Long run credit risk diversification: empirical decomposition of corporate bond spreads

Sun, David and Lin, William T. and Nieh, Chien-Chung

Takming University of Science and Technology

October 2007

Long Run Credit Risk Diversification: Empirical Decomposition of Corporate Bond Spreads

David Sun*

Department of Finance and Taxation, Takming University of Science and Technology

William T. Lin
Chien-Chung Nieh

Department of Banking and Finance, Tamkang University

This Version: October 2007

ABSTRACT

Following the reduced-form models of Duffee (1999) and Jarrow, Lando and Yu (2003), this study investigates the risk diversification issue of corporate bond portfolios. Considering especially long run market behavior, our empirical decomposition of corporate bond yield spreads indicates that the idiosyncratic component serves as a good vehicle for risk diversification. Moreover, the idiosyncratic spread provides significant inferences about observed conditional corporate bond default rate, while full spread does not. Applying an affine model from Duffie and Singleton (1999), we find that the idiosyncratic credit spreads do not respond empirically to Treasury yields, unlike what is suggested in the structural model of Longstaff and Schwartz (1995) and literatures that follow. Systematic credit spreads are however positively related to Treasury yields in the long-run, but negatively so in the short run, suggesting the validity of both the tax and the option hypotheses. A long-run and optimal decomposition scheme yields an idiosyncratic credit spread measure at a median of 60 b.p. for the Baa index and is specifically compatible with Duffee's model. It is insensitive to interest rate in the short-run, but would rise slightly with a positive shock in the long run at a rate of one to a hundred. Our findings in the study contribute to the risk practice of bond portfolio diversification.

Keywords: bond pricing, cointegration, credit risk, credit spread, diversifiable risk
JEL Classification: C32, E4, G13, G33

* Address all correspondence to David Sun, Departmet of Finance and Taxation, Takming University Science and Technology, No. 56, Huangshan Rd., Sec.1, Neihu District, Taipei, Taiwan 11451, Email: davidsun@mail.takming.edu.tw and TEL: (886) 2 26585801.

I. Introduction

The purpose of this study is to suggest a empirical method to separate the systematic and the unsystematic part of yield spreads, or credit spreads, on corporate bonds, which has crucial implication in risk diversification with bond portfolios. Existing literature has explored credit spreads under a framework where diversifiable *idiosyncratic* credit risk is considered. Empirical investigation in this area has not, however, been conducted rigorously to establish the role of *idiosyncratic* risk implied by credit rating of firms. Methods employed by previous works have also mostly focused on short-run relations and failed to cope with temporal pattern of credit spreads. Without solid evidences to support a proper formulation of credit spreads, adequate pricing of corporate bonds is thus unsatisfactory. This study follows the arguments of Duffee (1999) and Jarrow, Lando and Yu (2003) to examine decomposed credit spreads using corporate bond indices. The study of *idiosyncratic* credit risk has implications on diversification specifically as studies of individual corporate bond yields are relatively few. In our study, *systematic* and *idiosyncratic* components of credit spreads are examined separately so that diversification of default risk can be explicitly addressed. Following the affine approach of Duffie and Singleton (1999), we take a reduced-form model approach where we decompose credit spreads into two parts. One is related to the systematic characteristics of corporate bond as a defaultable contingent claim, while the other is more related to *idiosyncratic* default risk of bonds of different grades. Our study considers especially the difference between short and long run in the effects of underlying factors influencing credit spreads. Based on a simple linear scheme, we show that systematic credit spreads are related to common factors like interest rates which cannot be diversified away in portfolios. On the other hand, the *idiosyncratic* credit spreads are not related to common risks, implying a diversification benefit of holding bond portfolios.

Existing studies makes no distinction between the *systematic* and *idiosyncratic* credit risks, nor do they distinguish phenomena in the long run from those in the short run. These earlier explorations of credit spread determinants have been conducted by Longstaff and Schwartz (1995), Jarrow and Turnbull (1995), Collin-Dufresne, Goldstein and Martin (2001), among others. These studies have generally concluded that observed credit spreads are negatively related to short term interest rate, slope of the Treasury yield curve, and positively so to corporate leverage and asset volatility. Employing data on corporate bond indices, Neal, Rolph, and Morris (2000) and Joutz, Mansi and Maxwell (2001) introduced the idea of long-run and short-run effects of Treasury yields on credit spreads. Using the latest cointegration analysis, they showed that credit spreads are positively related to Treasury yields in the long-run, but negatively so in the short run. These results help greatly the pricing of corporate debt through the construction of yield spreads of individual bonds. However, critiques on these studies indicate that, without the separation of systematic and idiosyncratic components in credit spreads, the accuracy of the pricing mechanism will be substantially affected[1]. While the *structural* approach, or the Merton model, clearly requires a role for the *idiosyncratic* credit risks, which have different temporal patterns from the *systematic* risks such as those suggested by Elton *et al*. (2001). In practice, the construction of yield quotes incorporates both components distinctively as suggested by Saunders, Srinivasan and Walter (2002), which causes the persistence of observed yield spreads according to Duffee (1998).

In order to characterize clearly how diversification of credit risk affects corporate bond pricing behavior, the decomposition credit spreads is crucial. Previous studies have focused mostly on the innovation of credit spreads over time, rather than comparing them across firms as credit rating agencies do. Wilson (1998) formally introduced a model of credit spread decomposition by adopting a multi-factor model to calibrate the loss distribution of *systematic* and *idiosyncratic* risk components, with volatility of default rate as the *systematic* risk. Duffee (1999) approached the decomposition by explicitly modeling a default intensity process, where only the *systemati*c default risk is related to yield curve, while the *idiosyncratic* default risk is exogenous. Gatfaoui (2003) extended the argument to formally decompose credit risks into the two components in a Merton context. A closed-form bond formula was developed out of stochastic volatility of a firm's asset value. Jarrow *et al*. (2003) also extended arguments in Duffee (1999) to explore the diversification implication of the *idiosyncratic* default risk. Other studies such as Elton *et al*. (2001) and Pedrosa and Roll (1998) have also investigated the decomposition indirectly. Works above rely mainly on simulated results from individual corporate bonds, which need improvements in two areas. First, an empirical investigation on the decomposition is yet to be done, as time series issues on observed credit spreads have to be addressed to obtain reliable implications. Secondly, the actual quoted credit spread construction process requires the consideration of credit rating before achieving the final credit spread on the individual firm level. So a further study of decomposition on that level using yield index is necessary.

This study proposes a decomposition scheme based on an affine term structure model. Our model is shown to be supported by observed credit spreads and corporate defaults, and is also consistent with

---

[1] Duffee (1998) argued that much of the negative relation between credit spreads and Treasury yields could be due to the callable feature of corporate bond. Collin-Dufresne *et al*. (2001) indicated also that various market-wide as well as firm-specific factors could only explain a limited portion (25 percent, in there study) of the observed credit spread behaviors. Cambell and Tasker (2003) suggested that *idiosyncratic* volatility explained equally well the credit spread changes as credit ratings. Elton, Gruber, Agrawal and Mann (2001) even argue that observed credit spreads beyond tax premium can be explained by the Fama and French (1996) systematic factors.

existing literature. The results from our study strongly suggest the necessity of decomposing credit spreads, and they supply evidence to bridge the gap between theories from previous literatures and actual practice. Our analysis focuses on the decomposition at the portfolio or crediting level, rather than the individual firm level, which is more compatible with actual pricing practice than Duffee (1999) and Jarrow *et al*. (2003). The *idiosyncratic* credit spread produced through our more general decomposition scheme provides reasonable and useful estimates for spreads across credit rating groups, or the default spread as used in the literature. Our use of bond indices avoids possible liquidity related data problem with individual bonds, and our methods identifies empirically the proper model where *systematic* credit spread should be constructed. The general decomposition scheme proposed, which considers long term equilibrium governing yield spreads, also offers explanation to the puzzles raised by Duffee (1998) and Elton *et al*. (2001). Specifically, long-run results validate the tax differential effect as noted by Elton *et al*. (2001), which argues that the burden of local taxes on non-government bonds draws a tax premium on the yield spreads of corporate bonds in addition to the default premium. The tax premium is higher on bonds of lower grade, as their coupons, hence yields and spreads, are higher due to higher default risks. Short-run analysis strongly supports the option-based hypothesis of structural approach presented by Longstaff and Schwartz (1995), which characterizes a negative relationship between the yield spreads and the short term interest rates due to the fact that higher default risks are present at times of low interest rates. As the option hypothesis predicts a negative effect of interest rate on credit spreads, it is contrary to the tax hypothesis where the effect is positive. However our theoretical model offers an reconciliation of the two and our empirical results verify that with solid evidences. The cointegration approach employed in our study generates unambiguous causal inferences as compared to Neal *et al*. (2000) and Joutz *et al*. (2001). To the extent that this study offers explicitly a yield spread construction method, it contributes corporate bond pricing mechanism in general, and further examination of *idiosyncratic* credit spreads on the firm level.

The remainder of the paper is organized as follows. Section II presents an affine model of yield spreads, laying a foundation of credit spread decomposition to be examined subsequently. Section III describes our data and preliminary statistics. A ‘baseline’ credit spread regression is carried out to verify standard results anticipated in our data set, with the considerations of structural changes across subperiods. We then employ two approaches of cointegration analysis in section IV, which provides us with the validity of alternative models as well as long and short run relations between interest rate dynamics and credit spreads with a naive decomposition scheme. We then present results under different credit spread decomposition method. In section V we examined how actual corporate default rates are predicted by *idiosyncratic* credit spreads and if decomposition method matters. Robustness and related issues are discussed in section VI. Section VII summarizes the paper with conclusion, possible improvements and extensions.

II. An Affine Model of Credit Spreads

We propose in this section an affine model credit spread based on the framework of Duffie and Singleton (1999) and Liu, Longstaff and Mandell (2004). In the latter model, valuations of liquid and illiquid default-free bonds, and a defaultable bond are achieved simultaneously. As our interest in this study is in the spread between higher and lower grade corporate bonds, we include in our model only one default-free bond, one higher grade and one lower grade defaultable bond.

The default-free zero-coupon bond maturing at T has at time t a value of

$$D(t,T) = E_Q\left[\exp\left(-\int_t^T r_s ds\right)\right], \tag{1}$$

where r_s is the short rate and E_Q is the expectation with respect to measure Q, the risk-neutral counterpart of the physical or objective measure P. The value of a high grade defaultable bond will incorporate a liquid spread γ_s to compensate for the illiquidity compared with default-free bonds[2], and default intensity spread λ_s which is from a Poisson process with time varying parameter. At time t it can be expressed as

$$A(t,T) = E_Q\left[\exp\left(-\int_t^T [r_s + \gamma_s + \lambda_s] ds\right)\right], \tag{2}$$

which is identical to the expression in Liu *et al*. (2004) but the liquidity spread is imposed on the defaultable rather than the default-free bond. The use of a high-grade defaultable bond in place of the off-the-run default-free bond or swap in their model has certain implications. The high-grade defaultable bond resembles the off-the-run issue in its low liquidity relative to the on-the-run issue, and is similar to a swap in having default risk. Jarrow *et al*. (2003) focuses on the liquidity characteristic and treats an AAA bond as default-free. So (2) in essence relates to the two studies with reasonable theoretic support. Note that the yield or credit spread of $A(t,T)$ is modeled to be influenced by r_s only through default spread λ_s, which implies the absence of tax differential effect in the case of high grade bond.

[2] As our focus in the study is on the yield spreads of corporate issues, the modeling here is essentially a mix of the illiquid default-free bond and a defaultable bond as presented in Liu *et al*. (2004).

