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Diversification with Idiosyncratic Credit Spreads: A Pooled Estimation on Heterogeneous Panels

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ABSTRACT

Following the method of Pesaran, Shin and Smith (1999), this study extends the results of Sun, Lin and Nieh (2007) to investigate the risk diversification issue of individual corporate bonds in portfolios. This is one of the few studies on the decomposition of individual corporate yield spreads. Specifically we adopt the robust econometric method of ARDL-based Pooled Mean Group cointegration analysis on panels of corporate bond data which yields results with rich economic implications for fixed income portfolio management. Empirical decomposition of yield spreads indicates, on the individual corporate bond level, that the idiosyncratic component serves as a good vehicle for risk diversification while considering long run market behavior. In the long run systematic credit spreads are found to be consistent with the agency hypothesis where higher interest rate raises endogenous default risk and it is particularly meaningful for the Taiwanese capital market. Option hypothesis of the structural approach is still valid in the short run in predicting yield spreads to be inversely related to interest rate. Our findings contribute in general to the risk practice of bond portfolio diversification. In particular, the pooled estimation we conducted proves to be superior in working with individual corporate bond data panels and helps related studies in the area.

Keywords: bond pricing, credit spread, diversifiable risk, cointegration, heterogeneous panels, pooled mean group estimation.

JEL Classification: C32, E4, E21, G13, G33

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I. Introduction

The purpose of this study is to establish empirically the role of idiosyncratic credit risk in the practice of risk diversification through the application of a method specifically for individual corporate bond yield spread while extending the concept of credit spread decomposition. Following the method of Pesaran, *et al.* (1999), this study extends the results of Sun, Lin and Nieh (2007) to investigate the diversification issue of individual corporate bonds in portfolios. This study is unique in its focus specifically on individual corporate yield spreads. Adopting a superior econometric method, we have obtained in this study long and short run implications which are crucial in risk diversification within fixed income portfolios. To the extent that results from Sun, Lin and Nieh (2007) are good for establishing the distinction between *systematic* and *idiosyncratic* credit spreads with corporate bond indices, our study goes further to employs individual issues traded in the market in this work can actually help pricing of corporate bonds and portfolios in practice. So this work is practically applicable compared to Sun, Lin and Nieh (2007). Moreover, our method adopted in this study deals with time series panels following the ARDL approach proposed by Pesaran, *et al.* (1999), which has been used in various literatures but its panel version is technically more difficult and has rarely been applied except by the original authors. Therefore, this study provides important evidences for the role of idiosyncratic credit spreads in diversification of fixed income investments in a more practical perspective.

Existing literature has explored credit spreads under a framework where diversifiable idiosyncratic credit risk is considered. Empirical methods employed by previous works have also mostly focused on short-run relations and failed to cope with temporal pattern of credit spreads. Studies by Longstaff and Schwartz (1995), Jarrow and Turnbull (1995), Collin-Dufresne, Goldstein and Martin (2001) do not distinguish between systematic and idiosyncratic credit risks or the difference between long run short run. It is 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. 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, showing that credit spreads are positively related to Treasury yields in the long-run, but negatively so in the short run[1]. While the *structural* approach, or

[1] However, the lack of separation between systematic and idiosyncratic components of credit spreads is criticized. 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.

the Merton model, clearly requires a role for the idiosyncratic credit risks such as those suggested by Elton, Gruber, Agrawl and Mann (2001). Proper decomposition credit spreads is crucial characterizing how diversification of credit risk affects corporate bond pricing. Previous studies have focused mostly on the innovation over time rather than comparisons across firms as credit rating agencies do. Wilson (1998) introduced credit spread decomposition with a multi-factor model. Duffee (1999) used decomposition with default intensity process, where systematic default risk is related to yield curve while idiosyncratic default risk is exogenous. Gatfaoui (2003) formally decompose credit risks with a closed-form bond formula. Elton *et al*. (2001) and Pedrosa and Roll (1998) have also investigated the decomposition indirectly.

There are several issues requiring improvements from previous literatures. First, an empirical investigation on the decomposition is necessary to address time series issues on observed credit spreads. Sun, Lin and Nieh (2007) have performed it on US corporate bond indices and established methods in separating systematic and idiosyncratic yield spreads. Extending the decomposition to individual bond yield spreads is natural. Secondly, to the extent that credit risk is a universal issue there should be a framework where all relevant corporate yield spreads are considered in a dynamic panel so common and specific risks are separated accordingly. Typically as in Collin-Dufresne, Goldstein and Martin (2001), analyses are carried out individually for each firm and results are averaged within the same credit rating or maturity group. The commonality across firms is not accounted for during the estimation stage. A pooled time series method is capable of separating the *common* and the *fixed* effect. Third, the tax differential hypothesis by Elton *et al*. (2001) is only valid with US data as the specific tax treatment on bond income may not apply in other countries. So in the case of Taiwan an alternative hypothesis needs to be examined to support the positive long run relation between yield spread and interest rate found in Neal, *et al*. (2000), Joutz, *et al*. (2001) and Sun, Lin and Nieh (2007).

