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

Previous empirical studies on credit spread determinants consider a single credit spread regime over the entire sample period while the evidence often supports more than one switching regime in the credit spread dynamics. We analyse credit spread determinants in different mean-volatility-regimes. Our results do not support the single regime model. Specifically, when key determinants are closely related to economic cycles, their effects on credit spreads have opposite signs in high credit spread regimes. This is because economic cycles are shorter than credit cycles. Accounting for distinct regimes increases the explanatory power of credit spread determinants up to 60% for the 10-year AA to BB spreads.

Key words: 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

1 Introduction

Explaining observed credit spreads is still a puzzle even after the huge number of theoretical and empirical works on this subject. This is because spreads, defined as the difference between yields on risky corporate bonds and riskless bonds, tend to be many times larger than default spreads or what would be implied by only the default risk (see, Elton et al., 2001 and Huang and Huang, 2003). To solve the puzzle, the attention is first turned to the non-default factors (Collin-Dufresne et al., 2001; Driessen, 2003; Campbell et al., 2003; Huang and Kong, 2003; Longstaff et al., 2005; among others). However, even after accounting for non default factors (for example, market, liquidity and firm-specific factors), the puzzle remains unsolved because a large proportion of credit spreads remains unexplained. Then, many recent papers brought to light the behavior of credit spread series and support both switching regimes (Davies, 2004 and 2007 and Alexander and Kaeck, 2007) and counter-cyclical behavior (Koopman and Lucas, 2005). Yet, the connection between economic cycles and credit spread episodes remains unclear. In this paper, we show that this connection affects the contribution of different factors in explaining credit spread changes. The reason is that the credit cycle and the economic cycle start at almost the same time however the credit cycle is stickier and longer. 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 inversed between the end of the economic cycle and the end of the credit cycle. Previous empirical studies do not account for the credit spread behavior to explain credit spread differentials. This paper shows that doing so improves the contribution of different factors in explaining credit spread changes.

Credit spread determinants are covered in many previous works. Collin-Dufresne et al. (2001) consider market factors, firm-specific factors and macroeconomic factors but these factors do not explain more than 25% of credit spread changes. They conclude that the corporate bond market is driven by corporate bond specific supply/demand shocks. This result encouraged subsequent studies to investigate the role of both volatility and liquidity on corporate bond market. Driessen (2003) employs different methods and data to further decompose credit spreads. In particular, he allows for a liquidity premium. Campbell et al. (2003) consider the role of idiosyncratic equity volatility and find that this factor is directly related to the issuers' borrowing cost and is an important factor in understanding the movements in aggregate corporate bond spreads. Huang and Kong (2003) show that the historical return volatility and the macroeconomic indicators have significant power in explaining credit spread changes, especially for high yield corporate bonds. Their analysis suggests that changes in credit spreads for high-yield bonds are closely related to changes in interest rates and equity market factors.

Liquidity is approached by many subsequent empirical studies including Longstaff et al. (2005). Because direct liquidity measures are lacking in corporate bond market, these studies typically focus on bond characteristics such as coupon and age. However, liquidity factors constructed in this way are deterministic and may not capture the impact of stochastic variation in liquidity on credit spreads (Han et al., 2006). Liquidity measures frequently used in studies of the stock market liquidity (see for example, Amihud, 2002 and Hasbrouck, 2005) were applied to the corporate bond market (see, Downing et al., 2005; Bessembinder et al., 2005; Goldstein et al., 2006; Han et al., 2006). All these studies document the non negligible effect of liquidity in explaining credit spread changes especially when speculative-grade bonds are analysed. In this paper, we contribute to this literature by considering both default and nondefault components of credit spread. We include market factor, liquidity factor and default factor.

Previous studies on credit spread determinants consider only one credit spread regime even though the sample period may contain more than one. Taking into account a single regime may lead to conflicting results if the rising episode in the sample period is longer than the falling episode. Moreover, the range period may cover at least one NBER recession. This paper is the first that considers the time series analysis of credit spread determinants in different credit spread regimes. We first identify two credit-spread regimes: high-spread regime and low-spread regime as our sample period includes the 2001 NBER recession. The argument is that credit spreads are counter-cyclical, widening during recessions and narrowing during economic expansions (See for example Allen and Saunders, 2003; and Koopman and Lucas, 2005). Following Engle and Hamilton (1990), we model any given monthly change in the credit spread rate as deriving from one to two regimes, which could correspond to episodes of rising or falling 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 law that governs their transition. The parameter estimates can then be used to infer in which regime the process was at any historical date. This is done for many rating categories and maturity dates. Then, we examine determinants of credit spread changes in each regime. Interaction effects of these determinants with credit spread regimes reveal interesting economic relations. We find that factors closely related to the economic cycle have an opposite sign effect on the credit spread in the rising episode and factors closely related to the credit cycle have the same sign effect in the rising and falling episodes. We also find that the level, the slope, the implied volatility, the GDP, and the illiquidity factors significantly affect credit spread changes in both regimes but with distinct effect in each regime for many factors.

Overall, we find that there is significant merit in allowing for distinct regimes to analyse determinants of credit spread changes in terms of both the explanatory power and the identification of interesting economic relations. Specifically, we find that the level, the VIX volatility, and the illiquidity factor are more related to the economic cycle than to the credit cycle. They affect the credit spread with the expected 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 SMB factor, the realized default probability and the expected recovery rate are all closely related to the credit cycle. Their predicted signs remain the same in both regimes. Overall, 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 the illiquidity factors become the principal factors. Finally, the default and non default components considered may account 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, respectively. These explanatory powers improve when different factors are considered in different regimes and attain respectively 55.37%, 60.43%, 63.56%, and 47.07%.

The rest of the paper is organized as follows. Section 2 motivates our analysis of more than one credit-spread regime. Section 3 lists the main credit spread determinants. Some of these determinants are implied by the structural credit risk models, others are deduced from previous empirical studies and others are constructed and proposed. Section 4 describes the corporate bond data. Section 5 describes the algorithm used to extract spot rates. 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 Motivation

Time series of credit spreads undergo episodes in which the level and the volatility of the series change quite considerably. A striking example is provided in Figure 1 involving AA, A, BBB, BB, and B, U.S. corporate bonds from the industrial sector for 3, 5, and 10 remaining years-to- maturity. The period considered (1994-2004) covers the NBER 2001 recession.

[Insert Figure 1 here]

The figure shows that credit spreads, for all rating categories and maturities, exhibit at least two different regimes in terms of sudden changes in the level and the volatility over the period ranging from 1994 to 2004. We can at least distinguish a shift in the credit spread level over this period. Specifically, the level exceeds 2% in the period of 2001 to 2004 while it remains at less than 1% from 1995 to late 2000. A level of 2% is also observed in 1994. These shifts in the behavior of the credit spread may be associated with persistent financial crisis (Cerra et al., 2005; Hamilton, 2005) or sudden changes in government policy intensifying deep recessions and depressions (Hamilton, 1988; Sims and Zha, 2006; Davig, 2004). The high credit spread level of 1994 can be due to the precedent recession of 1991 and the high level of 2001-2004 may be due to the latest recession of 2001. This is not surprising since, in many recent findings, credit spreads are shown to be linked to the economic cycle (see for example Koopman and Lucas, 2005). These two preceding recessions last at most 8 months. However the high credit spread level lasts up to several years in both cases. As our sample period covers only the 2001 recession we base our analysis on the behavior of the credit spread around this period.

As can be seen in Figure 1, credit spreads shift from a falling episode to a rising episode just before the NBER official recession of November 2001 (shaded region). This first suggests that the rising episode is closely linked to the NBER recession since both regimes start at almost the same time. However, the NBER recession ends after 8 months (from March 2001 to November 2001) while credit spreads still continue to rise for several other months especially for the high-grade bonds. Economic and financial factors that affect the credit spread are also affected by the coming downturns and may be at the origin of this long rising episode (see, for example, Longstaff and Schwartz, 1995; Duffee, 1998; Collin-Dufresne et al., 2001; Perraudin and Taylor, 2003; Campbell et al., 2003; Huang et al. 2003; Han et al., 2006 among others). From an economic perspective, decreasing (resp. increasing) factors in period of recession adjust to coming period of expansion and start to increase (resp. decrease) after the recession ends. Since the credit spread is still rising even after the end of the recession, the effect of these factors on the credit spread becomes of opposite sign during months between the end of the recession and the end of the rising episode of the credit spread level.