A lower grade defaultable bond with similar structure is then modeled to have a value of

$$B(t,T) = E_Q\left[\exp\left(-\int_t^T [\phi_1 r_s + \phi_2 \gamma_s + \phi_3 \lambda_s] ds\right)\right] \tag{3}$$

at time t. The parameters ϕ_1, ϕ_2, and ϕ_3 are all positive and is modeled to reflect different sensitivity to the short rate, possible larger liquidity and credit or default spreads. Different from (2), the coefficient of short rate in (3), ϕ_1, is modeled to reflect the tax differential effect argued by Elton *et al*. (2001). As short rate goes up, in order for potential bondholders to hold the lower grade bond, more compensation is needed. Therefore ϕ_1 in (3) should be greater than 1, the coefficient of r_s in (1). The dynamics of the three endogenous variables are characterized by a general affine model with a set of four state variables which are Markovian under the equivalent martingale measure Q and square-root diffusions. The short rate is assumed, without loss of generality, to be driven by two state variables. They represent common shocks to the economy, as in Duffee (1999), which is different fro the three state variables as in Liu *et al*. (2004),

$$r_s = \delta_0 + X_1 + X_2, \tag{4}$$

where δ_0 is a constant. The liquidity spread in the high grade defaultable bond is assumed to take the form of

$$\gamma_s = \delta_1 + X_3, \tag{5}$$

where δ_1 is also a constant and the state variable X_3 represents the premium required for the illiquid corporate issues, regardless of default risks. The default intensity is assumed such that

$$\lambda_s = \delta_2 + \tau r_s + X_4, \tag{6}$$

where δ_2 and τ are both constants and the latter stands for the sensitivity of default to the short rate. According to the option-based structural models, such as Longstaff and Schwartz (1995), τ should be negative[3]. In this four-factor model, we use an affine term-structure model with general Gaussian processes to define the state variable vector $X=(X_1, X_2, X_3, X_4)$, using the notation of Liu *et al*. (2004),

$$dX = -\beta X dt + \Sigma dB^Q, \tag{7}$$

where β is a diagonal matrix and B^Q is a vector of independent standard Brownian motions under the risk-neutral measure of Q. Σ is a lower diagonal matrix containing covariances among the state variables, and it is assumed also that the covariance matrix $\Sigma\Sigma'$ is of full rank to allow correlations of state variables. Corresponding to this affine structure is the dynamics under the physical measure P,

$$dX = \kappa(\xi - X)dt + \Sigma dB^P, \tag{8}$$

where κ is also a diagonal matrix and ξ is a vector of long-term value of the state variables. The solutions to the default-free, high and low grade defaultable bonds can be solved under the risk-neutral dynamics (7). Their closed-form representation is as follows,

$$D(t,T) = \exp\left[-\delta_0(T-t) + a(t) + b'(t)X\right] \tag{9}$$

$$A(t,T) = \exp\left[-((1+\tau)\delta_0 + \delta_1 + \delta_2)(T-t) + c(t) + d'(t)X\right] \tag{10}$$

$$B(t,T) = \exp\left[-(\phi_1(1+\tau)\delta_0 + \phi_2\delta_1 + \phi_3\delta_2)(T-t) + e(t) + f'(t)X\right] \tag{11}$$

where

$$a(t) = \frac{1}{2}L'\beta^{-1}\Sigma\Sigma'\beta^{-1}L(T-t) - L'\beta^{-1}\Sigma\Sigma'\beta^{-2}(I - e^{-\beta(T-t)}) + \sum_{i,j}\frac{1-e^{-(\beta_{ii}+\beta_{jj})(T-t)}}{2\beta_{ii}\beta_{jj}(\beta_{ii}+\beta_{jj})}\Sigma\Sigma' L_i L_j,$$

$$b(t) = \beta^{-1}(e^{-\beta(T-t)} - I)L$$

and I is the identity matrix and $L'=[1,1,0,0]$. Functions c(t) and d(t) are the same as a(t) and b(t) except

[3] Without loss of generality, if we model λ to be just related to default-induced spread, tax differential effect would not be relevant here. ϕ_1 in (3) would be the only source for that effect.

that $L^{\prime}$ is defined as [1+τ, 1+τ,1,1], whereas *e*(t) and *f*(t) are the same as *a*(t) and *b*(t) except that $L^{\prime}$ is defined as [ϕ_1(1+τ), ϕ_1 (1+τ), ϕ_2, ϕ_3].

The credit spread of the high grade bond is thus a linear function of state variables in the form of

$$SP^A = \tau\delta_0 + \delta_1 + \delta_2 + \eta_1(t) + \omega_1\tau X_1 + \omega_2\tau X_2 + \omega_3 X_3 + \omega_4 X_4\,, \tag{12}$$

and the credit spread for the low grade bonds can be expressed similarly as

$$SP^B = \phi_1^{'}\delta_0 + \phi_2\delta_1 + \phi_3\delta_2 + \eta_2(t) + \omega_1\phi_1^{'}X_1 + \omega_2\phi_1^{'}X_2 + \omega_3\phi_2 X_3 + \omega_4\phi_3 X_4\,, \tag{13}$$

where ω's are functions of parameters and time, and $\phi_1^{'} = \phi_1(1+\tau)-1$. $\eta_1(t)$ and $\eta_2(t)$ are functions of time and parameters. Generalizing the characterizations of (3) to bonds of other grades, we could consider X_1 and X_2 as common risks as their effects are proportional across bonds. Although X_3 and X_4 drive the evolution of $A(t)$ as well as $B(t)$, their combinations in the two securities are different. The setup of our model treats the liquidity state variable X_3 as one distinguishing the defaultable bond from the default-free bond, unlike the specification in Liu *et al*. (2004) where the liquidity spread is to separate off-the-run default-free bonds from on-the-run issues. The difference in the combination of (X_3,X_4) in evaluating $A(t)$ and $B(t)$ allows the liquidity factor to also enter as a specific or unsystematic risk in SP^A and SP^B, in addition to the pure default spread factor X_4.

It is straightforward from (12) and (13) that the expression

$$ISP^B = \upsilon + SP^B - \frac{\phi_1^{'}}{\tau}SP^A\,, \tag{14}$$

where υ is a function of parameters and time, is free of common risks X_1 and X_2, and can be utilized to characterize the idiosyncratic component of the low grade bond. Note that the specification of (2) makes little distinction among r_s, γ_s and λ_s, which requires the valuation of three securities to separate them, as in Liu *et al*. (2004). As swap spreads have increasingly become a major benchmark of risky fixed income securities, the exact pricing structure in (2) turns less necessary. However, the specification of (3) allows us to focus on pricing risks contained in defaultable bonds of various credit grades, without referencing to the relationships among default-free bonds. The idiosyncratic credit spread measure in (14) serves as empirically testable tool to facilitate that purpose. It is also useful to verify the validity of both the option-based hypothesis and the tax differential effect. It is obvious that the coefficient of SP^A in (14) must be negative, like a hedge ratio, for common risks to be hedged using the two defaultable bonds. The hedging function of the idiosyncratic credit spread brought forward in (14) has profound implications on risk diversification in fixed income portfolios, as properly priced defaultable bonds of various grades suggest an accurate risk allocation where portfolio risks are accurately diversified. It is then required that $\phi_1^{'}<0$. With ϕ_1 required to be greater than 1 for the existence of tax effect, it should satisfy also the following inequality,

$$\frac{1}{1+\tau} > \phi_1 > 1 . \tag{15}$$

The upper limit of ϕ_1 in (15) depends on the magnitude of τ, which is larger for lower grade bonds. As larger tax effect also happens on lower grade bonds, the option and the tax effect are actually closely related to each other in this affine model. Only when there is room for higher credit risk premium is there a possibility to be subject to higher state taxes. With the framework of this section, we'll be able to test the validity of both effects.

III. Data and preliminary analysis

The Data

In order to avoid possible liquidity effect[4] on individual corporate bond yield spreads, we choose to explore our model with indices. The data employed in this study are the composite monthly and weekly yield observations from seasoned Aaa- and Baa-grade corporate bonds, which are compiled by the Moody's Investors Service and are obtained from the Board of Governors of the Federal Reserve System. Each index contains various major corporate bonds with different maturities. The data period starts from May 1953 and ends in September of 2003. The spreads are computed by taking the difference between the index yields and those of the 10- or 20-year treasury bonds. We have used monthly and weekly series of the Aaa and Baa yield spreads, or SP^{AAA} and SP^{BAA}. Also presented there is the difference between the two, or ISP^{BAA}, which will be used later as a *naive* proxy for idiosyncratic credit spreads[5]. Monthly yield spreads in the latest period, between 1982 and 2003, are much higher than the other three periods. Cambell and Tasker (2003) also noted in their data that credit spreads are especially higher in the late 1990's, given higher equity returns within the period. Even as the proportion of non-callable bond rises over time, which implies that it should have suppressed yield spread to some extent, the credit spread rises through time regardless. Whether this phenomenon is related to liquidity, taxes, business environment, or risks will be discussed later in this study. The data period is divided into three subpriods to examine potential structural changes of the capital market, with break points computed by an algorithm proposed by Bai and Perron (2003), with subsequent paragraphs in this section and Table II containing more descriptions. Besides the yield data, we have also used default rate data from Moody's. The default data is basically compiled annually, but the yield data is averaged weekly and then matched against the default data according years, whose details will be further described in in Section V and in Table VI.

It is worth noting that the kurtosis and skewness of the *levels* of SP^{AAA} and SP^{AAA} for the entire sampling period are not far from a normal distribution. The naive *idiosyncratic* credit spread, ISP^{BAA}, has higher values in both measures for the whole period. A separate analysis has also been done on the *changes* of yield spreads, which exhibit excessive kurtosis also, a result similar to findings from Pedrosa and Ross (1998). Various studies employed yield spread changes that could suffer this

[4] Collin-Dufresne *et al*. (2001) suggested that 'individual liquidity shock' causes a significant portion of unexplained variations in credit spreads of individual corporate bonds.

[5] It also corresponds to a special credit spread decomposition scheme, one which implies $\phi_1' = \tau$ in (14)

problem[6]. The liquidity effect on the individual corporate bond spreads in those studies worsens it further. Our subsequent analysis employs *levels* of yield spreads directly rather than *changes* to not only retain information contained in the original variable, but also avoid potential inferencing errors[7].

The Baseline Model and Preliminary Analysis

To explore the characteristics of τ in (6), the interest rate or systematic credit risk measure, we begin analysis with our sample from the following regression equation,

$$\Delta SP_{it} = \beta_{i0} + \beta_{i1}\Delta TB3M_t + \beta_{i2}\Delta TERM_t + e_{it}\text{, } i=1,2,\ldots I;\ t=1,2,\ldots T, \tag{16}$$

where ΔSP_{it} denotes the *change* of SP^{AAA}, SP^{BAA} or ISP^{BAA} at period t, whereas $\Delta TB3M_t$ is the change on 3-month Treasury Bill yield and $\Delta TERM_t$ is the difference between yields of 10 year Treasury Bond and 3-month TB. Equation (15) is called hereunder the *Baseline Model*, as many other works employ this equation in their analysis too. Duffee (1998) and Collin-Dufresne *et al*. (2001) carried out their analysis using a model like equation (15) finding both estimates of β_{i1} and β_{i2} to be negative, which draws the starting line of our analysis. As the *Baseline Model* estimates the two parameters independently and is hence more flexible than the specification in (4).

We establish estimation results of this model as a benchmark of inferences. Our estimation on this model differs from other works in that we examine the effect of structural change over the long sample period of 50 years. Break points carefully derived from it provide us with econometrically sensible subperiods for all subsequent analysis. First differences of original variables are used regardless of the said excessive kurtosis in their sampling distribution. Table II reports the results of OLS regressions of (15) on three series of credit spreads, for both monthly and weekly samples. The division of subperiods is according to break points found for ISP^{BAA}, the idiosyncratic credit spreads of Baa (difference between Aaa and Baa yields) from an endogenous multiple structural change algorithms according to Bai and Perron (2003)[8].

Results from (15) are consistent with predictions made by literatures adopting the structural

---

6 Pedrosa and Roll (1998) showed that a randomized Gaussian-mixture models yield spread changes better than a simple Gaussian distribution assumption.

7 It will shown subsequently in our paper that applying *changes* only in a short-run analysis would also miss the picture of long-run equilibrium which only applying *level* of variables can possibly capture.

8 The Bai and Perron procedure does allow for the consideration of heterscedasticity and autocorrelation. The number of breaks tends to be smaller (changing from 3 to 2) when taking into account the situations above. Parameter estimates for (15) turns out to maintain their signs with smaller magnitude, regardless of the number of breaks. The endogenous break identification procedure has also been carried out for both SP^{AAA} and SP^{BAA}, with locations of break points not far from what we have found for ISP^{BAA}.

approach. Under that approach, β_1 and β_2 should be negative and larger in magnitude for lower grade bond. Tax differential based approach argues, however, that the two parameters should be positive instead. To the extent that (15) is a short-run analysis, it validates the structural approach effect in the short run only. The estimation results from weekly observations in Panel B provide examination of effects from infrequent trading, as well as a benchmark contrast to subsequent long- and short-run analyses. The levels and standard errors of weekly coefficient estimates on SP^{AAA} and SP^{BAA} are uniformly 30% larger than those in the monthly panel. Duffee (1998) estimated a model very similar to (15), whose results are similar to ours, but not as large in magnitude after controlling for effects of the embedded option of callable bond issues[9]. Results from Collin-Dufresne *et al*. (2001) are also similar although the significance in the term structure coefficient is in inconclusive. As the R^2 is too low, they conclude that it is worth cautious attention when estimating determinants of credit spreads with an equation such as (15).

Results in Table II are different from previous studies in two areas, which also justify the use of Bai-Perron's structural change procedure. First, parameter estimates of β_1 and β_2 drop substantially from the earlier to the later subperiods, uniformly for both SP^{AAA} and SP^{BAA}, in both monthly and weekly panels. The monthly estimate for β_1 goes from -0.6284 in the first subperiod down to -0.2862 in the last subperiod, while β_2 goes from -0.7128 to -0.2910. If this phenomenon does not imply the credit spreads are becoming less sensitive to interest rate, then it might well be due to the reduction of callable bonds in the market as suggested by Duffee (1998)[10]. To the extent that our sample starts from 1953, when callable bonds are the majority, to the year of 2003, when the percentage of callable bonds is greatly reduced by about 60%, the uniformly smaller effects from interest rate dynamics implies the influence of callability. This phenomenon and the volatility of Treasury bill yields exemplify strongly structural changes over time when discussion credit spreads.

The second major difference our analysis in Table II brings about is that ISP^{BAA}, the idiosyncratic credit spread of BAA, responds much less to interest rates, given that it is a special case of our specification in (15). Estimates for β_1 and β_2 are much smaller in magnitude in all periods, and are at the order of tenth to twentieth of those for the full credit spreads. Especially in the last subperiod, the

---

[9] His analysis covered the period between 1985 and 1995, corresponding roughly to the third subperiod of our sample. With around 120 monthly observations for yields on all bonds with "medium" maturities (7 to 15 years), the estimated β_1 and β_2 for SP^{AAA} is respectively -0.021 and 0.001, both insignificant, while estimates for SP^{BAA} is respectively, and significantly, -0.249 and -0.147.

