Credit Spread Changes within Switching Regimes

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Abstract

Empirical studies on credit spread determinants consider a single-regime model over the entire sample period and find limited explanatory power. We model the rating-specific credit cycle by estimating Markov switching regimes from credit spread data. Accounting for endogenous credit cycles significantly enhances the explanatory power of credit spread determinants for all ratings and up to 67% for BBB spreads. The single regime model cannot be improved when conditioning on the NBER cycle. Our regime-based model highlights a positive relation between credit spreads and the risk-free rate in the high regime. Inverted relations are also obtained for other determinants including liquidity.

Keywords: Credit spread, Markov switching regimes, market risk, liquidity risk, default risk, credit cycle, NBER economic cycle.

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

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I Introduction

We study the determinants of credit spread changes within endogenous Markov switching regimes extracted directly from credit spread data. Although a large body of literature has investigated the determinants of credit spread changes, no one has provided a definitive answer to the puzzling disconnect between the set of explanatory variables implied by the theory and fluctuations in credit spreads. This research is the first to investigate the determinants of credit spreads within an endogenously defined switching regime framework. We find that the role of explanatory variables in explaining credit spread changes is dramatically enhanced when accounting for endogenously determined switching regimes. In contrast to a single regime model, where the coefficients on the explanatory variables are constant across time, a switching regime model allows for distinct effects across different regimes. This turns out to be a crucial modeling insight as some determinants have their effect strengthen, weaken or even reverse as we switch across regimes. These changing effects cannot be captured by a single regime model, which explains the limited power of the explanatory variables. By allowing for differential effects across different regimes, our model provides an intuitive and economically meaningful answer to the credit spread puzzle.

Despite the abundant theoretical and empirical works on the subject, determinants of credit spread changes remain puzzling. Elton, Gruber, Agrawal and Mann (2001) provide evidence that default risk factors implicit in credit ratings and historical recovery rates can account for only a small fraction of observed credit spreads. Huang and Huang (2003) find that calibrated structural models are unable to adequately account for historical credit spread patterns.[1] Collin-Dufresne, Goldstein and Martin (2001) consider a larger class of credit spread determinants, including non-default factors that, according to theory, could affect credit spread changes.[2] However, their model captures only 25% of credit spread changes. A principal component analysis applied to their residuals shows that most of the changes in credit spreads can be explained by a common systematic factor, yet this systematic factor is only partially linked to business climate indicators and macroeconomic variables.

Systematic credit risk factors are typically thought to correlate with macroeconomic conditions.[3] However, the causal relation between credit cycles and economic cycles is at best ambiguous. Within a theoretical framework, Lown and Morgan (2006) show that the credit cycle may affect the economic cycle. In contrast, Gorton and He (2008) suggest that the credit cycle has its own dynamics, which may be different from that of the economic cycle. This result supports the idea that the credit cycle may not be completely driven by macroeconomic fundamentals, and along with the findings of Collin-Dufresne, Goldstein and Martin (2001), casts doubt on conditioning regimes purely on macroeconomic information.

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

[2]Examples of studies investigating the ability of non-default risk factors (such as market, liquidity and firm-specific factors) to explain credit spread differentials include Driessen (2005), Campbell and Taksler (2003), Huang and Kong (2003), Davydenko, and Strebulaev (2004), Longstaff, Mithal, and Neis (2005), and Han and Zhou (2008).

[3]Fama and French (1989) and Chen (1991) suggest that credit spreads exhibit countercyclical behavior. Koopman and Lucas (2005) analyze the co-movements between credit spreads and macroeconomic variables and document the controversy surrounding the relation between credit risk drivers and the economic cycle (see also Koopman, Kraeussl, Lucas, and Monteiro (2009)). Their main conclusion supports the existence of countercyclical behavior but emphasizes the need for more research.

A number of papers use regime switches to capture state dependent movements in credit spread dynamics, yet they invariably assume that the regimes are driven by macroeconomic fundamentals (Hackbarth, Miao, and Morellec (2006); Bhamra, Kuehn, and Strebulaev (2010); Chen (2010); and David (2008)).[4] Other research applies switching regime models to the time series of credit spreads by conditioning on alternative inflationary and/or volatility environments (Davies (2004) and (2007)).[5] Our research extends the work of Collin-Dufresne, Goldstein and Martin (2001) by allowing for a switching regime structure in the dynamics of credit spreads. It also models credit spread regimes endogenously, in contrast to existing regime switching models that construct regimes based on macroeconomic fundamentals. Following Engle and Hamilton (1990), we model monthly changes in the level of credit spread rate as deriving from two endogenous regimes corresponding to episodes of high and low credit spreads.

We find that many key determinants have an altered effect on credit spread variations in high regimes relative to low regimes. The empirical works of Morris, Neale, and Rolph (1998) and Bevan and Garzarelli (2000), for example, suggest a positive relation between risk-free rates and credit spreads, whereas the structural models predict a negative relation. Our research provides an explanation for this contradiction, which is often attributed to the limits of the data.

We also analyze the effect of credit spread determinants by conditioning on the endogenous credit spread regimes, and contrast our results with those obtained by conditioning on two definitions of the economic cycle. The first definition uses the effective dates of the NBER recession and the second definition uses the NBER dates announcing the beginning and the end of the recession. We find that the explanatory power of the key credit spread determinants is limited in a model without regime shifts (single regime model) and does not significantly improve when we condition on either the NBER cycle or the announcement cycle. However, the explanatory power improves considerably when we condition on the endogenous credit spread regimes. Our model with endogenously determined regimes obtains about an adjusted R-squared of 61% on average when explaining 10-year AA to BB credit spread changes using the NAIC dataset.

Finally, an important shortcoming in the literature is to employ inadequate measures of liquidity in capturing the systematic factor. Thus, another extension of the literature consists in adding more sophisticated measures of liquidity.

The rest of the paper is organized as follows. Section II describes the data. Section III documents the long lasting pattern of credit spreads after NBER recessions. Section IV describes credit spread determinants considered in this study. In Section V, we model credit spread regimes endogenously. Sections VI and VII present the estimation procedure and the empirical results. Section VIII concludes the paper. The methodology used to obtain yield curves on credit spreads is described in the Appendix.

[4]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 macroeconomic conditions and different states of the economic cycle on the credit risk premium. The models explain the level of credit spreads by assuming significant variation in the market price of risk over the economic cycle.

[5]Specifically, Davies (2004) 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, VIX volatility and industrial production as explanatory variables. Most interestingly, he finds that the negative relation across the risk-free rate and the credit spread, consistent with Merton (1974), Longstaff and Schwartz (1995) and Duffee (1998), disappears in the high volatility regime.

II Data

Transaction prices. The National Association of Insurance Commissioners database (NAIC) provides transaction (rather than quoted) price data for U.S. corporate bonds. The database reports trades made since 1994 by American insurance companies, which are major investors in corporate bond markets. Three types of insurers report their trades in the NAIC database: Life insurance companies, Property and Casualty insurance companies, and Health Maintenance Organizations. The database accurately reflects trading activity in the bond market from 1994 onwards. Our sample period spans January 1994 to December 2004. When a transaction involves two insurance companies on the buy and sell side, it is reported twice in the database. In this case, only one transaction side is included in the sample.

Bond characteristics. Characteristics of corporate bonds are obtained from the Fixed Investment Securities Database (FISD). The FISD database, provided by LJS Global Information Systems Inc., includes descriptive information about U.S. issues and issuers (bond characteristics, industry type, characteristics of embedded options, historical credit ratings, default events, auction details, etc.). 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 because the swap rates that we use as a benchmark for risk-free rates have maturities below 15 years. Finally, we exclude bonds with over-allotment options, asset-backed and credit enhancement features and bonds associated with a pledge security. Issuers' credit ratings are reported by four rating agencies: Fitch, Duff and Phelps, Moody's, and Standard and Poor's. We include all bonds whose average Moody's credit rating lies between AA and BB. Triple-A credit spreads are not used because the average credit spread for medium term AAA-rated bonds is higher than that of A-rated bonds for several periods. This phenomenon was also noticed by Campbell and Taksler (2003), who used the same database. We filter out observations with missing trade details and ambiguous entries (ambiguous settlement data, negative prices, negative time to matury, etc.).

Summary statistics. Table 1 provides summary statistics for corporate bonds. For the period of 1994 to 2004, we account for 651 issuers with 2,860 outstanding issues in the industrial sector corresponding to 85,764 different trades. Given that insurance companies generally trade high quality bonds, most of the trades in our sample involve A- and BBB-rated bonds. These account for 40.59% and 38.45% of total trades, respectively. On average, bonds included in our sample are aged 4.3 years, have a remaining time-to-maturity of 6.7 years and a duration of 5.6 years.

[Insert Table 1 here]

The benchmark for risk-free rates. Hull, Predescu, and White (2004) argue that Treasury bond yields are contaminated by liquidity, taxation, and regulation issues. We follow their recommendation to use LIBOR-swap rates as the benchmark for risk-free rates. Swap rates are collected from DataStream and LIBOR rates from British Bankers' Association. To obtain smoothed yield curves for corporate bonds and LIBOR-swaps (hereafter swap curves) we use the Nelson-Siegel-Svensson algorithm. Our implementation of the algorithm is reported in the Appendix.

The observed credit spreads. Credit spreads are given by the difference between yields on corporate bonds and swap rates with the same maturities. Table 2 reports summary statistics.

[Insert Table 2 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 1990 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 is 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.