This suggests that the relation between credit spreads factors closely related to economic cycles tend to have the opposite sign in the rising episode. In the same spirit, the relation between the credit spread and factors closely related to the credit cycle tend to maintain the same sign in both episodes. Further, key determinants in falling and rising episodes may be different. Those that are strongly affected by the financial crisis are expected to be the most significant in rising episodes. In the single regime, certain factors may be discarded because they are thought to be insufficient to explain variations in the credit spread dynamic. For example, if the whole period contains only few months of rising episode and longer months of falling 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 rising episode and also overall. Moreover, if these factors behave inversely in two different credit spread regimes, their global effect may be offset in the single regime model.

Inspection of Figure 1 also points the apparent link between the NBER recession and the rising episode of the credit spread. The credit spread starts to increase before the beginning of the NBER recession of March 2001 and starts to decrease in the late 2003 just after the announcement in July 2003 that the NBER recession ended officially in November 2001 (NBER official website). Between November 2001 and July 2003, bondholders act as if the recession is still there and this is reflected on the high credit spreads in this period. In 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 related to the economic cycle such as the interest rate level, the market volatility and Fama-French factors among others. As a result, factors that are most affected by the behavior of the real GDP level will have an opposite sign with the credit spread in the period between the end of the recession and the end of the rising episode.

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 factor due to the uncertainty of default losses; 2) The expected default loss, which is related to the risk that, in the event of default, investors will not receive the full amount of the promised cash flow; 3) The liquidity factor which is due to the price impact of trades and investors trading frequencies which characterize the supply and demand for liquidity in the corporate bond market. We select sets of explanatory factors and decompose them into market factor, default factor and liquidity factor.

3.1 Market factor

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 (Litterman and Scheinkman, 1991 and Chen and Scott, 1993). Longstaff and Schwartz (1995) argue that a higher interest rate level increases the drift of the risk-neutral firm value process. This will result in a decrease in the probability of default and the credit spread. In addition, lower interest rates are usually associated with a weakening economy and thus higher credit spreads. We expect a negative relation between the term structure level and the credit spread. 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, we expect that the interest rate effect is stronger for bonds with lower rating.

The slope of the default-free term structure is measured as the spread between the long-term and the short-term rate. 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 as above, it should also decrease credit spreads. A positively sloped yield curve is associated with an improving economic activity, which might in turn increase a firm's growth rate and reduce its default probability. We use the 2-year Constant Maturity Treasury (CMT) for the level and the 10-year minus the 2-year CMT for the slope. The CMT rates are collected from the U.S. Federal Reserve Board and the CMT curve for all maturities is estimated using the Nelson-Siegel algorithm.

3.1.2 The GDP growth rate

The real GDP growth rate is among the principal factors used by the NBER in determining periods of recession and expansion in the economy. Empirical evidence indicates that the credit spread behaves cyclically over time (see, for example Van Horne, 1998). During periods of economic downturn, credit spreads are expected to increase as investors become more risk averse and firms have lower asset returns (Huang and Kong, 2003). We expect a negative relation between the GDP growth and credit spreads as credit spreads are known to be higher in periods of recessions when GDP growth rate is low. The estimates of real GDP issued by the NBER of U.S. Department of Commerce are only available quarterly. We use 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 (Campbell et al., 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) which is similar to the Russell 2000 index used in Huang and Kong (2003). 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, (bid-ask spread, ownership, share turnover and number of no trade days) and industry group representation.

3.1.4 Market price of risk

Price of risk is another factor that may affect credit spreads. A higher price of risk should lead to a higher credit spread reflecting the higher compensation required by investors for holding a riskier security. 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 factor

3.2.1 Realized default rates

According to Moody's, default includes three types of credit events: (a) a missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period; (b) a filling for bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal; or (c) a distressed exchange which occurs to help the borrower avoid loss. In 2001 a confluence of events, including the consequences of the bursting of the New Economy bubble, the prevalent confidence and integrity crises following the incidence of accounting fraud and mismanagement resulted in one of the most intense years of credit pressure around the globe. According to Moody's reports (Moody's, 2002), defaults in 2001 were notable for their size as well as their frequency; default rates tested levels not seen since 1991.

It is well documented that high default rates are associated with large credit spread (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 rate

Empirical studies on the recovery of defaulted corporate debt look at the distressed trading prices of corporate debt upon default (see for example, Altman et al., 1996, 2001; Carty and Lieberman, 1996; Hamilton and Carty, 1999; Griep, 2002; Keisman et al., 2003; and Varma et al., 2003). Moody's looks at these prices one month after default. The distressed trading prices reflect the present value of the expected payments to be received by the creditors after firm reorganization. This is why 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 as required by their portfolio governance rules or their own investment objectives. This type of investors may also manage their portfolio before default in such a way they can liquidate just after default. This portfolio management is based on their forecast of the expected future recovery rates. The recovery rate decreases 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. Empirical studies provide evidence that the average default rates and recovery rates are negatively correlated (see for example, Hu and Perraudin, 2002; Frye, 2003; and Altman et al., 2004). Bruche and Gonzalez-Aguado (2006) explain the negative relationship as a result of an unobserved credit cycle. Therefore, the default and the recovery rate are directly associated to the credit cycle and should be considered in the analysis of the credit spread determinants across regimes. 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 the month (t+2) expected recovery 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.

3.2.3 Liquidity factor

Liquidity is a vague concept since it is not observed directly and has a number of aspects that cannot be captured in a single measure. Illiquidity reflects the impact of order flow on price of the discount that a 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 volume. 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). Clearly, any candidate metric for liquidity, using only daily price, can have an impact on the 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 the latter source covers intra-daily prices since 2002 and do not cover all our sample period. We construct liquidity measures based on the Price Impact of Trades and on the Trading Frequencies.

3.2.4 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 range (0-5; 5-10; 10+). This ensures sufficient daily prices to compute the Amihud daily measure. For each day j of portfolio i, at month t :

$$Amihud^{i}_{j,t} = \frac{R^{i}_{j,t}}{Q^{i}_{j,t}}, \text{ with } R^{i}_{j,t} = \frac{\left|P^{i}_{j,t} - P^{i}_{j-1,t}\right|}{P^{i}_{j-1,t}} \tag{1}$$

where $P^{i}_{j,t}$ (in \$ per \$100 par) and $Q^{i}_{j,t}$ (in \$ million) are the transaction price and the trading volume, respectively. This measure reflects how much prices move due to a given value of a trade. Suppose we have N days in each month with at least one transaction. The estimation procedure is as follows: 1) For each day j, we average transaction prices available in each portfolio i; Then, for each month i, we compute $N-1$ Amihud-type measures for each portfolio; 3) Next, we average over all $N-1$ days to form monthly measures. 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:

$$\operatorname{mod} Amihud^{i}_{j,t} = \sqrt{Amihud^{i}_{j,t}} \tag{2}$$

The range measure 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. The range is then measured by the ratio of daily price range, normalized by daily mean price, to the total daily dollar trading volume. For each portfolio i, day j, we compute:

$$Range^{i}_{t} = \frac{1}{Q^{i}_{j,t}} \times \left[\frac{\max P^{i}_{j,t} - \min P^{i}_{j-1,t}}{\overline{P}^{i}_{t}} \times 100\right] \tag{3}$$

where $\overline{P}^{i}_{t}$ is the daily average price of portfolio i and $Q^{i}_{j,t} = \sum_{j} Q^{i}_{j}$ the total transaction volume of portfolio i in day j. The estimation procedure is as follows: 1) For each day j, we calculate the difference between the maximum and the minimum price 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.

Liquidity measures based on transaction prices Since transaction prices are of major concern in explaining the change in the credit spread, we add 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 the monthly measure. 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 also include the same measures after weighting them by the inverse of the bond duration.

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 total trading volume in a month to the number of bonds outstanding;
- The number of days, during the month, with at least one transaction; and
- The total number of transactions that occurred during the month.

Traditional measures of liquidity Since recent literature support the contribution of liquidity factor in explaining credit spread changes, we also consider traditional measures including bond age and coupon. Table 1 presents a summary of all the explanatory variables considered with examples of previous researches using the same factors in explaining credit spreads.

[Insert Table 1 here]

4 Corporate bond data

To extract credit spreads 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, a 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 enhancements 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. Campbell et al. (2003), using the NAIC database, find negative spreads for AAA rated bonds for some period. They also report that the average credit spreads for AAA rated bonds are higher than those of A rated bonds. 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 38.93% and 36.87% 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 5.61 years. Table 2 reports summary statistics.