[10] Güntay *et al*. (2003) reported that the percentage of callable bond among new issues between 1981 and 1988 was 76.5%, while it dropped substantially to only 29.6% between 1989 and 1997 (they also documented that callable bond percentage is higher for high rated bonds than for medium rate ones).

β_1 and β_2 estimates for SP^{BAA} are -0.3666 and -0.3137 respectively, while those for ISP^{BAA} are merely -0.0804 and -0.0227. Estimates for ISP^{BAA} are insignificant especially in the first and the last subperiod, in both monthly and weekly samples. Especially, the insignificance is even stronger when its sampling distribution, with positive skewness and high kurtosis, tends to produce incorrect significant results under standard *t*-values. Note that the callability issue could affect results in the first period while the second period would suffer from the ultra high interest rate problem, as argued in Duffee (1999) and Jarrow *et al*. (2003). In both cases, effects *unrelated* to credit risk could contaminate the results. If the idiosyncratic credit spread is properly identified under our specification, then it should not respond to interest rate, a state variable related to common or systematic credit risks. Results in Table II are partially consistent with this argument, given the contaminating factors outlined above. The *idiosyncratic* credit spread is only significantly related to Treasury yields in the second subperiod, between 1972 and 1987, when short-term interest rate is so high that it often exceeded the long bond yields[11]. As for how the substantially compressed credit spreads under high and volatile interest rates are related to the strong magnitude of coefficient t-statistics in the second subperiod, further investigation with non-linear or frontier related estimations may have to be carried out to make clarifications.

IV. Empirical decomposition of credit spreads

The so-called reduced-form models, first introduced by Jarrow and Turnbull (1995) assume explicitly that default probability and recovery rate of risky debt follow certain exogenous processes. These models allow liquidity and systematic credit risk premia to be modeled directly while the probability of default can be derived from the term structure of credit spread. Duffie and Singleton (1997) included in the analyses the spread between Aaa and Baa grade commercial papers as an exogenous default risk proxy. Notably, they used weekly data in their analysis, to capture the dynamic influences from the components of the two-factor model stipulated there. Duffee (1999) argued in fact that the yield spreads are supposed to be positive even for the highest-quality firms, due to liquidity and tax reasons. Jarrow *et al*. (2003) have actually used yield on Aaa grade bond as a proxy for default-free yield in short-run analysis to incorporate non-default related part of yield spreads. Duffie and Singleton (1997) used our measure of *idiosyncratic* credit spread, or the *default* spread, to proxy default risk. The

[11] Duffee (1999) indicated specifically that this is the problem with of the type of reduced-form model introduced by Duffie and Singleton (1997).

use of Aaa credit spread is also consistent with the notion of non-negative credit spreads in high quality firms. The examination of *idiosyncratic* credit spreads is important especially in its implication on credit risk diversification with bond portfolios.

As a variation of (6), Duffee (1999) set up a default model with three factors, which states the default intensity of the jth firm, h_{jt}, follows

$$h_{jt} = a_j + h_{jt}^* + \beta_{1j} s_{1t} + \beta_{2j} s_{2t}, \; j=1,2,...N; \; t=1,2,...T \tag{17}$$

with h_{jt}^* being an unpredictable square root process and s_{1t} and s_{2t} each corresponds to level of Treasury yield and the slope of Treasury yield curve. Credit spread of firm j is a monotone function of its default intensity, h_{jt}. (17) is also consistent with negative credit spreads when interest rates are very high. Jarrow *et al*. (2003) employed a similar model and showed that h_{jt}^* should be related to default risk diversifiable within a large portfolio. h_{jt}^* in (17) and α_j are supposed to be firm specific factors while s_{1t} and s_{2t} are common factors affecting credit spreads. In our terms, the systematic credit spread should be a function of the latter two, while the idiosyncratic credit spread a function of the former two. According to Duffee (1999), α_j for Aaa-rated near-zero-maturity zero-coupon bond translates into a minimal yield spread of 41.9 b.p. given that the default risk h_{jt}^* is zero. For our sample with medium maturity, coupons and certain default risks, estimates from (16), the *Baseline Model,* should be larger. We follow Duffee's specification, proxying h_{jt} with yield spreads and fit the parameter estimates from Table II back to the original *level* variables, and find that the median of α_j + h_{jt}^* is 149 b.p. for SP^{AAA} and 250 b.p. for SP^{BAA}, indicating possible over-risk-compensation[12] for s_{1t} and s_{2t} by the *Baseline Model*. In another word, the idiosyncratic component has been estimated to include premium for systematic credit risks.

As a naive scheme, we first use credit spread of Aaa index as the *systematic* credit spread, as SP^{AAA} combines features of a low-liquidity-effect default-free bonds and a defaultable swap. The *idiosyncratic* credit spread defined in (14) offers a testable framework which we can employ to make useful inferences. The following linear equation will be applied to investigate how credit spread decomposition should be carried out,

[12] Duffee (1999) showed that the difference between long- and short-end of the yield curve is less than 20 b.p. for Aaa-rated bonds and 70 b.p. for Baa-rated ones. Also the two measures are much higher than the sample means reported in Table I.

$$ISP_t^j = SP_t^j - \theta_j SP_t^{AAA}, \; j=1,2,...J; \; t=1,2,...T \tag{18}$$

where

$$\theta_j = \frac{\phi_{1j}^{'}}{\tau_j}$$

with $\phi_{1j}^{'}$ and τ_j as defined in (14) for the BAA and AA indices in our data. θ_j characterizes the relative magnitude of the option and the tax effect. (3) and (15) predicts θ_j to be positive and with a magnitude of greater that 1. Empirically, θ_j will also be the standardized long run cointegration coefficient between SP_t^j and SP_t^{AAA}. An estimation of θ_j being greater than 1 is therefore consistent with both effects on credit spreads. The *naive* idiosyncratic spread defined in the previous section, where θ_j is simply 1, serves as a special case of (14). In the paragraphs that follow, we will focus first on the simplified, naive situation first to obtain certain fundamental results under the linear time series model. After that we will examine the situation of a more general version of θ_j. As the approach undertaken differs from many previous studies, we will present observations of the need for the new methodology before proceeding with our analysis.

Problems of using credit spread changes

Changes in credit spreads have been used extensively, although *level* relationship is the focus of both the structural and reduced-form models. Given that using changes avoid partially problems arising from non-stationarity and autocorrelation in *level* of credit spreads, it is not without fundamental problems. The loss of information is the first problem. In the *Baseline Model* of equation (16), employing changes in credit spreads does not help examining that issue. On the other hand, if decomposing credit spreads helps revealing valuable information, then relying on observations of changes simply discards the information. The second problem of resorting to credit spread changes lies in their statistical properties. Aside from being leptokurtic as indicated by Pedrosa and Roll (1998), they are also found to persist over time in Duffee (1998). With regard to our sample, a separate analysis has also been carried out and we found the persistence to be significant as well[13]. Both Aaa and Baa

[13] The AR(1) autocorrelation coefficient, for the monthly sample, is 0.073 (significant at 10%) for AAA yield spread

yield spread changes in our monthly sample are also found to be persistent up to at least two periods in a Generalized Impulse Response analysis.

Long-run analysis with cointegration

Following Pedrosa and Roll (1998), we will reexamine in this section the long-run equilibrium relationship among the three variables in the Baseline Model. We adopt primarily the approach of AutoRegressive Distributed Lags (ARDL) in the context of Pesaran, Shin and Smith (2001), or PSS (2001), which stresses the crucial nature of level and long run relationships. As cointegration approach of long run equilibrium has been widely used following Johansen (1988, 1994), and Johansen and Juselius (1990), stationarity and the order of integration of data employed is crucial. In a separate analysis, we have found that *levels* of all the variables involved in (16) are nonstationary and integrated of order one, or I(1)[14]. Compared with other cointegration-based studies in this area, mostly based on the Johansen methodology, our Error Correction Model under ARDL, or ARDL-ECM, provides more unambiguous implications with fewer restrictions, including homogeneous order of integration on *all* variables. With the specific sequence of a two-stage test suggested by PSS (2001), we are able to identify specifically appropriate modes for each of the credit spread variables of interest. We obtain hence coherent statistical inferences, and economically sensible implications, from our analyses.

As most of previous studies focus on the short run phenomenon and derive inference based on relationships on differences of variables, our results provide comparatively economically consistent and econometrically consistent implications. Findings of our examinations are in line with predictions of mainstream literature but offer more specific explanations of unresolved issues. Non-stationarity in credit spreads could arise from common or firm-specific factors. If key variables of interest rate dynamics, such as $TB3M_t$ and $TERM_t$, are the only common factors, then the nonstationarity of credit spreads should be accounted for by them. However, if the residuals are still not stationary, then either credit spreads are related to other systematic factors or idiosyncratic factors unrelated to common factors. The ARDL model is used to identify exogenous or the *forcing* variables within the system, as well as long- and short-run driving intensity of them. More importantly, in the context of an ARDL-ECM, only one error-correction term will be present. A significant error-correction term in the related ECM acts as a sufficient condition for long run equilibrium relation, or cointegration. On the other

changes and 0.181 (significant at 1%) for BAA. But in the subperiods, autocorrelation correlation coefficient goes from an insignificant 0.018 in the first period to a strongly significant 0.249 in the third period. Autocorrelations are much more pronounced for the weekly sample, probably due to higher proportion of zeros from inactive trading in shorter intervals.

[14] The I(1) property of variable *TERM* is only marginally supported. Unit root tests vary across subperiods too.

hand, a significant result from a Variable Addition Test (VAT) on the levels of variables serves as a necessary condition to the validity of the system in interest.

In the model identification stage, we have used both the Johansen's Vector AutoRegressive (VAR) cointegration and PSS' ARDL-ECM approach. Results are similar but the latter yields more conclusive implications. Hence, our focus will be on the ARDL model, while providing estimation results from the other as a reference. In Table III, we report under the column Model I-Johansen both the number of cointegrating vectors and coefficients for them in ECM estimations. Five Vector AutoRegressive (VAR) models have been considered in a *Baseline Model* to identify the number of cointegrating vectors. The uniform result of the number 2 indicates that there are two linear relations among the three variables of interest which help achieving stationarity for the system. In the first column of ECM panel of Table III, two coefficients, one for each cointegrating vector, are obtained, for all three series of credit spreads in the context of Johansen (1988). For each of SP^{AAA}, SP^{BAA} and ISP^{BAA}, OLS estimation is performed on a Vector-ECM (VECM) with lags of credit spread and the other two interest rate variables, and the error-correction terms. The signs of the error correction terms are not all negative, indicating a problematic situation where opposing adjustments to a long-run equilibrium seem to take place[15]. Neal *et al*. (2000) encounters similar problems employing Johansen's cointegration approach[16]. Almost all error-correction coefficients are significant, implying to some extent the validity of cointegrating vectors in the sense of Engle and Granger (1987). Although the cointegrating vectors have been estimated to be linearly independent to each other, the opposing influences from $TB3M_{t-1}$ and $TERM_{t-1}$ on, say SP_t^{AAA}, do not seem to be consistent with results from the basic OLS procedures in Table II[17]. We have to therefore resort to an alternative which avoids canceling effects from multiple error correction terms.

Under ARDL approach, the existence of a unique valid long run relationship among variables, and hence a sole error-correction term, is the basis for estimation and inference. Short run, or difference-based, relationship cannot be supported unless a unique and stable equilibrium relationship holds in significant statistical sense. Both Neal *et al*. (2000) and Joutz *et al*. (2001) have made extensive discussion over a *positive* long run relationship between credit spread and interest rates

---

[15] We have used the Johansen's error correction version of cointegration estimation simply to show, as Rolph, *et al.* (2000) did, the problem of resorting to multivariate error correction cointegration analysis in a Johansen context as many studies did. The problematic result of opposing long run adjustments suggest the need of necessary remedies.

[16] They had to realign the two cointegrating vectors to remove offsetting effects from the same variable within two linear combinations. But the results derived after such procedure could run into potential problems in the sense of PSS (2001).

[17] A negative sign for *TERM* in both the coefficients with a cointegrating vector and the related error-correction term implies that an increase in $TERM_{t-1}$ would increase SP_t^{AAA} as well. With positive autocorrelated *TERM*, it is incompatible for us to observe an increase in $TERM_{t-1}$ alongside decreased SP_t^{AAA}, as the Baseline Model would generally predict.

versus a *negative* short run relationship within a Johansen framework. The long run relationship, which is represented by a cointegrating vector, however, needs not to be unique. We will demonstrate in this study evidences for each credit spread series a similarly *unique* and significantly *positive* long run relationship between credit spread and interest rates, as well as a significantly negative short run relationship. The validity of a unique (set of) long run coefficient(s) can be obtained by passing a VAT on the levels of all the variables involved, without having to resort to the result of a short-run oriented VECM estimation as with the Johansen model. In fact, according to arguments on the crucial nature of *level* relationship and the two-step testing procedures outlined in PSS (2001), the second-stage short run estimation is unnecessary and meaningless if the first-stage long run VAT is failed. In this regard, our results based on valid long run results offer firmer and logically more consistent evidences than previous literature in this field. It is further more our basis in pointing out problems arising from the traditional methods used in examining credit spread-interest rate relationship, and the importance of decomposing credit spread to separate the idiosyncratic credit risk from the systematic one.

