C.I.R.P.É.E
Centre Interuniversitaire sur le Risque,
les Politiques Économiques et l'Emploi

Cahier de recherche/Working Paper **09-29**

Detecting Regime Shifts in Corporate Credit Spreads

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Août/August 2009

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The authors acknowledge financial support from the Institut de Finance Mathématiques de Montréal (IFM2), the Tunisian Ministry of Education, the Canada Research Chair in Risk Management, the Center for Research on e-finance, and HEC Montreal. They thank Jan Ericsson and Nicolas Papageorgiou for helpful comments.

Abstract:
Studies about credit spread switching regimes typically make assumptions about the number of regimes for in-sample regime detection. This is because exploratory regime detection techniques are lacking in the literature. We employ a real time sequential technique to detect possible breakpoints in the mean and the variance of credit spreads. Our evidence shows that regime shifts are closely related to systematic shocks. Detected shifts in the mean and the variance have different patterns that provide new insights on the relation between economic and credit cycles. We also show that the employed out-of-sample detection technique can be valuable for market timing.

Keywords: Credit spread regimes, shifts in the mean and the variance, credit cycle, economic cycle, market timing

JEL Classification: C1, C32, C61, E32, G11, G33

1 Introduction

Understanding the dynamics of credit spreads is essential when pricing and hedging corporate bonds as well as the new generation of credit instruments such as credit derivatives and structured products. An important issue is how to assess the systematic component in the credit risk premium (Elton, et al., 2001; Allen and Saunders, 2003; Koopman, Lucas and Klaassen, 2005). If credit spreads are significantly driven by a systematic factor, then their time series should exhibit a countercyclical behavior. Previous work has brought to light the negative serial correlation between credit spreads and macroeconomic conditions. From this vein of the literature arises the recent debate on the relation between the credit cycle and the economic cycle. The classical thinking is that the credit cycle is driven by macroeconomic fundamentals (see for example Koopman and Lucas, 2005; Koopman et al., 2006). However, Lown and Morgan (2006) have suggested that the credit cycle may also affect the course of the economic cycle. To further investigate this relation, recent contributions apply switching regime models to capture state dependent movements in the credit spread dynamic (Davies, 2004 and 2007; Alexander and Kaeck, 2007; Dionne et al., 2007; David, 2008). However, the connection between the states identified and the business cycle remains unclear (Alexander and Kaeck, 2007). This paper readdresses this connection using a different approach.

The paper presents a nonparametric method – previously never applied in finance – for detecting regime shifts in the dynamics of the credit spread in real time. The proposed approach has been applied in the physical and biological literature to detect regime shifts in ecosystems (Rodionov, 2004, 2005, and 2006 for a complete review). It signals breakpoints in the mean and the variance of time series coming into sequences based on structural statistical tests. The technique has the advantage of letting the data speak and reveal possible shift points in real time. In contrast to existing studies on credit spreads with regime switching, it requires no assumptions about the number of the regimes. We apply this method to the time series of credit spreads for a sample of U.S. bonds rated from AA to BB over the 1994–2004 period.

Time series of credit spreads exhibit successive falling and rising episodes over time. These episodes can be observed in changes in the level and/or the volatility of credit spreads especially around periods of economic recession and financial crises. A striking example is shown in Figure 1. The figure plots the time series of 3-, 5-, and 10-year AA to BB credit spreads from 1994 to 2004. Our sample period covers the 2001 NBER recession (shaded region). Across ratings and maturities, the credit spread movements exhibit at least two different regimes in terms of sudden changes in their level and/or the volatility over the period considered. These shifts may be associated with a persistent financial crisis (Cerra and Saxena, 2005; Hamilton, 2005) or sudden changes in the economy (Hamilton, 1988; Sims and Zha, 2006; Davig, 2004).

[Insert Figure 1 here]

Closer inspection of Figure 1 indicates that, just before the 2001 recession, credit spreads shift from a falling episode to a rising episode. The rising episode characterizing the credit cycle seems to be closely related to the economic cycle since both cycles appear to start at almost the same time. However, the credit cycle seems to be longer than the economic cycle. Actually, the NBER recession starts in March 2001 and ends after eight months in November 2001 while credit spread levels remain high for several more years especially for long maturity bonds. When applied to the 1991 recession, the same scenario can explain the high credit spread level observed in late 1994. In addition, around the 2001 recession, credit spreads for low grade bonds start to slope upward until mid-2003 and then take a downward slope until the end of 2004. Since the end of the recession occurred in November 2001 but was officially announced in July 2003, an announcement effect might have triggered the credit spread behavior in the high episode. These observations should have important implications for credit risk management and for the regulation of banks. For example, portfolio managers expecting an upcoming recession will know that this recession may well be accompanied by a longer episode of high credit spreads.

Falling and rising episodes are driven by shifts either in the mean or in the variance of the credit spread rates or in both. Techniques already used in the credit spread literature consider the sample as a whole in their attempt to detect different regimes. These techniques take a confirmatory approach rather than an exploratory approach which control for the number of the shifts in the data. For example, Davies (2004 and 2007) analyzes credit spread determinants using a Markov switching estimation technique with the assumption of two volatility regimes. Alexander and Kaeck (2007) also use two-state Markov chains to analyze credit default swap determinants within distinct volatility regimes. All these studies use different period ranges and may cover more than just two regimes.

The method applied in this study is based on sequential Student's $t-$tests for shifts in the mean and on sequential $F-$tests for shifts in the variance. For each new observation in the data, we test the null hypothesis for possible regime shifts whether in the mean or in the variance of credit spreads. The potential shifts are then confirmed if subsequent data in the new regime pass a last confirmation test. This procedure is similar to the Sequential T-test Analysis of Regime Shifts (STARS) method developed by Rodionov (2004). It also incorporates the extension of Rodionov (2005 and 2006), in that it overcomes problems related to the way test statistics deteriorate toward the ends of time series and also accounts for outliers, serial correlation in the data, and any hidden noise process in the data that might be mistaken for a process with different regimes. For example, when the data generating process contains a positive autoregressive component whose behavior looks like a process with different regimes, then any long falling and rising episodes observed in the data may be mistaken for a change in the credit spread regime. Such hidden processes must therefore be removed from the data before the regime shift detection technique is applied.

Our results show that mean regimes and volatility regimes have different patterns but they both occur around the 2001 economic recession as well as around most of the important events that deeply affected the bond market in the period under analysis. Particularly, in a recession, mean regimes come on gradually whereas variance regimes emerge in one shot. Specifically, at the beginning of the credit cycle, we observe a credit spread level effect as well as a variance effect. Toward the end of the economic cycle, the variance effect will weaken but the level effect is likely to persist until the announcement date of the recession's end. The combined effect of shifts in the mean and the variance of credit spreads produces a credit cycle that is longer than the economic cycle even though both cycles start at almost the same time.

On the other hand, our evidence shows that the economic cycle has a complex relation with the entire rating structure of credit spreads. A level effect hits lower ratings early on, while shifts in the means of higher ratings are more contemporaneous with the official announcement of the recession. Further, these high ratings are also affected by a shift in the variance. Then, when the NBER announces the end of the recession in retrospect, the means of lower ratings start shifting downward. The whole rating structure of credit spreads will return to its original regime only long after the end of the recession. We therefore find that the credit spread dynamics is strongly persistent in the face of economic shocks and that credit spreads with high ratings are particularly sticky. Indeed, this persistence of the credit cycle over the economic cycle helps explain why previous studies have failed to agree about the exact impact of systematic factors on credit spreads (Elton et al. 2001; Campbell and Taksler, 2003; Elizalde, 2005; Avramov et al., 2007; among others). Our findings suggest that, due to the persistence effect, this impact should change around the economic recession and across ratings.

Finally, we test for the short-term market timing ability of the regime shift detection technique applied to the mean. We show that portfolio returns obtained with structural investment strategies based on the regime shift detection technique outperform (in most cases) those obtained with strategies based on extreme values. More specifically, the highest returns are obtained with strategies based on regime shifts, whether these are detected and not yet confirmed or detected and confirmed. Our results suggest that the regime shift detection technique extracts valuable and economically significant information.

The rest of the paper is organized as follows. Section 2 presents the regime shift detection technique. Section 3 describes the corporate bond data and the algorithm used to extract the credit spread term structure. Section 4 discusses empirical results and application of the method in market timing strategies. Section 5 concludes.

2 Regime shift detection technique

The procedure is based on the studies of Rodionov (2004, 2005, and 2006). We first filter the data by removing serial autocorrelation. At this step, we use the so-called "prewhitening" procedure to remove hidden noises generated by a stationary positive autoregressive process in the data. These noises may be easily mistaken for different regimes in the credit spread series. Second, we use the filtered data to make the test for shifts in the mean. Third, we remove shifts in the mean and test for shifts in the variance of credit spread residuals. All these steps are described in this section.

2.1 The prewhitening procedure

Consider that credit spread series are described by a structural time series $\{Y_t, t = 1, 2, ..., n\}$ that can be seen as the sum of a trend f_t and an error term ε_t:

$$Y_t = f_t + \varepsilon_t, \tag{1}$$

where ε_t are independently and normally distributed with zero mean and variance σ^2. There is a breakpoint c between the current regime with mean μ_1 and the new regime with mean μ_2 when the trend satisfies :

$$f_t = \begin{cases} \mu_1, t = 1, 2, ..., c-1, \\ \mu_2, t = c, c+1, ..., n. \end{cases} \tag{2}$$

The direct approach to regime shift detection is to formulate the null hypothesis: $\mu_1 = \mu_2 = \mu$ regarding the absence of a regime shift at $t = c$. After obtaining the estimates $\hat{\mu}_1$, $\hat{\mu}_2$, and $\hat{\sigma}^2$, the Student's $t-$test is then used to reject the null at the required probability level α. Working with relatively short time series, it is hard to draw any definitive conclusion about the underlying process based on the data alone. Indeed, we can reject the null not because credit spread series contain different regimes but because they contain a noise process that behaves like a process with different regimes. This is known in the corresponding literature as a *red noise process*. A stationary red noise process is usually modelled by a first order autoregressive process (AR1):

$$Y_t = \rho Y_{t-1} + \mu' + \varepsilon_t, \tag{3}$$

where $\mu' = (1-\rho)\,\mu$. For the process to be stationary, it is necessary for the AR1 parameter ρ to satisfy the condition $|\rho| < 1$. With $\rho > 0$, the process is a red noise. Each realization of a red noise process creates extended intervals or runs where the time series will remain above or below its mean value (Kendall and Stuart, 1966; Rudnick and Davis, 2003). These intervals can be misinterpreted as different regimes. Therefore it is necessary to either recalculate the significant level by taking into account the serial correlation or use a prewhitening procedure, which consists in estimating properly the AR1 coefficient ($\hat{\rho}$) and removing the red noises by using the difference $(Y_t - \hat{\rho}Y_{t-1})$.

