Credit Spread Changes

Under Switching Regimes

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Abstract

Many empirical studies on credit spread determinants consider a single regime model over the entire sample period and find limited explanatory power for theoretical determinants of credit spreads. In this paper, we show that accounting for different regimes enhances the explanatory power of these determinants. We also obtain that credit spreads have their own cycle which is different from the economic cycle. Then, we model the credit cycle independently from macroeconomic fundamentals using a Markov regime switching model. We find that, in contrast to the economic cycle, the introduction of the credit cycle increases the model's adjusted R-squared to up to 60% on average for the 10-year AA to BB credit spread changes.

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

JEL Classification: C32, C52, C61, G12, G13

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1 Introduction

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

To address this puzzle, many parallel and subsequent studies investigate the ability of non default risk factors (such as market, liquidity and firm-specific factors) to explain credit spread differentials. These studies include those of Collin-Dufresne et al. (2001), Driessen (2003), Campbell and Taksler (2003), Huang and Kong (2003), Longstaff et al. (2005), and Han and Zhou (2006) among others. However, even after accounting for non default factors the puzzle remains unsolved because a large proportion of credit spreads remains unexplained. In particular, Collin-Dufresne et al. (2001) perform a regression that includes all potential explanatory variables predicted by theoretical models but fail to explain more than 25% of credit spread changes. They state that "variables that should in theory determine credit spread changes in fact have limited explanatory power". Collin-Dufresne et al. (2001) have also detected a common systematic factor that potentially could explain the large part of the unexplained changes. However, several macroeconomic and financial candidates fail to measure it. It appears, then, that their model is missing an important component which may not be captured by macroeconomic fundamentals. This paper focuses on the drivers of the missing component in credit spread determinants. Thus, it extends the Collin-Dufresne et al. (2001) model by allowing for a regime switching structure in the credit spread dynamics.

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

The systematic credit risk factors are typically thought to correlate with macroeconomic conditions as the original works of Fama and French (1989) and Chen (1991) have suggested that credit spreads exhibit a countercyclical behavior. Recently, Koopman and Lucas (2005) analyze the co-movements between credit spreads and macroeconomic variables and document the controversy on the exact relation between credit risk drivers and the states of the economic cycle. Their main conclusion supports the existence of countercyclical behavior but emphasize the need for more research in this area. Other works directly contrast the dynamics of the credit and economic cycles. Using a theoretical setting, Lown and Morgan (2006) show that the credit cycle may affect the course of the economic cycle and Gorton and He (2003) suggest that the credit cycle may have their own dynamics which may be different from the economic cycle. So far, the link between the economic and the credit cycle remains unclear. It also appears reasonable to think that the credit cycle may not be completely driven by macroeconomic fundamentals.

A number of theoretical papers use regime switches to capture state dependent movements in credit spread dynamics driven by macroeconomic fundamentals. A common feature of these models is to adopt a Merton structural form model combined with a Markov regime switching process to capture the impact of the transition of macroeconomic conditions and different states of the economic cycle on the credit risk premium. Hackbarth et al. (2006) were among the first to study the impact of macroeconomic conditions on credit risk and dynamic capital structure within this framework. Bhamra et al. (2007), Chen (2008), and David (2008) allow for regime switching in macroeconomic fundamentals to capture the uncertainty in the business cycle. All these works attempt to match the level of historical credit spreads by assuming significant variation in the market price of risk over the economic cycle.

Other works apply regime models to the time series of credit spreads by conditioning on alternative inflationary and/or volatility environments. For example, Davies (2004) uses a Markov switching Vector Auto-Regression (VAR) estimation technique to model regimes in the credit spread dynamics. He finds that credit spreads exhibit distinct high and low volatility regimes. He also finds that allowing for different volatility regimes enhances the explanatory power of economic determinants of credit spreads. His model includes the term structure level and slope, the VIX volatility and the Industrial production as explanatory variables. Most interestingly, he finds that the negative relation across the risk free rate and the credit spread, in the spirit of Merton (1974), Longstaff and Schwartz (1995) and Duffee (1998), disappears in the high volatility regime. The empirical works of Morris, Neale, and Rolph (1998) and Bevan and Garzarelli (2000) also suggest a positive relation between risk free rates and credit spreads. Davies (2007) extends the work of Davies (2004) by allowing for a longer data history and reach similar results.

In this paper, we choose to include regime models to account for the systematic movements in the credit spread dynamics. However, our switching regime structure is derived endogenously without accounting for macroeconomic fundamentals. Then, we analyze the credit spread determinants by conditioning on the credit spread regimes and we contrast our results with those obtained by conditioning on the states of the economic cycle. We show that the explanatory power of key determinants is reduced in the model without regimes (single regime model). It is still limited when we condition on the states of the economic cycle but enhances when we condition on the credit spread regimes.

Following Engle and Hamilton (1990), we model any given monthly change in both the level and volatility of credit spread rate as deriving from two regimes, which could correspond to episodes of high or low credit spreads. The regime at any given date is presumed to be the outcome of an unobserved Markov Chain. We characterize the two regimes and the probability law for the transition between regimes. The parameter estimates can then be used to infer in which regime the process was at any historical date. The obtained regime switching structure for credit spreads characterizes our specification of the credit cycle. This is done for several rating categories and maturity dates.

Our results can be summarized as follows. First, we find that allowing for different credit regimes enhances the explanatory power of market, default, and liquidity factors. Second, we show that the regime switching structure for credit spreads characterising the credit cycle is longer and different from the NBER economic cycle. In particular, we show that the end of the credit cycle is triggered by an announcement effect and to some extent by a persistence effect. Third, we illustrate how the connection between the economic cycle and the credit cycle drives the opposite sign (with respect to the negative predicted sign) between the risk-free rate and the credit spread rate found in Morris, Neale, and Rolph (1998), Bevan and Garzarelli (2000) and Davies (2004, 2007). We document the origins of this opposite signs and extend the analysis to other market, default and liquidity factors. In particular, we show that variables whose dynamics is closely related to the dynamics of the GDP have an inversed sign in most months of the high regime in the credit cycle. This opposite sign reduces the total effect of these variables in the single regime model. This result helps to explain why in the single regime model of Collin-Dufresne et al. (2001) the explanatory power of key determinants is found to be limited. Fourth, we show that accounting for the regimes in the economic cycle does not improve the single regime model. We support these results using several robustness tests. Relative to the single regime model our results always favor the distinct regime model and the credit cycle regimes. Overall, we obtain an adjusted R-squared of 60% on average for the 10-year AA to BB credit spread changes.

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

2 Regimes in credit spreads

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

[Insert Figure 1 here]

Across ratings and maturities, the credit spread movements exhibit at least two different regimes in terms of sudden changes in their level and/or volatility over the period considered. We can at least distinguish a shift in the credit spread level over this period. Specifically, the level of corporate - swap yield spreads exceeds 200 bps in the period of 2001 to 2004 while it remains at less than 100 bps from 1995 to late 2000. A level of 200 bps is also observed in 1994. Closer inspection of Figure 1 indicates that, just before the 2001 recession, credit spreads shift from a low episode to a high episode. The high credit spread episode and the NBER economic cycle appear to start at almost the same time. However, the high episode in the credit cycle looks to be longer than the high episode in the economic cycle. If credit spreads are counter-cyclical increasing in recessions and decreasing in expansions then they should decrease when the recession ends. Dionne et al. (2008) use sequential statistical t-test to test for breakpoints in the level of credit spreads over the period considered. They detect positive shifts few months before the beginning of the 2001 recession (March 2001). They also detect other positive shifts after the end of the recession (November 2001). Negative shifts are not detected until mid-2003.

These results show that credit spreads are still increasing after the recession generating a longer credit cycle. Further, the official announcements of the recession are November 2001 for the beginning of the recession and July 2003 for the end. It seems that the high credit spread levels perceive the beginning of the economic recession. It is also likely that the announcement of the end of the economic cycle drives the end of the high episode of credit spreads. When applied to the 1991 recession, the same scenario can explain the high credit spread level observed in 1994 since NBER announced the end of this recession only in December 1992.

Moreover, Figure 1 shows that credit spreads shift from one to another episode gradually. This looks plausible since Duffee (1998) shows that yields on corporate bonds exhibit some persistence and take around a year to adjust to innovations in the bond market. Since low grade bonds are closely related to market factors (Collin-Dufresne et al., 2001), they take less time to adjust to new market conditions at the beginning and the end of the cycle.

Inspection of the credit spread behavior at the beginning and the end of the economic cycle reveals that credit spreads have in fact their own cycle. Thus, it may not be completely driven by observed macroeconomic fundamentals whose behavior is more related to the dynamics of the GDP. For this reason, we choose to endogenously model regimes in the credit spread dynamics using a switching regime model driven by a hidden Markov process.[2] Previous empirical work using switching regime models for credit spreads usually assume two different regimes for different period range of observed data. For example, Davies (2004 and 2007) analyzes credit spread determinants using a Markov switching estimation technique with the assumption of two volatility regimes. Alexander and Kaeck (2007) also use two-state Markov chains to analyze credit default swap determinants within distinct volatility regimes. Dionne et al. (2008) use the same period considered in this study and support the existence of two regimes. Therefore, we assume that two state dependent regimes are adequate to capture most of the variation in our credit spread series.

The ultimate question now is why should we account for different regimes to address the credit spread puzzle? Recent contributions apply regime models to capture state dependent movements in credit spreads. In these works, regimes in credit spreads are usually driven from macroeconomic fundamentals which are closely related to the dynamics of the GDP. However, The GDP often enters into periods of expansion well before the official announcement while credit spreads are likely to remain in a period of contraction until the announcement. Further, many key determinants follow the dynamics of the GDP and their effects on credit spreads may change following a systematic economic shock. In particular, many coefficient signs are inversed in the high credit spread regime relative to the low regime. Thus, the regimes in credit spreads are not necessarily driven by the dynamics of the GDP and should be modelled independently from the states of the economic cycle.

