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Trois Essais sur les Écarts de Crédit des Obligations Corporatives et le Risque de Défaut

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Résumé

Les écarts de crédit des obligations corporatives tendent à être beaucoup plus larges que ceux qui seraient induits par le risque de défaut associé (Huang and Huang, 2003). Ce résultat est connu sous le nom de «credit spread puzzle ».

Dans le premier essai, nous explorons la dynamique des écarts de crédit à travers les cotes et les maturités, en utilisant une technique de détection des sauts qui n'a jamais été appliquée en finance. Elle signale les points de rupture dans la moyenne et la variance de la série temporelle, arrivant en plusieurs séquences, en se basant sur des tests statistiques structurels. Les résultats montrent que les écarts de crédit, malgré le fait qu'ils sont contre cycliques, ont leurs propres patterns qui peuvent être différents de ceux des variables macroéconomiques. De plus, les points de ruptures détectés au niveau de la moyenne et de la variance ont des patterns différents ce qui aide à clarifier le lien existant entre le cycle économique et le cycle de crédit. Finalement, en testant l'habileté à court terme des stratégies d'investissement basées sur la technique de détection des régimes appliquée à la moyenne des écarts de crédit, nous montrons que la technique employée est la plus profitable hors échantillon.

Le deuxième essai analyse les déterminants des écarts de crédit dans différents régimes. Les études empiriques antérieures considèrent un modèle à un seul régime pour toute la période d'évaluation et trouvent un pouvoir explicatif limité. Ici, nous modélisons les cycles de crédit de façon endogène en utilisant un modèle Markovien de changement de régime.

Ensuite, nous démontrons qu'avec des cycles de crédit endogènes, le pouvoir explicatif des déterminants des écarts de crédit est amélioré. Le modèle à un seul régime ne peut pas être amélioré si les états des cycles économiques NBER sont considérés à la place des régimes. De plus, les modèles à régime mettent en lumière une relation positive entre les écarts de crédit et le taux sans risque dans le régime haut. Cette relation inverse est également obtenue avec d'autres déterminants.

Le troisième essai passe en revue la littérature sur le puzzle des écarts de crédit. Durant les dernières années, les modèles structurels existants ont été étendus de plusieurs façons pour réconcilier des faits plus réalistes reliés aux causes du défaut. Toutefois, ces modèles restent limités par leurs performances d'estimations. Très peu de modèles considèrent explicitement le rôle des conditions économiques dans l'événement de défaut ou la tendance des firmes à faire défaut en masse. Ces facteurs doivent être considérés en particulier étant donnée la présente instabilité des marchés financiers. Finalement, nous proposons de nouvelles perspectives qui peuvent faire partie du puzzle.

Mots clés : Puzzle des écarts de crédit, changement de régimes, cycles de crédit, cycles économiques, stratégies d'investissement.

Abstract

Credit spreads on corporate bonds tend to be many times larger than what would be implied by only the default risk (Huang and Huang, 2003). This thesis readdresses the credit spread puzzle.

The first essay explores the dynamics of credit spread -across ratings and maturities- using a technique for regime shift detection – previously never applied in finance. It signals in real time possible breakpoints in the time series of credit spreads. The results show that credit spreads, even though countercyclical, have their own pattern which may be different from macroeconomic fundamentals. Further, detected shifts in the mean and the variance have different patterns providing new insights on the relation between economic and credit cycles. Then, by testing for the short-term market timing ability of the regime shift detection technique, we show that the employed out-of-sample detection technique can be valuable for market timing.

The second essay analyzes the spread determinants in the different regime. Previous empirical studies consider a single credit spread regime over the entire sample period and find limited explanatory power. Here, we model the credit cycle endogenously using a Markov regime switching model. Then, we show that accounting for endogenous credit cycles enhances the explanatory power of credit spread determinants. The single regime model cannot be improved when conditioning on the states of the NBER economic cycle. Further, the regime-based model highlights a positive relation between credit spreads and

the risk-free rate in the high regime while this inverted relation is also obtained for some other determinants.

The third essay review the credit spread puzzle literature. During last few years, existing structural models have been extended in different ways to reconcile many realistic facts about what really drives default. Yet, they remain limited by their estimation accuracy. Few models account explicitly for the role of economic conditions in triggering default or the tendency for firms to default in wave which become essential to account for in particular given the recent turmoil in the global financial market. We also review empirical works taking on the task to test several predictions of existing models. Then, we provide new insights that may make part of the puzzle.

Key Words : Credit spread puzzle, switching regimes, credit cycles, economic cycles, market timing.

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À ma mère et mon père,
À mes deux soeurs et mes deux frères,
À mes deux beaux frères,
À selly et manna,
À M. Dionne et M. François,
À mes amies
À moi !

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Chapitre 1

Introduction générale

Les écarts de crédit, définis comme étant la différence entre les rendements risqués des obligations corporatives et les rendements sans risque des bons de Trésor, tendent à être beaucoup plus larges que ceux qui seraient induits par le risque de défaut associé (Huang and Huang, 2003). En effet, les écarts de crédit sont souvent considérés comme une compensation pour le risque de crédit. Cependant, en considérant uniquement ce risque, une large proportion de cet écart reste inexpliquée. Ce résultat est connu sous le nom de «credit spread puzzle ».

En utilisant une panoplie de facteurs de non défaut, Collin-Dufresne et al. (2001) n'ont réussi à expliquer que 25% des changements des écarts de crédit. De plus, ils ont détecté un facteur systématique commun à toutes les cotes et toutes les maturités, qui pourrait potentiellement expliquer une grande partie de la proportion inexpliquée des écarts de crédit. Toutefois, ce facteur ne peut pas être mesuré en utilisant plusieurs variables macroéconomiques. Cette thèse reconsidère le puzzle des écarts de crédit et s'intéresse particulièrement à l'origine du facteur manquant.

Dans le premier essai, nous explorons la dynamique des écarts de crédit à travers les cotes et les maturités, en utilisant une technique de détection des sauts qui n'a jamais été appliquée en finance. Typiquement, les écarts de crédit illustrent, à travers le temps, des épisodes avec des taux bas et décroissants et des épisodes avec des taux hauts et croissants. Ces épisodes peuvent être associés aux crises financières persistantes (Cerra and Saxena, 2005 ; Hamilton, 2005) ou aux changements brusques dans l'économie (Hamilton, 1988 ; Sims and Zha, 2006 ; Davig, 2004). La littérature est unanime sur le fait que les écarts de crédit ont un comportement contre cyclique. Et des modèles de régimes basés sur des variables macroéconomiques sont utilisés pour capturer les mouvements des écarts de crédit à travers les différents états de l'économie (Davies, 2004 and 2007 ; Alexander and Kaeck, 2007 ; Dionne et al., 2007 ; David, 2008). Toutefois, la connexion entre les états identifiés et le cycle économique reste ambiguë (Alexander and Kaeck, 2007). De plus, les modèles de régimes font typiquement des hypothèses sur le nombre de régimes dans la série observée. Par contre, la méthode que nous proposons a l'avantage de laisser les données parler et révéler les points de sauts possibles en temps réel. Elle signale les points de rupture dans la moyenne et la variance de la série temporelle, arrivant en plusieurs séquences, en se basant sur des tests statistiques structurels.

Les résultats montrent que les régimes de moyenne et de variance ont des patterns différents mais se produisent autour de la récession de 2001 ainsi qu'autour de la plupart des événements qui ont beaucoup affectés les marchés obligataires durant la période de l'analyse. L'effet combiné des régimes de moyenne et de variance des écarts de crédit produit un cycle de crédit qui est plus long que le cycle économique même si les deux cycles commencent presque en même temps.

De plus, notre évidence montre que le cycle économique a une relation complexe avec la structure des cotes des écarts de crédit. Un effet niveau affecte plutôt les cotes les plus basses, tandis que les sauts de moyenne pour les cotes les plus élevées sont plus contemporains par rapport à l'annonce officielle de la récession. De plus, ces cotes élevées sont aussi affectées par les sauts de la variance. La structure totale des écarts de crédit revient à son régime précédent juste après la fin de la récession. Ainsi, nous suggérons que la dynamique des écarts de crédit est persistante face aux chocs économiques. Cet effet est plus prononcé pour les cotes les plus élevées.

Finalement, nous testons les stratégies d'investissement en utilisant la technique de détection des régimes appliquée à la moyenne des écarts de crédit. Nous montrons que les rendements des portefeuilles formés avec des stratégies d'investissement structurelles basées sur la technique de détection de régime sont généralement plus élevés que ceux des portefeuilles formés avec les stratégies basées sur les valeurs extrêmes. Plus spécifiquement, les rendements les plus élevés sont obtenus avec les stratégies basées sur les régimes détectés mais pas encore confirmés. Nos résultats suggèrent que la technique de détection des régimes extrait une quantité d'information importante pour les stratégies de portefeuille.

Dans le deuxième essai, nous analysons les déterminants des écarts de crédit dans les épisodes croissants et décroissants. Les études empiriques antérieures considèrent un modèle à un seul régime pour toute la période d'évaluation et trouvent un pouvoir explicatif limité. L'origine du facteur manquant peut être du à un facteur systématique caché (Collin-Dufresne et al., 2001). Les études récentes appliquent les modèles de régimes pour capturer les mouvements des écarts de crédit à travers les états de l'économie. Dans ces travaux, les régimes sont souvent modélisés à partir des variables macroéconomiques qui sont très reliés à la dynamique du GDP (Davies, 2004 ; Hackbarth et al., 2006 ; Bhamra et al., 2007 ; Chen, 2008 ; and David, 2008). Toutefois, ces approches supposent implicitement que le vrai cycle de crédit coïncide avec le cycle économique, ce qui est à l'origine un long débat dans littérature cherchant à savoir si ces deux cycles sont vraiment reliés et comment.

Pour cette raison, nous avons choisi de modéliser les régimes d'une façon endogène sans prendre en considération les variables macroéconomiques. Nous analysons les déterminants des écarts de crédit conditionnellement à la présence de l'un des deux régimes, (un régime haut ou un régime bas). Puis nous comparons les résultats avec ceux obtenus si les états du cycle économique NBER sont considérés à la place des régimes. Nos résultats peuvent être résumés comme suit :

Premièrement, nous montrons que les effets réels des déterminants clés des écarts de crédit sont cachés dans le modèle à un seul régime. Le modèle n'est pas amélioré lorsque nous tenons compte de l'information contenue dans les états du cycle économique ou dans la période d'annonce de ce cycle. Toutefois, lorsque les régimes sont considérés les effets des variables explicatives sont plus apparents et le pouvoir explicatif du modèle à régime est beaucoup plus important que le modèle sans régime. Deuxièmement, nous montrons que la structure des régimes des écarts de crédit, caractérisant le cycle de crédit, est plus longue et différente du cycle économique de NBER. En particulier, nous montrons que la fin du cycle de crédit est déclenchée par un effet annonce et elle est affectée par un effet de persistance. Troisièmement, nous illustrons que la connexion entre le cycle économique et le cycle de crédit produit l'inversion de signe (sous respect du signe négatif prédit) entre le taux sans risque et les écarts de crédit trouvés dans Morris, Neale, and Rolph (1998), Bevan and Garzarelli (2000) and Davies (2004, 2007). Nous documentons les origines du signe inversé et nous étendons l'analyse aux autres facteurs de marché, de défaut, et de liquidité. En particulier, nous trouvons que, dans le régime haut, plusieurs déterminants ont un effet inverse sur les écarts de crédit. Ce signe opposé réduit l'effet total de ses variables dans le modèle à un seul régime (Collin-Dufresne et al., 2001).

Le troisième essai reconsidère le puzzle des écarts de crédit. Il est très bien connu que, dans un cadre structurel, les larges écarts de crédit observés ne peuvent pas être expliqués en utilisant l'historique des défauts. Plusieurs études empiriques récentes se sont basées sur les prédictions des modèles structurels pour résoudre le puzzle. La revue de cette littérature révèle une amélioration importante des ces études. . En particulier, plusieurs d'entre elles considèrent des hypothèses plus réalistes concernant la structure de capital de la firme et les causes du défaut. Par exemple, certains travaux considèrent l'effet de l'endettement de la firme, les crises de liquidité, les conditions macroéconomiques, et plus récemment, la tendance des firmes à faire défaut en masse. Toutefois, le modèle structurel reste limité par la performance d'estimation qui peut être altérée si des variables additionnelles augmentent la complexité du modèle. Par exemple, très peu de modèles considèrent explicitement le rôle des facteurs macroéconomiques dans l'événement de défaut ou l'effet de contagion du défaut. Les études empiriques ont testé les hypothèses les plus complexes. Elles ont réussi à expliquer plus que la moitié de la variation des écarts de crédit et ont ainsi contribué à résoudre une partie du puzzle. Toutefois, il reste toujours une pièce manquante. Celle-ci peut être reliée à la nature des données utilisées pour mesurer certains effets. Par exemple, pour mesurer l'effet de la liquidité,on peut avoir besoin des données à haute fréquence du marché obligataire. De telles données ne sont pas disponibles sur une période suffisamment longue. Elle peut-être aussi reliée à d'autres facteurs qui ne sont pas encore considérés par la littérature. Nous passons en revue et nous discutons le développement de cette littérature. Nous proposons également de nouvelles perspectives pour aider à résoudre le puzzle. Spécifiquement, les actions de la politique monétaire contrôlant le niveau agrégé du crédit et de la liquidité de l'économie peuvent faire partie du puzzle mais elles sont toujours ignorées par la littérature.

Chapitre 2

Detecting Regime Shifts in Corporate Credit Spreads

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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

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2.1 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 1.1. 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 1.1 here]

Closer inspection of Figure 1.1 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.

2.2 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.

2.2.1 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 :

$$Y_t = f_t + \varepsilon_t, \tag{2.1}$$

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 :

$$f_t = \begin{cases} \mu_1, t = 1, 2, ..., c-1, \\ \mu_2, t = c, c+1, ..., n. \end{cases} \tag{2.2}$$

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) :

$$Y_t = \rho Y_{t-1} + \mu' + \varepsilon_t, \tag{2.3}$$

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 :

$$Y_t = \rho Y_{t-1} + f_t' + \varepsilon_t \tag{2.4}$$

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).[2] 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

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

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 autoregressive coefficient.

2.2.2 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 :

$$diff = t_{\alpha}^{2m-2}\sqrt{2\overline{s}_m^2/m}, \tag{2.5}$$

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 :

$$\begin{cases} \overline{Z}_{crit}^{\uparrow} = \overline{Z}_{cur} + diff, \\ \overline{Z}_{crit}^{\downarrow} = \overline{Z}_{cur} - diff. \end{cases} \tag{2.6}$$

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 $\overline{Z}_{crit}^{\downarrow}$, 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 $\overline{Z}_{crit}$:

$$RSI = \frac{1}{m\bar{s}_m} \sum_{i=t_{cur}}^{j} \left(Z_i - \overline{Z}_{crit}\right), j = t_{cur}, t_{cur}+1, ..., t_{cur}+m-1. \tag{2.7}$$

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 $\overline{Z}_{crit} = \overline{Z}_{crit}^{\uparrow}$, or positive, when $\overline{Z}_{crit} = \overline{Z}_{crit}^{\downarrow}$, 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.

2.2.3 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 :

$$\frac{s^2_{cur}}{s^2_{new}} \gtrless F\left(\nu_1, \nu_2, \alpha_{var}\right), \tag{2.8}$$

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 $s^{2\downarrow}_{crit}$.

$$\begin{cases} s^{2\uparrow}_{crit} = s^2_{cur} F^{m,\nu_2}_{\alpha_{var}}, \\ s^{2\downarrow}_{crit} = s^2_{cur} / F^{m,\nu_2}_{\alpha_{var}}. \end{cases} \tag{2.9}$$

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 $\zeta_{cur}^2 < s_{crit}^{2\downarrow}$ 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 :

$$RSSI = \frac{1}{m} \sum_{i=t_{cur}}^{j} \left(\zeta_i^2 - s_{crit}^2\right), j = t_{cur}, t_{cur}+1, ..., t_{cur}+m-1. \tag{2.10}$$

If at any time during the testing period from t_{cur} to $t_{cur}+m-1$, the index turns negative, when $s_{crit}^2 = s_{crit}^{2\uparrow}$, or positive, when $s_{crit}^2 = s_{crit}^{2\downarrow}$, 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.

2.2.4 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 :

$$weight = \min\left(1, h/\left[diff/\sigma\right]\right) \tag{2.11}$$

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).

2.3 Data

2.3.1 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 enhancement features and bonds associated with a pledge security. Issuers credit ratings are reported by four rating agencies : Fitch Rating, Duff and Phelps Rating, Moody's Rating and Standard and Poor's Rating. We include all bonds whose average Moody's credit rating lies between AA and BB. AAA credit spreads are not used because we find them negative for some periods. We also find that the average credit spread for medium term AAA-rated bonds is higher than that of A-rated bonds. These same 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 1.1 reports summary statistics.

[Insert Table 1.1 here]

2.3.2 Credit spread curve

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

$$\begin{aligned} R(t,T) &= \beta_0 + \beta_1 \left[\frac{1-\exp(-\frac{T}{\tau_1})}{\frac{T}{\tau_1}} \right] + \beta_2 \left[\frac{1-\exp(-\frac{T}{\tau_1})}{\frac{T}{\tau_1}} - \exp(-\frac{T}{\tau_1}) \right] \\ &\quad + \beta_3 \left[\frac{1-\exp(-\frac{T}{\tau_2})}{\frac{T}{\tau_2}} - \exp(-\frac{T}{\tau_2}) \right] + \varepsilon_{t,j}, \end{aligned} \tag{2.12}$$

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 :

$$\widehat{\Omega}_t = \arg\min_{\Omega_t} \sum_{i=1}^{N_t} w_i^2 \left(P_{it}^{NS} - P_{it} \right)^2, \qquad w_i = \frac{1/D_i}{\sum_{i=1}^{N} 1/D_i}, \tag{2.13}$$

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.