[Insert Table 2 here]

4.1 Credit spread curve

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

$$\begin{aligned} R(t,T) &= \beta_0 + \beta_1 \left[\frac{1-\exp(-\frac{T}{\tau_1})}{\frac{T}{\tau_1}} \right] + \beta_2 \left[\frac{1-\exp(-\frac{T}{\tau_1})}{\frac{T}{\tau_1}} - \exp(-\frac{T}{\tau_1}) \right] \\ &+ \beta_3 \left[\frac{1-\exp(-\frac{T}{\tau_2})}{\frac{T}{\tau_2}} - \exp(-\frac{T}{\tau_2}) \right] + \varepsilon_{t,j}, \end{aligned} \tag{4}$$

with $\varepsilon_{t,j} \sim N(0, \sigma^2)$. $R(t,T)$ is the continuously compounded zero-coupon rate at time zero with time to maturity T. β_0 is the limit of $R(t,T)$ as T goes to infinity and is regarded as the long term yield. β_1 is the limit of the spread $R(t,T) - \beta_0$ as T goes to infinity and is regarded as the long to short term spread. β_2 and β_3 give the curvature of the term structure. τ_1 and τ_2 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 heteroscedasticity 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 and White (2004), we use the swap rate curve less 10 basis points as a benchmark risk-free curve. For robustness, we also estimate the Treasury zero curve and find that curve parallel to the swap curve (results are available upon request). Therefore, in this research, the choice of the benchmark curve should not affect the results.

5 Switching regime model

The vector system of the natural logarithm of corporate yield spreads $y_t = \ln(cs_t)$ is affected by two unobservable regimes $s_t = i\,\{1,2\}$. In each regime, the credit spread dynamic shifts because its mean or variance or both have changed to characterize the state where the process was in:

$$y_t/s_t\tilde{\ }N\left(\mu_{s_t}, \Omega_{s_t}\right) \tag{6}$$

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

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

where these probabilities sum to unity by construction. 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 function of six population parameters :

$$p(y_t|s_t;\theta) = \frac{1}{[2\pi]^{(n/2)}\left|\Omega_{s_t}\right|^{(1/2)}} \exp\left[\frac{-\left[y_t - \mu_{s_t}\right]' \Omega_{s_t}^{-1}\left[y_t - \mu_{s_t}\right]}{2}\right], \; s_t = 1, 2. \tag{8}$$

where $(\mu_1, \mu_2, \Omega_1, \Omega_2)$ designate respectivelythe credit spread mean in the first regime, the credit spread mean in the second regime, the credit spread volatility in the first regime and the credit spread volatility in the second regime. 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. Specifically, 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 MLE. Specifically, we maximize the generalized objective function rather than the Likelihood function:

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

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

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

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

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 $(y_1,...,y_T)$:

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

$$\widehat{p}_{11} = \frac{\sum_{t=2}^{T} p(s_t = 2, s_{t-1} = 2|y_1,...,y_T;\widehat{\theta})}{\sum_{t=2}^{T} p(s_{t-1} = 2|y_1,...,y_T;\widehat{\theta}) + \widehat{\rho} - \sum_{t=2}^{T} p(s_1 = 1|y_1,...,y_T;\widehat{\theta})}, \tag{13}$$

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

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

The model parameters are estimated using the EM principal of Dempster, Laird, and Rubin (1977) described in Engle and Hamilton (1990). 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-weight the observed data y_t. Calculation of simple sample statistics of 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 such calculation of probabilities and re-weighting 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. Further details of these calculations are provided in Engle and Hamilton (1990).

6 Methodology

The objective of this study is to analyse credit spread determinants in different credit spread regimes. 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) and Schwartz (SIC) selection criteria. We also examine the interaction effects of these determinants with the low and high regimes. For the factors to include in each model, we proceed as follows:

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

2. We use Vector Autoregressive Regression (VAR) to determine the relevant lags (max lag =3) to consider for each corporate bond based on the AIC;

3. We use forward and backward variable selection based on AIC and SIC;

4. We repeat step 3 with each factor and then with the mixed factor. This is done in the one- and two-regime models.

6.1 Single regime model

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

$$\Delta Y_{t,i,m} = \beta_{0,i,m} + \beta_{1,i,m} \Delta X_{t-L,i,m} + \varepsilon_{t,i,m}, \tag{15}$$

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.

6.2 Low and high regime model

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 $(n \times 1)$ an 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 to the following two models for the two regimes:

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

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.η represents the model error-term.

7 Results

7.1 Observed credit spreads

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

[Insert Table 3 here]

The mean spread is 286 basis points, and the median is 230 basis points. Higher 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 credit spread statistics for all, short, medium and long maturities, respectively. Investment grade bonds are upward sloping for all maturity terms whereas speculative grade bonds are upward sloping for short and medium terms and become 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.

7.2 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. As credit ratings become low, the mean of credit spreads become higher. For investment grade bonds (AA to BBB), the credit spread mean, in both regimes, increases with maturity describing an upward slopping credit spread curve. For speculative grade bonds (BB and B), the credit spread mean increases until the medium term and then decreases in the long term describing a credit spread curve that is upward slopping in the short and medium term and downward slopping in the long term. The credit spread variance, in both regimes, increases as credit ratings become lower. It also increases from short to medium term but decreases in the long term. These maximum likelihood estimates associate state 1 with an increase in the credit spread mean and variance. In this state, 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.

[Insert Table 4 here]

Thus, the mean in state 1 is always higher than the mean of state 2 for all ratings and maturities. The variance of the credit spread, 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 0.0% 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. The state 1 is also associated with a higher credit spread variance. Therefore, we refer to state 1 as high mean – high volatility regime (high regime) and to state 2 as low mean – low volatility regime (low regime). The point estimates of p_{11} range from 0.943

to 0.989, while the 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 regimes also support the specification of the regimes (Table 5). 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. The only exception is found with the variances in both regimes for the 5-year BB spreads.

[Insert Table 5 here]

Figure 2 plots times series of credit spreads along with the smoothed probabilities $p(s_t = 2|y_1, ..., y_T; \widehat{\theta})$ indicating the months when the process was in the high regime. The figure also shows that for all ratings and all 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. The credit spread switch back to state 1 almost at the peak of the recession (November 2001) for all ratings and maturities except for low-grade bonds with short maturities where the switching happens few months before. All credit spread series stay in the state of high regime (state 1) from 2001 to late 2004 although the latest NBER recession of 2001 lasts only few months. This indicates that the high-spread episode is different from the recession episode and corresponds to a high credit cycle rather than to an economic cycle. Furthermore, credit spreads seem to persist in the same regime (state 1 or state 2) many months before switching to another regime or returning to the previous regime. Thus, we can think that the high spreads observed in the figure for the early 1994 originates from the NBER recession of March 1991 and persists in the same regime until the late 1994.

[Insert Figure 2 here]

Dionne et al., 2008 use a non parametric approach to detect regime shifts in credit spreads over the same period considered in this study. Their results for 3-, 5-, and

10-year AA to BB credit spreads suggest at least two regimes accounting for both shifts in credit spread levels and variances. The timing and the number of the shifts vary with the rating and the maturity but are closely related to economic events. They also suggest that the assumption of two credit spread regimes is reasonable.

7.3 Credit spread determinants in different regimes

Since we consider different fixed maturities for each rating class rather an average of short, medium and long maturities, key determinants in each regime differ widely across ratings and maturities. We only present the results for 10-year bonds for AA to BB rating. To measure liquidity, we construct monthly factor from daily values. We require 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, we exclude them from this step of the analysis. Variable selection analysis based on VAR and univariate regressions on the first three lags are available upon request. In the remainder of this section, we present the results obtained with each group of explanatory variables and discuss the interaction effects with the credit spread regimes.

7.3.1 Market factor

Since we use portfolios of fixed maturities rather than portfolios of average maturities including short, medium and long term bonds, different lags (max lag=3) are considered for different rating classes based on the AIC. This procedure improves the explanatory power of the one-regime model (29.31%, 40.15%, 26.22%, and 16.45% respectively for AA-, A-, BBB-, and BB-rated bonds). Results of the single regime model are shown in Table 6.