Another problem arises when the time series contain regime shifts and a red noise, that is, if the underlying model is:

$$Y_t = \rho Y_{t-1} + f_t' + \varepsilon_t \tag{4}$$

where $f_t' = f_t - \rho f_{t-1}$. Then using all the available data to estimate ρ would be misleading. A possible solution to this problem is to use subsampling. The size of subsamples should be chosen so that the majority of them do not contain change points. Assuming that regime shifts occur at a regular interval of m months, this condition is satisfied if the subsample size n is less than or equal to $(m+1)/3$ (see Rodionov, 2006).[1] In this case, the estimate of ρ can be chosen as the median value among the estimates for all subsamples. In practice, however, finding the right value of n requires some experimentation. After the red noise is removed, the filtered time series $Z_t = f_t' + \varepsilon_t$ can be processed with the regime shift detection method described in Section 2.2.

The difficulty with the prewhitening procedure is to obtain an accurate estimate of the AR1 coefficient for short subsamples of size n since the traditional techniques such as the Ordinary Least Squares (OLS) and the Maximum Likelihood Estimation (MLE) lead to biased estimates for ρ. Therefore, two alternative methods are proposed in Rodionov (2006): the MPK (Marriott-Pope and Kendall) and the IP4 (Inverse Proportionality with 4 corrections) techniques. The MPK technique is based on the formula of the bias in the OLS estimate of AR1 (Marriott and Pope, 1954 and Kendall, 1954). The IP4 technique is based on the assumption that the bias is approximately proportionate to the size of the sample (Orcutt and Winokur, 1969, and Stine and Shaman, 1989). Both methods perform better than the OLS and are similar to one another for $n \geq 10$. Rodionov (2006) shows that, based on Monte Carlo estimations, IP4 substantially outperforms MPK for smaller subsamples. As we have a relatively small sample, we use the IP4 technique to estimate the

[1] For empirical application, we set n equal to the integer part of $(m+1)/3$.

autoregressive coefficient.

2.2 Shifts in the mean

Let $Z_1, Z_2, Z_3, ..., Z_i$ be the filtered credit spread series with new data arriving regularly. When a new observation arrives, a Student's $t-$test for the mean is performed to check whether this new observation represents a statistically significant deviation from the mean value of the current regime. We determine the difference $diff$ between mean values of two subsequent regimes that would be statistically significant at the level α_{mean} according to the Student's $t-$test as:

$$diff = t_{\alpha}^{2m-2}\sqrt{2\overline{s}_m^2/m}, \tag{5}$$

where m is the cut-off length of the regimes to be determined for the credit spread series which is similar to the cut-off point in low-pass filtering; t_{α}^{2m-2} is the value of the two-tailed $t-$distribution with $(2m-2)$ degrees of freedom at the given probability level α_{mean}. The sample variance $\overline{s}_m^2$ is assumed to be the same for both regimes and equal to the average variance over the $m-$month intervals in the time series $\{Z_t\}$. This makes $diff$ constant for the entire session with the given time series.

The sample mean of the initial m values is the estimate of the mean of the current regime $\left(\overline{Z}_{cur}\right)$. At the current time $t_{cur} = t_m + 1$, the mean value of the new regime $\overline{Z}_{new}$ is unknown, but we know that to qualify for a shift to the new regime, it should be equal or greater than the critical mean $\overline{Z}_{crit}^{\uparrow}$, if the shift is upward, and equal or less than $\overline{Z}_{crit}^{\downarrow}$, if the shift is downward, where:

$$\begin{cases} \overline{Z}_{crit}^{\uparrow} = \overline{Z}_{cur} + diff, \\ \overline{Z}_{crit}^{\downarrow} = \overline{Z}_{cur} - diff. \end{cases} \tag{6}$$

If the current value Z_{cur} is inside $\left]\overline{Z}_{crit}^{\downarrow}, \overline{Z}_{crit}^{\uparrow}\right[$ range, then it is assumed that the current regime has not changed and the null hypothesis H_0 about the existence of a shift in the mean at time t_{cur} is rejected. In this case, the value Z_{cur} is included in the current regime and the test continues with the next value. However, if the current value Z_{cur} is greater than $\overline{Z}_{crit}^{\uparrow}$ or less than $\overline{Z}^{\downarrow}_{crit}$, the month t_{cur} is marked as a potential change point c, and subsequent data are used to confirm or reject this hypothesis. The testing consists in calculating the Regime Shift Index (RSI) that represents a cumulative sum of normalized anomalies relative to the critical mean $\overline{Z}_{crit}$:

$$RSI = \frac{1}{m\bar{s}_m} \sum_{i=t_{cur}}^{j} \left(Z_i - \overline{Z}_{crit}\right), j = t_{cur}, t_{cur} + 1, ..., t_{cur} + m - 1. \tag{7}$$

If the anomaly $\left(Z_i - \overline{Z}_{crit}\right)$ is of the same sign as the one at the time of a regime shift, it would increase the confidence that the shift did occur. The reverse is true if anomalies have opposite signs. Therefore, if at any time during the testing period from t_{cur} to $t_{cur} + m - 1$ the RSI turns negative, when $\overline{Z}_{crit} = \overline{Z}^{\uparrow}_{crit}$, or positive, when $\overline{Z}_{crit} = \overline{Z}^{\downarrow}_{crit}$, the null hypothesis about the existence of a shift in the mean at time t_{cur} is rejected. In this case, the value Z_{cur} is included in the current regime, the RSI takes zero and the test continues for the next value. Otherwise, the time t_{cur} is declared a change point c and is significant at least at the probability level α_{mean}. The new regime becomes the base one, against which the test will continue further.

2.3 Shifts in the variance

The procedure for detecting regime shifts in the variance is similar to the one for the mean, except that it is based on the $F-$test instead of the Student's $t-$test. We now assume that the mean value of the time series is zero, that is, we work with the residuals $\{\zeta_i\}$ after shifts in the mean are removed from the original time series $\{Z_t, t = 1, 2, ..., n\}$. The $F-$test consists in comparing the ratio of the sample variances for two successive regimes with their critical value:

$$\frac{s^2_{cur}}{s^2_{new}} \gtrless F\left(\nu_1, \nu_2, \alpha_{var}\right), \tag{8}$$

where $F\left(\nu_1, \nu_2, \alpha_{var}\right)$ is the value of the $F-$distribution with ν_1 and ν_2 degrees of freedom and a significance level α_{var}. In our application $\nu_1 = \nu_2 = m - 1$. The variance s^2_{cur} is the sum of squares of ζ_i, where i spans from the previous shift point in the variance (which is the first point of the current regime) to $i = t_{cur} - 1$. At the current time t_{cur}, the variance s^2_{new} is unknown. For the new regime to be statistically different from the current regime, the variance s^2_{new} should be equal or greater than the critical variance $s^{2\uparrow}_{crit}$, if the current variance is increasing. However, if the current variance is decreasing, the variance s^2_{new} should be equal or less than $s^{2\downarrow}_{crit}$.

$$\begin{cases} s^{2\uparrow}_{crit} = s^2_{cur} F^{m,\nu_2}_{\alpha_{var}}, \\ s^{2\downarrow}_{crit} = s^2_{cur} / F^{m,\nu_2}_{\alpha_{var}}. \end{cases} \tag{9}$$

If at any time t_{cur}, the current value of ζ_{cur} satisfies the following conditions, $\zeta^2_{cur} > s^{2\uparrow}_{crit}$ when the shift is up or $\zeta^2_{cur} < s^{2\downarrow}_{crit}$ when the shift is down, this time is marked as a potential shift point, and subsequent values $\zeta_{cur+1}, \zeta_{cur+2}, ...$ are used to verify this hypothesis. The verification is based on the Residual Sum of Squares Index ($RSSI$) defined as:

$$RSSI = \frac{1}{m} \sum_{i=t_{cur}}^{j} \left(\zeta^2_i - s^2_{crit} \right), j = t_{cur}, t_{cur}+1, ..., t_{cur}+m-1. \tag{10}$$

If at any time during the testing period from t_{cur} to $t_{cur}+m-1$, the index turns negative, when $s^2_{crit} = s^{2\uparrow}_{crit}$, or positive, when $s^2_{crit} = s^{2\downarrow}_{crit}$, the null hypothesis about the existence of a shift in the variance at time t_{cur} is rejected, and the value ζ_{cur} is included in the current regime. Otherwise, the time t_{cur} is declared a change point c.

2.4 Handling outliers

Due to outliers, the average may not be representative for the mean value of the regimes, and this may significantly affect the results of the regime shift detection. Ideally the weight for the data value should be chosen such that it is small if that value is considered as an outlier. Following Rodionov (2006), in order to reduce the effect of outliers, we use the Huber's weight function which is calculated as:

$$weight = \min\left(1, h/\left[diff/\sigma\right]\right) \tag{11}$$

where h is is the Huber parameter and $[diff/\sigma]$ is the deviation from the expected mean value of the new regime normalized by the standard deviation averaged for all consecutive sections of the cut-off length in the series. The weights are equal to one if $[diff/\sigma]$ is less than or equal to the value of h. Otherwise, the weights are inversely proportional to the distance from the expected mean value of the new regime. Once the timing of the regime shifts is fixed, the mean values of the regimes are assessed using the following iterative procedure. First, the arithmetic mean is calculated as the initial estimate of the mean value of the regime. Then a weighted mean is calculated with the weights determined by the distance from that first estimate. The procedure is repeated one more time with the new estimate of the regime mean. Since we expect that most shifts in the mean are closely related to periods of NBER recession, the choice of the Huber parameter is challenging because most significant picks in the credit spread rates occur around this period and should not be considered as outliers. Thus, we repeat the procedures for a range of values of h from 1 to 10 (see robustness analysis in Section 4.4).

3 Data

3.1 Corporate bond data

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

Our sample is restricted to fixed-rate US dollar bonds in the industrial sector. We exclude bonds with embedded options such as callable, putable or convertible bonds. We also exclude bonds with remaining time-to-maturity below 1 year. With very short maturities, small price measurement errors lead to large yield deviations, making credit spread estimates noisy.

Bonds with more than 15 years of maturity are discarded since the swap rates that we use as risk free rates have maturities below 15 years. We finally exclude bonds with over-allotment options, asset-backed and credit enhancements features and bonds associated with a pledge security. Issuers credit ratings are reported by four rating agencies: Fitch Rating, Duff and Phelps Rating, Moody's Rating and Standard and Poor's Rating. We include all bonds whose average Moody's credit rating lies between AA and BB. AAA credit spreads are not used because we find them negative for some periods. We also find that the average credit spread for medium term AAA-rated bonds is higher than that of A-rated bonds. These same remarks are noticed by Campbell and Taksler (2003) using the same database. We also filter out observations with missing trade details and ambiguous entries (ambiguous settlement data, negative prices, negative time to maturities, etc.). In some cases, a transaction may be reported twice in the database because it involves two insurance companies on the buy and sell side. In this case, only one side is considered.

For the period ranging from 1994 to 2004, we account for 651 issuers with 2,860 outstanding issues in the industrial sector corresponding to 85,764 different trades. Since insurance companies trade generally high quality bonds, most of the trades in our sample are made with A and BBB rated bonds where they account respectively for 40.59% and 38.45% of total trades. On average, bonds included in our sample are recently issued bonds with an age of 4.3 years, a remaining time-to-maturity of 6.7 years and a duration of 5.61 years. Table 1 reports summary statistics.