Further, the extent to which these explanatory variables have limited explanatory power in the single regime model depends on the range of the period considered. For example, if the whole period contains a short high episode and a longer low episode, then the impact of

[2] The high credit spread episodes may be thought of as structural breaks since we are limited by a short sample of transaction data that includes only one recession. However, the switching regime model allows us to capture both episodes in the credit spread dynamics and to test for the contribution of key determinants in each of these episodes.

the sign reverse should not be very significant. However this impact becomes more important in the opposite case. Further, the credit spread variations in both episodes may be driven by different determinants. Those that are strongly affected by economic shocks are expected to be the most significant in high episodes. Accordingly, it is appealing to address the credit spread determinants in different credit spread regimes.

3 Credit spread determinants

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

3.1 Market factors

3.1.1 Term structure level and slope

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

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

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

3.1.2 The GDP growth rate

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

3.1.3 Stock market return and volatility

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

3.1.4 Market price of risk

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

3.2 Default factors

3.2.1 Realized default rates

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

3.2.2 Recovery rates

Empirical studies on the recovery of defaulted corporate debt look at the distressed trading prices of corporate debt upon default.[3] We use the Moody's monthly recovery rates from Moody's Proprietary Default Database for all U.S. senior unsecured issuers as well as senior subordinated issuers over our sample period. Since Moody's looks at these prices one month after default, we take month ($t+1$) release to measure month t recovery rates.[4] Following Altman et al. (2001), we also include month ($t+2$) recovery rates as a measure of the expected rates for both seniority classes.

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

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

3.3 Liquidity factors

Liquidity is not observed directly and has a number of aspects that cannot be captured by a single measure. Illiquidity reflects the impact of order flow on price of the discount that a seller concedes or the premium that a buyer pays when executing a market order (Amihud, 2002). Because direct liquidity measures are unavailable, most existing empirical studies typically use transaction volume and/or measures related to the bond characteristics such as coupon, size, age, and duration. Measures related to bond characteristics are typically either constant or deterministic and may not capture the stochastic variation of liquidity. Amihud (2002) suggests more direct measures of liquidity involving intra-daily transaction prices and trade volumes.[5]

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

3.3.1 Liquidity measures based on price impact of trades

The Amihud illiquidity measure This measure is defined as the average ratio of the daily absolute return to the dollar daily trading volume (in million dollars). This ratio characterizes the daily price impact of the order flow, i.e., the price change per dollar of daily trading volume (Amihud, 2002). Instead of using individual bonds, we use individual portfolio of bonds grouped by rating class (AA, A, BBB, and BB) and maturity ranges (0-5; 5-10; 10+). This ensures sufficient daily prices to compute the Amihud monthly measures.[6] For each portfolio i, at month t :

[5] These measures have been extensively used in the studies of stock market liquidity and are of direct importance to investors developing trading strategies.

[6] The Amihud monthly measure is obtained as follows: 1) For each day j, we average transaction prices available in each portfolio i; 2) Then, for each month t, we compute $N-1$ daily Amihud-type measures for each portfolio i; 3) Next, we average over all $N-1$ days to form monthly measures.

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

where N is the number of days within the month t, $P_{j,t}^i$ (in \$ per \$100 par) is the daily transaction price of portfolio i and $Q_{j,t}^i$ (in \$ million) the daily trading volume of portfolio i. This measure reflects how much prices move due to a given value of a trade. Hasbrouck (2005) suggests that the Amihud measure must be corrected for the presence of outliers by taking its square-root value, which measure is referred to as the modified Amihud measure. We also include the modified Amihud measure in our analysis:

$$\mathrm{mod}\, Amihud_t^i = \sqrt{Amihud_t^i} \tag{2}$$

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

$$Range_t^i = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{Q_{j,t}^i}\frac{\max P_{j,t}^i - \min P_{j,t}^i}{\overline{P}_{j,t}^i} \tag{3}$$

where N is the number of days within the month t, $\max P_{j,t}^i$ (in \$ per \$100 par) is the maximum daily transaction price of portfolio i, $\min P_{j,t}^i$ (in \$ per \$100 par) is the minimum daily transaction price of portfolio i, $\overline{P}_{j,t}^i$ (in \$ per \$100 par) is the daily average price of portfolio i and $Q_{j,t}^i$ (in \$ million) the daily transaction volume of portfolio i.[7] The range is an intuitive measure to assess the volatility impact as in Downing et al. (2005). It should reflect the market depth and determine how much the volatility in the price is caused by a given trade volume. Larger values suggest the prevalence of illiquid bonds.

Liquidity measures based on transaction prices Since transaction prices are of major concern in explaining credit spread changes, we construct new measures based on these prices. First, we use the daily median price of each portfolio i and then we average over all N days

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

to get monthly measures. We take the median because it is more robust to outliers than the mean. To better capture the effect of price volatilities, we also measure monthly price volatilities for each portfolio in each month. We further include the same measures after weighing bond prices by the inverse of bond durations.

3.3.2 Liquidity measures based on trading frequencies

Trading frequencies have been widely used as indicators for asset liquidity (Vayanos, 1998). We consider the following three measures:

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

Table 1 presents a summary of all the variables considered with examples of a previous study using the same variables to explain credit spreads or default risk. To overcome issues of stationarity observed in credit spread levels, we analyze the determinants of credit spread changes. Thus, all the explanatory variables considered are also defined in terms of changes (Δ) rather than levels. Following Collin-Dufresne et al. (2001) we also include the levels in the Fama French factors.

[Insert Table 1 here]

4 Corporate bond data

To extract credit spread curves for each rating class and maturity we use the Fixed Investment Securities Database (FISD) with U.S. bond characteristics and the NAIC with U.S. insurers' transaction data. The FISD database, provided by LJS Global Information Systems, Inc. includes descriptive information about U.S. 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 U.S. dollar bonds in the industrial sector. We exclude bonds with embedded options such as callable, putable or convertible bonds. We also exclude bonds with remaining time-to-maturity below 1 year. With very short maturities, small price measurement errors lead to large yield deviations, making credit spread estimates noisy. Bonds with more than 15 years of maturity are discarded since the swap rates that we use as risk free rates have maturities below 15 years. We finally exclude bonds with over-allotment options, asset-backed and credit enhancement features and bonds associated with a pledge security. We include all bonds whose average Moody's credit rating lies between AA and BB. AAA credit spreads are not used because we find them negative for some periods. We also find that the average credit spread for medium term AAA-rated bonds is higher than that of A-rated bonds. These same results are obtained by Campbell and Taksler (2003) using the same database. To measure liquidity, we have constructed monthly factors from daily values. This requires at least three transactions to occur in the same day unless the daily measure has missing value in that day. Since B-rated bonds do not have sufficient daily values, they have also been excluded.

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

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

4.3 years, a remaining time-to-maturity of 6.7 years and a duration of 5.6 years. Table 2 reports summary statistics.

[Insert Table 2 here]

5 Credit spread curves

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

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

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

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

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

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

6 Switching regime model

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The model parameters are estimated using the EM principal of Dempster, Laird, and Rubin (1977).[8] To implement the EM algorithm, one needs to evaluate the smoothed probabilities which can be calculated from a simple iterative processing of the data. These probabilities are then used to re-weigh the observed data y_t. Calculation of sample statistics of Ordinary Least Squares (OLS) regressions on the weighted data then generates new estimates of the parameter θ. These new estimates are then used to recalculate the smoothed probabilities, and the data are re-weighted with the new probabilities. Each calculation of probabilities and re-weighing the data are shown to increase the value of the likelihood function. The process is repeated until a fixed point for θ is found, and will then be the maximum likelihood estimate.

7 Single regime and regime-based models

We refer to the *single regime model* (Model 1) as the multivariate regression model involving changes in credit spreads as dependent variable and the best set of variables that better explains credit spread changes as independent variables. For each portfolio of corporate bonds rated i ($i =$ AA,...,BB) with remaining time-to-maturity m observed from January 1994 to December 2004, credit spread changes ($\Delta Y_{t,i,m}$) in month t may be explained by k independent variables $\Delta X_{t,i,m}$ within Model 1:

$$\text{Model 1:} \qquad \Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \varepsilon^1_{t,i,m}, \tag{15}$$

where $\beta^1_{0,i,m}$ and $\beta^1_{1,i,m}$ denote, respectively, the level and the slope of the regression line. Specifically, $\beta^1_{1,i,m}$ represents the global effect of key determinants on credit spread changes

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

over the whole period. $\Delta X^1_{t,i,m}$ is an $(1 \times k)$ vector representing the monthly changes in the set of k independent variables and $\varepsilon^1_{t,i,m}$ designates the error term for Model 1.

Based on Model 1 we also derive two additional models (Model 1E and Model 1C) which include an additional dummy variable characterizing the regimes in a particular cycle. Specifically, Model 1E includes a dummy variable for the regimes in the economic cycle ($regime^E_{t,i,m}$) while Model 1C includes a dummy variable for the regimes in the credit cycle ($regime^C_{t,i,m}$). Model 1E and Model 1C are different from each other and also from Model 1 in the sense that each of them may include a different best set of explanatory variables ($\Delta X^{1E}_{t,i,m}$ or $\Delta X^{1C}_{t,i,m}$, respectively for Model 1E and Model 1C) depending on the Akaike Information Criterion (AIC) used for model selection.

$$\text{Model 1E} \quad : \quad \Delta Y_{t,i,m} = \beta^{1E}_{0,i,m} + \Delta X^{1E}_{t,i,m}\beta^{1E}_{1,i,m} + \beta^{1E}_{2,i,m} \times regime^E_{t,i,m} + \varepsilon^{1E}_{t,i,m}, \quad (16)$$

$$\text{Model 1C} \quad : \quad \Delta Y_{t,i,m} = \beta^{1C}_{0,i,m} + \Delta X^{1C}_{t,i,m}\beta^{1C}_{1,i,m} + \beta^{1C}_{2,i,m} \times regime^C_{t,i,m} + \varepsilon^{1C}_{t,i,m}, \quad (17)$$

The single regime models (Model 1, Model 1E, and Model 1C) presume that the effects of all independent variables on credit spread changes remain the same throughout the whole sample period. Now, we assume that these effects are somehow affected by the regime in which credit spreads are. Therefore, we add to Model 1E and Model 1C interaction effects between explanatory variables and the regime in place.

