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Term Structure of Credit Spreads and the Macroeconomy in Japan: A Global Factor Approach

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Abstract

The purpose of this study is to extract the global factor from individual credit spreads of major Japanese corporate bonds using state-space modeling and examine the predictive contest of the credit spread for the real economy. The results indicate estimated global factors are important drivers of individual credit spreads. My results indicate that credit spreads global factors have a substantial predictive power for future Japanese economic activity. This study makes a contribution to forecasting the future macro variables.

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Keywords: Term Structure Model; Credit Spreads; Global Factor; State-Space Model; Forecasting Macroeconomic Variables

1 Introduction

Exploring the relationship between credit spreads and future real activity can be motivated by the "financial accelerator" theory developed by Bernanke and Gertler (1989) and Bernanke, Gertler,and Gilchrist (1996, 1999). A key concept in this framework is the external finance premium," the difference between the cost of external funds and the opportunity cost of internal funds due to financial market frictions. A rise in this premium makes outside borrowing more costly, reduces the borrower's spending and production, and consequently restricts aggregate economic activity. The external finance premium can fluctuate for many reasons. Changes in the premium could reflect real productivity

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shocks, monetary policy shocks, or problems in the financial sector affecting borrowers' balance sheets. For forecasting future output, however, it is immaterial where a shock to the external finance premium originates. While the external finance premium is not directly observable, credit spreads are a useful proxy.

Empirical evidence on the performance of credit spreads as predictors of real activity on the other hand is very scarce. The few existing studies consistently find that credit spreads are useful predictors of real activity. At the same time, it is an open debate which particular credit spread is the best proxy for the external finance premium. Gertler and Lown (1999) and Mody and Taylor (2004) argue that the right measure is a long-term high yield spread and they show that it outperforms other leading indicators| including the term spread since the data has become available in the mid-1980s.Chan-Lau and Ivaschenko (2001, 2002) on the other hand argue for the use of investment grade credit spreads and they also find some predictive power to support their allegation. Gilchrist, Yankov, and Zakrajsek (2009) construct expected default risk based portfolios and conclude that credit spreads on senior unsecured corporate debt have substantial forecasting power for future economic activity. Muller (2009) explores the information content of the whole term structure and across different rating classes. As far as I know there is no existing studies concerning the credit spread curve and the predictive power of real activity in Japan.

Most authors use the aggregate credit spread by rating categories in US corporate bond market. However it is difficult to analyze the corporate bond spread by using the aggregated credit spread in Japan although JSDA (Japan Securities Dealers Association) actually publishes the average value of aggregate corporate spreads on a daily basis. The problems lie in the fact that the size of Japanese corporate bond market is so small that the average value of the yield depends mainly on the issuers with the large amount of the issues such as electric power. To overcome the difficulty I apply Diebold,Li and Yue (2008) (henceforth DLY) method and extract the global factors in the term structure of credit spreads in the Japanese corporate bond yield spreads. Krishnan et al (2010) apply Nelson-Siegel model for credit spread of US corporations on individual firm basis and Kobayashi (2013) analyses Japanese corporate bonds. One of the limitations of these studies is to show goodness fit of the model by aggregating estimation results of individual firm of samples. The purpose of the paper is to extract the global factor of the credit spread from the term structure of the individual Japanese corporate bond spread date and examine the predictive content of the economic activity.

The remainder of this paper is structured as follows. In section 2 data and global yield curve model are described. In section 3 estimation methodology and estimation results are demonstrated. Section 4 presents forecasting exercise. Section 5 concludes with implications of my results for future research.

2 Data and global yield curve model

2.1 Estimation for data

Government bond yield

End-of-month price quotes for Japanese Government bonds from April 1997 through December 2011 were used, taken from Japan Bond Trading Co., Ltd. from maturity 1 year and 20 year. Because not every month has the same maturities available, I linearly interpolate nearby maturities to pool into fixed maturities of 3, 6, 9, 12, 24, 36, 48, 60, 72, 84, 96, 108, and 120 months. Government bond yield curve data are constructed using the Fisher, Nychka and Zervos (1995) approach.

Corporate bond yield

OTC Bond Transactions in the Japan Securities Dealers Association are used. Our sample comprises industrial, banking, and services sector firms in the Japan Securities Dealers Association at any time during the period Apr1997-Dec2011.It is necessary to have price data covering short to long time to maturity of corporate bond for a lot of companies at each time period. The criteria for selecting corporate bonds are constructed in the following manner.

1. Observation period: the firms whose time series has over 6 years during the period Apr1997-Dec2011 are selected. Data period starts at April 1997 in that the Japan Securities Dealers Association publishes data since April 1997.
2. Time to maturity: corporate bonds of different maturities that have at least 7 years for each month to estimate the level, slope and curvature factors of credit spreads are required.
3. Number of prices: a minimum of 5 prices of bonds of different maturities is required.
4. Industry: Electric power sector is eliminated in order to exclude spread widening after the Great East Japan

Earthquake.

Corporate bond spread is estimated by B spline model in this chapter. Corporate bond spread is constructed in a way that corporate bond yield is subtracted from the same maturity of government bond yield. Based on the above rule the final sample comprises 26 firms which are composed of 14 manufacturing firms and 12 non-manufacturing firms as described in Table (1). Figure (1) shows the time series of term structure of credit spreads of 4 four firms among selected 26 names. It is confirmed that these credit spread dynamics are driven by idiosyncratic factors while global factor plays an important role to determine the shape of the term structure of credit spreads.