[Insert Table 1 here]

3.2 Credit spread curve

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

$$\begin{aligned} R(t,T) &= \beta_0 + \beta_1 \left[\frac{1-\exp(-\frac{T}{\tau_1})}{\frac{T}{\tau_1}} \right] + \beta_2 \left[\frac{1-\exp(-\frac{T}{\tau_1})}{\frac{T}{\tau_1}} - \exp(-\frac{T}{\tau_1}) \right] \\ &\quad + \beta_3 \left[\frac{1-\exp(-\frac{T}{\tau_2})}{\frac{T}{\tau_2}} - \exp(-\frac{T}{\tau_2}) \right] + \varepsilon_{t,j}, \end{aligned} \tag{12}$$

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_0 is the limit of $R(t,T)$ as T goes to infinity and is regarded as the long term yield. β_1 is the limit of the spread $R(t,T) - \beta_0$ as T goes to infinity and is regarded as the long to short term spread. β_2 and β_3 give the curvature of the term structure. τ_1 and τ_2 measure the rate at which the short-term and medium-term components decay to zero. Each month t we estimate the parameters vector $\Omega_t = (\beta_{0t}, \beta_{1t}, \beta_{2t}, \beta_{3t}, \tau_{1t}, \tau_{2t})'$ by minimizing the sum of squared bond price errors over these parameters. We weigh each pricing error by the inverse of the bond's duration since long maturity bond prices are more sensitive to interest rates:

$$\widehat{\Omega}_t = \arg\min_{\Omega_t} \sum_{i=1}^{N_t} w_i^2 \left(P_{it}^{NS} - P_{it}\right)^2, \qquad w_i = \frac{1/D_i}{\sum_{i=1}^{N} 1/D_i}, \tag{13}$$

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

Credit spreads for corporate bonds paying a coupon is the difference between corporate bond yields and benchmark risk free yields with the same maturities. Following Hull et al. (2004), we use the swap rate curve less 10 basis points as a benchmark risk free curve. For robustness, we also estimated the Treasury yield curve and found that curve parallel to the swap curve (results are available upon request). So the choice of the benchmark should not affect our results.

4 Results

4.1 Observed credit spreads

We obtain credit spread curves for AA rated to BB rated bonds with maturities ranging from 1 to 15 years. Figure 1 – in the introduction – plots these results and Table 2 presents summary statistics.

[Insert Table 2 here]

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

4.2 Regime shifts

First, we detect shifts in the mean. The cut-off length is 12 months ($m = 12$). The probability level for the null hypothesis is 5% for the mean and the variance ($\alpha_{mean} = \alpha_{var} = 5\%$). The Huber parameter is fixed at 2 ($h = 2$). For the estimation of the AR1 coefficient, the subsample length is 4 months ($n = 4$). We discuss detailed results for 3-year and 10-year A bonds as a benchmark for short and long maturity bonds then we report results for all bonds in our sample. Figure 2 shows the results for shifts in the mean with and without prewhitening for the 3-year and 10-year A spreads.

[Insert Figure 2 here]

In four cases, there are three common shifts in the mean detected at almost the same period: a first negative shift in the late 1994 – early 1995, one positive shift in the early 2001 almost at the beginning of the NBER recession of March 2001 and a negative shift in the mid 2004 (Figure 2, Panel A and B). Thus, accounting only for the mean, these common shifts suggest two different mean regimes in credit spread dynamics over the period considered.

The $1994 - 1995$ negative shift in the mean signals a significant decrease in the level of credit spreads ($RSI < 0$). A level around 0.7% for 3-year A spreads and 1% for 10-year A spreads (Table 3). This low credit spread level also extends many months. The low level regime length is between 75 (northeast region) and 78 (northwest region) months for 3-year A spreads and between 71 (southeast region) and 76 (southwest region) months for 10-year A spreads (Table 3).

[Insert Table 3 here]

The early 2001 positive shift occurred in March 2001 for 3-year A spreads and between January and February 2001 for 10-year A spreads. This positive shift signals a significant increase in the credit spread level at the beginning of the recession ($RSI > 0$). For example, the 3-year credit spread mean shifts up from 0.7% to 3.15% in one shot (the northeast region). However, before prewhitening (northwest region), the increase in the mean comes in two steps to reach a 3.77% level in October 2001. This same pattern is observed for 10-year A spreads. In the southeast region, the 2001 positive shift drives the credit spread mean from 1% to 3.94%. Still, before prewhitening, a first positive shift occurs in February 2001 increasing the mean to 2.77% and a second shift occurs in October 2001 boosting it to 4.05%. Accounting for all 2001 positive shifts, the mean increases for up to 16 months (northwest region) and 18 months (northeast region) for 3-year A spreads. This tendency is more persistent for the long term spreads as the high mean extends 41 months in the case of 10-year A spreads.

The second negative shift is detected in July 2002 (northwest region) and September 2002 (northeast region) for 3-year A spreads. Following this shift, the credit spread mean is established around 2.4% which is still high relative to the 1994 level. A third negative shift then follows in July 2004 for both cases, setting the mean at a level of 1.34%. On the other side, we detect a single negative shift in the mean of 10-year A spreads in July 2004 driving its level from 4.05% to 2.8% (southwest region) and from 3.9% to 2.9% (southeast region).

Once again, long maturity spreads seem to remain high for more months than do short maturity spreads. Moreover, we notice that when the positive shift is gradual – occuring in two steps – the magnitude of the first shift seems to be higher than the magnitude of the second shift (see the magnitude of the RSI before prewhitening in Table 3). Conversely when the negative shift is gradual, the magnitude of the second shift is the highest (Table 3, Panel A).

The test for shifts in the variance is performed on the residuals after the stepwise trend is removed (Figure 3).[2] Results obtained for the variance have different patterns than those obtained for the mean. In contrast to the mean, the prewhitening procedure increases the number of the shifts detected for the variance. Also, with this procedure, the magnitudes of the shifts detected around the recession are bigger.

[Insert Figure 3 here]

In the southeast region of Figure 3, two negative shifts for the variance of 3-year A spreads are detected before the recession. A first negative shock occured in December 1994, dropping the variance level from 0.36% between January 1994 and November 1994 to 0.06% after that period. Then a second negative shock of smaller magnitude came in August 1996, setting the variance at 0.018%. The most serious shock, however, is detected in March 2001 at the beginning of the recession. The variance level jumps to 0.931% and stays high for 15 months until June 2002. After that, the variance level decreases to 0.157% in June 2003. Before prewhitening of the same series (northeast region), we detect only three shifts. The first negative shift of August 1996 drives the variance to 0.064%—almost the same level as that detected with prewhitening in the same month. Yet the second negative shift in August 2000 drops the variance very low (0.005%) for a period of six months, resembling the calm before the storm. In February 2001, the third big positive shift signals the 2001 recession. The variance level rises to 0.166%, very high relative to its level before that period but very low relative to the level detected after prewhitening. One reason could be that the negative shift of August 2000 has absorbed much of the credit spread variation between August 1996 and the beginning of the recession.

[2] We caution the reader to consider changes in the axis scale between Panel A and B.

[Insert Table 4 here]

In the southwest region, the shifts detected for 10-year spreads are more dispersed. A first negative shift is detected in February 1995, driving the variance level from 0.740% (from January 1994 to January 1995) to 0.114% (Table 4, Panel B, With Prewhitening). Another negative shift is detected in June 1996, lowering the level to 0.025%. The first positive shock increases the variance more than four times (0.153%) in February 1998. This is followed by a negative shock occurring in February 1999, which re-sets the variance at an intermediate level of 0.053%. Then the biggest positive shock in the variance occurs in January 2001, two months before the beginning of the recession. The level of the variance shifts up to 0.408% and stays there for 8 months. After that, the negative shift of September 2001 (0.063%) re-establishes the variance at almost the same low level it had before the recession. Another subsequent negative shift (detected in September 2002) drops the variance to its preceding level of June 1996 (0.023%). This low variance level is maintained until May 2004. The last positive shift then occurs in June 2004 driving the variance up to 0.261% where it stays for the rest of the period. Almost the same pattern is observed before prewhitening (northwest region)–and, even though showing fewer detected shifts and displaced locations, it still holds. However, the biggest shifts of February 1998 and January 2001 are detected at the same time with almost the same magnitudes and lengths of regimes. Once again, just after the recession, a negative shift drops the variance level to 0.050% in October 2001. Then, a last positive shift is only detected in December 2004.

As revealed by the shifts detected, we see that, especially around the 2001 recession, the variance regime is quick and short, while the mean regime is gradual and long. It is also interesting to see that the biggest shifts (for the mean and the variance) are detected either in March 2001 (3-A ratings) or in January 2001 (10-year A ratings). However, the NBER announces the start of the 2001 recession only in November 2001. This means that credit spread series absorbed the distress of the bond market well before the announcement, which provides an argument to support the fact that credit spread movements are driven by systematic shocks (Collin-Dufresne et al., 2001).

4.3 Can the shifts be related to economic cycles?

The aim of this section is to investigate the relation between patterns in the shifts of the mean and the variance of credit spreads and the 2001 recession as defined by the NBER. We also examine how these shifts can be related to specific financial events. Shifts in the mean and the residual variance –of different ratings and maturities– are reported, respectively, in Figure 4 and Figure 5.

[Insert Figure 4 and Figure 5]

Over the period considered, the NBER reports a single recession beginning in March 2001 and ending in November 2001 (the official announcement of the end of the cycle actually occurred in July 2003). Figure 4 indicates that, for the mean, most of the upward shifts (14 out of 20) are concentrated in the three months around March 2001. This is strong evidence that the beginning of the credit cycle roughly coincides with that of the economic cycle. Our results fall in line with the findings of Koopman and Lucas (2005) who suggest that risk premia on bonds contain a countercyclical component and that credit spreads are good predictors for future business cycle conditions. Closer inspection of Figure 4 reveals that the rising shifts for bonds with lower ratings (BBB and BB across all maturities) are gradual and detected earlier. Typically, a first shock affects such riskier bonds few months before the official recession. Then, a second similar shock is felt within the recession period. This finding suggests that the riskier bond spreads act as precursors of the economic cycle while more investment grade spreads (AA and A) only join the wave at the start of the economic recession. In the same spirit but different context, Lown and Morgan (2006) investigate the relation between financial market frictions and macroeconomic environment. Their general finding is that the credit cycle can influence the course of the business cycle while the causal connection remains unclear.

In addition, the credit cycle appears to last longer than the economic cycle. Since 1960, the average length of the NBER recession is less than 11 months. Each of the previous two recessions of 1991 and 2001 lasts 8 months. However, across all ratings and maturities, downward shifts are detected more than 3 years after initial upward shifts. For AA and A-10 year ratings, the downward shift is unique, suggesting strong persistence in the credit spread dynamics. For lower ratings, the downward shifts are gradual with the first one occurring around July 2003 – the NBER announcement that the recession ended in November 2001. Notice that the positive shifts detected around September 2001 may also be accentuated with the September 11 attacks which had a significant negative impact on the bond market.

Figure 5 shows that the NBER economic cycle and the shifts in the credit spread variance are also related. Across ratings and maturities, we detect a positive shift in the variance at or just before the recession and, in most cases (8 out of 12), we detect a negative shift after this period. In addition, shifts in the variance are likely to suggest that the corporate bond market anticipates well the coming period of recession. Thus, in four cases, the fears in the bond market are translated to significant jumps in the credit spread variance in November 2000 (4 to 5 months before the recession). This applies to BBB spreads for all maturities and 3-year BB spreads. Around the recession, in February 2001, eight positive shifts have also been detected (see Table 5).