Our study applies the decomposition scheme to individual corporate bonds in Taiwan. We have found comparable results that in the long run yield spreads are positively related to interest rate. In the short run, only systematic spreads are negatively related to interest rate. So our results further validate the proposition of the structural approach of default risk literature with the revision that the approach works only in the sense of *common* risk. The fact that idiosyncratic spreads are not related to common risks is a strong implication for diversification benefit in holding bond portfolios. Next, to overcome the issue of limited liquidity prevailing in the corporate bond markets in US as well as in Taiwan, we propose the use of a method by Pesaran *et al.* (1999) designed for dynamic panels. Our estimation results are consistent with literatures and the results for corporate indices as reported by Sun, Lin and Nieh (2007). The superior econometric method we adopted is one which could greatly improve the study of fixed income with data in the form of dynamic heterogeneous panels. Thirdly, our finding of positive long-run relation between yield spreads and interest rates suggests that over the long run the Leland and Toft (1996) model is correct as Bernanke and Gertler (1989) implies that higher interest rates, all else constant, will increase agency problems for borrowers. So high nominal rates would be associated with a high risk premium for corporate debt and it widens the gap between internal and external financing costs. This finding is meaningful for the corporate sector of Taiwan especially as endogenous over-leveraging practice has been an important cause of the elevating risks in corporate liabilities.

Technically we have adopted a robust method specifically for the analysis of individual corporate yield spread time series. The cointegration approach employed in our study generates unambiguous causal inferences as compared to Neal *et al*. (2000) and Joutz *et al*. (2001). Following Pesaran *et al.* (1999), our study uses a panel data estimation approach by exploiting potential similarities in the time series behavior among corporate bonds within a given credit rating. This method retains long run influences of common credit risk through ARDL-based Pooled Mean Group (PMG) estimation while allowing bond-specific short-run dynamics on the other hand. It also takes account of homogeneous long-run relationships in dynamic heterogeneous panels and thus is well-suited for our analysis. While restricting parameters in the long-run relation to be equal across bonds, ARDL-PMG allows short-run adjustment of specific parameters with superior statistical time series properties and yet rich economic implications for fixed income portfolio management.

The remainder of the paper is organized as follows. Section II presents a simple theoretic model of yield spreads and the foundation of credit spread decomposition to be examined subsequently. Section III describes our data and preliminary statistics. In Section IV an ordinary pooled regression is carried out on a *baseline* credit spread model. Two approaches of cointegration analysis are employed in that section, which provides us with the validity of alternative models. Robustness and related issues are also discussed. Section V concludes the paper.

II. A Model for Systematic and Idiosyncratic Credit Spreads

To characterize systematic and idiosyncratic risks driving corporate credit spreads, we use a framework adapted from Duffie and Singleton (1999) and Liu, Longstaff and Mandell (2006). 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

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

which is identical to the expression in Liu *et al*. (2006) but the liquidity spread is imposed on the defaultable rather than the default-free bond. (2) in essence relates Liu *et al*. (2006) to Jarrow *et al*. (2003) with reasonable theoretic support. A lower grade defaultable bond with similar structure is then modeled to have a value of

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

at time t. The parameters ϕ_1 and ϕ_2 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 agency effect argued by Leland and Toft (1996). As short rate goes up, in order for potential bondholders to hold the lower grade bond where stronger incentive for corporate management to raise debt ratio, more compensation is needed. Therefore ϕ_1 in (3) should be greater than 1, the coefficient of r_s in (1). Similarly, ϕ_2 should be greater than 1 as well to reflect the fact that more risky bonds are more sensitive to changes in default intensity. The dynamics of the three endogenous variables are characterized by a general affine model with a set of

[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*. (2006).

four state variables which are Markovian under the equivalent martingale measure Q and square-root diffusions. The short rate is assumed to be driven by two state variables[3] to represent common shocks to the economy,

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

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 structural models based on pricing theory of *option*, τ should be negative[4]. So the state variable vector $X = (X_1, X_2, X_3, X_4)$ with general Gaussian processes under an affine term-structure model is characterized by

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

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,

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[3] The interpretation of factors X_1 and X_2, which come from the affine model of Duffie and Singleton (1997), can be found in Longstaff and Schwartz (1992) and Duffee (2002). In a continuous time context, the first factor is related to a long term mean of instantaneous rate while to second one to the instantaneous variance.

[4] 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.

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

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). 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 difference in the combination of (X_3, X_4) in evaluating $A(t)$ and $B(t)$ allows the default premium factor X_4 enter as a specific or unsystematic risk.

On the physical measure P, the yield difference between the high grade and riskless bond, or the systematic spread, can be seen from (7) and (8) as governed by

$$\gamma_t + \tau\gamma_t + \eta_1(t)[(\beta - \kappa)X_t + \kappa\xi], \tag{9}$$

where $\eta_1(t)$ is a functions of parameters. The first term in (9) is an instantaneous spread compensating for holding a risky bond which is less liquid than a riskless bond. The second term is also a short-run spread covering default related risk at current state, which is indirectly related to the interest rate. The third term is a long run premium compensating for possible future default and liquidity related price changes. It amounts to about 73 b.p. for a 10-year bond based on US data according to Liu, *et al.* (2006). Similarly, the yield difference between the low grade and riskless bond can derived as

$$\phi_1\gamma_t + \phi_2\tau r_t + \eta_2(t)[(\beta - \kappa)X_t + \kappa\xi], \tag{10}$$

So the credit spread of the more risky bond should respond stronger to common risks X_1 and X_2 contained in the interest rate in the long run due to agency risk. It should be more sensitive to interest rate-induced default risk in the short run. Both have been well documented by Sun, Lin and Nieh (2007) using US corporate indices.