III Regimes in credit spreads

Time series of credit spreads undergo successive falling and rising episodes. The rising episodes are always observed during downturns, although they never perfectly match the NBER periods of 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, credit spread movements exhibit at least two regimes in terms of sudden changes in their level and/or volatility over the period considered. For instance, we can 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 high episodes of credit spreads, across ratings, begin at or a few months before the recession officially starts, yet several months before the NBER announcement is posted. They then span the entire recession period and extend to several months after the recession officially ends. If credit spreads are counter-cyclical (increasing in recessions and decreasing in expansions), then their levels should decrease when the recession ends. However, what we observe is a long-lasting episode of high credit spreads after recessions. Similarly, Duffee (1998) shows that yields on corporate bonds exhibit persistence and take about a year to adjust to innovations in the bond market. This finding is recently supported by Giesecke, Longstaff, Schaefer, and Strebulaev (2009), who assert that the average duration of an NBER recession, during 150 years of historical data, is about half the average duration of a default cycle (1.5 years versus 3.2 years).

Determinants of the long lasting pattern of credit spreads are beyond the scope of this paper. However, to motivate our choice of endogenous regimes, we provide economic explanations for why the credit cycle should be longer than the economic cycle. First, we acknowledge the difference between the patterns of the credit cycle, the economic cycle and their respective determinants. Then, we show that the explanatory power of key determinants suggested by the existing literature improves significantly when an endogenous credit cycle is considered. By endogenous we mean that the credit cycle can be independent from macro variables and NBER economic periods of recession. Our results shed light on one of the causes of the credit spread puzzle and the failure of several theoretical, yet intuitive determinants to explain credit spread changes.

During recessions, fluctuations in the aggregate economy may significantly affect firms' credit conditions and deteriorate firms' balance sheets (Bernanke and Gertler (1989)). Even after the recession ends, a firm with a weak balance sheet needs several years to successfully emerge from the effects of bad times. Thus, adverse credit conditions extend the recovery phase together with the high episode of credit spreads for several years after economic downturns. Similar to the 2001 scenario, the shift of credit spread levels from a high to a low episode in 1994 may therefore be interpreted as the end of the 1990 credit cycle. A similar long-lasting pattern is not common for macro variables such as GDP growth, unemployment, and other variables used in the NBER dating system. Thus, credit spreads and macro variables have distinctive cycles. In particular, after recessions macro variables enter periods of expansion before credit spreads do.

Further, the NBER announcement of the beginning and the end of a recession also seems to affect credit spread levels. Clearly, the announcement provides investors with additional information about the beginning and the end of a recession, thus affecting their uncertainty level and investment choices in the bond market. For example, in November 2001, credit spreads peak following the announcement of March 2001 as the official beginning date of the recession. Interestingly, the NBER recession effectively ended in November 2001. Thus, even when the recession was technically over in November 2001, the NBER announcement of that month may have shifted investor behavior to an opposite direction (see Maalaoui Chun, Dionne, and François (2010)).[6] It was only in July 2003 that NBER announced November 2001 as the official end date of the 2001 recession. Consistently, in July 2003, we observe the beginning of a gradual downward sloping of credit spreads visible especially with low grade bonds. Thus, the announcement of the end has the direct effect of reducing investor uncertainty (although market factors started expanding a few years earlier) and indirectly helps firms complete the recovery.[7]

Based on these observations, we argue that credit spreads have their own cycle and should be affected by economic variables other than NBER factors. Other credit spread determinants could also

[6]Using a real-time regime detection technique, Maalaoui Chun, Dionne, and François (2010) detect significant positive shifts in credit spread levels after the official end date of the 2001 NBER recession, signifying that credit spreads are still non-decreasing when the recession ended. This result is also verified over the 1990, and 2007 recessions.

[7]Other specific aspects of the financial system varying from cycle to cycle may also contribute to extending the recovery phase. For example, the recovery from the 1990 recession was delayed by the "financial headwinds" arising from regional shortages of bank capital (Bernanke and Lown (1991)). In the 2001 recession, the recovery may also have been delayed by repeated accounting scandals and the perceived high geopolitical risk marked by the Iraq War and the events of September 11. After the latest recession, the failure of large financial institutions, despite repeated government bailouts, is still slowering the recovery phase.

have their own dynamics: they may be more or less sticky following macroeconomic states or following firm-specific states. Therefore, some determinants enter periods of expansion before credit spreads do.[8] Consequently, as we switch across regimes, the effects of key determinants on credit spreads may strengthen, weaken or even reverse. These effects are hidden in the single regime model, thus reducing the total explanatory power of key determinants. In the same spirit, we argue that credit spread variations in different regimes are driven by different determinants. For these reasons, we choose to model regimes in the credit spread dynamics endogenously using a Markov switching regime model.[9]

Finally, we propose an alternative definition of the credit cycle, thus allowing for a credit cycle that is specified by the data itself. Our argument lies in the difference in the patterns of credit spreads across ratings and maturities as shown in Figure 1. Credit spreads with longer maturities are stickier. It is also documented for example in Collin-Dufresne, Goldstein, and Martin (2001) and Huang and Kong (2003), that credit spread changes for low grade bonds, contrarily to high grade bonds, are closely related to market factors. Therefore, we argue that each credit spread category (with respect to rating and maturity) defines its own credit cycle as it adjusts distinctively to new market conditions at the beginning and the end of the economic cycle.

Recent studies apply regime models to capture state dependent movements in credit spreads. In these works, regimes in credit spreads are often driven by macroeconomic fundamentals that are closely related to the dynamics of the GDP. However, these approaches are implicitly based on the assumption that the true credit cycle should coincide with the economic cycle, which is relaxed in this paper. Nonetheless, we presume that two state dependent regimes suffice to capture most of the variation in our credit spread series. Empirical studies using regime models for credit spreads usually assume two different regimes for different period ranges of observed data. For example, Davies ((2004) and (2007)) analyzes credit spread determinants using a Markov switching estimation technique assuming two volatility regimes. Alexander and Kaeck (2007) also use two-state Markov chains to analyze credit default swap determinants within distinct volatility regimes. Maalaoui Chun, Dionne, and François (2010) support the existence of two regimes in a larger sample period covering the last three recessions.[10]

IV Credit spread determinants

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

[8]Across ratings and maturities, plots of the time series of credit spreads against key determinants considered in this study provides further evidence. For conciseness, we did not report these plots but they are available upon request.

[9]The high credit spread episodes may be considered as structural breaks because 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.

[10]Their larger sample includes three different databases (Warga, NAIC, and TRACE). Because the NAIC database is only available from 1994 to 2006, their sample from the NAIC covers only the 2001 recession.

market. Accordingly, we decompose credit spread determinants into market factors, default factors and liquidity factors.

A Market factors

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-Svensson algorithm.

The term structure dynamics has two opposite effects on credit spreads (see Di Cesare and Guazzarotti (2010), for a related discussion). First, as structural models of credit risk stipulate, corporate default risk-neutral probabilities are directly related to the short rate, which is the risk-neutral return on corporate assets in place. Thus, an increase in the short rate results in lower credit spreads (Collin-Dufresne, Goldstein, and Martin (2001)).

The term structure has another effect on credit spreads. In addition to assets in place, the value of a firm also comprises the present value of growth options. The latter is directly affected by the dynamics of current and mostly future discount rates. Higher long maturity rates therefore impact negatively on corporate value and positively on credit spreads.

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. Because the estimates of real GDP growth rates provided by the Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce are available only quarterly, we use a linear interpolation to obtain monthly estimates.

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&P500 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&P600 Small Cap (SML) index. The SML measures the performance of the small capitalization sector of the U.S. equity market. It consists of 600 domestic stocks chosen for market size, liquidity and industry group representation.

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, Goldstein, and Martin (2001); Chen (2010)). We use the Fama-French SMB and HML factors (available on the Kenneth French website). Higher required risk premium should lead directly to a higher credit spread.

B Default factors

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 the first day of each month, we take the month (t) release to measure the month $(t-1)$ trailing 12-month default rates.

Recovery rates. Empirical studies on the recovery of defaulted corporate debt look at the distressed trading prices of corporate debt upon default.[11] We use 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. Because Moody's looks at these prices one month after default, we take month $(t+1)$ release to measure month t recovery rates.[12] Following Altman, Resti, and Sironi (2001), we also include month $(t+2)$ recovery rates as a measure of the expected rates for both seniority classes.

C Liquidity factors

Liquidity, not observed directly, has a number of aspects that cannot be captured by a single measure. Illiquidity reflects the impact of order flow on the 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 empirical studies 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.[13]

Clearly, any candidate metric for liquidity that uses daily prices exclusively could have an impact on credit spreads, which are measured based on these prices. We construct liquidity measures based on the price impact of trades and on the trading frequencies.

C.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 portfolios of bonds grouped by rating class (AA,

[11] See, for example, Altman and Kishore (1996), Hamilton and Carty (1999), Altman, Resti, and Sironi (2001), Griep (2002), and Varma, Cantor, and Hamilton (2003).

[12] 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.

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

A, BBB, and BB) and maturity ranges (0-5; 5-10; 10+). This ensures sufficient daily prices to compute the Amihud monthly measures.[14] For each portfolio i, at month t :

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

where N is the number of days in 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. An asset with a high Amihud value is putatively illiquid. Hasbrouck (2009) suggests that the Amihud measure must be corrected for the presence of outliers by taking its square-root value, a measure referred to as the modified Amihud measure. We also consider 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 in 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.[15] The range is an intuitive measure to assess the volatility impact as in Downing, Underwood, and Xing (2009). 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. As an alternative measure, we use price volatilities obtained by averaging daily price volatilities over the month (see also Petrasek (2010)).