Another important finding with shifts in the variance is that they are also detected outside the 2001 recession. For example, a positive shift is detected in April 1997 for 5-year A spreads and another positive shift is detected in March 1998 for the 10-year AA and BBB spreads. We all know that this period suffered from the consequences of the Asian financial crises of July 1997 which led to the stock market crash of October 1997. Another positive shift is detected in October 1998 for 10-year BB spreads which also coincides with the collapse of LTCM. These findings suggest that changes in the economy that affect the financial market may have played a role in the shifting of the volatility of our series (see for example Rudebusch and Wu, 2007).

[Insert Table 5 here]

Overall, it clearly appears that the relation between economic cycle and the entire rating structure of credit spreads is complex. A level effect is found to hit lower ratings early on, then reaches higher ratings few months later– before the official announcement of the recession. Further, these high ratings are also affected by a shift in the variance. Then, when NBER announces the end of the recession retrospectively, lower ratings start showing downward shifts in their mean. The whole rating structure of credit spreads will shift back to its original regime only long after the end of the recession. We therefore find that the credit spread dynamics is particularly slow to respond to the end of the economic shock and that the credit spreads of high ratings are particularly sticky. The persistence of the credit cycle over the economic cycle can be viewed as a reason to why previous studies have failed to agree about the exact impact of systematic factors on credit spreads (Elton et al. 2001; Campbell and Taksler, 2003; Elizalde, 2005; Avramov et al., 2006; among others). Our findings suggest that, due to the persistence effect, this impact should change around the economic recession and across ratings.

4.4 Robustness analysis

In this section, we analyze the effect of the choice of parameters on the number of the shifts detected for the means and the residual variances of credit spreads. The key set of parameters is (m, α_{mean}, h), where m is the cut-off length, α_{mean} is the significance level for shifts in the mean, and h is the Huber parameter. The choice of the significance level for shifts in the residual variance is less relevant at this step of the analysis since the number and the magnitude of shifts detected in the residual variance depends on the size of the residuals left after shifts in the mean have been removed. However, as the significance level α_{var} is low, the number of the shifts detected for the residual variance is reduced. In Table 6, we compare the number and the location of shifts reported in Table 3 and Table 4 where $m = 12, \alpha_{mean} = 5\%, h = 2$, and $\alpha_{var} = 5\%$ with those obtained with each new set of parameters (m, α_{mean}, h). Specifically, we report the triplet (shifts unchanged, shifts added, shifts dropped). Using the new parameters set, shifts unchanged count the number of shifts detected in the same locations or +/- one month around locations reported in Table 3 and Table 4. Shifts added count the number of shifts added outside these locations and shifts dropped count the number of shifts dropped from these locations. The cut-off length m takes three possible values: 6 months, 12 months and 18 months. The significance level α_{mean} takes two possible values: 5% and 10%. For each combination of these two parameters, we repeat the regime shift detection technique with and without prewhitening for different values of the Huber parameter: $h = 1, 2, 3, 5, 10$. The serial correlation is estimated for subsamples of size n equal to the integer part of $(m+1)/3$. Overall, our results are robust and they can be summarized as follows.

[Insert Table 6 here]

First, data values that are higher than h standard deviations are considered as outliers and are weighted inversely proportional to their distance from the mean value of the new regime: $weight = \min(1, h\sigma/diff)$. If the cut-off length $m = 12$ and the probability level $\alpha_{mean} = 5\%$, the critical difference between the regimes $diff = 0.85 \times \sigma$ which leads to a $weight = 1$. As the cut-off length increases, the $weight$ equals its limit value of one and the results remain the same for different values of h since all the data values have equal weights. As shown in Table 6, when $m \geq 12$, the number and the location of the shifts in the mean remains unchanged for different values of h. However, for shorter cut-off lengths and small Huber parameters, for example $m = 6$ and $h = 1$, values higher than one standard deviation will be weighted using $weight = 0.78$ at the 5% level. This has the effect to increase the length of the current regime, as the $diff$ increases for small cut-off lengths, and decrease the number and the magnitude of the shifts in the mean. This case appears especially after prewhitening for $h = 1$ since the procedure requires short subsample lengths. Second, as the cut-off length increases, the degree of freedom also increases, which translates into smaller $diff$ and higher values of the RSI for the regimes of m months or longer. However, the regimes shorter than the cut-off length can pass the test only if the magnitude of the shift is high. For example, for 3-year A credit spreads, when the cut-off length increases from 6 months to 18 months, at least 4 shifts remain unchanged. This proves that the shifts for the mean value of 3-year A spreads are determined correctly. On the other hand, the lower the probability level, the higher the $diff$ and the lower the RSI value which leads to a lower number of shifts. Third, the number and the location of shifts for the residual variance depend broadly on the size of the residuals left after shifts in the mean have been removed. For example, when the magnitude of the shift in the mean is reduced, the size of the residuals increases and the likelihood of a shift in the residual variance also increases. This explains the movements in the triplet of the variance between shifts added and shifts dropped for different confidence levels and cut-off lengths.

Finally, in comparing the procedure before and after prewhitening, it seems clear that prewhitening reduces the magnitude and the number of regime shifts in the mean. Rodionov (2006) used a Monte Carlo technique to evaluate this effect. He finds that prewhitening is a more conservative means of detecting regime shifts but has the advantage of reducing the number of false alarms. As a consequence, the number of shifts detected for the residual variance is often higher after prewhitening. Table 6 shows that, after prewhitening, most of the shifts in the residual variance remain unchanged for different set of parameters.

4.5 Market timing ability and regime shift detection

In this section, we assess the short-term market timing ability of the regime shift detection technique. We investigate whether short-term market timing strategies based on the regime shift detection technique can be more profitable than strategies based on extreme values. Using 12 constant maturity portfolios of credit spreads corresponding to different ratings (AA to BB) and maturities (3, 5, and 10 years), we implement trading strategies that rely on either shifts detected in credit spread means, or on extreme values of credit spreads.

The common investment rule across different strategies can be summarized as follows. Initial investment is set at \$100. The investment strategy starts with a long position at a time when observed prices are sufficiently low. Otherwise, invest the \$100 in LIBOR 1 month for subsequent months and wait for a signal to move into a long position. When the signal for the long position arrives, long x units of the credit spread portfolio and wait for a signal to short position. When the signal for the short position arrives, short the x units of the credit spread portfolio; invest in LIBOR 1 month for subsequent months and wait for a signal to long position. When no signal is observed, then remain invested in the asset you are holding.

In the regime shift detection technique, breakpoints are definitely accepted after passing two detection tests. The first test signals possible shift points based on the significant difference between the means of the current regime and the new regime at the required level α_{mean}. The second test confirms or rejects these possible shift points based on the value of RSI. Both cases are considered here. In the first case, the investor always takes a position when a possible shift point is detected and in the second case, the investor observes the possible shift point and waits until the shift is confirmed to take a position.

The market timing strategy based on the regime shift detection technique – hereafter referred to as the structural strategy – depends on whether we take a position upon first detection or upon confirmation of the shift. First detection strategy is based on comparing each value of the filtered data Z_{cur} to critical values $\left]\overline{Z}^{\downarrow}_{crit}, \overline{Z}^{\uparrow}_{crit}\right[$ (see Equation 6). When $Z_{cur} \geq \overline{Z}^{\uparrow}_{crit}$, we have a signal to long position and when $Z_{cur} \leq \overline{Z}^{\downarrow}_{crit}$, we have a signal to short position. If Z_{cur} is inside the critical interval $\left]\overline{Z}^{\downarrow}_{crit}, \overline{Z}^{\uparrow}_{crit}\right[$, there is no signal and we remain in the current position. In the confirmed detection strategy, the signal to take a long position is confirmed when $RSI > 0$ and the signal to short position is confirmed when $RSI < 0$. Otherwise, when $RSI = 0$, no signal is confirmed and we remain in the current position. Structural strategies assume the knowledge of the significant $diff$ at which we make the test for each new observation based on the two-tailed Student's $t-$test at the required significance level, the average unconditional variance of regimes, and on the initial cut-off length of the regimes. For robustness we use two possible cut-off lengths: 6 months and 12 months.

Investment strategies based on extreme values were recently used by Berge and Ziemba (2007) and Giot and Petitjean (2006). In the existing literature, extreme values are often determined in an arbitrary way. Berge and Ziemba (2007), for example, test 44 different strategies depending on combinations of exit and entry threshold levels. In this section, we alleviate concerns about data mining by setting the thresholds at the 5th and 20th lower and higher percentiles of the unconditional distribution of credit spreads.[3] Three different intervals are employed to define the critical values. These intervals are moving windows of historical prices observed over one year, three years, and five years (i.e., 12, 36, and 60 monthly observations). The combination of different threshold levels and historical interval lengths results in 6 different investment strategies based on extreme values. The long position is taken when the observed value of the credit spread is lower than the entry threshold level, and the short position is taken when it is higher than the exit threshold level. When the current value is between the exit and the entry threshold level, then the current position remains unchanged.

[3]Results obtained with the 5th and 10th lower and higher percentiles are similar, thus we report only one case.

Notice that all the strategies involve constant maturity portfolios. Even though portfolios with constant maturity credit spreads are not directly traded, they can be constructed by using asset rebalancing to keep the portfolio duration constant. We do not account for rebalancing costs since all the strategies described here are equally affected by them.

Portfolio returns along with the number of transactions corresponding to each strategy are given in Panel A of Table 7 to Table 10. Across ratings and maturities, the structural strategies are the winners in most of the cases: 8 out of 9 for AA spreads (Table 7, Panel A), 8 out of 9 for A spreads (Table 8, Panel A), 9 out of 9 for BBB spreads (Table 9, Panel A), and 9 out of 9 for BB spreads (Table 10, Panel A). For AA to BBB spreads, when the initial cut-off length is set at 12 months ($m = 12$), the highest returns are shared between the strategy based on shifts confirmed and the strategy based on possible shifts, whereas, for BB spreads, returns obtained with the strategy based on possible shifts are always the highest. In addition, the difference between the highest returns obtained with the structural strategies and the highest returns obtained with strategies based on extreme values ranges between 1% and 2% for AA to BBB spreads, while this difference goes up to 11% for BB spreads (see for example the last row in Panel A of Table 10). Moreover, shifts in the mean for spreads of lower ratings are shown to be detected earlier than shifts for higher ratings (Figure 4). This in turn makes the structural strategy — specifically upon first detection — more profitable for speculative grade bonds.

[Insert Table 7 to Table 10 here]

On the other hand, the highest returns obtained with the structural strategy based on first detection are supported by the large number of transaction that the strategy entails. Actually, the structural strategy based on first detection counts up to 28 transactions over the period considered while the strategy based on confirmed shifts counts at most 2 transactions and the extreme values strategy counts up to 10 transactions. This big difference in the number of transactions between different strategies raises the issue of including the effect of transaction costs. Thus, focusing on the strategy that is more economically profitable should be a matter of concern.

