Diversifying Risks in Bond Portfolios: A Cross-border Approach

David Sun and Shih-Chuan Tsai

Kainan University

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David Sun [*]

Kainan University

Shih-Chuan Tsai

National Taiwan Normal University

ABSTRACT

This study recalibrates corporate bond idiosyncratic risks in an international context. Applying a statistically powerful risk decomposition scheme, we show in this study that diversification is improved by the addition of a global risk benchmark. We build a long-run stationary yield spread decomposition scheme which provides better diversification effect. In addition to global liquidity and default risk factors, we also include country-specific default risk component, and all of them are free of measurement or availability issues. The idiosyncratic risk component is estimated as a fixed effect along with all the parameter estimates, rather than separately from an exogenous generating process. Our linear model is simple, yet it can be easily and promptly applied by practitioners.

Keywords: bond pricing; credit spread; systematic risk; diversification; global risk; heterogeneous panel; pooled mean group.

JEL Classification: C32, E4, E21, G13, G3

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[*] Corresponding author at: Department of Banking and Finance, Kainan University, Taoyuan, Taiwan 33857.

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1. Introduction

In the recent European sovereign debt crisis, corporate yield spreads are unusually high in some countries or regions, but not necessarily so elsewhere. It implies then opportunities for further cross-border diversification for fixed income portfolios. According to Bank of America, out of the overall 12 trillion dollars corporate bond market, 20% is held by ETF and mutual funds. Bond mutual funds invested $1.44 trillion in corporate bonds, up by almost $380 billion since the year of 2000. In studying systemic risks of corporate bonds, more studies than before now focus on global as well as regional factors, beyond those affecting only a certain country. As a result, it is also more important than ever to identify idiosyncratic risks in bonds so they that can be diversified away adequately in cross-border portfolios.

The composition and forming process of yield spreads over risk-free benchmarks determine if spreads are adequately assessed and practically applicable for practitioners to revise timely. Given that default risks, political or business cycle risks, as well as liquidity risks have been considered as three major corporate bond risk components in literature (see, among others, Dastidar & Phelps, 2011; Xie, Shi & Wu, 2008; Longstaff, Mithal & Neis, 2005; Chen, Lesmond & Wei, 2007; Block & Vaaler, 2004), signals used to proxy these components are often difficult to observe or measure with precision, making it impractical to utilize them directly. As international capital markets integrate, domestic economy is not the primary source of systemic risk any more. Duffie and Singleton (1999, 2003) ascribe fluctuations of sovereign yield spreads to international risk factors. Dungey, Martin and Pagan (2000) demonstrate a factor model incorporating both world as well as country risks is necessary. Collin-Dufresne, Goldstein and Martin (2001) examine the validity of structural model and find that credit spread changes are not so much related to firm-specific factors as systemic factors, and US bond liquidity factors are ideal candidates. Longstaff, Pan, Pedersen and Singleton (2011) show further that CDS spreads for many countries are more related to certain common and global factors than local economic variables. Ang and Longstaff (2013) employ both common and country-specific factors to demonstrate that systemic risk factors for U.S. and European CDS spreads are highly correlated with one another through financial markets, rather than macroeconomy.

The importance of global and cross-border risk factors makes it necessary to reconsider how idiosyncratic risks can be located properly for the purpose of portfolio management. Lerner and Wu (2005) suggest that full spreads could be under- or over-estimated under different credit ratings. Lin and Curtillet (2007) also indicate that it is inappropriate to just analyze full credit spreads. Wilson (1998) starts the research on credit spreads decomposition by studying systemic and idiosyncratic risks in the loss distribution. Duffee (1999) adopts a reduced-form model to decompose credit spreads, while Gatfaoui (2003) uses a structural model instead. Jarrow, Lando and Yu (2005) assume a perspective of investment portfolio and discuss how idiosyncratic risk can diversify risks in the portfolio. Churm and Panigirtzoglou (2007) incorporate the choice of default point in the calculation of spread decomposition[1] as an extension of Liu, Longstaff and Mandell (2006), where swap spreads are adopted as an estimation basis for idiosyncratic credit spreads. Huang and Huang (2012) contend that credit risk accounts for less than 30% of the investment grade corporate yield spreads according to various forms of structural frameworks. Chacko, Das and Fan (2012) argue that bond market illiquidity could be explained in part by illiquidity in equity market. On the method of decomposition, this project will extend the spread decomposition scheme proposed in Sun, Lin and Nieh (2008) to a three-factor model with cross-border context.

This study proposes a model to locate idiosyncratic risks in corporate yield spreads with the aid of global as well as country-specific systemic factors. Our model employs observed market risk measures rather than imputed default or liquidity risk variables. Specifically, on global systemic risks, we adopt a US capital market liquidity index as the liquidity factor, and US sovereign CDS as the default factor. While to account for country specific risks we employ the implied equity index volatility measures relative to VIX from US. Observed risk factors are better than imputed ones as they are produced by the same capital markets that price other market instruments so it is clear to market participants in trading corporate bonds what the implications of the risk factors are. With the aid of a statistically powerful risk decomposition scheme, we show in this study that diversification is improved significantly.

In terms of the econometric treatment on yield data, *changes* had been used (.e.g., Wilson, 1998; Duffee, 1999; Collin-Dufresne, et al., 2001;Dastidar & Phelps, 2011; Lee, Xie & Yau, 2011) to avoid partially problems arising from non-stationarity and autocorrelation in the *level* of credit spreads. But it is accompanied by fundamental drawbacks such as the loss of information, and being leptokurtic as indicated by Pedrosa and Roll (1998). Changes of yield spreads are also found to persist over time in Duffee (1998). Extending the credit spread decomposition model of Sun, Lin and Nieh (2008) and panel decomposition model of Lin and Sun (2007), we conduct our analysis centering on the Pooled Mean Group (PMG) panel time series model of Pesaran, Shin and

[1] This perspective is similar to Lin and Sun (2009), which is based on the model of Merton 1974) and analyzes nonlinear price changes of debt claims in the neighborhood of default point, whose direct contribution is to account for the differences in idiosyncratic credit spreads between investment and high-yield corporate bonds.

Smith (1999). The model emphasizes long-run relations, in addition to short-run cointegrations, among economic variables, and helps us building a long-run stationary yield spread decomposition scheme in the study.

We find from our analysis that, for all the countries, both the global and domestic systemic components are significant in constituting yield spreads of individual issues in each country. The inclusion of global risk, as well as liquidity, component performs better than alternative methods. The contributions of both the global and the domestic risk benchmarks are estimated with a statistically more powerful time series model in an econometrically long-run context. The idiosyncratic risk component is estimated as a fixed effect in our data panel along with all other parameter estimates, rather than being introduced separately from an exogenous generating process. As a result, parameter estimates from our yield decomposition model can be used to construct yield spreads directly, simply by employing observed market data. Our linear decomposition model may contain other econometric imperfections, but our estimates can be applied promptly and easily by practitioners.

Yield spread panels are often studied in regressions with fixed or random effects, in which homogeneity of parameters is imposed across all the group time series. While the long-run relationship can be predicted by economic theory, both the short-run dynamics and particularly the speed of adjustment to equilibrium mainly depend on group-specific factors. This study employs a panel estimation approach which allows heterogeneous short-run dynamics and how they revert to long-run equilibrium. Yet the approach constrains long-run equilibrium to be homogeneous across groups of corporate yield spreads. This modification of traditional methods proves to be consequential. For each country, the portfolio Value at Risk (VaR) measure on idiosyncratic risk falls significantly, which implies better cross-border diversification.

Our results help enhancing the performance of global fixed income portfolio diversification as we extend a domestic framework to a cross-border one. Secondly, the analysis of risk factors in international investment portfolio adds insights to the practice of pricing and risk management of international asset management, especially in effective cross-border and cross-segment management. A theoretical model for decomposition is introduced in Section 2, with details given in the Appendix. Section 3 gives an empirical decomposition scheme to fit our international bond data. Findings of empirical analysis are given in Section 4. Section 5 discusses robustness issues of our study and results, followed by concluding remarks in Section 6.

2. Risk decomposition in a global context

To characterize systematic and idiosyncratic risks driving corporate yield spreads, we use a framework adapted from Duffie and Singleton (1999), Liu, Longstaff and Mandell (2006) as well as Diaz and Gemmill (2006). We use the theoretical model of the former two to evaluate a corporate bond with global liquidity and credit risks and country-specific business risks, on top of firm level idiosyncratic risk. The reduced-form setup lends itself to our subsequent empirical analysis for the convenience of utilizing various observed risk measures. The rich implications of our analysis owe themselves to the separation of relevant risks.