2.4 Results

2.4.1 Observed credit spreads

We obtain credit spread curves for AA-rated to BB-rated bonds with maturities ranging from 1 to 15 years. Figure 1.1 – in the introduction – plots these results and Table 1.2 presents summary statistics.

[Insert Table 1.2 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.

2.4.2 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 1.2 shows the results for shifts in the mean with and without prewhitening for the 3-year and 10-year A spreads.

[Insert Figure 1.2 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 1.2, 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 1.3). 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 1.3).

[Insert Table 1.3 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 1.3). Conversely when the negative shift is gradual, the magnitude of the second shift is the highest (Table 1.3, Panel A).

The test for shifts in the variance is performed on the residuals after the stepwise trend is removed (Figure 1.3).[3] 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 1.3 here]

In the southeast region of Figure 1.3, 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

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

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.

[Insert Table 1.4 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 1.4, 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).

2.4.3 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 1.4 and Figure 1.5.

[Insert Figure 1.4 and Figure 1.5]

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 1.4 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 1.4 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 1.5 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 1.5).

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 1.5 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.

2.4.4 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 1.6, we compare the number and the location of shifts reported in Table 1.3 and Table 1.4 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 1.3 and Table 1.4. 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 1.6 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 1.6, 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 1.6 shows that, after prewhitening, most of the shifts in the residual variance remain unchanged for different set of parameters.

2.4.5 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 1.6). 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.[4] 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.

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 1.7 to Table 1.10. Across ratings and maturities, the structural strategies are the winners in most of the cases : 8 out of 9 for AA spreads (Table 1.7, Panel A), 8 out of 9 for A spreads (Table 1.8, Panel A), 9 out of 9 for BBB spreads (Table 1.9, Panel A), and 9 out of 9 for BB spreads (Table 1.10, 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

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

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 1.10). Moreover, shifts in the mean for spreads of lower ratings are shown to be detected earlier than shifts for higher ratings (Figure 1.4). This in turn makes the structural strategy — specifically upon first detection — more profitable for speculative grade bonds.

[Insert Table 1.7 to Table 1.10 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 excluding 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.[5] 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 1.7 to 1.10). 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 1.10, 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 1.7, 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 1.8, Panel B). The same pattern is observed for BBB spreads (Table 1.9, 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 1.10, Panel B and C).

When transaction costs are higher ($\phi = 1\%$), the winners (i.e., the highest returns) most often move from the confirmed shift and the first detection strategies with 12-month

[5] 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 : $r_t^{net} = r_t^{gross} - \ln(1-\phi)$.

cut-off lengths to the first detection strategy with a 6-month cut-off length (see for example Table 1.7, Panel C). The extreme values strategy wins only in three cases for A spreads (Table 1.8, Panel C) and 2 cases for BBB spreads (Table 1.9, 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.

2.5 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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Tableau 2.I: 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%				

Tableau 2.II: 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

Tableau 2.III: 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				

Tableau 2.IV: 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

Tableau 2.V: 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		

Tableau 2.VI: 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)

Tableau 2.VII: 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

Tableau 2.VIII: 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	$\underline{3.51}$	2	3.32	2	3.11	14	2.45	8	2.45	12	3.14	8
3	36	$\underline{2.94}$	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	$\underline{2.35}$	6
5	12	2.51	2	2.67	2	$\underline{3.77}$	16	2.60	12	2.65	10	2.74	8
5	36	1.69	2	1.90	2	$\underline{2.94}$	12	0.57	6	1.96	8	2.07	6
5	60	0.38	2	0.66	2	$\underline{3.59}$	12	-0.16	8	1.53	8	1.68	6
10	12	-2.87	2	-2.87	2	$\underline{4.53}$	28	1.54	8	1.19	8	1.32	8
10	36	0.27	2	0.27	2	$\underline{3.80}$	22	0.26	6	-0.37	6	-0.21	6
10	60	-1.51	2	-1.51	2	$\underline{2.98}$	20	-0.67	6	-1.24	6	-1.02	6
Panel B : Transaction cost = 0.5%													
3	12	3.50	2	3.31	2	$\underline{3.95}$	14	0.98	6	3.09	8	0.85	4
3	36	$\underline{2.93}$	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	$\underline{2.56}$	4
5	12	2.50	2	2.66	2	$\underline{3.69}$	16	2.54	12	2.50	8	2.05	6
5	36	1.68	2	1.89	2	$\underline{3.48}$	12	0.53	6	1.90	6	1.15	4
5	60	0.36	2	0.64	2	$\underline{2.82}$	10	-0.22	8	1.45	6	-0.07	4
10	12	-2.88	2	-2.88	2	$\underline{4.15}$	26	1.50	8	0.92	8	0.98	8
10	36	0.26	2	0.26	2	$\underline{3.67}$	22	0.22	6	-0.59	6	-0.05	6
10	60	-1.53	2	-1.53	2	$\underline{2.81}$	20	-1.23	4	-1.52	6	-1.72	4
Panel C : Transaction cost = 1.0%													
3	12	$\underline{3.31}$	2	3.12	2	2.00	3	2.39	1	1.89	6	3.22	3
3	36	$\underline{2.69}$	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	$\underline{2.29}$	1	0.04	4	1.57	3
5	12	2.31	2	2.47	2	2.44	7	0.93	5	$\underline{2.58}$	8	2.00	4
5	36	1.44	2	1.65	2	1.20	5	-0.49	3	$\underline{1.93}$	6	1.06	4
5	60	0.05	2	0.32	2	-0.02	3	0.19	1	0.98	6	$\underline{2.68}$	4
10	12	-3.07	2	-3.07	2	1.10	12	$\underline{3.97}$	4	0.58	8	0.93	6
10	36	0.02	2	0.02	2	-0.48	8	$\underline{3.51}$	4	-0.88	6	-0.44	4
10	60	-1.84	2	-1.84	2	-1.86	6	$\underline{3.47}$	2	-1.91	6	-1.84	2

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

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

Figure 2.I: 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.

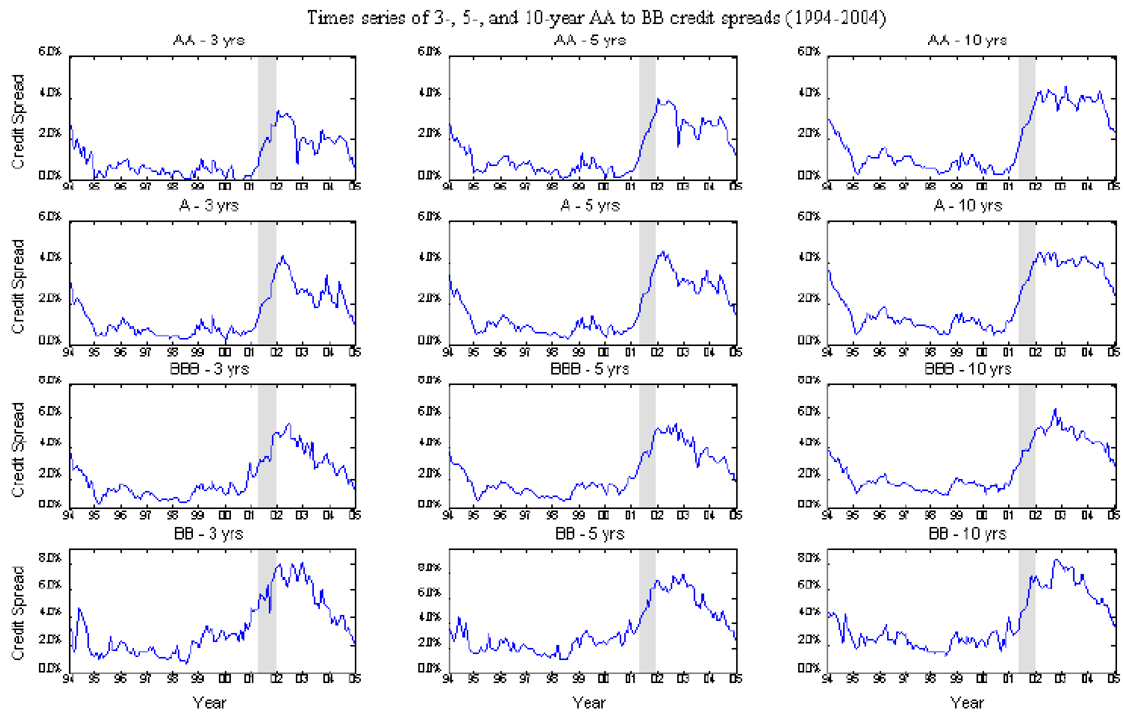


Figure 2.II: Shifts in the mean for 3-year and 10-year A-rated credit spreads, (1994-2004).

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.

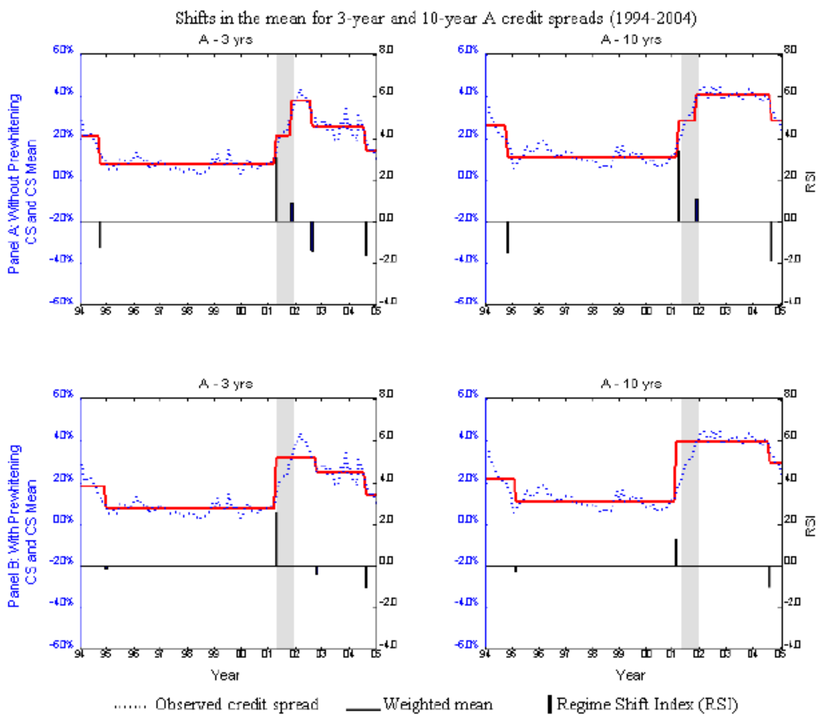


Figure 2.III: Shifts in the variance for 3-year and 10-year A-rated credit spreads, (1994-2004).

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.

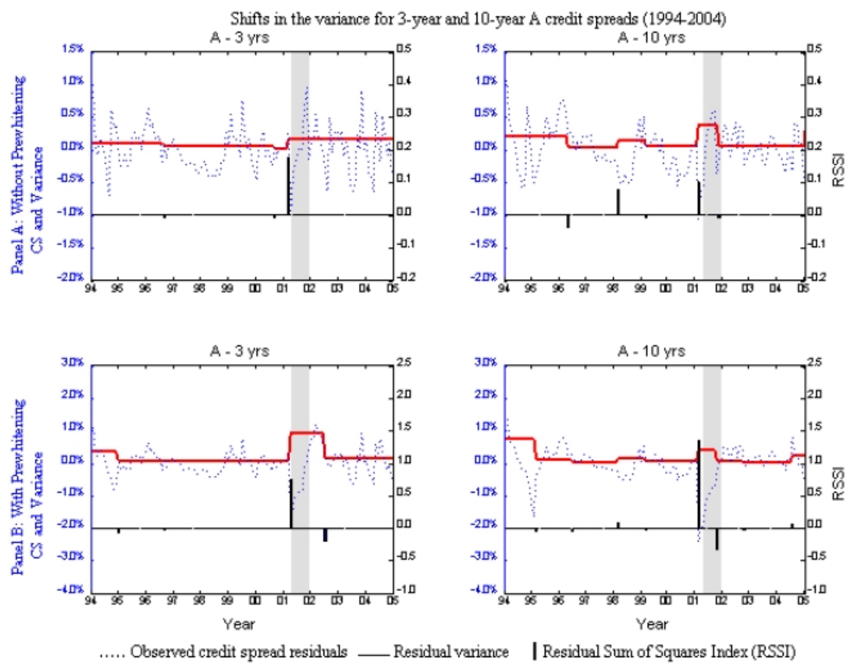


Figure 2.IV: Shifts in the mean for 3, 5, and 10-year AA to BB credit spreads, (Jan 1994-Dec 2004) after prewhitening.

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.

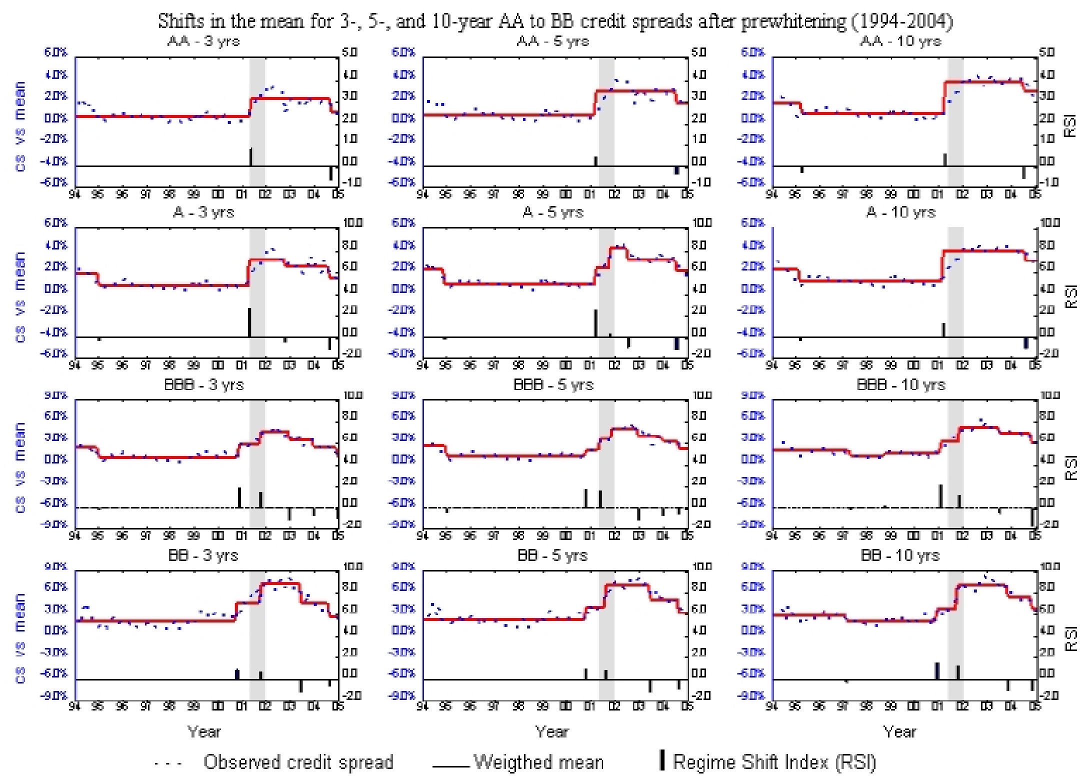
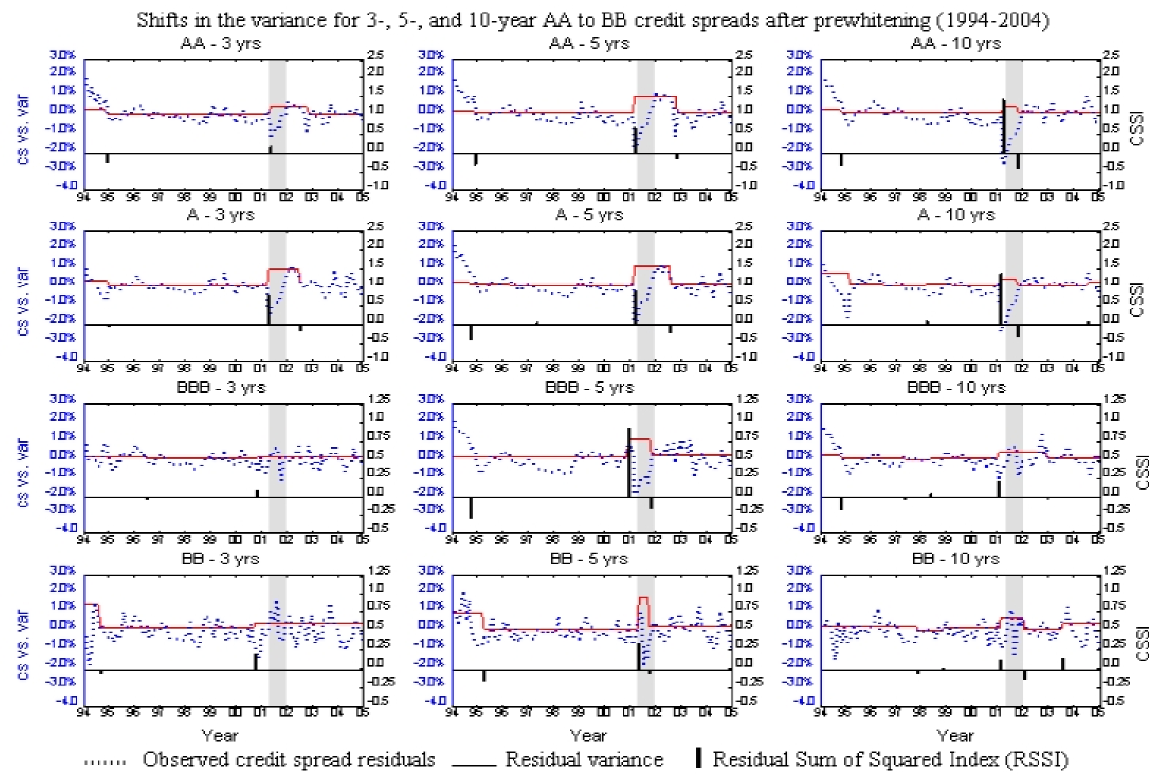


Figure 2.V: Shifts in the variance for 3, 5, and 10-year AA to BB credit spreads (Jan 1994-Dec 2004) after prewhitening.