The *regime-based models* (Model 2E and Model 2C) then specify the following dynamics for credit spread changes:

$$\begin{aligned} \text{Model 2E:} \quad & \Delta Y_{t,i,m} = \gamma^{2E}_{0,i,m} + \Delta X^{2E}_{t,i,m}\gamma^{2E}_{1,i,m} + \gamma^{2E}_{2,i,m} \times regime^E_{t,i,m} \\ & + \Delta X^{2E}_{t,i,m}\gamma^{2E}_{3,i,m} \times regime^{2E}_{t,i,m} + \eta^{2E}_{t,i,m}, \end{aligned} \quad (18)$$

$$\begin{aligned} \text{Model 2C:} \quad & \Delta Y_{t,i,m} = \gamma^{2C}_{0,i,m} + \Delta X^{2C}_{t,i,m}\gamma^{2C}_{1,i,m} + \gamma^{2C}_{2,i,m} \times regime^C_{t,i,m} \\ & + \Delta X^{2C}_{t,i,m}\gamma^{2C}_{3,i,m} \times regime^{2C}_{t,i,m} + \eta^{2C}_{t,i,m}, \end{aligned} \quad (19)$$

where for a particular cycle $j = 2E$, $2C$. Model 2E and Model 2C, once estimated, can be characterized for each regime:

$$\begin{cases} low - regime \ : \Delta Y_{t,i,m} = \widehat{\gamma}^{j}_{0,i,m} + \Delta X^{j}_{t,i,m}\widehat{\gamma}^{j}_{1,i,m} \\ high - regime \ : \Delta Y_{t,i,m} = \left(\widehat{\gamma}^{j}_{0,i,m} + \widehat{\gamma}^{j}_{2,i,m}\right) + \Delta X^{j}_{t,i,m}\left(\widehat{\gamma}^{j}_{1,i,m} + \widehat{\gamma}^{j}_{3,i,m}\right). \end{cases} \tag{20}$$

The parameters $\widehat{\gamma}^{j}_{0,i,m}$ and $\widehat{\gamma}^{j}_{1,i,m}$ denote, respectively, the estimated level and slope of the regression line in the low regime. The parameters $\left(\widehat{\gamma}^{j}_{0,i,m} + \widehat{\gamma}^{j}_{2,i,m}\right)$ and $\left(\widehat{\gamma}^{j}_{1,i,m} + \widehat{\gamma}^{j}_{3,i,m}\right)$ represent, respectively, the estimated level and slope of the regression line in the high regime. The Model 2E is in a high regime within the economic recession in the dates announced by the NBER and in a low regime otherwise. The Model 2C is in a high regime when the smoothed probability of the high regime obtained from the Markov switching model is equal to or higher than 0.5 and is in a low regime otherwise. The dummy variable for the regimes takes the value of 1 in the high regime and the value of 0 in the low regime. Model 1E and Model 1C include the same dummies for the regimes as in Model 2E and Model 2C, respectively.

For the five models specified above we repeat the same procedure for the selection of explanatory variables. We start with the same set of initial variable candidates. Then, we select the best explanatory variables set for each model by minimizing the AIC selection criteria. Specifically, for the variables to be included in a model, we proceed as follows:

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

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

3. In the multivariate regressions, we perform a forward and backward selection to minimize the value of AIC. We first use a forward selection by including the variable with the biggest jump in AIC. When we cannot reduce AIC by adding additional variables, we proceed with the backward variable selection.

Finally, we contrast the obtained models using several statistical tests.

8 Results

8.1 Observed credit spreads

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

[Insert Table 3 here]

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

8.2 High and low credit spread episodes

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

[Insert Table 4 here]

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

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

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

[Insert Table 5 here]

Figure 2 plots times series of credit spreads along with the smoothed probabilities $p(s_t = 1|y_1, ..., y_T; \widehat{\theta})$ indicating the months when the process was in the high regime. The figure also shows that for all ratings and maturities the probability that the credit spread is in the high regime at the beginning of the NBER recession (shaded region) is higher than 0.5. Further, credit spreads switch to state 1 (high regime) almost at the beginning of the recession (March 2001) except for low grade bonds with short maturities where the switching happens few months before. The first state is also prevalent for most months of 1994.

[Insert Figure 2 here]

All credit spread series stay in the high regime from 2001 to late 2004 although the 2001 recession lasts only for few months. This indicates that following the systematic shock of 2001, high spread levels are likely to persist in the high regime at least until the announcement date of July 2003. We also notice that high grade spreads (AA and A) are non decreasing for many months after the announcement date.

In the reminder of this section, we characterize the credit cycle – with respect to ratings and maturities – using the obtained regime switching structure for credit spreads. Specifically, we form a dummy variable that takes the value of one when the smoothed probability of being in the high regime is equal or higher than 0.5 and zero otherwise. To be convinced that we use the correct specification of the credit cycle we make two robustness checks. First, we regress each credit spread level on the corresponding dummy for the credit cycle. We find an adjusted R-squared of about 83% for AA and A spreads and about 80% for BBB and BB. Second, we regress each dummy on the average realized default probability to see whether the high regime prevails with a high default environment. We find an adjusted R-squared of about 57% for AA, A, and BBB spreads and about 60% for BB spreads. Thus, our specification of the credit cycle appears to be robust.

8.3 Models comparative explanatory powers

The main result in Collin-Dufresne et al. (2001) is that variables that should in theory explain credit spread changes have limited explanatory power in the single regime model (no more than an adjusted R-squared of 25%). The analysis of the five models described in Equation 15 to Equation 19 reveals new insights on the ability of key determinants to explain credit spread differentials. For conciseness, we only report the results for bonds with 10 years to maturity.

[Insert Table 6]

Our results show that the introduction of the regimes in the credit spread dynamics (Model 2C) enhances the explanatory power of key determinants. In particular, the total effect of these determinants throughout the whole sample period is weakened in the single regime models (Model 1, Model 1C, and Model 1E) thus reducing their explanatory power in most cases. Notice that all these models do not include interaction effects but may include a dummy variable to account for the sates in the credit cycle (Model 1C) or the economic cycle (Model 1E). We also find that by conditioning on the states of the economic cycle (Model 2E) we cannot significantly improve the explanatory power of the single regime models. Table 6 reports the adjusted R-squared for the five models considered here. Relative to Model 1 and Model 2E, Model 2C has the highest adjusted R-squared. However, relative to Model 1, Model 1C and Model 1E do not lead to a significant improvement. More interesting is that Model 2C has always the minimum value of AIC along with the highest explanatory power reaching on average 60% across all ratings. Detailed results for each of these models are reported in Table 7 to Table 10. As can be noted from these tables, the retained sets of explanatory variables in the five models are different since the model selection is based on the lowest AIC starting always from the same initial variables with respect to the collinearity issues.

[Insert Table 7 to Table 10]

To further support our results, we compare the regime-based model (Model 2C) and the single regime model (Model 1) using the same set of explanatory variables. First, we use the explanatory variables in Model 2C ($X^{2C}_{t,i,m}$) and derive the single regime model by setting the coefficients $\gamma^{2C}_{2,i,m} = 0$ and $\gamma^{2C}_{3,i,m} = 0$ in Equation 19. In this case, Model 2C and the obtained single regime model are nested and can be compared using the Likelihood Ratio Test (LRT). Table 11 shows that – for all ratings – the LRT favors Model 2C. Model 2C also performs better than the single regime model that includes an additional dummy variable for the regimes obtained by setting $\gamma^{2C}_{2,i,m} \neq 0$ and $\gamma^{2C}_{3,i,m} = 0$ in Equation 19. In both cases, the Chi2 is always statistically significant at least at the 1% level favoring Model 2C. In addition, when we compare both single regime models obtained from Equation 19 (i. e., $\gamma^{2C}_{2,i,m} = 0$ and $\gamma^{2C}_{3,i,m} = 0$ against $\gamma^{2C}_{2,i,m} \neq 0$ and $\gamma^{2C}_{3,i,m} = 0$) we find that the addition of the dummy variable for the regimes does not improve the single regime model. Hence, the enhanced explanatory power in Model 2C is driven by the interaction effects. Moreover, omitting interaction effects decreases the adjusted R-squared by roughly 10% for A spreads to up to 30% for AA spreads (Table 12). Table 12 also shows that the addition of the dummy variable for the regimes has only a marginal positive effect over the obtained single regime model. Still, this result holds only for AA and A spreads.

[Insert Table 10 and Table 11 here]

Next, we use the explanatory variables in Model 1 ($X^1_{t,i,m}$) and derive the regime-based model by adding two additional terms to Equation 15.

$$\begin{aligned} \Delta Y_{t,i,m} \quad = \quad & \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} \\ & + \Delta X^1_{1,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^{1C}_{t,i,m}, \end{aligned} \tag{21}$$

The first term is ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$) which is included to account for the regimes in the credit cycle. The second term is ($\Delta X^1_{t,i,m}\beta^1_{3,i,m} \times regime^C_{t,i,m}$) and it is included to account for the interaction effects of the explanatory variables in Model 1 with the regimes in the credit cycle. Model 1 and the obtained regime-based model are then nested. Table 13 shows that the LRT always favors the obtained regime-based model due to the addition of interaction terms. The addition of the dummy variable alone does not improve the results even in this case. The corresponding adjusted R-squared are reported in Table 14.