Because transaction prices are of prime importance in explaining credit spread changes, we construct a control variable based on these prices. We use the daily median price of each portfolio i and we average over all N days to get monthly measures.[16] We compute this measure along with the price volatility measure after weighing bond prices by the inverse of bond durations.

C.2 Liquidity measures based on trading frequencies.

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

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

[15]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) We divide this difference by the mean price and volume of the portfolio in the same day; 3) We average over all N days to form monthly measures.

[16]We take the median because it is more robust to outliers than the mean.

- 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 3 summarizes all the variables considered with references from previous studies using the same variables to explain credit spreads. 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 except the Fama French factors, which are already expressed as differences.

[Insert Table 3 here]

V Switching regime model

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 a hidden 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 the regime in which the process was at any historical date. The resulting regime switching structure for credit spreads characterizes our specification of the credit cycle. This is done for several rating categories and maturity dates.

Specifically, the vector system of the natural logarithm of corporate yield spreads y_t is affected by two unobservable regimes $s_t = \{1, 2\}$.[17] The conditional credit spread dynamics are 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 ($s_t = 2$):

$$y_t/s_t \sim N\left(\mu_{s_t}, \sigma_{s_t}\right), \qquad s_t = 1, 2. \tag{4}$$

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

$$p(s_t = j|s_{t-1} = i) = p_{ij}, \qquad i = 1, 2;\ j = 1, 2, \tag{5}$$

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 summarized through six parameters $\theta = \left(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22}\right)$:

$$p(y_t|s_t;\theta) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} \exp\left(\frac{-\left(y_t - \mu_{s_t}\right)^2}{2\sigma_{s_t}^2}\right),\ s_t = 1, 2. \tag{6}$$

[17] Our regimes are constructed based on the level and not on changes in credit spreads, thus concerns of data snooping are alleviated when regressing changes in credit spreads on these regimes.

The model resembles a mixture of normal distributions except 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:

$$\begin{aligned}\zeta(\theta) \;=\;& \log p(y_1,...,y_T;\theta) - \left(\nu\mu_1^2\right)/(2\sigma_1^2) - (\nu\mu_2^2)/(2\sigma_2^2) \\ & -\alpha\log\sigma_1^2 - \alpha\log\sigma_2^2 - \beta/\sigma_1^2 - \beta/\sigma_2^2,\end{aligned} \tag{7}$$

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

$$\widehat{\mu}_j = \frac{\sum_{t=1}^T y_t p(s_t=j|y_1,...,y_T;\widehat{\theta})}{\nu+\sum_{t=1}^T p(s_t=j|y_1,...,y_T;\widehat{\theta})} \tag{8}$$

$$\begin{aligned}\widehat{\sigma}_j^2 =\;& \frac{1}{\alpha+1/2\sum_{t=1}^T p(s_t=j|y_1,...,y_T;\widehat{\theta})}\times \\ & \left(\beta+1/2\sum_{t=1}^T\left(y_t-\widehat{\mu}_j\right)^2 p(s_t=j|y_1,...,y_T;\widehat{\theta})+(1/2)\nu\widehat{\mu}_j^2\right)\end{aligned} \tag{9}$$

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:

$$\widehat{p}_{11} = \frac{\sum_{t=2}^T p(s_t=1,s_{t-1}=1|y_1,...,y_T;\widehat{\theta})}{\sum_{t=2}^T p(s_{t-1}=1|y_1,...,y_T;\widehat{\theta})+\widehat{\rho}-p(s_1=1|y_1,...,y_T;\widehat{\theta})}, \tag{10}$$

$$\widehat{p}_{22} = \frac{\sum_{t=2}^T p(s_t=2,s_{t-1}=2|y_1,...,y_T;\widehat{\theta})}{\sum_{t=2}^T p(s_{t-1}=2|y_1,...,y_T;\widehat{\theta})-\widehat{\rho}+p(s_1=1|y_1,...,y_T;\widehat{\theta})}, \tag{11}$$

where $\widehat{\rho}$ in equations 10 and 11 represents the unconditional probability that the first observation came from regime 1:

$$\widehat{\rho} = \frac{(1-\widehat{p}_{22})}{(1-\widehat{p}_{11})+(1-\widehat{p}_{22})}. \tag{12}$$

The model parameters are estimated using the EM principle of Dempster, Laird, and Rubin (1977).[18] To implement the EM algorithm, one needs to evaluate the smoothed probabilities that can be calculated from a simple iterative processing of the data. These probabilities are then used to re-weigh

[18]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).

the observed data y_t. Calculation of sample statistics of Ordinary Least Squares (OLS) regressions on the weighted data generates new estimates of the parameter θ. These new estimates are 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 increases the value of the likelihood function. The process is repeated until a fixed point for θ is found, which will be the maximum likelihood estimate.

VI Single regime and regime-based models

The single regime model (Model 1) is the model that does not include conditioning on any regime variables. It is the multivariate regression model involving changes in credit spreads as a dependent variable and the 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:

$$\text{Model 1:} \qquad \Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \varepsilon^1_{t,i,m}, \tag{13}$$

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 total effect of key determinants on credit spread changes 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 derive three additional models (Model 1E, Model 1A, and Model 1C), which include an additional dummy variable characterizing the regimes in a particular cycle.

$$\text{Model 1E} \quad : \quad \Delta Y_{t,i,m} = \beta^{1E}_{0,i,m} + \Delta X^{1E}_{t,i,m}\beta^{1E}_{1,i,m} + \beta^{1E}_{2,i,m} \times regime^{E}_{t,i,m} + \varepsilon^{1E}_{t,i,m}, \tag{14}$$

$$\text{Model 1A} \quad : \quad \Delta Y_{t,i,m} = \beta^{1A}_{0,i,m} + \Delta X^{1A}_{t,i,m}\beta^{1A}_{1,i,m} + \beta^{1A}_{2,i,m} \times regime^{A}_{t,i,m} + \varepsilon^{1A}_{t,i,m}, \tag{15}$$

$$\text{Model 1C} \quad : \quad \Delta Y_{t,i,m} = \beta^{1C}_{0,i,m} + \Delta X^{1C}_{t,i,m}\beta^{1C}_{1,i,m} + \beta^{1C}_{2,i,m} \times regime^{C}_{t,i,m} + \varepsilon^{1C}_{t,i,m}. \tag{16}$$

The dummy variable in Model 1E characterizes the NBER economic cylce ($regime^{E}_{t,i,m}$). The economic cycle is in a high regime within the economic recession according to the official dates of the NBER and in a low regime otherwise. Model 1A includes the dummy variable that accounts for the announcement dates of the beginning and the end of the recession ($regime^{A}_{t,i,m}$). Model 1C includes a dummy variable for the regimes in the credit cycle ($regime^{C}_{t,i,m}$). The credit cycle is in the 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, Model 1A, and Model 1C may be 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 ($\Delta X^{1E}_{t,i,m}$, $\Delta X^{1A}_{t,i,m}$ or $\Delta X^{1C}_{t,i,m}$, respectively for Model 1E, Model 1A and Model 1C) providing the lowest Akaike Information Criterion (AIC) used for model selection.

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

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

$$\begin{aligned}\text{Model 2E:} \quad & \Delta Y_{t,i,m} = \gamma^{2E}_{0,i,m} + \Delta X^{2E}_{t,i,m}\gamma^{2E}_{1,i,m} + \gamma^{2E}_{2,i,m} \times regime^{E}_{t,i,m} \\ & +\Delta X^{2E}_{t,i,m}\gamma^{2E}_{3,i,m} \times regime^{2E}_{t,i,m} + \eta^{2E}_{t,i,m},\end{aligned} \tag{17}$$

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

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

where for a particular cycle $j = 2E, 2A, 2C$, Model 2E, Model 2A, 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. Model 2E, Model 2A, and Model 2C include the same dummies for the regimes as in Model 1E, Model 1A, and Model 1C, respectively.

For the seven models specified above we repeat the procedure for the selection of explanatory variables. We start with the same set of initial variable candidates. 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 the 10% level or higher;

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 variables, we proceed with the backward variable selection.

Finally, we obtain the best set of explanatory variables for each model. We contrast the models obtained using several statistical tests. For robustness, we also contrast them using the same set of explanatory variables.

VII Results

A High and low credit spread episodes

The switching regime model is estimated for each credit spread series separately, with respect to the rating and 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 decreases in the long term–consistent with a humped credit spread curve. The credit spread variance, in both regimes, increases as credit ratings decline. 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 the 5% level or higher (Table 5). The only exception is found with the variance of the 5-year BB spreads. We also find, in results 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 time 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. One exception is for low grade bonds with short maturities, where the switching happens a few months earlier. The first state is also prevalent for most months in 1994.

[Insert Figure 2 here]

All credit spread series stay in the high regime from 2001 to late 2004 although the 2001 recession lasts for only a few months. This indicates that following the systematic shock of 2001, high spread levels were 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) did not decrease 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 regime switching structure obtained for credit spreads. To ascertain that we are using the correct specification of the credit cycle, we perform the following robustness check (detailed results are available upon request). 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 spreads.

B Comparative explanatory powers of models

The main result in Collin-Dufresne, Goldstein, and Martin (2001) is that variables that should theoretically 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 seven models described in equation 13 to 19 provides new insights into the ability of key determinants to explain credit spread differentials. For conciseness, we report only the results for bonds with 10 years to maturity.