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.



Chapitre 3

Credit Spread Changes Within Switching Regimes

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Abstract

Many empirical studies on credit spread determinants consider a single-regime model over the entire sample period and find limited explanatory power. We model the credit cycle independently from macroeconomic fundamentals using a Markov regime switching model. We show that accounting for endogenous credit cycles enhances the explanatory power of credit spread determinants. The single regime model cannot be improved when conditioning on the states of the NBER economic cycle. Furthermore, the 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 some other determinants.

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

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

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3.1 Introduction

Explaining observed credit spreads is still puzzling even after the huge number of theoretical and empirical works on this subject. The reason is that the observed credit spreads, defined as the yield difference between risky corporate bonds and riskless bonds, tend to be larger than default spreads or what would be explained by only default risk. For example, Elton et al. (2001) argue that default risk factors implicit in credit ratings and historical recovery rates account for a small fraction of observed credit spreads. Huang and Huang (2003) document the same problem when they calibrate various existing structural models to be consistent with data on historical default loss experience.[2] They claim that no consensus has emerged from the existing credit risk literature on how much of the observed corporate spreads over Treasury yields can be explained by default risk.

To address this puzzle, many parallel and subsequent studies investigate the ability of non default risk factors (such as market, liquidity and firm-specific factors) to explain credit spread differentials. These studies include those of Collin-Dufresne et al. (2001), Driessen (2003), Campbell and Taksler (2003), Huang and Kong (2003), Longstaff et al. (2005), and Han and Zhou (2006) among others. However, even after accounting for non default factors the puzzle remains unsolved because a large proportion of credit spreads remains unexplained. In particular, Collin-Dufresne et al. (2001) perform a regression that includes all potential explanatory variables predicted by theoretical models but fail to explain more than 25% of credit spread changes. They state that "variables that should in theory determine credit spread changes in fact have limited explanatory power". Collin-Dufresne et al. (2001) have also detected a common systematic factor that potentially could explain the large part of the unexplained changes. However, several macroeconomic

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

and financial candidates fail to measure it. It appears, then, that their model is missing an important component which may not be captured by macroeconomic fundamentals. This paper focuses on the drivers of the missing component in credit spread determinants. Thus, it extends the Collin-Dufresne et al. (2001) model by allowing for a regime switching structure in the credit spread dynamics.

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

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

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

In this paper, we include regime models to account for the systematic movements in the credit spread dynamics. However, our switching regime structure is derived endogenously without accounting for macroeconomic fundamentals. Then, we analyze the credit spread determinants by conditioning on the credit spread regimes, and we contrast our results with those obtained by conditioning on the states of the economic cycle. First, we consider the effective dates of the NBER recession then we consider the announcement dates for the beginning and the end of the recession. We show that the explanatory power of key determinants is reduced in the model without regimes (single regime model). It is also limited when we condition on the states of the economic cycle or the announcement period, but improves when we condition on the credit spread regimes.

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

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

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

3.2 Regimes in credit spreads

Time series of credit spreads undergo successive falling and rising episodes over time. These episodes can be observed in changes in the level and/or the volatility of credit spreads, especially around an economic recession. A striking example is shown in Figure 2.1. 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 2.1 here]

Across ratings and maturities, the credit spread movements exhibit at least two different regimes in terms of sudden changes in their level and/or volatility over the period considered. 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 2.1 indicates that, just before the 2001 recession, credit spreads shift from a low episode to a high episode. The high credit spread episode and the NBER economic cycle appear to start at almost the same time. However, the high episode in the credit cycle seems longer than the high episode in the economic cycle. If credit spreads are counter-cyclical (increasing in recessions and decreasing in expansions) then they should decrease when the recession ends. Dionne et al. (2008) use the sequential statistical t-test to test for breakpoints in the level of credit spreads over the period considered. They detect positive shifts a few months before the beginning of the 2001 recession (March 2001). They also detect other positive shifts after the end of the economic recession (November 2001). Negative shifts are not detected until mid-2003.

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

Moreover, Figure 2.1 shows that credit spreads shift from one to another episode gradually. This looks plausible since Duffee (1998) shows that yields on corporate bonds exhibit persistence and take about a year to adjust to innovations in the bond market. Since low grade bonds are closely related to market factors (Collin-Dufresne et al., 2001), they take less time to adjust to new market conditions at the beginning and the end of the cycle.

The question now is : why should we account for different regimes to address the credit spread puzzle ? Inspection of the credit spread behavior at the beginning and the end of the economic cycle reveals that credit spreads have their own cycle. Even though the recession lasts for few months, credit spreads are likely to remain in a period of contraction until the announcement of the recession end. Other credit spread determinants could also have their own dynamics and may enter periods of expansion before credit spreads do.[3] Therefore, these determinants may have opposite effects on credit spreads in the high credit spread regime relative to the low regime. In that case, the total effect over the whole sample period could be reduced in the single regime model. Moreover, credit spread variations in different regimes may be driven by different determinants. For this reason, we choose to model regimes in the credit spread dynamics endogenously using a switching regime model driven by a hidden Markov process.[4]

Recent studies apply regime models to capture state dependent movements in credit spreads. In these works, regimes in credit spreads are often driven from 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. On the other hand, empirical work using regime models for credit spreads usually assume two different regimes for different periods of observed data. For example, Davies (2004 and 2007) analyzes credit spread determinants using a Markov switching estimation technique assuming two volatility regimes. Alexan-

[3] 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.

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

der and Kaeck (2007) also use two-state Markov chains to analyze credit default swap determinants within distinct volatility regimes. Dionne et al. (2008) use the same period considered in this work and support the existence of two regimes. Therefore, we presume that two state dependent regimes are adequate to capture most of the variation in our credit spread series.

3.3 Credit spread determinants

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

3.3.1 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 algorithm.

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

The slope is seen as a predictor of future changes in short-term rates over the life of the long term bond. If an increase in the slope increases the expected future short rate, then by the same argument it should decrease credit spreads. A positively sloped yield curve is associated with improving economic activity. This may in turn increase a firm's growth rate and reduce its default probability and 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 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 et al. 2001 ; Chen, 2008). We use the Fama-French SMB and HML factors (available on the Kenneth French website). A larger spread would indicate a higher required risk premium, which should directly lead to a higher credit spread.

3.3.2 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.[5] We use Moody's monthly recovery rates

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

from Moody's Proprietary Default Database for all U.S. senior unsecured issuers as well as senior subordinated issuers over our sample period. Since Moody's looks at these prices one month after default, we take month $(t+1)$ release to measure month t recovery rates.[6] Following Altman et al. (2001), we also include month $(t+2)$ recovery rates as a measure of the expected rates for both seniority classes.

3.3.3 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 existing empirical studies typically use transaction volume and/or measures related to the bond characteristics such as coupon, size, age, and duration. Measures related to bond characteristics are typically either constant or deterministic and may not capture the stochastic variation of liquidity. Amihud (2002) suggests more direct measures of liquidity involving intra-daily transaction prices and trade volumes.[7]

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. Therefore, we use daily transaction prices available on the National Association of Insurance Commissioners (NAIC) database rather than intra-daily prices from TRACE because data in the latter source start in 2002 and do not cover our sample period. We construct liquidity measures

[6] 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.

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

based on the price impact of trades and on the trading frequencies.

Liquidity measures based on price impact of trades

The Amihud illiquidity measure This measure is defined as the average ratio of the daily absolute return to the dollar daily trading volume (in million dollars). This ratio characterizes the daily price impact of the order flow, i.e., the price change per dollar of daily trading volume (Amihud, 2002). Instead of using individual bonds, we use individual portfolio of bonds grouped by rating class (AA, A, BBB, and BB) and maturity ranges (0-5 ; 5-10 ; 10+). This ensures sufficient daily prices to compute the Amihud monthly measures.[8] For each portfolio i, at month t :

$$Amihud_t^i = \frac{1}{N-1}\sum_{j=1}^{N-1}\frac{1}{Q_{j,t}^i}\frac{\left|P_{j,t}^i - P_{j-1,t}^i\right|}{P_{j-1,t}^i}, \tag{3.1}$$

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

$$\mathrm{mod}\, Amihud_t^i = \sqrt{Amihud_t^i} \tag{3.2}$$

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

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

t :

$$Range_t^i = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{Q_{j,t}^i}\frac{\max P_{j,t}^i - \min P_{j,t}^i}{\overline{P}_{j,t}^i} \tag{3.3}$$

where N is the number of days within the month t, $\max P_{j,t}^i$ (in \$ per \$100 par) is the maximum daily transaction price of portfolio i, $\min P_{j,t}^i$ (in \$ per \$100 par) is the minimum daily transaction price of portfolio i, $\overline{P}_{j,t}^i$ (in \$ per \$100 par) is the daily average price of portfolio i and $Q_{j,t}^i$ (in \$ million) the daily transaction volume of portfolio i.[9] The range is an intuitive measure to assess the volatility impact as in Downing et al. (2005). It should reflect the market depth and determine how much the volatility in the price is caused by a given trade volume. Larger values suggest the prevalence of illiquid bonds.

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

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

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 :

- 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 2.1 summarizes all the variables considered with examples 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. Following Collin-Dufresne et al. (2001) we include the levels in the Fama French factors.

[Insert Table 2.1 here]

3.4 Corporate bond data

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

Our sample is restricted to fixed-rate U.S. dollar bonds in the industrial sector. We exclude bonds with embedded options such as callable, putable or convertible bonds. We also exclude bonds with remaining time-to-maturity below 1 year. With very short maturities, small price measurement errors lead to large yield deviations, making credit spread estimates noisy. Bonds with more than 15 years of maturity are discarded because the swap rates that we use as risk-free rates have maturities below 15 years. Lastly, we exclude bonds with over-allotment options, asset-backed and credit enhancement features and bonds associated with a pledge security. We include all bonds whose average Moody's credit rating lies between AA and BB. AAA credit spreads are not considered because they are 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 anomalies are also found in Campbell and Taksler (2003) using the same database. To measure liquidity, we have constructed monthly factors from daily values. This requires at least three transactions to occur in the same day unless the value of the daily measure is missing for that day. Since B-rated bonds do not have sufficient daily values, they have also been excluded.

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

For the period ranging from 1994 to 2004, we analyze 651 issuers with 2,860 outstanding issues in the industrial sector corresponding to 85,764 different trades. Since insurance companies generally trade high quality bonds, most of the trades in our sample are made with A and BBB rated bonds, which account for 40.59% and 38.45% of total trades respectively. On average, bonds included in our sample are recently issued bonds with an age of 4.3 years, a remaining time-to-maturity of 6.7 years and a duration of 5.6 years. Table 2.2 reports summary statistics.

[Insert Table 2.2 here]

3.5 Credit spread curves

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

$$\begin{aligned} R(t,T) \quad &= \quad \beta_{0t} + \beta_{1t}\left[\frac{1-\exp(-\frac{T}{\tau_{1t}})}{\frac{T}{\tau_{1t}}}\right] + \beta_{2t}\left[\frac{1-\exp(-\frac{T}{\tau_{1t}})}{\frac{T}{\tau_{1t}}} - \exp(-\frac{T}{\tau_{1t}})\right] \\ &\quad +\beta_{3t}\left[\frac{1-\exp(-\frac{T}{\tau_{2t}})}{\frac{T}{\tau_{2t}}} - \exp(-\frac{T}{\tau_{2t}})\right] + \varepsilon_{t,j}, \end{aligned} \tag{3.4}$$

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

$$\widehat{\Omega}_t = \arg\min_{\Omega_t} \sum_{i=1}^{N_t} w_i^2 \left(P_{it}^{NS} - P_{it}\right)^2, \qquad w_i = \frac{1/D_i}{\sum_{i=1}^{N} 1/D_i}, \tag{3.5}$$

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

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

3.6 Switching regime model

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

$$y_t/s_t \sim N\left(\mu_{s_t}, \sigma_{s_t}\right), \qquad s_t = 1, 2. \tag{3.6}$$

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

$$p(s_t = j|s_{t-1} = i) = p_{ij}, \qquad i = 1,2;\; j = 1,2. \tag{3.7}$$

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

$$p(y_t|s_t;\theta) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} \exp\left(\frac{-\left(y_t - \mu_{s_t}\right)^2}{2\sigma_{s_t}^2}\right),\; s_t = 1,2. \tag{3.8}$$

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 :

$$\begin{aligned} \zeta(\theta) &= \log p(y_1, ..., y_T; \theta) - \left(\nu\mu_1^2\right)/(2\sigma_1^2) - (\nu\mu_2^2)/(2\sigma_2^2) \\ &\quad -\alpha \log \sigma_1^2 - \alpha \log \sigma_2^2 - \beta/\sigma_1^2 - \beta/\sigma_2^2, \end{aligned} \tag{3.9}$$

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

$$\widehat{\mu}_j = \frac{\sum_{t=1}^{T} y_t p(s_t = j|y_1, ..., y_T; \widehat{\theta})}{\nu + \sum_{t=1}^{T} p(s_t = j|y_1, ..., y_T; \widehat{\theta})} \tag{3.10}$$

$$\begin{aligned}\widehat{\sigma}_j^2 \quad &= \quad \frac{1}{\alpha + 1/2 \sum_{t=1}^{T} p(s_t = j|y_1, ..., y_T; \widehat{\theta})} \times \\ &\left(\beta + 1/2 \sum_{t=1}^{T} \left(y_t - \widehat{\mu}_j \right)^2 p(s_t = j|y_1, ..., y_T; \widehat{\theta}) + (1/2)\nu \widehat{\mu}_j^2 \right).\end{aligned} \tag{3.11}$$

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

$$\widehat{p}_{11} = \frac{\sum_{t=2}^{T} p(s_t = 1, s_{t-1} = 1|y_1, ..., y_T; \widehat{\theta})}{\sum_{t=2}^{T} p(s_{t-1} = 1|y_1, ..., y_T; \widehat{\theta}) + \widehat{\rho} - p(s_1 = 1|y_1, ..., y_T; \widehat{\theta})}, \tag{3.12}$$

$$\widehat{p}_{22} = \frac{\sum_{t=2}^{T} p(s_t = 2, s_{t-1} = 2|y_1, ..., y_T; \widehat{\theta})}{\sum_{t=2}^{T} p(s_{t-1} = 2|y_1, ..., y_T; \widehat{\theta}) - \widehat{\rho} + p(s_1 = 1|y_1, ..., y_T; \widehat{\theta})}, \tag{3.13}$$

where $\widehat{\rho}$ in Equations (2.12) and (2.13) represents the unconditional probability that the first observation came from regime 1 :

$$\widehat{\rho} = \frac{(1 - \widehat{p}_{22})}{(1 - \widehat{p}_{11}) + (1 - \widehat{p}_{22})}. \tag{3.14}$$

The model parameters are estimated using the EM principle of Dempster, Laird, and Rubin (1977).[10] 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 the observed data y_t. Calculation of sample statistics of Ordinary Least Squares (OLS) regressions on the weighted data then generates

[10] 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).

new estimates of the parameter θ. These new estimates are then used to recalculate the smoothed probabilities, and the data are re-weighted with the new probabilities. Each calculation of probabilities and re-weighing the data are shown to increase the value of the likelihood function. The process is repeated until a fixed point for θ is found, which will then be the maximum likelihood estimate.