Table 1. Breakdown of the selected firms

#	Name	Industry	#	Name	Industry
No1	TaiseiCorp	Construction	No14	NissanMotorCo	Assembling
No2	SumitomoChemicalCo	Primary materials	No15	ItochuCorp	Wholesale
No3	MitsubishiChemicalCorp	Primary materials	No16	MitsuiCorp	Wholesale
No4	JXHoldingsInc	Primary materials	No17	OrixCorp	Consumer credit
No5	NipponSteelCorp	Primary materials	No18	MitsubishiEstateCo	Real Estate
No6	SumitomoMetalIndustries	Primary materials	No19	TobuRailwayCo	Transportation
No7	KobeSteel	Primary materials	No20	TokyuCorp	Transportation
No8	MitsubishiMaterialsCorp	Primary materials	No21	TokyoMetroCo	Transportation
No9	SumitomoElectricIndustries	Primary materials	No22	KintetsuCorp	Transportation
No10	ToshibaCorp	Assembling	No23	TokyoGasCo	Utility
No11	MitsubishiElectricCorp	Assembling	No24	TohoGasCo	Utility
No12	Fujitsu	Assembling	No25	NipponTelegraphAndTelephoneCorp	Telecomminications
No13	KawasakiHeavyIndustries	Assembling	No26	KDDICorp	Telecomminications

(Note) : Based on the selection rule the final sample comprises 26 firms which composed of 14 manufacturing firms and 12 non-manufacturing firms.

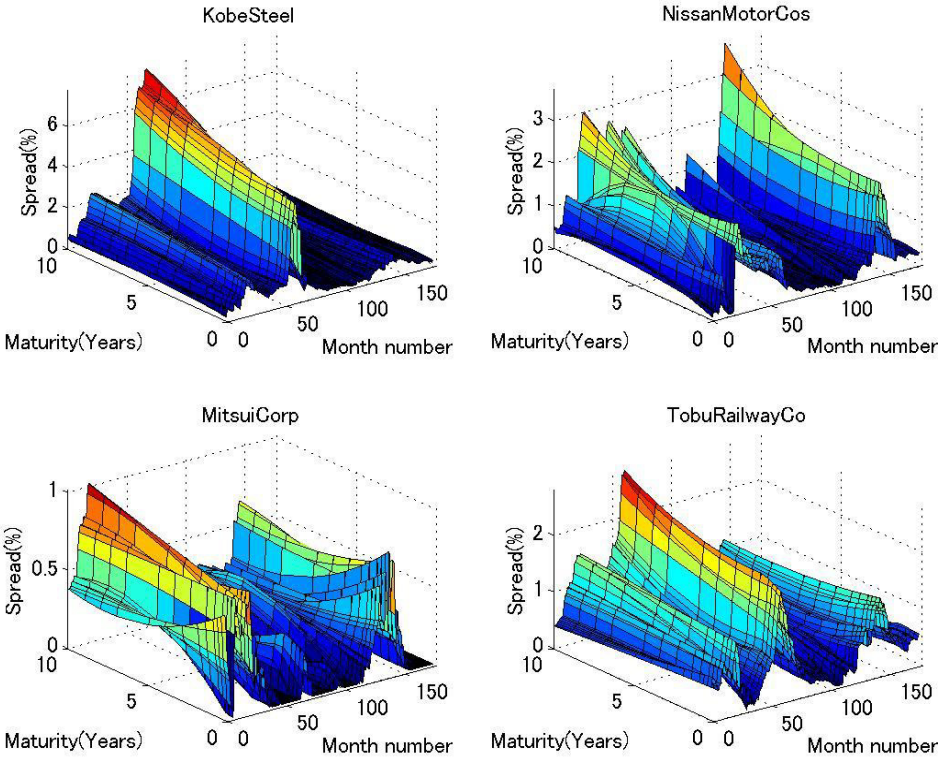

Fig.1. Credit spreads across companies and time

(Note) : The time series of term structure of credit spreads of 4 four firms among selected 26 names .All credit spread data are monthly, 1997.04 through 2011.12.

2.2 Single-Name credit spread

The popular Nelson-Siegel (1987) yield curve is routinely fit to cross sections of intra-country bond yields, and Diebold and Li (2006) proposed a dynamic version. Krisnan, Richen &Thomson (2010) and Kobayashi (2012) apply Diebold and Li model to credit spread. The original Nelson-Siegel model fits the yield curve with the simple functional form and I apply it to the credit spread.

$$cs_i(\tau) = l_i + s_i\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + c_i\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) + v_i(\tau), \tag{1}$$

where $cs_i(\tau)$ is the zero-coupon yield spread of firm i with τ months to maturity, and $l_{i,t}$, $s_{i,t}$, $c_{i,t}$ and λ are parameters $v_i(\tau)$ is a disturbance with standard deviation $\sigma_i(\tau)$.Diebold and Li (2006) modify the model by allowing the parameters to varying over time.

$$cs_{i,t}(\tau) = l_{i,t} + s_{i,t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + c_{i,t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) + v_{i,t}(\tau) \tag{2}$$

$l_{i,t}$, $s_{i,t}$, $c_{i,t}$ are interpreted as latent factor of the term structure of credit spread. They are level, slope and curvature factors respectively.