Our results show that the introduction of the regimes in the credit spread dynamics (Model 2C) enhances the explanatory power of the theoretical determinants. In particular, the total effect of these determinants throughout the sample period is weakened in the single regime models (Model 1, Model 1E, Model 1A, and Model 1C), thus reducing their explanatory power in most cases. None of these models include interaction effects, but some include a dummy variable to account for the states in the credit cycle (Model 1C) or the economic cycle (Model 1E and Model 1A). Therefore, the explanatory power of Model 2C is not driven by the addition of the prevailing cycle as an explanatory variable. We also find that conditioning on the states of the economic cycle (Model 2E) does not significantly improve the explanatory power of the single regime models. When we condition on the announcement period (Model 2A) we do better than Model 2E but not as well as Model 2C. Thus, Model 2E does not capture the total effect of the economic recession on credit spreads due to the late announcement, and Model 2A does not capture the effective period of recession. Table 6 reports the adjusted R-squared for the seven models considered here.

[Insert Table 6]

Relative to Model 1, Model 2A and Model 2E, Model 2C has the highest adjusted R-squared. However, Model 1E, Model 1A, and Model 1C do not lead to a significant improvement relative to Model 1. More interestingly, Model 2C always has the minimum value of AIC along with the highest explanatory power, which reaches on average 61% across all ratings. Detailed results for each of these models are reported in tables 7 to 10. As can be noted from these tables, the retained sets of explanatory variables in the seven models are different because the model selection is based on the lowest AIC, in all cases starting from the same initial variables with respect to the multicollinearity issues. Here, the Variance Inflation Factor (VIF) should not exceed the critical level of 10 for the regression to be retained.[19]

[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 statistic is always significant at the 1% level or higher, 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. Further, 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 yields only a marginal positive effect compared with the single regime model obtained. This result holds only for AA and A spreads.

[Insert Table 11 and Table 12 here]

Next, we use the explanatory variables in Model 1 ($X^{1}_{t,i,m}$) and derive the regime-based model by adding two terms to Equation 13.

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

The first term is ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$), which accounts for the regimes in the credit cycle. The second term is ($\Delta X^1_{t,i,m}\beta^1_{3,i,m} \times regime^C_{t,i,m}$), which accounts for the interaction effects of the explanatory

[19]A cut-off value of 10 for VIF has been proposed in Kutner, Nachtsheim, Neter (2004).

variables in Model 1 with the regimes in the credit cycle. Model 1 and the regime-based model obtained are thus nested. Table 13 shows that the LRT always favors the regime-based model obtained 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]

We repeat the analysis by conditioning on the states of the economic cycle. The resulting regime-base model is given by Equation 22.

$$\begin{aligned}\Delta Y_{t,i,m} \quad &= \quad \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^E_{t,i,m} \\ &\quad + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^E_{t,i,m} + \mu^{1E}_{t,i,m}. \end{aligned} \tag{22}$$

In this case, conditioning on the states of the economic cycle rather than the credit cycle does not lead to similar results (results, not reported here, are available upon request). The LRT always favors 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 $\beta^1_{3,i,m} = 0$ in Equation 22) 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 and Model 2A. Because all models include different sets of explanatory variables based on model selection criteria we perform two tests.[20] Initially, 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) to obtain Model 2E and then we condition on the announcement period (i.e., $regime^A_{t,i,m}$ instead of $regime^C_{t,i,m}$ in Equation 19) to obtain Model 2A. The adjusted R-squared for all rating classes dropped by about 20% on average in Model 2E and by about 14% on average in Model 2A. The results are reported in Table 15. We also find that most of the interaction coefficients are statistically significant with $regime^C_{t,i,m}$ and never significant with $regime^E_{t,i,m}$ and $regime^A_{t,i,m}$. Further, across all rating classes, the $F-$test does not reject the null hypothesis for all the coefficients of the interaction terms equal to zero (alpha=1%) when we condition on $regime^E_{t,i,m}$ and rejects the null hypothesis when we condition on $regime^C_{t,i,m}$. When we condition on $regime^A_{t,i,m}$ the $F-$test rejects only the null for AA and BBB ratings (Table 16).

[Insert Table 15 and Table 16 here]

Finally, we contrast the three models directly using the $J-$test (Davidson and MacKinnon (1981)) and the Cox-type test (Cox (1961), (1962); Pesaran (1974); Pesaran and Deaton (1978)) for non-nested models. The null hypothesis is performed on both sides. We first test whether Model 2C is better than Model 2E or Model 2A, then we test whether Model 2E or Model 2A is better than Model 2C. Both tests favor Model 2C and are statistically significant at the 5% level or higher. One exception applies for

[20]Many 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 Factor (VIF) becomes extremely high because these variables are strongly correlated with the states of the economic cycle.

the $J-$test, where it fails to discriminate between Model 2C and Model 2E for AA and A spreads and between Model 2C and Model 2A for BBB spreads (Table 17).

[Insert Table 17 here]

Overall, relative to the single regime model, our results invariably favor the regime-based model in which the contributions of the explanatory variables are conditioned by the regimes in the credit cycle. For robustness, we contrast the single regime model to the regime-based model using only one particular group of factors at a time. Based on the LRT in Table 18, we still favor the regime-based models (which are similar to Model 2C).

[Insert Table 18 here]

C Determinants in different regimes

Now we turn our attention to the effects of different factors on the variation in credit spreads. One should bear in mind that regression specifications differ from one model to another because they result from the minimization of the Akaike selection criteria. Our methodology, therefore, lets the data speak even though we narrow the search for elected variables among three groups of factors (market, default, and liquidity factors) as suggested by the financial theory (see Table 1). The constraint put on the VIF limits problems of potential spurious correlation.

Before commenting on specific variables, we report in Table 19 the relative explanatory power of different groups of factors. Table 19 displays for each rating category the adjusted R-squared for Model 1 and Model 2C obtained by regressing credit spread changes on one set of factors at a time: market factors, default factors, and liquidity factors. We follow the same procedure by minimizing the Akaike criteria, which implies different specification of regressions across ratings and models. As shown in Table 19, Model 2C improves the explanatory power of credit spread changes compared with Model 1. These improvements are uniform across groups of factors. The relative importance of each group of factors remains about the same. We shall therefore restrict our comments to Model 2C for the regime-based model and to Model 1 as a benchmark in the literature.

[Insert Table 19]

Market factors appear to contribute the most to the variation in credit spread changes, with an adjusted R-squared ranging from 30.24% for BB spreads to 43.17% for A spreads. This order of magnitude is very similar to results by Elton, Gruber, Agrawal and Mann (2001), who find that the Fama-French factors account for 40% of the explained credit spread levels for the same maturity of 10 years. Our results regarding default factors are also in line with their study. The adjusted R-squared attributable to default factors in our case range from 11.03% for AA spreads to 16.71% for BB spreads, while in their study default premium accounts on average for 17% of their explained spreads. Liquidity factors emerge as the second most important factor. Their explanatory power ranges from 15.88% for A spreads to 27.80% for BBB spreads. By comparison, Chen, Lesmond and Wei (2007) maintain that their liquidity measure explains 7% of the cross-sectional variation of investment grade spreads and

22% of speculative grade spreads–a figure that is close to the 24.00% adjusted R-squared that we find for BB spreads.

Determinants in the single regime model. Our results in the single regime model (Model 1) are consistent with the literature (Table 7 to Table 10). The level, the slope, the GDP, and the Small-Minus-Big factors are shown to be statistically significant across different ratings.[21] We enhance the explanatory power of Model 1 by introducing new measures of liquidity that are shown to be very significant across all ratings, especially for lower grade bonds. Further, age has a non-negligible positive effect for high grade bonds. A similar result is observed with price volatility for A and BB ratings.

Most of the variables have the predicted sign. For the slope, the positive predicted effect dominates. A positive sign is also found in Di Cesare and Guazzarotti (2010) and in Collin-Dufresne, Goldstein, and Martin (2001) for some cases. As far as default factors are concerned, variations in default probabilities have a significant and positive sign for three rating categories out of four. However, the variation in credit spreads is less sensitive to the variation in recovery rates. A negative and significant coefficient is obtained only for the BB rating.

Determinants in the regime-based model. In the regime-based model we analyze low regime coefficients $\widehat{\gamma}_1^{2C}$ and high regime coefficients $(\widehat{\gamma}_1^{2C} + \widehat{\gamma}_1^{2C})$ reported in Table 7 to Table 10.[22] To simplify the interpretation and to be consistent with the predictions in Table 1, we focus our discussion on contemporaneous variables and regard lagged variables as control.

Across ratings, the level is negative and statistically significant in the low regime. Interestingly, for AA and A ratings the level coefficient becomes positive. For instance, in Table 8, the coefficient for $\Delta level_t$ is -0.460 and the coefficient for $\Delta level_t \times regime_t$ is 0.607, making the total effect in the high regime equal to 0.147. Both coefficients are significant at the 1% level or higher. Figure 3 plots AA-rated to BB-rated credit spreads with 10 remaining years to maturity along with the CMT level. As shown in this figure, outside the high regime, the relation between the CMT level and credit spreads appears negative–consistent with the theoretical settings of Merton (1974), Longstaff and Schwartz (1995) and Duffee (1998). However, in the high regime the negative relation often disappears and the correlation between both series is positive, a puzzling finding in Davies (2004). Inside the shaded regions in Figure 3, AA and A credit spreads and risk-free rates are both on a decreasing trend. This result can explain why in previous empirical works like those of Morris, Neale, and Rolph (1998), and Bevan and Garzarelli (2000) the relation between risk-free rates and credit spreads was positive. We can attribute this temporarily positive relation to the persistence of the credit cycle in times when macro variables expand immediately after the NBER recession.[23] This relation is less pronounced and loses significance with low grade bonds, which are more sensitive to macroeconomic conditions (see for

[21]Because we use portfolios of fixed maturities rather than portfolios of average maturities including short, medium and long term bonds, different ratings and maturities are affected by different variables and lags.