【Table III】

In the long run, or cointegration, test under ARDL, we examine four alternative models, which can be found that only one model is fit for each of the three credit spread series. The model I in Table III is just the *Baseline Model* from (1). TB3M and TERM are the two potential independent or *forcing* variables considered, while credit spread is the dependent or outcome variable. The computed F-statistic for the VAT has a non-standard distribution according to PSS (2001). For the case of two forcing variables, the 5% critical value is 3.79 if both variables are I(0), and 4.85 if both are I(1). If the two variables are cointegrated or mixed with I(0) and I(1), then a critical value in between could reject the null hypothesis of no cointegration, or no *level* relationship. We learn from a separate unit root analysis that *TB3M* is I(1) and *TERM* is I(0) in some subperiods and that a separate analysis shows *TB3M* and *TERM* are cointegrated. However, PSS (2001) indicates that this does not imply we can apply critical values between the bounds as pretest problems could arise. VAT for Model I fails to reject the null hypothesis, which implies that *TB3M* and *TERM* *cannot* both be the forcing variables for SP^{AAA} or SP^{BAA}, in both monthly and weekly data sets. This is direct evidence against findings in various literatures[18], and even what has been reported in Table II. On the one hand, one cannot simply avoid the nonstationarity problem by using changes instead. *Level* relationship needs to be more exact to be applicable on the other hand. The above rejections of the *Baseline Model* for SP^{AAA} or SP^{BAA}

[18] Joutz *et al*. (2001), applying on a similar data set, reported almost identical results using Johansen cointegration analysis with *TB3M* and *TERM* as forcing variables. Our analysis here is a direct counter-evidence against their results.

cannot also be achieved with the lack of causality in the results from Johansen's cointegration approach. Neither do the results in Table III rely on the requirement of homogeneous order of integration, which our data violates to a certain degree.

The most important result with Model I is that the *Baseline Model* is only applicable to ISP^{BAA}. Our findings earlier in Table II seem to suggest the opposite. In fact, it will be shown later that we would need this result to make further inferences on the issue. Some of the error-correction coefficients for monthly data under Model I are reported for reference purpose. According to PSS (2001), ECM estimation should only be carried out after the first stage VAT is passed. The coefficients for SP^{AAA} and SP^{AAA} are then irrelevant regardless of their significance. Only estimates for ISP^{BAA} are valid, and they are significant according to a non-standard t-statistic table, whose critical values are much higher. Note also that the ARDL procedure allows for uneven lag orders, while the Johansen's VECM does not.

Model II and III in Table III attempts to find out if SP^{AAA} or SP^{BAA} provides information to each other. Under Model II, for SP^{AAA}, we would add SP^{BAA} to the *Baseline Model* as the third forcing variable, and for SP^{BAA}, we add in SP^{AAA}. Under Model III, the variable *TERM* is omitted. Neal *et al*. (2000) pointed out with their Johansen VECM estimation that neither Aaa nor Baa yields contains useful information to each other[19]. Results under Model II do not support the inclusion of three forcing variables in a long run equilibrium relationship with credit spreads of the two bond grades, regardless of the significance of ECM coefficients. As the F-statistics fall below the lower bound for SP^{AAA}, it suggests that even all the forcing variables, SP^{AAA}, *TB3M* and *TERM* are stationary, they should not be included. Model III, however, supports that, along with *TB3M*, SP^{AAA} help providing information about SP^{BAA}, but not vice versa. Both the VAT and ECM results are significant under non-standard critical values.

So we have identified appropriate long-run models for ISP^{BAA} (Model I) and SP^{BAA} (Model I), as well as for SP^{AAA}. In Model IV, with *TB3M* as the only forcing variable[20], the VAT and ECM both indicate that it cointegrates with and stabilizes SP^{AAA}. Similar argument may also apply to the case of ISP^{BAA} in Model I, which will be addressed in the next section and shown to be consistent with the reasoning here. It is apparent the ARDL two-stage procedure identifies precisely what model to be used for each variable of interest. Compared with the Johansen cointegration method, which does not make distinction in model selection, ARDL method offers more specific implication, both on model validity

---

[19] As there are two cointegrating vectors, hence error-correction terms, the definition of the coefficients, and its implication is somewhat different from ours in Table III. They rely on the standard tests on the coefficients for inferences on the dependent variable. In our analysis, the PSS second-stage non-standard t-test examines the fitted residual of the dependent rather than the forcing variable, which results from a potentially equilibrium system involving the forcing variable.

[20] This finding is consistent with the unit root test. *TERM* turns out to be stationary under the more powerful criteria of DF-GLS and NP, which makes it improper to be included as one of the candidates to stabilize a non-stationary SP^{AAA}.

and economic content which will be discussed later. More importantly, the analysis in this section establishes a foundation for decomposing credit spread. Evidences that follow will further indicate that the examination of idiosyncratic credit spread is crucial in determining how credit spreads are formed.

ARDL-ECM, long and short run estimates

【Table IVa, IVb】

After the identification of models, we now proceed to the error-correction version of ARDL, which provides more detailed inferences on model validity, long run equilibrium relationship and short run dynamics. Tables Va and Vb report estimation results for monthly and weekly data respectively. Beside ECM estimations for the entire sampling period, we also report results for subperiods, whose division follows Table II. The inferences in subperiods exhibit strong distinction, confirming the structural change hypothesis of Table II[21].

Model IV for generates interesting results and implications. VAT suggests that *TB3M* does not cointegrate with SP^{AAA} in the sense of PSS at least in the second and the third subperiods. Within periods where cointegration seems to exist, the long run coefficients for *TB3M* are uniformly insignificant. This is a special case of non-existence of level or long run equilibrium relationship that is characterized as degenerate in PSS (2001) even both stage of tests are passed. Compared with Joutz *et al* (2001), where long run coefficients for both *TB3M* and *TERM* are strongly significant, our inferences demonstrate the superiority of PSS approach of ARDL. The identification of dependent versus independent variable through VAT and the ECM estimation that follows warrants more discriminating results. Our analysis previously and here under Model IV indicates that *TB3M* is the only valid variable to influence SP^{AAA}, and it only does so in the short run! The short run coefficients for Model IV in all periods, wherever applicable, are nonetheless uniformly negative and significant, further confirming that the negative relation under the option hypothesis between credit spread and interest rate is merely a short run phenomenon. The magnitude of the *TB3M* coefficients is much smaller than what is reported in Table II.

Model III for SP^{BAA} in Table IVa is literally valid for the whole period only. Analyses for the subperiods either failed VAT or generate insignificant ECM coefficients. In terms of implications, it is somewhat different. As SP^{AAA} is modeled as a forcing variable, the *R*-squared reported is much higher than in Model IV. The short run coefficient of SP^{AAA} is also significant and very close to 1, suggesting

[21] The lack of stability in estimation across these periods can also be examined with a CUSUMSQ structural stability test for Model I according to Brown, Durbin and Evans (1975). Structural breaks identified in Table II coincide with locations where the test fails at

its informational content[22]. Short run coefficient for *TB3M* is significant and negative, but is only about one-tenth of the magnitude of corresponding coefficient in Table II, a natural result from the fact that SP^{AAA} seems to have absorbed almost all influence from *TB3M*. Unlike Model IV, long run coefficients for *TB3M* are significantly positive. It verifies the tax hypothesis as modeled in our affine model and and suggested in (15), and is similar to the findings of Liu *et al*. (2004).

Findings for Model I in Table IV confirm some of the results in Table II, but add more insights to previous models. Although the whole-period short run coefficient estimates for *TB3M* and *TERM* are both significantly negative and of about the same magnitude as in Table II, we can only find weak support for it in the subperiods. VAT is passed for Model I in the first subperiod, but the second-stage ECM coefficient test fails for both monthly and weekly data. So on the monthly analysis, only the results in the third subperiod is worth noticing, which produces insignificant short run coefficients for both variables. Our results here are different from Joutz *et al*. (2001) in the long run coefficients of *TERM*, which are insignificant in all periods. That is, the slope of the Treasury yield curve has no effect on the idiosyncratic credit spread of BAA in the long run, but only some weak effect in the short run.

The ARDL-ECM analysis in Table IVa and IVb brings about three implications. First, much of the information about SP^{BAA} is contained in SP^{AAA}, but not vice versa. Second, in the long run, interest rate dynamics has no influence on the systematic credit spread, or SP^{AAA}, but strong influence on SP^{BAA} through its unsystematic component ISP^{BAA} indirectly[23]. Last but not the least, interest rate dynamics does affect credit spreads in the short run through the systematic component, but not the unsystematic component in most of the subperiods, a result consistent with Table II. The negative relationship between ISP^{BAA} and interest rate dynamics in the whole-period estimation may have been related to how a credit spread is decomposed into a systematic and an unsystematic component, which will be the focus of our discussion in the next section. We then examine again the measure of $\alpha_j + h^*_{jt}$ in (17) following Duffee's specification and find the medians are now 84 b.p. for SP^{AAA} and 168 b.p. for SP^{BAA}, an indication of better risk-compensation identified by the superior ARDL time series method. The 42 b.p. above the minimum α_j credit spread of 41.9 b.p. reported by Duffee can be considered as made up of instantaneous default premium h^*_{jt} plus any term-related liquidity and default premia.

[22] A separate and similar ECM analysis has been conducted on the full monthly data set by placing SP^{AAA} as the outcome variable, while setting BAA^{SP} and *TB3M* as the forcing variables. The short run coefficient for was merely 0.67 and R-squared is 0.70. The long run coefficient is 0.65, 41% smaller than the estimate derived in IVa. On weekly data, the short and long run coefficients are 0.69 and 0.68 respectively. The latter is only half of the long run coefficient estimate reported in IVb. However, the weekly model does not pass the VAT, so its ECM results can only serve as a reference.

[23] As *TB3M* is included in both Model III and IV and it has no long run effect on SP^{AAA}, the almost equivalent long run coefficients estimated for *TB3M* in Model IV and I clearly suggest this possibility.

Results thus far support the use of *idiosyncratic* credit spread as a proper measure of firm-level credit risk level. While it exhibits a long-run and *positive* comoving pattern with interest rate dynamics, it does not necessarily do so in the short-run. It will be seen in our subsequent discussion that the negative short-run relation, if any, is merely a consequence of inaccurate specification of the idiosyncratic risks. The *systematic* credit spread does however exhibit significant dependence on the interest rates. Our results are also comparable with Neal *et al*. (2000) and Joutz *et al*. (2001) in that *systematic* credit spreads are related to Treasury rates negatively in the short run and positively in the long run[24].

ARDL-ECM for the general decomposition model

In the preceding paragraphs, systematic credit spread has been proxied by SP^{AAA}, while the idiosyncratic credit spread is simply the residual spread for a particular bond grade of interest. To the extent that the actual division of credit spread could be the result of market behavior, taking difference is equivalent to imposing a long run cointegration restriction on the two variables. The restriction works as if a cointegrating vector of (1,-1) can be derived from a long run equilibrium relationship. In order to properly capture the idiosyncratic credit spread, one should, when decomposing credit spreads, take into account how credit spreads of different grades co-move in the long run. Otherwise, the long run dynamics of the idiosyncratic credit spreads will be distorted. This requires the application of (18), which suggests a cointegrating vector of $(1, -\theta_j)$ between ISP^{BAA} and SP^{AAA}.

【Table V】

Table V compares alternative decomposition formulas to identify an appropriate definition of idiosyncratic credit spread. The first column is a natural, *naive* or default premium characterization. Results for ISP^{BAA} from Model I ARDL-ECM in Tables IVa and IVb are transcribed directly and placed on the top panel. On the bottom panel, we have added an analysis for ISP^{AA} in a Model I context as a cross section comparison. As data is only available within part of the original weekly sample from 1982 to 1993, we have thus dropped the estimation for SP^{AA} in all previous analyses. The results here, which have also been divided into two subperiods[25] according to a break point used for SP^{AAA} and SP^{BAA}, are,

[24] An anonymous referee has asked us to clarify the stability of this phenomenon in our study. We therefore note here that it is supported by results under Model IV in Table IVb, where the signs of long- and short-run coefficients are the same in the 1st sub-period. In the 2nd and 3rd sub-periods, although results are not reported due to insignificant VAT statistics, the sings maintain the same pattern as in the 1st sub-period.

[25] A CUSUMSQ test has also been carried out for SP^{AA}, and is rejected for stability for the whole period, as shown in Figure 2 and 3.

however, supportive of all the preceding findings[26]. Turning our focus on the idiosyncratic credit spread, we find Model I is accepted according VAT for all periods. The long run coefficients for ISP^{AA} are found to be positive for both *TB3M* and *TERM*, during the entire period of 12 years where data is available, but insignificant within both subperiods. The short run results are similar to those for ISP^{BAA}, in that they are negative earlier and insignificant in the later period. Findings in this column reconfirm the generality of those for ISP^{BAA} presented in the previous sections. So we can proceed with our analysis with the same methodology on the two idiosyncratic credit spreads as follows.