2.3 Multi-companies

Now, this section extends the basic model to a multi-company environment, following DLY. DLY (2008) extend Diebold and Li (2006) to a global context, modelling a potentially large set of country yield curves in a framework that allows for both global and country-specific factors. In an empirical analysis of term structures of government bond yields for the Germany, Japan, the UK and the US, they find that global yield factors do indeed exist and are economically important, generally explaining significant fractions of country yield curve dynamics, with interesting differences across countries. The method is applied to credit spreads in this study. From the single-company model, one may adapt it to an *N*-company approach, coupled with a similar space-state framework. The problem now is that the global credit spreads $CS_t(\tau)$ are not observed as well as the factors, that is:

$$CS_t(\tau) = L_t + S_t\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + V_t(\tau), \tag{3}$$

where $CS_t(\tau)$ is the theoretical global credit spread, $L_t =$ the global level, read, $S_t =$ the global slope.

The percent explained of global factors are demonstrated by principal component analysis in Figure (2).PCA shows over 60 percent variation of the level and 60 percent variation of the slope are driven by the first principal components.

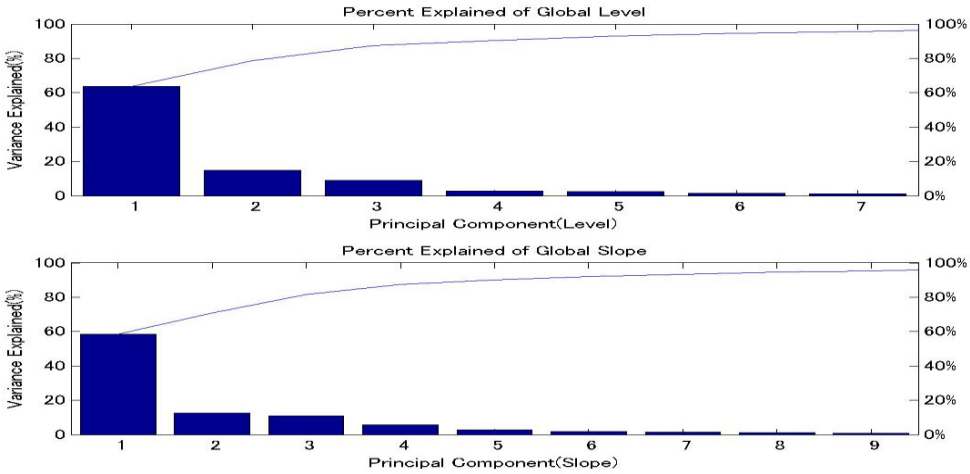

Fig. 2. Principal Component Analysis
(Note) : Percent explained of global factors are demonstrated by principal component analysis

2.4 State-Space Representation

These latent global factors are common to every company. It is assumed that the global credit spread factors follow a first-order AR(1) model and state equations measurement equation are described as follows:

$$\begin{pmatrix} L_t \\ S_t \end{pmatrix} = \begin{pmatrix} \Phi_{11} & \Phi_{21} \\ \Phi_{12} & \Phi_{22} \end{pmatrix} \begin{pmatrix} L_{t-1} \\ S_{t-1} \end{pmatrix} + \begin{pmatrix} U_t^l \\ U_t^s \end{pmatrix}, \tag{4}$$

where U_t^n are disturbances such that $E\left(U_t^n U_t^{n'}\right) = (\sigma^n)^2$ if $t = t'$ and $n = n'$ and 0 otherwise,$n = l, s$ .Then the model decomposes the company-specific, level, $l_{i,t}$ (slope, $s_{i,t}$) into a global level, L_t (slope, S_t)and some idiosyncratic factor, $\varepsilon_{i,t}^n$ whose mean is null:

$$l_{i,t} = \alpha_i^l + \beta_i^l L_t + \varepsilon_{i,t}^l \tag{5}$$
$$s_{i,t} = \alpha_i^s + \beta_i^s L_t + \varepsilon_{i,t}^s, \tag{6}$$

where $\{\alpha_i^l, \alpha_i^s\}$ are constant terms, $\{\beta_i^l, \beta_i^s\}$ are loadings on global factors, and $\{\varepsilon_{it}^l, \varepsilon_{it}^s\}$ are firm idiosyncratic factors, i=1,…N.

Becase constant terms are included in (5) and (6), It is postulated that the firm idiosyncratic factors have zero mean. Moreover, because of the magnitudes of global factors and factor loadings, I consider that the innovations to global factors and factor loadings have unit standard deviation, that is,$\sigma^n = 1, n = l, s$.

$$\begin{pmatrix} \epsilon_{i,t}^l \\ \epsilon_{i,t}^s \end{pmatrix} = \begin{pmatrix} \phi_{i,11} & \phi_{i,21} \\ \phi_{i,12} & \phi_{i,22} \end{pmatrix} \begin{pmatrix} \epsilon_{i,t-1}^l \\ \epsilon_{i,t-1}^s \end{pmatrix} + \begin{pmatrix} \mu_{i,t}^l \\ \mu_{i,t}^s \end{pmatrix}, \tag{7}$$

where μ_t^n are disturbances such that $E\left(\mu_t^n \mu_t^{n'}\right) = (\sigma^n)^2$ if $t = t'$ and $n = n'$ and i and 0 otherwise, $n = l, s$. In addition, I assume that $E\left[\mu_{t,t-s}^n U_t^{n'}\right] = 0$ for all n, n', i and s. In state-space representation equations (4) and (7) are state equations. They can be represented more compactly by using the following matrix notation:

$$\begin{pmatrix} cs_{i,t}(\tau_1) \\ cs_{i,t}(\tau_2) \\ \cdots \\ cs_{N,t}(\tau_J) \end{pmatrix}_{JN\times 1} = A\begin{pmatrix} \alpha_1^l \\ \alpha_1^s \\ \cdots \\ \alpha_N^s \end{pmatrix} + B\begin{pmatrix} L_t \\ S_t \end{pmatrix} + A\begin{pmatrix} \varepsilon_{i,t}^l \\ \varepsilon_{i,t}^s \\ \cdots \\ \varepsilon_N^s \end{pmatrix} + \begin{pmatrix} v_{i,t}(\tau_1) \\ v_{i,t}(\tau_2) \\ \cdots \\ v_{N,t}(\tau_J) \end{pmatrix} \tag{8}$$

where
N is the number of countries:
J is the number of maturities:
A and B are conforming matrices:

$$A = \begin{pmatrix} 1 & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} & 0 & \cdots & 0 \\ 1 & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} & & & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 1 & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} \end{pmatrix}_{JN\times 2J}$$

$$B = \begin{pmatrix} \beta_1^l & \beta_1^s\left(\frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1}\right) \\ \beta_1^l & \beta_1^s\left(\frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2}\right) \\ \cdots & \cdots \\ \beta_N^l & \beta_N^s\left(\frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2}\right) \end{pmatrix}_{JN\times 2}.$$

3 Estimation

3.1 Econometric Strategy

The estimation method in a multi-company environment can be done using equation (8).The state space can be estimated by the Kalman filter, so that fully efficient Gaussian maximum likelihood dynamics estimates can be obtained. In the single-company case, estimating the latent factors using the Kalman filter is relatively easy because the number of parameters is small. In the multi-company case, however, one-step maximum likelihood is difficult to implement, due to the large number of parameters. Hence, DLY propose a convenient multi-step estimation method which I follow. The first step is to obtain the latent factors (level and slope) for each company. The second step consists in taking the estimates previously obtained and using them in the above (4)-(7) equations to extract the global factors.

To make things easier, we follow DL and $\lambda = 0.0609$,the point where the curvature is maximum. Then we compute the factor loadings for each maturity and estimate the parameters $l_{i,t}$ and $s_{i,t}$ by ordinary least squares for each company i and period t. Hence, there are two estimated parameters in each month for each company. The numbers of coefficients estimated is 2 + 8N. In the measurement equation, there are 4N parameters to be estimated $\beta_i^l, \beta_i^s, \alpha_i^l, \alpha_i^s$, four for each company. In the state equations, there are 2 + 2N parameters to be estimated, two parameters relative to the global factors (Φ_{11}, Φ_{22}) and two parameters for the idiosyncratic factors for each company (ϕ_{11}, ϕ_{22}) .The standard deviation is considered constant over time. For idiosyncratic factors, there are 2N standard deviations for each company.

3.2 Estimation results

I report estimates of the term structure model (4)-(7), obtained using monthly credit spread 1997.04 - 2011.12.Table (2) indicates the estimated parameters are statistically significant at 5 % confidence level.

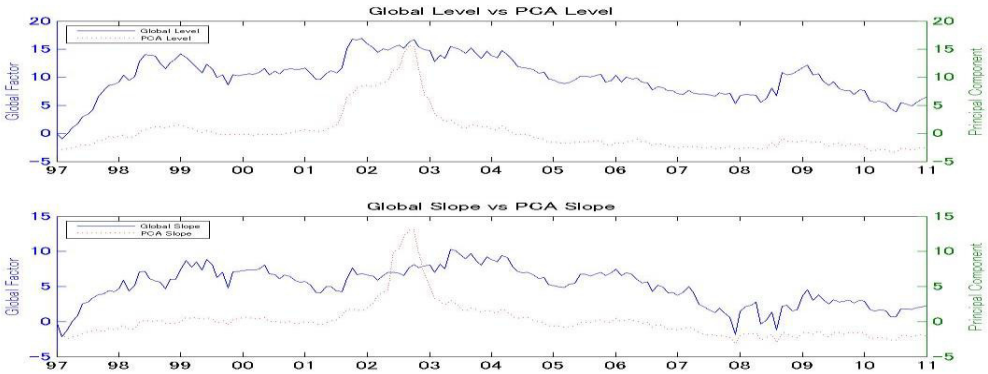

Fig. 3. global factor vs. first principal component of company level and slopes

(Note): I show the estimated global factor as a solid line and the first principal component as a dashed line, 1997.04 through 2011.12.
I show the estimated global factor as a solid line and the first principal component as a dashed line, 1997.04 through 2011.12.in Figure (4).The close linkage between the global factor vs. first principal component of company level and slopes is confirmed. The correlation between the global factor vs. first principal component of company level is 0.75 and the correlation between the global factor vs. first principal component of company slope is 0.63.