3.7 Single regime and regime-based models

We refer to the *single regime model* (Model 1) as the model that does not include a 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 :

$$\text{Model 1 :} \qquad \Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \varepsilon^1_{t,i,m}, \tag{3.15}$$

where $\beta^1_{0,i,m}$ and $\beta^1_{1,i,m}$ denote, respectively, the level and the slope of the regression line. Specifically, $\beta^1_{1,i,m}$ represents the 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.

$$\text{Model 1E} \quad : \quad \Delta Y_{t,i,m} = \beta^{1E}_{0,i,m} + \Delta X^{1E}_{t,i,m}\beta^{1E}_{1,i,m} + \beta^{1E}_{2,i,m} \times regime^{E}_{t,i,m} + \varepsilon^{1E}_{t,i,m} \tag{3.16}$$

$$\text{Model 1A} \quad : \quad \Delta Y_{t,i,m} = \beta^{1A}_{0,i,m} + \Delta X^{1A}_{t,i,m}\beta^{1A}_{1,i,m} + \beta^{1A}_{2,i,m} \times regime^{A}_{t,i,m} + \varepsilon^{1A}_{t,i,m} \tag{3.17}$$

$$\text{Model 1C} \quad : \quad \Delta Y_{t,i,m} = \beta^{1C}_{0,i,m} + \Delta X^{1C}_{t,i,m}\beta^{1C}_{1,i,m} + \beta^{1C}_{2,i,m} \times regime^{C}_{t,i,m} + \varepsilon^{1C}_{t,i,m} \tag{3.18}$$

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 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), then, specify the following dynamics for credit spread changes :

$$\text{Model 2E :} \quad \Delta Y_{t,i,m} = \gamma_{0,i,m}^{2E} + \Delta X_{t,i,m}^{2E} \gamma_{1,i,m}^{2E} + \gamma_{2,i,m}^{2E} \times regime_{t,i,m}^{E} + \Delta X_{t,i,m}^{2E} \gamma_{3,i,m}^{2E} \times regime_{t,i,m}^{2E} + \eta_{t,i,m}^{2E}, \tag{3.19}$$

$$\text{Model 2A :} \quad \Delta Y_{t,i,m} = \gamma_{0,i,m}^{2A} + \Delta X_{t,i,m}^{2A} \gamma_{1,i,m}^{2A} + \gamma_{2,i,m}^{2A} \times regime_{t,i,m}^{A} + \Delta X_{t,i,m}^{2A} \gamma_{3,i,m}^{2A} \times regime_{t,i,m}^{2A} + \eta_{t,i,m}^{2A}, \tag{3.20}$$

$$\text{Model 2C :} \quad \Delta Y_{t,i,m} = \gamma_{0,i,m}^{2C} + \Delta X_{t,i,m}^{2C} \gamma_{1,i,m}^{2C} + \gamma_{2,i,m}^{2C} \times regime_{t,i,m}^{C} + \Delta X_{t,i,m}^{2C} \gamma_{3,i,m}^{2C} \times regime_{t,i,m}^{2C} + \eta_{t,i,m}^{2C}, \tag{3.21}$$

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

$$\begin{cases} low - regime : \Delta Y_{t,i,m} = \widehat{\gamma}_{0,i,m}^{j} + \Delta X_{t,i,m}^{j} \widehat{\gamma}_{1,i,m}^{j} \\ high - regime : \Delta Y_{t,i,m} = \left(\widehat{\gamma}_{0,i,m}^{j} + \widehat{\gamma}_{2,i,m}^{j} \right) + \Delta X_{t,i,m}^{j} \left(\widehat{\gamma}_{1,i,m}^{j} + \widehat{\gamma}_{3,i,m}^{j} \right). \end{cases} \tag{3.22}$$

The parameters $\widehat{\gamma}_{0,i,m}^{j}$ and $\widehat{\gamma}_{1,i,m}^{j}$ denote, respectively, the estimated level and slope of the regression line in the low regime. The parameters $\left(\widehat{\gamma}_{0,i,m}^{j} + \widehat{\gamma}_{2,i,m}^{j} \right)$ and $\left(\widehat{\gamma}_{1,i,m}^{j} + \widehat{\gamma}_{3,i,m}^{j} \right)$ 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 same procedure for the selection of explanatory variables. We start with the same set of initial variable candidates. Then, we select the best explanatory variables set for each model by minimizing the AIC selection criteria. Specifically, for the variables to be included in a model, we proceed as follows :

1. We run univariate regressions on all factors described earlier and determine which variables are statistically significant at 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 additional variables, we proceed with the backward variable selection.

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

3.8 Results

3.8.1 Observed credit spreads

We obtain credit spread curves for AA-rated to BB-rated bonds with maturities ranging from 1 to 15 years. Figure 2.1 plots these results and Table 2.3 presents summary statistics.

[Insert Table 2.3 here]

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

3.8.2 High and low credit spread episodes

The switching regime model is estimated for each credit spread series separately, with respect to the rating and to the maturity. The parameter estimates $\widehat{\theta}$ are given in Table 2.4.

[Insert Table 2.4 here]

The mean of credit spreads is higher for lower ratings. For investment grade bonds (AA to BBB), the credit spread mean, in both regimes, increases with maturity – consistent with an upward sloping credit spread curve. For speculative grade bonds, the credit spread mean increases until the medium term and then decreases in the long term – consistent with a humped credit spread curve. The credit spread variance, in both regimes, increases as credit ratings 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 least at the 5% level (Table 2.5). The only exception is found with the variance of the 5-year BB spreads. We also find – results are not reported here – that the unconditional mean and variance of credit spreads in the single regime model are statistically different from those in the low and high regimes.

[Insert Table 2.5 here]

Figure 2.2 plots times series of credit spreads along with the smoothed probabilities $p(s_t = 1|y_1, ..., y_T; \widehat{\theta})$ indicating the months when the process was in the high regime. The figure also shows that for all ratings and maturities the probability that the credit spread is in the high regime at the beginning of the NBER recession (shaded region) is higher than 0.5. 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 2.2 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 are likely to persist in the high regime at least until the announcement date of July 2003. We also notice that high grade spreads (AA and A) do 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.

3.8.3 Comparative explanatory powers of models

The main result in Collin-Dufresne et al. (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 Equations 2.15 to 2.21 reveals 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.

[Insert Table 2.6]

Our results show that the introduction of the regimes in the credit spread dynamics (Model 2C) enhances the explanatory power of 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. Notice that all these models do not include interaction effects but may 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 by conditioning on the states of the economic cycle (Model 2E) we cannot 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 good as Model 2C. It appears then that 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 2.6 reports the adjusted R-squared for the seven models considered here. Relative to Model 1, Model 2A and Model 2E, Model 2C has the highest adjusted R-squared. However, relative to Model 1, Model 1E, Model 1A, and Model 1C do not lead to a significant improvement. More interestingly, Model 2C always has the minimum value of AIC along with the highest explanatory power, which reaches on average 60% across all ratings. Detailed results for each of these models are reported in Tables 2.7 to 2.10. 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.[11]

[Insert Table 2.7 to Table 2.10]

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 2.21. In this case, Model 2C and the obtained single regime model are nested and can be compared using the Likelihood Ratio Test (LRT). Table 2.11 shows that, for all ratings, the LRT favors Model 2C. Model

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

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 2.21. In both cases, the Chi2 statistic is always significant at least at the 1% level favoring Model 2C. In addition, when we compare both single regime models obtained from Equation 2.21 (i. e., $\gamma^{2C}_{2,i,m} = 0$ and $\gamma^{2C}_{3,i,m} = 0$ against $\gamma^{2C}_{2,i,m} \neq 0$ and $\gamma^{2C}_{3,i,m} = 0$) we find that the addition of the dummy variable for the regimes does not improve the single regime model. Hence, the enhanced explanatory power in Model 2C is driven by the interaction effects. Moreover, omitting interaction effects decreases the adjusted R-squared by roughly 10% for A spreads to up to 30% for AA spreads (Table 2.12). Table 2.12 also shows that the addition of the dummy variable for the regimes yields only a marginal positive effect compared with the obtained single regime model. Note that this result holds only for AA and A spreads.

[Insert Table 2.11 and Table 2.12 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 2.15.

$$\begin{aligned} \Delta Y_{t,i,m} &= \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} \\ &\quad + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^{1C}_{t,i,m}, \end{aligned} \tag{3.23}$$

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 variables in Model 1 with the regimes in the credit cycle. Model 1 and the regime-based model obtained are then nested. Table 2.13 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 2.14.

[Insert Table 2.13 and Table 2.14 here]

Then, we repeat the analysis by conditioning on the states of the economic cycle. The obtained regime-base model is given by Equation 2.24.

$$\begin{aligned}\Delta Y_{t,i,m} &= \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^E_{t,i,m} \\ &\quad + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^E_{t,i,m} + \mu^{1E}_{t,i,m}, \end{aligned} \tag{3.24}$$

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 favors always the single regime model ($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$ relative to $\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$ and $\beta^1_{2,i,m} \neq 0$ and $\beta^1_{3,i,m} = 0$ in Equation 2.24) 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. Since all models include different sets of explanatory variables based on model selection criteria we perform two different tests.[12] 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 2.21) 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 2.21) 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 2.15. We also find that most of the interaction coefficients are statistically significant with $regime^C_{t,i,m}$

[12] Notice that 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.

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 being 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 only rejects the null for AA and BBB ratings (Table 2.16).

[Insert Table 2.15 and Table 2.16 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 nonnested 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 are better than Model 2C. Both tests favor Model 2C and are statistically significant at the 5% level or higher. One exception applies for 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 2.17).

[Insert Table 2.17 here]

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

3.8.4 Determinants in different regimes

Our results in the single regime model (Model 1) are consistent with the existing literature (Table 2.7 to Table 2.10). The level, the slope, the GDP, as well as the Small-Minus-Big and the SML factors are shown to be statistically significant across different ratings.[13] We enhance the explanatory power of Model 1 by introducing new measures of liquidity which are shown to be very significant across all ratings. The significance level is even stronger for lower grade bonds, as the selected liquidity measures are based on transaction price movements in the bond market. These liquidity measures include the range, median price, price volatility, Amihud measure and turnover. We also find that the age has a non negligible effect for high grade bonds. All the variables have the predicted sign, except the CMT slope, which has a positive effect on credit spreads.[14]

Previous results show that Model 1 has limited explanatory power because it assumes that the explanatory variables have the same effect on credit spreads over distinct regimes. We also show that Model 2C is our best performing model (Table 2.11 to Table 2.17). Thus, we base our comments on the results obtained with Model 2C. Across ratings, the CMT level and slope are shown to be statistically significant in both regimes, while the effect of the slope is stronger in the high regime. Like the slope, the liquidity variables are found to be significant in both regimes but their significance is greater in the high regime, especially for low grade bonds. The age and the GDP are important only for AA and A spreads. Their contribution, while marginal, is stronger in the low regime. The SMB and the SML also make a marginal contribution in the high regime.

We now focus on the coefficient signs of different variables in different regimes. In particular, most of the signs in the low regime are inverted in the high regime, thus weakening their total effect in the single regime model. We summarize these signs in Table 2.18. As can be seen in this table, the signs of the explanatory variables in the single regime model

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

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

(Model 1) are, in most cases, the same as those in the low regime for Model 2C. However, except for the variables that are found to be closely related to the behavior of credit spreads (like the age, the CMT slope, and the realized default probability), all the other variables have an inverted sign in the high regime. These variables include most of the market factors and liquidity factors as well as the recovery rate. All these variables are likely to react to macroeconomic conditions well before credit spreads do. Actually, 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 due to the late NBER announcement, these variables are expanding well before the end of the high credit spread regime. It follows that after the economic recession, the sign effects are inverted especially for spreads with high grades and long maturities. These spreads are also slower to adjust to any new economic state. Model 2E fails to capture these inverted signs. That is why the explanatory power of the single regime model does not improve when we condition on the economic cycle. On the other hand, Model 2A does better than Model 2E because it captures most of the sign patterns. However, Model 2A does not capture the effective recession since the recession is always announced later on. Therefore, Model 2C performs best since it captures both the economic recession and the announcement period. The regimes in Model 2C also take into account the different patterns accross different ratings and maturities while the economic cycle and the announcement period are fixed across all spreads. As shown in Figure 2.2, the high regime in low grade bonds starts before the economic recession and ends also before the high regime of high grade bonds.

[Insert Table 2.18 here]

To better explain the pattern of the inverted signs for some variables in the high regime, we discuss the case of the CMT level. Across all ratings, Table 2.18 shows that the level has a negative sign in the low regime. However, in the high regime, this coefficient turns out to be positive and statistically significant for AA and A spreads. For example, for A spreads, the coefficient of the level is -0.460 in the low regime and becomes +0.147 in the high regime. Both coefficients are significant at least at the 5% level. Figure 2.3 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. As a matter of fact, the correlation between both series ouside the high regime is 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 found positive. Inside the shaded region (2001 recession), credit spreads are increasing and risk-free rates are decreasing. Then, between the end of the recession (November 2001) and the announcement of the end (July 2003), credit spreads and risk-free rates are often moving on the same direction. After the announcement of the recession end, the negative relation is clearly re-established. When the whole sample period contains one or more recessions, then the total effect of risk-free rates on credit spreads can be dominated by the high regime and the relation appears positive overall. 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 found positive. The same pattern for the CMT level is observed for the VIX, the SMB, the SML, the recovery rate, and the illiquidity factors based on bond transaction prices.

[Insert Figure 2.3 here]

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

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

For a last check, we analyzed each set of factors (market, default, liquidity) separately (results available upon request). This was done to test whether the inverted signs in the high regime are due solely to the correlation between different sets of factors considered in Model 2C. Variables included in each set of factors are also selected based on the lowest AIC. The results obtained with each set of factors – across ratings – are similar to those obtained with Model 2C. Thus, we still observe the sign inversions in the high regime. Further, for each factor model we contrast the single regime model to the regime-based model. Based on the LRT, we still favor the regime-based models which are similar to Model 2C but include market, liquidity or default factors (Table 2.19).

[Insert Table 2.19 here]

3.9 Conclusion

The main contribution of this study is to examine the impact of modeling the credit cycle endogenously on credit spread determinants. The credit cycle is derived from the switching regime structure for credit spreads. The obtained credit cycle and the NBER economic cycle exhibit different patterns.

Even though credit spreads are counter-cyclical, their high level following a systematic shock in the economy is triggered by an announcement effect and a persistence effect. These two effects produce a credit cycle that is much longer than the economic cycle. In particular, the NBER waits for a certain time before announcing the beginning and the end of a recession. It follows that, following the GDP, many credit spread determinants may adjust to the period of expansion well before credit spreads do. In the meantime, the coefficient signs of several determinants are often inverted in the high regime. These changes in the coefficient signs are hidden in the single regime model leading to limited total effects and thus reducing the explanatory power of the model. Our results thus offer new insights into the existing models in the credit risk literature using regime switches derived from macroeconomic fundamentals.

Our results suggest that by conditioning on credit spread regimes we enhance the explanatory power of the single regime model. Moreover, we show that the single regime model cannot be improved by conditioning on the states of the economic cycle or on the announcement period 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.

Moreover, our results show that different factors have different contributions in distinct credit spread regimes. This further suggests that the regime-based model also enhances the explanatory power of key determinants. The factors considered generate up to 60% of the variation in credit spread changes. Finally, our study is a further step to help solve the credit spread puzzle documented in recent research.

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Tableau 3.I: Explanatory variables considered in this study.

Variable	Notation	Description	Sign[†]	Example of related studies
		Panel A. Market factors		
Term structure level	$\Delta level$	Monthly series of 2-year CMT rates	-	Huang and Kong (2003)
Term structure slope	$\Delta slope$	Monthly series of 10-year CMT rates minus 2-year CMT rates	-	Huang and Kong (2003)
GDP	Δgdp	GDP growth rate	-	Altman et al. (2001)
Equity market return	Δsp	S&P500 index return	-	Huang and Kong (2003)
Equity market volatility	Δvix	VIX index implied return volatility	+	Campbell et al. (2003)
Fama-French Factors	hml	Fama-French High-Minus-Low factor	-	Collin-Dufresne et al. (2001)
	smb	Fama-French Small-Minus-Big factor	-	Collin-Dufresne et al. (2001)
Stock market index	Δsml	S&P600 Small-Cap	-	This paper
		Panel B. Default factors		
Realized default probability	$\Delta dpall$	Moody's trailing 12-month default rates of all U.S. corporate issuers	+	Huang and Kong (2003)
	$\Delta dpspec$	Moody's trailing 12-month default rates of U.S. speculative grade issuers	+	Huang and Kong (2003)
Realized recovery rates	$\Delta recsus$	Moody's monthly recovery rates for Senior Unsecured bonds	-	Altman et al. (2005)
	$\Delta recsub$	Moody's monthly recovery rates for Senior Subordinated bonds	-	Altman et al. (2005)
Expected recovery rates	$\Delta \exp recsus$	Moody's month (t+2) recovery rates for Senior Unsecured bonds	-	Altman et al. (2005)
	$\Delta \exp recsub$	Moody's month (t+2) recovery rates for Senior Subordinated bonds	-	Altman et al. (2005)
		Panel C. Liquidity factors		
Traditional bond measures	Δage	Bond's age	+	Han and Zhou (2006)
	Δcp	Bond's coupon	+	Han and Zhou (2006)
	$\Delta size$	Bond's size	+	Han and Zhou (2006)
	Δvol	Bond's volume	+	Chakravarty and Sarkar (1999)
Price impact of trades	$\Delta amih$	Amihud	+	Han and Zhou (2006)
	$\Delta mamih$	Modified Amihud	+	Han and Zhou (2006)
	$\Delta range$	Range	+	Han and Zhou (2006)
	$\Delta medp$	Median price	-	This paper
	$\Delta sigp$	Price volatility	+	This paper
Trading frequencies	$\Delta turn$	Turnover	-	Han and Zhou (2006)
	$\Delta freqall$	Monthly transaction frequency of all trades	-	Goldstein et al. (2006)
	$\Delta frepuni$	Monthly transaction frequency of a unique trade	-	Han and Zhou (2006)

[†] Sign refers to the coefficient signs obtained in previous studies using a single regime model.

Tableau 3.II: Summary statistics for U.S. corporate bonds.