We assume there are two types of fixed income securities, with one riskless and the other risky due to liquidity and credit risks. (A.1) gives the value of the riskless security based on a comm.on affine specification. (A.2) formulates the value of the risky security, which contains liquidity and default risks. The value of the globally riskless bond responds to one myopic and one hedging demand as in the standard affined model of Duffie and Singleton (1997) as in (A.3). A global liquidity factor is driven by a third state variable in (A.4), but the default risk has two components in (A.5). The first one is a global default factor related to the two global state variables in (A.3), while the second factor reflects default risks specific to a certain country. The solution, which follows Liu, et al. (2006) with variations, is given by (A.8).

The formulation of our model in terms of global liquidity relates in part to the findings of Chakco (2009), which indicates that liquidity risk factor is important and properly priced in corporate bond returns. In relatively less liquid bond portfolios, approximately one-third of the returns come from liquidity effect. Besides the systemic nature of liquidity risks argued in that study, Ericsson and Renault (2002), Longstaff, Mithan and Neiw (2005), and Chen Lesmond and Wei (2007) also ascribe yield spreads to corporate bond liquidity. Alessi and Detken (2011) compare the performance of a large number of global and domestic variables and find that global liquidity measures, based on the aggregate for 18 OECD countries, are the best early warning indicators. Bierut (2013) also shows that global liquidity measures outperform domestic measures as early warning indicators of asset price booms.

As data on CDS spread become more available, it serves well to measure systematic default risks (e.g., Blanco, Brennan & Marsh, 2005; Longstaff *et al.*, 2005). Ang and Longstaff (2011) find that systemic credit risk in the Eurozone is collectively strongly related to US financial market variables rather than to macroeconomic fundamentals of each country, using CDS spreads. In light of this finding, it seems less reasonable to relate country-specific risks in bond yields to sovereign

CDS spreads. Aizenman, Hutchinson and Jinjarak (2011) attempt to use macroeconomic fundamentals as an explanation to country-specific risk factors besides the default risk reflected in sovereign CDS spreads. Attinasi, Checherita and Nickel (2009) and De Santis (2012) suggest that risk aversion can be estimated by US top-grade corporate yield spreads. Equation (A.5) in this study makes a distinction between global and country-level default risks by relating the former to sovereign CDS spreads and the latter to implied volatility index of each country.

There is also literature stresses on the contagious effect of risks within a region as argued in Ang and Bekaert (2002). Diaz and Gemmill (2006) also suggest, using South American data, the distance-to-default measure owes 45% of its variance to regional factors. We leave discussions on regional influences later on in the study and assume for our main model that there is no more cross-country factors beyond the global liquidity and default risk factors. Although Bedendo and Colla (2013) provide evidence on spillover effects of credit risk in the Eurozone, their finding also contend that domestic demand still stands as an important factor. Our proxy of country-level default risk factor depends on the VIX-type measures to proxy risk appetite of individual countries covered in our study.

3. Three-factor Credit Spread Decomposition

Instead of using the usually seen change-based short-run model, we decompose yield spread with a level-based long-run model which has better implications for cross-border diversification. Duffee (1998) and Xie, et al. (2008) both examine a three-factor reduced form model for corporate yield spreads, but the focus is on the idiosyncratic rather on the systemic risks. Xie, et al. (2008) indicate that findings of Duffee (1998) omit certain common factors in a firm's default risk, while arguing that macroeconomic variables, in addition to term structure and default intensity, affect corporate yield spreads. Our focus in this study lies instead on systemic risks to capture the unexplained variations in yield spreads.

Based on the specification of (A.1)~(A.8) in the Appendix, the yield spread of a corporate bond issued in a particular country can be modeled to reflect the influence of short rate, global liquidity risk, default risks in the international and domestic markets, and the idiosyncratic risk of the issuer. Following the common practice in literature, we establish corporate bond yield spreads against corresponding government bond yields, which incorporates both state variables in (A.3) for instantaneous and term effects. The global liquidity measure is proxied by a publicly available global liquidity index. While the US sovereign CDS spread is used to proxy the global default risk factor. For country level credit risk, we take the relative implied volatility index of the country of interest against the S&P 500 VIX. Combining (A.3) through (A.8), we could consider, for a corporate bond issued by firm j at time t in a non-US country i, the yield spread against government bond yield as $\boldsymbol{SP}_{it}^{j}$ which is expressed in a linear form like

$$\boldsymbol{SP}_{it}^{j} = \gamma_{0i}^{j} + \gamma_{1i}^{j}\boldsymbol{LR}_{t}^{G} + \gamma_{2i}^{j}\boldsymbol{DR}_{t}^{G} + \gamma_{3i}^{j}\boldsymbol{DR}_{it}^{D} + \xi_{it}^{j}, j=1,2,\ldots,M,\ i=1,2,\ldots,N,\ t=1,2,\ldots,T \qquad (1)$$

where $\boldsymbol{LR}_{t}^{G}$ is the global liquidity factor, reflecting γ_s in (A.2). $\boldsymbol{DR}_{t}^{G}$, which is related to the second term of (A.5), denote the global systematic default risk benchmark, while $\boldsymbol{DR}_{it}^{D}$ stands for the country-specific default risk factor as implied by X_4 in (A.5). γ_{0i}^{j} is considered as the idiosyncratic spread and assumed, without loss of generality, to be invariable in time. Under the specification above, ξ_{it}^{j} would be a disturbance.

A commonly used empirical model for (1) is a pooling panel OLS regression on changes of $\boldsymbol{SP}_j$ with fixed or random effects (Duffee, 1998; Jacoby, Liao & Batten, 2009), but that would require estimated coefficients for regressors to be the same across all firms. Besides, yield spreads and term structure parameters are autocorrelated. Disturbances in (1) maybe nonstationary as Morris, Neal, and Rolph (2000) argue. Taking simple changes of $\boldsymbol{SP}_j$ only leads to discarding valuable information without helping much due to possible higher order autocorrelations. To avoid these problems we employ an ARDL version of (1) according to Pesaran and Smith (1995) in the following form, for a given country,

$$SP_{jt} = \sum_{k=1}^{p}\lambda_{jk}\boldsymbol{SP}_{j,t-k} + \sum_{k=1}^{q}\delta_{jk}^{'}\boldsymbol{X}_{j,t-k} + \boldsymbol{\mu}_j + \boldsymbol{\varepsilon}_{jt}, j=1,2,\ldots,M,\ t=1,2,\ldots,T, \qquad (2)$$

where j denotes a certain firm, $\boldsymbol{X}_{jt}=(\boldsymbol{LR}_{t}^{G}, \boldsymbol{DR}_{t}^{G}, \boldsymbol{DR}_{it}^{D})'$, $\boldsymbol{\delta}_{jk}=(\delta_{jk}^{1}, \delta_{jk}^{2}, \delta_{jk}^{3})'$, and $\boldsymbol{\varepsilon}_{jt}$ is the disturbance independently distributed across j and t with mean 0 and $\sigma_j^2 > 0$. $\boldsymbol{\mu}_j$ is assumed to be the fixed effect for firm j in the panel ARDL model of (2), and can be considered as reflecting the idiosyncratic risk in this firm's corporate bond yield in the sense of decomposition argued by Sun, et all (2007) as well as Dastidar and Phelps (2011).

If the variables in (2) are processes of I(1) and cointegrated[2], then the error term should be of

[2] Neal, Rolph, Dupoyet and Jiang (2012), among others, have argued that levels of the intermediate and long-term corporate as well as government bond yields are nonstationary while their changes appear to be stationary. Before that,

I(0) for all *j*. (2) can be reparameterized as an error correction form like

$$\Delta \boldsymbol{SP}_{jt} = \phi_j (\boldsymbol{SP}_{j,t-1} - \boldsymbol{\theta}_j' \boldsymbol{X}_{jt}) + \sum_{k=1}^{p-1} \lambda_{jk}^* \Delta \boldsymbol{SP}_{j,t-k} + \sum_{k=1}^{q-1} \delta_{jk}^{'*} \Delta \boldsymbol{X}_{j,t-k} + \boldsymbol{\mu}_j + \boldsymbol{\varepsilon}_{jt}, \tag{3}$$

where ϕ_j=-(1- $\sum_{k=1}^{p} \lambda_{jk}$), $\boldsymbol{\theta}_j$= $\sum_{k=0}^{q} \delta_{jk}$ /(1- $\sum_{k=1}^{p} \lambda_{jk}$), $\lambda_{jk}^* =$ - $\sum_{m=k+1}^{p} \lambda_{jm}$ and $\boldsymbol{\delta}_{jk}^* =$ - $\sum_{m=k+1}^{q} \delta_{jm}$ according to Pesaran, et al. (1999). ϕ_j is the speed of error-correction on the process' deviation from its long term equilibrium, which is the expression $\boldsymbol{SP}_{j,t-1} - \boldsymbol{\theta}_j' \boldsymbol{X}_{jt}$ in (3). If $\boldsymbol{SP}_j$ and ($\boldsymbol{LR}_t^G$, $\boldsymbol{DR}_t^G$, $\boldsymbol{DR}_{it}^D$)' are cointegrated then ϕ_j should be significantly negative in order for for ε_t to revert to 0. The vector $\boldsymbol{\theta}_j$ characterizes the long run relation between $\boldsymbol{SP}_j$ and ($\boldsymbol{LR}_t^G$, $\boldsymbol{DR}_t^G$, $\boldsymbol{DR}_{it}^D$)' . Short run effects are reflected by ϕ_j, λ_{jk}^* and the vector $\boldsymbol{\delta}_{jk}^*$. The ARDL model retains the *level* terms of $\boldsymbol{SP}_{j,t-1}$ and $\boldsymbol{X}_{jt}$, and is therefore superior to models employing only *changes* of yield spreads and explanatory variables.

