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Common factors in credit defaults swaps markets

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Common factors in credit defaults swaps markets*

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Abstract

We examine what are common factors that determine systematic credit risk and estimate and interpret the common risk factors. We also compare the contributions of common factors in explaining the changes of credit default swap (CDS) spreads during the pre-crisis, crisis and post-crisis period. Based on the testing result from the common principal components model, this study finds that the eigenstructures across the three subperiods are distinct and the determinants of risk factors differ from three subperiods. Furthermore, we analyze the predictive ability of dynamics in CDS indices changes by dynamic factor models.

JEL classification:C38; G32; E43

Keywords: credit default swaps; common factors; credit risk

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1. Introduction

The fixed income portfolios covering various classes of bonds are used to diversify risk or enhance investment returns. The investors holding fixed income portfolios may suffer from credit risk of different entities. This raises the question: whether there are common factors determining systematic credit risk across different entities, different countries and different maturities. For existing systematic credit risk factors, the diversification effect in the international bond investing must shrink. An examination into common credit risk factors enables us to realize the nature of correlated defaults. Several illustrations for correlated defaults have been proposed by Das et al. (2007). First, firms may be exposed to common or correlated risk factors. Second, the event of default by one firm may be contagious. Third, learning from default may generate default correlation. Our primary goals are to examine what are common factors determining systematic credit risk, to estimate and interpret the common risk factors. We estimate the market prices of risk factors and subsequently test their significances. Furthermore, time-variation of credit risk may be predictable based on specified dynamics in risk factors.

Understanding how corporate defaults are correlated is particularly important for the risk management of portfolios of corporate debt, since banks have to retain greater capital to survive default losses if defaults are heavily clustered in time. An understanding of the sources and degree of default clustering is also crucial for the rating and risk analysis of structured credit products, such as collateralized debt obligations (CDOs) and options on portfolios of default swaps, that are exposed to correlated default: An issue that became more serious since the US subprime crisis. Several attempts have been made in the literature to address this issue. The first one attempts to incorporate correlated default into the reduce-form credit risk modeling (Das et al, 2006; Das et al., 2007). The second work addresses this issue by assuming that default probabilities depend on firm-specific and market-wide factors. Typically, portfolio loss distributions are based on the correlating influence from such observable market-wide factors. A number of potentially observable factors from macroeconomic fundamentals have been proposed to analyze correlated defaults (Collin-Dufresen, et al, 2001; Benkert, 2004; Ericsson, et al., 2009). The last one, however, proposes some latent/unobservable factors mainly from the principal components analysis method to address this issue (Duffie et al., 2009; Cesare and Guazzarotti, 2010; Anderson, 2008). Considering the potential omitted latent factors is essential and crucial to avoid a downward biased estimate of tail losses. In one hand, it is inevitable that not all relevant risk factors are potentially observable by the econometricians. On the other hand, there is a potential for important risk factors that are simply not observable (Duffie et al, 2009).

Recent research claims that common latent factors increasingly and apparently explain the time-variation of credit risk. Anderson (2008) finds that a very high fraction of weekly variations in the implied default intensity is explained by a single common factor. Cesare and Guazzarotti (2010) find that CDS spread changes have been increasingly driven by a common factor during the US subprime crisis. However, both studies neither attempt to interpret the evident common factors nor illustrate how the factors influence the changes of CDS spreads. The focus of this paper is estimating and interpreting the common latent factors that determine CDS spread changes. Moreover, the rich cross-sectional collection of CDSs data, covering different maturities, different credit ratings, different entities and different countries, produces relatively robust common factors and makes the interpretation convincible.

The second goal of this study is to compare the contributions of common factors in explaining the CDS spreads changes during the pre-crisis, crisis and post-crisis period. We also compare the factor loadings before, during and post US subprime crisis to realize how the factors influence the CDS spreads changes of different maturities, different credit ratings and different countries. This investigation is motivated by Cesare and Guazzarotti (2010) who found that during the crisis CDS spreads appear to have been moving increasingly together. The fraction of CDS variation explained by the first principal component increases from 45% to 62%

during the crisis period, suggesting that CDS spreads changes during the crisis are increasingly driven by common or systematic factors and less by firm-specific factors. This finding is in line with Cesare and Guazzarotti (2010). The fraction of CDS variation explained by the first principal component increases from 58.7% to 72.3% during the crisis period, and then it declines to 47% after the crisis. The result of a likelihood ratio test that compares the common principal components model against the unrestricted model indicates that the eigenstructures across three subperiods are distinct.

Finally, this study attempts to model the time-variation of CDS spreads changes as captured by the dynamics of the common factors identified in the cross-sectional analysis. By doing this, we can examine the predictability of the CDS spreads changes. To capture and predict the time-variation of CDS index changes, various competing models including the static factor model, the dynamic factor model, the time-varying factor loading model, an approximate factor model with idiosyncratic errors that are serially and cross-sectionally correlated, are analyzed. We evaluate their out-of-sample forecasting performance and test their equal predictive ability subsequently.

In contract to the previous studies that propose observable market variables or firm-specific variables in determining CDS spreads, we focus on the commonalities in

CDS spreads and their factor loadings by applying principal components analysis. In particular, we interpret the common factors and their factor loadings to identify the systematic credit risk factors and their relative influences on the default risks of specific entities. We find that the eigenstructures are distinct for pre-, during and post-crisis period and the determinants of risk factors differ from three subperiods. The predictability of CDS spreads dynamics enables investors to hedge, speculate and arbitrage in the credit derivative markets.