The coupon is the bond's annual coupon payment. The age is the number of years since the issue date. The maturity is the number of years until the maturity date, upon issuance. The duration is the modified Macaulay duration in years. The size is the total dollar amount issued. The volume is the total dollar amount traded. Issues 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%				

Tableau 3.III: Summary statistics on credit spreads.

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

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

Tableau 3.IV: 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

Tableau 3.V: Confidence intervals for parameters of the high and low regimes.

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

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

Tableau 3.VI: 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 along with the Akaike Information Criteria (AIC) obtained for models described in Equations 2.15 to 2.21.

		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	0.561	0.662
	VIF	1.23	1.28	1.27	1.28	3.22	4.10	8.69
	AIC	-2.922	-2.930	-2.907	-2.906	-2.775	-3.015	-3.213
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

Tableau 3.VII: Determinants of credit spread changes within different models (Rating = AA).

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, variable coefficients in the low regime are given by $\widehat{\gamma}^j_{1,i,m}$ in Equation 2.22, while coefficients in the high regime are given by $(\widehat{\gamma}^j_{1,i,m} + \widehat{\gamma}^j_{3,i,m})$. 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 Variance Inflation Factor (VIF), which should be below the critical level of 10. ***, **, * indicate significance level at 1%, 5%, and 10%, respectively.

	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**
Δsmb_{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**
$\Delta smb_{t-2} \times regime_t$						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

Tableau 3.VIII: Determinants of credit spread changes within different models (Rating = A).

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, variable coefficients in the low regime are given by $\widehat{\gamma}^{j}_{1,i,m}$ in Equation 2.22, while coefficients in the high regime are given by $(\widehat{\gamma}^{j}_{1,i,m} + \widehat{\gamma}^{j}_{3,i,m})$. 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 Variance Inflation Factor (VIF), which should be below the critical level of 10. ***, **, * indicate significance level at 1%, 5%, and 10%, respectively.

	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
$\Delta dpall_t \times regime_t$							
$\Delta age_t \times regime_t$						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		
$Adj R2$	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

Tableau 3.IX: Determinants of credit spread changes within different models (Rating = BBB).

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, variable coefficients in the low regime are given by $\widehat{\gamma}^{j}_{1,i,m}$ in Equation 2.22, while coefficients in the high regime are given by $(\widehat{\gamma}^{j}_{1,i,m} + \widehat{\gamma}^{j}_{3,i,m})$. 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 Variance Inflation Factor (VIF), which should be below the critical level of 10. ***, **, * indicate significance level at 1%, 5%, and 10%, respecti-vely.

	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	0.042
$\Delta level_t$	-0.307***	-0.313***	-0.308***	-0.309***	-0.299***	-0.324***	-0.354***
$\Delta slope_t$	0.608***	0.549***	0.606***	0.606***	0.549***	0.392**	0.498**
$\Delta slope_{t-1}$							-0.374*
Δgdp_t	-0.022**	-0.017	-0.022**	-0.022**	-0.018	-0.029***	-0.025**
vix_{t-1}						0.008**	0.001
Δvix_{t-1}	0.007	0.006	0.007	0.007	0.007		0.004
Δvix_{t-3}	-0.008*	-0.008*	-0.008*	-0.008*	-0.009*	-0.003	0.010*
smb_{t-1}						-0.002	0.003
Δsml_{t-1}							-0.006*
Δdp_t	37.362*	31.261	39.518*	38.957*		7.851	33.03
$\Delta recsub_t$	0.002	0.003	0.002	0.002			0.001
$\Delta amih_t$	16.175***	16.303***	16.137***	16.154***	15.781***	15.620**	14.241
$\Delta amih_{t-2}$	10.125***	10.471***	10.094***	10.127***	9.262***		-5.404***
$\Delta range_{t-3}$	18.016***	19.370***	17.914***	17.975***	21.474**	21.517***	1.173
$\Delta medp_t$	-0.040***	-0.041***	-0.040***	-0.040***	-0.036**	-0.026	-0.045***
$\Delta sigp_t$	-0.016	-0.020*	-0.016	-0.016		-0.046***	
$\Delta sigp_{t-2}$							-0.058**
$\Delta turn_{t-2}$							-0.054**
$regime_t$		0.151	0.018	0.009	0.142	-0.017	-0.730**
$\Delta level_t \times regime_t$					-0.056	0.002	0.085
$\Delta slope_t \times regime_t$					-0.378	0.193	0.368
$\Delta slope_{t-1} \times regime_t$							0.627**
$\Delta gdp_t \times regime_t$					-0.038	-0.027	-0.02
$vix_{t-1} \times regime_t$						0.002	0.013
$\Delta vix_{t-1} \times regime_t$					0.012		0.025**
$\Delta vix_{t-3} \times regime_t$					0.01	-0.030***	-0.041***
$smb_{t-1} \times regime_t$						0.041**	0.021**
$\Delta sml_{t-1} \times regime_t$							0.017***
$\Delta dpall_t \times regime_t$						185.175***	19.345*
$\Delta recsub_t \times regime_t$							0.016***
$\Delta amih_t \times regime_t$					-20.896	-0.022	3.688
$\Delta amih_{t-2} \times regime_t$					66.822		10.783
$\Delta range_{t-3} \times regime_t$					-6.21	-5.401	24.554**
$\Delta medp_t \times regime_t$					0.022	-0.034	0.001
$\Delta sigp_t \times regime_t$						0.048**	
$\Delta sigp_{t-2} \times regime_t$							0.081***
$\Delta turn_{t-2} \times regime_t$							0.080***
$AdjR^2$	0.483	0.490	0.478	0.478	0.428	0.561	0.662
VIF	1.23	1.28	1.27	1.28	3.22	4.10	8.69
AIC	-2.922	-2.930	-2.907	-2.906	-2.775	-3.015	-3.213

Tableau 3.X: Determinants of credit spread changes within different models (Rating = BB).

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, variable coefficients in the low regime are given by $\widehat{\gamma}^{j}_{1,i,m}$ in Equation 2.22, while coefficients in the high regime are given by $(\widehat{\gamma}^{j}_{1,i,m} + \widehat{\gamma}^{j}_{3,i,m})$. 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 Variance Inflation Factor (VIF), which should be below the critical level of 10. ***, **, * indicate significance level at 1%, 5%, and 10%, respectively.

	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**
$\Delta gdp_t \times regime_t$							
$\Delta vix_{t-3} \times regime_t$					-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**	
$\Delta dpall_t \times regime_t$					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*
$\Delta sigp_t \times regime_t$					.0.029	-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

Tableau 3.XI: Likelihood Ratio Test for Model 2C against single regime models.

All the models evaluated here are derived from Equation 2.21, 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 2.21		
		($\gamma^{2C}_{2,i,m} \neq 0$, $\gamma^{2C}_{3,i,m} \neq 0$) 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)

Tableau 3.XII: Comparative adjusted R-squared relative to Model 2C.

Model 2C refers to the regime-based model in Equation 2.21. 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 2.21. 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 2.21.

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

Tableau 3.XIII: Likelihood Ratio Test for Model 1 against the regime-based model.

The regime-based model (Equation 2.23) is obtained by adding to Equation 2.15 a dummy variable for the regimes in the credit cycle ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$) as well as the terms of interactions ($\Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m}$).

$$\Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^{1C}_{t,i,m}, \quad (2.23)$$

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 2.23), we obtain Model 1 as described in Equation 2.15. In Column (3) we contrast Model 1 with the regime-based model ($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$ in Equation 2.23). 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 2.23	
		($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$) 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)

Tableau 3.XIV: 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 2.15 a dummy variable for the regimes in the credit cycle ($\beta^1_{2,i,m} \times regime^C_{t,i,m}$) as well as the terms of interactions ($\Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m}$) :

$$\Delta Y_{t,i,m} = \beta^1_{0,i,m} + \Delta X^1_{t,i,m}\beta^1_{1,i,m} + \beta^1_{2,i,m} \times regime^C_{t,i,m} + \Delta X^1_{t,i,m} \times \beta^1_{3,i,m} \times regime^C_{t,i,m} + \mu^{1C}_{t,i,m}, \quad (2.23)$$

Column (3) reports the adjusted R-squared for Model 1 which reduces to Equation 2.15 when ($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$ in Equation 2.23). 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 2.23		
	($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} \neq 0$)	($\beta^1_{2,i,m} = 0$, $\beta^1_{3,i,m} = 0$)	($\beta^1_{2,i,m} \neq 0$, $\beta^1_{3,i,m} = 0$)
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

Tableau 3.XV: 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 2.21. Column (2) reports the adjusted R-squared for Model 2C. Column (3) reports the adjusted R-squared for model in Equation 2.21 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 2.21 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	0.662	0.529	0.442
BB	0.537	0.383	0.344

Tableau 3.XVI: 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 2.21. 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 2.21 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 2.21 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)

Tableau 3.XVII: Comparing regime-based models.

We perform the J test and the Cox-type test for nonnested models. Model 2C is the regime-based model given by Equation 2.21. Model 2E is the regime-based model given by Equation 2.19. Model 2A is the regime based model given by Equation 2.20. 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. For the J test, t-stat (df) refers to the t-statistics along with the degrees of freedom into parenthesis.

		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)

Tableau 3.XVIII: Signs of exlanatory variables coefficients.

For each rating class, the first column report the coefficient signs of the explanatory variables of Model 1 (i.e., signs of $\beta^1_{1,i,m}$ in Equation 2.15). Then, the second and the third columns report the coefficient signs of the explanatory variables of Model 2C in the low regime (low) and the high regime (high), respectively (i.e., signs of $\gamma^{2C}_{1,i,m}$ and $(\gamma^{2C}_{1,i,m} + \gamma^{2C}_{3,i,m})$ in Equation 2.19, respectively.

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

Tableau 3.XIX: Likelihood Ratio Test for models with regimes vs. models without regimes.

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

Figure 3.I: 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.

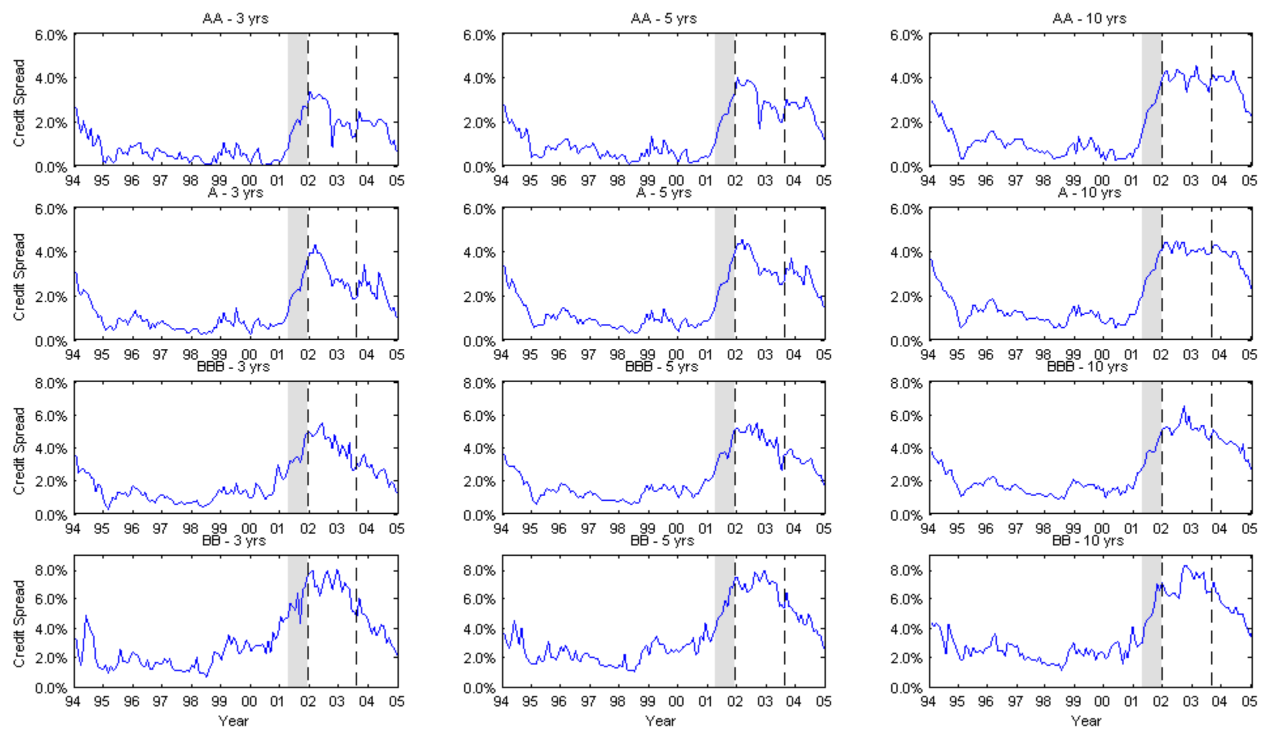


Figure 3.II: The smoothed probability of the high regime against credit spreads (1994-2004).

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.

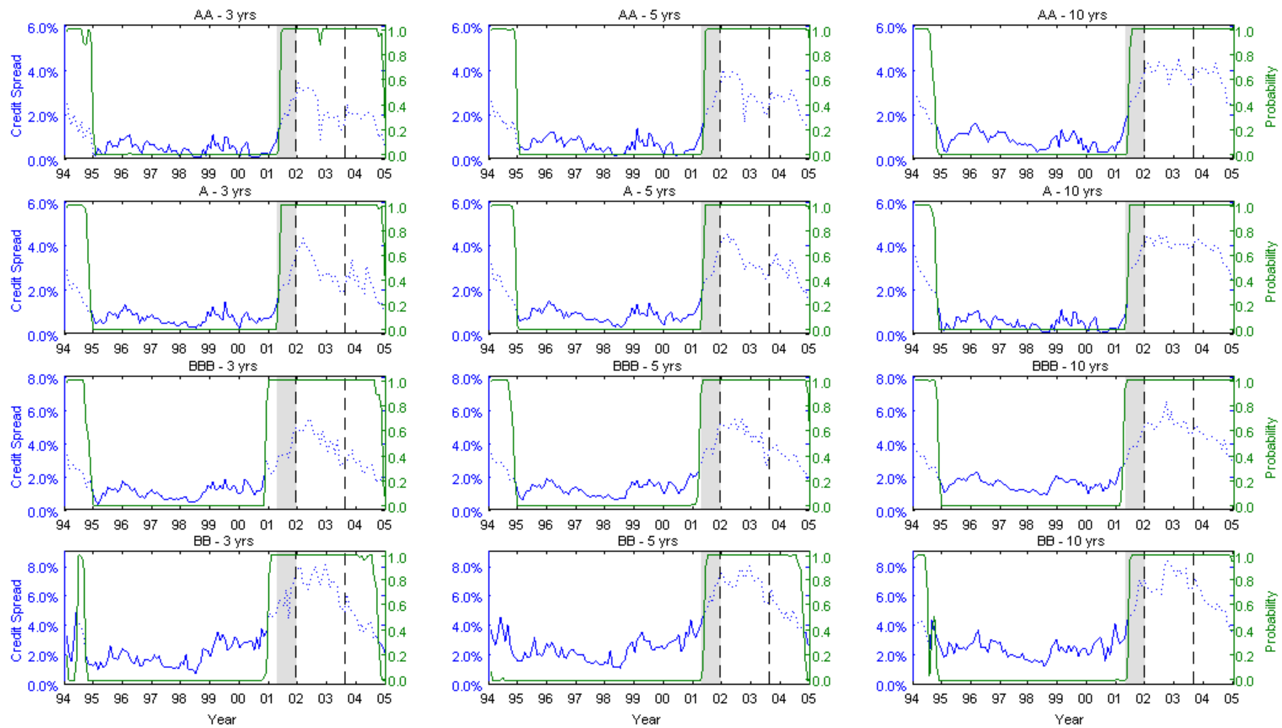
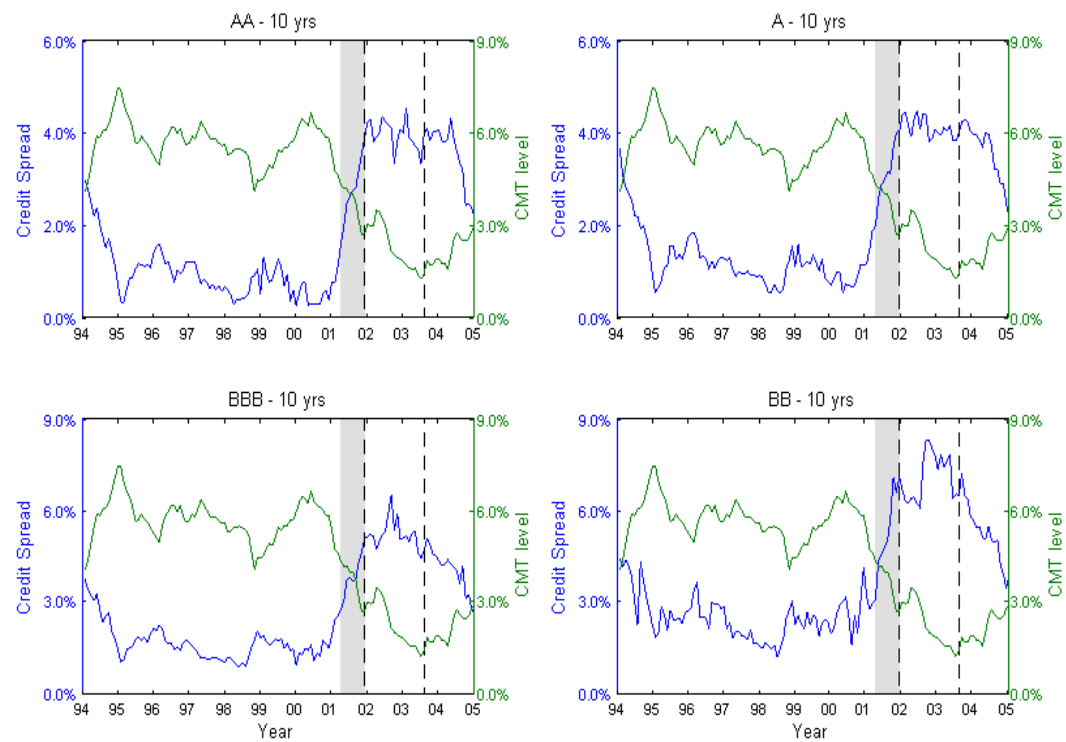


Figure 3.III: Observed credit spreads against the CMT level (1994-2004).