[Insert Table 6 here]

The term structure level and slope and the VIX are important determinants of credit spread changes for all bonds. The SMB factor is more significant for speculative grade bonds. As shown in Table 6, the CMT slope is positively related to credit spread changes and its contribution to the model is statistically significant at the 1% level for all ratings. Table 6 also shows that the level, the GDP and the SMB have negative signs as predicted. The first two lags (lag=0,1) of the VIX have positive signs while the second two lags (lag=2,3) have negative signs. The VIX volatility is significant for all ratings but its effect is more pronounced for BB spreads. The correlation between the VIX and AA, A, BBB, and BB spreads is, respectively, 0.48, 0.59, 0.48, and 0.20. 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. This is first due to the long term maturity considered here and second to the CMT yield curve used as a benchmark. 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 negative relation shows up especially with short and medium term bonds. 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. Considering credit spread regimes significantly improves the results for all ratings and especially for BBB and BB bonds. This is because credit spread regimes can be viewed as a characterisation of the credit cycle. Thus, BBB and BB spreads seem to be more affected by changes in the credit cycle. Their adjusted R-squared reaches respectively 36.99% and 30.24%.

[Insert Table 7 here]

In the low regime, the change in the level is statistically significant at least at the 5% level for all spreads while not significant in the high-regime. In the one-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 the time series of 10-year BB spread changes (Figure 2) shows that they increase at the beginning of the NBER 2001 recession and decrease by the mid-2003. However, 10-year AA, A, and BBB spreads decrease by the end of 2004. A broader examination of the dynamics of the level and the credit spread reveals that a possible explanation for this opposite sign in the high regime is due to the stikiness of the credit cycle over the economic cycle. Specifically, the credit cycle lasts longer than the economic cycle. When the recession starts (shaded region), the credit spread starts to increase and the interest level starts to decrease and when the recession ends the credit spread continues to increase for several other months while the interest rate level starts to decrease. Thus, the credit spread is related to the credit cycle and the level is related to the economic cycle. Since the credit spread is still increasing even after the end of the recession, the sign of factors closely related to the economic cycle is inversed in the high regime especially for high grade bonds.

As shown in Figure 3, the high regime starts few months before the NBER peak of March 2001. The NBER recession ends in November 2001 while the credit cycle ends in late 2004. The CMT level is decreasing with credit spread until July 2003 when the NBER announced officially that the end of the recession was in November 2001. Moreover, the relation between the CMT level and the 10-year AA credit spread is positive after July 2003 which explains the opposite sign in the high regime. This relation was also positive after November 2001 because interest rates start to increase just after the end of the recession while credit spreads continue to increase.

However, this relation becomes negative during 2002 specifically because this period was characterized by a significant decrease of interest rates. This explains why after this period and before the end of the credit cycle, the positive relation was re-established. Overall, factors that are closely related to the economic cycle change of sign when the credit spread change of regime. This in turn suggests that factors that are closely related to the credit cycle maintain the same sign in both regimes. This effect shows up even for the interest rate level even though the credit cycle period covers the 2002 period of falling interest rates.

The slope was significant in the one-regime model and remains statistically significant for all ratings in both regimes except in the high regime for BB spreads. The slope when significant maintains the same sign in both regimes. As shown in Figure 3, the slope is closely related to the credit cycle. In addition, the slope is measured by the difference between the 10-year and 2-year CMT yield curves. This difference can 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 the same time. As a result, the difference between these two curves may not be related to the economic cycle.

Besides, the level, the GDP, the VIX, the SML change of sign in both regimes. For example, for AA-spreads, the GDP is statistically significant in both regimes with an opposite sign in the low and 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. Also, the credit spread change, in both regimes, is closely related to the change in the VIX with the coefficients that are likely to be of opposite sign in different regimes. As suggested by univariate regressions, different lags in the VIX have different effects on the credit spread. All the coefficients have the opposite sign in the high regime since the VIX is also closely related to the economic cycle. The SMB like the slope maintains the same sign in both regimes. This suggests that the SMB is more important in the high regime especially for low grade bonds.

7.3.2 Default factor

The default factor involves essentially the change in the Moody's realized default probability of senior unsecured bonds; the Moody's expected recovery rates measured by the month (t+2) realized recovery rates. The expected recovery rate is performs better than the realized recovery rate in the single regime model. However, in the two-regime model, the expected recovery level introduces a high collinearity effect leading to a large Variance Inflation Factor (VIF). For this reason, we also use changes in this measure in order to compare the two models. The results are shown in Table 8 and Table 9.

[Insert Table 8 and 9 here]

Although not considered in the previous empirical studies, changes in the realized default probability and levels of expected recovery rates account at least for 9.28% up to 15% of the credit spread changes. The explanatory power worsens when we use changes instead of levels of expected recovery rates (Table 8). The coefficients of the default probability and the expected recovery rates are respectively higher and lower as credit ratings become lower. As expected, accounting for different credit spread regimes improves the explanatory power of the single regime model.

The regimes are all statistically significant at the 1% level (Table 9). The default probability remains significant overall for all the spreads but not significant in the high regime for AA and A spreads. We also notice that default probability coefficients are higher in the high regime for BBB and BB spreads. Changes in expected recovery rates remain significant for BB spreads as in the single regime model. However its sign is inversed in the high regime and its effect in more important. One possible explanation is that BB spreads decrease more quickly after the economic cycle even though their level remains high. At the same time, the recovery rates stay low during the high regime. For the other ratings, the results are not significant and thus remain inconclusive. Overall, the default factor affects more low-grade bonds rather than high-grade bonds.

7.3.3 Liquidity factor

In the recent literature, liquidity risk gains in popularity and becomes an appealing factor that significantly affects credit spreads (see, for example, Collin-Dufresne et al., 2001, Houweling et al., 2003, Perraudin and Taylor, 2003, and Ericsson et al. 2006). However, the effect of liquidity factor on the credit spread remains unclear. We still ignore whether liquidity have the same effect on bonds with different ratings and/or maturities (Houweling et al., 2002; Perraudin and Taylor, 2003; and Ericsson et al., 2006). Our preliminary univariate and multivariate regressions involve different sets of liquidity factors which include the traditional measures of liquidity such as coupon, size, age, duration and/or measures related to transaction prices and trading frequencies described above. 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, price volatility level, changes in the price volatility level, and change in the bond age. Table 10 and 11 present the results for the one- and two-regime models respectively.

[Insert Table 10 and 11 here]

In the low regime, liquidity factor explains at least 12.07% of A credit spread changes and up to 18.89% of BBB spreads. The liquidity factor is very important determinant in both regimes. This factor is constructed basically with daily transaction volumes and/or daily transaction prices of bond portfolios including bonds with same ratings, except for the age. Based on AIC and SIC criteria, the best factor involves different measures of liquidity for different bonds.

In the low volatility regime, the Amihud and the range are most important as bond grade becomes lower. 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.

The introduction of the regimes improves the model significance and explanatory power for all bonds. All the regimes are statistically significant at least at the 10% level except for BB bonds. The Amihud, the range, the median price and the price volatility seem to be closely related to the economic cycle. Their respective signs are inversed in the high regime. The range, the median price and the age are likely to keep the same sign in both regimes. The price volatility performs well in both regimes as it captures transaction price variations. It remains highly significant in both regimes while the median price measure performs better in the low regime rather than the high regime. Other measures of liquidity 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. 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 the AIC. Other measures based on trading frequencies affect more the level rather than the change in the level of credit spreads.

7.3.4 Mixed model

In the mixed model, we perform forward and backward variable selection based first on the three-factor models discussed above and on the AIC selection criteria. Mixed factors involve the change in the level, the change in the slope, the GDP growth rate, the changes in the VIX, the SMB level, the change in the SML factor, the change in the Amihud, the change in the range, the change in the median price, the change in the price volatility, the change in the age, the change in the realized default probability, and the level of the expected recovery rate. The results are shown in Table 12 and Table 13.

[Insert Table 12 and 13 here]

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. The merit owes to the relevant lags considered for each bond. The results, not reported here, are less significant when same lags and same factors are used for all rating classes especially when a fixed maturity class is involved. 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 credit regimes are statistically significant for all rating classes. The level and the slope are important determinants in both regimes. The GDP and the bond age contribute to the model variation only in the low regime. The VIX volatility and the illiquidity factor are most significant in the high regime but also contribute to the variation of credit spread changes in the low regime.

Results of the mixed model 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. The age, the GDP and the realized default probability are most important in the low-regime. 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 when the credit spread change of regime.

