Determinants of Credit Spread Changes within Switching Regimes

Georges Dionne — HEC Montreal

Pascal François — HEC Montreal

Olfa Maalaoui* — HEC Montreal

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Abstract

Empirical studies on credit spread determinants consider a single regime over the entire sample period while the evidence often supports switching regimes in the credit spread dynamics. We show that accounting for different regimes enhances the explanatory power of credit spread determinants. The regimes are modelled independently from macroeconomic fundamentals, within an unobserved Markov Chain process. They produce a credit cycle that is much longer than the economic cycle. The connection between these two cycles reveals interesting economic relations that affect the contribution of credit spread determinants. This result is hidden in the single regime model. We find that by accounting for different regimes we explain up to 60% of the 10-year AA to BB credit spread changes.

Keywords: Credit spread, switching regimes, default and non default components, credit cycles, economic cycles.

EFM Classification: 340, 450
JEL Classification: C11, C32, C52, C61, G12, G13

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1 Introduction

Explaining observed credit spreads is still puzzling even after the huge number of theoretical and empirical works on this subject. The reason is that the observed credit spreads, defined as the yield difference between risky corporate bonds and riskless bonds, tend to be larger than default spreads or what would be implied by only default risk. For example, Elton et al. (2001) argue that default risk factors implicit in credit ratings and historical recovery rates account for a small fraction of observed credit spreads. Huang and Huang (2003) document the same problem when they calibrate various existing structural models to be consistent with data on historical default loss experience.[1] They claim that no consensus has emerged from the existing credit risk literature on how much of the observed corporate spreads over Treasury yields can be explained by credit risk.

To address this puzzle, many parallel and subsequent studies investigate the ability of non default risk factors (such as market, liquidity and firm-specific factors) to explain credit spread differentials. These studies include those of Collin-Dufresne et al. (2001), Driessen (2003), Campbell and Taksler (2003), Huang and Kong (2003), Longstaff et al. (2005), and Han and Zhou (2006) among others. However, even after accounting for non default factors the puzzle remains unsolved because a large proportion of credit spreads remains unexplained. Collin-Dufresne et al. (2001) find that "variables that should in theory determine credit spread changes in fact have limited explanatory power." They have also detected a single common factor that potentially could explain the large part of the unexplained changes. However, several macro-economic and financial candidates fail to measure it.

In this paper, we readdress the credit spread determinants with special attention paid to the behavior of credit spread series. If credit spreads are significantly driven by a systematic factor, then their time series should exhibit a counter-cyclical behavior (Koopman and Lucas, 2005; Tang and Yan, 2006 and 2008 and David, 2008; among others). Previous work has brought to light the negative serial correlation between credit spreads and macroeconomic conditions. From this vein of literature arises the recent debate on the relation between the

[1] See also Delianedis and Geske (2001) and Amato and Remolona (2003) who reach the same results using similar approaches.

credit cycle and the economic cycle. The classical thinking is that the credit cycle is driven by macroeconomic fundamentals (see for example Koopman and Lucas, 2005; Koopman et al., 2006). However, Lown and Morgan (2006) have suggested that the credit cycle may also affect the course of the economic cycle. To further investigate this relation, recent contributions apply switching regime models to capture state dependent movements in the credit spread dynamic (Davies, 2004 and 2007; Alexander and Kaeck, 2007; David, 2008). Yet, the connection between the states identified and the economic cycle remains unclear (Alexander and Kaeck, 2007; David, 2008).

A key feature of this paper is to show that this connection affects the contribution of different factors in explaining credit spread changes. It is worth noting that this study is not meant to document the nature of this connection. We rather support the fact that a systematic shock affects the behavior of credit spreads and macroeconomic fundamentals in different ways. Specifically, it appears that credit spread dynamics is strongly persistent in the face of economic shocks. Indeed, this persistence of the credit cycle over the economic cycle helps explain why previous studies have failed to agree about the exact impact of systematic factors on credit spreads (Elton et al. 2001; Campbell and Taksler, 2003; Elizalde, 2005; Avramov et al., 2007; among others).

Following Engle and Hamilton (1990), we first model any given monthly change in the credit spread rate as deriving from two regimes, which could correspond to episodes of high or low credit spreads. The regime at any given date is presumed to be the outcome of an unobserved Markov Chain. We characterize the two regimes and the probability law for the transition between regimes. The parameter estimates can then be used to infer in which regime the process was at any historical date. Particularly, the obtained regime-switching structure characterizes our specification of the credit cycle. This is done for several rating categories and maturity dates. Second, we examine the determinants of credit spread changes in the presence and absence of different regimes. We show that interaction effects of these determinants with credit spread regimes reveal interesting economic relations hidden in the single regime model. Our general findings suggest that accounting for different regimes to analyze credit spread determinants increases the explanatory power up to 60% for the 10-year

AA to BB spreads.

A number of theoretical papers use regime switches to price credit risk. A common feature of these models is to adopt a Merton structural form model combined with a Markov regime switching process to capture the impact of the transition of macroeconomic conditions and different states of economic cycles on the market value of the firm. Hackbarth et al. (2006) were among the first to study the impact of macroeconomic conditions on credit risk and dynamic capital structure within this framework. Bhamra et al. (2007), Chen (2008), and David (2008) allow for regime switching in macroeconomic fundamentals to capture the uncertainty in the business cycle. All these works attempt to match the level of historical credit spreads by assuming significant variation in the market price of risk over the economic cycle. Our study is different from these works because we model the regime switching structure for credit spreads independently from macroeconomic fundamentals. In other words, the credit cycle and the economic cycle are derived separately. This approach allows us to examine how the connection between these two cycles may weaken the explanatory power of key determinants of observed credit spread changes.

Empirical works on credit spread determinants consider only one credit spread regime even though the sample period may contain more than one. Considering a single regime may lead to conflicting results if the high credit spread episode following a systematic shock is longer than the economic cycle. Over our sample period, we find that economic shocks generate sticky high credit spreads. This stickiness produces a credit cycle that is longer than the NBER economic cycle. Moreover, credit spreads are still increasing after the end of the economic cycle. As a result, the predicted signs of factors that are closely related to the economic cycle are reversed between the end of the economic cycle and the end of the credit cycle. We show that these patterns are hidden in the single regime model. Moreover, within this model the total effect of these factors may be offset over the entire sample period. Therefore, by accounting for different regimes, we explain the observed credit spreads better than existing empirical models and help solving the empirical puzzle discussed earlier.

Overall, our results suggest that the level, the VIX volatility, the recovery rate, and illiquidity factors are mostly driven by the economic cycle. They affect the credit spread with the predicted sign in the low credit spread episode and are likely to be of opposite sign in the high credit spread episode. We also find that the slope, the realized default probability and the bond age are all closely associated with the credit cycle. Their predicted signs remain the same in both regimes. Moreover, as credit rating becomes higher, the level and the slope are the dominant factors that capture the variation of credit spread changes in both regimes and, as credit rating becomes lower, the VIX volatility, the expected recovery rate and illiquidity factors become the principal factors. Finally, the default and nondefault factors considered may account respectively for 51.15%, 50.51%, 52.59%, and 43.26% of the variation of AA, A, BBB, and BB credit spreads with 10 remaining years-to-maturity. When different factors are considered for different regimes, these explanatory powers improve and attain respectively 55.37%, 60.43%, 63.56%, and 47.07%.

The rest of the paper is organized as follows. Section 2 documents the credit spread behavior and motivates our analysis of more than one credit spread regime. Section 3 lists the credit spread determinants considered in this study. In Section 4, we describe the corporate bond data. Section 5 describes the algorithm used to extract the term structure of observed credit spreads. In section 6, we model endogenously credit spread regimes. Sections 7 and 8 present the estimation procedure and the empirical results. Section 9 concludes.

2 Regimes in credit spreads

Time series of credit spreads undergo successive falling and rising episodes over time. These episodes can be observed in changes in the level and/or the volatility of credit spreads especially around an economic recession. A striking example is shown in Figure 1. The figure plots the time series of 3-, 5-, and 10-year AA to BB credit spreads from 1994 to 2004. Our sample period covers the 2001 NBER recession (shaded region).

[Insert Figure 1 here]

Across ratings and maturities, the credit spread movements exhibit at least two different regimes in terms of sudden changes in their level and/or volatility over the period considered. We can at least distinguish a shift in the credit spread level over this period. Specifically, the level of corporate - swap yield spreads exceeds 200 bps in the period of 2001 to 2004 while it remains at less than 100 bps from 1995 to late 2000. A level of 200 bps is also observed in 1994. Dionne et al. (2008) apply a nonparametric regime shift detection technique to the same data and over the same period. This technique is based on structural statistical tests to detect shifts in the mean and the variance of credit spreads. The method has the advantage of letting the data speak and reveal possible breakpoints in real time. Their results for 3-, 5-, and 10-year AA to BB spreads suggest that the detected shifts for the mean and the variance – taken together – support the existence of two regimes over the period considered. Accordingly, two state dependent regimes may be adequate to capture most of the variation in credit spread series. This motivates our choice of two regimes over the period considered.

Closer inspection of Figure 1 indicates that, just before the 2001 recession, credit spreads shift from a low episode to a high episode. The high episode characterizing the credit cycle seems to be closely linked to the economic cycle since both cycles appear to start at almost the same time. However, the credit cycle looks to be longer than the economic cycle. Actually, the NBER recession starts in March 2001 and ends after eight months in November 2001 while credit spread levels remain high for several more years especially for long maturity bonds. When applied to the 1991 recession, the same scenario can explain the high credit spread level observed in late 1994. In addition, around the 2001 recession, credit spreads for low grade bonds start to slope upward until mid-2003 and then take a downward slope until the end of 2004. Since the end of the recession occurred in November 2001 but was officially announced in July 2003, an announcement effect might have triggered the credit spread behavior in the high episode. Additionally, the upward sloping – especially for BBB and BB spreads – looks to start before March 2001 while the begining of the recession was only announced in November 2001. These observations raise more doubts on whether the recession leads the high spread levels or the reverse (David, 2008). Thus, time-variation in credit spreads may not be driven by observed macroeconomic fundamentals.

A good understanding of the high credit spread level around the recession may also explain why key determinants of credit spreads have rather limited explanatory power. Chen (2008) pointed out that understanding the high credit spreads in recessions is key to solving the credit spread puzzle. Observed high credit spread levels around the recession may be explained by investor's uncertainty about the future state of the economy. In our case, between November 2001 and July 2003, bondholders act as if the recession is still there. After this period, investors learn about the coming state of the economy and credit spreads start to slope down but with some persistence especially for high grade bonds. This persistence is documented in Duffee (1998). He shows that yield spreads appear to persist for more than a year to adjust to new information in the economy.

Additionally, at that same period, the real GDP which is viewed by the NBER as the best measure of the aggregate economic activity started an expansion in November 2001. The increase of the GDP since November 2001 affects factors closely associated with the economic cycle such as the interest rate level, the market volatility and the Fama-French factors among others while credit spreads are still in recession. As a result, factors that are most affected by the behavior of the real GDP level will not have the predicted sign effects on credit spreads in the period between the end of the recession and the end of the high episode. This suggests that the relation between yield spreads and factors closely linked to the economic cycle should have the opposite sign in the high episode. In the same spirit, the relation between yield spreads and factors closely linked to the credit cycle should maintain the same sign in both episodes.

Further, key determinants in the low and high episodes may be different. Those that are strongly affected by economic shocks are expected to be the most significant in high episodes. However, in the single regime model these factors may have limited explanatory power. For example, if the whole period contains few months in the high episode and longer months in the low episode, factors that are less volatile or deterministic, like variables related to bond characteristics, will form the most important factors overall. In the opposite case, only factors that are originally stochastic or volatile will dominate in the high episode and also overall. Moreover, if these factors behave inversely in two different regimes, their global effect may be offset in the single regime model. Therefore, it appears appealing to examine the credit spread determinants in distinct regimes.

3 Credit spread determinants

The credit spread on corporate bonds is the extra yield offered to investors to compensate them for a variety of risks: 1) The market risk due to the uncertainty of macroeconomic conditions; 2) The default risk which is related to the investor's exposure to default and loss given default; 3) The liquidity risk which is due to shocks in the supply and demand for liquidity in the corporate bond market. Therefore, we decompose credit spread determinants into market factors, default factors and liquidity factors.

3.1 Market factors

3.1.1 Term structure level and slope

Factors driving most of the variation in the term structure of interest rates are changes in the level and the slope. The level and the slope are measured using the Constant Maturity Treasury (CMT) rates. We use the 2-year CMT rates for the level and the 10-year minus the 2-year CMT rates for the slope. The CMT rates are collected from the U.S. Federal Reserve Board and the CMT curves for all maturities are estimated using the Nelson-Siegel algorithm.

Within the structural framework, the level affects the default probability and credit spreads. Lower interest rates are usually associated with a weakening economy and higher credit spreads. The predicted relation between the level and credit spreads is negative (Longstaff and Schwartz, 1995). In general, the effect of an interest rate change is always stronger for bonds with higher leverage (Collin-Dufresne et al., 2001). Because firms with a higher debt level often have a lower rating, this effect should be stronger for bonds with lower rating.

The slope is seen as a predictor of future changes in short term rates over the life of the long term bond. If an increase in the slope increases the expected future short rate, then by the same argument, it should decrease credit spreads. A positively sloped yield curve is associated with an improving economic activity. This may in turn increase a firm's growth rate and reduce its default probability and credit spreads.

3.1.2 The GDP growth rate

The real GDP growth rate is among the main factors used by the NBER in determining periods of recession and expansion in the economy. Empirical evidence indicates that credit spreads exhibit a counter-cyclical behavior. During periods of economic downturn, credit spreads are expected to increase as investors become more risk averse and firms have lower asset returns (see for example Huang and Kong, 2003; and Chen, 2008). We therefore expect a negative relation between the GDP growth rate and credit spreads. The estimates of real GDP growth rates provided by the Bureau of Economic Analysis (BEA) of the U.S. department of commerce are only available quarterly. We use a linear interpolation to obtain monthly estimates.