[22]These tables also report coefficients for the high regime dummy $\widehat{\gamma}_2^{2C}$. This coefficient should be interpreted with care given that we analyze monthly changes (and not levels) in credit spreads. As a matter of fact, we obtain positive and negative coefficients.

[23]The NBER reports that after an economic recession its committee usually waits to declare the end of the recession until it is confident that any future downturn in the economy would be considered a new recession and not a continuation of the preceding recession. Thus, macro variables are always expanding well before the end of the high credit spread regime. It follows that after the economic recession, inverted signs are observed for some variables, especially for spreads with high grades and long maturities.

example Collin-Dufresne, Goldstein, and Martin (2001) and Huang and Kong (2003)).

[Insert Figure 3 here]

The positive effect of the slope is reinforced in the high regime. The interaction effect is positive for all ratings except BB, indicating that, in times of recession, corporations typically lose more on their growth options than on their assets in place. As expected, the coefficient for the GDP is negative but the model does not capture any particular regime effect, nor do we observe a regime effect for the other market factors (Fama-French, SML, VIX). Although default factors improve the single regime model when they are considered separately in Table 18, their effect is absorbed by the introduction of other elected variables. For example, for A spreads, the default probability variable is not significant in any regime while it was significant in the single regime model. We also observe that the positive influence of the default probability in Model 1 is captured by the regime effect in Model 2C for BBB spreads. Recovery rates are not significant in Model 1 except for BB, while in Model 2C the effect is mixed. Regarding liquidity factors, the regime-based model shows that the age impact on high grade bonds and the price volatility on low grade bonds are concentrated in the low regime. The regime based-model fails to capture specific liquidity factors during the 2001 recession.

Table 20 summarizes the coefficient signs of elected variables in different regimes. In some instances the coefficient sign of lagged variables in the low regime is inverted in the high regime, thus weakening or even reversing the total effect. As mentioned earlier for the level effect, these sign inversions can be attributed to the persistence of the credit cycle over the NBER economic cycle.

[Insert Table 20 here]

VIII Conclusion

The main contribution of this study is to analyze credit spread determinants when modeling the credit cycle endogenously. We derive the credit cycle from the switching regime structure of credit spread levels. The credit cycle obtained is much more persistent than the NBER economic cycle.

By conditioning on credit spread regimes we enhance the explanatory power of the single regime model. Further, we show that the single regime model cannot be improved by conditioning on the states of the economic cycle or on the announcement periods of the NBER 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, whereas they are highly significant when we consider the credit cycle.

Furthermore, several variables see their effect strengthen, weaken or even reverse as we switch across regimes. Most notably, we find a positive relation between credit spreads and the risk-free rate in the high regime, which reconciles previous mixed evidence on this relation. We detect similar effect reversals for other macro determinants. This may be one cause of the superiority of the credit cycle model to the economic cycle model, but further investigation is required.

Finally, our study documents that market factors have greater explanatory power than default and liquidity factors. However, this result may be specific to the 2001 recession. The relative importance of this factor can vary from one recession to another. For example, Elton, Gruber, Agrawal, and Mann (2001) also find market factors to be more important than default factors for the 1990 recession. More recently, Dick-Nielsen, Feldhütter, and Lando (2009) show that liquidity factors have been particularly influential during the 2007 recession.

IX Appendix

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

$$\begin{aligned} R(t,T) &= \beta_{0t} + \beta_{1t}\left[\frac{1-\exp(-\frac{T}{\tau_{1t}})}{\frac{T}{\tau_{1t}}}\right] + \beta_{2t}\left[\frac{1-\exp(-\frac{T}{\tau_{1t}})}{\frac{T}{\tau_{1t}}} - \exp(-\frac{T}{\tau_{1t}})\right] \\ &\quad + \beta_{3t}\left[\frac{1-\exp(-\frac{T}{\tau_{2t}})}{\frac{T}{\tau_{2t}}} - \exp(-\frac{T}{\tau_{2t}})\right] + \varepsilon_{t,j}, \end{aligned} \tag{23}$$

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 because long-maturity bond prices are more sensitive to interest rates:

$$\widehat{\Omega}_t = \arg\min_{\Omega_t} \sum_{i=1}^{N_t} w_i^2 \left(P_{it}^{NS} - P_{it}\right)^2, \qquad w_i = \frac{1/D_i}{\sum_{i=1}^{N} 1/D_i}, \tag{24}$$

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 price 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 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, Predescu, and White (2004), we use the swap rate curve less 10 basis points as a benchmark risk-free curve.

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Table 1: Summary statistics on U.S. corporate bonds.

The table reports summary statistics on 10-year credit spreads for straight fixed-coupon corporate bonds in the industrial sector. The sample period covers January 1994 to December 2004. 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 is the number of unique issues. Issuers is the number of unique issuers. Total Trades is 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 2: 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 ranges 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 3: 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	-	Collin-Dufresne et al. (2001)
Term structure slope	$\Delta slope$	Monthly series of 10-year minus 2-year CMT rates	-/+	Collin-Dufresne et al.(2001)
GDP	Δgdp	GDP growth rate	-	Altman et al. (2001)
Equity market return	Δsp	S&P500 index return	-	Huang and Kong (2003)
Stock market index	Δsml	S&P 600 small cap	-	
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	-	Elton et al. (2001)
		Panel B. Default factors		
Realized default probability	$\Delta dpall$	Moody's trailing 12-month DR of all U.S. corporate issuers*	+	Huang and Kong (2003)
	$\Delta dpspec$	Moody's trailing 12-month DR of U.S. speculative grade issuers*	+	Huang and Kong (2003)
Realized recovery rates	$\Delta recsus$	Moody's monthly RR for Senior Unsecured bonds*	-	Altman et al. (2005)
	$\Delta recsub$	Moody's monthly RR for Senior Subordinated bonds*	-	Altman et al. (2005)
Expected recovery rates	$\Delta \exp recsus$	Moody's month (t+2) RR for Senior Unsecured bonds*	-	Altman et al. (2005)
	$\Delta \exp recsub$	Moody's month (t+2) RR for Senior Subordinated bonds*	-	Altman et al. (2005)
		Panel C. Liquidity factors		
Traditional bond measures	Δage	Bond's age	+	Han and Zhou (2008)
	Δcp	Bond's coupon	+	Han and Zhou (2008)
	$\Delta size$	Bond's size	+	Han and Zhou (2008)
	Δvol	Bond's volume	+	Chakravarty and Sarkar (1999)
Price impact of trades	$\Delta amih$	Amihud	+	Han and Zhou (2008)
	$\Delta mamih$	Modified Amihud	+	Han and Zhou (2008)
	$\Delta range$	Range	+	Han and Zhou (2008)
	$\Delta sigp$	Price volatility	+	
Trading frequencies	$\Delta turn$	Turnover	-	Han and Zhou (2008)
	$\Delta freqall$	Monthly transaction frequency of all trades	-	Goldstein et al. (2007)
	$\Delta frepuni$	Monthly transaction frequency of a unique trade	-	Han and Zhou (2008)

[†] Sign refers to the coefficient signs obtained in previous studies using a single regime model. *DR denotes default rates, RR denotes recovery rates.

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. industrial 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 shown in 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)	(0.070)
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)	(0.020)	(0.020)	(0.012)	(0.029)	(0.026)	(0.014)
p_{22}	0.979	0.981	0.982	0.980	0.982	0.982	0.979	0.980	0.982	0.979	0.991	0.982
	(0.015)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(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 designate the means of the high and low regimes, respectively. The parameters σ_1^2 and σ_2^2 designate 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 Factor (VIF), which should be below the critical level of 10, and the Akaike Information Criteria (AIC) obtained for models described in equations 13 to 19.

		Model 1	Model 1E	Model 1A	Model 1C	Model 2E	Model 2A	Model 2C
		single regime model	single regime models with dummy for the cycle			two regime models with interaction effects		
			Economic	Announc.	Credit	Economic	Announc.	Credit
AA	$AdjR^2$	0.432	0.438	0.426	0.426	0.331	0.502	0.604
	VIF	1.30	1.29	1.26	1.23	1.74	3.22	4.24
	AIC	-3.067	-3.077	-3.056	-3.063	-2.897	-3.105	-3.312
A	$AdjR2$	0.574	0.570	0.571	0.570	0.374	0.552	0.614
	VIF	1.39	1.41	1.33	1.42	3.93	3.31	4.15
	AIC	-3.672	-3.657	-3.667	-3.659	-3.274	-3.570	-3.718
BBB	$AdjR^2$	0.483	0.490	0.478	0.478	0.428	0.543	0.672
	VIF	1.23	1.28	1.27	1.28	3.22	2.28	8.06
	AIC	-2.922	-2.930	-2.907	-2.906	-2.775	-2.986	-3.249
BB	$AdjR^2$	0.383	0.363	0.388	0.379	0.317	0.435	0.537
	VIF	1.23	1.23	1.25	1.28	8.92	4.13	4.06
	AIC	-1.659	-1.640	-1.666	-1.645	-1.485	-1.641	-1.840

Legend for Table 7 to Table 10.