It is straightforward from (9) and (10) that, the difference between the yields of high and low grade bonds, or the idiosyncratic spread,

$$ISP^i = SP^i - \omega SP^{AAA} \tag{11}$$

is governed by the expression

$$\upsilon(t) + f(X_t),$$

where $\upsilon(t)$ and ω are functions of parameters, characterizes the behavior of idiosyncratic spread both in the short and long run. As the second term measures the long run effect, the idiosyncratic spread in the short run would be free of common risks X_1 and X_2 indirectly through default intensity parameter λ_t[5]. In the long run, (11) is affected by the *agency risk* implied directly from the common risks in r_t. 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 (11) serves as empirically testable tool to facilitate that purpose. It is also useful to verify the validity of both the *option* hypothesis and the *agency* effect. It is obvious that the coefficient of SP^{AAA} in (11) must be negative, like a hedge ratio, for common risks to be hedged using the two defaultable bonds. The hedging effect of the idiosyncratic credit spread brought forward in (11) 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.

III. The Data

As this study is based on established results on credit spreads with corporate bond indices in Sun, Lin and Nieh (2007), we would like to explore behavior of individual corporate bonds for more exact conclusions. Although traded yields of individual bonds could suffer from possible liquidity effect[6], we have made substantial efforts in data compilation and estimation methodology to minimize potential imperfections. Our summary introduction of yield spreads in Table 1 provides specifically days traded , as an indication of data quality, and durations of issues of different classes to justify the time frame of our sampling period and the selection terms of riskless government bonds. To draw parallel fundamental characteristics between our data and those in Sun, Lin and Nieh (2007), we have also conducted preliminary examinations in Table 2.

The data employed in this study are weekly traded yield observations from the over-the-counter

[5] A more detailed derivation is also provided in Sun *et al.* (2007).
[6] Collin-Dufresne *et al*. (2001) suggested that 'individual liquidity shock' causes a significant portion of unexplained variations in credit spreads of individual corporate bonds.

dealer market of the Gretai Securities Market of Taiwan. The range of the data is from January 1, 2003 to June 30, 2005. Excluding non-rated and unrated issues there are 1,100 out of a total of 2,206. Original daily closing observations are then averaged weekly for all issues with more than 50 days of trading data from 62 individual issues. We narrow the selection further to only the groups of *twAAA*, *twAA*, *twA* and *twBBB*, ratings given by the Taiwan Ratings Corporation. The top panel of Table 1 reports basic information on the selected issues. More than a third of the issues are from the same issuing companies and their observations spans orderly over the data period. The average coupon rate is at 3.48% and the average duration is 2.78. To construct yield spread data, we chose yields of 5-year on-the-run government bonds to match the average maturity of our corporate issues. The daily government bond yield data is obtained from the Electronic Bond Trading System (EBTS) of the Gretai Securities Market. Daily 5-year government bond yields are also averaged weekly, with an average yield of 1.88% and duration of 4.50. As the average yield of all government bonds with the average duration of 2.8 is at around 1.75% during the same period, we have adjusted the reported yields with the difference between this level and that of the 5-year issue. The bottom panel of Table 1 reports the full yield spreads of all ratings and the idiosyncratic spreads of the bottom three ratings. First of all, the levels of yield spreads are generally 20% lower than those in the US corporate bond market during the same period, where *AAA* yield spread was at around 72 basis points, *A* spread at around 99 and BBB at around 164. The difference between yield spreads of *twAA*, *twA* and *twBBB* and that of *twAAA*, which will be used later as a *naive* proxy for idiosyncratic credit spreads are also reported in the bottom panel of Table 1, which range from 40% to 65% of the full spreads. The idiosyncratic spreads are constructed for the verification of (11) with respect to long and short run relations to interest rates.

【Table 1】

IV. Empirical decomposition of credit spreads

Preliminary Pooled Estimation of a Baseline Model

To explore the short run characteristics of τ in (6), the interest rate or systematic credit risk measure, we begin analysis with our sample from the following *Baseline Model*, which many works employed,

$$\Delta SP_{it} = \beta_{i0} + \beta_{i1}\Delta RP_t + \beta_{i2}\Delta TERM_t + e_{it}\,,\ i=1,2,\ldots I;\ t=1,2,\ldots T\,, \tag{12}$$

where ΔSP_{it} denotes the *changes* of systematic spread such as SP^{AAA}, SP^{AA}, SP^{A} or SP^{BBB} as well as idiosyncratic spreads like ISP^{AA} , ISP^{A} or ISP^{BBB} at period t. For the simplicity of comparison, the idiosyncratic spreads considered in (12) are in the *naive* form where the coefficient ω in (11) is set to be 1 here. The independent variable ΔRP_t is the change of yields on the 10-day government bond repo traded on EBTS, and $\Delta TERM_t$ is the difference between yields of the 5-year government bond and the repo. Duffee (1998) and Collin-Dufresne *et al*. (2001) carried out their analysis using a model like equation (12) 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).

Table 2 reports the results of Seemingly Unrelated Regression estimation on separate panels of bonds in the *twAAA*, *twAA*, *twA* and *twBBB* rating groups as a benchmark of inferences. First differences of original variables are used regardless of excessive kurtosis in their sampling distribution. These preliminary results are consistent with predictions made by literatures of structural approach as well as the structural change model used in Sun, Lin and Nieh (2007). Both β_1 and β_2 are negative and larger in magnitude for lower grade bond. They are also comparable to the findings of Longstaff and Schwartz (1995) and Collin-Dufresne *et al*. (2001), which examined individual corporate yield spreads as well. The *agency risk* approach from Leland and Toft (1996) would imply, however, that the two parameters should be positive instead. To the extent that (12) is a short-run analysis, it validates the *option* or structural approach effect in that time frame.