The remainder of this research is organized as follows. The next section describes the data we used. Section 3 presents the methodology for decomposing the change of CDS spreads into the factor models, and provides economic interpretation for estimated factors. In section 4, we propose several competing factor specifications to capture and predict the times-variation of the CDS indices. Evaluating their out-of-sample forecasting performances and testing their equal predicting ability are both conducted in this section.

2. Data description

Credit default swap data are collectable from Markit, an aggregator of CDS pricing data from the leading-broker dealers. In terms of our focus on the commonality of CDS spreads, we are interested in the CDS indices rather than single name reference entity CDS contracts to mitigate the idiosyncratic factors and liquidity risk. Our concern coincides with Driessen et al. (2003) in studying the common factors in international bond returns. They suggest to use returns on portfolio of bonds instead of individual bond price since individual bond price data might contain more idiosyncratic risk. Markit provides a detailed CDS index series. The Markit CDX family of indices includes the most liquid baskets of names covering North American Investment Grade, High Yield, and also Emerging Markets single name credit default swaps. The Markit CDS indices roll semi-annually in March and September. Credit events that trigger settlement for individual components are bankruptcy and failure to pay. Credit events are settled via credit event auctions. The Markit iTraxx indices are rule based CDS indices and are comprised of the most liquid names in each of their respective market, Europe, Asia, Australia and Japan. Compared to single name CDS contracts, CDS indices are popular due to the following features. First, trading is more efficient because participants can trade large sizes quickly and confirm all trades electronically. Second, liquidity is enhanced because wide dealer and industry support allow for significant liquidity in all market conditions. Third, CDX and iTraxx indices are accepted as a key benchmark of the overall market credit risk. The last benefit is transparency that pricing is freely available daily on all indices.

We collect these indices ranging from Oct. 2004 to Jun. 2011. The indices are selected by its regions: North American (CDX), Europe (iTraxx EU), by maturities: 5- and 10-year, by credit rating: investment-grade (IG) and high-yield grade (HY). Therefore, eight indices with different regions, maturities and credit rating will be analyzed in the subsequent sections. The US subprime crisis period is covered so that we can compare the commonalities pre-, during- and post- crisis. The functioning of money market in the U.S. was severely impaired in the summer of 2007, and then even more following the collapse of Bear Sterns in mid-March 2008 and the bankruptcy of Lehman Brother in Sep. 2008. The turmoil from Jun. 2007 to Jul. 2009 is referred to a crisis period. After mapping the trading date among eight CDS indices, each index has 315 weekly observations: 134 in the pre-crisis period (from Oct. 2004 to May. 2007), 104 in the crisis period (from Jun. 2007 to Jul. 2009) and 76 in the post-crisis period (from Aug. 2009 to Jun. 2011). Table 1 summarizes the descriptive statistics for whole sample period, pre-crisis, crisis and post-crisis period. During the crisis period, the mean changes of CDS spreads are all apparently positive and the highest standard deviation in this period can be found.

The time-variations of CDS indices as displayed in Fig. 1 exhibit a changing dynamics. One noticeable feature is the high level of co-movement across various maturities and credit ratings. The presence of higher co-movement between CDS indices motivates the study of common factors. Obviously, in Fig. 1 the apparent spike during the outbreak of the U.S. subprime crisis shows an inversion of the risk structure. For a given maturity, a high-yield (HY) index should be higher than an investment-grade (IG) one to reflect a higher default risk premium. The default risk premium between a HY and an IG may expand during the financial crisis to reflect a shift in investor's risk appetite. For upcoming bad times, risk-averse investors raise default risk premium to reflect their attitudes towards bearing the default risk. Pan and Singleton (2008) claimed that a co-movement effect in the CDS markets may be explained by a shift in investor's risk appetite, especially for the turbulent period.

In addition, Fig. 1 shows the term structure of CDS markets. Normally, the slope of CDS term structure is upward, means that the short-term CDS spreads should be lower than the respective longer maturity CDS spreads to compensate a higher risk-taking in the longer maturity contract. Hence, the term structure is never inverted. But, the term structure did occasionally invert, especially during the financial crisis (Pan and Singleton, 2008). For upcoming crisis, the demand for short-term CDS contrast is appealing and bid-ask spreads of short-term CDS contrasts are comparable to longer-dated contracts. At this moment, the larger the bid-ask spread must be in the CDS market to cover the higher hedging cost faced by the protection sellers. As shown in Fig. 1, we have consistent evidence in the CDS term structure, an inverted slope in the crisis period and an upward slope in the rest of periods.

3. Factor representation of CDS spreads change

3.1. Model specifications

Let S_{it} be the observed change of CDS spreads for the *i*th cross-section unit at time *t*, for *i*=1,…,*N*, and *t*=1,…,*T*. The factor model for given *i*th unit is:

$$S_{it} = \boldsymbol{F}_t \lambda_i + e_{it} \tag{1}$$

where F_t is a vector of common factors and is not observable, λ_i is a vector of factor loadings associated with F_t, and e_{it} is the idiosyncratic component of S_{it}. It is assumed that factors and idiosyncratic disturbances are mutually uncorrelated $E(F_t, e_{it}) = 0$. We also assume that the residual variances are all equal to each other, since it allows us to estimate (1) by principal component analysis. Equation (1) is in fact the static factor representation of the change of CDS spreads. For the forecasting exercise in subsequent sections, we will invoke the assumptions about the cross-sectional and temporal dependence in the idiosyncratic errors.