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 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.



Chapitre 4

The Credit Spread Puzzle : Past, Present, and Future

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Abstract

It is well-known that the large historical credit spreads cannot be explained using observed default history within a structural framework, and therein lies the credit spread puzzle. Many empirical works build on the predictions of the structural models in solving the credit spread puzzle. The review of the recent literature reveals significant improvements. In particular, many of them account for more realistic assumptions about the capital structure of the firm and default triggers. However, theoretical models remain limited by their estimation accuracy if more complex assumptions are added. For example, few models account explicitly for the role of macroeconomic conditions in triggering default or the tendency for firms to default in wave. Empirical works take on the task to test more complex assumptions. We survey and discuss the development of this literature. We also provide new insights, currently ignored in the literature, which may help solving the puzzle. Specifically, monetary policy actions are shown to control for the aggregate level of credit and liquidity in the economy. Thus, monetary cycle may constitute a part of the puzzle.

Keywords : Credit spread puzzle, structural models, literature review.

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4.1 Overview of the puzzle

Credit spreads are defined as the difference between yields on risky corporate bonds and yields on a benchmark for risk free assets traditionally measured by yields on Treasury bonds with the same maturities. Since corporate bonds may default at any time while Treasury bonds may not, credit spreads are originally thought to be entirely due to default risk. However, observed credit spreads tend to be larger than what would be implied by only default risk.

The evidence of such discrepancy between observed and theoretical predicted credit spreads originates from the early works of Jones, Mason and Rosenfeld (1984). They find that the standard structural model of Merton (1974) fails to match the observed yield spreads of investment grade bonds (i.e. bonds rated BBB or higher).[2] Subsequent works were, then, devoted to testing the performance of structural models of credit risk in valuing corporate debt. Eom, Helwege and Huang (2004) studied several structural models (those of Merton, 1974 ; Geske, 1977 ; Longstaff and Schwartz, 1995 ; Leland and Toft, 1996 ; and Collin-Dufresne and Goldstein, 2001) and found that these models can generate different predictions for credit spreads. Nonetheless, the results are generally poor and these models produce a significant estimation error that may overvalue or undervalue corporate bonds. Earlier, Huang and Huang (2003) document the same problem when they calibrate a different group of structural models (those of Longstaff and Schwartz, 1995 ; Leland and Toft, 1996 ; Anderson and Sundaresan, 1996 ; Anderson, Sundaresan, and Tychon, 1996 ; Mella-Barral and Perraudin, 1997 ; and Collin-Dufresne and Goldstein, 2001) to be consistent with data on historical default loss experience. They show that all these models produce quite similar credit spreads that fall well below historical averages once they are calibrated to the observed data. Delianedis and Geske (2001) and Amato and Remolona (2003) reach

[2] See next section for a review of structural models.

a similar conclusion using related calibration methodologies. Yet, the existing credit risk literature does not provide a consensus on how much of the observed corporate spreads over Treasury yields is due to default risk. This is known as the *credit spread puzzle*.

According to Longstaff, Mithal, and Neis, (2005) ; and Ericsson, Reneby, and Wang, (2006), Credit Default Swap (CDS) prices are a purer measure of default risk and corporate bond prices and accordingly the structural models may be more successful in fitting CDS prices. Thus, several empirical studies use structural models to fit CDS data. For example, Hull, Nelken, and White (2004) test the Merton model ; Predescu (2005) examine the Merton and the Black and Cox models ; and Chen, Fabozzi, Pan, and Sverdlove (2006) test the Merton, the Black and Cox, and the Longstaff and Schwartz models. Recently, Huang and Zhou (2008) consider a larger set of models (those of Merton, 1974 ; Black and Cox, 1976 ; Longstaff and Schwartz, 1995 ; Collin-Dufresne and Goldstein, 2001 ; and Huang and Huang, 2003). They find that while these models generate different predictions of CDS prices they all have difficulty to explain the observed term structure.

A common feature between structural models is to consider the default risk factor as the only component that explains the observed credit spreads. Even in this case, the structural model fails to provide reasonable prediction for the spreads between BBB-rated and AAA-rated bonds which should be due only to default risk. Huang and Huang (2003) reported a predicted BBB over AAA spread of 31 basis points while the observed spread was as much as 103 basis points. Many parallel and subsequent works shift their focus on other potential risk factors. Such factors include the tax difference between interest earned on corporate and Treasury bonds, special bond features, illiquidity of corporate bonds relative to Treasury bonds, and macro-factors to explain credit spreads (see for example Elton, Gruber, Agrawal, and Mann, 2001 ; Collin-Dufresne, Goldstein, and Martin, 2001 ; Delianedis and Geske, 2001 ; Houweling, Mentink, and Vorst, 2005 ; Driessen, 2005 ; and

Feldhutter and Lando, 2005).

The rest of the paper is organized as follows. Section 2 briefly reviews the structural models of credit risk. Section 3 reviews some calibration efforts within these models. Section 4 outlines the decomposition of credit spreads into default and nondefault factors. Section 5 focuses on the credit spread behavior and its relation with the puzzle. Section 6 concludes.

4.2 Structural models of credit risk

4.2.1 The Merton model

Since the original option pricing model of Black and Scholes (1973), corporate liabilities are viewed as combinations of simple option contracts. A generalization of this framework was provided by Merton (1974, 1977) and led to the development of the structural-form models for the pricing of risky corporate bonds.[3] The approach directly relates the value of the firm's assets and their volatilities to the event of default. It assumes that a firm defaults on all its liabilities when the value of its assets falls below a default threshold (typically related to the face value of the outstanding debt).[4] Typically, the firm value process V is assumed to be risk-neutrally lognormal :

$$\frac{dV_t}{V_t} = (r - \gamma)dt + \sigma_v dW_t^Q \tag{4.1}$$

where r is the constant short risk-free rate, γ is the constant cash payout rate, σ_v is the volatility of assets and W^Q is the Brownian motion under the risk neutral measure Q.

[3] The Merton model assumes that the value of the firm's assets is composed of equity E and debt (a zero-coupon bond) with face value D and maturity T. The firm's equity is viewed as a European call option on the asset value with maturity T and strike price D.

[4] If the European call option expires in-the-money, i.e. the value of the firm's assets exceeds the face value of the outstanding debt, the bondholders receive D and the equityholders receive the remaining assets of the firm. The firm defaults when the European call option expires out-of-the-money, i.e. the value of the firm's assets falls below the face value of the outstanding debt. In this case, the bondholders are entitled to the remaining assets of the firm and nothing goes to the equityholders.

Within this framework, the default occurs when $V_T < D$. So, the default event becomes foreseeable assuming continuous observation of the firm value process as well as the volatility of assets. Further, to estimate this model, one needs to transform the debt structure of the firm into a zero-coupon bond with maturity T and face value D.

Using the structural setup, the risk premium H on a risky zero-coupon bond (i.e. credit spread) can be expressed as follows :

$$H = -\frac{1}{T-t} * \ln\left(\frac{1}{d}\Phi(h_1) + \Phi(h_2)\right) \tag{4.2}$$

with

$$d = De^{-r(T-t)}/V$$

and

$$h_1 = -\frac{\frac{1}{2}\sigma_v^2(T-t) - \ln(d)}{\sigma_v\sqrt{T-t}}$$

$$h_2 = -\frac{\frac{1}{2}\sigma_v^2(T-t) + \ln(d)}{\sigma_v\sqrt{T-t}}$$

where $H = R - r$ designates the spread between the yield to maturity on the risky debt (R) and the risk-free rate (r), provided the firm does not default. The parameter.D is the face value of the debt, V is the current value of the firm, $(T-t)$ is the time to maturity of the debt, σ_v is the volatility of assets, and Φ is the distribution function of a standard normal random variable.

Merton shows that the model setup leads to diffrent shapes for the term structure of credit spreads depending on the value of d. In particular, when $d \geq 1$, the term structure of credit spreads is downward sloping and when $d < 1$, it is first upward sloping then downward sloping leading to a hump shaped curve. Lee (1981) and Pitts and Selby (1983).re-examined this setup and correct for model inaccuracies to refine the graphical presentation for the term structure of credit spreads. Sarig and Warga (1989) demonstrates that the Merton model leads to a humped and downward sloping curves for bonds with low credit quality. Later, Helwege and Turner (1999) prove that the term structure of credit spreads, for all ratings, should be upward sloping.

Default models based on the structural-form setting tend to differ on how they specify the default threshold. When the default threshold is fixed exogenously as in the original Merton model, it acts as a safety covenant to protect bondholders (i.e. bondholders can force default if certain conditions are met).[5] When the default threshold is fixed endogenously, the equityholders may choose to optimally liquidate the firm at the expense of bondholders. Even when the value of the firm's assets falls below the required debt payments, equityholders can avoid default as long as they are willing to raise funds by selling new equity. In this case, the default threshold is set much lower than the face value of the debt.[6]

4.2.2 Extensions of the Merton model

The structural model has been for a long time criticized for its simplistic underlying assumptions which prevent it from generating credit spreads that match historical experiences. In order to reconcile many realistic facts about the capital structure of the firm, the dynamics of interest rates, default triggers and default mechanisms, the structural model has been extended in many ways. However, there is a big challenge between realistic assumptions and ease of implementation. Thus, all extensions modify the original Merton

[5] Examples of studies assuming an exogenous default threshold are Black and Cox (1976), Ingersoll (1977), Brennan and Schwartz (1980), Kim, Ramaswamy and Sundaresan (1993), Longstaff and Schwartz (1995), Duffie and Lando (2001), and Collin-Dufresne and Goldstein (2001), among others.

[6] Examples of studies assuming an endogenous default threshold are Black and Cox (1976), Geske (1977), Leland (1994, 1998), Leland and Toft (1996), Anderson and Sundaresan (1996), Mella-Barral and Perraudin (1997), Fan and Sundaresan (2000), Acharya and Carpenter (2002), among others.

model with the focus on staying easy to implement with closed or numerically feasible solutions for the pricing formular of the corporate debt and the default probability.

4.2.3 Default time

The original model assumes that default can only occur at the maturity of the debt. Black and Cox (1976) provided an important extension of this framework. In their model, default may occur at any time before maturity if the value of assets hits the default threshold (known in the literature as the first passage model). In other words, the firm's equity is viewed as an American (instead of a European) call option on the value of assets.[7] Instead of a zero-coupon bond, Geske (1977) proposes a model in which corporate bonds are paying coupons. Each coupon payment may cause default if equityholders cannot meet the payment even by issuing new equity.[8]

4.2.4 The default-free short rate

The original structural model also assumes that the default-free interest rates are constant. Further, the empirical evidence suggests a negative correlation between interest rates and credit spreads (Longstaff and Schwartz, 1995, and Duffee, 1998). Many structural models extend the original framework to allow for a stochastic interest rate process in which it is possible to introduce the correlation between the value of assets and interest rates. These models include Shimko, Tejima, and Deventer (1993), Kim, Ramaswamy and Sundaresan (1993), Nielsen, Saá-Requejo, and Santa-Clara (1993), Longstaff and Schwartz (1995), Briys and de Varenne (1997) and Hsu, Saá-Requejo and Santa-Clara (2002), among

[7] For those interested in this model, see also Lin (2007) who documents the existence of a small error in the pricing formula of Black-Cox and presents a correction for it.

[8] Equityholders are willing to issue new equity and meet coupon payments as long as the value of the equity option is higher than the required payment. At some point, new funds can not be raised because the dilution effect reduces the value of equity and the firm defaults.

others. Most of these models generate credit spreads that are higher than those predicted by the original structural model.[9]

4.2.5 The leverage ratio

In addition, the Merton model precludes the firm from issuing new debts before the maturity. This prevents the model from generating the correct shape for the term structure of credit spreads. Longstaff and Schwartz (1995) overcome this problem by relating the default threshold to the level of the outstanding debt. However, their model leads to leverage ratios that decline exponentially over time. Collin-Dufresne and Goldstein (2001) show that for most companies there is a target leverage ratio which they try to maintain by issuing new debt or retiring existing debt. By assuming a stationary leverage ratio, generated credit spreads are much larger and have a term structure that increases with maturity consistent with the findings of Helwege and Turner (1999).[10]

4.2.6 Complete information

Another basic feature of structural models is that default becomes a predictable event assuming that investors have continuous observation of the value of the firm's assets. Empirically, however, this assumption limits the model and leads to very low credit spreads. Duffie and Lando (2001) introduce a model with incomplete information in which this assumption is relaxed and default becomes impossible to predict. In their model, the value of the firm and the default threshold are not observable and investors have to draw inference from the available accounting data and other altered public information to measure it.

[9] Fouque, Sircar and Solna (2006) extend the Black and Cox (1976) model with constant interest rates by adding a stochastic volatility into the process of the firm value. They show that allowing for stochastic volatility increases credit spreads with short maturities.

[10] The assumption of a stationary leverage ratio allows the default threshold to migrate upward over time along with the firm value. This causes the credit spread to widen.

Giesecke and Goldberg (2004), Çetin, Jarrow, Protter, and Yildirim (2004), and Giesecke (2006), provide an extension of the information-based models. Mason and Bhattacharya (1981), Delianedis and Geske (2001), Zhou (2001), Huang and Huang (2003), and Huang (2005), also circumvent this assumption by incorporating jumps to default. This implies that the firm has always a positive probability to default even at the very short term. In other words, jumps allow structural models to generate positive (rather than almost zero) credit spreads for very short maturities.

4.2.7 Strategic Default

Most structural models do not distinguish between default and liquidation in the sense that default leads to an immediate liquidation of the firm's assets. Recent contributions allow for strategic default in which equityholders and bondholders engage in costless negotiations to fix the default threshold as soon as the firm falls into financial distress. In such situations, bondholders accept to receive less than promised cash flow payments because otherwise they will bear the cost of assets liquidation. Equityholders continue to service the debt strategically until the value of the firm's assets rebounds above the distress threshold. Models of Anderson and Sundaresan (1996), Mella-Barral and Perraudin (1997), Fan and Sundaresan (2000), and Acharya and Carpenter (2002) are few examples among others allowing for strategic default in this spirit.

4.2.8 Liquidation

In François and Morellec (2004), Moraux (2004), Broadie, Chernov, and Sundaresan (2007), and Galai, Raviv, and Wiener (2007), default can either lead to liquidation of the firm's assets (under Chapter 11 of the U.S. Bankruptcy Code) or to full recovery after costly renegotiation of the debt contract (under Chapter 7). For example, François and

Morellec (2004) assume that liquidation occurs when the value of the firm's assets falls below the distress threshold and remains under that level for a period of time exceeding a pre-determined grace period. Should the value of the firm's assets rebound above the threshold level before the end of the grace period, the bankruptcy procedure stops and the distress history is set to zero. This means that, each time the threshold level is hit, an additional grace period is granted to the firm to avoid liquidation. Theoretically, the firm can stay solvent even if the value of its assets remains below the threshold level for most of the duration of the debt contract. Moraux (2004) corrects for this disadvantage by fixing the duration of the total grace periods over the debt contract. Recently, Galai, Raviv, and Wiener (2007) extend the framework of Moraux (2004) to account for the effect of the distress severity on the decision to liquidate a firm. In their model, the firm distress is as severe as the value of the firm's assets is far below the default threshold. Broadie, Chernov, and Sundaresan (2007) also allow for the distress severity. However, as in François and Morellec (2004), their model does not adjust the grace period according to the distress history of the firm.

4.2.9 Liquidity

The predictions of the structural models are very sensitive to their assumptions about the determinants of the default threshold. Different default thresholds produce different levels of credit spreads. Davydenko (2007) shows that liquidity reasons should be considered as the main determinant that drives default for some firms especially those with high costs of external financing. Earlier, Ericsson and Renault (2006) show that the illiquidity premium increases when default becomes more likely. They construct a structural model that allows for debt renegotiation as in Fan and Sundaresan (2000) and introduce uncertainty about liquidation as in François and Morellec (2004). Hence, they allow the renegotiation in financial distress to be influenced by illiquidity of the market for distressed debt. By doing so, their model generates larger credit spreads even for corporate bonds with short maturities.