The difference of our results in Table 2 from previous studies is that the idiosyncratic spreads are much less responsive to interest rates, given that it is a special case of our specification in (12). Estimates for β_1 and β_2 are 60% smaller in magnitude, and the coefficients for the change of the yield curve slope have much weaker statistical significance. Note the results of Table 2 is obtained under *naive* decomposition scheme where ω is in (11) has been set to 1. If the idiosyncratic credit spread is properly identified then it should not respond to interest rate, a state variable related to common or systematic credit risks. Yield spread changes employed in (12) are not without problems[7]. Serial correlation biases the results potentially and the liquidity effect on the individual corporate bond spreads 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[8]. To improve the quality of results from Table 2 and correct for potential time series

[7] Pedrosa and Roll (1998) showed that a randomized Gaussian-mixture models yield spread changes better than a simple Gaussian distribution assumption.
[8] 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.

problems, we introduce an ARDL-based pooled method which takes into account time series issues in dynamic panels and validates variables to be included in each model.

Estimating Dynamic Heterogeneous Panels with ARDL-PMG

The estimation approach is formulated as the error-correction representation of the AutoRegressive Distributed Lags (ARDL) model in the context of Pesaran, Shin and Smith (2001), which stresses the crucial nature of level and long run relationships. As Pesaran and Shin (1999) have shown, this approach is suitable for cointegration analysis in single-equation models. Thus, the coefficients of the level regressors can be interpreted as the parameters of the long-run equilibrium relationship. For dynamic and heterogeneous panels, we need to address several issues involving the pooled estimations. First, one should be very careful about using standard pooled estimators such as fixed effect to estimate dynamic models (i.e. including lagged dependent variables) from panel data. The dynamic parameters are subject to large potential biases when the parameters differ across groups and the regressors are serially correlated. However, for some purposes, such as forecasting or estimating long-run parameters, the pooled estimators may perform well. Second, pooled (or cross-section) regressions can be measuring very different parameters from the averages of the corresponding parameters in time-series regressions. In many cases this difference can be expressed as a consequence of the dependence between the time-series parameters and the regressors. The interpretation of this difference will depend on the theory related to the substantive application. It is not primarily a matter of statistical technique. Third, the mechanical application of panel unit-root or cointegration tests is to be avoided. To apply these tests requires that the hypotheses involved are interesting in the context of the substantive application, which is again a question of theory rather than statistics.

The application of this ARDL-PMG model to panel data according to Pesaran et al. (1999) allows us to implement cross-equation restrictions to the long-run parameters by maximum likelihood estimation. The validity of the restrictions is tested by means of the Hausman test. Reference results are provided by mean group (MG) estimates, defined as the average of unrestricted single bond coefficients. Thus, we are able to evaluate whether imposing long-run homogeneity helps in revealing significant adjustment in yield spreads to interest rates as in (12). The model is formulated along the lines of Pesaran et al. (1999). It represents a variant of the ARDL (p,q,r) model which is set up in its error-correction representation as

$$\Delta SP_{j,t}^{i} = a + \phi_1 SP_{j,t-1}^{i} + \sum_{k=1}^{p-1} b_k \Delta SP_{j,t-k}^{i} + \sum_{l=0}^{q-1} c_l \Delta RP_{t-l} + \sum_{m=0}^{r-1} d_m \Delta TERM_{t-m} + \phi_2 RP_t + \phi_3 TERM_t + \varepsilon_{j,t}\,, \qquad (13)$$

where $i = 1, ..., I$ denotes the rating groups, $j=1,2,\ldots,N$ is for cross-section units and $t = 1, ..., T$ stands for time periods, The disturbances $\varepsilon_{j,t}$ are assumed to be independently distributed across j and t with mean 0 and variance σ_j^2. Using (13), we could analyze for each credit rating group i how systematic and idiosyncratic yield spreads respond to interest rate dynamics. Both the long and short run effects discussed in (11) can be addressed here as we are examining the *levels* as well as *changes* of yield spreads at the same time. By imposing a homogeneous assumption within each group on the coefficients for RP_t and $TERM_t$, we can extract information about the long and short run main effects crucial to test the agency risk and option hypotheses. On the other hand, the PMG model allows a *fixed effect* specification where lagged coefficients vary across individual time series. With the limited number of observations which are not all consecutive in time, this model provides statistical robustness while achieving the goal of our analysis. As *level* relationship is the focus of both the structural and reduced-form models, we argue that (13) offers a valid representation of how yield spreads should be decomposed. 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. 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).

PMG estimations for long and short run

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 (13) are nonstationary and integrated of order one, or I(1)[9]. 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 Pesaran, *et al.* (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

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

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 RP_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. In the single time series context, 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. Under PMG, Hausman test is used instead for the diagnosis of model validity. In the model identification stage, we have used both the Johansen's Vector AutoRegressive (VAR) cointegration and ARDL-ECM approach. Under a Johansen's cointegration model the signs of the error correction terms may not be all negative, indicating the opposing adjustment directions to a long-run equilibrium. Neal *et al*. (2000) encounters similar situation employing Johansen's cointegration approach[10]. Almost all error-correction coefficients are significant, implying to some extent the validity of cointegrating vectors in the sense of Engle and Granger (1987). This justifies our adoption of ARDL model over the Johansen method for the long run cointegration analysis on yield spreads..