We conduct another set of ARDL estimations on SP^{BAA} and SP^{AA}, to obtain long run coefficients against SP^{AAA}, which are used to construct an alternative measure of idiosyncratic credit spread. With the support of VAT[27], we adopt a long run coefficient of 1.35 for SP^{BAA} against SP^{AAA}, and 1.2 for SP^{AA} based on the weekly sample estimation results, which are used in place of 1 in the naive definition to construct our measure of idiosyncratic credit spreads. The same set of ARDL-ECM procedures are carried out on this new measure, yielding interesting results. As we are using the *residual* from a long run cointegration or equilibrium equation to fit against *TB3M* and *TERM*, which are systematic factors strongly influencing SP^{AAA} in the short run, it is reasonable to find this residual to be unrelated to driving factors of the independent variable to which the residual is supposed to be conditionally orthogonal. This is indeed the case in Table V. Under the *cointegration* definition of idiosyncratic credit spreads, neither ISP^{BAA} nor ISP^{AA} is significantly and *negatively* related to the interest rate dynamics. The estimate of β_1 for ISP^{BAA} under Model I has become -0.0072, a 94% drop in magnitude compared with what is under the *naive* scheme. On the other hand, for ISP^{AA} the estimate drops by 83% in magnitude. In the second subperiod for ISP^{AA} estimation, the short run coefficients are even turning significantly positive, an indication of misspecification resulted from using a single cointegration coefficient for structurally changing periods. The *R*-squared's have become fractional of those under the *naive* definition, suggesting the lack of explanatory power of the two forcing variables. Long run coefficients are, however, not much different. The coefficients of *TB3M* are of the same order of magnitude in the case of ISP^{BAA}, and also significantly positive for ISP^{AA}. So the *cointegration* scheme seems to retain long run characteristic of idiosyncratic credit spread, while removing contaminated short run effects due to inappropriate specifications. In another word, spirits incorporated in the *cointegration* method are compatible with the risk diversification discussed earlier in the specification

---

[26] The model identification outcome for SP^{AA} is similar to that for SP^{AAA}. Models I, II and III are all rejected with F-statistics at 3.54, 2.53 and 4.05 respectively. Model IV in VAT yields a significant 5.96 to be accepted. The ECM estimation results are similar to those for SP^{AAA} as well, with an ECM coefficient significantly at 3.63, above the PSS non-standard critical value at 3.22.

[27] The VAT F-statistics are 6.72 and 8.01 respective on monthly and weekly data out of an ARDL model on SP^{BAA} against the sole forcing variable SP^{AAA}, and the F-statistic is 6.91 from a similar model for SP^{AA}.

of the affine model.

The decomposition under the *cointegration* scheme is proposed as an alternative to the *naive* one. The application of the cointegration regression analysis needs to be examined for its validity in the decomposition process. As a robustness check against the above results, we have added an *arbitrary* approach to contrast them. The *arbitrary* scheme in Table V adopts arbitrarily a value of 1.5 as the long run coefficient for SP^{AAA} in constructing *idiosyncratic* credit spreads. Estimations in subperiods of SP^{AA} fail to pass VAT, indicating reduced relevancy among variables. All the short run coefficients become significantly positive, an implication of under-risk-compensation in constructing default premium. Long run coefficients are almost still the same. This exercise further suggests that short run coefficients are strongly sensitive to how the idiosyncratic credit spread is constructed. Properly identified unsystematic credit risk should not exhibit significant response to common economic variables in the short run. Correctly specified decomposition leaves only unsystematic risks in the idiosyncratic spreads. This is consistent with the predictions of our affine model in Section II. The magnitude of θ_j, the long run coefficient, confirms that being greater than 1 reflects the tax effects in (3). Furthermore, it also says that ϕ_1, the measure of tax effect in the numerator of θ_j, is limited by the magnitude of τ, a negative option effect, such that θ_j is also limited to certain extent. That is exactly the situation of our *arbitrary* case in Table V. If the tax burden for lower grade bond is over-compensated in the long run beyond the risks characterized by τ in the short run, then common risks would not have been properly hedged in as in (14). As a result, idiosyncratic spreads could be *positively* influenced by, instead of being independent of, the interest rate.

While long run relationship revealed in the system tells what economic behavior is in effect and how it governs the capital markets, models relying only on short run methodology and evidences could really be biased by the absence of long run aspects. Note again that the median ISP^{BAA} under the *cointegration* scheme is 60 b.p., which fits well within the equilibrium equation in the context of Duffee's definition[28], while the *naive* scheme produces a median of 81 b.p. for the monthly sample would turn out to have incorporated *too much* systematic effect. The identification of the idiosyncratic credit spread thus has support not only in the analytic sense, but also relates to actual market-quoted measures. The decomposition of credit spread is uniquely defined and also consistent across different credit ratings. In the next section, we will show that the decomposition is furthermore supported by

[28] Appling the cointegration equation and multiply 84 b.p., the $\alpha_j + h^*_{jt}$ measure for SP^{AAA} given in the previous section, by the cointegration coefficient 1.35 and then add 60 b.p. to it gives 173 b.p., very close to 168 b.p., the $\alpha_j + h^*_{jt}$ measure for SP^{BAA} also given in the last section.

observed corporate defaults in an even more direct way.

V. Informational content of idiosyncratic credit spread

So far we have established to a certain degree that, in the short run, idiosyncratic credit spread is *unrelated* to common factors. While systematic credit spread reflects premium to compensate for general risk of default, idiosyncratic credit spread is supposed to price unsystematic risk of default related to specific firm or sector. In this section, we would like to explore the above premise. We examine how the idiosyncratic credit spread of certain credit rating in our data responds to default risk particular to that grade. In addition, credit spread decomposition methods will also be compared to see if results are consistent with our findings from the last section.

In order to construct a realistic measure of *conditional* default intensity, we adopt Moody's dynamic cohort default rates instead of the widely used *unconditional* one-year default rate[29] at any given year. Cohort in a given year of a given senior rating is made up of all issuers in that year, which are followed through time to keep track of their default rates until leaving the rated universe. The existence of these dynamic cohorts allows multi-year cumulative default risk to be estimated. Comparisons made among default rates over different periods are thus sensitive not only to measure of default intensity that is absolute in, but also relative to, time, and hence *conditional*. To match the average age of bonds in our data, we limit our cohort range to between 13 and 18 years from issuance. For each given year between 1983 and 1999, there is then a panel of six groups with comparable default rate data. Although the average age of the issues in the Aaa or Baa indices could be lower than 15 years, we use the *change* in cumulative cohort default rates which are potentially realized two to three years after the bond yields are quoted to incorporate potential informational effect reflected in the credit spreads observed. The cumulative default rates of Baa-rated issues generally reached their peaks ranging from 10.5% to 11.25% between 1993 and 1997, whereas higher credit spreads are observed between 1986 and 1993 at around 200 to 300 b.p., compared to a sample mean of 169. As the number of default events are compiled over time but reported once at year end, we adopt a three-year moving average of cumulative cohort default rate to account for cross-year effects and possibly extended lead time before a default event[30] is declared or realized.

【Table VI】

Table VI reports estimation results on the informational content of the idiosyncratic credit spreads

[29] Both the unconditional and the cohort rate are 12-month trailing default rate utilizing a universe 12 months earlier as the base in calculation.

[30] Moody's default definition covers three types of default events. Missed/delayed interest and/or principal are the first one, while Chapter 11 or 7 filing and 'distressed exchange' (issuer's offer of less favorable terms or other default-preventing exchange with bondholders) are the other two.

ISP^{AA} and ISP^{BAA}. Besides comparing results for the original, full credit spread and idiosyncratic credit spread according to a naive decomposition scheme, we also include estimations for four alternative schemes. Following arguments in the last section, information on default rate for a certain rating should be contained only in the idiosyncratic credit spread of a bond of the given rating, rather than in the systematic credit spread, which reveals only information on common factors. This is indeed the case in Table VI, where default rates are shown not to be significantly related to full credit spreads of SP^{AA} and SP^{BAA}. After removing the systematic component, under the naive way or other alternatives, default rate becomes predictable and is significant and positively related to the idiosyncratic credit spread. We have also shown in this table that the above findings do not happen incidentally. If we decompose the credit spread arbitrarily, we would not obtain similar results. For SP^{AA}, in the case of ISP-I and ISP-II, idiosyncratic credit spread cannot significantly predict default rate as too little systematic component is removed. For SP^{BAA}, over- and under-risk-compensation prevent the idiosyncratic credit spread to properly reveal information about default rate in the case of ISP-I and ISP-V. To the extent that this is evidence that firm-level default risk is priced in the *idiosyncratic*, rather than the *systematic*, credit spreads, the decomposition of credit spreads is shown to be crucial in credit disk identification as well as corporate bond pricing practice.

VI. Related issues and discussions

Alternative credit spread measures

We have so far utilized yield spreads of Aaa and Baa indices against the 10-year Treasury bonds. As bonds included in the two groups have maturities longer than 10 years, we have to find out how our results are dependent on the choice of benchmark risk free rate. The 20-year Treasury rate is a reasonable candidate for alternative credit spread computation. Since it ceased to exist as of 1987, we are only able to compare results within a shorter period ending in December 1986. Substituting the 20-year based credit spreads produces comparable but weaker results than those in Table IVa. For the entire period through December 1986, VAT's under ARDL are significant and accepted for all three models, while ECM estimates are also similar, and long and short run coefficients are smaller or of about the same order of magnitude[31]. The results for subperiod 1 are also weaker in that Model IV for SP^{AAA} fails to pass VAT. For the other two models, neither of the ECM coefficients is significant, like in Table IVa. Federal Reserve Board has, however, constructed 20-year Treasury yields out of bonds with the same remaining life since October 1993, which we will use only as a reference. In this period, none of the models passes VAT after substituting in the 20-year based credit spreads as dependent variables, again comparable but weaker than what Table IVa reports. These findings indicate that the average maturity of bonds included in the Aaa and Baa indices is indeed between 10 and 20 years, and either credit spread measure could be as good as the other one. To the extent that we might have overstated the actual credit spreads as we subtract a smaller yield base previously, we have not found serious biases with our examination here. Using the 10-year yield base offers better data continuity and testing power as well. This further supports our analysis in section VI that what matters lies more in how we separate out the idiosyncratic credit spreads, and less on which one of the long term Treasury yields, which move closely together, we adopt to construct credit spreads.

Other Control Variables

Market return, commonly proxied by the return of S&P500 index, has been modeled as one of the control variables for credit spreads in many literatures, which represents general economy condition and is predicted to influence credit spreads negatively. We would like to examine the inclusion of this

[31] The F-statistics for Model IV, III and I are 5.96, 6.39 and 10.45 respectively, whereas the ECM coefficients are -3.76, -5.03 and -5.66. Short run coefficient for *TB3M* under Model IV is -0.0266, compared at -0.1136 with Table Va. Under Model III, it is -0.0628, compared at -0.0585. The short run coefficients for *TB3M* and *TERM* under Model I are -0.1813 and -0.1778 respectively, very close to their counterparts of -0,1282 and -0.1044.

variable, hereafter termed *SP500*, under our ARDL framework and compare the validity of it and how our results compare with others'. VAT suggests that the inclusion of *SP500* in all three models of I, III and IV is valid. The long run coefficients all fall under the *degenerate* case although all ECM coefficients are significant. Neither are any of the short run coefficients significant. The addition of *SP500* does not appear to affect the significance, sign and magnitude of *TB3M* and *TERM* as well. So there is no valid reason to include this variable in our models. The sign of the long run coefficients are all negative, while none of the short run coefficients are negative, a contrast to findings from other works too.

Next we examine an alternative to *TERM*, measure of slope of the yield curve, using instead the difference between 20-year and 3-month Treasury yields, which we would term *TERM20*. Similar to *TERM*, this variable lacks good support from our models. Together with *TB3M*, it is not rejected to be included in Model I with a significant F-statistic of 9.15, and the ECM coefficient is also estimated at a significant value of -5.02. The long run coefficient is however still insignificant, like *TERM*. There is no evidence supporting a significant role of *TERM20* in the subperiods as well. The ECM coefficient is not significant in the first subperiod, while VAT if failed for the last subperiod. As *TERM* is present only in model I, our comparison shows that few differences are produced with this replacement. We then construct yet another yield curve slope measure, *TERM10*, which is the difference between 20-year and 10-year Treasury yields. Substituting in this alternative generate similar estimation results. But the short run coefficient becomes insignificant, compared with significantly negative ones with *TERM* and *TERM20*[32]. So while all three measures fail to exhibit long run influences, the variables *TERM* and *TERM20* seem to capture better information contained in tem structure about the idiosyncratic credit spreads. As both are stationary and almost perfectly correlated with each other, our adoption of *TERM* is a better choice due to data availability.

Causality among yield spreads

For SP^{AAA} to serve as a proxy for the systematic credit spread which drives the dynamics of credit spreads of other rating, it is important to characterize certain causal relationships among these credit spreads. Granger Causality is examined here according to the specification of Granger (1969). We take fitted residuals from the *Baseline Model* in (16) to filter out effects from interest rate dynamics and carry out the Granger Causality tests, yielding results consistent with findings in section VI. The causality test results from the weekly data strongly indicates that, after filtering out interest rate

[32] For the entire period under Model I, ARDL-ECM produces a short run coefficient value of -0.2307 (p=0.000) for *TERM20*, but a value of 0.0058 (p=0.792) for *TERM15*. Note that also the

influences, change of SP^{BAA}, as well as SP^{AA}, is caused by that of SP^{AAA} in Granger's sense[33].

Persistence of yield spreads

Compared with monthly data, the more significant autoregressive relation in the weekly sample is due to higher estimate value rather that a reduction of standard error. Duffee (1998) had argued that the observed persistence of yield spreads were the result of slow adjustment of bond prices. Lack of liquidity or lower volatility of weekly yield spread, compared to its monthly counterpart, cannot seem to be ascribed as a key factor to this result. As seen in Table II, the estimated β_1 and β_2 are actually smaller in the monthly estimation. The same argument applies to lower-rated Baa yield spreads as opposed to AAA credit spreads. Saunders *et al*. (2002) reported that evidences from the OTC market that higher yield bonds have lower liquidity. Lack of trading should have generated stronger autoregressive effect. But it is stronger for Aa bonds than Baa bonds in the weekly data.