Table (2): Estimates of the term structure model

Global factor					
Φ_{11}	0.9851	**	Φ_{22}	0.974	**
Idiosyncratic factor					
ϕ_{11_01}	0.743	**	ϕ_{11_14}	0.874	**
ϕ_{22_01}	0.625	**	ϕ_{22_14}	0.763	**
ϕ_{11_02}	0.969	**	ϕ_{11_15}	0.863	**
ϕ_{22_02}	0.957	**	ϕ_{22_15}	0.590	**
ϕ_{11_03}	0.921	**	ϕ_{11_16}	0.964	**
ϕ_{22_03}	0.939	**	ϕ_{22_16}	0.900	**
ϕ_{11_04}	0.858	**	ϕ_{11_17}	0.980	**
ϕ_{22_04}	0.977	**	ϕ_{22_17}	0.926	**
ϕ_{11_05}	0.979	**	ϕ_{11_18}	0.980	**
ϕ_{22_05}	0.909	**	ϕ_{22_18}	0.899	**
ϕ_{11_06}	0.916	**	ϕ_{11_19}	0.829	**
ϕ_{22_06}	0.949	**	ϕ_{22_19}	0.970	**
ϕ_{11_07}	0.891	**	ϕ_{11_20}	0.950	
ϕ_{22_07}	0.937	**	ϕ_{22_20}	0.714	**
ϕ_{11_08}	0.679	**	ϕ_{11_21}	0.921	**
ϕ_{22_08}	0.755	**	ϕ_{22_21}	0.866	**
ϕ_{11_09}	0.968	**	ϕ_{11_22}	0.943	**
ϕ_{22_09}	0.961	**	ϕ_{22_22}	0.951	**
ϕ_{11_10}	0.949	**	ϕ_{11_23}	0.915	**
ϕ_{22_10}	0.875	**	ϕ_{22_23}	0.974	**
ϕ_{11_11}	0.957	**	ϕ_{11_24}	0.980	**
ϕ_{22_11}	0.945	**	ϕ_{22_24}	0.903	
ϕ_{11_12}	0.980	**	ϕ_{11_25}	0.920	
ϕ_{22_12}	0.945		ϕ_{22_25}	0.976	**
ϕ_{11_13}	0.645	**	ϕ_{11_26}	0.930	**
ϕ_{22_13}	0.621	**	ϕ_{22_26}	0.954	**
Standard deviation of Idiosyncratic factor					
σ_{l_01}	0.519	**	σ_{l_14}	0.445	**
σ_{s_01}	0.345	**	σ_{s_14}	0.279	**
σ_{l_02}	0.049	**	σ_{l_15}	0.233	**
σ_{s_02}	0.060	**	σ_{s_15}	0.348	**
σ_{l_03}	0.063	**	σ_{l_16}	0.055	**
σ_{s_03}	0.057	**	σ_{s_16}	0.110	**
σ_{l_04}	0.125	**	σ_{l_17}	0.346	**
σ_{s_04}	0.081	**	σ_{s_17}	0.241	**
σ_{l_05}	0.059	**	σ_{l_18}	0.055	**
σ_{s_05}	0.102	**	σ_{s_18}	0.109	**
σ_{l_06}	0.678	**	σ_{l_19}	0.169	**
σ_{s_06}	0.549	**	σ_{s_19}	0.144	**
σ_{l_07}	0.376	**	σ_{l_20}	0.091	**
σ_{s_07}	0.430	**	σ_{s_20}	0.149	**
σ_{l_08}	0.388	**	σ_{l_21}	0.062	**
σ_{s_08}	0.276	**	σ_{s_21}	0.128	**
σ_{l_09}	0.085	**	σ_{l_22}	0.129	**
σ_{s_09}	0.087	**	σ_{s_22}	0.094	**
σ_{l_10}	0.171	**	σ_{l_23}	0.068	**
σ_{s_10}	0.121	**	σ_{s_23}	0.310	**
σ_{l_11}	0.369	**	σ_{l_24}	0.056	**
σ_{s_11}	0.260	**	σ_{s_24}	0.112	**
σ_{l_12}	0.091	**	σ_{l_25}	0.056	**
σ_{s_12}	0.112	**	σ_{s_25}	0.063	**
σ_{l_13}	0.478	**	σ_{l_26}	0.073	**
σ_{s_13}	0.304	**	σ_{s_26}	0.123	**

Constant terms					
α_{l_01}	-0.564	*	α_{l_14}	-0.043	*
α_{s_01}	-0.045	*	α_{s_14}	-0.086	*
α_{l_02}	-0.294	**	α_{l_15}	-0.361	*
α_{s_02}	0.506	**	α_{s_15}	0.014	*
α_{l_03}	-0.253	*	α_{l_16}	-0.131	*
α_{s_03}	0.272	*	α_{s_16}	0.297	*
α_{l_04}	0.054	*	α_{l_17}	-0.541	*
α_{s_04}	-0.481	**	α_{s_17}	-0.118	*
α_{l_05}	0.295	**	α_{l_18}	-0.129	*
α_{s_05}	-0.149	*	α_{s_18}	0.196	*
α_{l_06}	-1.108	*	α_{l_19}	-0.296	*
α_{s_06}	0.561	*	α_{s_19}	0.558	*
α_{l_07}	-0.570	*	α_{l_20}	-0.561	**
α_{s_07}	-0.294	*	α_{s_20}	0.200	*
α_{l_08}	-0.571	*	α_{l_21}	-0.167	**
α_{s_08}	0.146	*	α_{s_21}	0.432	**
α_{l_09}	-0.219	*	α_{l_22}	-0.271	*
α_{s_09}	-0.061	*	α_{s_22}	0.044	*
α_{l_10}	-0.821	**	α_{l_23}	-0.333	**
α_{s_10}	0.177	*	α_{s_23}	3.119	**
α_{l_11}	-0.345	*	α_{l_24}	0.204	*
α_{s_11}	0.009	*	α_{s_24}	-0.086	*
α_{l_12}	-0.553	**	α_{l_25}	-0.089	*
α_{s_12}	0.685	**	α_{s_25}	-0.346	**
α_{l_13}	-0.114	*	α_{l_26}	-0.422	**
α_{s_13}	0.041	*	α_{s_26}	0.675	**
Loadings on global factors					
β_{l_01}	0.205	**	β_{l_14}	0.125	**
β_{s_01}	-0.148	**	β_{s_14}	-0.100	**
β_{l_02}	0.085	**	β_{l_15}	0.153	**
β_{s_02}	-0.115	**	β_{s_15}	-0.118	**
β_{l_03}	0.091	**	β_{l_16}	0.070	**
β_{s_03}	-0.131	**	β_{s_16}	-0.127	**
β_{l_04}	0.051	**	β_{l_17}	0.106	**
β_{s_04}	-0.098	**	β_{s_17}	-0.075	**
β_{l_05}	0.052	**	β_{l_18}	0.051	**
β_{s_05}	-0.078	**	β_{s_18}	-0.077	**
β_{l_06}	0.246	**	β_{l_19}	0.147	**
β_{s_06}	-0.119	**	β_{s_19}	-0.120	**
β_{l_07}	0.215	**	β_{l_20}	0.089	**
β_{s_07}	-0.136	**	β_{s_20}	-0.127	**
β_{l_08}	0.187	**	β_{l_21}	0.046	**
β_{s_08}	-0.164	**	β_{s_21}	-0.098	**
β_{l_09}	0.074	**	β_{l_22}	0.104	**
β_{s_09}	-0.101	**	β_{s_22}	-0.112	**
β_{l_10}	0.128	**	β_{l_23}	0.051	**
β_{s_10}	-0.114	**	β_{s_23}	-0.085	**
β_{l_11}	0.150	**	β_{l_24}	0.056	**
β_{s_11}	-0.147	**	β_{s_24}	-0.063	**
β_{l_12}	0.084	**	β_{l_25}	0.049	**
β_{s_12}	-0.132	**	β_{s_25}	-0.077	**
β_{l_13}	0.133	**	β_{l_26}	0.096	**
β_{s_13}	-0.143	**	β_{s_26}	-0.149	**