As explained before this is due to the fact that credit cycle lasts longer than the economic cycle. On the other hand, factors that are most related to the credit cycle such as the bond age, the slope, the realized default probability maintain the same sign in both regimes. However, these results are different for BB spreads. In the mixed model, the BB regime is positive and significant although negative for all other ratings.

It follows that the BB spread curve is more sensitive to the economic cycle rather than the credit cycle. As seen before in Figure 2, the slope of the 10-year BB credit spread curve is decreasing since mid 2003 around the official announcement date of the end of the NBER recession in November 2001. Another argument is the result with the CMT slope as it changes of sign in the high regime. However, the period between the November 2001 and July 2003 is still a period of increasing spreads for all rating classes. Economic factors that are closely related to the real GDP behave in the opposite way since November 2001. Other factors wait for the official announcement of July 2003 to react to the coming period of expansion. For this reason alternating signs across regimes are still observed even for BB spreads.

Overall, models with two credit spread regimes outperform models with one credit spread regime in terms of information content and explanatory power (Table 14). These results are based on the AIC information criteria.

[Insert Table 14 here]

7.3.5 Regime based factor model

The mixed model also improves when different factors are considered in different regimes. In Table 15, we reconsider all factors (not only those considered in the mixed model) and repeat the variable selection procedure based on the AIC information criteria. We consider different factors in the low and high credit spread regimes based on previous results. Table 15 shows that almost all the factors considered are statistically significant at least at the 10% level. The explanatory power of the model improves and attains 63.56% for BBB spreads. Overall, the regime-based model performs better than the mixed model. Results based on both AIC and SIC information criteria are given in Table 16.

[Insert Table 15 and 16 here]

Goodness-of-fit Table 17 shows the results of the Likelihood Ratio Test (LRT) for the goodness-of-fit between constrained and unconstrained models. The unconstrained models are single regime models involving the market factor, the default factor, the liquidity factor, the mixed factor or the regime-based factor. The constrained models are models involving these same factors within different regimes. The difference between models with regime and models without regime is statistically significant for all the factors. Obviously, the two-regime models outperform the single regime model as models with regimes have higher likelihood scores, with respect to additional model parameters.

[Insert Table 17 here]

7.4 Out-of-sample analysis of the credit cycle

Previous results show that accounting for the credit cycle in the analysis of the determinants of credit spread changes improves the model's information content. As shown in Figure 3, the credit cycle is different from the economic cycle since the first lasts longer than the second. Since there is much more experience in forecasting the credit spreads, we intend to test whether using these predictions the model succeeds in forecasting 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]

We find that the switching regime model used performs well out of sample given the predicted credit spread dynamic. 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.

8 Conclusion

The major contribution of this study is to examine the credit spread determinants in the presence of low- and high- credit spread regimes. We first characterize the credit spread switching regime model. The regime at any given date is presumed to be the outcome of an unobserved Markov Chain process. We infer the smoothed probabilities that govern the transition between low and high regimes. This procedure is done for different ratings and maturities. After that we examine determinants of credit spread changes in the one-regime model and in the two-regime model. We consider factors that gain popularity in the previous empirical studies and/or in the existing theoretical models. We also construct new illiquidity measures using the transaction prices and returns of portfolios grouped by rating and by maturity ranges. We show that the median price measure and the price volatility measure constructed from bond portfolio transaction prices play a major role in both regimes especially for low grade bonds. We also show that the Amihud and the range measures play a significant role in the liquidity factor model. We consider, in addition, the realized default probability and the level and changes in expected recovery rates to characterize the default environment. We find that the default factor play an important role, in both regimes, especially in the default factor model. Finally, we examine the interaction effects of the credit regimes with three set of factors: the market factor, the liquidity factor and the default factor. We also consider the mixed model when all factors are included at the same model and the regime-based model when different factors are included in different regimes.

We find that the level, the VIX volatility, the SMB, the SML, and the illiquidity variables are more related to the economic cycle than to the credit cycle. They affect the credit spread with the expected sign in the low regime and are likely to be of opposite sign in the high regime. One plausible explanation is as follows. All of these variables are more affected by the economic cycle rather than the credit cycle. When the NBER recession of November 2001, for example, starts, the credit spread increases, the interest rate decreases, the volatility becomes larger, and the bonds become more illiquid. However, after few months, when the recession ends, all the above variables behave in the opposite way to announce the coming upturns while the credit spread still continue to grow for several other months. Hence, the opposite sign in the high regime due to the different behavior of these variables and the credit spread in months between the end the economic recession and the end the credit cycle. Previous empirical studies presenting conflicting results for the relationship between the level, the slope and the credit spread may find a good argument in this study. Specifically, these conflicting results may only be due to the range of the period considered for the empirical study. If the whole period contains more months in the high regime than in the low regime, then the results will be driven from the high regime and inversely.

We also find that the slope, the bond age, the realized default probability and the expected recovery rate are all closely related to the credit cycle. Their expected signs remain the same in both regimes except for BB spreads. Overall, as credit rating becomes higher, the level, the slope, the VIX and the price volatility are the dominant factors that capture at least one third of the variation of credit spread changes in both regimes and as credit rating becomes lower the VIX volatility, the expected recovery rate and the illiquidity factors become the principal factors to consider. Results with BB spreads are somewhere different. First, when all the regimes are statistically significant they have a negative sign with AA, A, and

BBB spreads and a positive sign with BB spreads. Second, after the July 2003 announcement of the NBER end of the recession all credit spreads considered in this study are still none decreasing for several other months except the BB spreads. This suggests that contrarily to the investment grade bonds, the BB spreads are closely related to market conditions rather than to the credit cycle. It follows that the effect of the long credit cycle on BB spreads should be interpreted with respect to this downward slopping. For example, the slope is positive in the low and high regime of AA, A, and BBB spreads and becomes negative in the high regime of BB spreads. Even though BB spread series are downward slopping after the July 2003 announcement, their mean and volatility are still high and the series are still in the high regime. Thus, introducing the regimes also affects the results for BB spreads.

Finally, the addition of the credit cycle significantly improves all the models considered in this study in terms of significance level and explanatory power. We find that regimes are always significant in the mixed model and the regime-based model. We also show that models with regimes outperform models without regimes and the regime-based model outperforms the mixed model, based on the AIC and SIC information criteria. Finally, our procedure allows explaining up to 60% of credit spread changes for most rating classes.

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Table 1: Explanatory variables considered in this study.

Variable	Description	Sign	Example of related studies
Realized default probability	Moody's trailing 12-month default rates of all U.S. corporate issuers.	+	Huang and Kong, (2003)
	Moody's trailing 12-month default rates of U.S. speculative-grade issuers.	+	Huang and Kong, (2003)
Realized recovery rates	Moody's monthly recovery rates for Senior Unsecured bonds.	-	Altman et al. (2005)
	Moody's monthly recovery rates for Senior Subordinated bonds.	-	Altman et al. (2005)
Expected recovery rates	Moody's month (t+2) recovery rates for Senior Unsecured bonds.	-	Altman et al. (2005)
	Moody's month (t+2) recovery rates for Senior Subordinated bonds.	-	Altman et al. (2005)
Term structure level	Monthly series of 2-year CMT rates.	-	Huang and Kong (2003)
Term structure slope	Monthly series of 10-year CMT rates minus 2-year CMT rates.	-	Huang and Kong (2003)
Equity market return	S&P500 index return.	-	Huang and Kong, (2003); Bedendo et al,(2004)
Equity market volatility	VIX index implied return volatility.	+	Collin-Dufresne et al, (2001); Huang et al., (2003); Campbell et al., (2003)
GDP	The GDP growth rate.	-	Altman et al (2001)
Fama-French Factors	The HML, the SMB, and MktRf.	-	Elton et al. (2001); Collin-Dufresne et al.(2001)
Liquidity measures	Amihud and modified Amihud measures.	+	Amihud (2002); Hasbrouck (2005)
	The range (daily price change caused by a given trade volume).	+	Downing et al. (2005); Han et al. (2006)
	The turnover (monthly trading volume relative to number of bonds outstanding).	-	Vayanos (1998); Han et al. (2006) Campbell et al. (2003)
	Monthly transaction frequency of all trades.	-	Goldstein et al. (2006);Downing et al. (2005); Bessembinder et al. (2005);
	Monthly transaction frequency of a unique trade.	-	Han et al. (2006)
	The median price.	-	This paper
	The bond's age.	+	Han et al. (2006); Campbell et al. (2003)
	The bond's coupon.	+	Han et al. (2006); Campbell et al. (2003)
	The bond's size.	+	Han et al. (2006); Campbell et al. (2003)
	The bond's volume.	+	Batten et al. (2002)

Table 2: Summary statistics for US 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. Trades are the number of unique trades. AA to B are percentages of total trades with each bond category.

