0.653			
$\hat{p}_{11}$	0.840			
$V_t = 2$				
$\hat{\alpha}$	$4.573 \cdot 10^{4*}$	(1.768)	$3.118 \cdot 10^{4}$	(0.804)
$\hat{\beta}_{EUROSTX}$	-0.019^{***}	(-4.388)	-0.041^{***}	(-5.987)
$\hat{\beta}_{UNEMPL}$	-1.210^{***}	(-5.545)	-1.310^{***}	(-3.967)
$\hat{\beta}_{EUR\_USD}$			-0.040^{**}	(-4.429)
$\hat{\beta}_{GOV_{5yr}}$	-0.382^{***}	(-3.190)	-0.406^{**}	(-2.215)
$\hat{\beta}_{TERM_{10-1yr}}$	0.263^{***}	(2.992)	0.290^{**}	(2.168)
$\hat{\beta}_{ECON\_SENT}$	-0.017^{*}	(-1.689)	-0.045^{**}	(-2.340)
$\hat{\beta}_{EUR\_GBP}$			0.073^{***}	(4.215)
$\hat{\beta}_{\Delta S_{BBB,t-1}}$			0.118^{*}	(1.699)
$\hat{\sigma}$	$1.569 \cdot 10^{-3}$		$2.337 \cdot 10^{-3}$	
ρ_{V_t}	0.476			
$\hat{p}_{22}$	0.761			
R^2	0.703		0.795	
No. of obs.	145		145	

Notes: t-values are provided in brackets. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. In the EM algorithm, the transition probabilities p_{11} and p_{22} are calculated as a biproduct of the smoothed probabilities. Therefore, no standard errors and, thus, no t-values are available for these parameters. R^2 is regression R squared. R^2 is displayed for descriptive purposes only since our approach does not directly maximize R^2.

Table 6: Parameter estimates for the bivariate Markov switching models for the $BRIC_{uni}$ and the UIP_{rnd} criteria

Rating category	**AA**		**BBB**	
BMA criterion	$BRIC_{uni}/UIP_{rnd}$			
	Coeff.	t-value	Coeff.	t-value
$V_t = 1$				
$\hat{\alpha}$	$-8.520 \cdot 10^{-5**}$	(-1.903)	$-2.229 \cdot 10^{-4***}$	(-2.934)
$\hat{\beta}_{EUROSTX}$	-0.001	(-0.971)	-0.007^{***}	(-3.076)
$\hat{\beta}_{UNEMPL}$	-0.131^{**}	(-2.226)	-0.160	(-1.655)
$\hat{\beta}_{EUR\_USD}$			-0.004^{**}	(-2.523)
$\hat{\beta}_{GOV_{5yr}}$	-0.141^{***}	(-4.879)	-0.148^{***}	(-3.055)
$\hat{\beta}_{TERM_{10-1yr}}$	-0.023	(-0.0543)	-0.122^{*}	(-1.762)
$\hat{\beta}_{ECON\_SENT}$			-0.002	(-0.517)
$\hat{\beta}_{EUR\_GBP}$			-0.004	(-0.867)
$\hat{\sigma}$	$3.477 \cdot 10^{-4}$		$5.714 \cdot 10^{-4}$	
ρ_{V_t}	0.680			
$\hat{p}_{11}$	0.892			
$V_t = 2$				
$\hat{\alpha}$	$3.152 \cdot 10^{-4}$	(1.361)	$2.271 \cdot 10^{-4}$	(0.637)
$\hat{\beta}_{EUROSTX}$	-0.020^{***}	(-5.766)	-0.035^{***}	(-5.889)
$\hat{\beta}_{UNEMPL}$	-1.021^{***}	(-5.198)	-1.383^{***}	(-4.475)
$\hat{\beta}_{EUR\_USD}$			-0.042^{***}	(-5.047)
$\hat{\beta}_{GOV_{5yr}}$	-0.380^{***}	(-4.041)	-0.380^{**}	(-2.505)
$\hat{\beta}_{TERM_{10-1yr}}$	0.243^{***}	(2.981)	0.308^{**}	(2.426)
$\hat{\beta}_{ECON\_SENT}$			-0.060^{***}	(-4.141)
$\hat{\beta}_{EUR\_GBP}$			0.064^{***}	(3.937)
$\hat{\sigma}$	$1.556 \cdot 10^{-3}$		$2.372 \cdot 10^{-3}$	
ρ_{V_t}	0.465			
$\hat{p}_{22}$	0.875			
R^2	0.634		0.804	
No. of obs.	145		145	