(*Note*): I report estimates of the term structure model (4)-(7), obtained using monthly credit spread 1997.04-2011.12. ** * :95% and 90% significant respectively.

3.3 Variance decomposition

A specific company factor variance can be evaluated as a proportion of the global and idiosyncratic variances. By doing that, one can explain the magnitude of variations of each factor and infer the influence of global movements in the term structure of credit spreads. The formulation of company idiosyncratic factor can be extracted from equations

(5), (6) using a simple definition of variance as follows:

$$\mathrm{var}(l_{i,t}) = (\beta_i^l)^2 \mathrm{var}(L_t) + \mathrm{var}(\varepsilon_{i,t}^l) \quad (9)$$

$$\mathrm{var}(s_{i,t}) = (\beta_i^s)^2 \mathrm{var}(S_t) + \mathrm{var}(\varepsilon_{i,t}^s) \quad (10)$$

For each company, I decompose company level and slope factor variation into two parts coming from global factor variation and company-specific factor variation. I estimate the underlying model using monthly yield data, 1997.04 - 2011.12.Table (3) indicates the results of variance decomposition. Variation in the global factor is responsible for a large share of variation of the term structure of credit spreads. The global share is never less than 40 % and often much more than 60 %. However some of the credit spreads are driven by idiosyncratic factor.

Table 3. Variance decompositions of country level and slope factors

Level Factors Volatility

	TaiseiCorp	SumitomoChemicalCo	MitsubishiChemicalCorp	JXHoldingsInc	NipponSteelCorp	
Common Factor	47.4%	49.1%	75.3%	34.6%	32.2%	
Idiosyncratic Factor	52.6%	50.9%	24.7%	65.4%	67.8%	
	SumitomoMetalIndustries	KobeSteel	MitsubishiMaterialsCorp	SumitomoElectricIndustries	ToshibaCorp	
Common Factor	15.0%	17.4%	62.8%	44.0%	48.1%	
Idiosyncratic Factor	85.0%	82.6%	37.2%	56.0%	51.9%	
	MitsubishiElectricCorp	Fujitsu	KawasakiHeavyIndustries	NissanMotorCo	ItochuCorp	
Common Factor	30.3%	45.6%	37.7%	20.2%	54.5%	
Idiosyncratic Factor	69.7%	54.4%	62.3%	79.8%	45.5%	
	MitsuiCorp	OrixCorp	MitsubishiEstateCo	TobuRailwayCo	TokyuCorp	
Common Factor	48.7%	4.8%	25.3%	72.4%	72.0%	
Idiosyncratic Factor	51.3%	95.2%	74.7%	27.6%	28.0%	
	TokyoMetroCo	KintetsuCorp	TokyoGasCo	TohoGasCo	NTT	KDDICorp
Common Factor	54.1%	52.6%	55.5%	32.3%	51.0%	64.8%
Idiosyncratic Factor	45.9%	47.4%	44.5%	67.7%	49.0%	35.2%

Slope Factors Volatility

	TaiseiCorp	SumitomoChemicalCo	MitsubishiChemicalCorp	JXHoldingsInc	NipponSteelCorp	
Common Factor	44.6%	62.1%	79.7%	34.7%	48.9%	
Idiosyncratic Factor	55.4%	37.9%	20.3%	65.3%	51.1%	
	SumitomoMetalIndustries	KobeSteel	MitsubishiMaterialsCorp	SumitomoElectricIndustries	ToshibaCorp	
Common Factor	3.3%	5.2%	50.6%	53.5%	59.4%	
Idiosyncratic Factor	96.7%	94.8%	49.4%	46.5%	40.6%	
	MitsubishiElectricCorp	Fujitsu	KawasakiHeavyIndustries	NissanMotorCo	ItochuCorp	
Common Factor	33.0%	63.2%	48.3%	27.8%	34.6%	
Idiosyncratic Factor	67.0%	36.8%	51.7%	72.2%	65.4%	
	MitsuiCorp	OrixCorp	MitsubishiEstateCo	TobuRailwayCo	TokyuCorp	
Common Factor	63.7%	5.3%	39.8%	44.8%	44.8%	
Idiosyncratic Factor	36.3%	94.7%	60.2%	55.2%	55.2%	
	TokyoMetroCo	KintetsuCorp	TokyoGasCo	TohoGasCo	onTelegraphAndTelephone	KDDICorp
Common Factor	51.2%	49.0%	4.4%	32.2%	49.8%	50.9%
Idiosyncratic Factor	48.8%	51.0%	95.6%	67.8%	50.2%	49.1%

(*Note*) For each company, I decompose company level and slope factor variation into two parts coming from global factor variation and company-specific factor variation. I estimate the underlying model using monthly yield data, 1997.04 - 2011.12.