There issues left which we have not discussed thoroughly such as data aggregation, macroeconomic variable influences, alternative methods of cointegration, inferences from simulated systematic and unsystematic default parameters and other related issues will be addressed in a later version of this study.

[33] With fitted residuals from weekly changes of SP^{BAA} against SP^{AAA}, we obtain a significant F-statistic of 9.66 (p=0.0000) supporting the hypothesis of SP^{BAA} being Granger caused by SP^{AAA}, while the opposing hypothesis is rejected (F=0.61; p=0.6099). For SP^{AA}, weekly changes between January 15, 1982 and December 31, 1993 yield an F value of 6.55 (p=0.0002) for SP^{AAA} to Granger cause SP^{AA}, but fail to support the reverse causality (F=1.56; p=0.1969).

VII. Conclusion

This study provides an empirical framework to investigate the long run diversification of credit risks in bond portfolios. Specifically, our decomposition of credit spread produces direct measures of the two components, which makes diversification practice simpler. The idiosyncratic credit spread produced with our optimal long run decomposition scheme is uniquely compatible with models and measures produced separately by Duffee (1999). We have also identified, after decomposition, that the informational content on actual bond defaults is provided by the idiosyncratic component only, rather than the full credit spreads. The modeling of high and low grade corporate bonds in this work complements that of Liu *et al*. (2004) in dealing with tax, liquidity and default spreads in fixed income securities. The results from long and short run analysis are consistent with both the option and tax effects. Our study also helps clarifying unresolved issues in the literature such as structural changes of the model and yield spread persistence, among others. Our empirical analysis considers both long- and short-run phenomena as well as causal relations, which greatly improves estimation results from preceding studies. The general long-run credit spread decomposition scheme is statistically superior and economically meaningful, and is on the other hand compatible with corporate bond pricing practice and credit risk diversification.

There are several contributions brought about by this study. First, the estimation of idiosyncratic credit spread, after filtering out the systematic credit spread, helps the pricing of corporate bond by properly measuring credit risks. Second, our analysis takes into account the long run, as well as the short run, relations between credit spreads and interest rates, while most of the literatures focus on short run phenomenon only. Our methodology specifically enables us to distinguish the short-run structural or option approach effect from the long-run tax differential effect, besides providing better estimates empirically for a further examination of models presented before. Third, we have provided an optimal credit spread decomposition scheme by incorporating the long run behavior of credit spreads, which is consistent with the results of recent literatures. The decomposition is optimal in its risk allocation implications, and is consistent risk diversification in the pricing of bonds within fixed income portfolios. Finally, our empirical models resolve pending issues posed by previous literatures and provide evidences that connect observed corporate defaults to the idiosyncratic or specific credit spreads of a given credit rating.

We start with an affine model of term structure to specify the valuation of default-free and defaultable bonds, and then characterize the *systematic* credit spread as functions of interest rate term structure, and *idiosyncratic* credit spread as containing both liquidity and default spreads. To facilitate the estimation of parameters relevant to credit spread decomposition, we begin with a *Baseline Model* reexamining the relation between yield spread and interest rate, but the structural change yields significantly different subperiod results. Due to nonstationarity in time series of data, we adopt cointegration analysis for estimation, which is different from the OLS approach in most of the literature. Our ARDL approach along the line of PSS (2001) stresses model validity, level and long-run relationships, as opposed to the usual short-run approach using differences of variables. The two-stage tests introduced by PSS (2001) allow us to identify an appropriate model, which has not been considered previously. The ARDL approach also provides more straightforward causality than other cointegration methods. As in other studies, we have also found the credit spreads to be negatively related to interest rates in the short run and positively so in the long run. To decompose credit spreads better, we have suggested a few schemes to and found an optimal one. It is shown that what matters more is how to properly separate out the idiosyncratic credit spread, rather than how to construct credit spreads against risk-free benchmarks. To provide as independent evidence to the informational role of idiosyncratic credit spread on default risk, we carry out a panel study of Moody's cohorts over a 17-year period and find that idiosyncratic credit spread significantly predicts future default rates, while the full credit spread does not. Further more, properly separated credit spread predicts better as opposed to arbitrarily-separated or non-separated ones, an indication that an optimal decomposition does make a difference.

For the robustness of our analyses, we have obtained similar core results using alternative measure of yield spread, additional control or independent variables and subperiod analysis according an endogenous structural change modeling. We have also found significant causal effect from SP^{AAA} to SP^{BAA}, which supports using the former as a proxy for the systematic component of credit spread. An impulse response model with orthogonal innovations further supports our argument that there is no short run relationship between idiosyncratic credit spread and common factors. As this study focuses on yield spreads on the aggregate level, an immediate extension should be looking at the yield decomposition on the individual bond level. There the issues of market- or firm-specific factors can be examined in details. The separation of credit spread on the firm level would obviously be firm-specific as well, which could potentially offer insight to individual bond pricing practices. Finally, the dynamic behavior of yield spread is a crucial issue to be resolved, especially on how the persistence of credit spread sustains and what causes the dynamic patter to change.

References

Bai, Jushan, and Pierre Perron, 2003, Computation and analysis of multiple structural change models, *Journal of Applied Econometrics*, 18, 1-22.

Barnhill, Theodore M. Jr., Frederick L, Joutz and William F. Maxwell, 2000, Factors affecting the yields on noninvestment grade bond indices: a cointegration analysis, *Journal of Empirical Finance*, 7, 57-86.

Brown, R.L., J. Durbin, and J.M. Evans, 1975, Techniques for testing the constancy of regression relations over time (with discussion) *Journal of the Royal Statistical Society*, B37, 149-192.

Campbell, John Y., and Glen B. Tasker, 2003, Measuring corporate bond mortality and performance, *Journal of Finance*, 58, 2321-2349.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spenccer Martin, 2001, The determinants of credit spread changes, *Journal of Finance*, 56, 2177-2207.

Duffee, Gregory R., 1998, The relation between treasury yields and corporate bond yield spreads, *Journal of Finance*, 56, 2177-2207.

Duffee, Gregory R., 1999, Estimating the price of default risk, *Review of Financial Studies*, 12, 197-226.

Duffie, Darrell, and Kenneth Singleton, 1997, An econometric model of the term structure of interest-rate swap yields, *Journal of Finance*, 52, 1287-1321.

Duffie, Darrell, and Kenneth Singleton, 1999, Modeling Term Structure of Defaultable Bonds, *Review of Financial Studies*, 12, 687-720.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann, 2001, Explaining the rate spread on corporate bonds, *Journal of Finance*, 56, 247-277.

Engle, Rober F., and Granger, C. W. J., 1987, “Cointegration and Error Correction：Representation, Estimation, and Testing”, *Econometrica*, 55(2), 254-276

Gatfaoui, Hayette, 2003, Risk disaggregation and credit risk valuation in a Merton framework, *Journal of Risk*, 4, n3, 27-42

Güntay, Levent, Nagpurnanand Prabhala, and Haluk Unal, Derivatives Usage and Hedging: Evidence from Callable Bond Issues, Working Paper, University of Maryland

Granger, Clive W. J., 1969, Investigating causal relations by econometric methods and cross-spectral methods, *Econometrica*, 34, 424-438.

Jarrow, Robert A., David Lando, and Fan Yu, 2003, Default risk and diversification: theory and applications, Working Paper, Cornell University.

Jarrow, Robert A., and Stuard Turnbull, 1995, Pricing derivatives on financial securities subject to credit risk, *Journal of Finance*, 50, 53-86.

Jarrow, Robert A., and Stuard Turnbull, 2000, The interception of market and credit risk, *Journal of Banking and Finance*, 24, 271-299.

Johansen, S., 1988, Statistical Analysis of Cointegration Vectors and Dynamics and Control, *Journal of Econometrics*, 12, 231-254

Johansen, S., and Katarina Juselius, 1990, Maximum Likelihood Estimation and Inferences on Cointegration with Applications to the Demand for Money, *Oxford Bulletin of Economics and Statistics*, 52, 169-210

Johansen, S., 1994, The Role of the Constant and Linear Terms in Cointegration Analysis of Nonstationary Variables, *Econometric Review*, 13(2), 205-229

Joutz, Frederick L, Sattar A. Mansi and William F. Maxwell, 2001, The dynamics of corporate credit spreads, Working Paper, George Washington University and Texas Tech University.

Liu, J., Longstaff, Francis A., and Ravit E. Mandell, 2004, The Market Price of Risk in Interest Rate Swaps: The Roles of Default and Liquidity Risks, Working Paper, UCLA.

Longstaff, Francis A., and Eduardo Schwartz, 1995, A simple approach to valuing risky fixed and floating rate debt, *Journal of Finance*, 50, 789-821.

Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance*, 29, 449-470.

Neal, Robert, Doug Rolph, and Charles Morris, 2000, Interest rates and credit spread dynamics, Working Paper, Indiana University, University of Washington, and Federal Reserve Bank of Kansas City.

Pedrosa, Monica, and Richard Roll, 1998, Systematic risk in corporate bond credit spreads, *Journal of Fixed Income*, 8, 7-26.

Pesaran, M. H., Yongcheol Shin, and Richard J. Smith, 2001, Bounds Testing Approaches to the Analysis of Long-Run Relationship, *Journal of Applied Econometrics*, 16, 289-326

Saunders, Anthony, Anad Srinivasan, and Ingo Walter, 2002, Price formation in the OTC corporate bond markets: a field study of the inter-dealer market, *Journal of Economics and Business*, 54, 95-113.

Wilson, Thomas C., 1998, Portfolio credit risk, FEBNY Economic Policy Review, 71-82

Table I
Summary Statistics of Yield Spreads

Data in this table is constructed with the Moody's seasoned Aaa and Baa corporate bond indices and the 10-year Treasury bond yield. Monthly and weekly observation of treasury yields are available from periods earlier than the corporate bond indices, but are trimmed to fit the time frame of the latter. SP^{AAA} and SP^{BAA} are respectively the difference between the Aaa index and the 10-year Treasury bond yield, and that between the Baa index and the 10-year treasury yield. ISP^{BAA}, the difference between SP^{BAA} and SP^{AAA} is taken as a simple measure of yield spread contained in Baa index which is not related to the Aaa index, or a naive measure of idiosyncratic credit spread. The division of subperiods is according to results from the Bai-Perron procedure reported in Table II.

Data	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**
Panel (a): Monthly Data					
Whole Period (1953:05~2003:09; 605 observations)					
SP^{AAA}	0.7424	0.5025	0.8038	3.3763	68.7207 (0.0000)
SP^{BAA}	1.6929	0.7199	0.4505	2.6012	24.4718 (0.0000)
ISP^{BAA}	0.9504	0.4230	1.3806	5.0169	294.7316 (0.0000)
1st Period (1953:05~1972:04; 228 observations)					
SP^{AAA}	0.3999	0.3020	1.5697	5.8254	168.4041 (0.0000)
SP^{BAA}	1.1043	0.4869	1.4273	4.9645	114.1452 (0.0000)
ISP^{BAA}	0.7043	0.2271	0.8487	3.7960	33.3872 (0.0000)
2nd Period (1972:05~1982:07; 123 observations)					
SP^{AAA}	0.5954	0.3223	0.1785	2.7081	0.0902 (0.5798)
SP^{BAA}	1.8704	0.6173	0.4488	2.1725	7.6379 (0.0220)
ISP^{BAA}	1.2750	0.5058	0.5538	1.9383	12.0640 (0.0024)
3rd Period (1982:08~2003:09; 254 observations)					
SP^{AAA}	1.1211	0.4589	0.5378	3.4725	14.6057 (0.0007)
SP^{BAA}	2.1353	0.5629	0.8659	3.0761	31.8016 (0.0000)
ISP^{BAA}	1.0142	0.3842	1.5594	6.7971	255.5334 (0.0000)
Panel (b): Weekly Data					
Whole Period (1962:01:12~2003:10:10; 2,179 observations)					
SP^{AAA}	0.8326	0.5060	0.6205	3.2284	144.5698 (0.0000)
SP^{BAA}	1.8334	0.6965	0.2762	2.7501	33.3652 (0.0000)
ISP^{BAA}	1.0008	0.4324	1.2446	4.7654	845.5002(0.0000)
1st Period (1962:01:12~1972:08:04; 552 observations)					
SP^{AAA}	0.4914	0.3752	1.1972	3.6907	142.8301 (0.0000)
SP^{BAA}	1.2177	0.6058	0.9695	3.1201	86.8135 (0.0000)
ISP^{BAA}	0.7262	0.2676	0.6388	2.9786	37.5555 (0.0000)
2nd Period (1972:08:04~1987:08:21; 785 observations)					
SP^{AAA}	0.6743	0.3799	0.1826	2.8240	5.3742 (0.0680)
SP^{BAA}	2.0150	0.6455	0.4576	2.6890	30.5567 (0.0000)
ISP^{BAA}	1.3407	0.4737	0.7173	3.0386	67.3687 (0.0000)
3rd Period (1987:08:28~2003:10:10; 842 observations)					
SP^{AAA}	1.2040	0.4455	0.8291	3.0897	96.7479 (0.0000)
SP^{BAA}	2.0679	0.5422	0.9271	3.1943	121.9332 (0.0000)
ISP^{BAA}	0.8639	0.2282	0.6473	2.4475	69.5049 (0.0000)

Table II

Structural-Change Estimation Results of the Baseline Model (Bai-Perron procedure)

A Baseline Model defined as, $\Delta SP_{it} = \beta_{i0} + \beta_{i1}\Delta TB3M_t + \beta_{i2}\Delta TERM_t + e_{it}$, where ΔSP_{it} stands for the changes of yield spread measure of SP_t^{AAA}, SP_t^{BAA} or ISP_t^{BAA}, the difference between the first two, and $\Delta TB3M_t$ and $\Delta TERM_t$ are changes of three-month treasury yield and the yield difference between the 10-year and three-month treasuries respectively. This model is used to estimate endogenously possible structural changes over the sample period. The estimation procedure is according to the specification of Bai and Perron (2003). The number and locations of break points are obtained according to results of sequential procedure in particular. The estimation has also allowed for heterogeneity and autocorrelation in residuals, as well as AR(1) prewhitening prior to estimating the long run covariance matrix.