Pesaran and Smith (1995) show that a panel model like (3) can be estimated separately for each firm (*j*=1,2,…,M) first and then make inferences on the averages of coefficients from individual ARDL equations and standard errors of these averages. This approach, or the Mean Group (MG) estimation, is superior to a pooling panel model which has distinct fixed effects for each firm but common slope coefficients across all firms. The latter does not distinguish short-run effects from long-run ones, and also produces inconsistent results for a dynamic heterogeneous panel. The MG estimation is the first ARDL method used in this study for decomposing corporate yield spreads within a given country.

The second decomposition method is a Pooled Mean Group (PMG) model according to Pesaran, et al. (1999), which allows the intercept, short-run coefficients, and error variances to differ across groups, similar to the MG estimation method. The long-run coefficients under PMG are, however, constrained to be equal across groups like in a pooling model with fixed effects. So the second method requires the assumption of $\boldsymbol{\theta}_j = \boldsymbol{\theta}$, $\forall j$. To compare against the PMG method, we also include in our analysis a third method, which is the traditional pooling panel model with fixed effects, where both long- and short-run parameters are constrained to be equal across all firms within each country. To tell which model utilizes information better, tests according to

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Mehra (1994) and Campbell and Shiller (1987) have found similar results for long-term nominal interest rates.

Hausman (1978) is utilized.

Model in (15) estimates idiosyncratic spreads of each firm $\boldsymbol{\mu}_j$ separately. Its accuracy depends on whether all the other coefficients are estimated correctly. Although traditional pooling panel estimation could allow the fixed effect $\boldsymbol{\mu}_j$ to serve as an estimate for idiosyncratic spread, restricting all other coefficients to be the same would just result in inconsistent estimates of $\boldsymbol{\mu}_j$. The two main ARDL methods, MG and PMG, we employ both allow short-run coefficients and μ_j to differ across firms. So their estimates for (3) would produce more accurate idiosyncratic spreads than the traditional change-based panel model, and thus benefit practitioners more in diversification within or across borders.

4. Empirical Findings

Table 1

Summary Statistics of Investment-Grade Corporate Bond Spreads

	No. of Issues	Average Maturity	Average Rating[a]	AA Average Spreads (bp)	A Average Spreads (bp)	BBB Average Spreads (bp)
				3 to 7-year Maturities		
Canada	44	4.64	3.57	83.76	107.38	152.58
Germany	196	4.95	3.11	61.54	83.22	110.17
France	104	5.12	4.25	94.61	119.74	157.21
UK	119	5.56	4.90	113.30	149.04	187.69
US	221	5.03	4.14	92.76	115.46	148.39
				8 to 12-year Maturities		
Canada	29	8.87	3.98	137.20	169.63	204.66
Germany	147	9.25	3.42	104.76	133.17	173.43
France	110	10.18	4.73	168.03	201.71	249.13
UK	134	10.96	5.66	202.19	243.29	293.52
US	194	9.77	4.51	154.62	181.84	230.54

Value	1	2	3	4	5	6	7	8	9	10
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3
Standard & Poors	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-

Monthly investment-grade industrial corporate bond yields reported in this table are obtained from Bloomberg for the period between 2006 and 2011. Issues with floating coupon rates and embedded options are not included. Also, issues with unreasonably high or low prices are eliminated. Spreads for each issue in the corresponding maturity category are calculated against yields of average government bond with the closest matching maturity in the respective country.

[a] Rating scales are in the following chart.

For the estimation of (3) we use monthly pricing data of corporate bonds issued in Canada, Germany, France, UK and US from Bloomberg between January 2006 and December 2012. Only yields of investment-grade industrial coupon bonds with maturities between 3 and 12 years, and Standard & Poor credit ratings of AA, A or BBB, are collected and those with floating coupon rates and embedded options are not included. Unreasonably high or low prices are also discarded. Issues from other countries are not included as there are too few concurrent issues available to support the construction of spot yields. Table 1 shows that issues from France and UK have the longer maturities and lower credit ratings among the five countries. Government bond yields are obtained from Thompson Datastream for the same period.

The global liquidity index (GLI) data is compiled by the CrossBorder Capital using data from 80 countries worldwide. This measure predicts movements in international fixed income, equity, credit, currency, futures and options markets. The overall liquidity index of GLI between 1976 and 2012 is given in Figure 1.

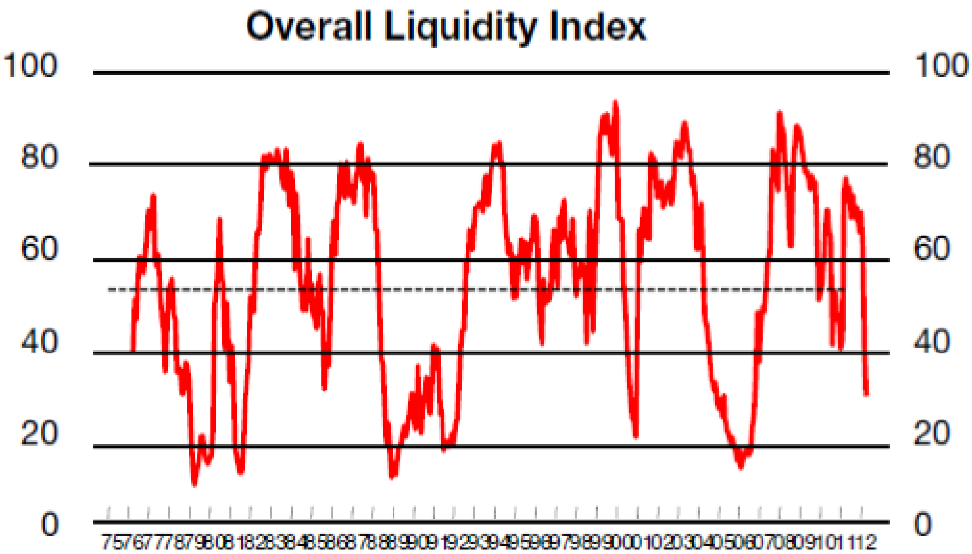

Figure 1 Monthly levels of overall Global Liquidity Index between 1976 and 2012
Index values are calculated as normalized 'Z scores' for each the 30 variables from 80 economies. The normalized values lie between 0 and 100, with an average of 50 as being neutral to a 40-month rolling average. Readings above 50 signal an improvement or increase against recent trend. Readings below 50 signal a deterioration or decrease compared to trend. The overall index values are weighted average of the Total Liquidity Index (TLI) of all individual countries. For each country, TLI is made up of four sub-indices, including the Central Bank Liquidity Index (CBLI), the Private Sector Liquidity Index (PSLI), the Cross-border Flow Index (FLI) and the Funding Condition Index (FCI).

The 5-year US CDS data, as the proxy for global default risk, comes from Datastream. In terms of country-specific default risk, we use a volatility ratio with country-specific implied volatility of country stock index as the numerator and the CBOE S&P 500 option VIX as the denominator. For UK, it is the FTSE 100 30-day implied volatility from Financial Times. 30-day implied volatility VDAX-New for DAX30 compiled by Deutsche Borse at Frankfurt is used for Germany. The Canadian implied volatility VXC is compiled from the S&P/TSX 60 Index options for 30 days. For France, VCAC provided by NYSE-EuroNext gives the implied volatility measure of CAC40 index options.

Yields of zero-coupon government bonds, as well as corporate bonds of each credit rating, with rounded maturities between 3 and 12 years are used. Individual corporate spreads are calculated for each rating-maturity category and then combined and averaged into a short maturity group (3 to 7 years) as well as a long maturity group (8 to 12 years). Table 1 also shows that average yield spreads for the former group are about 50 to 90 basis points lower than the latter in a given rating class. The yield spreads of long maturity US issues reported in Table 1 are compatible with the average yield spread between Moody's seasoned Baa corporate bond portfolio and 30-year US Treasury bond, which amounts to 223 basis points. For the Moody AA portfolio spread is around 152 bps. Our spread estimates for the long-maturity category are higher probably because our spreads are based on spot yields and also Moody portfolio includes issues from utility and financial companies.