3.1.3 Stock market return and volatility

Unlike the GDP growth rate, aggregate stock market returns are a forward looking estimate of macroeconomic performance. A higher (lower) stock market return indicates market expectations of an expanding (recessing) economy. Previous empirical findings suggest that credit spreads decrease in equity returns and increase in equity volatility (see for example Campbell and Taksler, 2003). To measure stock market performance, we use returns on the S&P 500 index and the return volatility implied in the CBOE VIX index which is based on the average of eight implied volatilities on the S&P100 index options. Data is collected from DATASTREAM. We also include the S&P 600 Small Cap (SML). The SML measures the performance of small capitalisation sector of the U.S. equity market. It consists of 600 domestic stocks chosen for market size, liquidity and industry group representation.

3.1.4 Market price of risk

A higher price of risk should lead to a higher credit spread reflecting the higher compensation required by investors for holding a riskier security (Collin-Dufresne et al. 2001; Chen, 2008). We use the Fama-French SMB and HML factors. A larger spread would indicate a higher required risk premium, which should directly lead to a higher credit spread.

3.2 Default factors

3.2.1 Realized default rates

It is well documented that high default rates are associated with large credit spreads (see for example Moody's, 2002). To measure default rates, we use Moody's monthly trailing 12-month default rates for all U.S. corporate issuers as well as for speculative grade U.S. issuers over our sample period. Because the effective date of the monthly default rate is on the first day of each month, we take the month (t) release to measure the month $(t-1)$ trailing 12-month default rates.

3.2.2 Recovery rates

Empirical studies on the recovery of defaulted corporate debt look at the distressed trading prices of corporate debt upon default.[2] Moody's looks at these prices one month after default.[3] We use the Moody's monthly recovery rates from Moody's Proprietary Default Database for all U.S. Senior Unsecured issuers as well as Senior Subordinated issuers over our sample period. We also include month $(t+2)$ recovery rates as a measure of the expected rates for both seniority classes. Because recovery rates are calculated around one month after default, we take month (t) release to measure month $(t-1)$ recovery rates.

Recovery rates decrease in period of recession and when non-defaulted firms in the industry become more illiquid. Thus the recovery rate is also associated with the prevalence of illiquid market.

3.3 Liquidity factors

Liquidity is not observed directly and has a number of aspects that cannot be captured by a single measure. Illiquidity reflects the impact of order flow on price of the discount that a

[2] See for example Altman and Kishore (1996), Hamilton and Carty (1999), Altman et al. (2001), Griep (2002), and Varma et al. (2003).

[3] The distressed trading prices reflect the present value of the expected payments to be received by the creditors after firm reorganization. Therefore, these prices are generally accepted as the market discounted expected recovery rates. Recovery rates measured in this way are most relevant for the many cash bond investors who liquidate their holdings shortly after default based on their forecasts of the expected future recovery rates.

seller concedes or the premium that a buyer pays when executing a market order (Amihud, 2002). Because direct liquidity measures are unavailable, most existing empirical studies typically use transaction volume and/or measures related to the bond characteristics such as coupon, size, age, and duration. Measures related to bond characteristics are typically either constant or deterministic and may not capture the stochastic variation of liquidity. Amihud (2002) suggests more direct measures of liquidity involving intra-daily transaction prices and trade volumes.[4]

Clearly, any candidate metric for liquidity, using only daily prices, could have an impact on credit spreads because the latter is measured from these prices. Therefore, we use daily transaction prices available on the NAIC database rather than intra-daily prices from TRACE because data in the latter source starts in 2002 and do not cover our sample period. We construct liquidity measures based on the price impact of trades and on the trading frequencies.

3.3.1 Liquidity measures based on price impact of trades

The Amihud illiquidity measure This measure is defined as the average ratio of the daily absolute return to the dollar daily trading volume (in million dollars). This ratio characterizes the daily price impact of the order flow, i.e., the price change per dollar of daily trading volume (Amihud, 2002). Instead of using individual bonds, we use individual portfolio of bonds grouped by rating class (AA, A, BBB, and BB) and maturity ranges (0-5; 5-10; 10+). This ensures sufficient daily prices to compute the Amihud monthly measures.[5] For each portfolio i, at month t :

$$Amihud_t^i = \frac{1}{N-1}\sum_{j=1}^{N-1}\frac{1}{Q_{j,t}^i}\frac{\left|P_{j,t}^i - P_{j-1,t}^i\right|}{P_{j-1,t}^i}, \tag{1}$$

where N is the number of days within the month t, $P_{j,t}^i$ (in \$ per \$100 par) is the daily

[4] These measures have been extensively used in the studies of stock market liquidity and are of direct importance to investors developing trading strategies (see for example Amihud and Mendelson, 1986; and Amihud, 2002).

[5] The Amihud monthly measure is obtained as follows: 1) For each day j, we average transaction prices available in each portfolio i; Then, for each month t, we compute $N-1$ daily Amihud-type measures for each portfolio i; 3) Next, we average over all $N-1$ days to form monthly measures.

transaction price of portfolio i and $Q^i_{j,t}$ (in \$ million) the daily trading volume of portfolio i. This measure reflects how much prices move due to a given value of a trade. Hasbrouck (2005) suggests that the Amihud measure must be corrected for the presence of outliers by taking its square-root value, which measure is referred to as the modified Amihud measure. We also include the modified Amihud measure in our analysis:

$$\mathrm{mod}\, Amihud^i_t = \sqrt{Amihud^i_t} \tag{2}$$

The range measure The range is measured by the ratio of daily price range, normalized by the daily mean price, to the total daily trading volume. For each portfolio i, at month t:

$$Range^i_t = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{Q^i_{j,t}}\frac{\max P^i_{j,t} - \min P^i_{j,t}}{\overline{P}^i_{j,t}} \tag{3}$$

where N is the number of days within the month t, $\max P^i_{j,t}$ (in \$ per \$100 par) is the maximum daily transaction price of portfolio i, $\min P^i_{j,t}$ (in \$ per \$100 par) is the minimum daily transaction price of portfolio i, $\overline{P}^i_{j,t}$ (in \$ per \$100 par) is the daily average price of portfolio i and $Q^i_{j,t}$ (in \$ million) the daily transaction volume of portfolio i.[6] The range is an intuitive measure to assess the volatility impact as in Downing et al. (2005). It should reflect the market depth and determine how much the volatility in the price is caused by a given trade volume. Larger values suggest the prevalence of illiquid bonds.

Liquidity measures based on transaction prices Since transaction prices are of major concern in explaining credit spread changes, we construct new measures based on these prices. First, we use the daily median price of each portfolio i and then we average over all N days to get monthly measures. We take the median because it is more robust to outliers than the mean. To better capture the effect of price volatilities, we also measure monthly price volatilities for each portfolio in each month. We further include the same measures after weighing bond prices by the inverse of bond durations.

[6] The range monthly measure is obtained as follows: 1) For each day j, we calculate the difference between the maximum and the minimum prices recorded in the day for each portfolio i; 2) Then, we divide this difference by the mean price and volume of the portfolio in the same day; 3) Next, we average over all N days to form monthly measures.

3.3.2 Liquidity measures based on trading frequencies

Trading frequencies have been widely used as indicators for asset liquidity (Vayanos, 1998). Intuitively, all else equal, bonds that are more illiquid would trade less frequently. We consider the following three measures:

- The monthly turnover rate, which is the ratio of the total trading volume in the month to the number of outstanding bonds;
- The number of days, during the month, with at least one transaction; and
- The total number of transactions that occurred during the month.

Table 1 presents a summary of all the variables considered with examples of a previous study using the same variables to explain credit spreads or default risk.

[Insert Table 1 here]

4 Corporate bond data

To extract credit spread curves for each rating class and maturity we use the Fixed Investment Securities Database (FISD) with US bond characteristics and the National Association of Insurance Commissioners (NAIC) with US insurers' transaction data. The FISD database, provided by LJS Global Information Systems, Inc. includes descriptive information about US issues and issuers (bonds characteristics, industry type, characteristics of embedded options, historical credit ratings, bankruptcy events, auction details, etc.). The NAIC database includes transactions by american insurance companies, which are major investors in corporate bonds. Specifically, transactions are made by three types of insurers: Life insurance companies, property and casualty insurance companies, and Health Maintenance Organizations (HMOs). This database was recently used by Campbell and Taksler (2003), Davydenko and Strebulaev (2004), and Bedendo, et al. (2004).

Our sample is restricted to fixed-rate US dollar bonds in the industrial sector. We exclude bonds with embedded options such as callable, putable or convertible bonds. We also exclude bonds with remaining time-to-maturity below 1 year. With very short maturities, small price measurement errors lead to large yield deviations, making credit spread estimates noisy. Bonds with more than 15 years of maturity are discarded since the swap rates that we use as risk free rates have maturities below 15 years. We finally exclude bonds with over-allotment options, asset-backed and credit enhancement features and bonds associated with a pledge security. Issuers credit ratings are reported by four rating agencies: Fitch Rating, Duff and Phelps Rating, Moody's Rating and Standard and Poor's Rating. We include all bonds whose average Moody's credit rating lies between AA and BB. AAA credit spreads are not used because we find them negative for some periods. We also find that the average credit spread for medium term AAA-rated bonds is higher than that of A-rated bonds. These same results are obtained by Campbell and Taksler (2003) using the same database. To measure liquidity, we have constructed monthly factors from daily values. This requires at least three transactions to occur in the same day unless the daily measure has missing value in that day. Since B-rated bonds do not have sufficient daily values, they have also been excluded.

We also filter out observations with missing trade details and ambiguous entries (ambiguous settlement data, negative prices, negative time to maturities, etc.). In some cases, a transaction may be reported twice in the database because it involves two insurance companies on the buy and sell side. In this case, only one side is considered.

For the period ranging from 1994 to 2004, we account for 651 issuers with 2,860 outstanding issues in the industrial sector corresponding to 85,764 different trades. Since insurance companies trade generally high quality bonds, most of the trades in our sample are made with A and BBB rated bonds where they account respectively for 40.59% and 38.45% of total trades. On average, bonds included in our sample are recently issued bonds with an age of 4.3 years, a remaining time-to-maturity of 6.7 years and a duration of 5.6 years. Table 2 reports summary statistics.

[Insert Table 2 here]

5 Credit spread curves

To obtain credit spread curves for different ratings and maturities, we use the extended Nelson-Siegel-Svensson specification (Svensson, 1995):

$$
\begin{aligned}
R(t,T) \quad = \quad & \beta_{0t} + \beta_{1t}\left[\frac{1-\exp(-\frac{T}{\tau_{1t}})}{\frac{T}{\tau_{1t}}}\right] + \beta_{2t}\left[\frac{1-\exp(-\frac{T}{\tau_{1t}})}{\frac{T}{\tau_{1t}}} - \exp(-\frac{T}{\tau_{1t}})\right] \\
& + \beta_{3t}\left[\frac{1-\exp(-\frac{T}{\tau_{2t}})}{\frac{T}{\tau_{2t}}} - \exp(-\frac{T}{\tau_{2t}})\right] + \varepsilon_{t,j},
\end{aligned} \tag{4}
$$

with $\varepsilon_{t,j} \sim N(0,\sigma^2)$. $R(t,T)$ is the continuously compounded zero-coupon rate at time t with time to maturity T. β_{0t} is the limit of $R(t,T)$ as T goes to infinity and is regarded as the long term yield. β_{1t} is the limit of the spread $R(t,T)-\beta_{0t}$ as T goes to infinity and is regarded as the long to short term spread. β_{2t} and β_{3t} give the curvature of the term structure. τ_{1t} and τ_{2t} measure the rate at which the short-term and medium-term components decay to zero. Each month t we estimate the parameters vector $\Omega_t = (\beta_{0t}, \beta_{1t}, \beta_{2t}, \beta_{3t}, \tau_{1t}, \tau_{2t})'$ by minimizing the sum of squared bond price errors over these parameters. We weigh each pricing error by the inverse of the bond's duration since long-maturity bond prices are more sensitive to interest rates:

$$
\widehat{\Omega}_t = \arg\min_{\Omega_t} \sum_{i=1}^{N_t} w_i^2 \left(P_{it}^{NS} - P_{it}\right)^2, \qquad w_i = \frac{1/D_i}{\sum_{i=1}^{N} 1/D_i}, \tag{5}
$$

where P_{it} is the observed price of the bond i at month t, P_{it}^{NS} the estimated price of the bond i at month t, N_t is the number of bonds traded at month t, N is the total number of bonds in the sample, w_i the bond's i weight, and D_i the modified Macaulay duration. The specification of the weights is important because it consists in overweighting or underweighting some bonds in the minimization program to account for the heteroskedasticity of the residuals. A small change in the short term zero coupon rate does not really affect the prices of the bond. The variance of the residuals should be small for a short maturity. Conversely, a small change in the long term zero coupon rate will have a larger impact on prices suggesting a higher volatility of the residuals.

Credit spreads for corporate bonds paying a coupon is the difference between corporate bond yields and benchmark risk free yields with the same maturities. Following Hull et al. (2004), we use the swap rate curve less 10 basis points as a benchmark risk free curve.