We compare the ability of different models 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 (Economic). Model 1A refers to the single regime model with a dummy for the regimes within the announcement dates of the beginning and the end of the economic cycle (Announc.). Model 1C refers to the single regime model with a dummy for the regimes in the credit cycle (Credit). Model 2E, Model 2A, and Model 2C refer to the regime-based models including interaction effects with the regimes within the economic cycle, the announcement cycle and the credit cycle, respectively. For $j = E, A, C$ in the regime based model, reported coefficients are $\widehat{\gamma}^{j}_{1,i,m}$ in the low regime and $\widehat{\gamma}^{j}_{3,i,m}$ in the high regime. For the interpretation of the total effect in the high regime one should consider $(\widehat{\gamma}^{j}_{1,i,m} + \widehat{\gamma}^{j}_{3,i,m})$ as indicated in Equation 20. 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 Factor (VIF), which should be below the critical level of 10. ***, **, * indicate a significance level at 1%, 5%, and 10%, respectively. This legend applies to Table 7 to Table 10.

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

	Model 1	Model 1E	Model 1A	Model 1C	Model 2E	Model 2A	Model 2C
	single regime model	single regime models with dummy for the cycle			two regime models with interaction effects		
		Economic	Announc.	Credit	Economic	Announc.	Credit
$intercept$	-0.007	-0.045	0.078**	0.096**	-0.016	0.057	0.075*
$\Delta level_t$	-0.170*	-0.167*	-0.176*	-0.153	-0.083	-0.329***	-0.356***
$\Delta slope_t$	0.826***	0.785***	0.768***	0.774***	0.741***	0.278*	0.083
$\Delta slope_{t-1}$						0.471***	0.366**
Δgdp_t	-0.027***	-0.021**	-0.025**	-0.026***		-0.019*	-0.021**
Δvix_{t-2}					-0.009**	-0.014**	-0.018***
smb_t	0.011**	0.011**	0.011**	0.011**	0.009*	0.008	0.010**
smb_{t-2}						-0.004	-0.004
Δsml_t	0.004*	0.004**	0.004*	0.004*		0.002	0.002
Δsml_{t-2}						-0.001	-0.001
$\Delta recsub_t$	0.003	0.003*					-0.001
Δage_t	0.075**	0.073**	0.078**	0.073**		0.088***	0.127***
$\Delta amih_{t-1}$						0.005***	-0.007
$\Delta range_{t-1}$	0.936**	0.806*	1.037**	0.927**	1.011**		
$\Delta medp_t$	-0.051***	-0.053***	-0.052***	-0.052***		-0.041***	-0.025*
$\Delta sigp_{t-1}$	2.820**	3.754***	2.917**	3.728***	3.266**		
$\Delta sigp_{t-2}$	-0.02		-0.019			-0.017	-0.040**
$\Delta turn_t$							-0.034
$\Delta turn_{t-3}$	-0.034**	-0.031*	-0.032**	-0.031*			
$regime_t$		0.148*	-0.054	-0.055	0.177*	0.061	-0.003
$\Delta level_t \times regime_t$					0.083	0.101	0.373**
$\Delta slope_t \times regime_t$					-0.169	0.691	1.352***
$\Delta slope_{t-1} \times regime_t$						-0.051	-0.335
$\Delta gdp_t \times regime_t$						-0.043	-0.013
$\Delta vix_{t-2} \times regime_t$					0.012*	0.060***	0.046***
$smb_t \times regime_t$					-0.006	0.012	-0.022**
$smb_{t-2} \times regime_t$						0.035***	0.028***
$\Delta sml_t \times regime_t$						0.003	0.005
$\Delta sml_{t-2} \times regime_t$						0.021**	0.011**
$\Delta recsub_t \times regime_t$							0.016***
$\Delta age_t \times regime_t$						-0.006	-0.123*
$\Delta amih_{t-1} \times regime_t$						-0.745	1.021*
$\Delta range_{t-1} \times regime_t$					-26.100		
$\Delta medp_t \times regime_t$						-0.046	-0.024
$\Delta sigp_{t-1} \times regime_t$					1.881		
$\Delta sigp_{t-2} \times regime_t$						-0.116*	-0.002
$\Delta turn_t \times regime_t$							0.074**
$AdjR^2$	0.432	0.438	0.426	0.426	0.331	0.502	0.604
VIF	1.3	1.29	1.26	1.23	1.74	3.22	4.24
AIC	-3.067	-3.077	-3.056	-3.063	-2.897	-3.105	-3.312

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

	Model 1	Model 1E	Model 1A	Model 1C	Model 2E	Model 2A	Model 2C
	single regime model	single regime models with dummy for the cycle			two regime models with interaction effects		
		Economic	Announc.	Credit	Economic	Announc.	Credit
$intercept_t$	0.023	0.021	0.036	0.032	0.018	0.047	0.108***
$\Delta level_t$	-0.346***	-0.346***	-0.347***	-0.341***	0.018	-0.363***	-0.460***
$\Delta level_{t-3}$	-0.128**	-0.127**	-0.154***	-0.127**		-0.124*	-0.104
$\Delta slope_t$	0.621***	0.618***	0.644***	0.626***	0.814***	0.683***	0.241*
Δgdp_t	-0.012*	-0.012	-0.013*	-0.013*	-0.014	-0.015**	-0.029***
Δvix_t			-0.007**			-0.009*	
Δvix_{t-1}							0.005
Δsml_t	0.003*	0.003*		0.003*			
Δsml_{t-1}						-0.001	-0.005***
$\Delta dpall_t$	27.971**	27.686***	21.506	25.079*			
Δage_t	0.183***	0.183***	0.186***	0.183***		0.173***	0.204***
$\Delta range_t$	-6.786	-6.769		-6.705	-7.759	-4.151	
$\Delta range_{t-2}$							13.762**
$\Delta medp_t$	-0.077***	-0.077***	-0.078***	-0.077***		-0.088***	-0.102***
$\Delta sigp_t$	4.242***	4.229***	0.029**	4.184***	3.328*		
$\Delta turn_{t-3}$	-0.050***	-0.050***	-0.050***	-0.050***	-0.049**		
$regime_t$		0.008	-0.046	-0.015	0.077	0.038	-0.241**
$\Delta level_t \times regime_t$					-0.033	0.138	0.607***
$\Delta level_{t-3} \times regime_t$						0.198	-0.104
$\Delta slope_t \times regime_t$					-0.079	0.391	0.973***
$\Delta gdp_t \times regime_t$					-0.003	-0.047	0.020
$\Delta vix_t \times regime_t$						0.036**	
$\Delta vix_{t-1} \times regime_t$							-0.021***
$\Delta sml_t \times regime_t$						0.014**	
$\Delta sml_{t-1} \times regime_t$							0.001
$\Delta age_t \times regime_t$						0.051	-0.193**
$\Delta range_t \times regime_t$					79.900	32.500***	
$\Delta range_{t-2} \times regime_t$							-26.037***
$\Delta medp_t \times regime_t$						0.035	0.102***
$\Delta sigp_t \times regime_t$					-19.868		
$\Delta turn_{t-3} \times regime_t$					0.002		
$AdjR2$	0.574	0.570	0.571	0.570	0.374	0.552	0.614
VIF	1.39	1.41	1.33	1.42	3.93	3.31	4.15
AIC	-3.672	-3.657	-3.667	-3.659	-3.274	-3.570	-3.718

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

	Model 1	Model 1E	Model 1A	Model 1C	Model 2E	Model 2A	Model 2C
	single regime model	single regime models with dummy for the cycle			two regime models with interaction effects		
		Economic	Announc.	Credit	Economic	Announc.	Credit
$intercept$	-0.007	-0.051	-0.017	-0.015	0.043	-0.079	0.242*
$\Delta level_t$	-0.307***	-0.313***	-0.308***	-0.309***	-0.299***	-0.328***	-0.282**
$\Delta slope_t$	0.608***	0.549***	0.606***	0.606***	0.549***	0.473***	0.539**
$\Delta slope_{t-1}$							-0.181
Δgdp_t	-0.022**	-0.017	-0.022**	-0.022**	-0.018	-0.021*	-0.029**
Δvix_{t-1}	0.007	0.006	0.007	0.007	0.007		0.001
Δvix_{t-3}	-0.008*	-0.008*	-0.008*	-0.008*	-0.009*	-0.003	0.011**
smb_{t-1}						-0.002	0.003
Δsml_{t-1}							-0.006**
$\Delta dpall_t$	37.362*	31.261	39.518*	38.957*		23.274	6.024
$\Delta recsub_t$	0.002	0.003	0.002	0.002			0.001
$\Delta amih_t$	16.175***	16.303***	16.137***	16.154***	15.781***	16.101**	15.271
$\Delta amih_{t-2}$	10.125***	10.471***	10.094***	10.127***	9.262***		-17.258
$\Delta range_{t-3}$	18.016***	19.370***	17.914***	17.975***	21.474**	22.065***	1.173
$\Delta medp_t$	-0.040***	-0.041***	-0.040***	-0.040***	-0.036**	-0.025	-0.017
$\Delta sigp_t$	-0.016	-0.020*	-0.016	-0.016		-0.048***	
$\Delta sigp_{t-2}$							-0.052**
$\Delta turn_{t-2}$							-0.054**
$regime_t$		0.151	0.018	0.009	0.142	0.1555	-0.325**
$\Delta level_t \times regime_t$					-0.056	-0.299	0.031
$\Delta slope_t \times regime_t$					-0.378	0.182	0.395
$\Delta slope_{t-1} \times regime_t$							0.634**
$\Delta gdp_t \times regime_t$					-0.038	-0.050	-0.031
$\Delta vix_{t-1} \times regime_t$					0.012		0.029**
$\Delta vix_{t-3} \times regime_t$					0.01	-0.028***	-0.037***
$smb_{t-1} \times regime_t$						0.033*	0.019*
$\Delta sml_{t-1} \times regime_t$							0.015***
$\Delta dpall_t \times regime_t$						151.511***	66.372**
$\Delta recsub_t \times regime_t$							0.011**
$\Delta amih_t \times regime_t$					-20.896	-0.289	0.287
$\Delta amih_{t-2} \times regime_t$					66.822		24.502*
$\Delta range_{t-3} \times regime_t$					-6.21	-6.902	27.921***
$\Delta medp_t \times regime_t$					0.022	-0.034	-0.031
$\Delta sigp_t \times regime_t$						0.050**	
$\Delta sigp_{t-2} \times regime_t$							0.078***
$\Delta turn_{t-2} \times regime_t$							0.080***
$AdjR^2$	0.483	0.490	0.478	0.478	0.428	0.543	0.672
VIF	1.23	1.28	1.27	1.28	3.22	2.82	8.06
AIC	-2.922	-2.930	-2.907	-2.906	-2.775	-2.986	-3.249