To interpret the latent factors, we estimate them using principal components and represent (1) as a set of panel data across *N* units and times

$$\underset{(T \times N)}{\boldsymbol{S}} = \underset{(T \times r)}{\boldsymbol{F}} \; \underset{(r \times N)}{\boldsymbol{\Lambda}^{\mathrm{T}}} + \underset{(T \times N)}{\boldsymbol{e}} \tag{2}$$

Equation (2) assumes r common factors through $r \times N$ matrix $\boldsymbol{\Lambda}^{\mathrm{T}}$ (factor loadings) and a $T \times N$ matrix $\boldsymbol{e}$ containing firm-specific residuals. Because the factors $\boldsymbol{F}$ are unobserved, one would like to construct a portfolio - a factor representing portfolios (FRP) - that is sensitive to movements of a given $\boldsymbol{F}$ but insensitive to movements in all other factors. The FRPs are not uniquely determined (Knez et al., 1994; Christiansen C., 1999; Driessen et al., 2003), but they can be used later for interpreting the common factors. For factor *i*, the weights of this factor representing portfolio are equal to the *i*th factor loading $\boldsymbol{\lambda}_i$ normalized to sum up to one. The *i*th FRP at *t* is thus:

$$\mathrm{FRP}_{it} = \boldsymbol{S}_t \boldsymbol{\lambda}_i \tag{3}$$

3.2. Common principal components in the different subperiods

The explanatory power of principal components analysis is reported in Table 2. We choose a four-factor model because in general it can explain up to 90.5% of the variance in the changes of CDS indices. To capture the time-variation in the changes of CDS indices in subsequent sections, we follow the method of Bai and Ng (2002) to estimate the number of factors in a formal statistical procedure.

For the full time period, the first factor explains 63% of the variance of the change of CDS spreads, the explained variance for the second, third and fourth factors are 12.1%, 8%, 7.4%. If we concentrate on three subperiods, the first factor explains 58.7% of the variance in the pre-crisis period, 72.3% of the variance in the crisis period and 47% of the variance in the post-crisis period. The fraction of CDS variation explained by the first principal component increases from 58.7% to 72.3% during the crisis period, and then it declines to 47% after the crisis. Overall, a four-factor model explains 90.5% of the change of CDS spreads but in crisis it sharply rises to 94.1% of explanatory ability, indicating that during the crisis, CDS spreads are increasingly driven by common or systematic factors and less by idiosyncratic factors.

To formally test whether the eigenstructures across three subperiods are distinct, we perform a likelihood ratio test for comparing a restricted (the Common Principal Components (CPC) model) against the unrestricted model (the model where all covariances are treated separately). The likelihood ratio statistic is given by

$$\mathrm{T}_{(n_1,n_2,\ldots,n_h)} = -2\log\frac{L(\hat{\Sigma}_1,\ldots,\hat{\Sigma}_h)}{L(S_1,\ldots,S_h)} \tag{4}$$

where $\Sigma_i = \Gamma\Lambda_i\Gamma^{\mathrm{T}}, i = 1, \ldots, h,$ is a positive definite $N \times N$ covariance matrix for every i, $\Gamma = (\gamma_1, \ldots, \gamma_N)$ is an orthogonal $N \times N$ transformation matrix and $\Lambda_i = \mathrm{diag}(\vartheta_{i1}, \ldots, \vartheta_{iN})$ is the matrix of eigenvalues where assumes that all ϑ_i are distinct. The CPC is motivated by the similarity of the covariance matrices in the h-sample problem. The basic assumption of CPC is that the space spanned by the eigenvectors is identical across several groups, whereas variances associated with the components are allowed to vary (Flury, 1988).

Let S be the sample covariance matrix of an underlying N-variate normal distribution with sample size n. Then the distribution of nS has n-1 degree of freedom and is known as the Wishart distribution.

$$nS \sim W_N(\Sigma, n-1)$$

Hence, for Wishart covariance matrices $S_{i,}$ $i = 1, \dots, h$ with sample size $n_{i,}$ the likelihood function can be expressed as

$$L(\Sigma_1, \dots, \Sigma_h) = \mathrm{C} \prod_{i=1}^{h} \exp\left[\mathrm{tr}\left\{-\frac{1}{2}(n_i - 1)\Sigma_i^{-1} S_i\right\}\right] |\Sigma_i|^{-\frac{1}{2}(n_i - 1)} \quad (5)$$

where C is a constant independent of the parameters Σ_i. See Härdle and Simar (2011), inserting (5) to (4), the likelihood ratio statistic is obtained and has a χ^2 distribution as min(n_i) tends to infinity with

$$h\left\{\frac{1}{2}N(N-1)+1\right\} - \left\{\frac{1}{2}N(N-1)+hN\right\} = \frac{1}{2}(h-1)N(N-1)$$

degree of freedom. Using h=3 subperiods sample covariance matrix data, the calculation yields 897.54 for the likelihood ratio statistic, which corresponds to a zero p-value for the $\chi^2(56)$ distribution. Hence, the CPC model is rejected against the unrestricted model, where PCA is applied to each subperiod separately. The finding indicates that the eigenstructures across three subperiods, pre-, during and post-crisis, are dramatically distinct. There is no common eigenstructures (e.g. of CPC type) for these periods. Indeed, the outbreak of subprime credit crisis has caused a structure change in the commonality of CDS markets.

3.3. Interpreting the factors

Interpreting the unobservable factors is meaningful because it enables us to realize what common factors drive the changes of CDS spreads. In fact, it allows into understand the unobservable factors via observable time series, see Collin-Dufresen, et al (2001), Benkert (2004) and Ericsson, et al. (2009). This approach is robust and flexible because we neither have to know what the exact factors are nor worry about measurement errors in the factors.