Transaction costs are considered proportional to the value of the trade. When a transaction occurs in a given month, the return on the portfolio for that month is reduced by the cost of the transaction. However, introducing transaction costs will also reduce the number of transactions, since threshold levels in the extreme values strategy and critical values in the structural strategies are all considered in net values. Then, the dual effect of introducing transaction costs will be the reduction of portfolio returns as well as the reduction of the number of transactions. This makes the overall effect of transaction costs uncertain and may lead to an increase in the final portfolio returns. To obtain net portfolio returns, we multiply the gross terminal value of each strategy by $(1-\phi)^{\delta}$, where ϕ is the transaction cost as a percentage of the total value of the transaction and δ is the number of transactions according to signals given by the strategies.[4] Following Berge and Ziemba (2007), we consider two possible values for transaction costs: 0.5% and 1%. In terms of dollar values, the upper bound (exit threshold) is divided by $(1+\phi)$ and the lower bound (entry threshold) is divided by $(1-\phi)$.

The introduction of transaction costs has negative and positive effects on portfolio returns. Across different strategies, the number of transactions is either left unchanged or reduced (Panels B and C of Figure 7 to 10). However, in some cases, the portfolio return is augmented because the introduction of transaction costs pushes the investor to be more conservative (see for example the highest returns obtained with 3-year BB spreads in Table 10, Panel C). Even so, the structural strategy remains the most profitable overall.

With low transaction costs ($\phi = 0.5\%$), movements in the highest returns are not frequent and, in all cases, remain within the findings for structural strategies. For example, for AA spreads, the highest return obtained with the first detection strategy and a cut-off length of 6 months moved to the 12 months cut-off length within the same strategy (Table 7, Panel B). Also, for A spreads, we lost one highest return on the side of the confirmed shift strategy and gained one highest return on the side of the first detection strategy (Table 8, Panel B). The same pattern is observed for BBB spreads (Table 9, Panel B). For BB spreads, the gross returns are high enough to keep them in the winners circle even after introducing higher transaction costs (Table 10, Panel B and C).

When transaction costs are higher ($\phi = 1\%$), the winners (i.e., the highest returns) most

[4]The net terminal value of each portfolio can be obtained using net returns and vice versa. Since returns are all log returns, when a transaction occurs, the net return of the portfolio in the corresponding month is: $r_t^{net} = r_t^{gross} - \ln(1-\phi)$.

often move from the confirmed shift and the first detection strategies with 12-month cut-off lengths to the first detection strategy with a 6-month cut-off length (see for example Table 7, Panel C). The extreme values strategy wins only in three cases for A spreads (Table 8, Panel C) and 2 cases for BBB spreads (Table 9, Panel C).

We also analyze the same returns with the buy-and-hold investment strategy. The results are not reported here. Most of the portfolio returns obtained with the buy-and-hold strategy are negative even when transaction costs are null. Unlike the extreme values strategy, the buy-and-hold strategy involves two transactions like the structural strategy based on confirmed shifts. Moreover, under the buy-and-hold strategy, the long position is taken in late January 1999, well before the beginning of the recession and the short position is taken in December 2004 after the recession ends. Nevertheless, it does appear that the buy-and-hold strategy is not profitable, as it depends solely on portfolio values at the beginning and the end of the investment window.

Overall, structural strategies based on first detection, which are more aggressive, outperform in most cases extreme values strategies, especially for lower ratings. Returns obtained with the more conservative structural strategies based on confirmed shifts are also higher, in most cases, than those obtained with extreme values strategies. Further, when transaction costs are very high, the first detection strategy remains profitable especially for lower ratings. Overall, the regime shift detection technique is shown to be valuable in market timing.

5 Conclusion

Using an exploratory rather than a confirmatory approach, we test for shifts in the mean and the variance of AA to BB credit spreads with maturities of 3, 5, and 10 years. Contrarily to the existing literature modeling switching regimes in the credit spread series, our methodology detects possible breakpoints in the data in real time. Further, it does not require any assumption about the number of the regimes.

Our results reveal that credit spread episodes are related to systematic components driven by the economic recession and the financial crises. These systematic components affect credit spreads in different manners. The economic cycle triggers jumps in the level and the variance of credit spreads, whereas financial crises most often hit the variance. Mean regimes appear to last longer and to move gradually between different states, whereas variance regimes are short and occur in one shot. Therefore, contrarily to the variance, the mean effect remains significant after the official recession and continues to increase until the end of the recession is announced. Taken together, the mean and the variance regimes characterize a credit cycle that lasts longer than the economic cycle. A noteworthy finding is that shifts in the variance —while the evidence is weak— are also detected around most financial crises felt in the US economy during the period considered.

Our paper is aimed to be more descriptive than explanatory. As such, it raises more questions than answers. It would be interesting to extend the analysis to a larger sample data covering more than one economic recession. However, the challenge is to find a long sample of bond transaction data. The unique comprehensive source with such data – NAIC database – starts only in 1994.

Finally, the regime shift detection technique is shown to be valuable and economically significant in the market timing of investment strategies. We show that, in the majority of cases, more profitable portfolio returns are obtained with structural investment strategies based on the regime shift detection technique. More specifically, the highest returns are obtained with structural strategies based on first detection, and returns obtained with structural strategies based on confirmed shifts are very often higher than those obtained with extreme values strategies. It is also shown that, even after accounting for very high transaction costs, the structural strategy is still the winner. Our findings also suggest that the structural strategy is more profitable for lower ratings in terms of dollar gains, essentially because shifts in lower ratings are detected earlier than other ratings.

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Table 1: Summary statistics for US corporate bonds.

The maturity is the number of years until the maturity date, upon issuance. The duration is the modified Macaulay duration in years. The size is the total dollar amount issued. The volume is the total dollar amount traded. Issues are the number of unique issues. Issuers are the number of unique issuers. Trades are the number of unique trades. 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 in the industrial sector, over the period 1994-2004, by rating and remaining maturity. The benchmark risk-free yield is the swap curve less 10 basis points fitted to all maturities using the Nelson-Siegel-Svensson algorithm. The spreads are given as annualized yields in basis points.

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

Table 3: Changing points for shifts in the mean of 3- and 10-year spreads.

This table reports months of shifts in the credit spread means, credit spread means in each regime, regimes length in month, and the Regime Shift Index (RSI). The period considered spans from Jan-94 to Dec-04, the significance level is 0.05 and the cutoff length is 12 months.

Without prewhitening				With prewhitening			
Shift point	Mean (%)	Length (mth)	RSI	Shift point	Mean (%)	Length (mth)	RSI
Panel A: 3-year A bonds							
Sep-94	0.704	78	-1.247	Dec-94	0.684	75	-0.178
Mar-01	2.103	7	3.028	Mar-01	3.149	18	2.522
Oct-01	3.767	9	0.849	Sep-02	2.426	22	-0.416
Jul-02	2.489	24	-1.396	Jul-04	1.388	6	-1.078
Jul-04	1.389	6	-1.601				
Panel B: 10-year A bonds							
Oct-94	1.082	76	-1.481	Feb-95	1.058	71	-0.263
Feb-01	2.775	8	3.365	Jan-01	3.936	41	1.266
Oct-01	4.054	33	1.103	Jun-04	2.936	7	-0.982
Jul-04	2.798	6	-1.818				

Table 4: Changing points for shifts in the variance of 3- and 10-year spreads.
This table reports months of shifts in the zero mean credit spread variances, zero mean credit spread variances in each regime, regimes length in month, and the Residual Sum of Squares Index Sum (RSSI). The period considered spans from Jan-94 to Dec-04, the significance level is 0.05 and the cut-off length is 12 months.

Without prewhitening				With prewhitening			
Shift point	Mean (%)	Length (mth)	RSSI	Shift point	Mean (%)	Length (mth)	RSSI
Panel A: 3-year A bonds							
Aug-96	0.064	48	-0.006	Dec-94	0.060	20	-0.048
Aug-00	0.005	6	-0.006	Aug-96	0.058	55	-0.003
Feb-01	0.166	47	0.176	Mar-01	0.931	15	0.750
				Jun-02	0.157	31	-0.186
Panel B: 10-year A bonds							
Apr-96	0.028	22	-0.037	Feb-95	0.114	16	-0.027
Feb-98	0.153	12	0.076	Jun-96	0.025	20	-0.031
Feb-99	0.014	23	-0.008	Feb-98	0.153	12	0.084
Jan-01	0.370	9	0.101	Feb-99	0.053	23	-0.001
Oct-01	0.050	38	-0.007	Jan-01	0.408	8	1.348
Dec-04	0.391	1	0.018	Sep-01	0.063	12	-0.314
				Sep-02	0.023	21	-0.015
				Jun-04	0.261	7	0.072

Table 5: Summary for positive shift points and corresponding events.

This table reports the location of positive shift points in the mean and the variance of 3-, 5- and 10-year AA to BB credit spreads. Panel A contains shifts in the mean and Panel B contains shifts in the zero mean variance. Date corresponds to the month or +/- one month from this location when the shift is detected. Event corresponds to financial crises and the economic recession felt in the US market during months of the shifts.

Date	AA 3yrs	AA 5yrs	AA 10yrs	A 3yrs	A 5yrs	A 10yrs	BBB 3yrs	BBB 5yrs	BBB 10yrs	BB 3yrs	BB 5yrs	BB 10yrs	Related event
	Panel A: Location of positive shifts in the mean												
Nov-00							x	x	x	x	x	x	
Feb-01	x	x	x	x	x	x		x			x	x	NBER 2001 recession
Sep-01					x		x	x	x	x	x	x	September 11 attacks
	Panel B: Location of positive shifts in the variance												
Apr-97					x								Asian crisis
Mar-98			x						x				
Oct-98												x	Russian crisis, LTCM collapse
Nov-00							x	x	x	x			
Feb-01	x	x	x	x	x	x					x	x	NBER 2001 recession
Jul-03												x	Announcement of recession end
Jun-04					x								
Dec-04											x		

Table 6: Sensitivity analysis for model parameters.

We compare the number and the location of shifts reported in Table 3 and Table 4 where $m = 12, \alpha_{mean} = 0.05$, and $h = 2$ with those obtained for each new set of parameter through the triplet (shifts unchanged, shifts added, shifts dropped). The parameter m is the cut-off length, α_{mean} is the significance level for shifts in the mean, and h is the Huber parameter. The significance level for shifts in the variance is $\alpha_{var} = 0.05$ and the subsample size for serial correlation n is equal to the integer part of $(m+1)/3$. The case analyzed in the paper is in box.