Notes: t-values are provided in brackets. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. In the EM algorithm, the transition probabilities p_{11} and p_{22} are calculated as a biproduct of the smoothed probabilities. Therefore, no standard errors and, thus, no t-values are available for these parameter. R^2 is regression R squared. R^2 is displayed for descriptive purposes only since our approach does not directly maximize R^2.

Table 7: Parameter estimates for the bivariate Markov switching models for the $BRIC_{rnd}$ criterion

Rating category	**AA**		**BBB**	
BMA criterion	$BRIC_{rnd}$			
	Coeff.	t-value	Coeff.	t-value
$V_t = 1$				
$\hat{\alpha}$	$1.318 \cdot 10^{-4***}$	(-2.631)	$-3.832 \cdot 10^{-4***}$	(-3.069)
$\hat{\beta}_{EUROSTX}$	-0.004***	(-2.796)	-0.019***	(-6.279)
$\hat{\beta}_{UNEMPL}$	-0.303***	(-4.680)	-0.583***	(-3.749)
$\hat{\beta}_{EUR\_USD}$			-0.007**	(-2.621)
$\hat{\beta}_{GOV_{5yr}}$	-0.194***	(-8.088)		
$\hat{\beta}_{TERM_{10-1yr}}$	0.052	(1.557)		
$\hat{\beta}_{ECON\_SENT}$			-0.004***	(-0.547)
$\hat{\sigma}$	$4.716 \cdot 10^{-4}$		$1.147 \cdot 10^{-3}$	
ρ_{V_t}	0.654			
$\hat{p}_{11}$	0.929			
$V_t = 2$				
$\hat{\alpha}$	$4.117 \cdot 10^{-4}$	(1.282)	$3.957 \cdot 10^{-4}$	(0.803)
$\hat{\beta}_{EUROSTX}$	-0.026***	(-5.862)	-0.035***	(-4.458)
$\hat{\beta}_{UNEMPL}$	-1.172***	(-4.999)	-1.628***	(-4.356)
$\hat{\beta}_{EUR\_USD}$			-0.028***	(-3.616)
$\hat{\beta}_{GOV_{5yr}}$	-0.378***	(-3.380)		
$\hat{\beta}_{TERM_{10-1yr}}$	0.246***	(2.764)		
$\hat{\beta}_{ECON\_SENT}$			-0.135***	(-7.468)
$\hat{\sigma}$	$1.666 \cdot 10^{-3}$		$2.609 \cdot 10^{-3}$	
ρ_{V_t}	0.341			
$\hat{p}_{22}$	0.929			
R^2	0.703		0.795	
No. of obs.	145		145	

Notes: t-values are provided in brackets. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. In the EM algorithm, the transition probabilities p_{11} and p_{22} are calculated as a biproduct of the smoothed probabilities. Therefore, no standard errors and, thus, no t-values are available for these parameters. R^2 is regression R squared. R^2 is displayed for descriptive purposes only since our approach does not directly maximize R^2