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

	Model 1	Model 1E	Model 1A	Model 1C	Model 2E	Model 2A	Model 2C
	single regime model	single regime models with dummy for the cycle			two regime models with interaction effects		
		Economic	Announc.	Credit	Economic	Announc.	Credit
$intercept$	0.113	-0.023	0.100	0.084	-0.017	-0.029	-0.176
$\Delta level_t$	-0.411**	-0.378**	-0.292*	-0.416**	-0.371**	-0.450***	-0.534***
$\Delta slope_{t-1}$					0.576*	0.316	0.622**
Δgdp_t			-0.036*				
Δgdp_{t-1}	-0.037*			-0.033			
Δvix_{t-3}	-0.026***	-0.027***	-0.028***	-0.026***	-0.030***	-0.030***	-0.017
smb_t					-0.003	0.003	0.006
Δsmb_{t-1}	-0.013**	-0.015**	-0.015**	-0.013**	-0.015*	-0.018***	-0.018***
$\Delta dpall_t$	190.17***	189.62***	191.42***	196.78***	146.57***	188.50***	171.51***
$\Delta dpall_{t-1}$	-94.750**	-97.932**	-75.353*	-89.126**	-86.108*	-75.929	-99.343**
$\Delta recsus_t$	-0.023*		-0.006**	-0.023*			0.003
$\Delta amih_t$	-0.005*	-0.048*	-0.005*	-0.005*	-0.006**	-0.005*	-0.006**
$\Delta amih_{t-3}$	-0.004**	-0.005**	-0.006***	-0.004**		-0.005**	-0.005*
$\Delta medp_t$	-0.106***	-0.097***	-0.101***	-0.106***	-0.083***	-0.099***	-0.099***
$\Delta medp_{t-3}$					-0.037	-0.041*	-0.057**
$\Delta sigp_t$	0.018***	0.020***	0.020***	0.019***	0.019***	0.032***	0.043***
$\Delta sigp_{t-1}$						-0.013	-0.016*
$\Delta turn_t$						-0.038	
$\Delta turn_{t-3}$	0.032			0.032			
$regime_t$		0.279*	0.093	0.045	0.041	0.371**	0.788***
$\Delta level_t \times regime_t$					1.332	0.270	0.49
$\Delta slope_{t-1} \times regime_t$					-0.049	1.258	-0.575**
$\Delta vix_{t-3} \times regime_t$					-0.015	0.034	-0.034**
$smb_t \times regime_t$					-0.079	-0.079	-0.062**
$\Delta smb_{t-1} \times regime_t$					-0.079	0.063**	0.027*
$\Delta dpall_t \times regime_t$					725.684	376.735**	34.287
$\Delta dpall_{t-1} \times regime_t$					-161.861	-173.781	26.733
$\Delta recsus_t \times regime_t$							-0.018***
$\Delta amih_t \times regime_t$					0.032	2.913*	0.009
$\Delta amih_{t-3} \times regime_t$						-0.124	-0.004
$\Delta medp_t \times regime_t$					-0.186	0.028	0.065*
$\Delta medp_{t-3} \times regime_t$					0.104	-0.037	0.070*
$\Delta sigp_t \times regime_t$					.029	-0.052**	-0.046***
$\Delta sigp_{t-1} \times regime_t$						0.002	0.004
$\Delta turn_t \times regime_t$						0.481***	
$AdjR^2$	0.383	0.363	0.388	0.379	0.317	0.435	0.537
VIF	1.23	1.23	1.25	1.28	8.92	4.13	4.06
AIC	-1.659	-1.640	-1.666	-1.645	-1.485	-1.641	-1.84

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

All the models evaluated here are derived from Equation 19, characterizing 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 versus the model obtained by setting the coefficients ($\gamma^{2C}_{2,i,m} \neq 0$ and $\gamma^{2C}_{3,i,m} = 0$). These restrictions add a dummy variable to the single regime model 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	LRT (df)	81.50 (16)	80.18 (15)	1.32 (1)
	$P-value$	(0.000)	(0.000)	(0.251)
A	LRT (df)	44.81 (10)	42.43 (9)	2.38 (1)
	$P-value$	(0.000)	(0.000)	(0.122)
BBB	LRT (df)	85.88 (18)	82.16 (17)	0.00 (1)
	$P-value$	(0.000)	(0.000)	(0.978)
BB	LRT (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	0.672	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 25) is obtained by adding to Equation 13 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 ($\Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m}$).

$$\begin{aligned} \Delta Y_{t,i,m} &= \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} \\ &\quad + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^{1C}_{t,i,m}, \end{aligned} \tag{25}$$

When the coeffcients $\beta^1_{2,i,m}$ and $\beta^1_{3,i,m}$ are set as equal to zero ($\beta^1_{2,i,m} = 0, \beta^1_{3,i,m} = 0$ in Equation 25), we obtain Model 1 as described in Equation 13. 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 25). 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 25	
		($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$) 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	LRT (df)	31.21 (13)	0.86 (1)
	$P - value$	(0.003)	(0.355)
A	LRT (df)	18.59 (12)	0.24 (1)
	$P - value$	(0.098)	(0.625)
BBB	LRT (df)	32.84 (13)	0.20 (1)
	$P - value$	(0.001)	(0.655)
BB	LRT (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 13 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 ($\Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m}$):

$$\begin{aligned}\Delta Y_{t,i,m} \quad = \quad & \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} \\ & + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^{1C}_{t,i,m},\end{aligned} \tag{25}$$

Column (3) reports the adjusted R-squared for Model 1 which reduces to Equation 13 when ($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$ in Equation 25). 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 25		
	($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$)	($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$)	($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} = 0$)
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: Comparative adjusted R-squared for the regime based models.

We report the adjusted R-squared for Model 2C (Credit), Model 2A (Announc.) and Model 2E (Economic) using the set of explanatory variables ($\Delta X^{2C}_{t,i,m}$) in Equation 19. Column (2) reports the adjusted R-squared for Model 2C. Column (3) reports the adjusted R-squared for model in Equation 19 when we condition on the states of the economic cycle (i.e., $regime^{E}_{t,i,m}$ instead of $regime^{C}_{t,i,m}$). Column (4) reports the adjusted R-squared for model in Equation 19 when we condition on the announcement period (i.e., $regime^{A}_{t,i,m}$ instead of $regime^{C}_{t,i,m}$).

	Model 2C	Model 2A	Model 2E
	Credit	Announc.	Economic
AA	0.604	0.482	0.324
A	0.614	0.524	0.471
BBB	0.672	0.529	0.442
BB	0.537	0.383	0.344

Table 16: Test statistics for the regime based models.

We report the results of the $F-$statistic applied to Model 2C (Credit), Model 2A (Announc.) and Model 2E (Economic) using the set of explanatory variables ($\Delta X^{2C}_{t,i,m}$) in Equation 19. The null hypothesis states that all the coefficients of the interaction terms are equal to zero. Column (2) reports the results for Model 2C. Column (3) reports the results for model in Equation 19 when we condition on the states of the economic cycle (i.e., $regime^{E}_{t,i,m}$ instead of $regime^{C}_{t,i,m}$). Column (4) reports the results for model in Equation 19 when we condition on the announcement period (i.e., $regime^{A}_{t,i,m}$ instead of $regime^{C}_{t,i,m}$).

		Model 2C	Model 2A	Model 2E
		Credit	Announc.	Economic
AA	F-statistic	5.57	2.79	0.39
	$p-value$	(0.000)	(0.001)	(0.948)
A	F-statistic	4.72	1.53	0.43
	$p-value$	(0.000)	(0.148)	(0.916)
BBB	F-statistic	5.25	1.95	0.64
	$p-value$	(0.000)	(0.023)	(0.802)
BB	F-statistic	4.34	1.39	0.84
	$p-value$	(0.000)	(0.171)	(0.601)

Table 17: Comparing regime-based models.