Treating US as the benchmark country, we apply (3) on the spot yield spreads of the other four countries with the help of the ***xtpmg*** procedure provided in the *Stata* package, which is available only after 2007. Allowing heterogeneous short-run dynamics helps giving better statistical properties to long-run parameters, which are $\boldsymbol{\theta}_j$ under the MG method and $\boldsymbol{\theta}$ under the PMG method. For comparison, we add in a traditional panel fixed-effect model, which constrains ϕ_j, λ^*_{jk} and the vector $\boldsymbol{\delta}^*_{jk}$ to be the same across j. For simplicity, we adopt the error correction form of an ARDL(1,1,1,1) version of (3), for all of the four maturity-rating categories[3], as follows,

$$\Delta \boldsymbol{SP}_{jt} = \phi_j(\boldsymbol{SP}_{j,t-1} - \boldsymbol{\theta}'_j \boldsymbol{X}_{jt}) + \lambda^*_j \Delta \boldsymbol{SP}_{j,t-1} + \boldsymbol{\delta}'^*_j \Delta \boldsymbol{X}_{j,t-1} + \boldsymbol{\mu}_j + \boldsymbol{\varepsilon}_{jt}, \tag{4}$$

where ϕ_j=-(1-λ_j), $\boldsymbol{\theta}_j = \delta_j/(1-\lambda_j)$, $\lambda^*_j = -\lambda_j$ and $\boldsymbol{\delta}^*_j = -\delta_j$. The traditional panel fixed-effect model

[3] According the Variable Addition Test (VAT) specified in Pesaran, et al. (2001), ARDL(2,2,1,1) should be chosen for the short maturity-rating A category, with lags selected based on Schwarz Bayesian Criterion. ARDL(1,2,2,1), ARDL(2,2,1,1) and ARDL(1,1,2,1) are the appropriate models according to VAT for the long maturity-rating A, short maturity-rating BBB and long maturity-rating BBB respectively. Analyzing the ARDL(1,1,1,1) model instead, however, affects mainly the short-run estimates. Long-run estimates, which are our focus, are only slightly different.

constrains ϕ_j, λ_j^* and vector $\boldsymbol{\delta}_j^*$ to be the same across j, while the MG method loops through all firms in each country and reports the unweighted average of $\boldsymbol{\theta}_j$, ϕ_j, λ_j^* and $\boldsymbol{\delta}_j^*$. The PMG method constrains $\boldsymbol{\theta}_j$ to be equal to $\boldsymbol{\theta}$ for all j but reports also the average of ϕ_j, λ_j^* and $\boldsymbol{\delta}_j^*$.

Table 2 gives the results, for issues with short maturities and the rating of A, from the dynamic Fixed Effect (FE), Mean Group (MG) ARDL and Pooled Mean Group (PMG) ARDL estimations based on (4). Few of the long-run decomposition coefficients ($\boldsymbol{\theta}_j$) and the short-run ones ($\boldsymbol{\delta}_j^*$) from the dynamic FE model are significant, except for the long run coefficient for $\boldsymbol{RP}_t$ and the error correction coefficient. Most of the long-run decomposition coefficients from the PMG ARDL model are significant at the 1% level, while only half of the coefficients from the MG ARDL mo del are significant. The short-run decomposition coefficients are mostly insignificant. The error correction coefficients (ϕ_j) are, however, uniformly significant across all three models, with the PMG and MG models exhibiting stronger significance. Across the four countries studied, estimates for issues in Germany and UK appear to exhibit stronger statistical significance in general. Hausman tests results indicate that PMG model utilization information better than the MG and dynamic FE models.

Estimated coefficients for $\boldsymbol{SP}_t^G$, the global systematic benchmark, are also uniformly more significant than $\boldsymbol{SP}_t^D$, the local systematic benchmark across all four countries in Table 3. The lack of significance in estimated decomposition coefficients from the dynamic FE model suggests that its weaker statistical power stems from cross-panel constraining both the long- and short-run coefficient estimates to be the same across spread time series of all firms. The highly significant Hausman test result in comparing the dynamic FE against the MG method is consistent with the statement above, so is the fact that coefficient estimates from the latter model are in general more significant those from the former. Although the PMG model requires, for each country, all the long-run decomposition coefficients to be the same across individual corporate spread series, which causes the estimated standard deviations from the PMG method to be higher than those from the MG method, significance in long-run coefficients and Hausman tests between the two models are in favor of PMG over MG.

Table 2
Cross-border Yield Spread Decomposition with ARDL Error Correction Estimations,
Short maturities and credit rating A

	Canada	*Germany*	*France*	*UK*
		Dynamic FE Model		
Error correction (long-run)				
LR_t^G	0.2807 (0.1713)	0.2141 (0.1342)	0.3159 (0.1984)	0.3026** (0.1185)
DR_t^G	0.1739 (0.1362)	0.1031 (0.0755)	0.1552 (0.1236)	0.1218 (0.1094)
DR_t^D	0.2404** (0.0837)	0.1364** (0.0556)	0.1835* (0.0878)	0.3135** (0.0992)
Short-run				
ϕ	-0.1236* (0.0538)	-0.1481** (0.0419)	-0.1148* (0.0557)	-0.1669** (0.0542)
ΔLR_t^G	0.0203 (0.1014)	-0.0317* (0.0168)	0.0183 (0.1125)	-0.0545* (0.0252)
ΔDR_t^G	0.4165 (0.9836)	-0.9006 (0.8815)	0.2455 (1.1356)	-1.3793 (1.0066)
ΔDR_t^D	-2.2980 (1.7361)	-1.5059* (0.8213)	-3.0773 (1.9980)	-3.3837* (1.6061)
		MG Model		
Error correction (long-run)				
LR_t^G	0.3171** (0.1461)	0.2224** (0.0846)	0.3479** (0.1376)	0.3631** (0.1064)
DR_t^G	0.1998 (0.1010)	0.1313* (0.0625)	0.1928* (0.0861)	0.1893* (0.0887)
DR_t^D	0.2605** (0.0481)	0.2139** (0.0491)	0.2858** (0.0776)	0.3007** (0.0713)
Short-run				
ϕ	-0.2377** (0.0401)	-0.2678** (0.0338)	-0.2273** (0.0446)	-0.2761** (0.0385)
ΔLR_t^G	-0.0475* (0.0221)	-0.0647** (0.0188)	0.0019 (0.0449)	-0.0529** (0.0164)
ΔDR_t^G	-0.2098 (0.2046)	-0.7293 (0.4756)	-0.1786 (0.5327)	-0.4489 (0.2855)
ΔDR_t^D	-2.7776* (1.3592)	-1.6331** (0.6695)	-3.3015* (1.6234)	-3.1903** (1.1220)
		PMG Model		
Error correction (long-run)				
LR_t^G	0.3628** (0.1493)	0.2561** (0.0521)	0.3733** (0.1443)	0.4101** (0.1246)
DR_t^G	0.2264 (0.1215)	0.1787** (0.0649)	0.2512* (0.1208)	0.2418* (0.1025)
DR_t^D	0.2718** (0.0527)	0.2220** (0.0655)	0.2945** (0.0790)	0.3252** (0.0706)
Short-run				
ϕ	-0.2686** (0.0419)	-0.2709** (0.0375)	-0.2554** (0.0497)	-0.2888** (0.0320)
ΔLR_t^G	-0.0431 (0.0249)	-0.0626** (0.0201)	-0.0550* (0.0276)	-0.0501** (0.0188)
ΔDR_t^G	-0.3551 (0.8035)	-0.7559 (0.5213)	-0.1603 (0.6081)	-0.3445 (0.9294)
ΔDR_t^D	-2.2520 (1.5335)	-1.7893** (0.6804)	-3.1314 (1.8525)	-3.2107** (1.0049)

Hausman Tests

MG (unrestricted) over *Dynamic FE* (restricted)	$\chi^2(2)=11.37$	(p=0.0034)	*MG* is preferred over *FE*
MG (unrestricted) over PMG (restricted)	$\chi^2(2)=7.35$	(p=0.0253)	*PMG* is preferred over *MG*

For simplicity, we adopt the error correction form of the ARDL(1,1,1,1) version of (1) like

$$\Delta SP_{jt} = \phi_j(SP_{j,t-1} - \theta_j' X_{jt}) + \lambda_j^* \Delta SP_{j,t-1} + \delta_j'^* \Delta X_{j,t-1} + \mu_j + \varepsilon_{jt},$$

where ϕ_j=-(1-λ_j), $\theta_j = \delta_j$/(1-λ_j), $\lambda_j^* = -\lambda_j$ and $\delta_j^* = -\delta_j$. The traditional panel fixed-effect model constrains ϕ_j, λ_j^* and vector δ_j^* to be the same across j, while the MG method loops through all firms in each country and reports the unweighted average of θ_j, ϕ_j, λ_j^* and δ_j^*. The PMG method constrains θ_j to be equal to θ for all j but reports also the average of ϕ_j, λ_j^* and δ_j^*.