[Insert Table 13 and Table 14 here]

Then, we repeat the analysis by conditioning on the states of the economic cycle. The obtained regime-base model is given by Equation 22.

$$\Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^E_{t,i,m} + \Delta X^1_{1,i,m} \times \beta^1_{3,i,m} \times regime^E_{t,i,m} + \mu^{1E}_{t,i,m}, \quad (22)$$

In this case, conditioning on the states of the economic cycle rather than the credit cycle does not lead to similar results. The LRT favors always the single regime model ($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$ relative to $\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$ and $\beta^1_{2,i,m} \neq 0$ and $\beta^1_{3,i,m} = 0$) with the significance level of 1%. In addition, the single regime model has the highest adjusted R-squared and the lowest AIC.

For instance, we contrast Model 2C with Model 2E. Since both models include different sets of explanatory variables based on model selection criteria we perform two different tests.[9] First, using the same set of explanatory variables as in Model 2C ($\Delta X^{2C}_{t,i,m}$), we condition on the states of the economic cycle (i.e., $regime^E_{t,i,m}$ instead of $regime^C_{t,i,m}$ in Equation 19). In this case, the adjusted R-squared dropped by about 20% on average for all rating classes. We also find that most of the interaction coefficients are statistically significant with $regime^C_{t,i,m}$ while never significant with $regime^E_{t,i,m}$. Further, the F-test does not reject the null hypothesis for all the coefficients of the interaction terms being equal to zero (alpha=1%) when we condition on $regime^E_{t,i,m}$ and rejects the null when we condition on $regime^C_{t,i,m}$.

Finally, we contrast directly both models using the $J-$test (Davidson and MacKinnon, 1981) and the Cox-type test (Cox 1961, 1962; Pesaran 1974; Pesaran and Deaton 1978) for nonnested models. The null hypothesis is performed on both sides. We first test whether Model 2C is better than Model 2E then we test whether Model 2E is better than Model 2C. Both tests favor Model 2C and are statistically significant at the 5% level. One exception applies for AA and A spreads, where only the $J-$test fails to discriminate between both models (Table 15).

[9] Notice that most of the variables are dropped from Model 2E (relative to Model 2C) because of collinearity issues. For example, in most cases, the realized default probability, the recovery rate and some illiquidity variables fail the F-test for the regression to be statistically significant. Further, when these variables are included in the interaction terms the Variance Inflation Factors (VIF) almost explode because they are highly correlated with the states of the economic cycle.

[Insert Table 15 here]

Overall, relative to the single regime model, our results always favor the regime-based model where the contributions of the explanatory variables are conditioned by the regimes in the credit cycle.

8.4 Determinants in different regimes

Our results in the single regime model (Model 1) are consistent with the existing literature. The level, the slope, the GDP, as well as the Small-Minus-Big and the SML factors are shown to be statistically significant across different ratings.[10] We, further, enhance the explanatory power of Model 1 by introducing new measures of liquidity which are shown to be very significant across all ratings. The significance level is even stronger for lower grade bonds as the selected liquidity measures are based on transaction price movements in the bond market. These liquidity measures include the range, the median price, the price volatility, the Amihud and the turnover. We also find that the age has a non negligible effect for high grade bonds. All the variables have the predicted sign, except the CMT slope which has a positive effect on credit spreads.[11]

Previous results show that Model 1 has limited explanatory power since it assumes that the explanatory variables have the same effect on credit spreads over distinct regimes. We also show that Model 2C is our favorite model relative to the other models. Thus, we base our comments on the results obtained with Model 2C. Across ratings, the CMT level and slope are shown to be statistically significant in both regimes while the effect of the slope is stronger in the high regime. Like the slope, the liquidity variables are found to be significant in both regimes but their significance is more important in the high regime especially for low grade bonds. The age and the GDP are only important for AA and A spreads. Their

[10] Since we use portfolios of fixed maturities rather than portfolios of average maturities including short, medium and long term bonds, different ratings and maturities are found to be affected by different variables and lags.

[11] We find that changes in the CMT slope and changes in credit spreads are positively correlated. The correlation coefficient is 0.43 on average across ratings. In terms of levels, this coefficient is even stronger (0.92).

contribution while marginal is stronger in the low regime. The SMB and the SML have also a marginal contribution in the high regime.

Now, we focus on the coefficient signs of different variables in different regimes. In particular, most of the signs in the low regime are inversed in the high regime weakening their total effect in the single regime model. We summarize these signs in Table 16. As can be seen in this table, the signs of the explanatory variables in the single regime model (Model 1) are, in most cases, the same as those in the low regime for Model 2C. However, except for the variables that are closely related to the behavior of credit spreads (like the age, the CMT slope, and the realized default probability), all the other variables have an inversed sign in the high regime. These variables include most of the market factors and liquidity factors as well as the recovery rate. All these variables are likely to follow the behavior of the GDP rather than the behavior of credit spreads. On the other hand, according to the NBER, their committee usually wait to make a decision about the end of the recession until it was confident that any future downturn in the economy would be considered a new recession and not a continuation of the precedent recession. Thus due to the late NBER announcement, these variables are consistently in expansion well before the end of the high credit spread regime. It follows that after the economic recession, the sign effects are inversed especially for spreads with high grades and long maturities. These spreads are also more persistent to adjust to any new economic state.

[Insert Table 16 here]

Across all ratings, Table 16 shows that the level has a negative sign in the low regime. However, in the high regime, this coefficient turns out to be positive and statistically significant for AA and A spreads. For example, for A spreads, the coefficient of the level is -0.460 in the low regime and becomes +0.147 in the high regime. Both coefficients are significant at least at the 5% level. This same pattern is also observed for the VIX, the SMB, the SML, the recovery rate, and the illiquidity factors based on bonds transaction prices.

On the other hand, the CMT slope, the bond age and the realized default probability have the same signs in both regimes. For example, for A-rated bonds, the coefficient of the month t slope in the low regime is +0.241 and is statistically significant at the 10% level. In the high regime, this coefficient increases to 0.973 and is statistically significant at the 1% level. Similar to the slope, the realized default probability and the age have positive signs in both regimes but for the age the effect is weaker in the high regime. For A spreads, the coefficient of the age is +0.204 in the low regime and is significant at the 1% level while in the high regime its effect significantly decreases to +0.11.

The evidence for the GDP is weaker since its coefficient in the high regime is not statistically significant. However, for AA to BBB spreads, the GDP is statistically significant at least at the 5% with the predicted sign in the low regime. Moreover, for AA to BBB spreads, the F-test rejects the null hypothesis for the coefficient of the GDP to be equal to zero in the low regime and accepts the null for the coefficient to be equal to zero in the high regime. The F-test is significant at least at the 5% level. This further suggests that the economic cycle is different from the prevailing credit cycle. Thus, macroeconomic fundamentals may not capture total state dependent movements in the credit spread dynamics.

To support our findings about the sign inversion in the high regime we perform a straight forward test. Instead of introducing the regimes and their interaction effects, we rather estimate Model 2C over two sample periods covering each a different regime. The first period spans from January 1995 to December 2000 which is commonly a period of low regime for all ratings. The second period spans from November 2001 to December 2004 and covers basically the period between the end of the effective recession and the end of the credit cycle. In most cases, we still find evidence of the coefficient signs inversion in the subsample corresponding to the high regime in Model 2C. Results are reported in Table 17.

[Insert Table 17 here]

For a last check, we have also analyzed each set of factors (market, default, liquidity) separately (results available upon request). This is done to test whether the inversed signs in the high regime are only due to the correlation between different sets of factors considered in Model 2C. Variables included in each set of factor are also selected based on the lowest AIC. The results obtained with each set of factors – across ratings – are similar to those obtained with Model 2C. Thus, we still observe the sign inversions in the high regime. Further, for each factor model we contrast the single regime model to the regime-based model. We find based on the LRT that we still favor the regime based models which are similar to Model 2C but including market, liquidity or default factors (Table 18).

[Insert Table 18 here]

9 Conclusion

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

Our main result suggests that by conditioning on the regimes in the credit spread dynamics we enhance the explanatory power of the single regime model. Moreover, we show that the single regime model cannot be improved when we condition on the states of the economic cycle. In particular, most of the interaction terms in the regime-based model are almost never significant when considering the states of the economic cycle while they are highly significant when we consider the credit cycle.

Regimes in credit spreads are not necessarily related to the states of the economic cycle. The long high credit spread regime is shown to be basically due to an announcement effect and to some extent a persistence effect. In particular, the NBER wait for a long time before announcing the end of a recession. It follows that the dynamics of credit spread determinants that are closely related to the behavior of the GDP adjust to the period of expansion well before credit spreads do. In the meantime, the coefficient signs of these determinants are often inversed in the high regime. These changes in the coefficient signs are hidden in the single regime model leading to limited total effects and thus reducing the explanatory power of the model.

Moreover, our results show that different factors have different contributions in distinct credit spread regimes. This further suggests that the regime-based model also enhances the explanatory power of key determinants. The factors considered contribute to up to 60% to the variation of credit spread changes. Finally, our study is devoted to help in solving the credit spread puzzle documented in the recent works. Our results give new insights to the existing theoretical models on the credit risk literature using regimes switches derived from macroeconomic fundamentals.

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Table 1: Explanatory variables considered in this study.