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 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

[10] 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).

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 Hausman test 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. Compared with the Johansen cointegration method, which does not make distinction in model selection, ARDL method offers more specific implication, both on model validity and economic content which will be discussed later. More importantly, the analysis in this section establishes a foundation for decomposing credit spread.

【Table 3】

In the long run, or cointegration, PMG approach we examine three alternative models, which can be found that only one model is fit for each of the three types of credit spread series. PMG I is used to examine the how the high grade issues respond to the short rate as a confirmation of the systematic default effect caused by short rate from the structural models. This model is applied only to the high grade issues as it is argued in Sun, Lin and Nieh (2007) that the common default effect on lower grade issues is passed indirectly from the high grade issues. PMG II is considered to verify the validity of this argument which considers influences from both the high grade issue and the short rate. After the systematic effect is addressed, PMG III analyzes the idiosyncratic effect only. PMG I in Table 3 can be seen to take the form of the *Baseline Model* from (12) without $TERM_t$, which has been dropped as its inclusion in our estimation fails to pass the validation test. That implies that RP_t and $TERM_t$ cannot *both* be the forcing variables for SP^i. This is direct evidence against findings in various literatures[11], and what the preliminary results exhibit in Table 2. 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. So this rejection of the *Baseline Model* cannot also be recovered with the lack of causality in the results from Johansen's cointegration approach. Neither do the results in Table 3 rely on the requirement of homogeneous order of integration, which our data violates to a certain degree. The *Baseline Model* is only applicable to ISP^i. Note also that the ARDL procedure allows for uneven lag orders, while the Johansen's VECM does not. Model PMG I shows that in the long run interest rate has no effect, indicating that for top quality firms *agency risk* is insignificant. In the short run, issues with rating do respond significantly to RP_t, validating the short run nature of the option hypothesis of structural approach. Note the difference between results in Table 3 and Table 2 is that we are examining long and short run effects *simultaneously*. Our analysis indicates that RP_t is the only

[11] 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.

valid variable to influence SP^{AAA}, and it only does so in the short run. Also the magnitude of the RP_t coefficients is only about 60% of what is reported in Table 2.

Model PMG II for SP^{AA} , SP^{A} and SP^{BBB} in Table 3 is somewhat different. The validity of these models is supported by the coefficients of the *ECM* term, an evidence of cointegration among time series considered in the models. Under this model SP^{AAA} is modeled as a forcing variable and the long run coefficients of SP^{AAA} are all significantly positive and greater than 1. Short run coefficients are also significant and very close to 1, suggesting the informational content of SP^{AAA}[12]. Long run coefficients for RP_t are significantly positive for certain the two groups with lower credit rating, suggesting the agency risks are more prominent in the more risky bonds. This verifies the long run agency hypothesis as modeled in our affine model and suggested in (11), and is similar to the findings of Liu *et al.* (2006).Short run coefficients RP_t are negative and significant, but are only about one-fourth of the magnitude of corresponding coefficients in Table 2, a natural result from the fact that SP^{AAA} seems to have absorbed almost all influence from RP_t.

Under PMG III, long run agency effect is supported only for the two lower rating groups. Since it is still the *naive* form we are using for the estimation here, the idiosyncratic spread could contain some common risk effect of the systematic spread due to inappropriate decomposition. The clarification of this issue will be discussed in the next model. For there are no significant long run effects across all three rating groups, indicating the possible spillover common risk effects, if any, would have come from RP_t only. The short run coefficients for the two interest rate variables are significant for all three groups. They are however much smaller in magnitude, about one-fourth, compared to Table 2 in the *Baseline Model*. All the models under PMG III are also supported in the cointegration context as all the *ECM* coefficients are significant as well.

The PMG estimation results in Table 3 bring about three implications. First, much of the information about SP^{AA}, SP^{A} or SP^{BBB} 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 has strong influence on yield spreads of other rating groups through their unsystematic component ISP^i indirectly[13]. Last but not the least, interest rate dynamics does affect credit spreads in the short run through the systematic component, a result consistent with Table 2.

As a variation of (6) and a basis for comparison, we would consider the reduced-form model from Duffee (1999). It is a default model with three factors, which states the default intensity of the *jth* firm,

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[12] A separate and similar ECM analysis has been conducted by placing SP^{AAA} as the outcome variable, while setting other yield spreads and RP_t as the forcing variables. The long run coefficient is much smaller.

[13] As *RP* has no long run effect on SP^{AAA} in PMG I and III and it, the almost equivalent long run coefficients estimated for *RP* in the two models clearly suggest this possibility.

h_{jt}, follows

$$h_{jt} = \alpha_j + h^*_{jt} + \beta_{1j}s_{1t} + \beta_{2j}s_{2t},\ j=1,2,\ldots N;\ t=1,2,\ldots T \quad (14)$$

with h^*_{jt} being an unpredictable square root process and s_{1t} and s_{2t} each corresponds to level of short rate and the slope of yield curve. h^*_{jt} in (14) 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 short maturity, coupons and certain default risks, estimates from (12), the *Baseline Model,* should be larger. We follow Duffee's specification, proxying h_{jt} with yield spreads and fit the parameter estimates from Table 2 back to the original *level* variables, and find that the median of α_j + h^*_{jt} is 89 b.p. for SP^{AAA} and 198 b.p. for SP^{BBB}, indicating (14) implies the existence of possible over-risk-compensation[14] 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. We then examine again the measure of α_j + h^*_{jt} in (13) following Duffee's specification and find the medians are now 71 b.p. for SP^{AAA} and 158 b.p. for SP^{BAA}, an indication of better risk-compensation identified by the superior ARDL time series method. The 29 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. 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 imprecise specification of the idiosyncratic risks.