6 Switching regime model

The vector system of the natural logarithm of corporate yield spreads y_t is affected by two unobservable regimes $s_t = \{1, 2\}$. The conditional credit spread dynamics is presumed to be normally distributed with mean μ_1 and variance σ_1^2 in the first regime ($s_t = 1$) and mean μ_2 and variance σ_2^2 in the second regime ($s_t = 2$) :

$$y_t/s_t \sim N\left(\mu_{st}, \sigma_{st}\right), \qquad s_t = 1, 2. \tag{6}$$

The model postulates a two-state first order Markov process for the evolution of the unobserved state variable:

$$p(s_t = j|s_{t-1} = i) = p_{ij}, \qquad i = 1, 2;\ j = 1, 2. \tag{7}$$

where these probabilities sum to unity for each state s_{t-1}.The process is presumed to depend on past realizations of y and s only through s_{t-1}. The probability law for $\{y_t\}$ is then summarized through six population parameters $\left(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22}\right)$:

$$p(y_t|s_t;\theta) = \frac{1}{\sqrt{2\pi}\sigma_{st}} \exp\left(\frac{-\left(y_t - \mu_{s_t}\right)^2}{2\sigma_{st}^2}\right),\ s_t = 1, 2. \tag{8}$$

The model resembles a mixture of normal distributions with the difference that the draws of y_t are not independent. Specifically, the inferred probability that a particular y_t comes from the first distribution corresponding to the first regime depends on the realization of y at other times including the second regime. Following Hamilton (1988), the model incorporates a Bayesian prior for the parameters of the two regimes. The maximization problem will be a generalization of the Maximum Likelihood Estimation (MLE). Specifically, we maximize the generalized objective function:

$$\begin{aligned} \zeta(\theta) &= \log p(y_1, ..., y_T; \theta) - \left(\nu \mu_1^2\right) / (2\sigma_1^2) - (\nu \mu_2^2)/(2\sigma_2^2) \\ &\quad -\alpha \log \sigma_1^2 - \alpha \log \sigma_2^2 - \beta/\sigma_1^2 - \beta/\sigma_2^2, \end{aligned} \tag{9}$$

where (α, β, ν) are specific Bayesian priors. This maximization produces the parameters of the distribution of the credit spreads in each regime:

$$\widehat{\mu}_j = \frac{\sum_{t=1}^T y_t p(s_t = j | y_1, ..., y_T; \widehat{\theta})}{\nu + \sum_{t=1}^T p(s_t = j | y_1, ..., y_T; \widehat{\theta})} \tag{10}$$

$$\begin{aligned} \widehat{\sigma}_j^2 &= \frac{1}{\alpha + 1/2 \sum_{t=1}^T p(s_t = j | y_1, ..., y_T; \widehat{\theta})} \times \\ &\quad \left(\beta + 1/2 \sum_{t=1}^T \left(y_t - \widehat{\mu}_j\right)^2 p(s_t = j | y_1, ..., y_T; \widehat{\theta}) + (1/2) \nu \widehat{\mu}_j^2 \right). \end{aligned} \tag{11}$$

The probabilities that the process was in the regime 1 ($\widehat{p}_{11}$) or 2 ($\widehat{p}_{22}$) at date t conditional to the full sample of observed data $(y_1, ..., y_T)$ are given by:

$$\widehat{p}_{11} = \frac{\sum_{t=2}^T p(s_t = 1, s_{t-1} = 1 | y_1, ..., y_T; \widehat{\theta})}{\sum_{t=2}^T p(s_{t-1} = 1 | y_1, ..., y_T; \widehat{\theta}) + \widehat{\rho} - p(s_1 = 1 | y_1, ..., y_T; \widehat{\theta})}, \tag{12}$$

$$\widehat{p}_{22} = \frac{\sum_{t=2}^T p(s_t = 2, s_{t-1} = 2 | y_1, ..., y_T; \widehat{\theta})}{\sum_{t=2}^T p(s_{t-1} = 2 | y_1, ..., y_T; \widehat{\theta}) - \widehat{\rho} + p(s_1 = 1 | y_1, ..., y_T; \widehat{\theta})}, \tag{13}$$

where $\widehat{\rho}$ in Equations (12) and (13) represents the unconditional probability that the first observation came from regime 1:

$$\widehat{\rho} = \frac{(1 - \widehat{p}_{22})}{(1 - \widehat{p}_{11}) + (1 - \widehat{p}_{22})}. \tag{14}$$

The model parameters are estimated using the EM principal of Dempster, Laird, and Rubin (1977).[7] To implement the EM algorithm, one needs to evaluate the smoothed probabilities which can be calculated from a simple iterative processing of the data. These probabilities are then used to re-weigh the observed data y_t. Calculation of sample statistics of Ordinary Least Squares (OLS) regressions on the weighted data then generates new estimates of the parameter θ. These new estimates are then used to recalculate the smoothed probabilities, and the data are re-weighted with the new probabilities. Each calculation of probabilities and re-weighing the data are shown to increase the value of the likelihood function. The process is repeated until a fixed point for θ is found, and will then be the maximum likelihood estimate.

7 Methodology

The objective of this study is to analyze credit spread determinants in different credit spread regimes. With the same set of initial variables, we first select key determinants in the one-regime model. Then we select key determinants in the two-regime model. In both cases, key determinants are based on Akaike (AIC) selection criteria. We also examine the interaction effects of these determinants with the low and high regimes. For the factors to be included in each model, we proceed as follows:

1. We run univariate regressions on all factors described earlier and determine which set of variables is statistically significant at least at the 10% level;

2. We use the Vector Autoregressive Regression (VAR) to determine the relevant lags (max lag = 3) to consider for each of the variables – with respect to credit spread rating and maturity – based on AIC;

3. In the multivariate regressions, we use forward and backward variable selection based on AIC.

We repeat step 3 with each factor and then with all factors. These steps are done for the model with and without regimes. A last step of the analysis consists in considering the

[7] The EM algorithm is defined as the alternate use of E- and M-steps. The E-step estimates the complete-data sufficient statistics from the observed data and previous parameter estimates. The M-step estimates the parameters from the estimated sufficient statistics. Further details of these calculations are provided in Engle and Hamilton (1990).

interation variables as a new set of variables in step 3 (referred to as the regime-based factor model).

7.1 Single regime model

Let $Y_{i,m}$ denote an $(n \times 1)$ vector containing values of the time series of credit spreads on corporate bonds rated i ($i =$ AA,...,BB) with remaining time-to-maturity m, observed from January 1994 to December 2004 and $X_{i,m}$ an $(n \times k)$ matrix containing the values of k series of independent variables. The dynamics of changes in $Y_{i,m}$ are presumed to be driven by the following multivariate regression:

$$\Delta Y_{t,i,m} = \beta_{0,i,m} + \beta_{1,i,m} \Delta X_L^{i,m} + \varepsilon^{i,m}, \tag{15}$$

where $L = 0, ..., 3$ is the specified lag for each factor, $\beta_{0,i,m}$ and $\beta_{1,i,m}$ denote, respectively, the level and the slope of the regression line. Specifically, β_1 represent the global effect of the key determinant on the credit spread changes over the whole period. ΔX is an $(n \times k)$ matrix representing the monthly changes in the set of k independent variables and ε designates the error term.

7.2 Low and high regime models

For each individual bond with rating class i and a remaining time-to-maturity m, we specify a two-regime model as:

$$\begin{aligned} \Delta Y_{t,i,m} &= \gamma_{0,i,m} + \gamma_{1,i,m} \Delta X_{t-L,i,m} \\ &\quad + \gamma_{2,i,m} R_{t,i,m} + \gamma_{3,i,m} R_{t,i,m} \Delta X_{t-L,i,m} + \eta_{t,i,m}, \end{aligned} \tag{16}$$

where $L = 0, ..., 3$ is the specified lag for each factor, $i =$AA,...,BB, m the bond's remaining time-to-maturity. ΔY is an $(n \times 1)$ vector and designates monthly credit spread changes, ΔX is an $(n \times k)$ matrix representing monthly changes in the set of k independent variables. R is $(n \times 1)$ a vector which takes the value of one in the high-spread episode and zero otherwise.

Specifically, R is obtained from the smoothed probabilities of the high-spread regime. It takes the value of 1 (in the high regime) when these probabilities are equal to or higher than 0.5 and 0 otherwise. Equation (16) yields the following two models for the two regimes:

$$\begin{cases} low-regime: \Delta Y_{t,i,m} = \gamma_{0,i,m} + \gamma_{1,i,m} \Delta X_{t-L,i,m} + \eta_{t,i,m}, \\ high-regime: \Delta Y_{t,i,m} = \left(\gamma_{0,i,m} + \gamma_{2,i,m}\right) + \left(\gamma_{1,i,m} + \gamma_{3,i,m}\right) \Delta X_{t-L,i,m} + \eta_{t,i,m}. \end{cases} \tag{17}$$

where, γ_0 and γ_1 represent, respectively, the model intercept and coefficient in the low-spread regime, $(\gamma_0 + \gamma_2)$ and $(\gamma_1 + \gamma_3)$ represent, respectively, the model intercept and coefficient in the high-spread regime. The parameter η represents the error term.

8 Results

8.1 Observed credit spreads

We obtain credit spread curves for AA-rated to BB-rated bonds with maturities ranging from 1 to 15 years. Figure 1 plots these results and Table 3 presents summary statistics.

[Insert Table 3 here]

Across all maturities, the mean spread is 286 basis points and the median spread is 230 basis points. Relatively high mean and median spreads are due to the sample period selected which includes the recession of 2001 and the residual impact of the 1991 recession – reflected in the high level of the credit spread in 1994. Panels A to D present summary statistics for all, short, medium and long maturities, respectively. The term structure of credit spreads for investment grade bonds is upward sloping whereas that for speculative grade bonds is upward sloping for short and medium terms and becomes downward sloping for long terms. Also, credit spread standard deviations are clearly higher for speculative grade bonds across maturities suggesting more variable and unstable yields for this bond group.

8.2 High and low credit spread episodes

The switching regime model is estimated for each credit spread series separately, with respect to the rating and to the maturity. The parameter estimates $\widehat{\theta}$ are given in Table 4.

[Insert Table 4 here]

The mean of credit spreads is higher for lower ratings. For investment grade bonds (AA to BBB), the credit spread mean, in both regimes, increases with maturity – consistent with an upward sloping credit spread curve. For speculative grade bonds, the credit spread mean increases until the medium term and then decreases in the long term – consistent with a humped credit spread curve. The credit spread variance, in both regimes, increases as credit ratings become low. It also increases from short to medium term but decreases in the long term.

In state 1, the credit spread mean ranges between 2.0% and 4.2% for investment grade bonds and between 5.6% and 8.0% for speculative grade bonds. However, in state 2, the credit spread mean ranges between 0.5% and 1.5% for investment grade bonds and between 2.0% and 4.4% for speculative grade bonds. Thus, across ratings and maturities, the mean of state 1 is always higher than the mean of state 2. The variance of the credit spreads, in state 1, ranges between 0.4% and 1.1% for investment grade bonds and between 2.1% and 3.6% for speculative grade bonds. However, in state 2, the variance ranges between 0% and 0.1% for investment grade bonds and between 0.6% and 1.0% for speculative grade bonds – which is much lower than the credit spread variance in state 1. Overall, these maximum likelihood estimates associate state 1 with a higher credit spread mean and variance. Therefore, we refer to state 1 as a high mean – high volatility regime (high regime) and to state 2 as a low mean – low volatility regime (low regime).

The point estimates of p_{11} range from 0.943 to 0.989, while the point estimates of p_{22} range from 0.978 to 0.991. These probabilities indicate that if the system is either in regime 1 or regime 2, it is likely to stay in that regime. Confidence intervals for the mean and the variance of credit spreads in each regime also support the specification of the regimes. Across ratings and maturities, the mean and the variance of the high regime are statistically different from those of the low regime at least at the 5% level (Table 5). The only exception is found with the variance of the 5-year BB spreads. We also find – results are not reported here – that the unconditional mean and variance of credit spreads in the single regime model are statistically different from those in the low and high regimes.

[Insert Table 5 here]

Figure 2 plots times series of credit spreads along with the smoothed probabilities $p(s_t = 1|y_1, ..., y_T; \widehat{\theta})$ indicating the months when the process was in the high regime. The figure also shows that for all ratings and maturities the probability that the credit spread is in the high regime at the beginning of the NBER recession (shaded region) is higher than 0.5. Further, credit spreads switch to state 1 (high regime) almost at the beginning of the recession (March 2001) except for low grade bonds with short maturities where the switching happens few months before. The first state is also prevalent for most months of 1994. All credit spread series stay in the high regime from 2001 to late 2004 although the 2001 recession lasts only for a few months. This indicates that following the systematic shock of 2001, high spread levels are likely to persit in the high regime even though downward sloping for BBB and BB ratings after the annoucement. Moreover, these high episodes produce credit cycles that are different from the economic cycle.

[Insert Figure 2 here]

8.3 Credit spread determinants in different regimes

Since we use portfolios of fixed maturities rather than portfolios of average maturities including short, medium and long term bonds, different ratings and maturities are found to be affected by different variables and lags. We only report the results for 10-year bonds for AA to BB ratings.

8.3.1 Market factors

Considering different explanatory variables for different ratings and maturities improves the significance power of the single regime model (29.31%, 40.15%, 26.22%, and 16.45% respectively for AA, A, BBB, and BB spread changes). Results are provided in Table 6.

[Insert Table 6 here]

The results with the single regime model are consistent with previous empirical studies and can be summarized as follows. The level, the slope and the VIX are important determinants of credit spread changes for all bonds. The level, the GDP and the SMB have negative signs as predicted. The VIX volatility has alternate signs since different lags are considered at the same time. Specifically, the first two lags (lag=0,1) have positive signs with the credit spread changes while the second two lags (lag=2,3) have negative signs. The VIX volatility is significant for all ratings and its effect is stronger on BB spreads. The slope while statistically significant at the 1% level for all ratings has a positive sign. This is first due to the long term maturity considered here and second to the CMT yield curve used as a benchmark. Figure 3 plots the 10-year AA spreads against the CMT level and slope. This plot shows a negative correlation with the level and a positive correlation with the slope. When the slope is defined as the difference between DATASTREAM 10-year and 2-year benchmark Treasury yields as in Collin-Dufresne et al. (2001) the predicted negative relation shows up. However, the CMT yield curve fits better our data in term of significance level and explanatory power.