5.4 Discussion

Our finding that systematic risk factors play a more vital role during periods of crisis is in line with the results of Davies (2004) for the US although his paper lacks our cautious preselection process for the risk factors. This similarity is interesting since the sample period covered in Davies (2004) does not include the global financial crisis. This supports the notion that increased significance of systematic risk factors during times of market stress may be a more general pattern. This is also somehow corroborated by the finding of Koopman et al. (2009) that rating downgrades are much more related to fundamentals than rating upgrades. Compared with the findings of Alexander and Kaeck (2008) for the European CDS market, the pattern of a stronger impact of systematic risk factors during times of market turbulence is confirmed but more pronounced in our results. According to their findings, coefficients for the corporate iTraxx subindex tend to be larger in absolute size but are also related to lower t-values when market volatility is higher. However, the sample period used in Alexander and Kaeck (2008) spans from June 2004 to June 2007, excluding the global financial crisis. Thus, the regimes extracted in their paper are more related to times of low and mediocre volatility than to low and high like in our case. Chun et al. (2014a) comes to the finding that, in general, the functional relationship between corporate bond spreads and a given determinant can change between the two states - it can become stronger, weaker or even reverse. Again, this ambiguity is clear evidence that determinants for corporate bond spreads should be modeled regime-dependent. However, the lack of clarity in the findings and several insignificant variables in the paper make drawing further conclusions difficult.

6 Conclusion

This paper investigates whether and to what extent the relation between corporate bond spreads and the underlying risk factors differs between times of market stress and normal periods. Unlike existing papers dealing with this topic, we are the first to consider the European market. As US firms rely, in comparison to European ones, much more on bond funding than on bank loans, simply transferring the US results would seem doubtful.

Another point that makes our study unique is that we choose risk factors via BMA, a tool to facilitate the objective selection of explanatory variables. The usage of four different optimality criteria for the BMA serves as a way to ensure the robustness of this approach. This elaborated variable selection process leads to mainly significant parameter estimates and to high coefficients of determination - the vast amount of literature seems to come to less clear findings than we do. Interestingly, our results reveal some differences compared to former studies. We include an economic sentiment indicator and the unemployment rate in our models - variables which have barely been considered for US data. Moreover, our liquidity measures proved to be irrelevant based on BMA. Conceivably, the liquidity component has already been captured by another risk factor. The remaining selected systematic risk factors are in line with the literature and cover stock market returns and various term structure variables, among others.

Markov switching techniques enable an endogenous separation of low and high volatility regimes based upon the data. Put differently, we examine differences in the way the preselected systematic risk factors affect corporate bond spreads under stressed and under normal market conditions. This is of particular interest because the global financial crisis revealed clearly that corporate bond spreads can change by far more than the pure credit risk component would suggest.

Our analysis of euro-denominated AA and BBB bond indices reveals a clear separation between normal market conditions, on the one hand, and periods of crisis and excessive volatility, on the other. The crisis regime covers the time of the global financial crisis as well as the European sovereign debt crisis. Our evidence suggests a stronger linkage between bond prices and fundamentals when the market is in turmoil - this is in line with previous findings for the US market. When a high volatility regime prevails, coefficients of systematic risk factors are larger in absolute terms and statistically more significant. These results are corroborated by the implemented Markov switching model with time-varying transition probabilities. In this setting, the transition between the regimes is governed by changes in the corporate bond spread and variables intended to capture monetary policy and macroeconomic conditions. Consequently, the systematic component of default risk plays a more important role during times of crisis relatively to the idiosyncratic part.

Our findings suggest that bond market investors tend to rely more on fundamental-based pricing when they face times of crisis. Further, the strong linkage to systematic risk factors during times of crisis can make bond market investors particularly vulnerable to movements of the stock market and changes in the overall economic condition. Moreover, our evidence reveals that the regimes governing AA and BBB bonds are partly distinct. In particular, crisis regimes tend to be longer lasting in the case of BBB bonds.

Our results call for a thorough and prudent treatment of corporate bond spread risk to strengthen the resilience of banks and other financial intermediaries. The enhanced regulatory standards for banking book instruments by the BCBS seem to be a step in the right direction.

References

Alexander, C. and A. Kaeck (2008). Regime dependent determinants of credit default swap spreads. *Journal of Banking & Finance 32(6)*, 1008–1021.

BCBS (2009). *Guidelines for computing capital for incremental risk in the trading book*. Bank for International Settlements.