Davydenko (2007) relates liquidity issues to the cost of external financing and suggests that structural models that does not account for realistic financing frictions are likely to lack accuracy in predictions. He classifies the structural models into those in which the firm defaults following a financial distress or an economic distress. A firm is in financial distress when its current cash flows are insufficient to meet its debt payments (for example in the models of Kim, Ramaswamy, and Sundaresan, 1993 ; and Anderson and Sundaresan, 1996). This suggests that temporary cash shortage may precipitate default even for firms with very good prospects.[11] A firm is in economic distress when the market value of its assets is declining signalling that the firm's prospects deteriorate (for example in the models of Black and Cox, 1976 ; Leland, 1994 ; and Leland and Toft, 1996). This suggests that economic distress may cause default even if the firm is willing to meet the current debt payment. In these models, liquidity crisis is not relevant to default if the value of assets is above the threshold because equityholders can raise outside financing. In practice, however, we observe that many distressed firms do not necessarily default. Further, distressed firms may have access to external financing and may carry cash reserves, accumulated during good times, to reduce the necessity for costly external financing during bad times.

Davydenko (2007) finds that at the event of default most firms are insolvent both economically and financially. So, financial and economic distress are closely related and should be considered simultaneously to explain observed defaults. However, the relative importance of the type of distress is also sensitive to the financing constraints (i.e. the availability and costs of external financing) :

[11] This is the case in which firms are restricted from using external financing and maintaining cash reserves.

> "A temporary cash shortage can trigger default only to the extent that the firm is restricted from raising new financing against its remaining assets. In the absence of such restrictions, firms can overcome liquidity shortages by raising new cash as long as the firm's business remains valuable. Thus, if external financing is costless, then cash shortages are irrelevant, and the firm does not default until it is in deep economic distress. In contrast, if the required cash cannot be raised at any cost, any temporary cash shortage will push the firm into default, despite its sound economic fundamentals. Between these two extreme cases, firms for which external financing is neither costless nor infinitely costly should be able to overcome some but not all liquidity shortages (P. 6)."

The evidence presented so far suggests that early structural models have ignored important potential default triggers such as liquidity and emphasizes the need for more research in this area. The effect of Macro economy in triggering default has also been ignored in these models.[12] Recently, Chen (2007) constructs a structural model in which the default is conditioned by shifts in macroeconomic fundamentals. He shows that the optimal endogenous default threshold based on cash flows is countercyclical. This leads to default probabilities that are higher when the economy enters into a recession and lower when it enters into an expansion. Earlier, Chen, Collin-Dufresne, and Goldstein (2009) find evidence of this same pattern while in their model the default threshold is modeled exogenously. These results suggest that predicted credit spreads exhibit a countercyclical behavior consistent with observed credit spreads. However, at this point, what drives this counter-cyclicality could be a liquidity premium, a systematic risk premium or both.

[12] Adding business cycle conditions on models based on the pricing of an American option raises the issue of dimensionality and may lead to less accuracy in the predictions of these models (Chen, 2007).

4.2.10 Contagion default

Most interestingly, Chen (2007) finds that firms are likely to default in wave. Their model predicts that default waves occur when expected growth rates, volatility, and risk premiums experience a significant shift. Earlier, Hackbarth, Miao, and Morellec (2006) reach a similar conclusion but relate default waves to a significant negative shift in the level of the cash flows of the firms, which is likely to occur in bad times. Thus, contagion defaults is another factor that appears to warrant a detailed investigation in future research. Table 3.1 summarizes extensions of the structural models.

[Insert Table 3.1]

4.2.11 Other credit risk models

Structural models are not the only exiting credit risk models. There is also an extensive literature on the reduced-form approach that builds on some limits of the structural-form models (for example the predictability of default event). This literature originated with Jarrow and Turnbull (1992) and studied later by Jarrow and Turnbull (1995) and Duffie and Singleton (1999) among others. In summary, it assumes that default is an unpredictable event which is exogenous to the underlying economic variables of the firm. The default event is driven by a hazard rate and does not need to specify lower boundary conditions on the value of assets as required by the structural model. The parameters of the hazard rate are rather inferred from observed default probabilities and recovery rates. The reduced-form models add more flexibility and easiness to match observed data. They are generally applied to the valuation of credit derivatives due to their relative estimation accuracy. However, theoretical determinants of credit spreads are generally limited in these models.[13]

[13] For a review of reduced-form models see Elizalde (2005a, 2005b).

4.3 Estimation of structural models

Many empirical works implement the structural models to test its estimation accuracy. For example, Jones, Mason, and Rosenfeld (1984) implement the Merton model using callable coupon bonds and come up with a large model pricing error. Kim, Ramaswamy, and Sundaresan (1993) implement the variant of the structural model in whcih the short rate process r is a one factor CIR process. Collin-Dufresne and Goldstein (2001) provide a numerical procedure for computing zero coupon bond prices using the longstaff and Schawrtz two-factor model. Huang and Huang (2003), and Eom, Helwege and Huang (2004) calibrate many structural models to be consistent with data on historical default loss experience. They show that most of these models produce large pricing errors and generate quite similar credit spreads once they are calibrated to observed data.

The empirical estimating of structural models call for paramters that are not directly observable such as the value (V_t) and the volatility of the firms assets (σ_v). There is several ways of calibrating V_t and σ_v. The first method uses the Itô's Lemma to obtain a system of two equations in which the only two unknown variables are V_t and σ_v. This method is used for example in Jones, Mason, and Rosenfeld (1984), Eom, Helwege and Huang (2004), Delianedis and Geske (2003), and Ericsson and Reneby (2005). Duan (1994) proposes another method of estimating V_t and σ_v, based on maximum likelihood estimation.using equity prices and firm assets value.

Duan, Gauthier, Simonato, and Zaanoun (2003) extend the maximum likelihood approach introduced by Duan (1994) by introducing the possibility that distressed firms may survive. Duan and Fulop (2005) account for the fact that observed equity prices might be contaminated by trading noises. They find that when we introduce trading noises in the model we obtain lower estimates for σ_v and higher default probabilities.

Bruche (2005) proposes to calibrate structural models by using not only equity data but any of the firm's traded claims (i.e. bonds, equity, CDS, etc.). The method uses a simulated maximum likelihood procedure and is shown to improve the efficiency of the model estimation.

Jones, Mason, and Rosenfeld (1984) use a different method to calibrate structural models. They simply estimate the asset value as the sum of the equity market value, the market value of traded debt and the estimated value of non traded debt. Then, given the time series of V_t, they can obtain σ_v.

Hull, Nelken and White (2004) use implied volatilities of options on the firm's equity to estimate model's parameters. Specifically, using two equity implied volatilities and an estimate of the firm's debt at maturity, they obtain the estimates of σ_v and the leverage ratio of the firm $\frac{De^{-r(T-t)}}{V_t}$. Using these two estimates, one can calculate the default probability.

To estimate the default threshold, most studies follow Sundaram (2001) who suggests that default threshold in pratice is comprised between the book value of all liabilities and the book value of short-term liabilities. So, the default threshold is chosen between these two values. For example, Davydenko (2005) find the default threshold to be around 72% of the firm's face value of debt.

4.4 Decomposing credit spreads

Extensive empirical works emerged following the original structural model to test the theoretical results on credit spreads implied by straigth corporate bonds. They address the question of how one may decompose corporate credit spreads into different components to fully explain their levels or changes.[14] Most of these studies reveal the inability of

[14] Corporate bonds may present different features. For example they may be callable, putable, convertible, subordinated, etc. This may be part of the puzzle because the price of the corporate bond will be affected by the presence of such features and predicted credit spreads will lack accuracy. For example, Duffee (1998) shows that credit spreads of callable bonds reflect also variations in the value of the call option. Because the price of a noncallable bond equals the prices of a callable bond plus the call option, prices of these

default factors, explicit in structural models, to explain these spreads. This led to a recent revolution in the literature about credit spread determinants with the focus shifting from traditional default-based factors to new liquidity-based and market-based factors. The logic behind is that structural models predict default using the information on asset values. However, asset values are also affected by other factors, not directly related to default, such as liquidity, market condition, and investors preferences. Actually, these views appear in the early empirical work of Fisher (1957) well before the setting of the original structural models. He suggests that credit spreads are not only determined by credit ratings but should also account for factors related to firm characteristics like yield-to-maturity, call features, coupon size and investors preferences for liquid bonds.

4.4.1 Default factors

According to structural models the only reason for corporate credit spreads over Treasury yields to exist would be to compensate for the default risk which is affected by : 1) the default probability (DP), and 2) the loss given default or one minus the recovery rate (RR) in the event of default. So, DP and RR are key inputs in assessing the proportion of corporate yield spreads explained by default risk.

Most empirical studies have only been able to explain a small fraction of the credit spread changes using default factors. For example, Huang and Huang (2003) show that default risk can only explain 20% on credit spreads for investment-grade bonds. Elton, Gruber, Agrawal, and Mann (2001) show that the average historical default loss rate for corporate bonds (implicit in credit ratings and historical recovery rates) is typically much smaller than the risks involved. It also accounts for only a small fraction of the observed

bonds are affected differently by changes in interest rates. When the interest rate decreases, the price of a callable bond will not increase as much as the price of a noncallable bond. This is because the value of the option also increases. In addressing the puzzle, the literature on credit spreads attempted to correct for these effects by studying bonds without such special features (straight).

credit spreads (no more than 25%), especially for bonds with high credit quality of all maturities. Their results are obtained from a reduced form model. A parallel study by Delianedis and Geske (2001) using a structural model presents similar results. Both studies conclude that taxes, liquidity, and market risk factors, all play a role in explaining the credit spread. The question is whether they can account for the puzzle.[15] To assess default risk component, one needs an estimate of the term structure of default probability, i.e. the firm's default probability for different time horizons as well as a measure for the recovery rate in the event of default.

4.4.2 Default Probability

Issuers default probabilities can be obtained directly from the reduced form models or simply using other statistical approaches. A typical reduced form model considers that the default event is driven by an unpredictable Poisson process and there is always a positive probability that the firm defaults even at the very short term. Statistical approaches suggest the use of databases on historical default frequencies from Moody's and Standard and Poor's. For example, to compute the term structure of the default probability we have to estimate transition probabilities between rating classes. This is the approach used in Elton, Gruber, Agrawal, and Mann (2001).

Empirical studies report few issues related to the statistical approach. First, the method needs to specify the estimation period over which we compute transition probabilities and default. Bangia et al. (2002), show that the estimates of the transition matrix are very sensitive to the period in which they are computed and they largely differ across business and credit cycles.

[15] Perraudin and Taylor (2003) apply the methodology of Elton, Gruber, Agrawal, and Mann (2001) to Eurobond data. They have also included default factors in their model. After adjusting the observed credit spreads for effective taxes and expected losses, they find that expected losses are much lower that a liquidity premium reprensenting around 30 basis points.

Second, because default is a rare event, the typical cohort approach used by Moody's and Standard and Poor's produce transition probabilities matrices with many cells equal to zero (Altman, 1998). This means that the estimates of these cells are zero but the true probabilities are different from zero. Such estimates are likely to underestimate the proportion of credit spreads due to default risk (see for example, Carty and Fons, 1993 ; and Carty, 1997). Lando and Skodeberg (2002) overcome this problem by showing that a continuous-time analysis of rating transitions using generator matrices improves the estimates of rare transitions even when they are not directly observed in the data.

The third issue is related to the quality of the data used in the computation of default and transition probabilities. In some cases, the data cannot provide clear information about issuers' rating movements over the period considered. For example, the issuer may sometimes be not rated or enters the cohort at the beginning of the estimation period but leaves for reasons other than default. It may also enter the cohort after the beginning of the estimation period. All these special cases may have considerable impact on the final estimates and affect studies using transition matrices to price defaultable bonds (see for example, Lando, 1998 ; and Jarrow, Lando and Turnbull, 1997 ; Dionne et al., 2009).

4.4.3 Recovery rate

Under the Merton model, credit risk factors depend on the structural characteristics of the firm such as asset volatility and leverage. In this model as well as in models assuming that default can only occur at the maturity of the debt (for example Black and Cox 1976), the RR is determined endogenously. It represents the creditors' payoff, which is a function of the residual value of the defaulted firm's assets. Further, under this framework, DP and RR are inversely related.

In models in which default may occur any time between the issuance and maturity of the debt (for example in Longstaff and Schwartz, 1995), the RR in the event of default is exogenous and independent from the firm's asset value. It represents, in general, a fixed ratio of the outstanding debt value and is therefore independent from the DP. Longstaff and Schwartz (1995) show that it is possible to obtain a reliable estimate of the RR by looking at the default history and the recovery ratios for different firms.

Overall, the empirical performance of the structural models is shown to remain limited because : 1) the firm's assets are not directly observable, 2) structural-form models cannot incorporate changes in the credit rating of the risky corporate debt, which occur frequently just before default, and 3) default is a foreseeable event given continuous observation of the firm's asset value. Reduced form models do not suffer from these limits because they make separate explicit assumptions about the dynamic of both DP and RR. So, these variables are modeled independently from the structural features of the firm, its asset volatility and leverage. In general, these models assume an exogenous RR that is independent from the DP.

Reduced form models make different assumptions about the parameterization of the RR. For example, Jarrow and Turnbull (1995) assume that a bond is priced at default. This price represents an exogenously specified fraction of an otherwise equivalent default-free bond (refereed to as the recovery of market value). Duffie and Singleton (1999) use this assumption about recovery and provide a model with closed-form solutions for the term-structure of credit spreads. Duffie (1998) assumes that, at default, the bondholder receives the same fixed payment for different bonds with the same seniority level regardless of coupon levels or maturities. This payment is proportional to the face value of the debt (refereed to as the recovery of face value). So, under this assumption, one can use the statistics provided by Moody's (2000) which gives the market price of distressed bonds one month after default in order to compute the RR.

Altman, Resti, and Sironi (2001) provide an excellent empirical analysis of the dynamic of RR and its relation with the DP. They show that DP and RR are negatively related, consistent with the Merton model (see also Altman, Brady, Resti, and Sironi, 2005). Further, they show that estimates of the default component in credit spreads may differ with respect to the assumption about the RR.

4.4.4 Nondefault factors

Taxes

Elton, Gruber, Agrawal, and Mann (2001) show that a tax premium accounts for a significantly larger portion of corporate credit spreads over Treasury yields than do a default premium. For example, they find that for A-rated bonds with maturity of 10 years, taxes account for 36.1 percent of credit spreads while expected loss accounts only for 17.8 percent. Actually, corporate bonds are at a tax disadvantage relative to Treasury bonds. The interest earned on corporate bonds (i.e. the coupon payment) is taxed at the federal and state levels, whereas the interest earned on Treasury bonds is only taxed at the federal level. Thus, corporate spreads should contain a premium to account for this tax difference (about 4.875% difference in taxation).

In practice, however, there is two arguments going against the significance of this tax effect, as reported by the Federal Reserve Bank. They point out that the marginal investor in the corporate bond market is likely to be a bank, an institutional investor or another legal entity. For these investors, the interest earned on corporate and Treasury bonds is exposed to the same tax treatment. In addition, major changes in tax laws are not frequent, so the tax effect is unlikely to capture the frequent, large swings observed in the credit spread dynamics. Yet, the tax effect is controversial and depends on who is the marginal investor ?

Term structure of interest rates

Many studies considered the level and the slope of the Treasury yield curve as important drivers of credit spread differentials. The interest rate level appears in the pricing formula of the Merton model as the discount rate of the expected cash flows of the option at maturity. Longstaff and Schwartz (1995) show that a high level of the short risk-free interest rates increases the risk-neutral drift of the firm value process and take it away from the default threshold. The slope does not appear explicitly in the structural model setup. However, Brennan and Schwartz (1979) related the dynamics of the rates with the shortest and the longest maturity. In their model, the whole term structure of interest rates may be expressed by these two rates.[16] If the short-rate could be mean reverting about the long rate as in the Longstaff and Schwartz model, changes in the slope should affect the expected future short rate. So, structural models predict an inverse relation between the term structure of the default-free rate (level and slope) and the credit spread. Duffee (1998) takes on the task to test these predictions. He finds that, for noncallable corporate bonds across most ratings and maturities, the level and slope of the Treasury yields curve can explain almost 20% of credit spread changes.

Assets volatility

Following the structural setup based on an option pricing formula, credit spreads are also affected by the volatility of the assets of the firm. The total firm volatility includes both idiosyncratic volatility and systematic or market-wide volatility. Since options values increase with total volatility, then, the model predicts that credit spreads should increase with volatility. Campbell and Taksler (2003) test this prediction. They evaluate the volatility effect on credit spreads, across firms and over time, while controlling for composition

[16] Litterman and Scheinkman (1991) and Chen and Scott (1993) also show that the term structure of interest rates can be almost fully represented by changes in the level and the slope.

effects, demand for liquidity provided by Treasury bonds, and special features of corporate bonds. Consistent with the Merton model, the idiosyncratic volatility explains as much variation in credit spreads as do credit ratings. Both factors account for about one third of credit spreads.

Leverage

The extension in Collin-Dufresne and Goldstein (2001) emphasizes the importance of the default threshold to the leverage ratio of the firm. Their model generates credit spreads that are larger for leverage firms below target. With mean reverting leverage ratios, default is triggered when the leverage ratio approaches unity.

Reference curve

Although empirical studies often use U.S Treasury yields as a benchmark for the risk free rate to obtain credit spreads, this is not the only possible choice. Duffie and Singleton (2003) suggest the term structure of swap, agency, and high grade corporate bond yields. According to them the choice of the risk free rate depends on : "1) pricing conventions in markets, 2) data availability, 3) desires by financial institutions to standardize pricing models across markets and countries, and 4) institutional considerations that affect the relative pricing of the reference and corporate markets. (P. 162)".