[Insert Figure 3 here]

The results for the two regime model are given in Table 7. All the regimes are statistically significant at least at the 10% level except for BB spreads. Considering credit spread regimes significantly improves the explanatory power of the model. The adjusted R-squared of AA, A, BBB, and BB spreads increases to 31.04%, 43.17%, 36.99%, and 30.24%, respectively. As seen through these numbers, the effect of the regimes appears to be more important for BBB and BB bonds.

[Insert Table 7 here]

In the low regime, changes in the level are statistically significant at least at the 5% level for all spreads while not significant in the high regime. In the single regime model, the level has a negative sign for all spreads. However, in the two regime model, the sign of the level becomes positive for AA, A, and BBB spreads and remains negative for BB spreads. Inspection of Figure 2 shows that BB spreads start to slope upward at the beginning of the 2001 recession and then take a downward slope by the mid-2003. However, AA, A, and BBB spreads take this downward slope only by the end of 2004.

One reason for the reversed sign lies on the behavior of credit spreads towards systematic shocks. When the 2001 recession begins in March 2001 (shaded region), the credit spread starts to increase and the interest rate level starts to decrease. Then, when the recession ends in November the interest rate level starts to decrease following the GDP however the credit spread is still non decreasing until 2004. Indeed, this is due to the bond market uncertainty (in November) about the future economic condition since the end of the recession was officially announced in July 2003. In addition, even after the announcement the credit spreads remain very high relative to their level before the recession. This is consistent with the persistence of credit spreads to adjust to new market innovations documented in Duffee (1998). Due to this uncertainty, changes in the credit spreads after the announcement may be increasing or decreasing until the bond market absorbs all the information about the coming period of expansion.

Figure 3 shows this pattern with the CMT level. The CMT level is negatively related to credit spreads until November 2001. Then, the relation becomes positive until mid-2002. Around this year the relation is uncertain since this period was characterized by a significant decrease of interest rates. The positive relation appears again after July 2003 and the negative relation was clearly re-established only by the end of 2004. This same pattern is also observed with factors that are closely associated with the economic cycle. Therefore, the level, the GDP, the VIX, and the SML change of sign in the high regime. For example, for AA-spreads, the GDP is statistically significant in both regimes with an opposite sign in the high regime. In addition, while the GDP is significant in the low regime for A and BBB spreads at least at the 5% level it becomes not significant in the high regime. If the credit cycle can be assimilated to the economic cycle, the GDP would be significant overall and especially in the high regime.

The slope was significant in the single regime model and remains statistically significant for all ratings in both regimes except in the high regime for BB spreads. The slope when statistically significant maintains the same sign in both regimes. As shown in Figure 3, the curve of the slope is closely related to the credit spread curve. In addition, the slope is measured by the difference between the 10-year and 2-year CMT curves. This difference is likely to absorb any changes in both interest rate curves. Specifically, both the 2-year and 10-year curves decrease at the beginning of the recession and increase at the end of the recession at almost the same time. As a result, the difference between these two curves may not be related to the economic cycle. This same pattern is also observed with the SMB for low grade bonds – while the evidence is weak.

Our results suggest that variables that are closely related to the credit cycle should have an important effect in the high regime since they are more associated with the behavior of credit spreads. We also advocate the need to consider the impact of modeling the credit cycle separately from macroeconomic fundamentals in order to account for the announcement effect and the persistent effect discussed earlier.

8.3.2 Default factors

Default factors essentially involve the change in the Moody's realized default probability of senior unsecured bonds and the Moody's expected recovery rates. The expected recovery rate performs better than the realized recovery rate in the single regime model. When the regimes are considered, the expected recovery level introduces a high collinearity effect leading to a large Variance Inflation Factor (VIF). For this reason, we use changes in this measure in the two regime model.

Changes in the realized default probability and levels of expected recovery rates – Although not considered in previous empirical studies – account at least for 9.28% and up to 15% of credit spread changes (Table 8). These explanatory powers worsen when changes instead of levels of recovery rates are considered. The coefficients of the default probability and the expected recovery rates, in the single regime model, are consistent with theoretical predictions. They are, respectively, higher and lower as credit ratings become lower.

[Insert Table 8 here]

Interestingly, when the regimes are involved, they are statistically significant at the 1% level (Table 9). This is an additional argument supporting our specification of the credit cycle since high default probabilities are known to drive high credit spreads. Moreover, the sign effect of default probabilities is maintained the same in both regimes. However, the sign effect of recovery rates is inversed in the high regime consistent with the results of Altman and Kishore (1996) who suggest that recovery rates are closely related to macroeconomic conditions.

Overall, our results suggest that default factors affect lower grade bonds since these bonds are more likely to default. In addition, the effect of default factors for these bonds is more pronounced in the high regime.

[Insert Table 9 here]

8.3.3 Liquidity factors

The results based on AIC reveal that the best set of liquidity variables involves changes in the Amihud measure, changes in the range, changes in the median price, the price volatility level, changes in the price volatility level, and changes in the bond age.[8]

In the single regime model, liquidity factors explain at least 12.07% of credit spread changes of A-rated bonds and up to 18.89% of BBB-rated bonds (Table 10). The Amihud and the range measures are found to be the most important for bonds with lower grade. The median price is statistically significant for all bonds while different lags are more informative for different ratings. The price volatility is also statistically significant for most ratings. The age is only significant for AA and A bonds.

[Insert Table 10 here]

[8] Other measures of liquidity that are also explored such as the change in the bond duration, the change in the coupon rate, the change in the bond size, the change in the transaction volume, the change in measures based on transaction frequencies are omitted to avoid problems of collinearity. Most of these measures including the duration and the volume are correlated whether with the Amihud or the median price measures and thus excluded from the model based on AIC. Other measures based on trading frequencies are found to affect more the level rather than changes in the level of credit spreads.

Then, in the two regime model, all the regimes are statistically significant at least at the 10% level, except for BB bonds. All liquidity measures constructed from bond prices and/volumes switch to the opposite sign in the high regime. This result suggests that liquidity factors are more related to macroeconomic conditions. The Age measure can be seen as a robustness check for the impact of the high regime on key determinants. Its sign effect remains unchanged in both regimes and overall for high grade bonds with long maturity.

Overall, our measures of liquidity allow capturing a non negligible proportion of credit spread changes especially when the regimes are included. Relative to the single regime model, liquidity factors in the presence of switching regimes increase the adjusted R-squared by about one third (it reaches 18.12%, 15.88%, 27.80%, and 24.00% for AA, A, BBB, and BB spreads, respectively).

[Insert Table 11 here]

8.3.4 All factors

In this section, we include all factors in the same regression based on AIC. All factors include the GDPgrowth rate, the SMB as well as changes in the level, the slope, the VIX, the SML, the Amihud, the range, the median price, the price volatility, the age, the realized default probability, and the expected recovery rate.

In the single regime, the model explains respectively 38.42%, 48.62%, 45.88%, and 32.73% of AA, A, BBB, and BB credit spread changes (Table 12).

[Insert Table 12 here]

Still, the introduction of the regimes improves the model both in term of significance level and explanatory power. In the two regime model, the adjusted R-squared accounts respectively for 51.15%, 50.51%, 52.59%, and 46.38% of AA, A, BBB, and BB credit spread changes. Table 13 shows that all the regimes are statistically significant for all rating classes. The coeficient of the BB regime is positive and significant although negative for all other ratings. It follows that the BB spread curve is closely related to the behavior of macroeconomic fundamentals.

[Insert Table 13 here]

As explained before, credit spreads start to adjust to the coming expansion only after the annoucement when investors are less risk averse and uncertainty in the bond market is reduced. However, the adjustment is also affected by the rating structure. Particularly, credit spreads for investment grade bonds are stickier and takes more time to come back to their level preceeding the recession. Thus, the results with BB spreads are different. Moreover, the period between November 2001 and July 2003 is still a period of recession for bondholders that's why in this period credit spreads are still increasing (Figure 2). However, economic factors that are closely associated with the real GDP was already adjusted to the end of the recession. For this reason alternating signs in the high regime are observed even for BB spreads.

Results obtained with the model including all factors confirm what precedes. The level, the slope, the VIX, the median price and the price volatility are important determinants of credit spread changes in both regimes. Moreover, factors related to the economic cycle such as, the level, the VIX, the SMB, the SML, the GDP, and the recovery rate change of sign in the high regime and their effect may be reduced in the single regime model. Overall, models with two credit spread regimes outperform models with a single regime in terms of information content and explanatory power. Tests of this performance based on AIC information criteria are shown in Table 14.

[Insert Table 14 here]

8.3.5 Regime based factor model

In this model, we consider different factors for different regimes. We repeat the variable selection procedure based on the AIC information criteria and we consider all the variables involved in this study as well as the interaction variables. Results are reported in Table 15.

[Insert Table 15 here]

Almost all variables retained are statistically significant at least at the 10% level. The explanatory power of the model improves especially for BBB spreads (63.56%). The inversed sign effects in the high regime discussed earlier are also observed in this model with the same variables. Overall, the regime based model performs better than all models involved in this study. Performance tests based on AIC and SIC information criteria are shown in Table 16.

[Insert Table 16 here]

Robustness checks A first check is to repeat the analysis with the economic cycle rather than the credit cycle (results are available upon request). Across ratings, the interaction effects are all non significant. Further, the adjusted R-squared are not improved and rather worsen in most cases. Moreover, when we add only the dummy variable for the economic cycle to the single regime model, its effect is not significant at the 10% level while its sign is positive. Then, when the dummy variable for the credit cycle is added, its effect is only significant at the 10% level for BB spreads. This is not surprising since the credit cycle is derived from the level of credit spreads whereas the regressions involve changes in credit spread levels. These results show that the enhancement of the explanatory power of the model is mostly driven by the interaction variables.

A second check is compute the Likelihood Ratio for models with and without regimes. Table 17 reports the Likelihood Ratio Test (LRT) for constrained and unconstrained models. The unconstrained models are models with two regimes involving market factors, default factors, liquidity factors, all factors and the regime based factor. The constrained models are single regime models with each of these factors. The difference between models with regimes and models without regimes is statistically significant in all cases. Models with regimes have higher likelihood scores and appear to perform better than single regime models.

[Insert Table 17 here]

8.4 Out-of-Sample analysis of the credit cycle

Previous results show that accounting for different regimes improves the explanatory power of credit spread determinants. Thus, it would be interesting to test the out-of-sample ability of the regime switching model. This requires the out-of-sample estimation of the smoothed probability of the system to be in the high regime. Since there is much more experience in forecasting the credit spreads, we intend to test whether using short term predictions of credit spreads allows us to forecast the future credit cycle. We start the analysis in May 2000, 10 months before the beginning of the last NBER recession of March 2001. We estimate the smoothed probabilities of the high regime predicted by the model using only the credit spread series from January 1994 to May 2000. The probability estimate for May 2000 is the first point of the curve reported in Figure 4. Then, we add another monthly data point (credit spread value of June 2000) and re-estimate the smoothed probabilities of the high regime using data from January 1994 to June 2000. The probability estimate for June 2000 is the second point of the curve reported in Figure 4. We continue so forth until December 2004. The results are shown in Figure 4 for the 10-year AA spreads.

[Insert Figure 4 here]

The switching regime structure for AA spreads obtained in this way is consistent with the one obtained using all the observed data. Further, we now know from Figure 2 that the credit cycle generally starts whether before or at the beginning of the NBER recession. Specifically, it is likely to start before the economic recession when the credit rating is low and the time-to-maturity is short. However, it starts almost with the economic cycle when the credit rating is high and the time-to-maturity is long. In both cases, the credit cycle lasts longer than the economic cycle and both cycles should be considered separately. We also notice that the fact that the effective NBER recession ends many months before the NBER announcement have significant effects on the behavior of the economic factors and thus the announcement date should also be considered when the economic cycle is involved. Finally, both the economic cycle and the credit cycle should be considered jointly in the analysis of empirical and theoretical studies involving credit spread dynamics.

9 Conclusion

The major contribution of this study is to examine the impact of modeling the credit cycle independently from macroeconomic fundamentals on credit spread determinants. The credit cycle is derived from the switching regime structure for credit spreads. The obtained credit cycle and the NBER economic cycle exhibit different patterns. Even though credit spreads are counter-cyclical, their high level following a systematic shock in the economy is triggered by an announcement effect and a persistence effect. These two effects produce a credit cycle that is much longer than the economic cycle. Moreover, the connection between these two cycles is affected by the bonds rating structure.

Key determinants of credit spreads are whether closely associated with the behavior of credit spreads or the behavior of macroeconomic fundamentals. Following a systematic shock in the economy, the uncertainty in the bond market is absorbed differently by these two types of determinants. Factors that are closely associated with the GDP growth rate adjust to economic shocks contemporaneously. However, the other factors wait for the announcement of the future state and still take several months to adjust to it. In the meantime, credit spreads are non decreasing until the uncertainty in the bond market vanishes. Therefore within this period of uncertainty, the sign effect of the first set of factors is inversed. This sign effect shows up when credit spread determinants are studied within different regimes and is hidden in the single regime model. Therefore, accounting for different regimes improves the explanatory power of a large set of factors that should in theory explain credit spread changes.

Moreover, our results also show that different factors have different contributions in each of the two regimes considered in this study. This further suggests that a regime based factor model also enhances the explanatory power of key determinants. The factors considered contribute to up to 60% to the variation of credit spread changes.

Finally, our study is devoted to help solving the credit spread puzzle documented in a large set of recent works. Our different approach shows how existing models can be improved by modelling the credit cycle and the economic cycle separately since the connection between these two cycles remains still unclear.