Table 3 reports the estimated factor loadings for the whole sample and for the crisis period. To get a better feeling of the interpretation from Table 3, we plot four factor loadings estimated from the whole sample period against maturities and credit ratings in Fig. 2. For factor 1, the factor loadings all have the same sign and same magnitude across maturities and ratings. It can be interpreted as a *level effect*. The CDS spreads, resembles in bond assets, are sensitive to the level and movement of interest rate. As pointed out by Longstaff and Schwartz (1995), the static effect of a higher spot rate increases the risk-neutral drift of the firm value process, which reduces the probability of default and in turn, reduces the CDS spreads. Further empirical evidences are supported by Duffie (1998) and the above references.

Factor 2 can be interpreted as *credit effect*. For both CDX and iTraxx Europe, the factor loadings of IG are higher than those of HY grade, meaning a high association of CDS spreads with the credit condition. Basically, the CDS spreads increase as credit deteriorates. It is not easy to interpret factor 3 in the CDX case, but factor 3 in iTraxx Europe case can be linked to a *volatility effect.* In Table 3 and Fig. 2, we find that for iTraxx Europe, the factor loadings of HY are higher than those of IG. The contingent-claims approach implies that the debt claim has features similar to a short position in a put option. Since option values increase with volatility, increased volatility increases the probability of default. In particular, the HY spreads are more sensitive to volatility than IG ones. Finally, we interpret factor 4 as a *term structure effect*. This is intuitively clear because in Table 3 and Fig. 2, the sign of loading of five-year CDS spreads is always negative while that of ten-year CDS spreads is positive. This is in accordance with Pan and Singleton (2008) who found that the term structure of CDS spreads is associated with default risk premium. An increase in the default risk premium pushes up the long-term CDS spreads more than the short-term CDS spreads, leading to a steeper term structure of CDS spreads. Alternatively, the expectation hypothesis can illustrate the term structure of CDS spreads because high CDS slope may indicate that investors expect deterioration in credit quality.

Besides a graphical inspection of the shape of the factor loadings, a regression on FRP returns and other variables may help to interpret the shape of the factor loadings. As further variables in this regression, one may include the change of interest rate level, change of credit spread, change of interest rate term structure and the change of stock index volatility. The one-year Treasury bond rate represents level of the risk-free interest rate in U.S., while the one-year Euribor rate measures level of the risk-free interest rate in Europe. The difference between the ten-year treasury bond rate and the one-year treasury bond rate is used to evaluate the slope of the yield curve in U.S.. In Europe, the term structure of interest rate is measured by the spread between ten-year yield of Merrill Lynch Euro Union Government bond index and one-year Euribor rate. The credit spread in U.S. is the difference between the average Moody’s Baa yield and the average Moody’s Aaa yield of U.S. corporate bonds. In Europe, it is the difference between the Markit iBoxx Europe high-yield index, which represents the sub-investment grade fixed-income market for Euro denominated corporate bonds, and the Markit iBoxx Europe investment-grade index. To capture the volatility, we use CBOE VIX index in the North American market and apply VSTOXX index in the European market. Putting things together yields the equation:

$$\mathrm{FRP}_{i,t} = \alpha_i + \beta_{i,1} \vartriangle level_t^{US} + \beta_{i,2} \vartriangle yieldCurve_t^{US} + \beta_{i,3}\sigma_t^{US}$$
$$+\gamma_{i,1} \vartriangle level_t^{Europe} + \gamma_{i,2} \vartriangle yieldCurve_t^{Europe} + \gamma_{i,3}\sigma_t^{Europe} + \varepsilon_{i,t}^{MC} \qquad (6)$$

where *i* refers to *i*th common factor.

The regression results in Table 4 show that in general the U.S. determinant variables relative to European ones successfully explain the estimated factors, especially for VIX variables. The European credit spread and its yield curve have some power in explaining the common risk factors. However, the results in the case of three subperiods display some interesting distinctions in Table 5. Before the crisis, the variables from the U.S. financial markets are dominant, which is consistent with the findings in the whole sample period. During the crisis, the variables from both markets play a role in explaining the common factors. Meanwhile, the regression analysis during the crisis exhibits the highest R^2. However, after the U.S. subprime crisis, only the variables from the European market contribute the factor explanation, and this finding can be realized because of the recent European credit crisis. By analyzing three subperiods, we find that the ingredients of the latent factors are not always invariant and agree that the latent factor model is more robust because we never know what the risk factors are and when are they replaced by others as time goes by. That the determinants of risk factors for three subperiods are distinct corresponds to the finding in the previous section that the eigenstructures vary across the three subperiods.

In sum, for the whole sample period, the common risk factors in the CDS markets are mostly determined by the conditions of U.S. market. But during the crisis, the European interest rate term structure and credit quality shed lights on the common risk factors. However, the interpretation for the post-crisis period only attributes to the European variables.

3.4. Factor risk prices

If we fit the factor model into the framework of the arbitrage pricing theory (Ross, 1976), Equation (1) can be restated as

$$S_{it} = \boldsymbol{\Upsilon}\lambda_i + \boldsymbol{F}_t\lambda_i + e_{it} \tag{7}$$

The elements of the *r*-dimentional vector $\boldsymbol{\Upsilon}$ can be interpreted as the market prices of factor risk. Note that (7) implies that the expected changes of CDS indices satisfy

$$\mathrm{E}(S_{it}) = \boldsymbol{\Upsilon}\lambda_i \tag{8}$$

Given the estimated factor loadings λ_i, we can estimate the prices of factor risk $\boldsymbol{\Upsilon}$ by the generalized methods of moments (GMM) (Hansen, 1982) on the moment restrictions in (8). This is equivalent to a GLS regression of the average changes of CDS indices on the factor loading matrix λ_i. Since we have adopted a four-factor model in the previous sections, the GMM method enables us to estimate the prices of factor risk in this model and test their significance. As shown in Table 6, the market prices of four-factor model are all significant, and the first two factors, the *level factor* and the *credit factor*, exhibit appealing size in their risk prices. If we consider a five-factor model, the risk prices are significant in the first four factors but insignificant in the fifth factor.