ARDL-PMG estimations for the general decomposition model

As a naive scheme, we first use credit spread of *twAAA* as the *systematic* credit spread, as it

[14] 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.

combines features of a low-liquidity-effect default-free bond. The *idiosyncratic* credit spread defined in (11) offers a testable framework which we can employ to make useful inferences. Result from PMG II in Table 3 predict ω to be positive and with a magnitude of greater that 1. Empirically, ω will also be the standardized long run cointegration coefficient between SP_t^i and SP_t^{AAA}. The *naive* idiosyncratic spread defined in the previous section, where ω is simply 1, serves as a special case of (11). In the paragraphs that follow, we will focus on a more general version of ω. As the approach undertaken differs from many previous studies, we will present rationales for the new methodology before proceeding with our analysis.

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 (11), which suggests a cointegrating vector of $(1, -\omega)$ between ISP^i and SP^{AAA}.

【Table 4】

Table 4 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^{AA}, ISP^{A} and ISP^{BBB} from PMG III in Tables 3 are transcribed directly and placed here. We then proceed with another scheme of yield spread decomposition and conduct a PMG estimation based for it. To replace the *naive* coefficient of 1 in (11), we adopt a *cointegration* scheme which takes from Table 3 the long run coefficients for SP^{BAA} under PMG II as the new coefficients for ω. For SP^{AA}, 1.1 is used and we used 1.2 for SP^{A} and 1.25 for SP^{BBB} respectively in column 2 of Table 4. As we are using the *residual* from a long run cointegration or equilibrium equation to fit against *RP* and *TERM*, which are systematic factors driving 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 column 2. Under the *cointegration* definition of idiosyncratic credit spreads, none of the idiosyncratic spreads from three rating groups are significantly *negatively* related to the interest rate dynamics. The estimate of β_1 for ISP^{AA} drops 40% in magnitude compared with what is under the *naive* scheme. On the other hand, for ISP^{A} and SP^{BBB} the estimates drop by about the same amount in magnitude as well. Long run coefficients for *RP* are, however, about the same and still significantly positive and the coefficients for *TERM* stay insignificant. So the *cointegration* scheme seems to retain the long run characteristic of agency effect for idiosyncratic credit spread, while removing contaminated short run effects due to inappropriate decomposition specifications. In another word, spirits incorporated in the *cointegration* method are compatible with the risk diversification discussed earlier in the specification of the affine model.

As a robustness check against the above results, we have added an *arbitrary* approach to contrast them. The *arbitrary* scheme in column of Table 4 adopts arbitrarily a value of 1.5 as the long run coefficient for SP^{AAA} in constructing *idiosyncratic* credit spreads. Under this comparative scheme, all the short run coefficients become significantly positive, an indication of under-risk-compensation in constructing default premium. Long run coefficients are slightly higher and still significantly positive for *RP*. 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 ω affects the first term in (11) or the instantaneous spread in the short run. But ω influence little the second term, the long run risk premium. Moreover, as the magnitude of long run coefficients for *RP* is uniformly higher for lower grade groups regardless of how idiosyncratic spread is identified, we consider this a consistency with the agency risk hypothesis. 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 if we apply numbers in Table 1 we would find the mean ISP^{BBB} under the *cointegration* scheme to have become is 84.8 b.p., which fits well within the equilibrium equation in the context of Duffee's definition[15], while the *naive* scheme produces a median of 94 b.p. 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 in an practical sensed in relating market-quoted measures. The decomposition of credit spread is uniquely defined and also consistent across different credit ratings.

[15] Appling the cointegration equation and multiply 89 b.p., the $\alpha_j + h^*_{jt}$ measure for SP^{AAA} given in the previous section, by the cointegration coefficient 1.25 and then add 84.8 b.p. to it gives 196 b.p., very close to 198 b.p., the $\alpha_j + h^*_{jt}$ measure for SP^{BAA} also given in the last section.

V. Conclusion

We have adopted a unique estimation technique in an empirical framework to investigate long run diversification of credit risks for individual corporate bonds. Specifically, we have in our yield decomposition applied an ARDL-based Pooled Mean Group estimation on dynamic heterogeneous panels of corporate bond yield spreads. The idiosyncratic credit spread produced with our optimal long run decomposition scheme is uniquely compatible with models and measures produced separately by Duffee (1999). The modeling of high and low grade corporate bonds in this work complements that of Liu *et al*. (2006). The results from long and short run analysis are consistent with both the option and agency effects. 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.

We believe our study contributes to the practice of fixed income portfolio investments and related literature in several ways. First, the estimation of idiosyncratic credit spread, after filtering out the systematic credit spread, helps pricing of corporate bond by properly measuring credit risks. Second, our analysis takes into account long run, as well as 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 option approach effect from the long-run agency risk 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.