References

[1] Alexander, C., and Kaeck, A. (2007), "Regime Dependent Determinants of Credit Default Swap Spreads", Journal of Banking and Finance, 32, 1008-1021.

[2] Allen, L., and Saunders, A. (2003), "A Survey of Cyclical Effects in Credit Risk Measurement Models, Technical Report", BIS Working Paper, 126.

[3] Altman, E., and Kishore, V. (1996), "Almost Everything You Wanted to Know about Recoveries on Defaulted Bonds", Financial Analysts Journal, 52, 57-64.

[4] Altman, E., Brady, B., Resti, A., and Sironi, A. (2005), "The Link between Default and Recovery Rates: Theory, Empirical Evidence, And Implications", Journal of Business, 78, 2203-2228.

[5] Altman, E., Resti, A., and Sironi, A. (2001), "Analyzing and Explaining Default Recovery Rates", International Swaps Dealers Association (ISDA), London.

[6] Altman, E., Resti, A., and Sironi, A. (2004), "Default Recovery Rates in Credit Risk Modeling: A Review of the Literature and Empirical Evidence", Economic Notes, 33, 183-208.

[7] Amato, J. D., and Remolona, E. M. (2003), "The Credit Spread Puzzle", The BIS Quarterly Review, 22, 51-64.

[8] Amihud, Y. (2002), "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects", Journal of Financial Markets, 5, 31-56.

[9] Avramov, D., Jostova, G., and Philipov, A. (2007), "Understanding Changes in Corporate Credit Spreads", Financial Analysts Journal, 63, 90-105.

[10] Batten, J., Fetherston, T., and Hoontrakul, P. (2002), "Modeling the Credit Spreads and Long-Term Relationships of Thai Yankee Bond Issues", Asian Economic Journal,16, 379-397.

[11] Bedendo, M., Cathcart, L., and El-Jahel, L. (2004), "The Shape of the Term Structure of Credit Spreads: An Empirical Investigation", Working Paper, Imperial College London, Tanaka Business School.

[12] Bessembinder, H., Maxwell, W., and Venkataraman, K. (2005), "Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds", Journal of Financial Economics, 82, 251-288.

[13] Bhamra, H. S., Kuehn, L. A., and Strebulaev, I. A. (2007), "The Levered Equity Risk Premium and Credit Spreads: A Unified Framework", Working Paper, University of British Columbia and Stanford.

[14] Bruche, M., and Gonzalez-Aguado, C. (2006), "Recovery Rates, Default Probabilities and the Credit Cycle", Working Paper, CEMFI; Financial Markets Group and Centre for Monetary and Financial Studies (CEMFI).

[15] Campbell, J., and Taksler, B. (2003), "Equity Volatility and Corporate Bond Yields", Journal of Finance, 58, 2321-2350.

[16] Chen, H. (2008), "Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure", Working Paper, Massachusetts Institute of Technology.

[17] Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. (2001), "The Determinants of Credit Spread Changes", Journal of Finance, 56, 2177-2208.

[18] David, A. (2008), "Inflation Uncertainty, Asset Valuations, and the Credit Spreads Puzzle", Review of Financial Studies, Forthcoming.

[19] Davies, A. (2004), "Credit Spread Modelling with Regime Switching Techniques", Journal of Fixed Income, 14, 36-48.

[20] Davies, A. (2007), "Credit Spread Determinants: An 85 Year Perspective", Journal of Financial Markets, 11, 180-197.

[21] Davig, T. (2004), "Regime Switching Debt and Taxation", Journal of Monetary Economics, 51, 837-859.

[22] Davydenko, S. A., and Strebulaev, I. A. (2004), "Strategic Actions and Credit Spreads: An Empirical Investigation", Journal of Finance, 62, 2633-2671.

[23] Delianedis, G., and Geske, R. (2001), "The Components of Corporate Credit Spreads", Working Paper, The Anderson School at UCLA.

[24] Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977), "Maximum Likelihood from Incomplete Data via the EM Algorithm", Journal of the Royal Statistical Society, 39, 1-38.

[25] Dionne, G., François, P., and Maalaoui, O. (2008), "Detecting Regime Shifts in Corporate Credit Spreads", Working Paper, HEC Montreal.

[26] Downing, C., Underwood, S., and Xing, Y. (2005), "Is Liquidity Risk Priced in the Corporate Bond Market?", Working Paper, Rice University.

[27] Driessen, J. (2003), "Is Default Event Risk Priced in Corporate Bonds?", University of Amsterdam.

[28] Duffee, G. (1998), "The Relation between Treasury Yields and Corporate Bond Yield Spreads", Journal of Finance, 53, 2225-2241.

[29] Elizalde, A. (2005), "Do We Need to Worry about Credit Risk Correlation?", Journal of Fixed Income, 15, 42-59.

[30] Elton, E. J., Gruber, M. J., Agrawal, D., and Mann, C. (2001), "Explaining the Rate Spread on Corporate Bonds", Journal of Finance, 56, 247-277.

[31] Engle, C., and Hamilton, J. D. (1990), "Long Swings in the Dollar: Are They in the Data and Do Markets Know It?", American Economic Review, 80, 689-713.

[32] Frye, J. (2003), "A False Sense of Security", Risk, August, 63-67.

[33] Goldstein, M., Hotchkiss, E. S., and Sirri, E. R. (2006), "Transparency and Liquidity: A Controlled Experiment on Corporate Bonds", Review of Financial Studies, 20, 235-273.

[34] Griep, C. (2002), "Higher Ratings Linked to Stronger Recoveries", Special Report, Standard and Poor's.

[35] Hackbarth, D., Miao, J., and Morellec, E. (2006), "Capital Structure, Credit Risk, and Macroeconomic Conditions", Journal of Financial Economics, 82, 519-550.

[36] Hamilton, J. D., and Carty, L. V. (1999), "Debt Recoveries for Corporate Bankruptcies", Moody's Risk Management Services.

[37] Hamilton, J. D. (1988), "Rational-Expectations Econometric Analysis of Changes in Regime: An Investigation of the Term Structure of Interest Rates", Journal of Economic Dynamics and Control, 12, 385-423.

[38] Hamilton, J. D. (2005), "What's Real about the Business Cycle?", Federal Reserve Bank of St-Louis Review, 87, 435-452.

[39] Han, S., and Zhou, H. (2006), "Nondefault Bond Spread and Market Trading Liquidity", Federal Reserve Board.

[40] Hasbrouck, J. (2005), "Trading Costs and Returns for U.S. Equities: The Evidence from Daily Data", Working Paper, New York University.

[41] Hu, Y., and Perraudin, W. (2002), "The Dependence of Recovery Rates and Defaults", Working Paper, London Business School.

[42] Huang, J., and Huang, M. (2003), "How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk?", Working Paper, Pennsylvania State University.

[43] Huang, J., and Kong, W. (2003), "Explaining Credit Spread Changes: New Evidence from Option-Adjusted Bond Indexes", Journal of Derivatives, 11, 30-44.

[44] Hull, J., Predescu, M., and White, A. (2004), "The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements", Journal of Banking and Finance, 28, 2789-2811.

[45] Koopman, S. J., and Lucas, A. (2005), "Business and Default Cycles for Credit Risk", Journal of Applied Econometrics, 20, 311-323.

[46] Koopman, S. J., Kraeussl, R., Lucas, A., and Monteiro, A. A. (2006), "Credit Cycles and Macro Fundamentals", Working Paper, Vrije Universiteit Amsterdam and Tinbergen Institute.

[47] Longstaff, F., and Schwartz, E. (1995), "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt", Journal of Finance, 50, 789-820.

[48] Longstaff, F., Mithal, S., and Neis, E. (2005), "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market", Journal of Finance, 60, 2213-2253.

[49] Lown, C., and Morgan, D. (2006), "The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey", Journal of Money, Credit and Banking, 38, 1575-1597.

[50] Moody's (2002), "Default & Recovery Rates of Corporate Bond Issuers", Special Comment, Moody's Investors Service.

[51] Sims, C., and Zha, T. (2006), "Were there Regime Switches in U.S. Monetary Policy?", American Economic Review, 96, 54-81.

[52] Svensson, L. (1995), "Estimating Forward Rates with the Extended Nelson and Siegel Method", Sveriges RiksBank Quarterly Review, 3, 13-26.

[53] Tang, D. Y., and Yan, H. (2006), "Macroeconomic Conditions, Firm Characteristics, and Credit Spreads", Journal of Financial Services Research, 29, 177-210.

[54] Tang, D. Y., and Yan, H. (2008), "Market Conditions, Default Risk and Credit Spreads", Working Paper, University of Hong Kong and University of South Carolina.

[55] Varma, P., Cantor, R., and Hamilton, D. (2003), "Recovery Rates on Defaulted Corporate Bonds and Preferred Stocks, 1982-2003", Special Comment, Moody's Investors Service.

[56] Vayanos, D. (1998), "Transaction Costs and Asset Prices: A Dynamic Equilibrium Model", Review of Financial Studies, 11, 1-58.

Table 1: Explanatory variables considered in this study.

Variable	Notation	Description	Predicted sign	Example of related studies
		Panel A. Market factors		
Term structure level	$\Delta level$	Monthly series of 2-year CMT rates.	-	Huang and Kong (2003)
Term structure slope	$\Delta slope$	Monthly series of 10-year CMT rates minus 2-year CMT rates.	-	Huang and Kong (2003)
GDP	Δgdp	GDP growth rate.	-	Altman et al (2001)
Equity market return	Δsp	SP500 index return.	-	Huang and Kong (2003)
Equity market volatility	ΔVIX	VIX index implied return volatility.	+	Campbell et al. (2003)
Fama-French Factors	HML	Fama-French High-Minus-Low factor,	-	Collin-Dufresne et al. (2001)
	SMB	Fama-French Small-Minus-Big factor,	-	Collin-Dufresne et al. (2001)
Stock market index	ΔSML	SP600 Small-Cap	-	This paper
		Panel B. Default factors		
Realized default probability	Δdp	Moody's trailing 12-month default rates of all U.S. corporate issuers,	+	Huang and Kong (2003)
	$\Delta dpspec$	Moody's trailing 12-month default rates of U.S. speculative grade issuers.	+	Huang and Kong (2003)
Realized recovery rates	$\Delta recov$	Moody's monthly recovery rates for Senior Unsecured bonds,	-	Altman et al. (2005)
	$\Delta recsub$	Moody's monthly recovery rates for Senior Subordinated bonds.	-	Altman et al. (2005)
Expected recovery rates	$\Delta \exp recov$	Moody's month (t+2) recovery rates for Senior Unsecured bonds,	-	Altman et al. (2005)
	$\Delta \exp recsub$	Moody's month (t+2) recovery rates for Senior Subordinated bonds.	-	Altman et al. (2005)
		Panel C. Liquidity factors		
Traditional bond measures	Δage	Bond's age,	+	Han and Zhou (2006)
	Δcp	Bond's coupon,	+	Han and Zhou (2006)
	$\Delta size$	Bond's size,	+	Han and Zhou (2006)
	Δvol	Bond's volume.	+	Batten et al. (2002)
Price impact of trades	$\Delta amih$	Amihud,	+	Han and Zhou (2006)
	$\Delta mamih$	Modified Amihud,	+	Han and Zhou (2006)
	$\Delta range$	Range,	+	Han and Zhou (2006)
	$\Delta medprice$	Median price,	-	This paper
	$\Delta sigprice$	Price volatility.	+	This paper
Trading frequencies	$\Delta turnover$	Turnover.	-	Han and Zhou (2006)
	$\Delta freqall$	Monthly transaction frequency of all trades,	-	Goldstein et al. (2006)
	$\Delta frepuni$	Monthly transaction frequency of a unique trade.	-	Han and Zhou (2006)

Table 2: Summary statistics for U.S. corporate bonds.

The coupon is the bond's annual coupon payment. The age is the number of years since the issue date. The maturity is the number of years until the maturity date, upon issuance. The duration is the modified Macaulay duration in years. The size is the total dollar amount issued. The volume is the total dollar amount traded. Issues are the number of unique issues. Issuers are the number of unique issuers. Total Trades are the number of unique trades. Trades (%) are percentages of total trades within each bond category (AA to BB).

Variable		Number	Mean	St. Dev	Min	Max
Coupon ($)			7.398	1.201	0.900	15.000
Age (years)			4.305	3.148	0.083	21.569
Maturity (years)			6.699	4.302	1.000	15.000
Duration (years)			5.607	3.065	0.707	14.756
Size ($)			3.37×10^5	4.73×10^5	0.10×10^5	1.00×10^8
Volume ($)			3.72×10^6	6.04×10^6	0.10×10^5	1.78×10^8
Issuers		651				
Issues		2,860				
Total Trades :		85,764				
Trades (%) :						
	AA	10.01%				
	A	40.59%				
	BBB	38.45%				
	BB	10.95%				

Table 3: Summary statistics on credit spreads.

This table reports summary statistics on credit spreads for straight fixed-coupon corporate bonds in the industrial sector, over the period 1994-2004, by rating and remaining maturity. The benchmark risk-free yield is the swap curve less 10 basis points fitted to all maturities using the Nelson-Siegel-Svensson algorithm. The spreads are given as annualized yields in basis points.