* Significant at the 5% level.
** Significant at the 1% level.

Results in Table 2 also exemplify the advantage of applying an ARDL model in a hetergeneous panel. As level of terms retain more information than the difference terms of yield spreads, stronger significance exhibited by the long-run decomposition coefficients than the short-run ones demonstrates that an ARDL model works better in studying corporate yield spreads, possibly due to the information provided by level terms of lagged dependent variable as well as the level term of current independent variables. Based on the average yield and interest rate data within our data period, the PMG analysis in Table 2 predicts that the average long-run Canadian rating A short maturity corporate yield spread to amount to roughly 152 bps, only 13 bps below the observed average, while for UK that difference is about 10 bps. Through properly estimated long-run decomposition coefficients and μ_j, the fixed effect or the proxy for idiosyncratic risk in individual corporate spreads, our analysis would substantially help managing risks of holding corporate bond portfolios in a long period of time.

Table 3, 4 and 5 give results from the same procedures for the categories of long-maturity with rating BBB, short-maturity with rating A, as well as long-maturity with rating BBB. Uniformly significant error correction coefficients suggest apparent cointegration relationships exist among yield spreads and the four independent variables. Both the long- and shor-run coefficients go up in magnitude and the extent of significances is stronger with longer maturities and lower bond ratings[4]. Similar to the pattern in Table 3, across all the maturity-rating categories and countries, PMG model produces the largest coefficients and dynamic FE the smallest. The pattern of standard deviations is just the opposite. Hausman test results reported in each of the three tables also suggest the PMG procedure is superior to the MG and dynamic FE ones. In general, reconstructed yield spread estimates from coefficients given by the PMG model are slightly lower than the observed figures shown in Table 1, possibly due to apparent down-trend of yield spreads within the data period. It is also worth noting that the responses of yields to country default risk are in general stronger for issues with lower credit rating, validating the notion, brought up initially in Section 2, that the direct influence of short rate on yield spread should increase with credit risks.

[4] This is also consistent with findings in Lin and Sun (2009), which are based on US data and predict that yield spreads of bonds with lower credit rating would be more responsive to systematic risks.

Table 3

Cross-border Yield Spread Decomposition with ARDL Error Correction Estimations,

Short maturities and credit rating BBB

	Canada		***Germany***		***France***		***UK***	
			Dynamic FE Model					
Error correction (long-run)								
LR_t^G	0.2887	(0.3921)	0.2242*	(0.1042)	0.3056	(0.3559)	0.3350**	(0.1623)
DR_t^G	0.2125	(0.1406)	0.1671	(0.1293)	0.2271	(0.1642)	0.2489	(0.2094)
DR_t^D	0.2514	(0.1308)	0.1770**	(0.0758)	0.2692	(0.1425)	0.3953**	(0.1218)
Short-run								
ϕ	-0.1839*	(0.0964)	-0.1682**	(0.0521)	-0.1305*	(0.0585)	-0.1895**	(0.0638)
ΔLR_t^G	0.0287	(0.1495)	0.0198	(0.0344)	0.0290	(0.0955)	0.0808	(1.1563)
ΔDR_t^G	0.2332	(0.6697)	-0.9234	(0.9705)	0.0276	(0.6529)	-1.0005	(1.2560)
ΔDR_t^D	-1.8239	(1.9069)	-1.6434	(1.3371)	-1.1239	(1.4101)	-1.1191	(1.3987)
			MG Model					
Error correction (long-run)								
LR_t^G	0.3049**	(0.1086)	0.2433**	(0.0846)	0.3274**	(0.1178)	0.3454**	(0.1369)
DR_t^G	0.2390*	(0.1115)	0.1835**	(0.0425)	0.2638*	(0.1235)	0.2993	(0.1661)
DR_t^D	0.3323**	(0.0774)	0.2571**	(0.0551)	0.3558**	(0.0848)	0.4007**	(0.0992)
Short-run								
ϕ	-0.2854**	(0.0593)	-0.3036**	(0.0451)	-0.2518**	(0.0604)	-0.3157**	(0.0522)
ΔLR_t^G	-0.0535*	(0.0269)	-0.0777**	(0.0232)	-0.0733*	(0.0349)	-0.0529**	(0.0164)
ΔDR_t^G	-0.4198	(0.2834)	-0.7548	(0.4234)	-0.5985	(0.5610)	-0.8758	(0.6949)
ΔDR_t^D	-3.2528*	(1.5678)	-2.2480*	(1.1294)	-3.6420*	(1.7881)	-2.5596**	(1.1027)
			PMG Model					
Error correction (long-run)								
LR_t^G	0.3287**	(0.0959)	0.2834**	(0.0669)	0.3635**	(0.1031)	0.3834**	(0.1156)
DR_t^G	0.2791**	(0.0982)	0.2206**	(0.0404)	0.3017**	(0.1093)	0.3208**	(0.1200)
DR_t^D	0.3494**	(0.0695)	0.2689**	(0.0425)	0.3740**	(0.0704)	0.4203**	(0.0775)
Short-run								
ϕ	-0.2994**	(0.0501)	-0.3237**	(0.0404)	-0.2994**	(0.0385)	-0.3753**	(0.0480)
ΔLR_t^G	-0.0510*	(0.0252)	-0.0714**	(0.0230)	-0.0677*	(0.0325)	-0.0488**	(0.0156)
ΔDR_t^G	-0.3915	(0.1994)	-0.7878	(0.4101)	-0.4065	(0.6081)	-0.7932	(0.5825)
ΔDR_t^D	-3.0511*	(1.5492)	-1.9676**	(0.8180)	-3.4298*	(1.7332)	-2.7685**	(1.0032)

Hausman Tests			
MG (unrestricted) over *Dynamic FE* (restricted)	$\chi^2(2)=10.86$	(p=0.0044)	*MG* is preferred over *FE*
MG (unrestricted) over PMG (restricted)	$\chi^2(2)=6.21$	(p=0.0448)	*PMG* is preferred over *MG*

* Significant at the 5% level.
** Significant at the 1% level.

Table 4
Cross-border Yield Spread Decomposition with ARDL Error Correction Estimations,
Long maturities and credit rating A

	Canada		*Germany*		*France*		*UK*	
Dynamic FE Model								
Error correction (long-run)								
LR_t^G	0.3796*	(0.1793)	0.2169**	(0.0908)	0.3878*	(0.1827)	0.4154*	(0.2110)
DR_t^G	0.2550	(0.1599)	0.1894	(0.1009)	0.2029	(0.1684)	0.3038	(0.1889)
DR_t^D	0.2778**	(0.1047)	0.1964**	(0.0719)	0.2957**	(0.1068)	0.3343**	(0.1201)
Short-run								
ϕ	-0.1695**	(0.0828)	-0.1553**	(0.0517)	-0.1284**	(0.0523)	-0.1774**	(0.0567)
ΔLR_t^G	-0.0392	(0.1115)	0.0198	(0.0344)	0.0290	(0.0955)	0.0808	(1.1563)
ΔDR_t^G	0.2567	(0.5883)	-0.9234	(0.9705)	0.0276	(0.6529)	-1.0005	(1.2560)
ΔDR_t^D	-2.2376	(1.3506)	-1.6434	(1.3371)	-1.1239	(1.4101)	-1.1191	(1.3987)
MG Model								
Error correction (long-run)								
LR_t^G	0.3927**	(0.1675)	0.2253**	(0.0704)	0.3968**	(0.1774)	0.4292**	(0.1998)
DR_t^G	0.2835**	(0.1363)	0.2189**	(0.0921)	0.3086**	(0.1410)	0.3168*	(0.1544)
DR_t^D	0.3769**	(0.0902)	0.2123**	(0.0570)	0.3629**	(0.0928)	0.3705**	(0.1092)
Short-run								
ϕ	-0.2620**	(0.0565)	-0.2744**	(0.0409)	-0.2485**	(0.0546)	-0.3011*	(0.0473)
ΔLR_t^G	-0.0621**	(0.0249)	-0.0824**	(0.0222)	-0.0841**	(0.0286)	-0.0793**	(0.0147)
ΔDR_t^G	-0.4776	(0.2613)	-0.8135	(0.4202)	-0.6502	(0.4568)	-0.8086	(0.5097)
ΔDR_t^D	-3.8814**	(1.4485)	-2.5371**	(1.0076)	-3.9749**	(1.5135)	-2.7419**	(1.0203)
PMG Model								
Error correction (long-run)								
LR_t^G	0.4214**	(0.1559)	0.3107**	(0.0592)	0.4235**	(0.1610)	0.4454**	(0.1635)
DR_t^G	0.3033*	(0.1243)	0.2293**	(0.0840)	0.3252**	(0.1307)	0.3438**	(0.1349)
DR_t^D	0.4120**	(0.0700)	0.2976**	(0.0463)	0.4198**	(0.0729)	0.4335**	(0.0917)
Short-run								
ϕ	-0.2828**	(0.0533)	-0.3110**	(0.0387)	-0.2754**	(0.0332)	-0.3555**	(0.0426)
ΔLR_t^G	-0.0767**	(0.0199)	-0.0887**	(0.0230)	-0.0885**	(0.0251)	-0.0861**	(0.0127)
ΔDR_t^G	-0.4898*	(0.2207)	-0.8381*	(0.4006)	-0.7047	(0.4250)	-0.8889*	(0.4843)
ΔDR_t^D	-3.9624**	(1.2321)	-2.7885**	(0.7354)	-4.0095**	(1.4039)	-3.2473**	(0.0844)