To establish formally an economically and practically sensible way of identifying specific risk in corporate bond pricing, we start with an affine model of term structure to specify the valuation of default-free and defaultable bonds. We 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. 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-PMG approach along the line of Pesaran, *et al.* (1999) stresses model validity, levels of variables in interest and long-run relationships, as opposed to the usual short-run approach using differences of variables. 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. 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. Overall the evidences provided by our study indicate that risk decomposition into systematic and specific components is crucial in a theoretical sense and useful practically as well. With the limited liquidity of corporate bond trading, our method proves to be an efficient one in extract vital implications. More efficient and precise estimates would still require larger amount of data with better quality given the size and depth of the local fixed income market.

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Table 1
Summary Statistics of Weekly Yield Spreads of the Most Active Taiwan Corporate Bonds

Data in this table is constructed with traded corporate bonds in the over-the-counter market organized by the Gretai Securities Market. Between January 1, 2003 and June 30, 2005, only issues with more than 50 days of traded prices are included in our data set. Non-rated issues are excluded as well. To compute yield spreads, we use traded prices and implied yields of on-the-run 5-year government bonds for the same period. The idiosyncratic spread is the difference between computed yield spreads of issues rated other than *twAAA* and that of *twAAA*..

Panel (a): Basic Data

Bond Rating	**No. of Issues**	**Trading days**			**Duration**		
		Ave.	*Max.*	*Min.*	*Ave.*	*Max.*	*Min.*
twAAA	25	124	375	52	3.82	7.79	1.02
twAA	7	78	125	54	2.29	3.78	0.95
twA	13	90	201	51	3.03	5.82	1.07
twBBB	3	143	224	94	2.25	3.20	1.31

Panel (b): Traded Yields and Yield Spreads

Bond Rating	**Yield**			**Yield Spreads**			**Idiosyncratic Spreads**		
	Ave.	*Max.*	*Min.*	*Ave.*	*Max.*	*Min.*	*Ave.*	*Max.*	*Min.*
twAAA	2.14	3.39	1.43	0.65	1.42	0.40	-	-	-
twAA	2.32	4.90	1.48	0.94	3.49	0.42	0.31	2.05	0.01
twA	2.71	5.95	1.52	1.27	4.42	0.47	0.60	3.11	0.04
twBBB	3.03	6.83	1.58	1.55	5.45	0.54	0.94	3.98	0.12

Table 2
Panel Estimations on Individual Corporate Credit Spreads, Baseline Model

A Baseline Model defined as, $\Delta SP_{it} = \beta_{i0} + \beta_{i1}\Delta RP_t + \beta_{i2}\Delta TERM_t + e_{it}$, where ΔSP_{it} stands for the changes of yield spread measure of full yield spreads like SP_t^{AAA}, $SP_t^{AA}, SP_t^{A}, SP_t^{BBB}$ or idiosyncratic spreads, the difference between full spreads and that of *twAAA*, such as ISP_t^{AA}, ISP_t^{A} and ISP_t^{BBB}. Whereas $\Delta TB3M_t$ and $\Delta TERM_t$ are changes of three-month treasury yield and the yield difference between the 5-year and 10-day government bond RP respectively. To correct possible effect of maturity, raw yield spreads are adjusted first with durations of individual issues. Data for issues from the same credit rating is grouped into panels and a Seeming Unrelated Regression (SUR) is performed for each panel. 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
twAAA			
SP^{AAA}	0.0163 (0.0229)	-0.2204** (0.0659)	-0.2074* (0.1044)
twAA			
SP^{AA}	0.0255 (0.0164)	-0.2484* (0.0510)	-0.2196 (0.1266)
ISP^{AA}	0.0034 (0.0042)	-0.1070* (0.0553)	-0.0894 (0.0578)
twA			
SP^{A}	0.0311 (0.0194)	-0.2718 (0.2258)	-0.2382* (0.1192)
ISP^{A}	0.0051 (0.0048)	-0.1192* (0.0912)	-0.0933 (0.0591)
twBBB			
SP^{AA}	0.0375 (0.0203)	-0.3125 (0.1841)	-0.2897* (0.1279)
ISP^{BBB}	0.0060 (0.0052)	-0.1314** (0.0553)	-0.1064* (0.0529)

* Significant at 5% level.

** Significant at 1% level.

Table 3

Pooled Mean Group (PMG) Estimations for Corporate Credit Spreads of Rating Groups

ARDL (Autoregressive Distributed Lag) - Error Correction Results

This PMG model follows that of Pesaran, *et al.* (1999) using a Gauss algorithm with maximum likelihood estimation procedure. Across each credit rating panel of corporate bond data, long and short run coefficients are restricted to be the same across issues. However, long run results with short run fixed effects differ not much from the pooled estimation reported in this table. The ARDL-ECM procedures are carried out for three sets of data, based on appropriate ARDL models outlined in Sun, Lin and Nieh (2007). The basic equation for Model I apply to rating group *twAAA* only and take the form of

$$\Delta SP_t^{AAA} = a + \sum_{i=1}^{l} b_i \Delta SP_{t-i}^{AAA} + \sum_{j=0}^{m} c_j \Delta RP_{t-j} + \phi_1 SP_{t-1}^{AAA} + \phi_2 RP_{t-1} + \varepsilon_t ,$$

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. *RP* stands for the yield on 10-day government repos. Model II and III apply to *twAA*, *twA and twBBB*, where the equation for Model II becomes

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

while for Model III SP^{AAA} would be replaced simply by *RP*. A likelihood ratio test) has been conducted for the validity of each model before the error-correction estimation can be carried out. The error-correction coefficient is Φ_1 just of each equation.