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				
% of Trades :						
	AA	9.60%				
	A	38.93%				
	BBB	36.87%				
	BB	10.50%				
	B	4.10%				

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 yield 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, A, BBB, BB, B-rated US corporate spreads maturing in 3-, 5-, and 10-years. (m_1, s_1^2) and (m_2, s_2^2) represent the level and the volatility of the credit spreads in the first and second regime, respectively; where $m_i = \exp([2\mu_i + \sigma_i^2]/2)$,$s_i^2 = \exp([2\mu_i + 2\sigma_i^2] - \exp[2\mu_i + \sigma_i^2])$, $i = 1, 2$. p_{11} and p_{22} are the conditional probabilities of the process being in state 1 and 2, respectively. ρ is the unconditional probability that the first observation come from state 1. The standard errors are into parentheses. Standard errors are in parenthesis.

Par.	AA			A			BBB			BB			B		
	3 Yr	5 Yr	10Yr	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	9.561	8.704	8.024
	(0.099)	(0.105)	(0.112)	(0.121)	(0.112)	(0.108)	(0.142)	(0.163)	(0.139)	(0.231)	(0.206)	(0.198)	(0.3467)	(0.383)	(0.306)
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	3.622	3.983	4.399
	(0.037)	(0.037)	(0.046)	(0.036)	(0.037)	(0.047)	(0.048)	(0.055)	(0.043)	(0.091)	(0.086)	(0.070)	(0.122)	(0.104)	(0.114)
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	0.969	0.971	0.943
	(0.021)	(0.015)	(0.013)	(0.022)	(0.014)	(0.013)	(0.020)	(0.020)	(0.012)	(0.029)	(0.026)	(0.014)	(0.025)	(0.024)	(0.035)
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	0.991	0.989	0.978
	(0.015)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.0145)	(0.015)	(0.009)	(0.014)	(0.009)	(0.011)	(0.015)
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	4.027	5.471	3.594
	(0.088)	(0.112)	(0.123)	(0.124)	(0.123)	(0.114)	(0.193)	(0.215)	(0.202)	(0.449)	(0.348)	(0.375)	(0.972)	(1.179)	(0.788)
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	1.206	0.775	1.037
	(0.016)	(0.017)	(0.026)	(0.015)	(0.016)	(0.027)	(0.027)	(0.031)	(0.023)	(0.099)	(0.096)	(0.063)	(0.195)	(0.134)	(0.165)
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	0.762	0.728	0.723

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

This table reports the confidence intervals for the means and variances of the high and low credit spread regimes. Credit spreads are rated from AA to B and have 3, 5, or 10-year remaining time-to maturity. The confidence level is 0.05.

Rating	tm (yrs)	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]
B	3	8,881; 10,240]	[3,383; 3,861]	[2,122; 5,932]	[0,824; 1,588]
	5	[7,953; 9,455]	[3,779; 4,187]	[3,160; 7,782]	[0,512; 1,037]
	10	[7,424; 8,624]	[4,175; 4,622]	[2,049; 5,138]	[0,714; 1,360]

Table 6: Explanatory power of the market factor in 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 $(\Delta slope)$, month (t) change in the GDP of the last month, months (t) to $(t-3)$ change in the VIX index, (ΔVIX), and month t Small-minus-Big Fama-French factor (SMB).

	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)	(-0,16)		(-0,046)
ΔVIX_{t-3}				-0,026
				(-0,008)
ΔSMB_t			-0,005	-0,024
			(-0,149)	(-0,022)
$AdjR^2$	29,31%	40,15%	26,22%	16,45%

Table 7: Explanatory power of the market factor in the two-regime model.
This table includes months (t) and $(t-3)$ changes in the 2-year CMT rates $(\Delta level_t)$, months (t) changes in the 10-year minus 2-year CMT rates $(\Delta slope_t)$, months $(t-1)$ and $(t-2)$ GDP (GDP), months (t) to $(t-3)$ change in the VIX index, (ΔVIX), and month (t) and $(t-2)$ Small-minus-Big Fama-French factor (ΔSMB), month $(t-1)$ change in the S&P600 Small Cap SML (ΔSML), and the dummy variable $(regime_{t,i})$ specific to each rating j that takes one in month t of high regime and zero in month t of low regime.

	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)
GDP_{t-1}	-0,036	-0,031		
	(0,017)	(0,009)		
GDP_{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)

Table 7 (Continued)

$regime_t$	-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)
$GDP_{t-1} \times regime_t$	0,012	0,021		
	(0,043)	(0,251)		
$GDP_{t-2} \times regime_t$			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 the default factor in the single regime model. This table includes the month t change in the realized default probability (ΔDP) and the month t level and change of the expected recovery rate, respectively ($ExpRECOV$, $\Delta ExpRECOV$).

	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)	
$\Delta RECOV_t$		-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 the default factor in the two-regime model. This table includes the month t change in the realized default probability (ΔDP), the month t change of the expected recovery rate ($\Delta ExpRECOV$), and the dummy variable ($regime_{t,i}$) specific to each rating j that takes one in month t of high regime and zero in month t of low regime.

	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)
$\Delta RECOV_t$	-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)
$\Delta RECOV_t \times regime_t$	-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 the liquidity factor in the single regime model.
This table includes the change in months (t) and $(t-3)$ changes in the Amihud measure $(\Delta Amih)$, months $(t-1)$ and $(t-3)$ changes in the range $(\Delta Range)$, month (t) and $(t-3)$ changes in the median price $(\Delta Medprice)$, the month (t) bond price volatility $(\mathrm{Si}\, gret)$, months (t) and $(t-2)$ changes in bond price volatility $(\Delta\, \mathrm{Si}\, gret)$, and the month (t) change in the bond age.

	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)
$\mathrm{Si}\, gret_t$	-4.324	-6.866		
	(0.006)	(0.002)		
$\Delta\, \mathrm{Si}\, gret_t$	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 the liquidity factor in the two-regime model.
This table includes the change in months (t) and $(t-3)$ changes in the Amihud measure $(\Delta Amih)$, months $(t-1)$ and $(t-3)$ changes in the range $(\Delta Range)$, month (t) and $(t-3)$ changes in the median price $(\Delta Medprice)$, the month (t) bond price volatility $(\mathrm{Si}\, gret)$, months (t) and $(t-2)$ changes in bond price volatility $(\Delta\, \mathrm{Si}\, gret)$, the month (t) change in the bond age, and the dummy variable $(regime_{t,i})$ specific to each rating j that takes one in month t of high regime and zero in month t of low regime.

	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)
$\mathrm{Si}\, gret_t$	2.018	1.018	8.585	
	(0.537)	(0.827)	(0.032)	
$\Delta\, \mathrm{Si}\, gret_t$				0.033
				(0.002)
$\Delta\, \mathrm{Si}\, gret_{t-1}$	-0.166	-3.890	-8.635	
	(0.948)	(0.302)	(0.010)	
ΔAge_t	0.075	0.137		
	(0.145)	(0.032)		

Table 11 (Continued)

	AA10	A10	BBB10	BB10
$regime_t$	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)
$\mathrm{Si}\,gret_t \times regime_t$	-0.075	-0.102	-0.119	
	(0.050)	(0.059)	(0.001)	
$\Delta\,\mathrm{Si}\,gret_t \times regime_t$				-0.027
				(0.024)
$\Delta\,\mathrm{Si}\,gret_{t-1} \times regime_t$	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)		
$AdjR^2$	18.12%	15.88%	27.80%	24.00%

Table 12: Explanatory power of the mixed factor in the single regime model.

This table includes month (t) and ($t-3$) changes in the level ($\Delta level$), months (t) change in the slope ($\Delta slope$), month (t) GDP (GDP), months (t) to ($t-3$) changes in the VIX index (ΔVIX), month (t) small minus big Fama French factor (SMB), month (t) and ($t-3$) changes in the Amihud measure,($\Delta Amih$), month ($t-1$) change in the range ($\Delta Range$), month (t) change in the median price ($\Delta Medprice$), months (t) and ($t-1$) changes in bond price volatility ($\Delta\,\mathrm{Si}\,gret$), month ($t$) change in the bond age (ΔAge), month (t) change in the realized default probability (ΔDP), and month (t) change in the expected recovery rate ($\Delta ExpRECOV$).