			Without prewhitening				With prewhitening			
			Mean		Variance		Mean		Variance	
m	α	h	A-3 yrs	A-10 yrs	A-3 yrs	A-10 yrs	A-3 yrs	A-10 yrs	A-3 yrs	A-10 yrs
6	0.05	1	(4,2,0)	(3,1,0)	(1,0,2)	(4,2,2)	(4,1,0)	(3,0,0)	(2,1,2)	(6,1,2)
6	0.05	2	(5,1,0)	(4,0,0)	(2,0,1)	(4,2,2)	(4,1,0)	(3,0,0)	(2,1,2)	(5,1,3)
6	0.05	3	(5,1,0)	(4,0,0)	(2,0,1)	(4,2,2)	(4,1,0)	(3,0,0)	(2,0,2)	(3,0,5)
6	0.05	5	(5,1,0)	(4,0,0)	(2,0,1)	(4,2,2)	(4,1,0)	(3,0,0)	(2,0,2)	(3,0,5)
6	0.05	10	(5,1,0)	(4,0,0)	(2,0,1)	(4,2,2)	(4,1,0)	(3,0,0)	(2,0,2)	(3,0,5)
6	0.10	1	(5,4,0)	(4,5,0)	(1,0,2)	(4,4,2)	(4,4,0)	(3,1,0)	(2,3,2)	(8,2,0)
6	0.10	2	(5,4,0)	(4,6,0)	(2,0,1)	(4,4,2)	(4,3,0)	(3,0,0)	(2,2,2)	(8,0,0)
6	0.10	3	(5,4,0)	(4,6,0)	(2,0,1)	(4,4,2)	(4,3,0)	(3,0,0)	(2,2,2)	(8,0,0)
6	0.10	5	(5,4,0)	(4,6,0)	(2,0,1)	(4,4,2)	(4,3,0)	(3,0,0)	(2,2,2)	(8,0,0)
6	0.10	10	(5,4,0)	(4,6,0)	(2,0,1)	(4,4,2)	(4,3,0)	(3,0,0)	(2,2,2)	(8,0,0)
12	0.05	1	(5,0,0)	(4,0,0)	(2,0,1)	(4,0,2)	(4,0,0)	(2,0,1)	(4,0,0)	(7,1,1)
12	0.05	2	(5,0,0)	(4,0,0)	(3,0,0)	(6,0,0)	(4,0,0)	(3,0,0)	(4,0,0)	(8,0,0)
12	0.05	3	(5,0,0)	(4,0,0)	(3,0,0)	(6,0,0)	(4,0,0)	(3,0,0)	(4,0,0)	(8,0,0)
12	0.05	5	(5,0,0)	(4,0,0)	(3,0,0)	(6,0,0)	(4,0,0)	(3,0,0)	(4,0,0)	(7,1,1)
12	0.05	10	(5,0,0)	(4,0,0)	(3,0,0)	(6,0,0)	(4,0,0)	(3,0,0)	(4,0,0)	(6,1,2)
12	0.10	1	(5,2,0)	(4,0,0)	(2,1,1)	(5,2,1)	(3,2,1)	(3,0,0)	(3,2,1)	(7,1,1)
12	0.10	2	(5,2,0)	(4,0,0)	(3,1,0)	(5,3,1)	(4,1,0)	(3,0,0)	(3,1,1)	(6,2,2)
12	0.10	3	(5,2,0)	(4,0,0)	(3,1,0)	(5,3,1)	(4,1,0)	(3,0,0)	(3,1,1)	(6,2,2)
12	0.10	5	(5,2,0)	(4,0,0)	(3,1,0)	(5,3,1)	(4,1,0)	(3,0,0)	(3,1,1)	(6,2,2)
12	0.10	10	(5,2,0)	(4,0,0)	(3,1,0)	(5,3,1)	(4,1,0)	(3,0,0)	(3,1,1)	(6,2,2)
18	0.05	1	(4,0,1)	(4,0,0)	(2,2,1)	(4,1,2)	(3,0,1)	(2,0,1)	(3,1,1)	(6,2,2)
18	0.05	2	(4,0,1)	(4,0,0)	(2,2,1)	(3,1,2)	(3,0,1)	(2,0,1)	(3,0,1)	(6,2,2)
18	0.05	3	(4,0,1)	(4,0,0)	(2,2,1)	(3,1,2)	(3,0,1)	(2,0,1)	(3,0,1)	(6,2,2)
18	0.05	5	(4,0,1)	(4,0,0)	(2,2,1)	(3,1,2)	(3,0,1)	(2,0,1)	(3,0,1)	(5,2,3)
18	0.05	10	(4,0,1)	(4,0,0)	(2,2,1)	(3,1,2)	(3,0,1)	(2,0,1)	(3,0,1)	(5,2,3)
18	0.10	1	(4,0,1)	(4,1,0)	(2,1,1)	(4,1,2)	(3,1,1)	(2,0,1)	(4,2,0)	(7,0,1)
18	0.10	2	(4,0,1)	(4,1,0)	(2,1,1)	(4,1,2)	(3,1,1)	(2,0,1)	(4,1,0)	(6,0,2)
18	0.10	3	(4,0,1)	(4,1,0)	(2,1,1)	(4,1,2)	(3,1,1)	(2,0,1)	(3,1,1)	(6,0,2)
18	0.10	5	(4,0,1)	(4,1,0)	(2,1,1)	(4,1,2)	(3,1,1)	(2,0,1)	(3,1,1)	(6,0,2)
18	0.10	10	(4,0,1)	(4,1,0)	(2,1,1)	(4,1,2)	(3,1,1)	(2,0,1)	(3,1,1)	(6,0,2)

Table 7: Market timing based on regime shift detection technique and extreme values (Rating = AA).

Column 1 reports selected maturities of 3, 5, and 10 years (Tm). Column 2 reports the number of months of the moving windows used to estimate extreme values (Hist.). Following columns report portfolio returns (Ret.) and number of transactions (Nb.) for each strategy. Structural strategies are based on shifts confirmed with the value of RSI at the 5% level or possible shifts when they are detected but not yet confirmed. Initial cut-off lengths m in the structural strategy are 6 or 12 months. Extreme Values (EV) for entry and exit threshold are taken from the 5th and 20th lower and higher percentiles. Panels A, B, and C present the results when transaction costs are respectively 0.0%, 0.5%, and 1.0%. The highest return, across different strategies, is underlined.

		Structural based on shifts confirmed				Structural based on possible shifts				EV [20%, 80%]		EV [5%, 95%]	
Tm	Hist.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret.	Nb.	Ret.	Nb.
Panel A: Transaction cost = 0.0%													
3	12	4.05	2	4.26	2	3.47	15	3.31	11	2.34	10	2.84	8
3	36	3.62	2	3.88	2	3.59	11	2.88	8	1.79	8	2.42	6
3	60	2.95	2	3.30	2	3.26	11	2.71	8	1.31	6	1.70	6
5	12	2.88	2	3.75	1	3.99	18	4.00	10	2.90	8	2.90	8
5	36	2.15	2	3.25	1	4.10	18	3.27	10	2.44	6	2.44	6
5	60	0.99	2	2.46	1	4.96	16	2.49	10	2.26	6	2.26	6
10	12	0.90	2	0.90	2	3.80	20	1.97	10	1.99	10	2.94	10
10	36	-0.32	2	-0.32	2	2.43	16	1.29	10	0.96	8	2.14	8
10	60	-2.30	2	-2.30	2	0.99	14	-0.47	8	0.40	8	1.98	8
Panel B: Transaction cost = 0.5%													
3	12	4.04	2	4.25	2	3.40	15	2.92	11	3.21	6	2.66	4
3	36	3.61	2	3.87	2	3.52	11	2.98	8	2.57	6	1.88	4
3	60	2.94	2	3.28	2	3.17	11	2.64	8	1.91	6	0.63	4
5	12	2.87	2	3.75	1	3.90	18	3.72	10	2.58	8	3.01	4
5	36	2.14	2	3.24	1	4.36	16	3.21	10	2.06	6	2.32	4
5	60	0.98	2	2.45	1	4.83	16	3.96	10	1.76	6	1.83	4
10	12	0.89	2	0.89	2	3.70	20	1.92	10	2.28	10	1.94	8
10	36	-0.33	2	-0.33	2	2.33	16	1.23	10	1.44	8	1.02	6
10	60	-2.32	2	-2.32	2	0.87	14	-1.74	6	1.40	8	0.49	6
Panel C: Transaction cost = 1.0%													
3	12	3.85	2	4.06	2	2.13	3	4.38	2	2.45	4	3.85	2
3	36	3.37	2	3.63	2	1.22	3	4.03	2	1.63	4	3.37	2
3	60	2.62	2	2.96	2	2.14	3	3.51	2	0.29	4	2.62	2
5	12	2.67	2	3.65	1	4.37	7	1.83	3	2.80	6	2.20	2
5	36	1.90	2	3.12	1	4.38	6	0.85	3	2.06	6	1.31	2
5	60	0.66	2	2.29	1	3.97	6	-0.74	3	1.48	6	-0.13	2
10	12	0.70	2	0.70	2	0.91	10	4.28	4	2.37	10	1.72	8
10	36	-0.57	2	-0.57	2	-0.04	12	3.90	4	1.68	8	0.64	6
10	60	-2.63	2	-2.63	2	-1.91	10	3.33	4	1.36	8	-0.02	6

Table 8: Market timing based on regime shift detection technique and extreme values (Rating = A).

Column 1 reports selected maturities of 3, 5, and 10 years (Tm). Column 2 reports the number of months of the moving windows used to estimate extreme values (Hist.). Following columns report portfolio returns (Ret.) and number of transactions (Nb.) for each strategy. Structural strategies are based on shifts confirmed with the value of RSI at the 5% level or possible shifts when they are detected but not yet confirmed. Initial cut-off lengths m in the structural strategy are 6 or 12 months. Extreme Values (EV) for entry and exit threshold are taken from the 5th and 20th lower and higher percentiles. Panels A, B, and C present the results when transaction costs are respectively 0.0%, 0.5%, and 1.0%. The highest return, across different strategies, is underlined.

		Structural based on shifts confirmed				Structural based on possible shifts				EV [20%, 80%]		EV [5%, 95%]	
Tm	Hist.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret.	Nb.	Ret.	Nb.
Panel A: Transaction cost = 0.0%													
3	12	3.51	2	3.32	2	3.11	14	2.45	8	2.45	12	3.14	8
3	36	2.94	2	2.70	2	2.34	10	1.70	6	1.94	10	2.71	6
3	60	2.04	2	1.73	2	1.58	8	1.10	6	1.37	8	2.35	6
5	12	2.51	2	2.67	2	3.77	16	2.60	12	2.65	10	2.74	8
5	36	1.69	2	1.90	2	2.94	12	0.57	6	1.96	8	2.07	6
5	60	0.38	2	0.66	2	3.59	12	-0.16	8	1.53	8	1.68	6
10	12	-2.87	2	-2.87	2	4.53	28	1.54	8	1.19	8	1.32	8
10	36	0.27	2	0.27	2	3.80	22	0.26	6	-0.37	6	-0.21	6
10	60	-1.51	2	-1.51	2	2.98	20	-0.67	6	-1.24	6	-1.02	6
Panel B: Transaction cost = 0.5%													
3	12	3.50	2	3.31	2	3.95	14	0.98	6	3.09	8	0.85	4
3	36	2.93	2	2.69	2	2.06	8	1.66	6	2.62	6	1.50	4
3	60	2.03	2	1.71	2	1.51	8	1.17	6	1.87	6	2.56	4
5	12	2.50	2	2.66	2	3.69	16	2.54	12	2.50	8	2.05	6
5	36	1.68	2	1.89	2	3.48	12	0.53	6	1.90	6	1.15	4
5	60	0.36	2	0.64	2	2.82	10	-0.22	8	1.45	6	-0.07	4
10	12	-2.88	2	-2.88	2	4.15	26	1.50	8	0.92	8	0.98	8
10	36	0.26	2	0.26	2	3.67	22	0.22	6	-0.59	6	-0.05	6
10	60	-1.53	2	-1.53	2	2.81	20	-1.23	4	-1.52	6	-1.72	4
Panel C: Transaction cost = 1.0%													
3	12	3.31	2	3.12	2	2.00	3	2.39	1	1.89	6	3.22	3
3	36	2.69	2	2.45	2	1.06	3	1.55	1	1.25	4	2.58	3
3	60	1.71	2	1.39	2	0.19	1	2.29	1	0.04	4	1.57	3
5	12	2.31	2	2.47	2	2.44	7	0.93	5	2.58	8	2.00	4
5	36	1.44	2	1.65	2	1.20	5	-0.49	3	1.93	6	1.06	4
5	60	0.05	2	0.32	2	-0.02	3	0.19	1	0.98	6	2.68	4
10	12	-3.07	2	-3.07	2	1.10	12	3.97	4	0.58	8	0.93	6
10	36	0.02	2	0.02	2	-0.48	8	3.51	4	-0.88	6	-0.44	4
10	60	-1.84	2	-1.84	2	-1.86	6	3.47	2	-1.91	6	-1.84	2

Table 9: Market timing based on regime shift detection technique and extreme values (Rating = BBB).