BCBS (2016a). *Interest rate risk in the banking book*. Bank for International Settlements.

BCBS (2016b). *Minimum capital requirements for market risk*. Bank for International Settlements.

Beaver, W. H., R. A. Lambert, and D. Morse (1980). The information content of security prices. *Journal of Accounting and Economics 2(1)*, 3–28.

Blanco, R., S. Brennan, and I. W. Marsh (2005). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. *Journal of Finance 60(5)*, 2255–2281.

Boss, M. and M. Scheicher (2002). The determinants of credit spread changes in the euro area. In *BIS Papers No 12: Market functioning and central bank policy*, pp. 181–199. Bank for International Settlements, Basel.

Brown, L. D. (1993). Earnings forecasting research: its implications for capital markets research. *International Journal of Forecasting 9(3)*, 295–320.

Campbell, J. Y. and G. B. Taksler (2003). Equity Volatility and Corporate Bond Yields. *Journal of Finance 58(6)*, 2321–2349.

Chen, L., P. C. Collin-Dufresne, and R. S. Goldstein (2009). On the Relation Between the Credit Spread Puzzle and the Equity Premium Puzzle. *Review of Financial Studies 22(9)*, 3367–3409.

Chun, O. M., G. Dionne, and P. François (2014a). Credit spread changes within switching regimes. *Journal of Banking & Finance 49*, 41–55.

Chun, O. M., G. Dionne, and P. François (2014b). Detecting Regime Shifts in Credit Spreads. *Journal of Financial and Quantitative Analysis 49(5-6)*, 1339–1364.

Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin (2001). The Determinants of Credit Spread Changes. *Journal of Finance 56(6)*, 2177–2207.

Collins, D. W., S. P. Kothari, and J. D. Rayburn (1987). Firm size and the information content of prices with respect to earnings. *Journal of Accounting and Economics 9(2)*, 111–138.

Corsetti, G., M. Pericoli, and M. Sbracia (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. *Journal of International Money and Finance 24(8)*, 1177–1199.

Curtin, R. (2007). Consumer Sentiment Surveys: Worldwide Review and Assessment. *Journal of Business Cycle Measurement and Analysis 3(1)*, 7–42.

Davies, A. (2004). Credit Spread Modeling with Regime-Switching Techniques. *Journal of Fixed Income 14(3)*, 36–48.

Dempster, A. P., N. M. Laird, and D. B. Rubin (1977). Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society. Series B (Methodological) 39(1)*, 1–38.

Diebold, F. X. ., J. H. Lee, and G. C. Weinbach (1994). *Nonstationary Time Series Analysis and Cointegration*, Chapter Regime switching with time-varying transition probabilities, pp. 283–302. Oxford: Oxford University Press.

Dougal, C., J. Engelberg, C. A. Parsons, and E. D. van Wesep (2015). Anchoring on Credit Spreads. *Journal of Finance 70(3)*, 1039–1080.

Driessen, J. (2005). Is Default Event Risk Priced in Corporate Bonds? *Review of Financial Studies 18(1)*, 165–195.

Duffee, G. R. (1998). The Relation Between Treasury Yields and Corporate Bond Yield Spreads. *Journal of Finance 53(6)*, 2225–2241.

Duffie, D. (1999). Credit Swap Valuation. *Financial Analysts Journal 55(1)*, 73–87.

Elton, E. J., M. J. Gruber, D. Agrawal, and C. Mann (2001). Explaining the Rate Spread on Corporate Bonds. *Journal of Finance 56(1)*, 247–277.

Ericsson, J., K. Jacobs, and R. Oviedo (2009). The Determinants of Credit Default Swap Premia. *Journal of Financial and Quantitative Analysis 44(1)*, 109–132.

Estrella, A. and G. A. Hardouvelis (1991). The Term Structure as a Predictor of Real Economic Activity. *Journal of Finance 46(2)*, 555–576.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33(1)*, 3–56.