Hausman Tests

MG (unrestricted) over *Dynamic FE* (restricted)	$\chi^2(2)=11.09$	(p=0.0039)	*MG* is preferred over *FE*
MG (unrestricted) over PMG (restricted)	$\chi^2(2)=6.44$	(p=0.0399)	*PMG* is preferred over *MG*

* Significant at the 5% level.
** Significant at the 1% level.

Table 5
Cross-border Yield Spread Decomposition with ARDL Error Correction Estimations,
Long maturities and credit rating BBB

	Canada		*Germany*		*France*		*UK*	
Dynamic FE Model								
Error correction (long-run)								
LR_t^G	0.3610*	(0.1761)	0.2743*	(0.0915)	0.3702*	(0.1810)	0.4132**	(0.1234)
DR_t^G	0.3134	(0.1847)	0.2667	(0.1396)	0.3273	(0.1997)	0.3218	(0.2021)
DR_t^D	0.3887*	(0.1520)	0.2929**	(0.0787)	0.3914*	(0.1518)	0.4133**	(0.1349)
Short-run								
ϕ	-0.2071**	(0.0915)	-0.1920**	(0.0709)	-0.1556**	(0.0863)	-0.1895**	(0.0661)
ΔLR_t^G	-0.0411	(0.1346)	0.0048	(0.0344)	0.0076	(0.0955)	-0.0639	(0.0624)
ΔDR_t^G	0.1024	(0.6004)	-1.1453	(1.2232)	-1.3897	(0.8055)	-1.0005	(1.4981)
ΔDR_t^D	-2.4435	(1.3883)	-1.8896	(1.5904)	-1.4465	(1.6274)	-1.1191	(1.5734)
MG Model								
Error correction (long-run)								
LR_t^G	0.4032**	(0.1158)	0.3099**	(0.0827)	0.4209**	(0.1025)	0.4665**	(0.0842)
DR_t^G	0.3682**	(0.1504)	0.3160**	(0.1053)	0.3741**	(0.1621)	0.3817**	(0.1698)
DR_t^D	0.4306**	(0.0883)	0.3215**	(0.0692)	0.4322**	(0.1033)	0.4464**	(0.0756)
Short-run								
ϕ	-0.2881**	(0.0849)	-0.2912**	(0.0675)	-0.2769**	(0.0721)	-0.3305*	(0.0539)
ΔLR_t^G	-0.0731**	(0.0277)	-0.0893**	(0.0319)	-0.0841**	(0.0286)	-0.0869**	(0.0201)
ΔDR_t^G	-0.5104	(0.2900)	-0.9494	(0.4445)	-0.6502	(0.4568)	-0.8818	(0.7360)
ΔDR_t^D	-4.1035**	(1.5885)	-2.7344**	(1.1769)	-3.9749**	(1.5135)	-2.8323**	(1.1783)
PMG Model								
Error correction (long-run)								
LR_t^G	0.4466**	(0.0914)	0.3576**	(0.0710)	0.4663**	(0.0933)	0.4960**	(0.0728)
DR_t^G	0.3830*	(0.1102)	0.3421**	(0.0923)	0.4102**	(0.1267)	0.4273**	(0.1413)
DR_t^D	0.4653**	(0.0668)	0.3693**	(0.0505)	0.4723**	(0.0914)	0.4857**	(0.0680)
Short-run								
ϕ	-0.3008**	(0.0801)	-0.3354**	(0.0502)	-0.2995**	(0.0665)	-0.3764**	(0.0498)
ΔLR_t^G	-0.0840**	(0.0229)	-0.0915**	(0.0289)	-0.0885**	(0.0251)	-0.0928**	(0.0175)
ΔDR_t^G	-0.5457*	(0.2621)	-0.9648*	(0.4213)	-0.7047	(0.4250)	-0.9190*	(0.5679)
ΔDR_t^D	-4.3478**	(1.3796)	-3.1308**	(0.8405)	-4.0095**	(1.4039)	-3.1415**	(1.1062)

Hausman Tests			
MG (unrestricted) over *Dynamic FE* (restricted)	$\chi^2(2)$=9.15	(p=0.0103)	*MG* is preferred over *FE*
MG (unrestricted) over PMG (restricted)	$\chi^2(2)$=5.79	(*p*=0.0553)	*PMG* is preferred over *MG*

* Significant at the 5% level.
** Significant at the 1% level.

To demonstrate the crucial implication of potential diversification benefit from our PMG ARDL estimation method, we take $\boldsymbol{\mu}_j$, the estimated fixed effect or proxy for idiosyncratic component in (4), and compare it against the following model,

$$\Delta \boldsymbol{SP_{it}} = \eta_i + \gamma_{1i}\Delta \boldsymbol{DR_t^D} + \gamma_{1i}\Delta \boldsymbol{RP_t} + \gamma_{3i}\Delta \boldsymbol{TS_t} + \nu_{jt}, \quad i=1,2,\ldots,N, \tag{5}$$

for specific country. In (5), $\boldsymbol{RP_t}$ is a short-term interest rate measure and we use th

$\Delta \boldsymbol{SP_{it}} = \eta_i + \gamma_{1i}\Delta \boldsymbol{DR_t^D} + \gamma_{1i}\Delta \boldsymbol{RP_t} + \gamma_{3i}\Delta \boldsymbol{TS_t} + \nu_{jt}$ e repo rate for this model. The term $\boldsymbol{TS_t}$ is term premium measure and the yield difference between 10- and 1-year government bonds is used. η_j would be the alternative idiosyncratic component and ν_{jt} is the disturbance term. (5) emulates the commonly adopted change-based *domestic* yield spread decomposition model, like the one in Duffee (1998), as a benchmark for our performance comparison.

Table 6
VaR Analysis of Corporate Bond Portfolios,
Cross-border PMG ARDL approach versus traditional domestic approach

	Canada		*Germany*		*France*		*UK*	
	Cross-*Border*	*Domestic*	Cross-*Border*	*Domestic*	Cross-*Border*	*Domestic*	Cross-*Border*	*Domestic*
Short Maturities, A								
Portfolio 1% VaR[a]	-119.35	-139.97	-103.29	-111.94	-128.68	-146.89	-132.68	-145.80
S.D. of individual VaR's[a]	30.83	45.11	29.45	43.26	41.71	59.64	32.63	47.36
Paired *t*-tests	$t_{\text{d.f.:19}}$=-1.83	p=0.0129	$t_{\text{d.f.:78}}$=-2.14	p=0.0176	$t_{\text{d.f.:44}}$=-2.43[b]	p=0.0096	$t_{\text{d.f.:49}}$=-2.34	p=0.0116
R^2	0.2664	0.2235	0.2110	0.1938	0.2849	0.2375	0.3001	0.2423
Short Maturities, BBB								
Portfolio 1% VaR[a]	-131.21	-154.14	-109.38	-119.15	-134.77	-153.32	-134.64	-148.45
S.D. of individual VaR's[a]	35.27	50.51	32.91	48.55	43.85	61.41	34.69	50.08
Paired *t*-tests	$t_{\text{d.f.:21}}$=-2.50[b]	p=0.0104	$t_{\text{d.f.:89}}$=-2.31	p=0.0116	$t_{\text{d.f.:52}}$=-2.59[b]	p=0.0062	$t_{\text{d.f.:51}}$=-2.37	p=0.0107
R^2	0.2216	0.1711	0.1979	0.1653	0.2442	0.1856	0.2556	0.1889
Long Maturities, A								
Portfolio 1% VaR[a]	-135.46	-163.38	-113.81	-125.74	-136.22	-156.89	-136.54	-151.07
S.D. of individual VaR's[a]	34.09	50.26	33.53	49.59	44.63	63.19	40.81	55.11
Paired *t*-tests	$t_{\text{d.f.:12}}$=-2.34	p=0.0187	$t_{\text{d.f.:65}}$=-2.36	p=0.0106	$t_{\text{d.f.:52}}$=-2.82[b]	p=0.0034	$t_{\text{d.f.:59}}$=-2.37[b]	p=0.0104
R^2	0.2983	0.2644	0.2525	0.2441	0.3040	0.2617	0.3139	0.2665
Long Maturities, BBB								
Portfolio 1% VaR[a]	-138.06	-170.86	-118.42	-132.34	-140.13	-164.18	-139.96	-157.48
S.D. of individual VaR's[a]	30.83	45.11	35.31	53.76	46.61	66.24	43.67	58.02
Paired *t*-tests	$t_{\text{d.f.:13}}$=-2.69[b]	p=0.0090	$t_{\text{d.f.:68}}$=-2.63[b]	p=0.0053	$t_{\text{d.f.:53}}$=-3.17[b]	p=0.0013	$t_{\text{d.f.:63}}$=-2.79	p=0.0035
R^2	0.2723	0.2345	0.2406	0.2227	0.2889	0.2492	0.2945	0.2417