Variable	Notation	Description	Sign†	Example of related studies
		Panel A. Market factors		
Term structure level	$\Delta level$	Monthly series of 2-year CMT rates	-	Huang and Kong (2003)
Term structure slope	$\Delta slope$	Monthly series of 10-year CMT rates minus 2-year CMT rates	-	Huang and Kong (2003)
GDP	Δgdp	GDP growth rate	-	Altman et al. (2001)
Equity market return	Δsp	SP500 index return	-	Huang and Kong (2003)
Equity market volatility	Δvix	VIX index implied return volatility	+	Campbell et al. (2003)
Fama-French Factors	hml	Fama-French High-Minus-Low factor	-	Collin-Dufresne et al. (2001)
	smb	Fama-French Small-Minus-Big factor	-	Collin-Dufresne et al. (2001)
Stock market index	Δsml	SP600 Small-Cap	-	This paper
		Panel B. Default factors		
Realized default probability	$\Delta dpall$	Moody's trailing 12-month default rates of all U.S. corporate issuers	+	Huang and Kong (2003)
	$\Delta dpspec$	Moody's trailing 12-month default rates of U.S. speculative grade issuers	+	Huang and Kong (2003)
Realized recovery rates	$\Delta recsus$	Moody's monthly recovery rates for Senior Unsecured bonds	-	Altman et al. (2005)
	$\Delta recsub$	Moody's monthly recovery rates for Senior Subordinated bonds	-	Altman et al. (2005)
Expected recovery rates	$\Delta \exp recsus$	Moody's month (t+2) recovery rates for Senior Unsecured bonds	-	Altman et al. (2005)
	$\Delta \exp recsub$	Moody's month (t+2) recovery rates for Senior Subordinated bonds	-	Altman et al. (2005)
		Panel C. Liquidity factors		
Traditional bond measures	Δage	Bond's age	+	Han and Zhou (2006)
	Δcp	Bond's coupon	+	Han and Zhou (2006)
	$\Delta size$	Bond's size	+	Han and Zhou (2006)
	Δvol	Bond's volume	+	Chakravarty and Sarkar (1999)
Price impact of trades	$\Delta amih$	Amihud	+	Han and Zhou (2006)
	$\Delta mamih$	Modified Amihud	+	Han and Zhou (2006)
	$\Delta range$	Range	+	Han and Zhou (2006)
	$\Delta medp$	Median price	-	This paper
	$\Delta sigp$	Price volatility	+	This paper
Trading frequencies	$\Delta turn$	Turnover	-	Han and Zhou (2006)
	$\Delta freqall$	Monthly transaction frequency of all trades	-	Goldstein et al. (2006)
	$\Delta frepuni$	Monthly transaction frequency of a unique trade	-	Han and Zhou (2006)

† Sign refers to the coefficient signs obtained in the single regime model.

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

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

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

Table 3: Summary statistics on credit spreads.

This table reports summary statistics on credit spreads for straight fixed-coupon corporate bonds over the swap curve less 10 basis points, in the industrial sector. The covered period range from 1994 to 2004. The spreads are given as annualized yields in basis points.

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

Table 4: Parameter estimates of the switching regime model.

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

Par.	AA			A			BBB			BB		
	3 Yr	5 Yr	10Yr	3 Yr	5 Yr	10Yr	3 Yr	5 Yr	10Yr	3 Yr	5 Yr	10Yr
μ_1	2.009	2.514	3.437	2.531	2.902	3.594	3.337	3.641	4.193	5.633	6.079	5.918
	-0.099	-0.105	-0.112	-0.121	-0.112	-0.108	-0.142	-0.163	-0.139	-0.231	-0.206	-0.198
μ_2	0.476	0.606	0.851	0.717	0.834	1.119	1.091	1.264	1.525	2.044	2.472	2.453
	-0.037	-0.037	-0.046	-0.036	-0.037	-0.047	-0.048	-0.055	-0.043	-0.091	-0.086	-0.07
σ_1^2	0.431	0.578	0.573	0.574	0.619	0.491	0.983	0.995	1.058	2.108	1.449	1.809
	-0.088	-0.112	-0.123	-0.124	-0.123	-0.114	-0.193	-0.215	-0.202	-0.449	-0.348	-0.375
σ_2^2	0.091	0.104	0.156	0.087	0.094	0.147	0.161	0.167	0.129	0.574	0.626	0.385
	-0.016	-0.017	-0.026	-0.015	-0.016	-0.027	-0.027	-0.031	-0.023	-0.099	-0.096	-0.063
p_{11}	0.973	0.986	0.988	0.975	0.987	0.988	0.973	0.980	0.989	0.953	0.969	0.987
	-0.021	-0.015	-0.013	-0.022	-0.014	-0.013	-0.02	-0.02	-0.012	-0.029	-0.026	-0.014
p_{22}	0.979	0.981	0.982	0.980	0.982	0.982	0.979	0.980	0.982	0.979	0.991	0.982
	-0.015	-0.014	-0.013	-0.014	-0.014	-0.014	-0.015	-0.014	-0.0145	-0.015	-0.009	-0.014
ρ	0.574	0.420	0.406	0.562	0.407	0.401	0.565	0.503	0.379	0.693	0.777	0.425

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

This table reports the confidence intervals for the means and the variances of the high and the low credit spread regimes. Credit spreads are rated from AA to BB (Rating) and have 3, 5, or 10 remaining years to maturity (Tm). The parameters μ_1 and μ_2 designates the means of the high and low regimes, respectively. The parameters σ_1^2 and σ_2^2 designates the variances of the high and low regimes, respectively. The confidence level is 5%.

Rating	Tm	μ_1	μ_2	σ_1^2	σ_2^2
AA	3	[1.815; 2.203]	[0.403; 0.548]	[0.258; 0.603]	[0.060; 0.122]
	5	[2.308; 2.720]	[0.533; 0.678]	[0.358; 0.797]	[0.071; 0.137]
	10	[3.217; 3.656]	[0.761; 0.941]	[0.332; 0.814]	[0.105; 0.207]
A	3	[2.294; 2.768]	[0.646; 0.787]	[0.331; 0.817]	[0.057; 0.116]
	5	[2.682; 3.121]	[0.761; 0.906]	[0.378; 0.860]	[0.063; 0.125]
	10	[3.382; 3.806]	[1.027; 1.211]	[0.267; 0.714]	[0.094; 0.199]
BBB	3	[3.059; 3.615]	[0.997; 1.185]	[0.605; 1.361]	[0.108; 0.214]
	5	[3.321; 3.960]	[1.156; 1.372]	[0.574; 1.416]	[0.106; 0.227]
	10	[3.920; 4.465]	[1.441; 1.609]	[0.662; 1.454]	[0.084; 0.174]
BB	3	[5.180; 6.086]	[1.866; 2.222]	[1.228; 2.988]	[0.380; 0.768]
	5	[5.675; 6.483]	[2.303; 2.640]	[0.767; 2.131]	[0.438; 0.814]
	10	[5.530; 6.306]	[2.316; 2.590]	[1.074; 2.544]	[0.261; 0.508]

Table 6: Comparative adjusted R-squared.

For each rating class (AA to BB) in Column (1), we report the adjusted R-squared ($AdjR^2$), the Variance Inflation Factors (VIF) along with the Akaike Information Criteria (AIC) obtained for models described in Equation 15 to Equation 19.

		Model 1	Model 1E	Model 1C	Model 2E	Model 2C
		Single regime model	Single regime models with dummy for the cycle		Two regime models with interaction effects	
			Economic	Credit	Economic	Credit
AA	$AdjR^2$	0.432	0.438	0.426	0.331	0.604
	VIF	1.30	1.29	1.23	1.74	4.24
	AIC	-3.067	-3.077	-3.063	-2.897	-3.312
A	$AdjR2$	0.574	0.570	0.57	0.374	0.614
	VIF	1.39	1.41	1.42	3.93	4.15
	AIC	-3.672	-3.657	-3.659	-3.274	-3.718
BBB	$AdjR^2$	0.483	0.49	0.478	0.428	0.662
	VIF	1.23	1.28	1.28	3.22	9.00
	AIC	-2.922	-2.930	-2.906	-2.775	-3.213
BB	$AdjR^2$	0.383	0.363	0.379	0.317	0.537
	VIF	1.23	1.23	1.28	8.92	4.06
	AIC	-1.659	-1.640	-1.645	-1.485	-1.840

Table 7: Determinants of credit spread changes within different models (Rating = AA).

We compare different models ability to explain credit spread differentials. Model 1 refers to the single regime model. Model 1E refers to the single regime model with a dummy for the regimes in the economic cycle. Model 1C refers to the single regime model with a dummy for the regimes in the credit cycle. Model 2E and Model 2C refers to the regime-based models including interaction effects with the regimes in the economic cycle and the credit cycle, respectively. Variable selections are based on the minimization of AIC using the same set of initial explanatory variables. We control for the degree of collinearity using the Variance Inflation Factors (VIF). ***, **, * indicate the significance level at 1%, 5%, and 10%, respectively.

	Model 1	Model 1E	Model 1C	Model 2E	Model 2C
	Single regime model	Single regime models with dummy for the cycle		Two regime models with interaction effects	
		Economic	Credit	Economic	Credit
$intercept$	-0.007	-0.045	0.096**	-0.016	0.075*
$\Delta level_t$	-0.170*	-0.167*	-0.153	-0.083	-0.356***
$\Delta slope_t$	0.826***	0.785***	0.774***	0.741***	0.083
$\Delta slope_{t-1}$					0.366**
Δgdp_t	-0.027***	-0.021**	-0.026***		-0.021**
Δvix_{t-2}				-0.009**	-0.018***
smb_t	0.011**	0.011**	0.011**	0.009*	0.010**
Δsmb_{t-2}					-0.004
Δsml_t	0.004*	0.004**	0.004*		0.002
Δsml_{t-2}					-0.001
$\Delta recsub_t$	0.003	0.003*			-0.001
Δage_t	0.075**	0.073**	0.073**		0.127***
$\Delta amih_{t-1}$					-0.007
$\Delta range_{t-1}$	0.936**	0.806*	0.927**	1.011**	
$\Delta medp_t$	-0.051***	-0.053***	-0.052***		-0.025*
$\Delta sigp_{t-1}$	2.820**	3.754***	3.728***	3.266**	
$\Delta sigp_{t-2}$	-0.02				-0.040**
$\Delta turn_t$					-0.034
$\Delta turn_{t-3}$	-0.034**	-0.031*	-0.031*		
$regime_t$		0.148*	-0.055	0.177*	-0.003
$\Delta level_t \times regime_t$				0.083	0.373**
$\Delta slope_t \times regime_t$				-0.169	1.352***
$\Delta slope_{t-1} \times regime_t$					-0.335
$\Delta gdp_t \times regime_t$					-0.013
$\Delta vix_{t-2} \times regime_t$				0.012*	0.046***
$smb_t \times regime_t$				-0.006	-0.022**
$\Delta smb_{t-2} \times regime_t$					0.028***
$\Delta sml_t \times regime_t$					0.005
$\Delta sml_{t-2} \times regime_t$					0.011**
$\Delta recsub_t \times regime_t$					0.016***
$\Delta age_t \times regime_t$					-0.123*
$\Delta amih_{t-1} \times regime_t$					1.021*
$\Delta range_{t-1} \times regime_t$				-26.10	
$\Delta medp_t \times regime_t$					-0.024
$\Delta sigp_{t-1} \times regime_t$				1.881	
$\Delta sigp_{t-2} \times regime_t$					-0.002
$\Delta turn_t \times regime_t$					0.074**
$AdjR^2$	0.432	0.438	0.426	0.331	0.604
VIF	1.30	1.29	1.23	1.74	4.24
AIC	-3.067	-3.077	-3.063	-2.897	-3.312

Table 8: Determinants of credit spread changes within different models (Rating = A).