Feldkircher, M. and S. Zeugner (2009). Benchmark Priors Revisited: On Adaptive Shrinkage and the Supermodel Effect in Bayesian Model Averaging. *IMF Working Paper 09/202*.

Fernández, C., E. Ley, and M. Steel (2001). Benchmark priors for Bayesian model averaging. *Journal of Econometrics 100(2)*, 381–427.

Forbes, K. J. and R. Rigobon (2002). No contagion, only interdependence: measuring stock market comovements. *Journal of Finance 57(5)*, 2223–2261.

Giesecke, K., F. A. Longstaff, S. Schaefer, and I. Strebulaev (2011). Corporate bond default risk: A 150-year perspective. *Journal of Financial Economics 102(2)*, 233–250.

Goldberg, L. and D. Leonard (2003). What Moves Sovereign Bond Markets? The Effects of Economic News on U.S. and German Yields. *Current Issues in Economics and Finance 9(9).*

Hamilton, J. D. (1990). Analysis of time series subject to changes in regime. *Journal of Econometrics 45(1-2)*, 39–70.

Han, B., A. Subrahmanyam, and Y. Zhou (2015). The Term Structure of Credit Spreads and the Cross-Section of Stock Returns. *Rotman School of Management Working Paper No. 2560693* .

Hayden, E., A. Stomper, and A. Westerkamp (2014). Selection versus averaging of logistic credit risk models. *Journal of Risk 16(5)*, 39–52.

Huang, J. and M. Huang (2012). How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk? *Review of Asset Pricing Studies 2(2)*, 153–202.

Jarrow, R. A. and S. M. Turnbull (1995). Pricing Derivatives on Financial Securities Subject to Credit Risk. *Journal of Finance 50(1)*, 53–85.

Kim, C. J. (1994). Dynamic Linear Models with Markov-Switching. *Journal of Econometrics 60(1-2)*, 1–22.

Koopman, S. J., R. Kräussl, A. Lucas, and A. B. Monteiro (2009). Credit cycles and macro fundamentals. *Journal of Empirical Finance 16(1)*, 42–54.

Longstaff, F. A., S. Mithal, and E. Neis (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *Journal of Finance 60(5)*, 2213–2253.

Longstaff, F. A. and E. S. Schwartz (1995). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *Journal of Finance 50(3)*, 789–819.

Madigan, D. and J. York (1995). Bayesian graphical models for discrete data. *International Statistical Review 63(2)*, 215–232.

Merton, R. C. (1974). ON THE PRICING OF CORPORATE DEBT: THE RISK STRUCTURE OF INTEREST RATES. *Journal of Finance 29(2)*, 449–470.

Pavlova, I., A. M. Hibbert, J. R. Barber, and K. Dandapani (2015). Credit Spreads and Regime Shifts. *Journal of Fixed Income 25(1)*, 58–74.

Raftery, A. (1995). Bayesian Model Selection in Social Research. *Sociological Methodology 25*, 111–163.

Raftery, A., D. Madigan, and J. Hoeting (1997). Bayesian Model Averaging for Linear Regression Models. *Journal of the American Statistical Association 92(437)*, 179–191.

Sala-i-Martin, X., G. Doppelhofer, and R. I. Miller (2004). Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *The American Economic Review 94(4)*, 813–835.

Shroff, P. K. (1999). The Variability of Earnings and Non-Earnings Information and Earnings Prediction. *Journal of Business Finance & Accounting 26(7-8)*, 863–882.

Wheelock, D. C. and M. E. Wohar (2009). Can the Term Spread Predict Output Growth and Recessions? A Survey of the Literature. *Federal Reserve Bank of St. Louis Review 91(5)*, 419–440.

Zellner, A. (1986). On assessing prior distributions and Bayesian regression analysis with g prior distributions. In P. Goel and A. Zellner (Eds.), *Bayesian Inference and Decision Techiques - Essays in Honor of Bruno de Finetti*, pp. 233–243. Elsevier, Amsterdam.