Table 6 also contains the GMM *J*-statistic, a test -statistic for testing the overidentifying restrictions in (8), and the corresponding *p*-value. The *J*-statistic acts as an omnibus test statistic for model misspecification. In a well specified overidentifying model with valid moment conditions, the *J*-statistic behaves like a chi-square random variable with degrees of freedom equal to the number of overidentifying restrictions. Typically, a large *J*-statistic indicates a mis-specified model. In Table 6, the *J*-statistics in the both four- and five-factor models cannot reject the null, implying that the both models are well-specified. Furthermore, the four- and five-factor models provide a good fit of the average change of CDS indices, as measured by the R^2 of the GLS regression, which is equal to 95.42% and 95.89%, respectively. The results from *J*-statistic, R^2 of the GLS and the significance of factor prices suggest that the four-factor model is efficient enough to describe the average changes of CDS indices.

4. Method of asymptotic principal components and forecast performance

4.1. Competing factor models

To capture and predict the time-variation of CDS index changes, various competing models including the static factor model, the dynamic factor model, the time-varying factor loading model, an approximate factor model with idiosyncratic errors that are serially and cross-sectionally correlated, are analyzed. In the static model (1), the errors are assumed to be *iid* and normally distributed. The independence assumption may be questionable, because the errors are serially correlated or cross-correlated. Following Stock and Watson (2002), we therefore adjust the stochastic of the errors terms. The competing models are:

$$S_{it} = \boldsymbol{F}_t \lambda_{it} + e_{it}$$

$$\lambda_{it} = \lambda_{i0} + \rho_i \lambda_{i,t-1} + \varepsilon_{it} \tag{9}$$

$$(\boldsymbol{I} - \boldsymbol{B}_1 L - \cdots - \boldsymbol{B}_h L^h)\boldsymbol{F}_t = \boldsymbol{u}_t \tag{10}$$

$$\boldsymbol{u}_t = \boldsymbol{H}_t^{1/2} \boldsymbol{\eta}_t \tag{11}$$

$$vech(\boldsymbol{H_t}) = \boldsymbol{c} + \sum_{j=1}^{q} \boldsymbol{A_j} vech\left(\boldsymbol{u}_{t-j}\boldsymbol{u}_{t-j}^{\mathrm{T}}\right) + \sum_{j=1}^{p} \boldsymbol{D_j} vech\left(\boldsymbol{H}_{t-j}\right) \tag{12}$$

$$(1 - \alpha L)e_{it} = v_{it} + \theta_1 v_{i+1,t} + \theta_2 v_{i-1,t} \tag{13}$$

$$v_{it} = \sigma_{it} \eta_{it} \tag{14}$$

$$\sigma_{it}^2 = \delta_0 + \delta_1 \sigma_{i,t-1}^2 + \delta_2 v_{i,t-1}^2 \tag{15}$$

where $i = 1, \ldots, N, t = 1, \ldots, T$, $\boldsymbol{F}_t$ is $T \times r$ and $\boldsymbol{\lambda}_{it}$ is $r \times 1$. The variables $\{\boldsymbol{\varepsilon}_{it}\}$, $\{\eta_{it}\}$, $\boldsymbol{\eta}_t$ are mutually independent *iid* N(0,1) random variables.

If the factors evolve as a vector autoregressive (VAR) model as in (10) with autoregressive parameters $\boldsymbol{B}_i$, $i = 1, \ldots, h$., then dynamic factor model is obtained. The residual vector $\boldsymbol{u}_t$ in (11), (12) are conditional heterogeneous and follow a vector GARCH model. The error terms in (13) are serially correlated, with an AR(1) coefficient α and cross-correlated coefficients θ_1 and θ_2. The innovations v_{it} in (14) and (15) are assumed to be conditional heterogeneous and follow a GARCH(1,1) process with parameters $\delta_0, \delta_1, and\ \delta_2$. In practice, when factors are constructed over a long period, some degree of temporal instability is inevitable. Therefore, we assume that the factor loading in (9) can evolve through time and has a serial correlation ρ_i to allow temporal instability in the factor model.

Before estimating the parameters in the above models, we need to extract the common factors in advance. The asymptotic principal components technique is implemented here. One starts with an arbitrary number of factors $k(k < min\{N, T\})$ and estimates λ^k and F^k by solving :

$$(\lambda^k, F^k) = \arg \min_{\Lambda^k, F^k} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(S_{it} - \boldsymbol{F}_t^k \lambda_i^k\right)^2 \tag{16}$$

subject to the normalization of either ${\boldsymbol{\Lambda}^k}^{\mathrm{T}} \boldsymbol{\Lambda}^k / N = I_k$ with $\boldsymbol{\Lambda}^k = \left[\lambda_1^k \ldots \lambda_N^k\right]^{\mathrm{T}}$ or ${\boldsymbol{F}^k}^{\mathrm{T}} \boldsymbol{F}^k / T = I_k$. One of solutions in (14) is given by $\left(\hat{\Lambda}^k, \hat{F}^k\right)$, where $\widehat{\boldsymbol{\Lambda}}^k$ is $\sqrt{N}$

times the eigenvectors corresponding to the k largest eigenvalues of the $N \times N$ matrix $\boldsymbol{S}^{\mathrm{T}}\boldsymbol{S}$, and $\widehat{\boldsymbol{F}}^{\boldsymbol{k}} = \boldsymbol{S}\widehat{\boldsymbol{\Lambda}}^{k}/N$.