Later, Hull, Predescu, and White (2004) show that Treasury bonds which are viewed as risk-free securities are not totally risk-free. Their rates are lower than the pure risk free rate because they are subject to liquidity and regulation issues. As Treasury bonds are traded far more than corporate bonds, the observed high corporate credit spreads over Treasury bonds may contain a premium that accounts for this difference in liquidity. Moreover, financial institutions are committed to use Treasury bonds in order to fulfill a variety of regulatory requirements. For these financial institutions, the minimum capital required to support an investment in Treasury bonds is substantially smaller than the minimum capital required for supporting a similar investment in low risk corporate bonds. Therefore, the term structure of swap is considered as a better benchmark for the risk-free rate.

Liquidity

Corporate bonds are shown to be illiquid. Because liquid securities are more attractive and less costly to sell, investors demand an additional compensation for holding less liquid securities. Using a structural approach, Ericsson and Renault (2006) document a positive correlation between illiquidity and default components. They also find support for a liquidity spread that decreases with the maturity of the bond.

The problem with liquidity is that it has a number of aspects that cannot be captured by a single measure because it is not directly observed. In general, 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 existing empirical studies typically use transaction volume and/or measures related to the bond characteristics such as coupon, size, age, and duration.

For example, Houweling, Mentink, and Vorst (2005) employ nine proxies for standard liquidity measures to estimate the liquidity premium between liquid and illiquid portfolios. They find a premium ranging from 13 to 23 basis points.[17] They conclude that illiquidity is priced in the bond market and its pattern is time-varying. Driessen (2005) reaches similar results. Jong and Driessen (2006) find a premium that accounts for around 60 basis points for investment grade bonds and is much higher, around 150 basis points, for non investment

[17] Their proxies reflect the issued amount of the bond, the age of the bond, the number of missing prices in the sample, the volatility of bond yields, the number of active traders competing for the same bond, the bond yield dispersion relative to the average yields. They also consider whether the bond is listed on a stock exchange, whether it is denominated in euros and whether it could be considered an on-the-run security.

grade bonds, with long maturity.

Since measures related to bond characteristics are typically either constant or deterministic and may not capture the stochastic variation of liquidity subsequent studies use Amihud-based measures of liquidity involving intra-daily transaction prices and trade volumes. These measures have been extensively used in the studies of stock market liquidity and are of direct importance to investors developing trading strategies. They are based whether on price impact of trades (for example, the Amihud and Range measures) or on trading frequencies.

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. The ratio characterizes the daily price impact of the order flow, i.e., the price change per dollar of daily trading volume (Amihud, 2002). For each portfolio i, at month t :

$$Amihud_t^i = \frac{1}{N-1}\sum_{j=1}^{N-1}\frac{1}{Q_{j,t}^i}\frac{\left|P_{j,t}^i - P_{j-1,t}^i\right|}{P_{j-1,t}^i}, \tag{4.3}$$

where N is the number of days within the month t, $P_{j,t}^i$ (in \$ per \$100 par) is the daily transaction price of portfolio i and $Q_{j,t}^i$ (in \$ million) the daily trading volume of portfolio i.

The Amihud measure reflects how much prices move due to a given value of a trade. Hasbrouck (2005) proposes a modified Amihud measure that accounts for the presence of outliers :

$$\operatorname{mod} Amihud_t^i = \sqrt{Amihud_t^i} \tag{4.4}$$

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 :

$$Range_t^i = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{Q_{j,t}^i}\frac{\max P_{j,t}^i - \min P_{j,t}^i}{\overline{P}_{j,t}^i} \tag{4.5}$$

where N is the number of days within the month t, $\max P_{j,t}^i$ (in \$ per \$100 par) is the maximum daily transaction price of portfolio i, $\min P_{j,t}^i$ (in \$ per \$100 par) is the minimum daily transaction price of portfolio i, $\overline{P}_{j,t}^i$ (in \$ per \$100 par) is the daily average price of portfolio i and $Q_{j,t}^i$ (in \$ million) the daily transaction volume of portfolio i.[18]

The range is an intuitive measure to assess the volatility impact as in Downing et al. (2005). It should reflect the market depth and determine how much the volatility in the price is caused by a given trade volume. Larger values suggest the prevalence of illiquid bonds.

Liquidity measures based on trading frequencies Vayanos (1998) suggests that asset liquidity may be captured by measures related to trading frequencies. Such measures include :

- 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.

Han and Zhou (2006) examine the relationship between the nondefault component of corporate bond spread and liquidity measures based on the price impact of trades, tran-

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

saction costs, and trading frequencies constructed from intraday bond transactions data. They find that illiquidity factors increase with the nondefault bond spread especially for the high investment grade bond. The evidence is weaker for the low investment grade bond and statistically inconclusive for the speculative grade bond. Maalaoui, Dionne and François (2009) also find that direct trading liquidity measures have a statistically significant effect on credit spreads.

4.4.5 Empirical evidence

Building on the prediction of the structural models, Collin-Dufresne, Goldstein, and Martin (2001) aimed to empirically test the explanatory power of several factors on credit spreads. Specifically, they perform a regression analysis that includes the level and the slope of interest rates, a measure of the volatility of assets, a measure of the leverage ratio, a proxy for the probability of negative jumps in the firm value, as well as a proxy for the state of the economy (which is not explicitly derived from the structural model). Despite this careful setup, they fail to explain more than 25% of credit spread changes. Their results present the puzzle that such factors have little explanatory power. The authors have also detected a common systematic factor that potentially could explain the large part of the unexplained changes. However, several macroeconomic and financial candidates fail to measure it. They conclude that their model is missing an important factor common to all firms in their sample. This factor is principally driven by local supply and demand shocks and is likely to be independent of both theoretical credit risk factors and standard proxies for liquidity. Many studies explore this issue.[19]

Driessen (2005) makes another carefully orchestrated decomposition of credit spreads in which he accounts for most of the factors discussed earlier. First, he includes the level

[19] See for example Maalaoui, Dionne, and François (2009) and references therein.

and the slope of the Treasury yields curve to capture the 20% fraction of credit spreads found in Duffee (1998). Second, he estimates a time-varying liquidity risk premium factor as deemed appropriate by the results in Houweling, Mentink, and Vorst (2005). Third, he follows Collin-Dufresne, Goldstein and Helwege (2003) in estimating a risk premium that accounts for both default jumps and contagion effects.[20] Fourth, he accounts for the commonality observed by Collin-Dufresne, Goldstein, and Martin (2001) and includes an effective state tax effect of 4.875%, building on the insights provided by Elton, Gruber, Agrawal, and Mann (2001). Another meticulous decomposition that left about one third of BBB credit spreads unexplained. Driessen concludes that the missing factor is likely to be caused by a tendency for firms to default in waves, casting doubt on the accuracy of the estimated jump risk premium. Table 3.2 outlines empirical works investigating the decomposition of credit spreads.

[Insert Table 3.2 here]

Thus far, recent empirical studies still have difficulties in explaining the credit spread puzzle. The question today, in particular given the recent turmoil in the global financial markets, is to what extent changes in the market price of risk or changes in investor risk preferences are part of the puzzle. As any such changes affects the prices of all assets including corporate bonds and equities, the common factors from the stock market and the bond market are likely to control for theses effects. Chen, Collin-Dufresne, and Goldstein (2009) address this question. They relate the credit spread puzzle and the equity premium puzzle since they measure premiums of claims to the same firm value.[21] Specifically, they test whether models that have been successful in explaining the equity premium can explain

[20] Notice that the estimation approach in Collin-Dufresne, Goldstein and Helwedge (2003) is based on a reduced-form approach.

[21] The equity premium puzzle refers to the historical observed premium – the return earned by equity in excess of that earned by a Treasury bond – that appears too high relative to the risks involved.

credit spreads once they are calibrated to equity data. They use the Campbell and Cochrane (1999) habit formation model which accounts for time varying risk-aversion, and the Bansal and Yaron (2004) model which includes highly persistent shocks to expected growth and volatility of consumption. Both models account for changes in investors preferences through the volatility of the marginal utility of consumption. Notice that this factor is not implied by structural models as a potential determinant of credit spreads because these models are derived from the principle of arbitrage. Unexpectedly, after controlling for the expected losses, both models can only generate low credit spreads. Their results also suggest that the countercyclical behavior in credit spreads is likely to be driven by a procyclical liquidity premium. So, the cyclical behavior of credit spreads may contain some information about what drives credit spreads especially in periods of economic downturns when default and losses are more severe.

4.5 The credit spread behavior

The studies reviewed earlier show that more than half of credit spread changes is left unexplained. The missing piece is likely to be unrelated to the financial health of the firm and reflects a compensation for a certain common systematic factor. This factor can reflect a liquidity risk, which is time-varying ; a risk premium possibly caused by contagion defaults ; and market sentiment (investor's preferences) especially in economic downturns. Movements in corporate bond spreads may potentially represent a forward-looking metrics for market sentiment. Extracting the information contained in credit spread movements and understanding their pattern in recessions is a key to solving the credit spread puzzle (Chen, 2007 ; and Maalaoui, Dionne, and François, 2009). We discuss this issue more in details.

4.5.1 Cyclical patterns in credit spreads

Credit risk factors are typically thought to correlate with macroeconomic conditions. Empirical evidence going back to the original works of Fama and French (1989), and Chen (1991) show that the credit risk component, measured by the spread between average yields on BBB-rated and AAA-rated corporate bonds tends to widen during economic downturn and narrow during periods of expansion. However, few theoretical models account explicitly for macroeconomic conditions by allowing for a dynamic countercyclical default threshold (see for example Hackbarth, Miao, and Morellec, 2006 ; Chen, 2007 ; and David, 2008).

The empirical literature that relate credit spread movements to the states of the economy disagree about the exact connection between the credit cycle and the economic cycle. Early works suggest that the credit cycle contains important information about the economic cycle. For example, Friedman and Kuttner (1992) and Stock and Watson (1989) show that the short term credit spreads over Treasury rates may be a leading indicator of the business cycle. Guha and Hiris (2002) find the same results when they analyze the long term credit spread movements and their relation with aggregate business conditions. They demonstrate that turning points of the aggregate credit spread contain significant information about the future turning points of the real activity. Recent works also agree about the countercyclical behavior of credit spreads but remain inconclusive about the causal relation between economic and credit cycles (Koopman and Lucas, 2005). Using a theoretical setting, Lown and Morgan (2006) show that the credit cycle may affect the course of the economic cycle, whereas Gorton and He (2003) suggest that the credit cycle may have its own dynamics, which may be different from those of the economic cycle.

More recently, Dionne, François, and Maalaoui (2008) analyze the turning points in the time series of short and long term credit spreads and find different patterns across ratings and maturities. Their results support the findings of Gorton and He (2003). Interestingly, they show that credit spreads, especially with short maturities and low ratings, shoot up well before the NBER effective date of recession and shoot down after the NBER announcement of the recession end. Maalaoui, Dionne, and François (2009) reach similar results using a different approach. They also suggest that the systematic component in credit spreads may not be totally captured by macroeconomic fundamentals. Then, by modelling the credit cycle endogenously they are able to enhance the explanatory power of credit spread determinants. Specifically, they find 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 credit spread episode. Inverted relations are also obtained for some other determinants. This pattern in the high episode may explain why in the empirical study of Collin-Dufresne, Goldstein and Martin (2001) the total effect of credit spread determinants is limited.

Most of the existing studies refer to the NBER dating of an economic downturn to specify the economic cycle. Macroeconomic fundamentals are also viewed as a good proxy for the economic cycle since they are closely related to the dynamics of the Gross Domestic Product (GDP). David (2008) and Maalaoui, Dionne, and François (2009) provide evidence that contrasts with these views. For example, David (2008) finds an R2 of 9.6% when he regresses the historical Baa-Aaa spread on the NBER recession indicator. Maalaoui, Dionne, and François (2009), show that the credit cycle is much longer than the economic cycle. They also prove that by conditioning on the credit spread regimes, derived endogenously, they significantly improve the explanatory power of credit spread determinants. Further, their model cannot be improved by conditioning on the NBER economic cycle.

Recent studies applying regime models to capture state dependent movements in credit spreads usually relate the economic states to changes in macroeconomic fundamentals and find counterfactual results (Davies, 2004 and 2007 ; Alexander and Kaeck, 2007 ; and David, 2008). In doing so, they are implicitly assuming that the true credit cycle coincides with the economic cycle, which is not likely to be the case. For example, David (2008) uses regime switching structure for fundamentals to estimate investors beliefs about the hiden sates in the economy.

4.5.2 The monetary policy : Is it part of the puzzle ?

The monetary policy controls for the aggregate credit levels and may possibly signal an aggregate liquidity crisis in the economy. Many studies suggest that the high credit level in the economy may induce it into a recession. Other studies find that the time-varying pattern of the liquidity factor may be the cause of the countercyclical behavior of credit spreads (Chen, Collin-Dufresne, and Goldstein, 2009). This suggests that the monetary policy cycle and the cyclical patterns in credit spreads may be related and to some extent this relation may be part of the credit spread puzzle.

Monetary policy can be defined as any policy relating to the supply of money. Financial institutions create money and credit through reserves supplied in the aggregate by the Federal Reserve. Then, these reserves can also be traded between individual financial institutions to adjust their current reserve positions with their required positions. This market is known as the federal funds market and the rate prevailing to these transactions is the federal funds rate. Most of these transactions are on a one day basis, so the federal funds rate is very short term.

Typically, the Federal Reserve announces a target rate for federal funds and intervenes in the market as needed to keep the effective rate close to its target. When the aggregate demand for liquidity increases to a certain level, signalling a liquidity crisis, the Federal Reserve intervenes to reduce the target rate. Thus, monetary policy actions perceive the liquidity distress in the economy which is also related to an economic distress.

Further, monetary policy is of particular interest to market makers since it can have important effects on aggregate demand and through it on real GDP, and unemployment. Actually, changes in money supply have the potential to bring about major changes in the growth of GDP and employment. However, this evidence only holds over the short run where a rapid rate of growth of the money supply can cause domestic demand to expand. Over the longer run, money supply growth has its primary effect on the rate of inflation and little if any is felt on the real GDP and employment. Structural models predict a close relation between credit spreads and the short risk-free rate. Since the federal funds rate is closely related to the short risk-free rate it may then be related to credit spread yields.

Actual studies have ignored the relation between monetary policy and the credit cycle and future work in this area may be very promising. Further, since the target rate is announced few months before effective rate is observed it would help investors to predict the future path of credit spreads.

4.6 Conclusion

To address the credit spread puzzle, many works are built on the predictions of the structural-form models. The review of the literature reveals significant improvements in the recent models. In particular, many of them account for more realistic assumptions about what triggers the default event. For example, recent works account for the effects of firm leverage, liquidity distress, macroeconomic conditions, and most recently, to the tendency for firms to default in wave. The structural model remains, however, limited by the model estimation accuracy which may be altered when additional variables increase its complexity.

Empirical studies are generally successful in explaining more than half of the credit spread differentials and contribute to solve part of the puzzle. Still, there remains a missing piece of the puzzle. This missing piece may be related to the nature of the data available to account for some effects. For example, to account for the effect of a time-varying liquidity, one may need high frequency data from the bond market. Such data are still not available over a long time horizon. It may also be related to other factors that are still not considered in the existing literature. For example, the effect of the monetary policy actions, which control for the aggregate level of credit and liquidity in the economy, is currently ignored. So, we still need further research in this area.

Finally, this survey may provide the reader with a perspective on the importance researchers are giving to the credit risk literature and highlights open research questions to support future works.

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Tableau 4.I: Extensions of the structural models.

Highlights	Example of related work
Default may occur at any time before maturity if the value of assets hits the default threshold	Black and Cox (1976)
Corporate bonds pay coupons and each coupon payment may cause default	Geske (1977)
Default-free short rate is stochastic	Shimko, Tejima, and Deventer (1993), Kim, Ramaswamy and Sundaresan (1993).
The firm has a stationary leverage ratio	Collin-Dufresne and Goldstein (2001)
Information based models (default is impossible to predict)	Duffie and Lando (2001), Giesecke and Goldberg (2004).
Jump to default (default is a surprise event)	Mason and Bhattacharya (1981), Delianedis and Geske (2001).
Strategic default	Anderson and Sundaresan (1996), Fan and Sundaresan (2000).
Liquidation	François and Morellec (2004), Moraux (2004) Broadie, Chernov, and Sundaresan (2007), Galai, Raviv, and Wiener (2007).
Renegotiation in financial distress and illiquidity of the market for distressed debt	Ericsson and Renault (2006)
Illiquidity of the market for distressed debt and cost of external financing	Davydenko (2007)
Contagion default	Chen (2007), Hackbarth, Miao, and Morellec (2006).

Tableau 4.II: Decomposition of credit spreads.

Highlights	Example of related work
Default factor	Elton, Gruber, Agrawal, and Mann (2001), Maalaoui, Dionne and François (2009).
Taxes	Elton, Gruber, Agrawal, and Mann (2001), Driessen (2005).
Term structure of interest rate	Duffee (1998), Driessen (2005), Collin-Dufresne and Goldstein (2001), Maalaoui, Dionne and François (2009).
Asset volatility	Campbell and Taksler (2003).
Leverage	Collin-Dufresne and Goldstein (2001).
Liquidity	Houweling, Mentink, and Vorst (2005), Driessen (2005), Jong and Driessen (2006), Han and Zhou (2006) with CDS, Maalaoui, Dionne and François (2009).
Jumps	Collin-Dufresne and Goldstein (2001)
Macro factors	Collin-Dufresne and Goldstein (2001), Maalaoui, Dionne and François (2009).