We calculate $\boldsymbol{\mu}_j$ according to (2) based on parameter estimates from Table 2 through 5 for all firms in each country, as the proxies for idiosyncratic component of our corporate yield decomposition. Then we construct a traditional domestic approach counterpart in an ordinary panel OLS model, for each country, like,

$$\Delta \boldsymbol{SP_{it}} = \eta_i + \gamma_{1i}\Delta \boldsymbol{DR_t^D} + \gamma_{1i}\Delta \boldsymbol{RP_t} + \gamma_{3i}\Delta \boldsymbol{TS_t} + \nu_{jt}, \; i=1,2,\ldots,N,$$

where η_j is corresponding idiosyncratic component from the alternative model. To compute VaR estimates, we rank $\boldsymbol{\mu}_j$ and η_j derived from the two models for all the firms in a given country. The bottom values of μ and η for each firm are identified as our approximated historically simulated 1% VaR (quantile) estimates for the two models respectively. For each of the four countries, equally weighted portfolios are constructed separately for short and long maturities, as well as for ratings A and BBB. Each country's portfolio VaR is the average of all the individual firm VaR's.

a Numbers are in basis points.

b Significant at the 1% level.

In each of the four countries studied, historically simulated 1% one-tailed Value-at-Risk (VaR) estimates from ranked individual PMG-produced $\boldsymbol{\mu}_j$ are identified for every single issue within a given maturity-rating category in the country. As there are only at most 66 observations for any issue, the smallest $\boldsymbol{\mu}_j$ is selected as a proxy for the VaR estimate. A similar procedure is carried out on ranked η_j, and VaR estimates are obtained accordingly. For each of the four countries, equally weighted portfolios are constructed separately for short and long maturities, as well as for ratings A and BBB. The average of all individual firm's VaR's in each country would be adopted, in the spirit of Venkatesh (2003), as portfolio VaR of that country. Paired *t*-test results are given in Table 6 for each country and each maturity-rating category respectively.

Overall, the down side VaR estimates for the PMG model average at -132.93 b.p., while the average for the alternative model is -155.73 b.p.. The results of paired *t* tests are barely significant at the 1% level, except for France, within the category of short maturity and rating A. Lower and more significant *p* values appear as we move to longer maturity and lower credit rating, across all countries. The VaR analysis of bond portfolios in Table 6 indicates that the benefit of diversifying idiosyncratic risks produced by our PMG ARDL procedure is substantially greater than an alternatively constructed change-based *domestic* panel OLS procedure. Furthermore, combining all the VaR estimates across all four countries for a given maturity-rating category yields *t*-statistics more than twice as large, suggesting potential existence of further cross-border diversification benefits very much needed by managers of international bond portfolios.

The R-squared values given in Table 6 also indicate the cross-border approach produces lower residual variations than the domestic model. Residual errors in the cross-border model on average account for 10% to 15% more yield spread variations than an alternative domestic model. The differences are more prominent in a lower credit rating or longer maturity. Countries with higher bond risks, such as France and UK, are also where a cross-border model performs much better.

5. Robustness Discussions

We have adopted global liquidity index to account for the influence of world capital market liquidity on yield spreads of corporate bonds in our data set. The alternative measure could be the Capital Markets Liquidity Index (CPMKTL), which is the only benchmark of the component of the

U.S. capital markets and a modified market value weighted index. The index includes about 98% of the U.S. long term investment grade liquidity markets of investment grade fixed income securities issued by U.S. government and agencies, as well as U.S. corporations. Municipal securities, Asset-Backed Securities, Collateralized Debt Obligations, Mortgage-Backed Securities and floating rate securities are however excluded. Index values between 2006 and 2013 are given in Figure 2.

Figure 2 Monthly Levels of Capital Market Liquidity Index between 2006 and 2013

Index values are compiled by Dorchester Capital Management, LLC and include 1,443 securities. The index is rebalanced monthly. 105 daily, weekly, monthly and quarterly statistics are combined to determine the current allocation of assets in the U.S. investment grade capital markets. The inputs to this weighting process are taken from U.S. Federal Deposit Insurance Corporation statistics, U.S. Federal Reserve Board statistical reports, and derived from Dorchester's own extensive database.

This alternative index reflects the liquidity situation of the most important capital market of the world. It can also be seen that this index is much less volatile than the Global Liquidity Index. We substitute the Capital Market Liquidity Index in place of the Global Liquidity Index in (4). Compared with coefficients estimated for the latter in Tables 2 to 5, the alternative global liquidity proxy produces coefficient estimates with less significance. The reduction of significance is particularly prominent in a lower credit rating or longer maturity. The advantage of the PMG method over the MG or the FE methods remains. If we also substitute GLI for CPMKTL in the VaR analysis in Table 6, we find similar results, where the paired *t*-test results are less significant for lower credit rating or longer maturity. This robustness test indicates that the GLI used for our study is more relevant as a global liquidity measure in explaining the yield spreads of the four countries.

On the global default risk proxy, we look into the FitchSolutions' Probability of Default Index for North America as well as Europe as alternatives. It is estimated to provide a view of a firm's credit condition given its current equity price and available financial information. Fitch's model incorporates an option-based barrier model with hybrid adjustment of firms' financial and market information. Our barrier-option based PD provides a forward-looking structural default probability. Changes in this structural default probability provide leading information about changes in the credit quality of a debt issuer, and thus help to understand impending rating change and default. The model makes use of a small, but very carefully selected subset of accounting and market variables. The Fitch model covers approximately 27,000 entities globally, with 13,000 in the US and Canada, plus another 14,000 firms from more than 70 other countries. For all firms, the model provides daily output of estimated default probability (PD) for both one-year and five-year horizons.

Figure 3 FitchSolutions Probability of Default Index, North America, 2001-2008

The index reveals a point-in-time estimate of market and/or sector-level credit quality. The ranking of these regions' indices implies their relative risk levels. Included for the North America region are nine industries are selected and both 1-year and 5-year PD indices are calculated. These industries are defined according to Industry Classification Benchmark codes offered by Dow Jones Indexes and FTSE and include Basic Materials, Consumer Goods, Consumer Services, Health Care, Industrials, Oil and Gas, Technology, Telecommunications and Utilities. The levels of the index reflects the likelihood of a default event occurring in a specified horizon (1-year or 5-year) provided that one randomly picked a debt from the applicable universe. For a given universe, FitchSolutions' PD index is computed as the average of individual firms' PDs weighted by their outstanding debt. It is a weighted sum of conditional probabilities of default with weights being the probability of that condition being satisfied, which, by Bayes' rule in probability theory, yields an unconditional probability of default once a universe is fixed. The PD index is unconditional in the sense that the probability is not firm specific, but it is still conditioning on the available information up to date. Recall that each individual PD is estimated on market information and financial performance metrics. By simply pooling individual PDs together, the PD index naturally inherits this information and ensures itself a well informed estimator of sector and/or segment credit risk. However, information enters the index in such a way that no one firm's PD movement can dominate the index behavior and the effect of big increases in one firm can be offset by reverse movements of others. Therefore, our PD index indeed reflects the systematic credit risk rather than firm specific or idiosyncratic risk.

The FitchSolutions PD basically measures regional default risks. Adopting these measures in the spirit of Diaz and Gemmill (2006), we first replace US CDS with FitchSolutions PD North America in (4) while leaving other terms unchanged. This alternative produces results less significant than the US CDS used originally, possibly because the latter is more familiar to market participants. If, however, we apply the Europen PD instead, the performance becomes better, especially in the lower credit rating group.