4.2. Out-of-sample forecasting performance

In this section, we focus on evaluating the forecasting performance. Using the previous one-year weekly data, we estimate the parameters and produce one-week ahead forecast. Table 7 summarizes the forecasting performance. The dynamic factor model is specified in (10), (11) and (12). The dynamic factor model with dependent errors is based on additional assumptions about the error terms referred to (13), (14) and (15). The time-varying factor loading model is the most general and able to accommodate all of the possibility from (9) to (15).

The out-of-sample forecasting performance can be evaluated by (a) mean squared error (MSE) between observed CDS spreads and the predicted CDS spreads from the competing factor models; (b) mean absolute error (MAE); (c) mean correct prediction (MCP) of the direction of change in CDS spreads. The MCP exhibits the average numbers from N CDS indices are correctly forecasted based on their signs of changes; (d) the trace of R^2 of the multivariate regression of $\widehat{\boldsymbol{S}}$ onto $\boldsymbol{S}$,

$$\mathrm{R}^2_{\hat{\mathrm{S}},\mathrm{S}} = \hat{E} \parallel \boldsymbol{P_S}\widehat{\boldsymbol{S}} \parallel^2 / \hat{E} \parallel \widehat{\boldsymbol{S}} \parallel^2 = \hat{E}tr\left(\widehat{\boldsymbol{S}}^{\mathrm{T}}\boldsymbol{P_S}\widehat{\boldsymbol{S}}\right) / \hat{E}tr\left(\widehat{\boldsymbol{S}}^{\mathrm{T}}\widehat{\boldsymbol{S}}\right), \tag{17}$$

where $\hat{E}$ denotes the expectation estimated by averaging the relevant statistic and $\boldsymbol{P_S} = \boldsymbol{S}(\boldsymbol{S}^{\mathrm{T}}\boldsymbol{S})^{-\boldsymbol{1}}\boldsymbol{S}^{\mathrm{T}}$. As shown in Table 7, the time-varying factor loading model exhibits the best one-week ahead point-forecast performance with the lowest MSE, MAE and the highest MCP, trace of R^2. In addition, the forecasting performances under different numbers of factors in each competing model are measured. The number of factors ranges from one to seven because of $k < min\{N, T\}$. These k estimated factors in the competing factor models will be used to estimate r (the true number of factors). Table 7 indicates that the dynamic and the time-varying factor loading model constitute a marked improvement over the static factor model. The static factor model with a poorest forecast performance may suggest that the factors exhibit persistency, predictability and temporal instability, and these characteristics contribute to the prediction on the changes of CDS indices. To make more solid conclusions, we need to check equal predictive ability against the static factor model, see Section 4.3.

Determining the number of factors can be regarded as a model selection problem, that is a trade-off between goodness of fit and parsimony. Following Bai and Ng (2002), the number of factors is estimated by an information criteria function (IC):

$$k = \arg\min_{0 \le k \le kmax} IC(k) \tag{18}$$

where $IC(k) = \ln\left(V\left(k, \widehat{\boldsymbol{F}}^k\right)\right) + kg(N, T)$. $V\left(k, \widehat{\boldsymbol{F}}^k\right) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(S_{it} - \widehat{\boldsymbol{F}}_t^k \lambda_i^k\right)^2$ is simply the average residual variance, and $g(N, T)$ is a penalty function for overfitting. Let $kmax = min\{N, T\}$ be a bounded integer such that $r \le kmax$. Bai and Ng (2002) have proposed three specific formulations of $g(N,T)$ that depend on both N and T.

$$IC_{p1}(k) = \log\left(V\left(k, \widehat{\boldsymbol{F}}^k\right)\right) + k\left(\frac{N+T}{NT}\right)\log\left(\frac{NT}{N+T}\right) \tag{19}$$

$$IC_{p2}(k) = \log\left(V\left(k, \widehat{\boldsymbol{F}}^k\right)\right) + k\left(\frac{N+T}{NT}\right)\log(min\{N,T\}) \tag{20}$$

$$IC_{p3}(k) = \log\left(V\left(k, \widehat{\boldsymbol{F}}^k\right)\right) + k\left(\frac{\log(min\{N,T\})}{min\{N,T\}}\right) \tag{21}$$

Table 7 summarizes the results of *IC* function and shows that for both static factor model and dynamic factor model, the one-factor model, with the minimized information criteria, is the best one to model the common factors in the changes of CDS spreads. However, for both dynamic factor with dependent errors model and time-varying factor loading model, the two-factor model is adequate enough to capture the time-variation in the changes of CDS indices.

4.3. Testing equal predictive ability

To formally assess the statistical significance of the superior out-of-sample performance of the competing dynamic factor models over the static factor model, we employ the equal predictive ability test of Diebold and Mariano (1995) and report the testing results in Table 8. Diebold and Mariano (1995) proposed a method for measuring and assessing the significance of divergences between two competing forecasts, and allow for forecast errors that are potentially non-Gaussian, serially correlated and contemporaneously correlated.

To be specific, let d_t be the loss differential between two forecast errors. The null hypothesis is no difference in the accuracy of two competing forecasts, that is $\mathrm{E}d_t = 0$. The asymptotic distribution of the sample mean loss differential is :

$$\sqrt{T}\left(\bar{d} - \mu\right) \sim N(0{,}2\pi f_d(0)) \tag{22}$$

where $f_d(0)$ is the spectral density of the loss differential at frequency 0.