We compare different models ability to explain credit spread differentials. Model 1 refers to the single regime model. Model 1E refers to the single regime model with a dummy for the regimes in the economic cycle. Model 1C refers to the single regime model with a dummy for the regimes in the credit cycle. Model 2E and Model 2C refers to the regime-based models including interaction effects with the regimes in the economic cycle and the credit cycle, respectively. Variable selections are based on the minimization of AIC using the same set of initial explanatory variables. We control for the degree of collinearity using the Variance Inflation Factors (VIF). ***, **, * indicate the significance level at 1%, 5%, and 10%, respectively.

	Model 1	Model 1E	Model 1C	Model 2E	Model 2C
	Single regime model	Single regime models with dummy for the cycle		Two regime models with interaction effects	
		Economic	Credit	Economic	Credit
$intercept_t$	0.023	0.021	0.032	0.018	0.108***
$\Delta level_t$	-0.346***	-0.346***	-0.341***	0.018	-0.460***
$\Delta level_{t-3}$	-0.128**	-0.127**	-0.127**		-0.104
$\Delta slope_t$	0.621***	0.618***	0.626***	0.814***	0.241*
Δgdp_t	-0.012*	-0.012	-0.013*	-0.014	-0.029***
Δvix_{t-1}					0.005
Δsml_t	0.003*	0.003*	0.003*		
Δsml_{t-1}					-0.005***
$\Delta dpall_t$	27.971**	27.686***	25.079*		
Δage_t	0.183***	0.183***	0.183***		0.204***
$\Delta range_t$	-6.786	-6.769	-6.705	-7.759	
$\Delta range_{t-2}$					13.762**
$\Delta medp_t$	-0.077***	-0.077***	-0.077***		-0.102***
$\Delta sigp_t$	4.242***	4.229***	4.184***	3.328*	
$\Delta turn_{t-3}$	-0.050***	-0.050***	-0.050***	-0.049**	
$regime_t$		0.008	-0.015	0.077	-0.241**
$\Delta level_t \times regime_t$				-0.033	0.607***
$\Delta level_{t-3} \times regime_t$					-0.104
$\Delta slope_t \times regime_t$				-0.079	0.973***
$\Delta gdp_t \times regime_t$				-0.003	0.020
$\Delta vix_{t-1} \times regime_t$					-0.021***
$\Delta sml_t \times regime_t$					
$\Delta sml_{t-1} \times regime_t$					0.001
$\Delta dpall_t \times regime_t$					
$\Delta age_t \times regime_t$					-0.193**
$\Delta range_t \times regime_t$				79.900	
$\Delta range_{t-2} \times regime_t$					-26.037***
$\Delta medp_t \times regime_t$					0.102***
$\Delta sigp_t \times regime_t$				-19.868	
$\Delta turn_{t-3} \times regime_t$				0.002	
$AdjR2$	0.574	0.570	0.57	0.374	0.614
VIF	1.39	1.41	1.42	3.93	4.15
AIC	-3.672	-3.657	-3.659	-3.274	-3.718

Table 9: Determinants of credit spread changes within different models (Rating = BBB).

We compare different models ability to explain credit spread differentials. Model 1 refers to the single regime model. Model 1E refers to the single regime model with a dummy for the regimes in the economic cycle. Model 1C refers to the single regime model with a dummy for the regimes in the credit cycle. Model 2E and Model 2C refers to the regime-based models including interaction effects with the regimes in the economic cycle and the credit cycle, respectively. Variable selections are based on the minimization of AIC using the same set of initial explanatory variables. We control for the degree of collinearity using the Variance Inflation Factors (VIF). ***, **, * indicate the significance level at 1%, 5%, and 10%, respectively.

	Model 1	Model 1E	Model 1C	Model 2E	Model 2C
	Single regime model	Single regime models with dummy for the cycle		Two regime models with interaction effects	
		Economic	Credit	Economic	Credit
$intercept$	-0.007	-0.051	-0.015	0.043	0.042
$\Delta level_t$	-0.307***	-0.313***	-0.309***	-0.299***	-0.354***
$\Delta slope_t$	0.608***	0.549***	0.606***	0.549***	0.498**
$\Delta slope_{t-1}$					-0.374*
Δgdp_t	-0.022**	-0.017	-0.022**	-0.018	-0.025**
vix_{t-1}					0.001
Δvix_{t-1}	0.007	0.006	0.007	0.007	0.004
Δvix_{t-3}	-0.008*	-0.008*	-0.008*	-0.009*	0.010*
smb_{t-1}					0.003
Δsml_{t-1}					-0.006*
Δdp_t	37.362*	31.261	38.957*		33.030
$\Delta recsub_t$	0.002	0.003	0.002		0.001
$\Delta amih_t$	16.175***	16.303***	16.154***	15.781***	14.241
$\Delta amih_{t-2}$	10.125***	10.471***	10.127***	9.262***	-5.404***
$\Delta range_{t-3}$	18.016***	19.370***	17.975***	21.474**	1.173
$\Delta medp_t$	-0.040***	-0.041***	-0.040***	-0.036**	-0.045***
$\Delta sigp_t$	-0.016	-0.020*	-0.016		
$\Delta sigp_{t-2}$					-0.058**
$\Delta turn_{t-2}$					-0.054**
$regime_t$		0.151	0.009	0.142	-0.730**
$\Delta level_t \times regime_t$				-0.056	0.085
$\Delta slope_t \times regime_t$				-0.378	0.368
$\Delta slope_{t-1} \times regime_t$					0.627**
$\Delta gdp_t \times regime_t$				-0.038	-0.020
$vix_{t-1} \times regime_t$					0.013
$\Delta vix_{t-1} \times regime_t$				0.012	0.025**
$\Delta vix_{t-3} \times regime_t$				0.010	-0.041***
$smb_{t-1} \times regime_t$					0.021**
$\Delta sml_{t-1} \times regime_t$					0.017***
$\Delta dpall_t \times regime_t$					19.345*
$\Delta recsub_t \times regime_t$					0.016***
$\Delta amih_t \times regime_t$				-20.896	3.688
$\Delta amih_{t-2} \times regime_t$				66.822	10.783
$\Delta range_{t-3} \times regime_t$				-6.210	24.554**
$\Delta medp_t \times regime_t$				0.022	0.001
$\Delta sigp_{t-2} \times regime_t$					0.081***
$\Delta turn_{t-2} \times regime_t$					0.080***
$AdjR^2$	0.483	0.49	0.478	0.428	0.662
VIF	1.23	1.28	1.28	3.22	9.00
AIC	-2.922	-2.930	-2.906	-2.775	-3.213

Table 10: Determinants of credit spread changes within different models (Rating = BB).

We compare different models ability to explain credit spread differentials. Model 1 refers to the single regime model. Model 1E refers to the single regime model with a dummy for the regimes in the economic cycle. Model 1C refers to the single regime model with a dummy for the regimes in the credit cycle. Model 2E and Model 2C refers to the regime-based models including interaction effects with the regimes in the economic cycle and the credit cycle, respectively. Variable selections are based on the minimization of AIC using the same set of initial explanatory variables. We control for the degree of collinearity using the Variance Inflation Factors (VIF). ***, **, * indicate the significance level at 1%, 5%, and 10%, respectively.