	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)
GDP_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)
$\Delta\,\mathrm{Si}\,gret_t$		3.926		0.015
		(0.026)		(0.007)
$\Delta\,\mathrm{Si}\,gret_{t-1}$	-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)
$\Delta RECOV_t$	-0.002		-0.002	-0.004
	(0.110)		(0.182)	(0.171)
$AdjR^2$	38.42%	48.62%	45.88%	32.73%

Table 13: Explanatory power of the mixed factor in the two-regime model.

This table includes month (t) changes in the level ($\Delta level$), months (t) change in the slope ($\Delta slope$), month (t) GDP (GDP), months (t−1) to (t−3) changes in the VIX index (ΔVIX), month (t) small minus big Fama French factor (SMB), month (t−1) change in SML (ΔSML), month (t) change in the Amihud measure,($\Delta Amih$), month (t) change in the range ($\Delta Range$), month (t) change in the median price ($\Delta Medprice$), months (t) and (t−1) changes in bond price volatility ($\Delta \mathrm{Si}\, gret$), month ($t$) change in the bond age (ΔAge), month (t) change in the realized default probability (ΔDP), month (t) change in the expected recovery rate ($\Delta ExpRECOV$),and the dummy variable ($regime_{t,i}$) specific to each rating j that takes one in month (t) if the regime is high and zero if the regime is low.

	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)
GDP_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)
$\Delta \mathrm{Si}\, gret_t$	1.200			0.023
	(0.539)			(0.002)
$\Delta \mathrm{Si}\, gret_{t-1}$		-0.377	-4.207	
		(0.886)	(0.075)	
ΔAge_t	0.098	0.201		
	(0.020)	(0.001)		
ΔDP_t				120.791
				(0.006)
$\Delta RECOV_t$				-0.005
				(0.025)

Table 13 (Continued)

	AA10	A10	BBB10	BB10
$regime_{t,i}$	-0.195	-0.136	-0.151	0.258
	(0.006)	(0.039)	(0.057)	(0.026)
$\Delta level_t \times regime_{t,i}$	0.134	0.113	-0.029	-0.435
	(0.144)	(0.000)	(0.451)	(0.303)
$\Delta slope_t \times regime_{t,i}$	1.207	0.634	0.246	-1.520
	(0.000)	(0.006)	(0.163)	(0.027)
$GDP_t \times regime_{t,i}$	0.043	0.022	0.023	
	(0.030)	(0.242)	(0.309)	
$\Delta VIX_{t-1} \times regime_{t,i}$	-0.020	-0.016		
	(0.025)	(0.004)		
$\Delta VIX_{t-2} \times regime_{t,i}$	0.013		0.013	0.001
	(0.013)		(0.038)	(0.955)
$\Delta VIX_{t-3} \times regime_{t,i}$			-0.034	0.015
			(0.000)	(0.395)
$SMB_t \times regime_{t,i}$	-0.009		-0.015	-0.063
	(0.408)		(0.043)	(0.063)
$\Delta SML_{t-1} \times regime_{t,i}$				-0.001
				(0.869)
$\Delta Amih_t \times regime_{t,i}$			2.231	-0.171
			(0.198)	(0.970)
$\Delta Range_t \times regime_{t,i}$	-2.521		20.500	0.044
	(0.314)		(0.086)	(0.463)
$\Delta Medprice_t \times regime_{t,i}$	-0.008	-0.002	0.006	0.044
	(0.279)	(0.633)	(0.017)	(0.463)
$\Delta\,\mathrm{Si}\,gret_t \times regime_{t,i}$	0.049			-0.032
	(0.035)			(0.010)
$\Delta\,\mathrm{Si}\,gret_{t-1} \times regime_{t,i}$		0.032	0.068	
		(0.294)	(0.009)	
$\Delta Age_t \times regime_{t,i}$	-0.039	-0.108		
	(0.479)	(0.448)		
$\Delta DP_t \times regime_{t,i}$				161.298
				(0.082)
$\Delta RECOV_t \times regime_{t,i}$				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 Factor	AA	-2.987	-2.901
	A	-3.405	-3.384
	BBB	-2.718	-2.634
	BB	-1.555	-1.398
Liquidity Factor	AA	-2.707	-2.688
	A	-3.007	-3.005
	BBB	-2.607	-2.522
	BB	-1.398	-1.391
Default Factor	AA	-2.686	-2.683
	A	-3.003	-3.017
	BBB	-2.454	-2.468
	BB	-1.329	-1.366
Mixed Factor	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.

The table includes month (t) changes in the level ($\Delta level$), months (t) change in the slope ($\Delta slope$), month (t) GDP (GDP), months ($t-1$) to ($t-2$) changes in the VIX index (ΔVIX), month (t) small minus big Fama French factor (SMB), month ($t-1$) change in SML (ΔSML), months (t) and ($t-3$) changes in the Amihud measure,($\Delta Amih$), month (t) change in the range ($\Delta Range$), month (t) change in the median price ($\Delta Medprice$), months (t) and ($t-1$) changes in bond price volatility ($\Delta \mathrm{Si}\, gret$), month ($t$) change in the bond age (ΔAge), month (t) change in the realized default probability (ΔDP), month (t) change in the expected recovery rate ($\Delta ExpRECOV$). The dummy variable ($regime_{t,i}$) specific to each rating j that takes one in month (t) if the regime is high and zero if the regime is low.

	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)
GDP_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)
$\Delta \mathrm{Si}\, gret_t$				0.036
				(0.000)
$\Delta \mathrm{Si}\, gret_{t-1}$	-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)
$\Delta RECOV_t$				-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)
$SML_{t-1} \times regime_t$	0.008	0.005	0.004	
	(0.034)	(0.012)	(0.100)	
$SMB_t \times regime_t$	0.018		-0.013	-0.060
	(0.003)		(0.029)	(0.021)
$\Delta VIX_{t-1} \times regime_t$		-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)
$\Delta Amih_t \times regime_t$			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)		
$\Delta \mathrm{Si}\, gret_t \times regime_t$				-0.022
				(0.133)
$\Delta \mathrm{Si}\, gret_{t-1} \times regime_t$	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)
$\Delta RECOV_t \times regime_t$	0.010		0.012	0.097
	(0.032)		(0.004)	(0.091)
$Adj R^2$	55.37%	60.43%	63.56%	47.07%

Table 16: Information content of mixed model with regimes vs. regime based model.

		Mixed 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 factor	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 factor	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 factor	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)
Mixed factor	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 factor	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 B 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.