	All	AA	A	BBB	BB
Panel A: Spreads for all maturities					
Mean	286	147	167	226	333
Median	230	98	122	171	271
St. Dev.	159	113	107	132	184
5% quantile	109	20	49	84	126
95% quantile	583	353	357	475	690
Panel B: Spreads for maturity 1-3 years					
Mean	260	97	131	196	330
Median	196	68	91	145	267
St. Dev.	172	81	94	132	218
5% quantile	75	7	31	52	96
95% quantile	596	267	320	460	746
Panel C : Spreads for maturity 3-7 years					
Mean	293	146	174	230	360
Median	231	96	119	173	293
St. Dev.	164	112	117	138	191
5% quantile	116	22	50	76	145
95% quantile	614	363	393	501	733
Panel D : Spreads for maturity 7-15 years					
Mean	291	170	175	233	326
Median	240	111	131	178	265
St. Dev.	153	128	107	130	173
5% quantile	117	26	54	96	130
95% quantile	569	387	357	472	661

Table 4: Parameter estimates of the switching regime model.

This table contains the parameters of the switching regime model for AA-rated to BB-rated US corporate spreads maturing in 3, 5, and 10 years. The first two moments (m_1, s_1^2) and (m_2, s_2^2) represent, respectively, the mean and the variance of the credit spreads in the first and second regime; where $m_i = \exp([2\mu_i + \sigma_i^2]/2)$,$s_i^2 = \exp([2\mu_i + 2\sigma_i^2] - \exp[2\mu_i + \sigma_i^2])$, $i = 1, 2$. The parameters p_{11} and p_{22} are the conditional probabilities of the process being in state 1 and 2, respectively. The parameter ρ is the unconditional probability that the first observation comes from state 1. The standard errors are into parentheses.

Par.	AA			A			BBB			BB		
	3 Yr	5 Yr	10Yr	3 Yr	5 Yr	10Yr	3 Yr	5 Yr	10Yr	3 Yr	5 Yr	10Yr
m_1	2.009	2.514	3.437	2.531	2.902	3.594	3.337	3.641	4.193	5.633	6.079	5.918
	(0.099)	(0.105)	(0.112)	(0.121)	(0.112)	(0.108)	(0.142)	(0.163)	(0.139)	(0.231)	(0.206)	(0.198)
m_2	0.476	0.606	0.851	0.717	0.834	1.119	1.091	1.264	1.525	2.044	2.472	2.453
	(0.037)	(0.037)	(0.046)	(0.036)	(0.037)	(0.047)	(0.048)	(0.055)	(0.043)	(0.091)	(0.086)	(0.070)
p_{11}	0.973	0.986	0.988	0.975	0.987	0.988	0.973	0.980	0.989	0.953	0.969	0.987
	(0.021)	(0.015)	(0.013)	(0.022)	(0.014)	(0.013)	(0.020)	(0.020)	(0.012)	(0.029)	(0.026)	(0.014)
p_{22}	0.979	0.981	0.982	0.980	0.982	0.982	0.979	0.980	0.982	0.979	0.991	0.982
	(0.015)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.0145)	(0.015)	(0.009)	(0.014)
σ_1^2	0.431	0.578	0.573	0.574	0.619	0.491	0.983	0.995	1.058	2.108	1.449	1.809
	(0.088)	(0.112)	(0.123)	(0.124)	(0.123)	(0.114)	(0.193)	(0.215)	(0.202)	(0.449)	(0.348)	(0.375)
σ_2^2	0.091	0.104	0.156	0.087	0.094	0.147	0.161	0.167	0.129	0.574	0.626	0.385
	(0.016)	(0.017)	(0.026)	(0.015)	(0.016)	(0.027)	(0.027)	(0.031)	(0.023)	(0.099)	(0.096)	(0.063)
ρ	0.574	0.420	0.406	0.562	0.407	0.401	0.565	0.503	0.379	0.693	0.777	0.425

Table 5: Confidence intervals for parameters of the high and low regimes.

This table reports the confidence intervals for the means and the variances of the high and the low credit spread regimes. Credit spreads are rated from AA to BB (Rating) and have 3, 5, or 10 remaining years to maturity (Tm). The parameters m_1 and m_2 designates the means of the high and low regimes, respectively. The parameters σ_1^2 and σ_2^2 designates the variances of the high and low regimes, respectively. The confidence level is 5%.

Rating	Tm	m_1	m_2	σ_1^2	σ_2^2
AA	3	[1.815; 2.203]	[0.403; 0.548]	[0.258; 0.603]	[0.060; 0.122]
	5	[2.308; 2.720]	[0.533; 0.678]	[0.358; 0.797]	[0.071; 0.137]
	10	[3.217; 3.656]	[0.761; 0.941]	[0.332; 0.814]	[0.105; 0.207]
A	3	[2.294; 2.768]	[0.646; 0.787]	[0.331; 0.817]	[0.057; 0.116]
	5	[2.682; 3.121]	[0.761; 0.906]	[0.378; 0.860]	[0.063; 0.125]
	10	[3.382; 3.806]	[1.027; 1.211]	[0.267; 0.714]	[0.094; 0.199]
BBB	3	[3.059; 3.615]	[0.997; 1.185]	[0.605; 1.361]	[0.108; 0.214]
	5	[3.321; 3.960]	[1.156; 1.372]	[0.574; 1.416]	[0.106; 0.227]
	10	[3.920; 4.465]	[1.441; 1.609]	[0.662; 1.454]	[0.084; 0.174]
BB	3	[5.180; 6.086]	[1.866; 2.222]	[1.228; 2.988]	[0.380; 0.768]
	5	[5.675; 6.483]	[2.303; 2.640]	[0.767; 2.131]	[0.438; 0.814]
	10	[5.530; 6.306]	[2.316; 2.590]	[1.074; 2.544]	[0.261; 0.508]

Table 6: Explanatory power of market factors in the single regime model.

This table includes months (t) and ($t-3$) changes in the 2-year CMT rates ($\Delta level$), months (t) and ($t-1$) changes in the 10-year minus 2-year CMT rates ($\Delta slope$), the month (t) GDP growth rate (ΔGDP), months (t) to ($t-3$) changes in the VIX index (ΔVIX), and the month (t) level of Small-minus-Big Fama-French factor (SMB). The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	-0.003	0.037	-0.008	-0.002
	(0.874)	(0.279)	(0.725)	(0.961)
$\Delta level_t$			-0.216	-0.323
			(0.033)	(0.073)
$\Delta level_{t-3}$	-0.257	-0.205		
	(0.003)	(0.002)		
$\Delta slope_t$	0.814	0.825	0.84	
	(0.000)	(0.000)	(0.000)	
$\Delta slope_{t-1}$				0.877
				(0.006)
ΔGDP_t	-0.051			
	(0.026)			
ΔVIX_t			0.007	
			(0.206)	
ΔVIX_{t-1}		0.006		0.018
		(0.085)		(0.076)
ΔVIX_{t-2}	-0.008	-0.013		-0.020
	(0.096)	(0.160)		(0.046)
ΔVIX_{t-3}				-0.026
				(0.008)
SMB_t			-0.005	-0.024
			(0.149)	(0.022)
$Adj R^2$	29.31%	40.15%	26.22%	16.45%

Table 7: Explanatory power of market factors in the two regime model.

This table includes months $(t-1)$ and $(t-3)$ changes in the 2-year CMT rates ($\Delta level$), the month (t) change in the 10-year minus 2-year CMT rates ($\Delta slope$), months $(t-1)$ and $(t-2)$ GDP growth rate (ΔGDP), months $(t-1)$ to $(t-3)$ changes in the VIX index (ΔVIX), the month (t) level and changes of Small-minus-Big Fama-French factor (SMB) and (ΔSMB), respectively, the month $(t-1)$ change in the S&P600 Small Cap SML (ΔSML), and the dummy variable ($regime$) specific to each bond type. It takes one in months of the high regime and zero in months of the low regime. The interactions of the above variables with the high spread regime are also considered. The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	0.149	0.127	0.168	0.033
	(0.014)	(0.007)	(0.014)	(0.507)
$\Delta level_{t-1}$	-0.069	-0.106		-0.130
	(0.454)	(0.149)		(0.483)
$\Delta level_{t-3}$			0.012	
			(0.899)	
$\Delta slope_t$	0.494	0.636	0.848	1.157
	(0.014)	(0.000)	(0.000)	(0.002)
ΔGDP_{t-1}	-0.036	-0.031		
	(0.017)	(0.009)		
ΔGDP_{t-2}			-0.040	
			(0.021)	
ΔVIX_{t-1}		0.011	0.007	
		(0.007)	(0.262)	
ΔVIX_{t-2}	-0.011		-0.001	-0.027
	(0.026)		(0.886)	(0.007)
ΔVIX_{t-3}				-0.023
				(0.019)
SMB_t				-0.016
				(0.158)
ΔSMB_t			-0.001	
			(0.761)	
ΔSML_{t-1}				-0.017
				(0.000)
$regime_t$	-0.203	-0.137	-0.155	-0.051
	(0.018)	(0.037)	(0.081)	(0.555)
$\Delta level_{t-1} \times regime_t$	0.055	0.104		-0.342
	(0.048)	(0.000)		(0.015)
$\Delta level_{t-3} \times regime_t$			0.108	
			(0.010)	
$\Delta slope_t \times regime_t$	0.555	0.253	0.250	-0.801
	(0.002)	(0.067)	(0.075)	(0.104)
$\Delta GDP_{t-1} \times regime_t$	0.012	0.021		
	(0.043)	(0.251)		
$\Delta GDP_{t-2} \times regime_t$			0.023	
			(0.356)	
$\Delta VIX_{t-1} \times regime_t$		-0.016	-0.029	
		(0.007)	(0.001)	
$\Delta VIX_{t-2} \times regime_t$	0.012		0.018	0.011
	(0.043)		(0.005)	(0.375)
$\Delta VIX_{t-3} \times regime_t$				0.004
				(0.724)
$SMB_t \times regime_t$				-0.059
				(0.021)
$\Delta SMB_t \times regime_t$			-0.017	
			(0.038)	
$\Delta SML_{t-1} \times regime_t$				0.015
				(0.000)
$AdjR^2$	31.04%	43.17%	36.99%	30.24%

Table 8: Explanatory power of default factors in the single regime model.

This table includes the month (t) change in the realized default probability (ΔDP) and the month (t) level or change of the expected recovery rate ($Exprecov$) and ($\Delta Exprecov$), respectively. The p-values are into parentheses.

	AA10		A10		BBB10		BB10	
$intercept_t$	0.145	-0.0049	0.133	-0.0098	0.147	-0.0072	0.244	-0.0001
	(0.028)	(0.830)	(0.017)	(0.616)	(0.046)	(0.778)	(0.055)	(0.997)
ΔDP_t	60.353	68.320	66.658	73.850	79.391	86.730	121.983	129.250
	(0.006)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)	(0.002)
$Exprecov_t$	-0.003		-0.003		-0.004		-0.006	
	(0.016)		(0.007)		(0.025)		(0.040)	
$\Delta Exprecov_t$		-0.0002		-0.0006		-0.0011		-0.0059
		(0.862)		(0.618)		(0.520)		(0.039)
$AdjR^2$	10.03%	5.84%	15.00%	10.10%	11.56%	8.33%	9.28%	9.31%

Table 9: Explanatory power of default factors in the two regime model.

This table includes the month (t) change in the realized default probability (ΔDP), the month (t) change in the expected recovery rate ($\Delta Exprecov$), and the dummy variable ($regime$) specific to each bond type. It takes one in months of the high regime and zero in months of the low regime. The interactions of the above variables with the high spread regime are also considered. The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	-0.045	-0.041	-0.056	-0.060
	(0.108)	(0.062)	(0.083)	(0.209)
ΔDP_t	67.27	71.423	58.680	120.335
	(0.017)	(0.002)	(0.100)	(0.009)
$\Delta Exp\,\mathrm{Re}\,cov_t$	-0.0003	-0.001	-0.0012	-0.006
	(0.835)	(0.659)	(0.446)	(0.024)
$regime_t$	0.1725	0.147	0.1659	0.292
	(0.002)	(0.002)	(0.002)	(0.009)
$\Delta DP_t \times regime_t$	64.22	11.323	95.560	182.222
	(0.189)	(0.782)	(0.055)	(0.069)
$\Delta Exprecov_t \times regime_t$	-0.004	-0.019	0.002	0.152
	(0.610)	(0.177)	(0.802)	(0.016)
$AdjR^2$	11.03%	15.34%	14.92%	16.71 %

Table 10: Explanatory power of liquidity factors in the single regime model.

This table includes months (t) and ($t-3$) changes in the Amihud measure ($\Delta Amih$), months ($t-3$) changes in the range ($\Delta Range$), months (t) and ($t-1$) changes in the median price ($\Delta Medprice$), the month (t) level and changes of bond price volatility ($\mathrm{Si}\,gprice$) and ($\Delta\,\mathrm{Si}\,gprice$), respectively, and the month (t) change in the bond age (ΔAge). The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	0.141	0.140	-0.005	0.000
	(0.014)	(0.009)	(0.840)	(0.996)
$\Delta Amih_t$			1.815	
			(0.000)	
$\Delta Amih_{t-3}$			-0.737	-0.593
			(0.063)	(0.019)
$\Delta Range_{t-3}$			19.400	
			(0.003)	
$\Delta Medprice_t$	-0.038			-0.072
	(0.005)			(0.002)
$\Delta Medprice_{t-1}$		0.032	0.036	0.033
		(0.061)	(0.037)	(0.166)
$\mathrm{Si}\,gprice_t$	-4.324	-6.866		
	(0.006)	(0.002)		
$\Delta\,\mathrm{Si}\,gprice_t$	3.342	4.525		0.013
	(0.032)	(0.029)		(0.015)
ΔAge_t	0.085	0.158		
	(0.027)	(0.005)		
$AdjR^2$	11.08%	12.07%	18.53%	14.65%

Table 11: Explanatory power of liquidity factors in the two regime model.