	Model 1	Model 1E	Model 1C	Model 2E	Model 2C
	Single regime model	Single regime models with dummy for the cycle		Two regime models with interaction effects	
		Economic	Credit	Economic	Credit
$intercept$	0.113	-0.023	0.084	-0.017	-0.176
$\Delta level_t$	-0.411**	-0.378**	-0.416**	-0.371**	-0.534***
$\Delta slope_{t-1}$				0.576*	0.622**
Δgdp_t					
Δgdp_{t-1}	-0.037*		-0.033		
Δvix_{t-3}	-0.026***	-0.027***	-0.026***	-0.030***	-0.017
smb_t				-0.003	0.006
Δsmb_{t-1}	-0.013**	-0.015**	-0.013**	-0.015*	-0.018***
$\Delta dpall_t$	190.169***	189.618***	196.785***	146.567***	171.508***
$\Delta dpall_{t-1}$	-94.750**	-97.932**	-89.126**	-86.108*	-99.343**
$\Delta recsus_t$	-0.023*		-0.023*		0.003
$\Delta amih_t$	-0.005*	-0.048*	-0.005*	-0.006**	-0.006**
$\Delta amih_{t-3}$	-0.004**	-0.005**	-0.004**		-0.005*
$\Delta medp_t$	-0.106***	-0.097***	-0.106***	-0.083***	-0.099***
$\Delta medp_{t-3}$				-0.037	-0.057**
$\Delta sigp_t$	0.018***	0.020***	0.019***	0.019***	0.043***
$\Delta sigp_{t-1}$					-0.016*
$\Delta turn_{t-3}$	0.032		0.032		
$regime_t$		0.279*	0.045	0.041	0.788***
$\Delta level_t \times regime_t$				1.332	0.49
$\Delta slope_{t-1} \times regime_t$				-0.049	-0.575**
$\Delta gdp_t \times regime_t$					
$\Delta vix_{t-3} \times regime_t$				-0.015	-0.034**
$smb_t \times regime_t$				-0.079	-0.062**
$\Delta smb_{t-1} \times regime_t$				-0.079	
$\Delta dpall_t \times regime_t$				725.684	34.287
$\Delta dpall_{t-1} \times regime_t$				-161.861	26.733
$\Delta recsus_t \times regime_t$					-0.018***
$\Delta amih_t \times regime_t$				0.032	0.009
$\Delta amih_{t-3} \times regime_t$					-0.004
$\Delta medp_t \times regime_t$				-0.186	0.065*
$\Delta medp_{t-3} \times regime_t$				0.104	0.070*
$\Delta sigp_t \times regime_t$				.0.029	-0.046***
$\Delta sigp_{t-1} \times regime_t$					0.004
$AdjR^2$	0.383	0.363	0.379	0.317	0.537
VIF	1.23	1.23	1.28	8.92	4.06
AIC	-1.659	-1.640	-1.645	-1.485	-1.840

Table 11: Likelihood Ratio Test for Model 2C against single regime models.

All the models involved here are derived from Equation 19 characterising Model 2C where ($\gamma^{2C}_{2,i,m} \neq 0$, $\gamma^{2C}_{3,i,m} \neq 0$). Column (3) reports the Likelihood Ratio Test (LRT) for Model 2C against the model obtained by setting the coefficients ($\gamma^{2C}_{2,i,m} = 0$ and $\gamma^{2C}_{3,i,m} = 0$). These restrictions reduce Model 2C to the single regime model. Column (4) reports the LRT for Model 2C against the model obtained by setting the coefficients ($\gamma^{2C}_{2,i,m} \neq 0$ and $\gamma^{2C}_{3,i,m} = 0$). These restrictions add to the single regime model a dummy variable for the regimes in the credit cycle. Column (5) reports the LRT for both single regime models with and without the dummy variable for the regimes in the credit cycle (i. e., $\gamma^{2C}_{2,i,m} \neq 0$ and $\gamma^{2C}_{3,i,m} = 0$ against $\gamma^{2C}_{2,i,m} = 0$ and $\gamma^{2C}_{3,i,m} = 0$).

		Constraints on the Coefficients in Equation 19		
		($\gamma^{2C}_{2,i,m} \neq 0$, $\gamma^{2C}_{3,i,m} \neq 0$) against ($\gamma^{2C}_{2,i,m} = 0$, $\gamma^{2C}_{3,i,m} = 0$)	($\gamma^{2C}_{2,i,m} \neq 0$, $\gamma^{2C}_{3,i,m} \neq 0$) against ($\gamma^{2C}_{2,i,m} \neq 0$, $\gamma^{2C}_{3,i,m} = 0$)	($\gamma^{2C}_{2,i,m} \neq 0$, $\gamma^{2C}_{3,i,m} = 0$) against ($\gamma^{2C}_{2,i,m} = 0$, $\gamma^{2C}_{3,i,m} = 0$)
AA	LR (*df*)	81.50 (16)	80.18 (15)	1.32 (1)
	$P-value$	(0.000)	(0.000)	(0.251)
A	LR (*df*)	44.81 (10)	42.43 (9)	2.38 (1)
	$P-value$	(0.000)	(0.000)	(0.122)
BBB	LR (*df*)	85.88 (18)	82.16 (17)	0.00 (1)
	$P-value$	(0.000)	(0.000)	(0.978)
BB	LR (*df*)	62.87 (15)	61.74 (14)	1.12 (1)
	$P-value$	(0.000)	(0.000)	(0.289)

Table 12: Comparative adjusted R-squared relative to Model 2C.

Model 2C refers to the regime-based model in Equation 19. Column (2) reports the adjusted R-squared for Model 2C. Column (3) reports the adjusted R-squared for Model 2C with the constraints ($\gamma^{2C}_{2,i,m} = 0$ and $\gamma^{2C}_{3,i,m} = 0$) in Equation 19. Column (4) reports the adjusted R-squared for Model 2C with the constraints ($\gamma_{2,i,m} \neq 0$ and $\gamma_{3,i,m} = 0$) in Equation 19.

	Model 2C	Model 2C with ($\gamma^{2C}_{2,i,m} = 0, \gamma^{2C}_{3,i,m} = 0$)	Model 2C with ($\gamma^{2C}_{2,i,m} \neq 0, \gamma^{2C}_{3,i,m} = 0$)
AA	0.604	0.360	0.361
A	0.614	0.495	0.503
BBB	0.662	0.464	0.459
BB	0.537	0.343	0.343

Table 13: Likelihood Ratio Test for Model 1 against the regime-based model.

The regime-based model (Equation 21) is obtained by adding to Equation 15 a dummy variable for the regimes in the credit cycle ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$) as well as the terms of interactions ($\Delta X^1_{1,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m}$).

$$\Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} + \Delta X^1_{1,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^1_{t,i,m}, \tag{21}$$

When the coeffcients ($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$) in Equation 21, we obtain Model 1 as described in Equation 15. In Column (3) we contrast Model 1 with the regime-based model ($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$ in Equation 21). In Column (4) we contrast Model 1 with the single regime model augmented by the dummy variable for the regimes ($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} = 0$).

		Constraints in the coefficients of Equation 21	
		($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$) against ($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$)	($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$) against ($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} = 0$)
AA	LR (*df*)	31.21 (13)	0.86 (1)
	$P - value$	(0.003)	(0.355)
A	LR (*df*)	18.59 (12)	0.24 (1)
	$P - value$	(0.098)	(0.625)
BBB	LR (*df*)	32.84 (13)	0.20 (1)
	$P - value$	(0.001)	(0.655)
BB	LR (*df*)	42.73 (13)	0.08 (1)
	$P - value$	(0.000)	(0.772)

Table 14: Comparative adjusted R-squared relative to Model 1.

Column (2) reports the adjusted R-squared for the regime-based model obtained by adding to Equation 15 a dummy variable for the regimes in the credit cycle ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$) as well as the terms of interactions ($\Delta X^1_{1,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m}$).:

$$\Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} + \Delta X^1_{1,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^1_{t,i,m}, \tag{21}$$

Column (3) reports the adjusted R-squared for Model 1 which reduces to Equation 15 when ($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$) in Equation 21. Column (4) reports the adjusted R-squared for Model 1 augmented by the dummy variable for the regimes in the credit cycle ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$).

	Constraints on the coefficients of Equation 21		
	($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$)	($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$)	($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} = 0$)
AA	0.502	0.432	0.436
A	0.590	0.573	0.571
BBB	0.549	0.483	0.479
BB	0.490	0.368	0.363

Table 15: Comparing regime-based models.

We perform the J test and the Cox-type test for nonnested models. Model 2C is the regime-based model given by Equation 19 and Model 2E is the regime-based model given by Equation 18. We test two null hypothesis. The first one states that Model 2C is better than Model 2E and the second one states that Model 2E is better than Model 2C. For the J test, t-stat (df) refers to the t-statistics along with the degrees of freedom into parenthesis.

Panel A: J test		AA	A	BBB	BB
H_0: Model 2C is better	t-stat (df)	2.01 (96)	2.08 (107)	1.69 (91)	1.33 (97)
H_1: Model 2E is better	$p - value$	(0,047)	(0.040)	(0.095)	(0,186)
H_0: Model 2E is better	t-stat (df)	9.63 (101)	7.12 (108)	9.62 (97)	7.51 (100)
H_1: Model 2C is better	$p - value$	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Cox test					
H0: Model 2C is better	$N(0,1)$	-1.28	-0.63	-0.59	-0.50
H1: Model 2E is better	$p - value$	(0.099)	(0.265)	(0.278)	(0.307)
H0: Model 2E is better	$N(0,1)$	-46.58	-52.07	-37.48	-20.22
H1: Model 2C is better	$p - value$	(0.000)	(0.000)	(0.000)	(0.000)

Table 16: Signs of exlanatory variables coefficients.

For each rating class, the first column report the coefficient signs of the explanatory variables of Model 1 (i.e., signs of $\beta^1_{1,i,m}$ in Equation 15). Then, the second and the third columns report the coefficient signs of the explanatory variables of Model 2C in the low regime (low) and the high regime (high), respectively (i.e., signs of $\gamma^{2C}_{1,i,m}$ and $(\gamma^{2C}_{1,i,m} + \gamma^{2C}_{3,i,m})$ in Equation 19, respectively.