Next we examine the effect of replacing the country-specific default risk factor by regional volatility index in Europe. Instead of using the ratio between implied country equity volatility and VIS, we adopt the ratio between VSTOXX, the implied volatility of EURO STOXX 50 options, and VIX. The values of VSTOXX in the last five years are given in Figure 4.

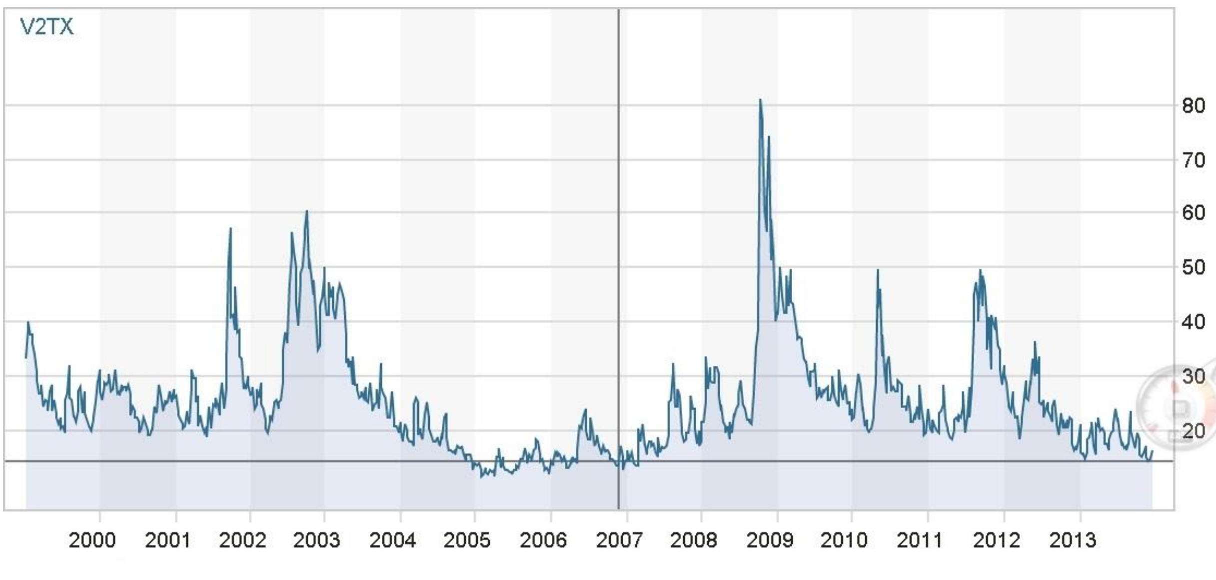

Figure 4 FitchSolutions Probability of Default Index, North America, 2001-2008
The index reveals a point-in-time estimate of market and/or sector-level credit quality. The ranking of these regions' indices implies their relative risk levels. Included for the North America region are nine industries are selected and both 1-year and 5-year PD indices are calculated. These industries are defined according to Industry Classification

The VSTOXX index, being a European market sentiment indicator, can serve as a regional credit risk factor for European countries, as how regional market volatility in South America affects distance-to-default of individual countries in Diaz and Gemmill (2006). Applying the alternative volatility ratio in (4) yields estimates with less significance compared with volatility ratios based on individual country volatilities. In addition, we also analyze another model which include in (4) both this alternative ratio and the original country-specific ratios. Coefficient estimates for both ratios exhibit weaker significances, possibly due to multicollinearity between the two ratios.

6. Conclusion

This study recalibrates corporate bond idiosyncratic risks in the context of international portfolio diversification. Based on the ideas of Venkatesh (2003), Churm and Panigirtzoglou (2007), Xie, et al. (2008), Dastidar and Phelps (2011), Ang and Longstaff (2011) and Alessi and Detken (2011), we extend the model of Sun, et al. (2007) to a cross-border context. The empirical framework of Pesaran, et al. (1999) is used to process the cross-border heterogeneous panels. By introducing a statistically powerful risk decomposition scheme, we show in this study that diversification is improved as both global and domestic risk benchmarks are utilized. Not only fixed income portfolio management, but also the pricing of traditional and innovative financial instruments can benefit from the scheme proposed in this very study.

In addition to domestic default risk factor proxied by relative equity market volatility, we also include a global liquidity and default risk benchmarks. The ARDL panel time series model of Pesaran, et al. (1999), which emphasizes long-run relations among economic variables, helps us building a long-run stationary yield spread decomposition scheme in our study. We could use, in place of country-specific volatility measures, alternatively the European market relative volatility as a regional default risk factor. The US sovereign CDS measure can also be replaced by international CDS index. However, the inclusion of a global risk component provides more abundant and explicit information, which the traditional domestic model lacks, for pricing and risk management practices of fixed income portfolios. The global and domestic risk benchmarks are easily measurable and observable. The idiosyncratic risk component is estimated as a fixed effect in a data panel along with all the parameter estimates, rather than being introduced separately from a exogenous generating process. Our linear model may contain other econometric imperfections, but our estimates can be applied promptly and easily by practitioners.

The idiosyncratic component of yield spread has been estimated from three different models. Hauseman tests show that the PMG ARDL method is the best in utilizing available information.

The VaR analysis verifies that the idiosyncratic risks generated under this procedure have substantially better diversification implication than an alternatively constructed change-based domestic panel OLS procedure. So the results of our study not only extend a purely domestic fixed income model to a cross-border one, but they also help enhancing the diversification capability of international fixed income portfolios.

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Appendix

Assume there is a globally default-free zero-coupon bond maturing at T has at time t a value of

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

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.

A defaultable bond incorporates in addition a default intensity spread λ_s which is from a Poisson process with time varying parameter, as well as a liquid spread γ_s to compensate for the illiquidity compared with default-free bonds[5]. The value of this bond would be

$$\boldsymbol{B}(\boldsymbol{t},\boldsymbol{T}) = \boldsymbol{E}_Q\left[\exp\left(-\int_t^T [\phi_1 \boldsymbol{r}_s + \phi_2\lambda_s + \phi_3\gamma_s]\boldsymbol{ds}\right)\right], \tag{A.4}$$

at time t. The three coefficients, ϕ_1, ϕ_2 and ϕ_3, are all positive and modeled in to reflect different sensitivity to the short rate, possible larger liquidity and default spreads. ϕ_1 could be considered as reflecting the agency effect argued by Leland and Toft (1996), should be greater than 1. So $\boldsymbol{B}(\boldsymbol{t},\boldsymbol{T})$ or its yield is expected to be more responsive, than $D(t,T)$ or its yield, to the short rate. Similarly, ϕ_2 and ϕ_3 should both be greater than 1 as well, reflecting the fact that more risky bonds are more sensitive to changes in default intensity and market liquidity.

The dynamics of the three endogenous variables are characterized by a general affine model with four state variables which are Markovian under the equivalent martingale measure Q and square-root diffusions. The short rate is assumed to be

[5] 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).

driven by two state variables[6] to represent common shocks to the economy,

$$r_s = \delta_0 + X_1 + X_2, \tag{A.3}$$

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

$$\gamma_s = \delta_1 + X_3, \tag{A.4}$$

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

$$\lambda_s = \delta_2 + \tau r_s + X_4, \tag{A.5}$$

where δ_2 and τ are both constants and the latter stands for the sensitivity of default to the short rate. Structural models would predict τ to be negative. The second term in (A.5) can be considered as a globally applicable default risk, while X_4 reflects default risks applicable only to a certain country.

The state variable vector $\boldsymbol{X} = (X_1, X_2, X_3, X_4)$, with general Gaussian processes under an affine term-structure model, should be characterized by

$$dX = -\beta X dt + \Sigma dB^Q, \tag{A.6}$$

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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[6] 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 the second one to the instantaneous variance.

$$dX = \kappa(\xi - X)dt + \Sigma dB^{P}, \tag{A.7}$$

where κ is also a diagonal matrix and ξ is a vector of long-term value of the state variables. The solutions to (A.1) through (A.2) can be solved under the risk-neutral dynamics (A.6). Generalizing the characterizations of (A) to bonds with various credit ratings, we could consider X_1 and X_2 as globally common risks as their effects are proportional across all bonds.

The yield difference between the ***B***(t,T) and riskless bond can be derived on the physical measure P as

$$\phi_1 r_t + \phi_2 \varpi r_t + \phi_3 \gamma_s + \eta^a(t)(\beta - \kappa)X_t + \eta^b(t)\kappa\xi, \tag{A.8}$$

where $\eta^a(t)$ and $\eta^b(t)$ are functions of parameters. The first term in (A.8) 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. The last term is related to the risk-adjusted long-run level of bond yield spread.

The yield spread of the corporate bonds containing idiosyncratic risks should exhibit in the long run stronger responses to X_1 and X_2 contained in the interest rate 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.