4 Predicting Economic Activity

I now turn to the information content of credit spreads for economic activity. Specifically, their forecasting performance is examined both in - sample and out-of-sample. $x_t = (L_t, S_t)'$ denotes the vector of estimated global factors of the level and slope of the credit spreads. The vector of macroeconomic variables contains (1) GDP growth (g), (2) inflation (consumer price index)(π) and (3) unemployment rate (ue) and is given by $m_t = (g_t, \pi_t, ue_t)'$. The GDP growth data g_t is picked from Cabinet Office on quarterly basis and quarterly data is converted by the method of spline interpolation in monthly data. The consumer price index, π_t and unemployment rate, ue_t are collected from Ministry of Internal Affairs and Communications. Hence z_t is composed of vector of credit factors and macro variables, $z_t = (m_t', x_t')'$, and fully reflects the available information at time t. μ is the vector of intercept , ϵ_{t+h} is white noise. The state vector follows a VAR (1) process,

$$z_{t+h} = \mu + \Phi z_t + \epsilon_{t+h}, \text{ where } \epsilon \sim N(0, \mathrm{I}), \quad (11)$$

$$m_{t+h} = \mu + \Phi m_t + \epsilon_{t+h}, \text{where } \epsilon \sim N(0, \mathrm{I}) \quad (12)$$

4.1 In-Sample Predictive Power of Credit Spreads

This section examines the in-sample predictive content of credit spreads using OLS regressions of equation (13) and (14) .I first examine the in-sample predictive power of global factors of credit spreads for three measures of economic activity. Table (4) contains the results of R squares of OLS regressions for the 3, 6, 12 and 24 months. In the tables, the explanatory power of each forecasting equation as measured by the adjusted R squared is demonstrated. As a benchmark, the item in both tables contains the in - sample fit from the VAR specification that excludes all term structure factors of credit spreads.

Table 4. In-Sample Predictive Content of Credit Spreads for Economic Activity; R squares of OLS regressions

	Forecast Horizon h=3(months)			Forecast Horizon h=12(months)		
	GDP	CPI	UE	GDP	CPI	UE
Model	Adjusted R-squared			Adjusted R-squared		
Macro+Common factors	0.753	0.749	0.908	0.690	0.475	0.549
Macro only	0.732	0.748	0.896	0.433	0.409	0.495

	Forecast Horizon h=6(months)			Forecast Horizon h=24(months)		
	GDP	CPI	UE	GDP	CPI	UE
Model	Adjusted R-squared			Adjusted R-squared		
Macro+Common factors	0.604	0.551	0.777	0.374	0.087	0.067
Macro only	0.503	0.523	0.777	0.334	-0.002	-0.009

(Note) Monthly data from April 1997 to December 2011.

Table (4) examines the in-sample explanatory power of credit spreads both at short forecast horizons, namely 3 and 6 months and at longer forecast horizons, namely 12 and 24 months. At 6 and 12 horizons, the information content of credit spreads for three measures of economic activity is considerable. For example, GDP and global factors of credit spreads explain about 70 percent of the variation in the 12-month ahead growth rate, representing a significant increases in the goodness-of fit relative to the specification that relies only on lags of GDP and lags of CPI and Unemployment.

4.2 Out-of-Sample Predictive Power of Credit Spreads

I now examine the predictive content of credit spreads for our two measures of economic activity using out-of-sample forecasts. Specifically, for each forecast horizon h, we estimate the forecasting VAR using 60 months data. I then calculate the (annualized) h-month ahead economic variables and the associated forecast errors. The forecast data is then updated with an additional month of data, the VAR parameters are re-estimated using this new larger observation window, and new forecasts are generated. This procedure is repeated through the end of the sample, thereby generating a sequence of out-of-sample forecasts for the three measures of economic activity. Table (5) contains the results of this exercise; the results for 3,6,12 and 24 months horizons are presented. To quantify the out-of-sample forecasting performance of the different VAR specifications, the entries under the column heading “RMSE” report the square root of the mean squared forecast error (in annualized percentage points) for each specification. To compare the predictive accuracy of credit spreads with that of only macro economic indicators, the entries under the column heading “Ratio” contain the ratio of the mean squared forecast error (MSFE) of the VAR specification augmented with credit spreads global factors with the MSFE of the specification that includes only macro economic variables. To assess whether the difference in predictive accuracy between these two non-nested models is statistically significant, the entries under the column heading “CW test” contain the p-values of the Clark and West (2007) test of the null hypothesis of equal predictive accuracy.