	PMG I	PMG II	PMG III
	SP^{AAA} *-RP*	SP^{i} - SP^{AAA} *-RP*	ISP^{i} *-RP-TERM*
twAAA			
RP - LR	0.0751 (0.0616)		
ΔRP - SR	-0.1334** (0.0390)		
ECM(-1) [c]	-0.0252 (0.0094)$^{++}$		
twAA			
SP^{AAA} *- LR*		1.0743* (0.5161)	
RP - LR		0.1935 (0.1090)	0.1284 (0.0737)
TERM - LR			0.1123 (0.0724)
ΔSP^{AAA} *- SR*		0.8899** (0.0271)	
ΔRP - SR		-0.0711* (0.0223)	-0.0370* (0.0178)
ΔTERM - SR			-0.0291* (0.0133)
ECM(-1)		-0.0298^{++} (0.0113)	-0.0284^{++} (0.0105)
twA			
SP^{AAA} *- LR* [a]		1.1762** (0.0388)	
RP - LR		0.2281** (0.0094)	0.1363* (0.0619)
TERM - LR			0.1236 (0.0717)
ΔSP^{AAA} *- SR* [b]		0.9512** (0.0386)	
ΔRP - SR		-0.0894** (0.0291)	-0.0429** (0.0194)
ΔTERM - SR			-0.0334* (0.0155)
ECM(-1) [c]		-0.0489^{++} (0.0137)	-0.0495^{++} (0.0211)
twBBB			
SP^{AAA} *- LR* [a]		1.2594** (0.0419)	
RP - LR		0.2776* (0.1237)	0.1531** (0.0696)
TERM - LR			0.1442 (0.0792)
ΔSP^{AAA} *- SR* [b]		1.0099* (0.0521)	
ΔRP - SR		-0.0995** (0.0337)	-0.0503** (0.0207)
ΔTERM - SR			-0.0390** (0.0176)
ECM(-1) [c]		-0.0549^{++} (0.0185)	-0.0567^{++} (0.0179)

[a] LR stands for long-run coefficient estimates from ARDL, 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.

Table 4
PMG Results for Idiosyncratic Spreads under 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 alternatives. The cointegration method takes into account rational forecast and the arbitrary method attempts to capture possible over-risk-compensation. As in Table 3, a likelihood ratio test) is conducted for the validity of each model before the error-correction estimation can be carried out.

	Naive[a]	**Cointegration**[b]	**Arbitrary**[c]
twAA	$(ISP^{AA} = SP^{AA} - SP^{AAA})$	$(ISP^{AA} = SP^{AA} - 1.1*SP^{AAA})$	$(ISP^{AA} = SP^{AA} - 1.5*SP^{AAA})$
RP - LR	0.1284** (0.0737)	0.1195** (0.0716)	0.1367** (0.0721)
TERM - LR	0.1123 (0.0724)	0.0932 (0.0698)	0.1103 (0.0746)
ΔRP - SR	-0.0370* (0.0178)	-0.0172 (0.0181)	0.1665** (0.0530)
ΔTERM - SR	-0.0291* (0.0133)	-0.0108 (0.0126)	0.1529** (0.0594)
ECM(-1)	-0.0284++ (0.0105)	-0.0346++ (0.0111)	-0.0285++ (0.0122)
twA	$(ISP^{A} = SP^{A} - SP^{AAA})$	$(ISP^{A} = SP^{A} - 1.2*SP^{AAA})$	$(ISP^{A} = SP^{A} - 1.5*SP^{AAA})$
RP - LR	0.1363* (0.0619)	0.1477** (0.0663)	0.1596** (0.0634)
TERM - LR	0.1236 (0.0717)	0.1089 (0.0728)	0.1278 (0.0758)
ΔRP - SR	-0.0429** (0.0194)	-0.0251 (0.0221)	0.1354** (0.0219)
ΔTERM - SR	-0.0334* (0.0155)	-0.0203 (0.0159)	0.1199** (0.0154)
ECM(-1)	-0.0495++ (0.0211)	-0.0590++ (0.0101)	-0.0481++ (0.0207)
twBBB	$(ISP^{BBB} = SP^{BBB} - SP^{AAA})$	$(ISP^{BBB} = SP^{BBB} - 1.25*SP^{AAA})$	$(ISP^{BBB} = SP^{BBB} - 1.5*SP^{AAA})$
RP - LR	0.1531** (0.0696)	0.1721** (0.0721)	0.1893** (0.0707)
TERM - LR	0.1442 (0.0792)	0.1220 (0.0795)	0.1318 (0.0771)
ΔRP - SR	-0.0503** (0.0207)	-0.0312 (0.0214)	0.1644** (0.0226)
ΔTERM - SR	-0.0390** (0.0176)	-0.0297 (0.0168)	0.1447** (0.0171)
ECM(-1)	-0.0567 (0.0179)++	-0.0666++ (0.0184)	-0.0506** (0.0168)

[a] Naive decomposition refers to taking the simple difference between the credit spread of bond grade of interest and the credit spread of *twAAA* index. The numbers in this column are taken directly from the third column of Table 3.
[b] Cointegration decomposition refers to subtracting *twAAA* spread multiplied by a cointegration ratio. The ratio is estimated with an ARDL procedure and the long-run coefficient of *twAAA* spread from the estimation is used as the ratio.
[c] Arbitrary decomposition subtracts 1.5 times *twAAA* 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).