The statistical significance of the difference in forecast errors between the competing factor models is summarized in Table 8. The tabulated *p*-values indicate that we can reject the null hypothesis of equal forecasting ability between the static factor model and the time-varying factor model. We also reject the equal predicting ability between the static factor model and the dynamic factor with dependent errors model. With the exception in CDX five-year IG and ten-year HY indices, the equal predictive ability between the static factor model and the dynamic factor model is rejected. Furthermore, to claim that the time-varying factor model is the best one, we compare its forecast ability with the dynamic factor model and the dynamic factor with dependent errors model, and find that there exists the significant differences in their predicting ability in the both cases.

In sum, the results in Table 7 together with Table 8 reveal a statistically significant superior predictive ability of the time-varying factor model for most of cases, suggesting that the common factors drive the time-variation of CDS indices and the dynamics in the factors exhibit moderate predictability in the short-run. In addition, the temporal instability in the common factors is inevitable and contributes to forecasting. By comparing the performance between the dynamic factor model and the dynamic factor with dependent error model, the serial or cross correlation in the errors have little effect on the forecasts. The finding implies that the systematic component factors dominate the predicting performance. The predictability of CDS spreads changes enables investors to hedge, speculate and arbitrage in the credit derivative markets.

5. Conclusion

The commonalities in CDS spreads and their factor loadings are analyzed in this study. We collect CDS indices in North American and Europe with 5- and 10-year maturities, and with different credit rating (IG and HY) from Oct. 2004 to Jun. 2011. The market prices of factor risks estimated by GMM method suggest that a four-factor model provides a good fit in describing the changes of CDS indices. The estimated risk factors can be interpreted as the *level*, the *credit*, the *volatility* and the *term structure* effect. By conducting a test if there are common principal components, we find that the eigenstructures are distinct for the pre-, during and post-crisis periods. The first factor explains 58.7% of the variance in the pre-crisis period, 72.3% of the variance in the crisis period and 47% of the variance in the post-crisis period, indicating that during the crisis, CDS spreads are increasingly driven by common or systematic factors and less by idiosyncratic factors. The determinants of risk factors differ for the three subperiods. The common risk factors in the pre-crisis period are mostly determined by the conditions of U.S. market. During the crisis, the European interest rate term structure and credit quality shed lights on the common risk factors. However, the interpretation for the post-crisis period only attributes to the European variables.

The time-variation of CDS indices changes is modeled via various competing models. We apply the asymptotic principal component technique to extract the common factors, and then determine the number of factors by information criteria functions. The out-of-sample forecasting performance and the result of equal predictive ability indicate that the common factors drive the time-variation of CDS indices and the dynamics in the factors exhibit moderate predictability in the short-run. In addition, the temporal instability in the common factors is inevitable and contributes to forecasting, but the serial or cross correlation in the errors have little effect on the forecasts. The predictability of CDS spreads changes enables investors to hedge, speculate and arbitrage in the credit derivative markets.

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Table 1. summary statistics for whole sample period, pre-, during and post-crisis period.

	whole samples		pre-crisis		crisis		post-crisis	
	mean	St. Dev	mean	St. Dev	mean	St. Dev	mean	St. Dev
CDX.IG.5Y	0.47	18.68	-0.21	2.51	1.71	16.65	-0.01	32.43
CDX.IG.10Y	0.17	7.02	-0.16	2.64	0.83	11.58	-0.15	2.98
CDX.HY.5Y	-0.12	17.23	-0.31	3.20	0.29	25.57	-0.35	17.96
CDX.HY.10Y	0.46	14.01	-0.14	3.58	1.25	21.36	0.43	13.02
EU.IG.5Y	0.17	10.21	-0.19	1.63	0.42	15.14	0.48	10.74
EU.IG.10Y	0.35	8.62	-0.11	2.06	1.02	13.22	0.24	7.86
EU.HY.5Y	0.86	38.60	-1.65	11.86	4.43	58.11	0.43	36.13
EU.HY.10Y	1.06	29.35	-1.08	13.15	4.93	43.30	-0.44	26.18

Notes: The whole sample period covers from Oct. 2004 to Jun. 2011. The indices are selected by its regions: North American (CDX), Europe (iTraxx EU), by maturities: 5- and 10-year, by credit rating: investment-grade (IG) and high-yield grade (HY). We have 134 weekly observations in the pre-crisis period (from Oct. 2004 to May. 2007), 104 observations in the crisis period (from Jun. 2007 to Jul. 2009) and 76 observations in the post-crisis period (from Aug. 2009 to Jun. 2011). The CDS indices are quoted as basis point and their mean and standard deviation are reported.

Table 2. Explained variance by principal component analysis

	% variance explained				Total variance explained
	Factor 1	Factor 2	Factor 3	Factor 4	
Whole sample	63.0%	12.0%	8.0%	7.5%	90.5%
Pre-crisis	58.7%	13.3%	9.0%	7.6%	88.6%
Crisis	72.3%	12.4%	5.4%	4.0%	94.1%
Post-crisis	47.0%	16.5%	12.6%	10.2%	86.5%

Notes: For whole sample period and three subperiods, the table presents the proportion of the total variance of the changes of CDS spreads explained by the variation of a given factor.