	β_0	β_1	β_2
Monthly, Whole Period (1953:05~2003:09; 605 observations) [a]			
SP^{AAA}	0.0062 (0.0088)	-0.3049** (0.0242)	-0.3376** (0.0261)
SP^{BAA}	0.0439 (0.0121)	-0.4302** (0.0278)	-0.4459** (0.0341)
ISP^{BAA}	0.0007 (0.0070)	-0.1256** (0.0266)	-0.1120** (0.0301)
Monthly, First Subperiod (1953:05~1972:04; 228 observations)			
SP^{AAA}	0.0129* (0.0058)	-0.6284** (0.0510)	-0.7128** (0.0567)
SP^{BAA}	0.0145* (0.0070)	-0.7014** (0.0562)	-0.8268** (0.0682)
ISP^{BAA}	0.0034 (0.0042)	-0.0674 (0.0353)	-0.1094** (0.0418)
Monthly, Second Subperiod (1972:05~1982:07; 123 observations)			
SP^{AAA}	0.0127 (0.0167)	-0.2582** (0.0363)	-0.2855** (0.0478)
SP^{BAA}	0.0393 (0.0239)	-0.5183** (0.0484)	-0.5801** (0.0680)
ISP^{BAA}	0.0266 (0.0155)	-0.2602** (0.0380)	-0.2947** (0.0498)
Monthly, Third Subperiod (1982:08~2003:09; 254 observations)			
SP^{AAA}	0.0078 (0.0072)	-0.2862** (0.0502)	-0.2910** (0.0319)
SP^{BAA}	-0.0154 (0.0090)	-0.3666** (0.03002)	-0.3137** (0.0252)
ISP^{BAA}	0.0076 (0.0064)	-0.0804 (0.0414)	-0.0227 (0.0258)
Weekly, Whole Period (1962:01:19~2003:10:10; 2,179 observations)			
SP^{AAA}	0.0018 (0.0021)	-0.4196** (0.0181)	-0.4367** (0.0210)
SP^{BAA}	0.0031 (0.0032	-0.5746** (0.0160)	-0.5612** (0.0221)
ISP^{BAA}	0.0008 (0.0022)	-0.0680** (0.0188)	-0.0630** (0.0173)
Weekly, First Subperiod (1962:01:19~1972:08:04; 552 observations)			
SP^{AAA}	0.0046 (0.0030)	-0.8641** (0.0404)	-0.8951** (0.0405)
SP^{BAA}	0.0053* (0.0026)	-0.8497** (0.0375)	-0.9164** (0.0378)
ISP^{BAA}	0.0007 (0.0015)	0.0144 (0.0199)	-0.0213 (0.0220)
Weekly, Second Subperiod (1972:08:11~1987:08:21; 785 observations)			
SP^{AAA}	0.0011 (0.0027)	-0.3778** (0.0170)	-0.4035** (0.0251)
SP^{BAA}	0.0019 (0.0037)	-0.6089** (0.0250)	-0.6180** (0.0340)
ISP^{BAA}	0.0008 (0.0029)	-0.2312** (0.0212)	-0.2145** (0.0236)
Weekly, Third Subperiod (1987:08:28~2003:10:10; 842 observations)			
SP^{AAA}	-0.0020 (0.0018)	-0.4611** (0.0404)	-0.3454** (0.0255)
SP^{BAA}	-0.0021 (0.0020)	-0.4716** (0.0431)	-0.3468** (0.0198)
ISP^{BAA}	0.0001 (0.0014)	-0.0106 (0.0152)	-0.0014 (0.0188)

[a] Break points and subperiod estimates for ISP^{BAA} only are generated from the Bai-Perron procedure, while all estimates for SP^{AAA} and SP^{BAA}, and the whole period estimates for ISP^{BAA}, are from OLS procedures.

* Significant at 5% level.

** Significant at 1% level.

Table III

Cointegration Test Comparisons, Johansen Maximum Likelihood Rank Test VS PSS ARDL Variable Addition Test and ARDL-ECM t-test

We compare cointegration analysis results from the two methods. We focus on comparisons among various models to identify a valid one for the three series of credit spreads, according to PSS (2001). Specifically, we conduct a two-stage testing procedure where an F-test is carried out first and followed by a t-test. Through the screening process outlined in this table, we identify one appropriate model for each of SP^{AAA}, SP^{BAA} and ISP^{BAA}, which will be used for subsequent estimation and testing. Model I is the Baseline Model in (16), whereas Model II for SP^{AAA} is Model I with SP^{BAA} added as an additional independent variable. Similarly, Model II for SP^{BAA} has SP^{AAA} as the added explanatory variable to its Model I version. Model III is the same as Model II except that the term *TERM* is excluded. Model IV applies to SP^{AAA} only, with *TB3M* as the sole explanatory variable beside lag terms of SP^{AAA}.

	Model I-Johansen[a]	Model I-ARDL[d]	Model II-ARDL	Model III-ARDL	Model IV-ARDL
Cointegration Test – Johansen Maximum Likelihood Rank Test and ARDL Variable Addition Test[b], Monthly - Whole Period					
SP^{AAA}	2	4.0618 - ARDL(1,4,4)	2.7133 - ARDL(1,2,4,4)	4.2192 - ARDL(1,1,4)	6.8953 - ARDL(1,4)$^{+}$
BAA^{SP}	2	3.9315 - ARDL(1,4,4)	4.0618 - ARDL(1,2,4,4)	7.8490 - ARDL(1,1,4)$^{+}$	
BAA^{ISP}	2	10.6400 - ARDL(1,4,4)$^{+}$			
Error-Correction Model – ECM(-1)[c], Monthly - Whole Period					
SP^{AAA}	-0.0281*, 0.0012	-0.0200 (0.0084)	-0.0438 (0.0137)	-0.0554 (0.0133)$^{++}$	-0.0362** (0.0102)$^{++}$
BAA^{SP}	-0.0064**, 0.0054**	-0.0179 (0.0074)	-0.0578 (0.0118)$^{++}$	-0.0689 (0.0115)$^{++}$	
BAA^{ISP}	-0.0514**, 0.0063**	-0.0555 (0.0129)$^{++}$			
Cointegration Test – Johansen Maximum Likelihood Rank Test and ARDL Variable Addition Test, Weekly - Whole Period					
SP^{AAA}	2	3.7114 - ARDL(1,4,4)	2.7720 - ARDL(1,2,4,4)	4.7305 - ARDL(1,1,4)	6.2832 - ARDL(1,4)$^{+}$
SP^{BAA}	2	4.2255 - ARDL(1,4,4)	4.5827 - ARDL(1,2,4,4)$^{+}$	8.0105 - ARDL(1,1,4)$^{+}$	
ISP^{BAA}	2	13.4228 - ARDL(1,4,4)$^{+}$			
Error-Correction Model – ECM(-1), Weekly - Whole Period					
SP^{AAA}	-0.0100*, -0.0005*	-0.0091 (0.0024)$^{++}$	-0.0263 (0.0046)$^{++}$	-0.0260 (0.0042)$^{++}$	-0.0139 (0.0034)$^{++}$
SP^{BAA}	-0.0082**, 0.0010**	-0.0064 (0.0018)$^{++}$	-0.0222 (0.0033)$^{++}$	-0.0215 (0.0032)$^{++}$	
ISP^{BAA}	-0.0232**, 0.0033**	-0.0119 (0.0029)$^{++}$			

[a] Cointegration rank test is performed on the Baseline Model (16) with the number of cointegrating vectors reported. For the error correction analysis, the model with intercept and no trend is used. For the monthly analysis, a two-lag VAR model is selected according to SBC, and a one-lag model is used for weekly data.

[b] Consider an ARDL(l,m,n) model for SP^{AAA}, $\Delta SP_t^{AAA} = a + \sum_{i=1}^{l} b_i \Delta SP_{t-i}^{AAA} + \sum_{j=0}^{m} c_j \Delta TB3M_{t-j} + \sum_{k=0}^{n} d_k \Delta TERM_{t-k} + \phi_1 SP_{t-1}^{AAA} + \phi_2 TB3M_{t-1} + \phi_3 TERM_{t-1} + \varepsilon_t$. An OLS estimation is conducted without the level terms and the Variable Addition Test is to compute the F-statistic for the restriction of $\Phi_1=\Phi_2=\Phi_3=0$ after adding the level terms and compare it against a table of non-standard critical values provided in p. 300 of PSS (2001). We've used case III in the table with unrestricted intercept and no trend.

[c] ECM(-1) stands for the error-correction term from the previous period, whose coefficients are estimated in an even-order Vector Error Correction model for the Johansen cointegration analysis. Under ARDL-ECM, however, the lag orders of independent variables, or the 'forcing variable' in PSS' term, can differ from one another.

[d] For Model I and III, a Variable Addition test is performed in the fashion of PSS (2001). The results in the Error-Correction section are for reference only if the F-test is failed.

* Significant at 5% level under a t-test.

** Significant at 1% level under a t-test.

\+ Significant at 5% level under an F-test according to the asymptotic critical value bounds outlined in PSS (2001). For Model IV, which has one independent variable, the critical value is -5.73, regardless of the dependent variable's being I(0) or I(1). For Model I and III, which has two dependent variables, the critical value is -4.85, while it is -4.35 for Model II with three independent variables.

++ Significant at 5% level under a t-test according to the asymptotic critical value bounds outlined in PSS (2001). For Model IV, the critical value is -3.22. For Model I and III, it is -3.53, and -3.78 for Model II.

Table IVa

Autoregressive Distributed Lag-Error Correction Model Estimation Results, Monthly Data

The ARDL-ECM procedures are carried out for three sets of data, based on appropriate ARDL models following analysis in Table III. The first one, for SP^{AAA}, comes from Model IV of Table III, while the one for SP^{BAA} is Model III there. The third model, for ISP^{BAA}, is the Baseline Model in (16), or Model I in Table III, which is,

$$\Delta SP_t^{AAA} = a + \sum_{i=1}^{l} b_i \Delta AAA_{t-i}^{sp} + \sum_{j=0}^{m} c_j \Delta TB3M_{t-j} + \sum_{k=0}^{n} d_k \Delta TERM_{t-k} + \phi_1 SP_{t-1}^{AAA} + \phi_2 TB3M_{t-1} + \phi_3 TERM_{t-1} + \varepsilon_t \,,$$

where l, m and n are respective number of lags for difference terms of the three variables and are optimally selected according the Schwartz Bayesian Criterion, and ε_t is assumed to be a white noise. The division of subperiods is according to results from the Bai-Perron procedure reported in Table II. A Variable Addition Test (VAT) has to yield a significant F-statistic value before the Error-Correction estimation can be carried out.

	Model IV	**Model III**	**Model I**
	SP^{AAA} -$TB3M$	SP^{BAA} - SP^{AAA} -$TB3M$	ISP^{BAA} -$TB3M$-$TERM$
Whole Period (1953:05~2003:09, 605 obs.)			
VAT F-statistic	6.8953^{+}	7.8490^{+}	10.6400^{+}
SP^{AAA} - LR[a]		1.1094** (0.1080)	
TB3M - LR	0.0677 (0.0561)	0.1344** (0.0194)	0.1263** (0.0233)
TERM - LR			-0.0036 (0.0717)
ΔSP^{AAA} - SR[b]		0.9512** (0.0286)	
ΔTB3M - SR	-0.1136** (0.0116)	-0.0585** (0.0091)	-0.1282** (0.0133)
ΔTERM - SR			-0.1044** (0.0165)
ECM(-1)[c]	-0.0362 (0.0102)$^{++}$	-0.0689 (0.0115)$^{++}$	-0.0555 (0.0129)$^{++}$
R-Squared	0.1943 - *ARDL(3,3)*[d]	0.7682 - *ARDL(6,1,5)*	0.3127 - *ARDL(2,3,4)*
1st Period (1953:05~1972:04, 228 obs.)			
VAT F-statistic	7.7442^{+}	9.2856^{+}	5.4444^{+}
SP^{AAA} - LR		0.6186 (0.6861)	
TB3M - LR	0.0807 (0.0466)	0.2135 (0.1390)	0.1784 (0.0937)
TERM - LR			-0.1283 (0.3924)
ΔSP^{AAA} - SR		0.9834** (0.0271)	
ΔTB3M - SR	-0.1959** (0.0305)	0.0071** (0.0022)	-0.0660** (0.0238)
ΔTERM - SR			-0.1093** (0.0293)
ECM(-1)	-0.1117 (0.0261)$^{++}$	-0.0331(0.0213)	-0.0184 (0.0215)
R-Squared	0.2019 - *ARDL(1,1)*	0.8747 - *ARDL(2,1,0)*	0.1970 - *ARDL(4,4,4)*
2nd Period (1972:05~1982:07, 123 obs.)			
VAT F-statistic	3.9514	3.7815	3.6471
3rd Period (1982:08~2003:09, 254 obs.)			
VAT F-statistic	5.1896	4.5142	9.7515^{+}
TB3M - LR			0.0457 (0.0286)
TERM - LR			0.0874 (0.0584)
ΔTB3M - SR			-0.0409 (0.0225)
ΔTERM - SR			-0.0367 (0.0226)
ECM(-1)			-0.0848 (0.0180)$^{++}$
R-Squared			0.1921 - *ARDL(2,1,3)*

[a] 'LR' stands for long-run coefficient estimates from the ARDL procedures, which is of the exact opposite sign in a cointegrating vector.
[b] 'SR' stands for short-run coefficient estimates from the ARDL procedures
[c] ECM(-1) stands for the last period error correction term in the ARDL model.
[d] Numbers in parenthesis are respective lags for the three variables used in the ARDL estimation and are selected according to the Schwartz Bayesian Criterion.
* Significant at 5% level under a t-test.
** Significant at 1% level under a t-test.
\+ Significant at 5% level under an F-test according to the asymptotic critical value bounds outlined in PSS (2001).
\+\+ Significant at 5% level under a t-test according to the asymptotic critical value bounds outlined in PSS (2001).