Table 5. Out-of-Sample Predictive Content of Credit Spreads for Economic Activity

	Forecast Horizon h=3(months)								
	GDP			CPI			UE		
Model	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest
Macro+Common factors	1.338	1.145	2.2%	0.442	1.016	23.5%	0.162	1.200	2.10%
Macro only	1.431	-	-	0.442	-	-	0.177	-	-

	Forecast Horizon h=6(months)								
	GDP			CPI			UE		
Model	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest
Macro+Common factors	1.718	1.310	0.2%	0.570	1.026	25.0%	0.211	1.224	0.12%
Macro only	1.966	-	-	0.566	-	-	0.243	-	-

	Forecast Horizon h=12(months)								
	GDP			CPI			UE		
Model	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest
Macro+Common factors	1.581	1.964	1.6%	0.569	1.185	0.8%	0.283	1.165	0.2%
Macro only	2.241	-	-	0.620	-	-	0.344	-	-

	Forecast Horizon h=24(months)								
	GDP			CPI			UE		
Model	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest	RMSE	Ratio	CWTest
Macro+Common factors	2.376	1.077	3.2%	0.829	1.097	3.00%	0.490	1.117	3.24%
Macro only	2.465	-	-	0.882	-	-	0.522	-	-

(*Note*) Each VAR specification also includes a constant, current, of (1)GDP growth ,(2)CPI and (3)unemployment rate and (4)credit global factors of the term structure of credit spreads. "Ratio" denotes the ratio of the MSFE of nested model (only macro-economic indicators) relative to the MSFE of the full model that includes the global factors of credit spreads. CW test denote the p-value for the Clark and West (2007) test of the null hypothesis that the difference between the MSFE from the model that includes standard credit spreads and the MSFE from the model that exclude global factors is equal to zero.

"Ratio" shows all figures except CPI at 6 months horizon exceeds one, which suggests that credit factors have predictive power for the future macro economic activities. The out-of-sample forecasting performance of credit spreads global factors for GDP,CPI and unemployment rate exceeds that of only macro economic indicators at short-horizons, although at the three-month forecast horizon, the differences in predictive accuracy are not statistically significant at conventional levels. At the six-month horizon, however, the predictive accuracy of portfolio credit spreads global factors exceeds that of only macro model by about 10 percent for GDP and CPI, improvements that are statistically significant at the 10 percent level for GDP. In the case of the 12-month horizon, credit spreads factors yield a reduction in the RMSE on the order of 20 percent relative to the specification that includes only the macro economic variables for GDP and there are improvements that are statistically significant at the 10 percent level for all three indicators. The results reported in Table (5) indicate significant improvements in the out-of-sample forecasting performance of VAR specifications that rely on corporate bond spreads global factors especially for long-run forecast horizon. To assess whether these improvements are due to a specific sub-period, Figure (3) plots the realized values of out-of-sample forecasts of GDP, CPI and Unemployment rate for 12-month horizon.

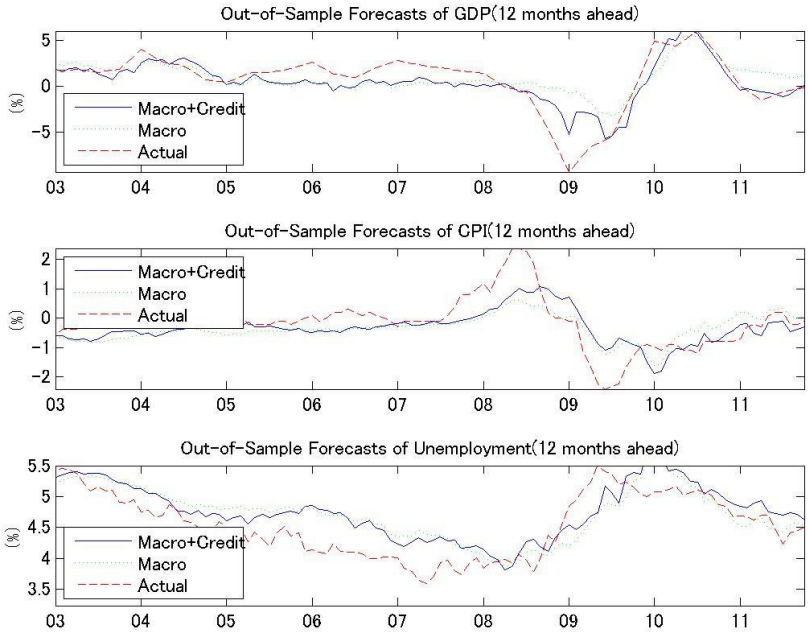

Fig. 4. Out-of-Sample Forecasts of Economic Activity Indicators

(Note): The panels of the figure depict out-of-sample forecasts of GDP, CPI and Unemployment rate for 12-month horizon. The line shows forecasts by VAR model using (1) macro and credit global factor(solid line) ,(2) macro factor(dotted line) and (3) the actual data(dashed line).

As indicated by the solid line, forecasts of economic activity using credit global factor track quite well year-over-year growth in the dashed actual series in both recessionary and expansionary times. In addition, the substantial gain in predictive accuracy obtained from using credit global factors rather than mere macro indicators does not seem to reflect a specific sub period. Importantly, the model incorporating credit global factors captures much better the slowdown in economic activity associated with the 2008-2009 recession relative to the specification based on only macro variables.

5 Concluding Remarks

In this paper, I extract the global factor from individual credit spreads of major Japanese corporate bonds using state-space modelling and examine the predictive contest of the credit spread for the real economy. The results indicate estimated global factors are important drivers of individual credit spreads and that the credit spreads global factors have a substantial predictive power for future Japanese economic activity especially for 12 months horizon. This study makes a contribution to forecasting the future macro variables. There are possible challenges for future work. The level of the credit spread depends on credit rating or credit quality. Model extension including credit quality factor between global and idiosyncratic factor should be studied further.

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