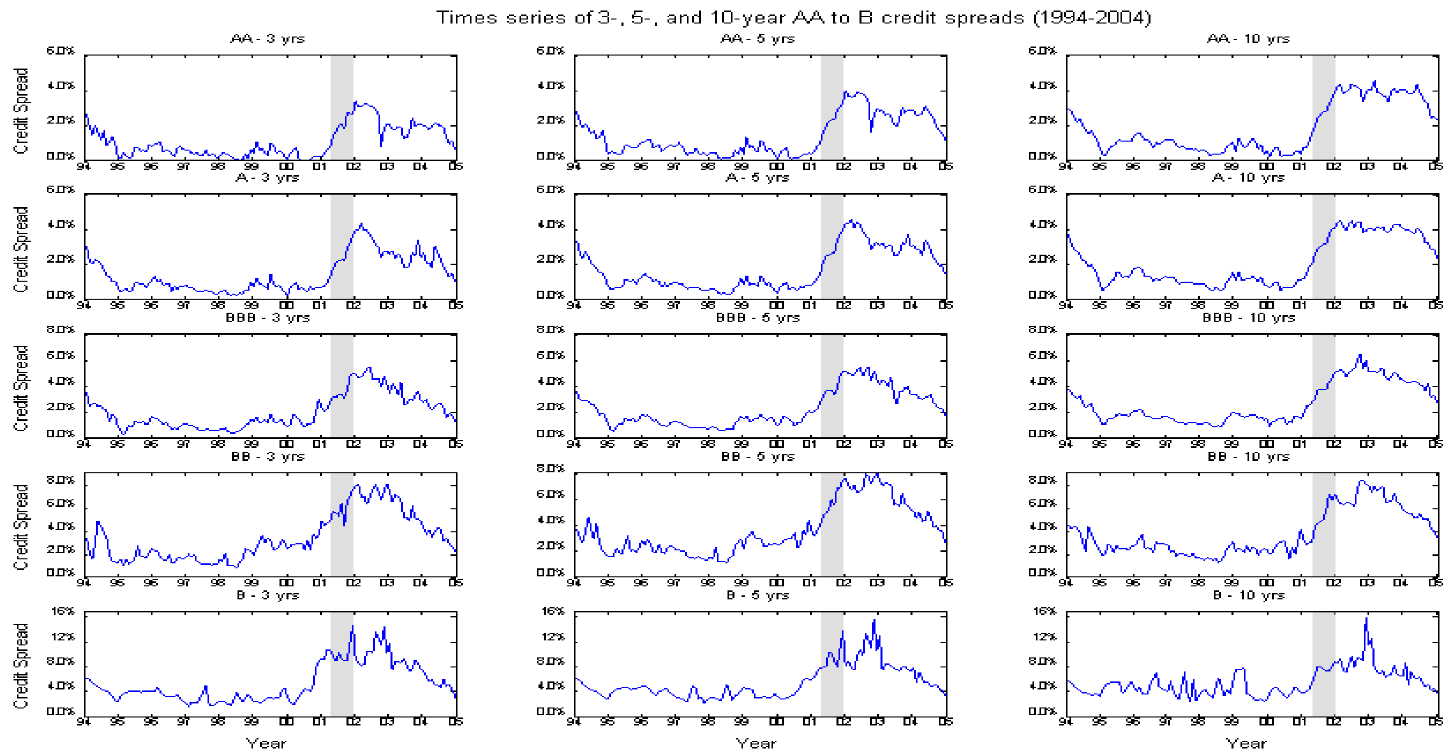

Figure 2: The smoothed probability of high regime against credit spreads (1994-2004).

This figure plots in the right-hand side 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, it plots the credit spreads (bleu line) for AA, A, BBB, BB corporate bonds maturing in 3-, 5-, and 10-year. The shaded region represents the NBER 2001 recession.

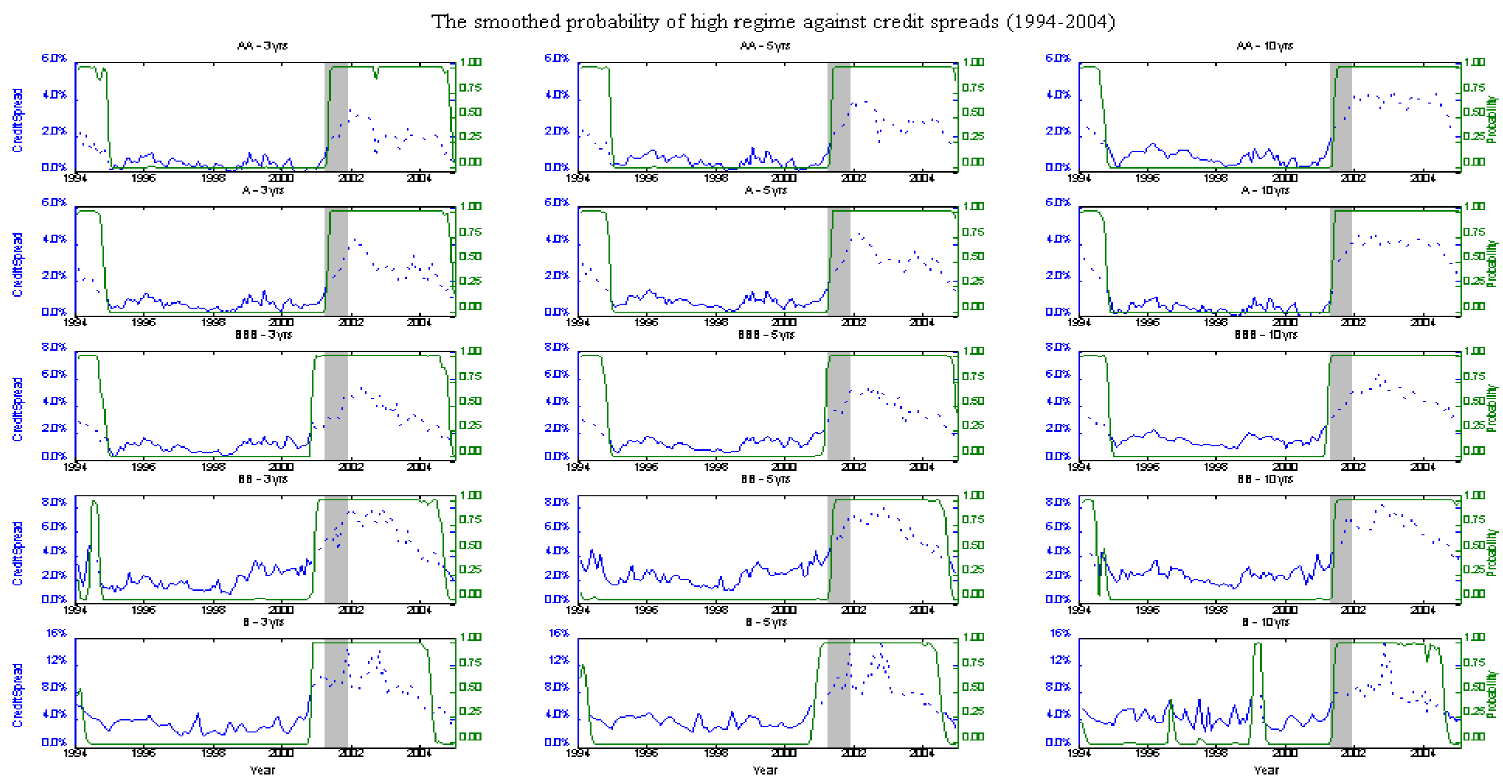

Figure 3: Economic vs. credit cycle (10-year AA credit spreads).

In this figure, the dash-dot line presents the CMT-level, the dark line presents the CMT-slope, the dotted line presents the 10-year AA spreads, the solid line presents the smoothed probability that the credit spread is in the high regime and the shaded region presents the NBER 2001 recession.

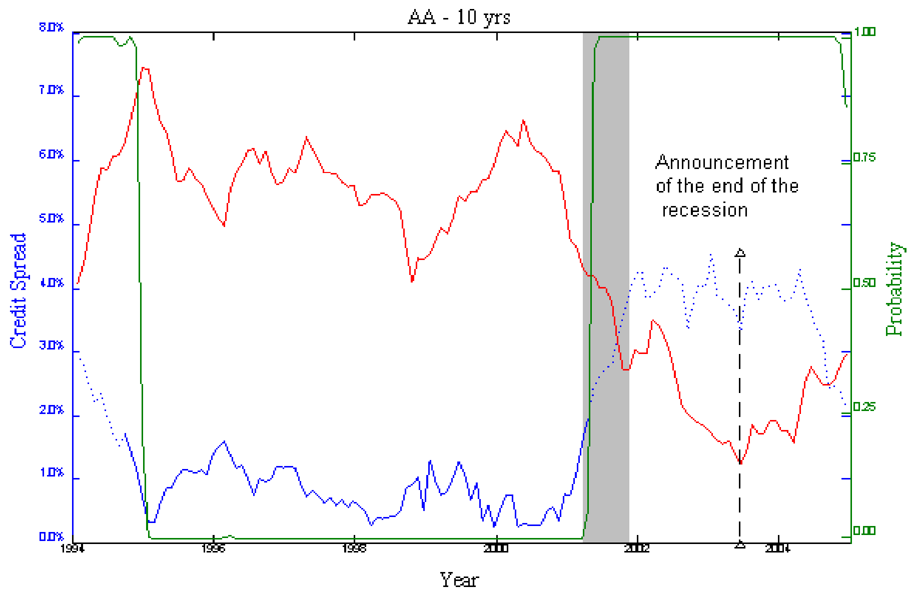

Figure 4: Out-of-sample smoothed probabilities for 10-year AA spreads.).

The figure presents each last estimate point from smoothed probability curves obtained each from credit spread data including each month a new out-of sample estimation for 10-year AA spreads. The first data set includes credit spread data from December 2004 to May 2000. The first probability estimate point in this figure corresponds to the last point in the smoothed probability curve obtained from the first data set. Then, the second data set includes the next new credit spread data of June 2000 which gives the second point estimate of the smoothed probability, and so on until. The last data set is the one including the last credit spread observation of December 2004. The shaded region presents the NBER 2001 recession.