Column 1 reports selected maturities of 3, 5, and 10 years (Tm). Column 2 reports the number of months of the moving windows used to estimate extreme values (Hist.). Following columns report portfolio returns (Ret.) and number of transactions (Nb.) for each strategy. Structural strategies are based on shifts confirmed with the value of RSI at the 5% level or possible shifts when they are detected but not yet confirmed. Initial cut-off lengths m in the structural strategy are 6 or 12 months. Extreme Values (EV) for entry and exit threshold are taken from the 5th and 20th lower and higher percentiles. Panels A, B, and C present the results when transaction costs are respectively 0.0%, 0.5%, and 1.0%. The highest return, across different strategies, is underlined.

		Structural based on shifts confirmed				Structural based on possible shifts				EV [20%, 80%]		EV [5%, 95%]	
Tm	Hist.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret.	Nb.	Ret.	Nb.
Panel A: Transaction cost = 0.0%													
3	12	2.96	2	2.96	2	1.71	13	0.73	8	2.19	8	2.32	8
3	36	2.25	2	2.25	2	2.19	9	1.08	4	1.40	6	1.55	6
3	60	1.13	2	1.13	2	1.70	9	0.88	4	0.79	6	0.79	6
5	12	2.11	2	2.23	2	0.98	10	-0.07	6	1.75	8	1.66	6
5	36	1.19	2	1.34	2	1.88	10	0.58	6	0.72	6	0.60	4
5	60	-0.29	2	-0.08	2	2.56	8	4.25	2	-0.19	6	-0.35	4
10	12	-1.11	2	1.33	2	4.75	17	3.47	11	-0.52	6	-0.18	6
10	36	-2.83	2	0.22	2	4.03	15	2.17	11	-2.09	4	-1.66	4
10	60	-2.22	2	-1.58	2	5.51	13	1.17	9	-3.15	4	-2.72	2
Panel B: Transaction cost = 0.5%													
3	12	2.95	2	2.95	2	1.51	11	0.33	6	1.46	6	0.06	2
3	36	2.24	2	2.24	2	2.13	9	1.06	4	0.60	4	0.60	2
3	60	1.11	2	1.11	2	1.63	9	0.85	4	-0.48	4	1.12	2
5	12	2.10	2	2.22	2	0.93	10	-0.10	6	1.36	6	1.48	6
5	36	1.18	2	1.33	2	1.33	8	0.54	6	0.35	4	0.46	4
5	60	-0.30	2	-0.10	2	3.04	8	4.23	2	-0.68	4	-0.10	2
10	12	-1.12	2	1.32	2	4.67	17	3.41	11	-0.09	6	0.01	6
10	36	-2.84	2	0.21	2	4.97	13	2.11	11	-1.42	4	-1.42	4
10	60	-2.24	2	-1.59	2	5.40	13	1.09	9	-2.92	4	-2.88	2
Panel C: Transaction cost = 1.0%													
3	12	2.75	2	2.75	2	3.02	4	2.46	4	-0.04	2	3.17	2
3	36	2.00	2	2.00	2	1.26	4	1.87	2	0.48	2	2.52	2
3	60	0.79	2	0.79	2	1.44	4	3.12	0	-1.02	2	1.49	2
5	12	1.91	2	2.03	2	2.22	6	4.63	2	1.18	6	-0.66	2
5	36	0.94	2	1.09	2	0.48	6	3.75	0	0.20	4	-0.72	2
5	60	-0.62	2	-0.42	2	3.15	6	3.12	0	-0.88	4	0.07	2
10	12	-1.31	2	1.13	2	4.28	13	2.08	9	-0.30	6	0.25	6
10	36	-3.08	2	-0.03	2	2.90	11	1.51	11	-1.67	4	-1.24	4
10	60	-2.56	2	-1.91	2	3.11	11	2.08	6	-3.05	2	-3.05	2

Table 10: Market timing based on regime shift detection technique and extreme values (Rating = BB).

Column 1 reports selected maturities of 3, 5, and 10 years (Tm). Column 2 reports the number of months of the moving windows used to estimate extreme values (Hist.). Following columns report portfolio returns (Ret.) and number of transactions (Nb.) for each strategy. Structural strategies are based on shifts confirmed with the value of RSI at the 5% level or possible shifts when they are detected but not yet confirmed. Initial cut-off lengths m in the structural strategy are 6 or 12 months. Extreme Values (EV) for entry and exit threshold are taken from the 5th and 20th lower and higher percentiles. Panels A, B, and C present the results when transaction costs are respectively 0.0%, 0.5%, and 1.0%. The highest return, across different strategies, is underlined.

		Structural based on shifts confirmed				Structural based on possible shifts				EV [20%, 80%]		EV [5%, 95%]	
Tm	Hist.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret. m=12	Nb.	Ret. m=6	Nb.	Ret.	Nb.	Ret.	Nb.
Panel A: Transaction cost = 0.0%													
3	12	1.69	2	3.06	2	5.07	19	2.07	10	2.02	14	1.74	4
3	36	0.67	2	2.39	2	5.13	17	2.48	8	1.21	12	0.73	4
3	60	-0.98	2	1.31	2	5.37	13	4.75	8	0.19	8	-0.98	2
5	12	0.78	2	2.77	2	6.77	20	3.20	12	2.34	10	1.96	6
5	36	-0.47	2	2.02	2	7.09	14	3.19	10	1.28	8	1.01	6
5	60	0.34	2	0.82	2	5.16	8	3.25	6	0.54	6	-0.58	4
10	12	-1.59	2	1.80	2	8.51	18	1.84	8	0.65	8	3.40	8
10	36	-3.42	2	0.80	2	6.69	12	0.19	6	-1.09	6	1.60	6
10	60	-3.45	2	-0.80	2	11.58	10	-0.23	4	-2.26	4	0.15	4
Panel B: Transaction cost = 0.5%													
3	12	1.68	2	3.05	2	4.98	19	2.02	10	1.24	6	1.41	2
3	36	0.66	2	2.37	2	4.89	15	2.98	8	0.39	4	0.32	2
3	60	-0.99	2	1.29	2	5.27	13	4.69	8	-0.84	2	-0.84	2
5	12	0.77	2	2.76	2	7.44	20	3.14	12	1.34	8	0.28	2
5	36	-0.49	2	2.01	2	7.00	14	3.13	10	0.63	6	-1.09	2
5	60	0.33	2	0.80	2	5.10	8	3.20	6	-0.91	4	-1.71	2
10	12	-1.60	2	1.79	2	6.07	14	1.80	8	1.39	8	3.57	8
10	36	-3.44	2	0.79	2	6.61	12	0.15	6	-0.05	6	1.94	6
10	60	-3.47	2	-0.82	2	11.50	10	1.22	4	-0.70	4	0.77	4
Panel C: Transaction cost = 1.0%													
3	12	1.49	2	2.86	2	1.04	8	0.29	6	-0.42	2	1.68	2
3	36	0.42	2	2.14	2	2.20	8	1.89	5	-0.35	2	0.65	2
3	60	-1.31	2	0.97	2	3.65	8	0.65	5	-1.00	2	-1.00	2
5	12	0.58	2	2.57	2	3.76	8	2.32	6	-0.24	4	0.18	2
5	36	-0.72	2	1.77	2	4.55	8	0.89	6	-1.22	2	-1.22	2
5	60	0.01	2	0.48	2	5.70	6	1.72	4	-2.11	2	-1.54	2
10	12	-1.79	2	1.60	2	5.26	10	2.65	8	1.89	8	3.17	8
10	36	0.55	2	0.55	2	5.57	8	0.55	6	-0.04	6	1.56	6
10	60	-1.14	2	-1,14	2	5.89	6	0.58	4	-0.52	4	0.44	4

Figure 1: Times series of credit spreads (1994-2004).
The figure presents the time series of credit spreads for US corporate bonds rated from AA to BB with 3, 5, and 10 remaining years-to-maturity over the period ranging from 1994 to 2004. The shaded region represents the 2001 NBER period of recession.