	Rating = AA			Rating = A			Rating = BBB			Rating = BB		
	Model 1	Model 2C		Model 1	Model 2C		Model 1	Model 2C		Model 1	Model 2C	
		Low	High		Low	High		Low	High		Low	High
$\Delta level_t$	neg*	neg***	pos**	neg***	neg***	pos***	neg***	neg***	neg	neg**	neg***	neg
$\Delta level_{t-3}$				neg**	neg	neg						
$\Delta slope_t$	pos***	pos	pos***	pos***	pos*	pos***	pos***	pos**	pos			
$\Delta slope_{t-1}$		pos**	pos					neg*	pos**		pos**	pos**
Δgdp_t	neg***	neg**	neg	neg*	neg***	neg	neg**	neg**	neg			
Δgdp_{t-1}										neg*		
vix_{t-1}								pos	pos			
Δvix_{t-1}					pos	neg***	pos	pos	pos**			
Δvix_{t-2}		neg***	pos***									
Δvix_{t-3}							neg*	pos*	neg***	neg***	neg	neg**
smb_t	pos**	pos**	neg**								pos	neg**
smb_{t-1}								pos	pos**	neg**	neg***	
Δsmb_{t-2}		neg	pos***									
Δsml_t	pos*	pos	pos	pos*								
Δsml_{t-1}					neg***	neg		neg*	pos***			
Δsml_{t-2}		neg	pos**									
$\Delta dpall_t$				pos**			pos*	pos	pos*	pos***	pos***	pos
$\Delta dpall_{t-1}$										neg**	neg**	neg
$\Delta recsub_t$	pos	neg	pos***				pos	pos	pos***	neg*	pos	neg***
Δage_t	pos**	pos***	pos*	pos***	pos***	pos**						
$\Delta amih_t$							pos***	pos	pos	neg*	neg**	pos
$\Delta amih_{t-1}$		neg	pos*									
$\Delta amih_{t-2}$							pos***	neg***	pos			
$\Delta amih_{t-3}$										neg**	neg*	neg
$\Delta range_t$				neg								
$\Delta range_{t-1}$	pos**											
$\Delta range_{t-2}$					pos**	neg***						
$\Delta range_{t-3}$							pos***	pos	pos**			
$\Delta medp_t$	neg***	neg*	neg	neg***	neg***	pos***	neg***	neg***	neg	neg***	neg***	neg*
$\Delta medp_{t-3}$											neg**	pos*
$\Delta sigp_t$				pos***			neg			pos***	pos***	neg***
$\Delta sigp_{t-1}$	pos**										neg*	neg
$\Delta sigp_{t-2}$	neg	neg**	neg					neg**	pos***			
$\Delta turn_t$		neg	pos**									
$\Delta turn_{t-2}$								neg**	pos***			
$\Delta turn_{t-3}$	neg**			neg***						pos		
$regime_t$		neg			neg**			neg**			pos***	

Table 17: Regression results for the regime-based model in different subsamples.

We test for the signs and effects of the coefficients of the explanatory variables in Model 2C. Instead of adding the dummy variable and the interaction terms with the regimes, we test the model in two different sample period. The first subsample covers the common period of the low regime accross ratings and spans from January 1995 to December 2000. The second period covers the period tranche in the high regime starting after the announcement of the beginning of the recession. It spans from November 2001 to December 2004.

	Rating = AA		Rating = A		Rating = BBB		Rating = BB	
	Jan95-Dec00	Nov01-Dec04	Jan95-Dec00	Nov01-Dec04	Jan95-Dec00	Nov01-Dec04	Jan95-Dec00	Nov01-Dec04
$intercept$	0.051	0.083	0.090**	-0.061	0.011	-0.207	-0.126	0.689**
$\Delta level_t$	-0.394***	0.06	-0.512***	0.189	-0.326***	-0.393*	-0.596***	0.195
$\Delta level_{t-3}$			-0.111	-0.159				
$\Delta slope_t$	0.257	1.272***	0.083	1.095***	0.367	0.761*		
$\Delta slope_{t-1}$	0.389*	0.07			-0.167	0.310	0.563	-0.257
Δgdp_t	-0.016	-0.040*	-0.024***	0.011	-0.025**	-0.078**		
vix_{t-1}					0.001	0.006		
Δvix_{t-1}			0.002	-0.023**	0.003	0.051**		
Δvix_{t-2}	-0.017**	0.032**						
Δvix_{t-3}					0.007	-0.028**	-0.019*	-0.037**
smb_t	0.011**	-0.014					0.007	-0.081**
Δsmb_{t-1}					0.004	0.031*	-0.017***	0.003
Δsmb_{t-2}	-0.004	0.027***						
Δsml_t	0.003	0.007***						
Δsml_{t-1}			-0.007***	-0.006*	-0.006*	0.017**		
Δsml_{t-2}	-0.001	0.012**						
$\Delta dpall_t$					24.252	16.897	183.909***	196.633**
$\Delta dpall_{t-1}$							-95.699**	-53.077
$\Delta recsub_t$	-0.001	0.009			0.001	0.008		
$\Delta recsus_t$							0.002	-0.015*
Δage_t	0.126***	0.024	0.182***	0.023				
$\Delta amih_t$					49.319**	19.462***	-0.010***	0.004
$\Delta amih_{t-1}$	-0.005	0.003						
$\Delta amih_{t-2}$					-5.453	4.167		.
$\Delta amih_{t-3}$							-0.009**	-0.007*
$\Delta range_{t-2}$			14.178**	-8.956*				
$\Delta range_{t-3}$					1.259	33.566***		
$\Delta medp_t$	-0.032*	-0.055***	-0.116***	0.008	-0.032	-0.082**	-0.091***	-0.063*
$\Delta medp_{t-3}$							-0.082**	0.015
$\Delta sigp_t$							0.042***	0.002
$\Delta sigp_{t-1}$							-0.023**	-0.008
$\Delta sigp_{t-2}$	-0.018	-0.049**			-0.068***	0.027*		
$\Delta turn_t$	-0.029	0.044*						
$\Delta turn_{t-2}$					-0.044	0.029		
$AdjR^2$	0.371	0.717	0.516	0.605	0.443	0.678	0.470	0.381
VIF	1.48	2.33	1.43	2.18	1.60	2.81	1.37	2.12
AIC	-3.220	-3.1925	-3.770	-3.580	-3.514	-2.590	-2.009	-1.593

Table 18: Likelihood Ratio Test for models with regimes vs. models without regimes.

		AA	A	BBB	BB
Market factors	LR (*df*)	17.43 (5)	14.00 (5)	30.68 (7)	29.64 (7)
	$P-value$	(0.004)	(0.015)	(0.000)	(0.000)
Liquidity factors	LR (*df*)	18.20 (7)	9.12 (5)	23.15 (6)	28.14 (7)
	$P-value$	(0.011)	(0.104)	(0.001)	(0.000)
Default factors	LR (*df*)	10.53 (3)	11.54 (3)	12.87 (3)	14.25 (3)
	$P-value$	(0.014)	(0.001)	(0.004)	(0.003)

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

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

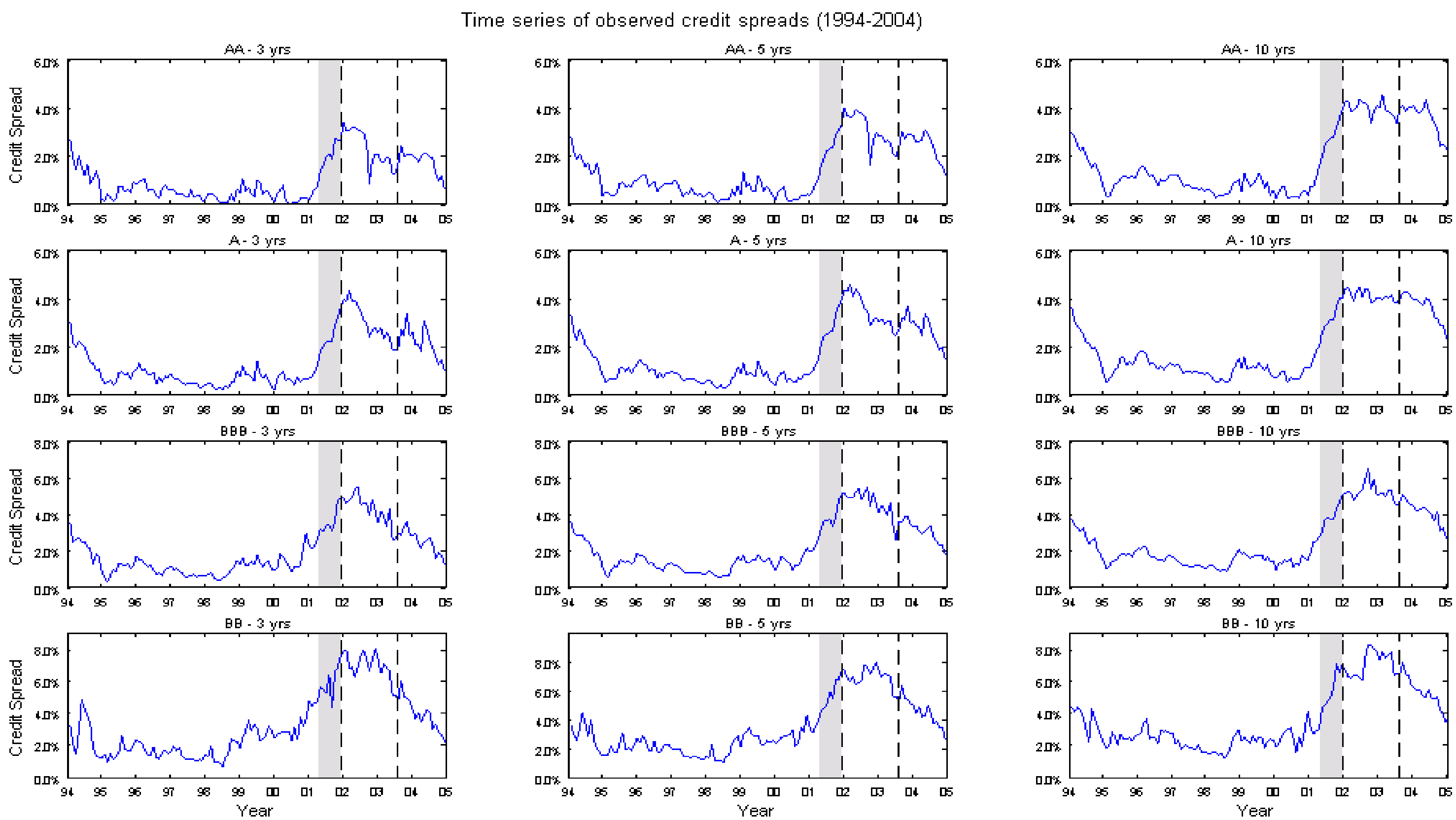

Figure 2: The smoothed probability of the high regime against credit spreads (1994-2004).

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