Table IVb

Autoregressive Distributed Lag Estimation-Error Correction Model Estimation Results, Weekly Data

The ARDL-ECM procedures here are the same as that in Table IVa. The division of subperiods is according to results from the Bai-Perron procedure reported in Table II. All the numbers of lags in ARDL models are selected according to the Schwartz Bayesian Criterion as in the previous table. A Variable Addition Test (VAT) has to yield a significant F-statistic value before the Error-Correction estimation can be carried out.

	Model IV	**Model III**	**Model I**
	SP^{AAA} -TB3M	*SP^{BAA} - SP^{AAA} -TB3M*	*ISP^{BAA} -TB3M-TERM*
Whole Period (1962:01:12~2003:10:10, 2,179 obs.)			
VAT F-statistic	6.2832+	8.0105+	13.4228+
SP^{AAA} - LR[a]		1.3473** (0.1014)	
TB3M - LR[a]	-0.0199 (0.0438)	0.1535** (0.0196)	0.1438** (0.0178)
TERM - LR			0.0714 (0.0410)
ΔSP^{AAA} - SR		0.9249** (0.0147)	
ΔTB3M - SR	-0.1532** (0.0073)	-0.0839** (0.0055)	-0.1554** (0.0075)
ΔTERM - SR			-0.1223** (0.0089)
ECM(-1)[c]	-0.0139 (0.0034)++	-0.0229 (0.0032)++	-0.0234 (0.0035)++
R-Squared	0.2118 - *ARDL(3,2)*[d]	0.7539 - *ARDL(2,2,2)*	0.2167 - *ARDL(2,2,1)*
1st Period (1962:01:12~1972:08:04, 552 obs.)			
VAT F-statistic	5.8044+	8.3221+	5.4243+
SP^{AAA} - LR		1.5494** (0.1157)	
TB3M - LR	0.0471 (0.0768)	0.1340** (0.0400)	0.2263(0.0602)
TERM - LR			0.2842 (0.0926)
ΔSP^{AAA} - SR		0.9298** (0.0155)	
ΔTB3M - SR	-0.2968** (0.0266)	0.0036** (0.0010)	0.0046** (0.0015)
ΔTERM - SR			-0.0245* (0.0119)
ECM(-1)	-0.0302* (0.0079)++	-0.0268 (0.0078)	-0.0205 (0.0080)
R-Squared	0.2688 - *ARDL(2,2)*	0.8852 - *ARDL(2,2,0)*	0.0863 - *ARDL(2,0,1)*
2nd Period (1972:08:11~1987:08:21,785 obs.)			
VAT F-statistic	5.0993	5.8144+	9.4037+
SP^{AAA} - LR		1.5278** (0.2375)	
TB3M - LR		0.1656** (0.0331)	0.1529** (0.0273)
TERM - LR			-0.0522 (0.0545)
ΔSP^{AAA} - SR		1.0170** (0.0295)	
ΔTB3M - SR		-0.0839** (0.0087)	-0.2423** (0.0126)
ΔTERM - SR			-0.2230** (0.0156)
ECM(-1)		-0.0333 (0.0065)++	-0.0344 (0.0063)++
R-Squared		0.7377 - *ARDL(2,1,2)*	0.3841 - *ARDL(2,2,2)*
3rd Period (1987:08:28~2003:10:10, 842 obs.)			
VAT F-statistic	1.5179	1.1408	2.5147

[a] 'LR' stands for long-run coefficient estimates from the ARDL procedures, which is of the exact opposite sign in a cointegrating vector.
[b] 'SR' stands for short-run coefficient estimates from the ARDL procedures
[c] ECM(-1) stands for the last period error correction term in the ARDL model.
[d] Numbers in parenthesis are respective lags for the three variables used in the ARDL estimation and are selected according to the Schwartz Bayesian Criterion.
* Significant at 5% level under a t-test.
** Significant at 1% level under a t-test.
\+ Significant at 5% level under an F-test according to the asymptotic critical value bounds outlined in PSS (2001).
\++ Significant at 5% level under a t-test according to the asymptotic critical value bounds outlined in PSS (2001).

Table V
Comparisons of ARDL Results for Idiosyncratic Credit Spreads from Alternative Decomposition Schemes

The following analysis compares how idiosyncratic spreads respond to interest rate dynamics under alternative definitions. The simple or the naïve definition is used as a benchmark against the other two. The cointegration method takes into account rational forecast and the arbitrary method attempts to capture possible over-risk-compensation. The top panel compares results for BAA credit spread in both monthly and weekly observations, while the bottom panel presents additional results for AA-grade weekly credit spreads in a special period where data is available and two subperiods.

	Naive[a]	Cointegration[b]	Arbitrary[c]
	($ISP^{BAA} = SP^{BAA} - SP^{AAA}$)	($ISP^{BAA} = SP^{BAA} - 1.35*SP^{AAA}$)	($ISP^{BAA} = SP^{BAA} - 1.5*SP^{AAA}$)
ISP^{BAA} under alternative decompositions			
Monthly, Whole Period (1953:05~2003:09, 605 obs.)			
VAT F-statistic	10.6400+	10.9620+	8.3289+
TB3M - LR	0.1263** (0.0233)	0.1204** (0.0248)	0.1166** (0.0287)
TERM - LR	-0.0036 (0.0717)	0.0259 (0.0665)	0.0313 (0.0743)
ΔTB3M - SR	-0.1282** (0.0133)	-0.0072 (0.0154)	0.0481** (0.0169)
ΔTERM - SR	-0.1044** (0.0165)	-0.0220 (0.0191)	0.0792** (0.0209)
ECM(-1)	-0.0555 (0.0129)++	-0.0606 (0.0143)++	-0.0569 (0.0140)++
R-Squared	0.3127 - *ARDL(2,3,4)*	0.1614 - *ARDL(3,3,3)*	0.1490 - *ARDL(3,3,3)*
Weekly, Whole Period (1962:01:12~2003:10:10, 2,179 obs.)			
VAT F-statistic	13.4228+	18.1947+	13.9326+
TB3M - LR	0.1438** (0.0178)	0.1504** (0.0167)	0.1586** (0.0182)
TERM - LR	0.0714 (0.0410)	0.0990** (0.0366)	0.0978** (0.0394)
ΔTB3M - SR	-0.1554** (0.0075)	-0.0158 (0.0092)	0.0714** (0.0103)
ΔTERM - SR	-0.1223** (0.0089)	-0.0168 (0.0109)	0.1033** (0.0122)
ECM(-1)	-0.0234 (0.0035)++	-0.0290 (0.0044)++	-0.0296** (0.0046)
R-Squared	0.2167 - *ARDL(2,2,1)*	0.0808 - *ARDL(2,3,2)*	0.0979 - *ARDL(2,3,2)*
	($ISP^{AA} = SP^{AA} - SP^{AAA}$)	($ISP^{AA} = SP^{AA} - 1.2*SP^{AAA}$)	($ISP^{AA} = SP^{AA} - 1.5*SP^{AAA}$)
ISP^{AA} under alternative decompositions			
Weekly Data, 1982:01:08~1993:12:31, 626 obs.			
VAT F-statistic	9.3270+	8.9161+	6.7660+
TB3M - LR	0.0387** (0.0114)	0.1887** (0.0277)	0.1166** (0.0287)
TERM - LR	0.0749** (0.0264)	0.1692** (0.0636)	0.0313 (0.0743)
ΔTB3M - SR	-0.0927** (0.0118)	-0.0162 (0.0134)	0.0481** (0.0169)
ΔTERM - SR	-0.0760** (0.0142)	-0.0073 (0.0032)	0.0792** (0.0209)
ECM(-1)	-0.0731 (0.0131)++	-0.0432 (0.0091)++	-0.0569 (0.0140)++
R-Squared	0.1291 - *ARDL(1,1,1)*	0.0695 - *ARDL(2,2,0)*	0.1490 - *ARDL(3,3,3)*
Weekly Data, Period W-1, 1982:01:08~1987:08:21,294 obs.			
VAT F-statistic	4.9972+	5.0796+	3.8002
TB3M - LR	0.0155 (0.0177)	0.0555** (0.0255)	
TERM - LR	0.0568 (0.0469)	0.1166 (0.0640)	
ΔTB3M - SR	-0.1273** (0.0180)	0.0042 (0.0022)	
ΔTERM - SR	-0.1204** (0.0222)	0.0088 (0.0051)	
ECM(-1)	-0.0932 (0.0214)++	-0.0757 (0.0221)++	
R-Squared	0.1919 - *ARDL(1,1,1)*	0.0416 - *ARDL(1,0,0)*	
Weekly Data, Period W-2, 1987:08:28~1993:12:31, 332 obs.			
VAT F-statistic	5.9732+	4.8483+	3.3721
TB3M - LR	0.0099 (0.0133)	0.0364* (0.0166)	
TERM - LR	0.0298 (0.0227)	-0.0363 (0.0284)	
ΔTB3M - SR	0.0011 (0.0015)	0.0989** (0.0153)	
ΔTERM - SR	0.0034 (0.0027)	0.1108** (0.0172)	
ECM(-1)	-0.1135 (0.0255)++	-0.1026 (0.0230)++	
R-Squared	0.0570- *ARDL(1,0,0)*	0.2061 - *ARDL(1,2,1)*	

[a] Naive decomposition refers to taking the simple difference between the credit spread of bond grade of interest and the credit spread of Aaa index

[b] Cointegration decomposition refers to subtracting Aaa spread multiplied by a cointegration ratio. The ratio is estimated with an ARDL procedure and the long-run coefficient of Aaa spread from the estimation is used as the ratio.

[c] Arbitrary decomposition subtracts 1.5 times AAA spread.

* Significant at 5% level under a t-test.

** Significant at 1% level under a t-test.

\+ Significant at 5% level under an F-test according to the asymptotic critical value bounds outlined in PSS (2001).

++ Significant at 5% level under a t-test according to the asymptotic critical value bounds outlined in PSS (2001).

Table VI
Informational Content of Credit Spreads about Bond Defaults,
Based on Moody's Cohorts between 1970 and 1990 - Panel (SUR) Estimation Results[a]

Estimation is performed on a cross section of panel 6 cohort groups, where each group contains data for corporate bonds with the same number of years from issuance. The youngest cohort is 13 years, while the oldest group is 18 years from issuance. The dependent variable is the change of cumulative default rate since issuance of a given cohort for years ranging from 1983 to 1999. The independent variable is various versions of ISP^{BAA} and ISP^{AA}, as shown below. The estimation is carried out with two lags of independent variable and one lag of default rate. SP^{AA}, SP^{BAA} and SP^{AAA} in the following table are annual average of weekly spreads from 10-year Treasury yield respectively.

ISP Specification[a]	ISP^{AA}	*D-W Statistic*	ISP^{BAA}	*D-W Statistic*
Full Credit Spread	-0.8785 (0.4025)	2.24	0.4082 (0.3005)	2.32
ISP-I (a spread from 0.2 SP^{AAA})*	-0.8113 (0.4620)	2.21	0.5274 (0.3445)	2.33
ISP-II (a spread from 0.8 SP^{AAA})*	0.3621* (1.0611)	2.12	1.2712* (0.5957)	2.36
ISP-III (a spread from SP^{AAA})	2.6447* (1.1096)	2.05	1.4886* (0.6851)	2.35
ISP-IV ((a spread from 1.1 SP^{AAA})*	3.2309** (1.0492)	2.16	1.4223* (0.6904)	2.33
ISP-V ((a spread from 1.2 SP^{AAA})*	3.1215** (0.9996)	2.21	1.2457 (0.6638)	2.30

[a] Seeming Unrelated Regression procedure has been carried out on a common effect model. There are totally 75 annual observations, between 1983 and 1999, for the estimation on ISP^{BAA}, and 39 annual observations, between 1983 and 1993, for the estimation on ISP^{AA}.

[b] ISP stands for idiosyncratic credit spread, where ISP-I is constructed by subtracting 0.2* SP^{AAA} from either SP^{AA} or SP^{BAA}, and ISP-II subtracts 0.8*SP^{AAA}. ISP-III is the naive definition of ISP, while the last two specifications subtract from full credit spread of SP^{AA} and SP^{BAA} respectively 1.1 and 1.2 times SP^{AAA}.

[*] Significant at 5% level.

[**] Significant at 1% level.