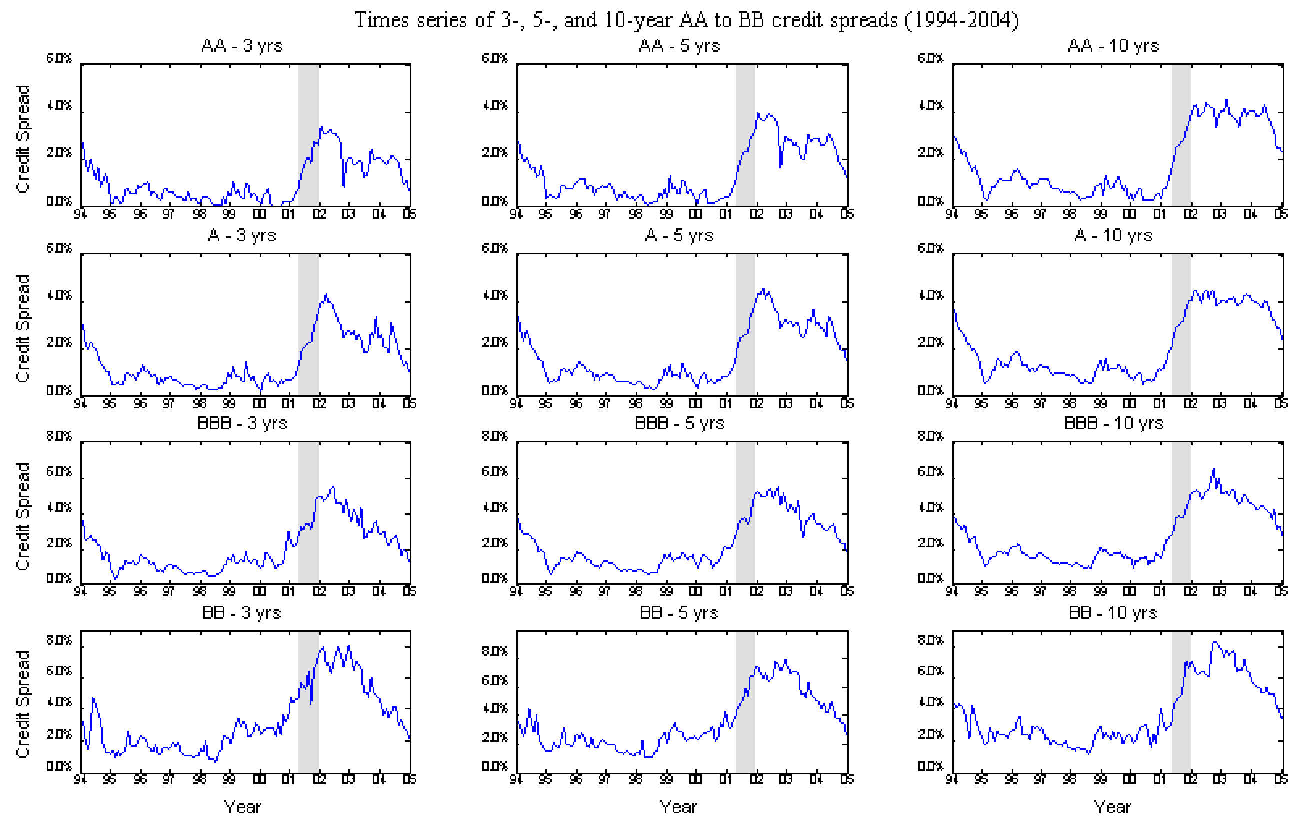

Figure 2: Shifts in the mean for 3-year and 10-year A-rated credit spreads, (1994-2004).
In this figure we plot the time series of 3-year and 10-year A-rated observed credit spreads, the weighted means of the regimes using the Huber's weight function with h=2 , the Regime Shift Index (RSI). Panel A presents shifts in the mean without prewhitening and Panel B presents shifts after prewhitening. The probability for H0 is 0.05, the cut-off length is 12 months. The estimated AR1 coefficients are, respectively, 0.71 and 0.87 for 3-year and 10-year credit spreads before prewhitening and 0.73 and 0.87 after prewhitening. The shaded region represents the NBER period of recession.

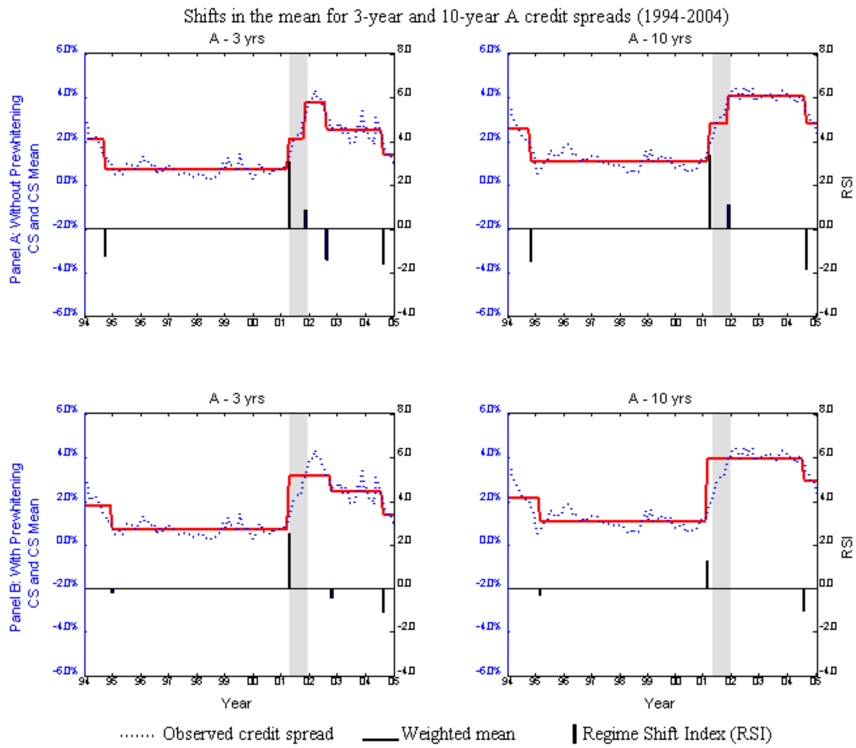

Figure 3: Shifts in the variance for 3-year and 10-year A-rated credit spreads, (1994-2004). In this figure we plot the credit spread residuals (zero-mean) of 3-year and 10-year A-rated credit spreads, the variance of residuals, and the Residual Sum of Squares Index Sum (RSSI). Panel A presents shifts in the variance without prewhitening and Panel B presents shifts after prewhitening. The probability for H0 is 0.05 and the cut-off length is 12 months. The shaded region represents the NBER period of recession.

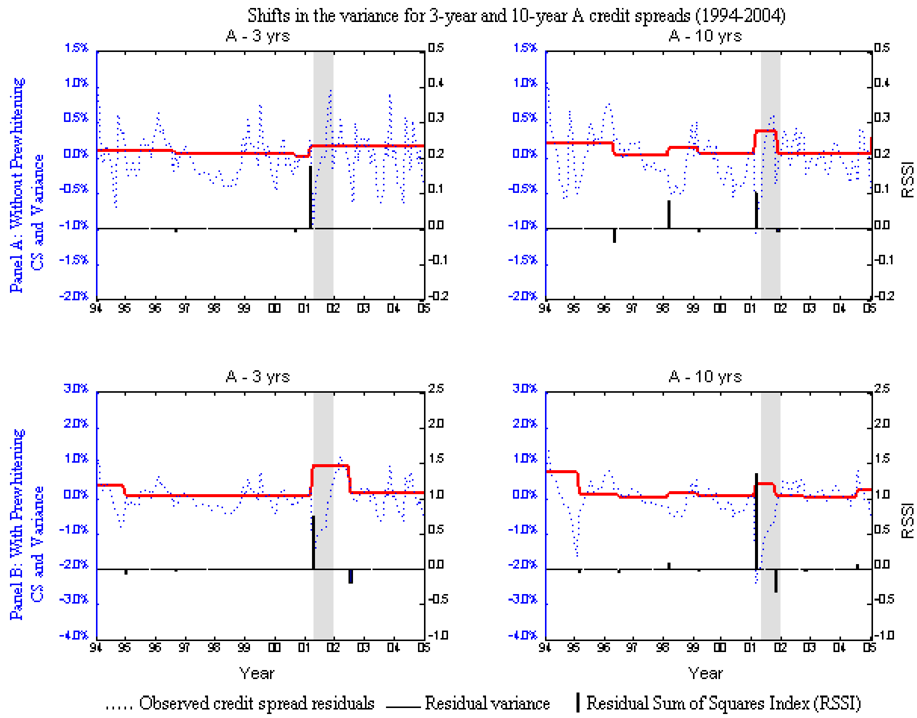

Figure 4: Shifts in the mean for 3, 5, and 10-year AA to BB credit spreads, (Jan 1994-Dec 2004) after prewhitening.
In this figure we plot the time series of 3, 5, and 10-year AA to BB credit spreads, the weighted means of the regimes using the Huber's weight function with h=2, the Regime Shift Index (RSI). The probability for H0 is 0.05, and the cut-off length is 12 months.

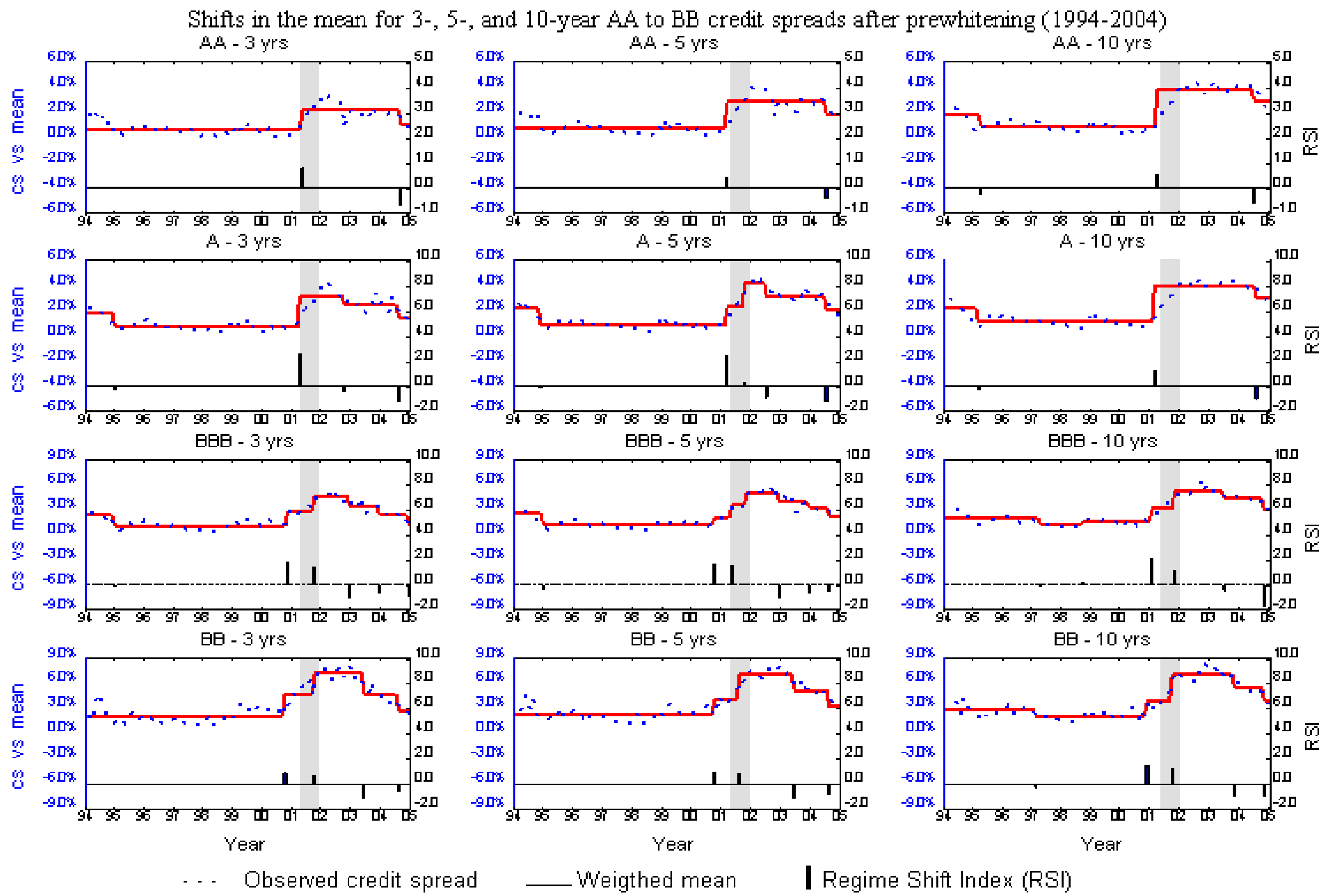

Figure 5: Shifts in the variance for 3, 5, and 10-year AA to BB credit spreads (Jan 1994-Dec 2004) after prewhitening.
In this figure we plot the credit spread residuals (zero-mean) of 3, 5, and 10-year AA to BB bonds, the variance of residuals, and the Residual Sum of Squares Index Sum (RSSI). The probability for H0 is 0.05 and the cut-off length is 12 months.