We perform the $J-$ test and the Cox-type test for non-nested models. Model 2C is the regime-based model given by Equation 19. Model 2E is the regime-based model given by Equation 17. Model 2A is the regime based model given by Equation 18. We test four null hypotheses: (1) Model 2C is better than Model 2E; (2) Model 2E is better than Model 2C; (3) Model 2C is better than Model 2A; and (4) Model 2A is better than Model 2C. (df) refers to degrees of freedom.

		AA	A	BBB	BB
Panel A: J test					
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)
H_0: Model 2C is better	t-stat (df)	1.44 (96)	1.23 (107)	2.31 (93)	1.19 (97)
H_1: Model 2A is better	$p-value$	(0,153)	(0.221)	(0.023)	(0,237)
H_0: Model 2A is better	t-stat (df)	6.32 (96)	5.61 (107)	8.22 (93)	6.14 (97)
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)
H0: Model 2C is better	$N(0,1)$	-0.875	-0.666	-0.753	-0.861
H1: Model 2A is better	$p-value$	(0.191)	(0.253)	(0.226)	(0.194)
H0: Model 2A is better	$N(0,1)$	-9.963	-10.131	-13.66	-11.81
H1: Model 2C is better	$p-value$	(0.000)	(0.000)	(0.000)	(0.000)

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)
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)
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)

Table 19: Explanatory power of market, default, and liquidity factors.

	AA	A	BBB	BB
Panel A: Single regime model (Model 1)				
Market factors	29.31	40.15	26.22	16.45
Default factors	5.84	10.10	8.33	9.31
Liquidity factors	11.08	12.07	18.53	14.65
Panel B: Two-regime model (Model 2C)				
Market factors	31.04	43.17	36.99	30.24
Default factors	11.03	15.34	14.92	16.71
Liquidity factors	18.12	15.88	27.80	24.00

Table 20: Signs of explanatory variables coefficients.

For each rating class, the first, second, and third columns report coefficient signs of the explanatory variables of Model 1, Model 2C in the low (low) and the high (high) regime, respectively (i.e., signs of $\beta^1_{1,i,m}$ in Equation 13, $\gamma^{2C}_{1,i,m}$ and $(\gamma^{2C}_{1,i,m} + \gamma^{2C}_{3,i,m})$ in 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	pos						
$\Delta slope_t$	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			
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***	pos*
smb_{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***	

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 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.

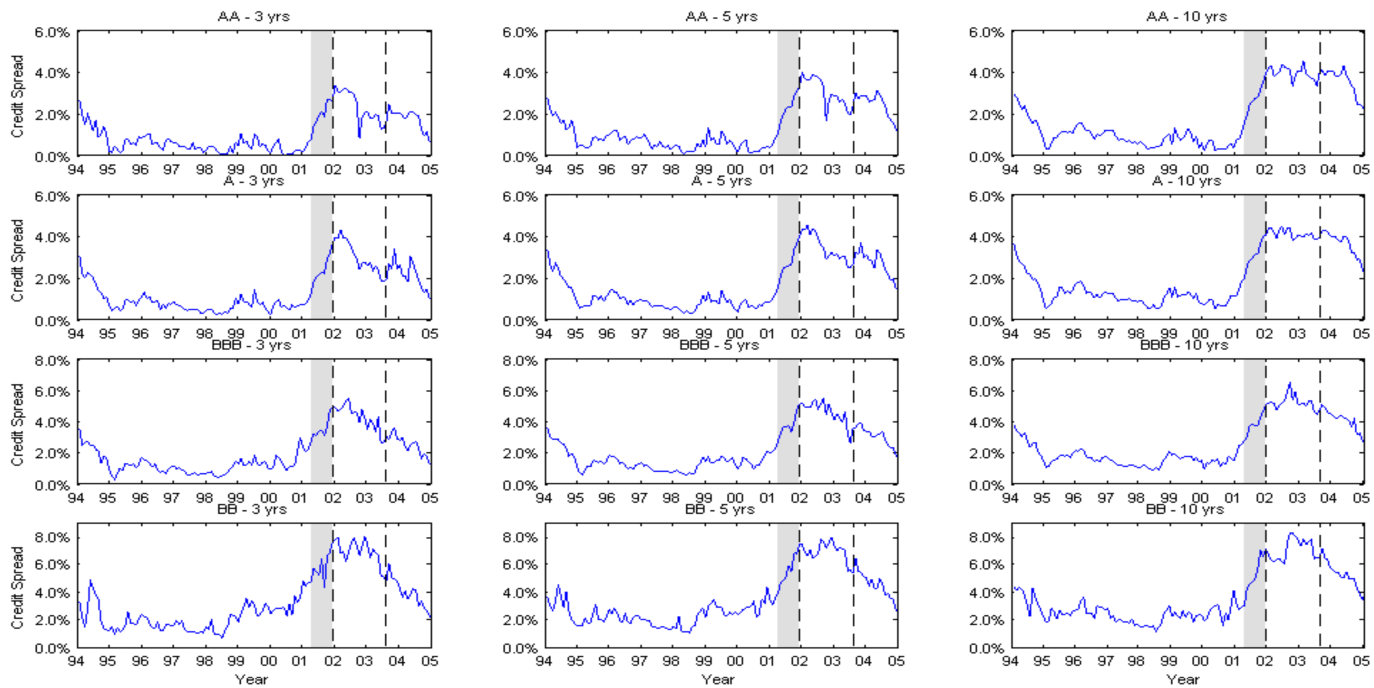

Figure 2: The smoothed probability of the high regime against credit spreads (1994-2004).

In the righthand side of the axis the figure plots the smoothed probabilities $p\left(s_t = 2|y_1, ..., y_T; \widehat{\theta}\right)$ that the process was in the high regime at any given month over the sample period. In the lefthand side of the axis, it plots the credit spreads (dotted line in the high spread regime) for AA to BB corporate bonds with 3, 5, and 10 remaining years to maturity. 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.

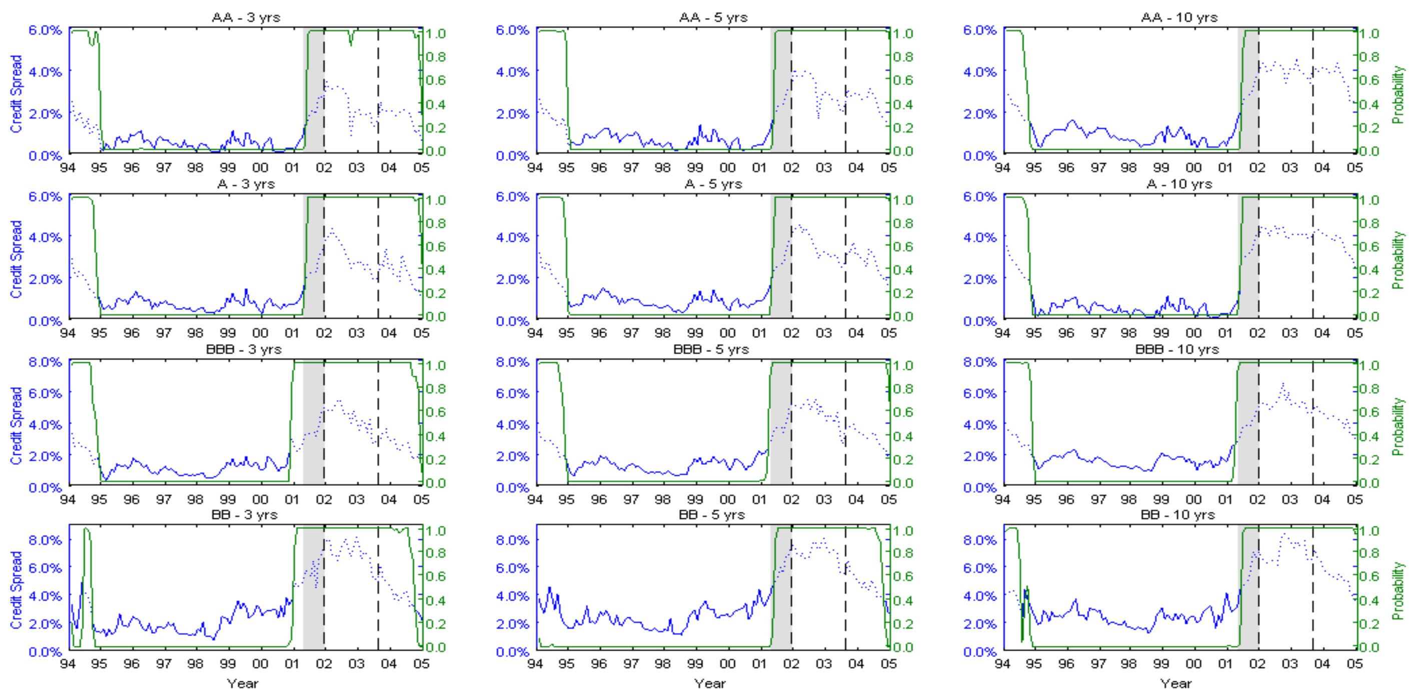

Figure 3: Observed credit spreads against the CMT level (1994-2004).

The figure plots the CMT level in the righthand side of the axis and the observed credit spreads in the lefthand side of the axis. Credit spreads are rated AA to BB corporate bonds with 10 remaining years to maturity. The shaded region represents the area where the level of AA, A, and BBB credit spreads and the level of CMT tend to have similar slope signs.