This table includes months (t) and $(t-3)$ changes in the Amihud measure ($\Delta Amih$), months (t) and $(t-3)$ changes in the range ($\Delta Range$), months (t), $(t-1)$, and $(t-3)$ changes in the median price ($\Delta Medprice$), the month (t) level of bond price volatility ($\mathrm{Si}\,gprice$), months (t) and $(t-1)$ changes in the bond price volatility ($\Delta\,\mathrm{Si}\,gprice$), the month (t) change in the bond age (ΔAge), and the dummy variable ($regime$) specific to each bond type. It takes one in months of the high regime and zero in months of the low regime. The interactions of the above variables with the high spread regime are also considered. The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	-0.038	-0.004	-0.171	0.023
	(0.692)	(0.968)	(0.069)	(0.658)
$\Delta Amih_t$			-0.237	
			(0.898)	
$\Delta Amih_{t-3}$			0.764	-0.307
			(0.670)	(0.309)
$\Delta Range_t$	-1.971			
	(0.534)			
$\Delta Range_{t-3}$			8.701	
			(0.410)	
$\Delta Medprice_t$	-0.042			-0.076
	(0.002)			(0.002)
$\Delta Medprice_{t-1}$		0.042		0.023
		(0.016)		(0.312)
$\Delta Medprice_{t-3}$				0.020
				(0.372)
$\mathrm{Si}\,gprice_t$	2.018	1.018	8.585	
	(0.537)	(0.827)	(0.032)	
$\Delta\,\mathrm{Si}\,gprice_t$				0.033
				(0.002)
$\Delta\,\mathrm{Si}\,gprice_{t-1}$	-0.166	-3.890	-8.635	
	(0.948)	(0.302)	(0.010)	
ΔAge_t	0.075	0.137		
	(0.145)	(0.032)		
$regime_t$	0.222	0.207	0.244	-0.058
	(0.092)	(0.095)	(0.011)	(0.510)
$\Delta Amih_t \times regime_t$			1.818	
			(0.338)	
$\Delta Amih_{t-3} \times regime_t$			-1.648	-0.642
			(0.369)	(0.201)
$\Delta Range_t \times regime_t$	1.204			
	(0.705)			
$\Delta Range_{t-3} \times regime_t$			20.900	
			(0.081)	
$\Delta Medprice_t \times regime_t$	0.004			0.006
	(0.316)			(0.115)
$\Delta Medprice_{t-1} \times regime_t$		-0.001		-0.006
		(0.600)		(0.073)
$\Delta Medprice_{t-3} \times regime_t$				0.012
				(0.002)
$\mathrm{Si}\,gprice_t \times regime_t$	-0.075	-0.102	-0.119	
	(0.050)	(0.059)	(0.001)	
$\Delta\,\mathrm{Si}\,gprice_t \times regime_t$				-0.027
				(0.024)
$\Delta\,\mathrm{Si}\,gprice_{t-1} \times regime_t$	0.065	0.082	0.137	
	(0.034)	(0.048)	(0.000)	
$\Delta Age_t \times regime_t$	0.016	0.015		
	(0.799)	(0.738)		
$Adj\,R^2$	18.12%	15.88%	27.80%	24.00%

Table 12: Explanatory power of all factors in the single regime model.

This table includes months $(t-1)$ and $(t-3)$ changes in the 2-year CMT rates ($\Delta level$), the month (t) change in the 10-year minus 2-year CMT rates ($\Delta slope$), the month (t) GDP growth rate (ΔGDP), months (t), $(t-2)$, and $(t-3)$ changes in the VIX index (ΔVIX), the month (t) level of the Small-minus-Big Fama-French factor (SMB), months (t) and $(t-3)$ changes in the Amihud measure ($\Delta Amih$), the month $(t-1)$ change in the range ($\Delta Range$), the month (t) change in the median price ($\Delta Medprice$), months (t) and $(t-1)$ changes in the bond price volatility ($\Delta\,\mathrm{Si}\,gprice$), the month (t) change in the bond age (ΔAge), the month (t) change in the realized default probability (ΔDP), and the month (t) change in the expected recovery rate ($\Delta Exprecov$). The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	0.088	0.045	-0.010	0.153
	(0.136)	(0.173)	(0.637)	(0.203)
$\Delta level_t$			-0.406	-0.330
			(0.000)	(0.057)
$\Delta level_{t-3}$	-0.158	-0.177		
	(0.050)	(0.005)		
$\Delta slope_t$	0.791	0.793	0.624	0.397
	(0.000)	(0.000)	(0.000)	(0.193)
ΔGDP_t		-0.016		
		(0.069)		
ΔVIX_t		0.005	0.010	
		(0.161)	(0.049)	
ΔVIX_{t-2}	-0.006			-0.012
	(0.159)			(0.183)
ΔVIX_{t-3}	-0.008			-0.027
	(0.080)			(0.002)
SMB_t			-0.006	-0.011
			(0.086)	(0.280)
$\Delta Amih_t$			1.746	-0.416
			(0.000)	(0.119)
$\Delta Amih_{t-3}$			-1.054	-0.608
			(0.001)	(0.008)
$\Delta Range_{t-1}$	0.979		19.300	
	(0.025)		(0.000)	
$\Delta Medprice_t$	-0.037	-0.032	-0.061	-0.077
	(0.002)	(0.032)	(0.000)	(0.001)
$\Delta\,\mathrm{Si}\,gprice_t$		3.926		0.015
		(0.026)		(0.007)
$\Delta\,\mathrm{Si}\,gprice_{t-1}$	-2.690		-0.018	
	(0.040)		(0.095)	
ΔAge_t		0.131	0.095	
		(0.003)	(0.109)	
ΔDP_t	26.257	35.354		122.908
	(0.162)	(0.017)		(0.002)
$\Delta Exprecov_t$	-0.002		-0.002	-0.004
	(0.110)		(0.182)	(0.171)
$Adj\,R^2$	38.42%	48.62%	45.88%	32.73%

Table 13: Explanatory power of all factors in the two regime model.

This table includes the month (t) change in the 2-year CMT rates ($\Delta level$), the month (t) change in the 10-year minus 2-year CMT rates ($\Delta slope$), the month (t) GDP growth rate (ΔGDP), months ($t-1$) to ($t-3$) changes in the VIX index (ΔVIX), the month (t) level of the Small-minus-Big Fama-French factor (SMB), the month ($t-1$) change in the S&P600 Small Cap SML (ΔSML), the month (t) change in the Amihud measure ($\Delta Amih$), the month (t) change in the range ($\Delta Range$), the month (t) change in the median price ($\Delta Medprice$), months (t) and ($t-1$) changes in the bond price volatility ($\Delta\,\mathrm{Si}\,gprice$), the month ($t$) change in the bond age (ΔAge), the month (t) change in the realized default probability (ΔDP), the month (t) change in the expected recovery rate ($\Delta Exprecov$), and the dummy variable ($regime$) specific to each bond type. It takes one in months of the high regime and zero in months of the low regime. The interactions of the above variables with the high spread regime are also considered. The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	0.151	0.144	0.145	-0.019
	(0.005)	(0.002)	(0.020)	(0.652)
$\Delta level_t$	-0.279	-0.109	-0.164	-0.310
	(0.003)	(0.109)	(0.088)	(0.073)
$\Delta slope_t$	0.145	0.489	0.619	0.636
	(0.470)	(0.003)	(0.001)	(0.049)
ΔGDP_t	-0.038	-0.037	-0.035	
	(0.004)	(0.001)	(0.025)	
ΔVIX_{t-1}		0.011		
		(0.005)		
ΔVIX_{t-2}	-0.008		-0.001	-0.021
	(0.065)		(0.901)	(0.046)
ΔVIX_{t-3}			0.007	-0.028
			(0.266)	(0.005)
SMB_t	0.016		-0.001	0.018
	(0.002)		(0.819)	(0.100)
ΔSML_{t-1}				-0.007
				(0.202)
$\Delta Amih_t$			-0.885	-0.388
			(0.601)	(0.193)
$\Delta Range_t$	2.061		3.498	
	(0.407)		(0.724)	
$\Delta Medprice_t$	-0.039	-0.016	-0.004	-0.083
	(0.002)	(0.276)	(0.734)	(0.000)
$\Delta\,\mathrm{Si}\,gprice_t$	1.200			0.023
	(0.539)			(0.002)
$\Delta\,\mathrm{Si}\,gprice_{t-1}$		-0.377	-4.207	
		(0.886)	(0.075)	
ΔAge_t	0.098	0.201		
	(0.020)	(0.001)		
ΔDP_t				120.791
				(0.006)
$\Delta Exprecov_t$				-0.005
				(0.025)

Table 13 (Continued).

	AA10	A10	BBB10	BB10
$regime_t$	-0.195	-0.136	-0.151	0.258
	(0.006)	(0.039)	(0.057)	(0.026)
$\Delta level_t \times regime_t$	0.134	0.113	-0.029	-0.435
	(0.144)	(0.000)	(0.451)	(0.303)
$\Delta slope_t \times regime_t$	1.207	0.634	0.246	-1.520
	(0.000)	(0.006)	(0.163)	(0.027)
$\Delta GDP_t \times regime_t$	0.043	0.022	0.023	
	(0.030)	(0.242)	(0.309)	
$\Delta VIX_{t-1} \times regime_t$	-0.020	-0.016		
	(0.025)	(0.004)		
$\Delta VIX_{t-2} \times regime_t$	0.013		0.013	0.001
	(0.013)		(0.038)	(0.955)
$\Delta VIX_{t-3} \times regime_t$			-0.034	0.015
			(0.000)	(0.395)
$SMB_t \times regime_t$	-0.009		-0.015	-0.063
	(0.408)		(0.043)	(0.063)
$\Delta SML_{t-1} \times regime_t$				-0.001
				(0.869)
$\Delta Amih_t \times regime_t$			2.231	-0.171
			(0.198)	(0.970)
$\Delta Range_t \times regime_t$	-2.521		20.500	0.044
	(0.314)		(0.086)	(0.463)
$\Delta Medprice_t \times regime_t$	-0.008	-0.002	0.006	0.044
	(0.279)	(0.633)	(0.017)	(0.463)
$\Delta \mathrm{Si}\,gprice_t \times regime_t$	0.049			-0.032
	(0.035)			(0.010)
$\Delta \mathrm{Si}\,gprice_{t-1} \times regime_t$		0.032	0.068	
		(0.294)	(0.009)	
$\Delta Age_t \times regime_t$	-0.039	-0.108		
	(0.479)	(0.448)		
$\Delta DP_t \times regime_t$				161.298
				(0.082)
$\Delta Exprecov_t \times regime_t$				0.106
				(0.097)
$AdjR^2$	51.15%	50.51%	52.59%	43.26%

Table 14: Information content of models with regimes vs. models without regimes.

		Akaike (AIC)	
		Model with two regimes	Model with single regime
Market factors	AA	-2.987	-2.901
	A	-3.405	-3.384
	BBB	-2.718	-2.634
	BB	-1.555	-1.398
Liquidity factors	AA	-2.707	-2.688
	A	-3.007	-3.005
	BBB	-2.607	-2.522
	BB	-1.398	-1.391
Default factors	AA	-2.686	-2.683
	A	-3.003	-3.017
	BBB	-2.454	-2.468
	BB	-1.329	-1.366
All factors	AA	-3.159	-2.999
	A	-3.502	-3.500
	BBB	-2.950	-2.883
	BB	-1.704	-1.579

Table 15: Explanatory power of the regime based factor.

This table includes the month (t) change in the level ($\Delta level$), the month (t) change in the slope ($\Delta slope$), the month (t) GDP growth rate (ΔGDP), months ($t-1$) to ($t-2$) changes in the VIX index (ΔVIX), the month (t) level of the Small-minus-Big Fama-French factor (SMB), the month ($t-1$) change in the S&P600 Small Cap (ΔSML), months (t) and ($t-3$) changes in the Amihud measure ($\Delta Amih$), the month (t) change in the range ($\Delta Range$), the month (t) change in the median price ($\Delta Medprice$), months (t) and ($t-1$) changes in the bond price volatility ($\Delta \mathrm{Si}\,gprice$), the month ($t$) change in the bond age (ΔAge), the month (t) change in the realized default probability (ΔDP), the month (t) change in the expected recovery rate ($\Delta Exprecov$), and the dummy variable ($regime$) specific to each bond type. It takes one in months of the high regime and zero in months of the low regime. The interactions of the above variables with the high spread regime are included when they are selected based on the Akaike information criteria. The p-values are into parentheses.

	AA10	A10	BBB10	BB10
$intercept_t$	-0.090	0.141	0.111	-0.009
	(0.191)	(0.004)	(0.008)	(0.840)
$\Delta level_t$	-0.499	-0.333	-0.299	-0.307
	(0.000)	(0.000)	(0.001)	(0.065)
$\Delta slope_t$	0.297	0.323	0.727	0.766
	(0.020)	(0.020)	(0.000)	(0.016)
ΔGDP_t	-0.017	-0.023	-0.031	
	(0.061)	(0.001)	(0.001)	
ΔVIX_{t-1}	0.007	0.007	0.010	
	(0.021)	(0.123)	(0.035)	
ΔVIX_{t-2}	-0.021			-0.024
	(0.000)			(0.009)
SMB_t				0.019
				(0.059)
ΔSML_{t-1}	0.006	-0.004		-0.006
	(0.001)	(0.055)		(0.133)
$\Delta Amih_t$				-0.436
				(0.045)
$\Delta Amih_{t-3}$			15.912	
			(0.000)	
$\Delta Range_t$				-2.521
				(0.047)
$\Delta Medprice_t$	-0.046	-0.079	-0.048	-0.083
	(0.000)	(0.000)	(0.001)	(0.000)
$\Delta \mathrm{Si}\,gprice_t$				0.036
				(0.000)
$\Delta \mathrm{Si}\,gprice_{t-1}$	-0.032		-0.048	
	(0.010)		(0.019)	
ΔAge_t	0.066	0.157	0.119	
	(0.030)	(0.000)	(0.019)	
ΔDP_t				118.609
				(0.005)
$\Delta Exprecov_t$				-0.005
				(0.017)

Table 15 (Continued).

	AA10	A10	BBB10	BB10
$regime_t$	-0.294	-0.087	-0.556	0.275
	(0.027)	(0.005)	(0.001)	(0.012)
$\Delta level_t \times regime_t$	0.408	-0.250	0.161	-0.519
	(0.007)	(0.005)	(0.217)	(0.206)
$\Delta slope_t \times regime_t$	1.261	0.340	0.634	-1.978
	(0.000)	(0.112)	(0.003)	(0.003)
$\Delta VIX_{t-1} \times regime_t$		-0.025	-0.036	
		(0.000)	(0.000)	
$\Delta VIX_{t-2} \times regime_t$	0.043		0.009	0.021
	(0.000)		(0.033)	(0.220)
$SMB_t \times regime_t$	0.018		-0.013	-0.060
	(0.003)		(0.029)	(0.021)
$\Delta SML_{t-1} \times regime_t$	0.008	0.005	0.004	
	(0.034)	(0.012)	(0.100)	
$\Delta Amih_t \times regime_t$			7.617	
			(0.015)	
$\Delta Amih_{t-3} \times regime_t$		-14.708		
		(0.035)		
$\Delta Range_t \times regime_t$	0.739	-10.089	22.240	
	(0.079)	(0.009)	(0.000)	
$\Delta Medprice_t \times regime_t$		-0.026		
		(0.140)		
$\Delta \mathrm{Si}\, gprice_t \times regime_t$				-0.022
				(0.133)
$\Delta \mathrm{Si}\, gprice_{t-1} \times regime_t$	0.041	0.058	0.069	
	(0.010)	(0.002)	(0.003)	
$\Delta DP_t \times regime_t$	36.896		84.695	153.623
	(0.188)		(0.004)	(0.080)
$\Delta Exprecov_t \times regime_t$	0.010		0.012	0.097
	(0.032)		(0.004)	(0.091)
$AdjR^2$	55.37%	60.43%	63.56%	47.07%

Table 16: Comparision of the model including all factors with the regime based model.

		All factors model with regimes	Regime based model
Akaike (AIC)	AA	-3.159	-3.262
	A	-3.502	-3.700
	BBB	-2.950	-3.213
	BB	-1.704	-1.801
Schwartz (SIC)	AA	-2.671	-2.818
	A	-3.149	-3.276
	BBB	-2.459	-2.723
	BB	-1.081	-1.333

Table 17: Likelihood Ratio test for models with regimes vs. models without regimes.

		AA	A	BBB	BB
Market factors	LR $Chi2$	17.430	14.000	30.680	29.640
	df	5	5	7	7
	$P-value$	(0.004)	(0.015)	(0.000)	(0.000)
Liquidity factors	LR $Chi2$	18.200	9.120	23.150	28.140
	df	7	5	6	7
	$P-value$	(0.011)	(0.104)	(0.001)	(0.000)
Default factors	LR $Chi2$	10.530	11.54	12.87	14.25
	df	3	3	3	3
	$P-value$	(0.014)	(0.001)	(0.004)	(0.003)
All factors	LR $Chi2$	43.610	29.330	45.940	43.560
	df	12	8	11	14
	$P-value$	(0.000)	(0.000)	(0.000)	(0.000)
Regime based factors	LR $Chi2$	79.700	-	-	45.090
	df	10			9
	$P-value$	(0.000)			(0.000)

Figure 1: Times series of credit spreads (1994-2004).

The figure presents the time series of credit spreads for US corporate bonds rated from AA to BB with 3, 5, and 10 remaining years-to-maturity over the period ranging from 1994 to 2004. The shaded region represents the 2001 NBER period of recession.

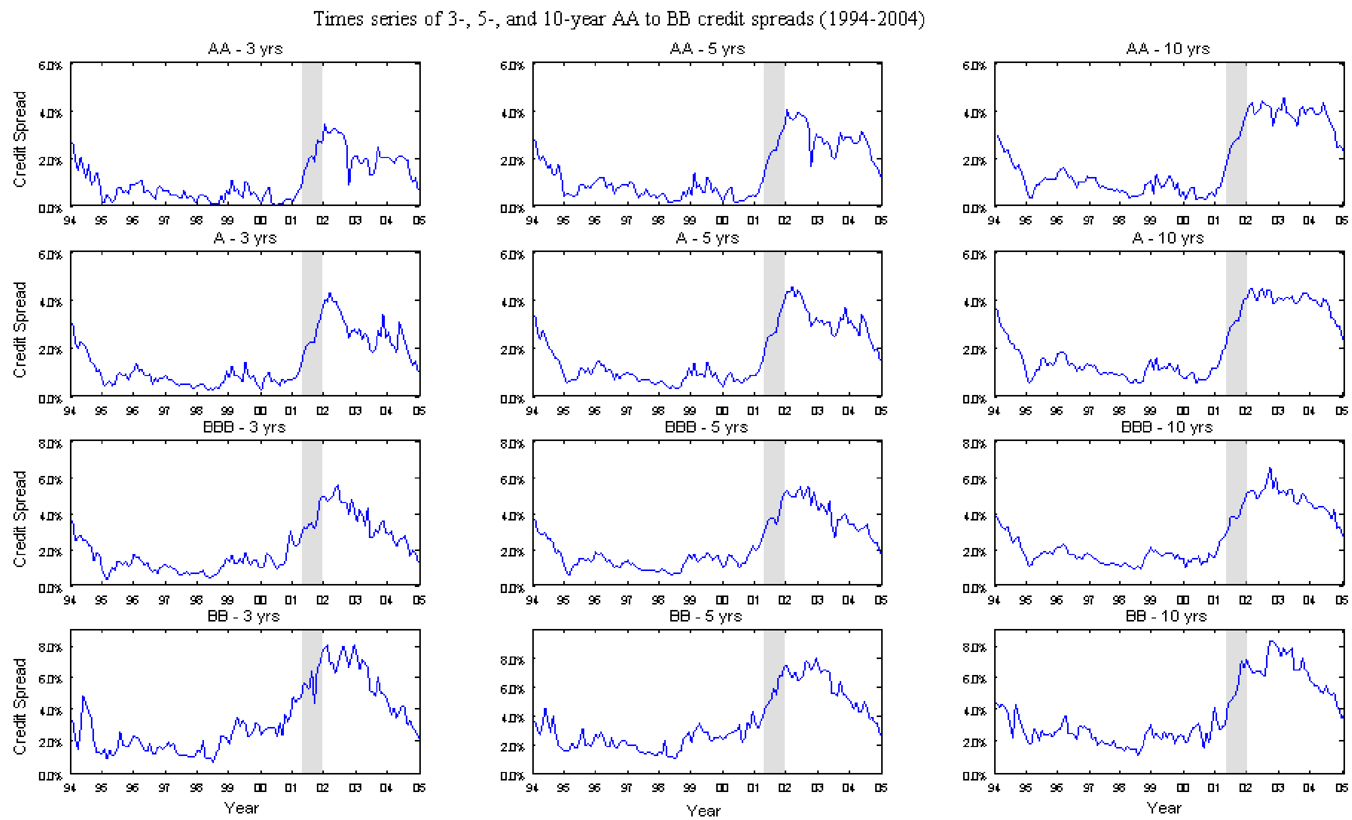

Figure 2: The smoothed probability of the high regime against credit spreads (1994-2004).

This figure plots in the right hand side of the axis the smoothed probabilities $p\left(s_t = 2|y_1, ..., y_T; \widehat{\theta}\right)$ that the process was in the high regime at each date in the sample. In the left hand side of the axis, it plots the credit spreads (dotted line in the high spread regime) for AA to BB corporate bonds maturing in 3, 5, and 10 remaining years to maturity. The shaded region represents the 2001 NBER period of recession.

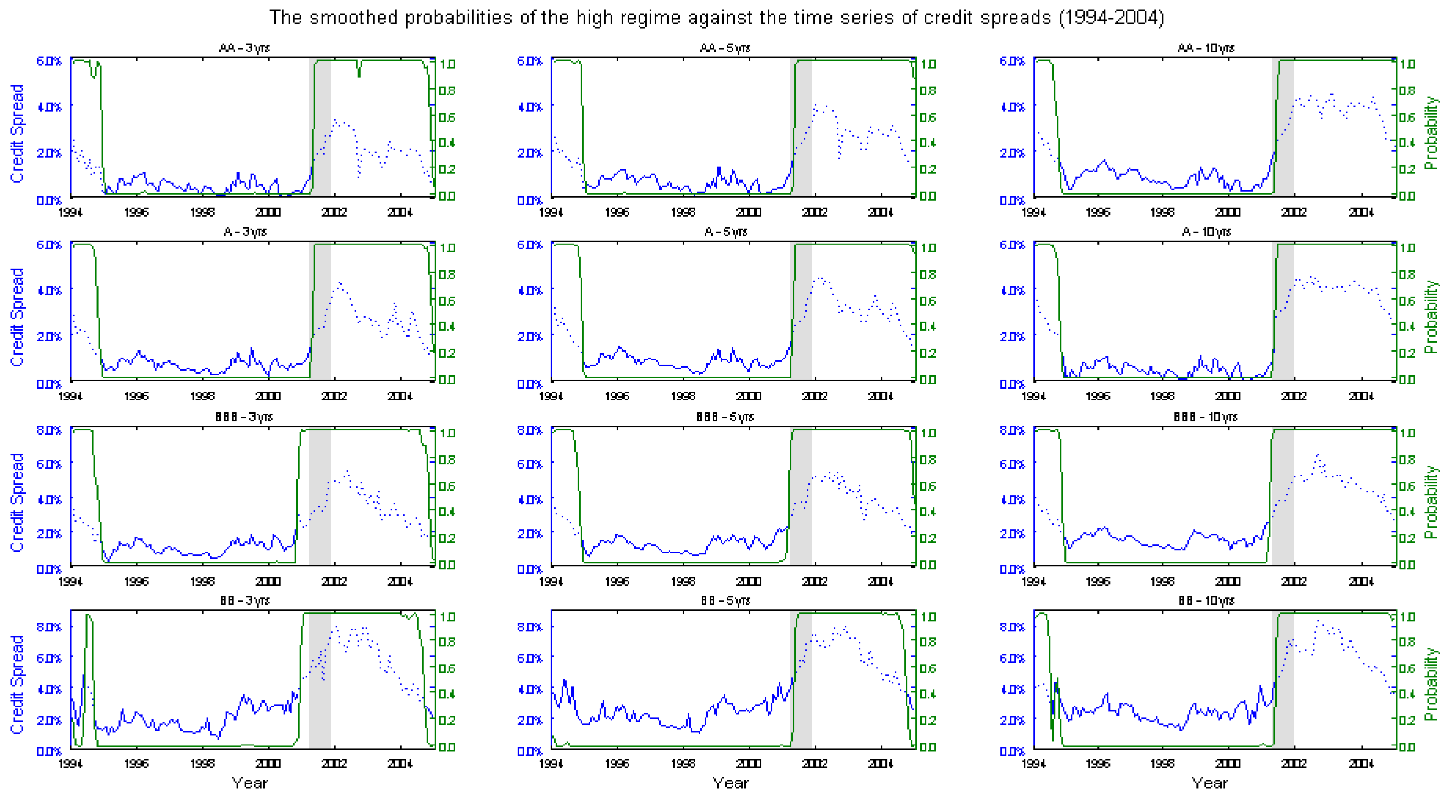

Figure 3: Economic cycle vs. credit cycle (10-year AA credit spreads).

In this figure, we present the CMT level against the 10-year AA credit spreads and the smoothed probability of the high spread regime. The shaded region represents the 2001 NBER period of recession.

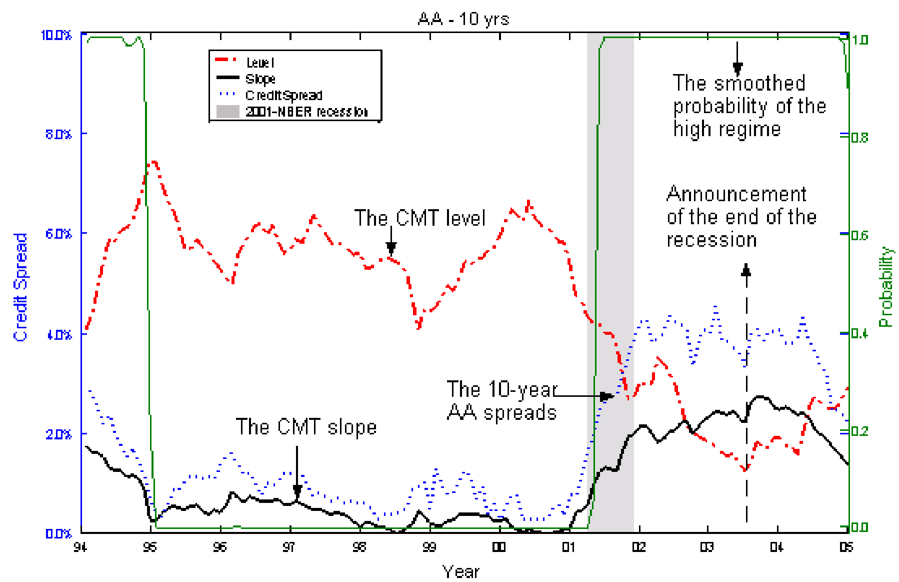

Figure 4: Out-of-sample smoothed probabilities for the 10-year AA spreads.

The figure presents the last point estimate in the smoothed probability curves obtained each from different sets of 10-year AA credit spread data. The first data set spans from January 1994 to May 2000. The second data set is augmented with the observation of the next month (June 2000). The last data set spans from January 1994 to December 2004. The shaded region presents the 2001 NBER period of recession.