Table 3. Estimated factor loadings

	Whole sample period				Crisis period			
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
CDX.IG5Y	0,337	0,921	0,353	-0,079	0.267	0.666	0.481	0.148
CDX.IG10Y	0,308	0,278	-0,697	0,431	0.305	0.518	-0.391	-0.581
CDX.HY5Y	0,379	-0,039	-0,178	-0,522	0.384	-0.127	-0.389	0.153
CDX.HY10Y	0,389	-0,066	0,002	0,221	0.376	-0.136	-0.454	0.118
EU.IG5Y	0,372	-0,025	-0,208	-0,585	0.377	0.032	-0.004	0.590
EU.IG10Y	0,401	-0,063	0,017	0,251	0.382	0.014	0.207	0.086
EU.HY5Y	0,385	-0,175	0,406	-0,003	0.362	-0.360	0.339	-0.148
EU.HY10Y	0,380	-0,184	0,387	0,285	0.351	-0.347	0.315	-0.475

Notes: this table reports the estimated factor loadings for the whole sample and for the crisis period.

Table 4. Regression analysis for interpreting estimated factors portfolios (whole sample period)

	U.S.				Europe				
	Level	Credit	σ	Yield Curve	Level	Credit	σ	Yield Curve	R^2
FRP1	-1.189	1.284	3.410	-0.825	-0.224	1.777	0.927	1.620	0.56
	(-4.79)	(5.17)	(2.98)	(-4.26)	(0.74)	(5.61)	(0.78)	(5.18)	
FRP2	0.390	-0.112	-2.218	0.396	0.228	-0.188	1.095	-0.425	0.26
	(2.93)	(-0.84)	(-3.62)	(3.81)	(1.40)	(-1.02)	(1.57)	(-2.32)	
FRP3	-0.415	0.357	1.373	-0.491	-0.401	0.649	0.783	0.690	0.41
	(-2.95)	(2.54)	(2.12)	(-4.48)	(-2.33)	(3.49)	(1.11)	(3.75)	
FRP4	0.010	-0.246	0.733	-0.075	-0.056	-0.049	-0.218	0.015	0.16
	(0.02)	(-3.11)	(2.11)	(-1.22)	(-0.57)	(-0.45)	(-0.63)	(0.19)	

Notes: The one-year treasury bond rate represents level of the risk-free interest rate in U.S., while The one-year Euribor rate measures level of the risk-free interest rate in Europe. The difference between the ten-year treasury bond rate and the one-year treasury bond rate is used to evaluate the slope of the yield curve in U.S.. In Europe, the term structure of interest rate is measured by the spread between ten-year yield of Merrill Lynch Euro Union Government bond index and one-year Euribor rate. The credit spread in U.S. is the difference between the average Moody's Baa yield and the average Moody's Aaa yield of U.S. corporate bonds. In Europe, it is the difference between the Markit iBoxx Europe high-yield index and the Markit iBoxx Europe investment-grade index. The volatilities in the U.S. and in Europe are measured by CBOE VIX and VSTOXX index, respectively. The estimated coefficients in (6), *t*-statistics in parentheses and the adjusted R^2 are reported.

Table 5. Regression analysis for interpreting estimated factors portfolios (three subsample periods)

		U.S.				Europe				
		Level	Credit	σ	Yield Curve	Level	Credit	σ	Yield Curve	R^2
Pre-Crisis	FRP1	0.283	1.046	2.560	-0.035	-0.662	-0.013	-0.986	-0.478	0.46
		(1.46)	(2.99)	(2.69)	(-0.15)	(-1.69)	(-0.04)	(-1.05)	(-1.20)	
	FRP2	0.218	0.493	1.549	0.032	-0.294	0.036	-0.443	-0.394	0.29
		(1.36)	(1.70)	(1.97)	(0.16)	(-0.91)	(0.14)	(-0.57)	(-1.20)	
	FRP3	0.042	0.165	0.718	0.104	-0.008	0.100	-0.334	-0.151	0.17
		(0.52)	(1.14)	(1.82)	(1.08)	(-0.05)	(0.78)	(-0.86)	(-0.91)	
	FRP4	0.199	0.241	1.153	0.025	-0.245	-0.010	-0.120	-0.298	0.31
		(1.69)	(1.13)	(1.99)	(0.17)	(-1.03)	(-0.05)	(-0.21)	(-1.23)	
During Crisis	FRP1	-1.558	-0.074	1.322	-1.314	1.200	1.910	1.376	2.077	0.61
		(-3.38)	(-0.14)	(0.54)	(-3.13)	(1.95)	(3.59)	(0.64)	(3.58)	
	FRP2	-0.711	0.004	2.264	-0.638	-0.102	0.671	-0.859	0.756	0.48
		(-2.43)	(0.01)	(1.46)	(-2.41)	(-0.26)	(1.99)	(-0.63)	(2.06)	
	FRP3	-0.126	-0.031	1.070	-0.403	-0.599	0.156	0.260	0.118	0.40
		(-0.61)	(-0.13)	(0.98)	(-2.15)	(-2.18)	(0.65)	(0.27)	(0.45)	
	FRP4	0.141	0.183	-1.532	0.241	0.098	-0.336	0.265	-0.274	0.32
		(0.70)	(0.79)	(-1.44)	(1.32)	(0.36)	(-1.45)	(0.28)	(-1.08)	
Post-Crisis	FRP1	-0.729	0.611	1.575	-0.063	4.163	1.861	2.445	1.044	0.60
		(-0.58)	(1.02)	(0.71)	(-0.13)	(2.27)	(3.06)	(1.06)	(1.96)	
	FRP2	0.314	-0.198	0.718	-0.054	0.172	0.101	-0.449	0.061	0.03
		(0.37)	(-0.49)	(0.48)	(-0.17)	(0.14)	(0.25)	(-0.29)	(0.17)	
	FRP3	-0.952	-0.047	2.946	-0.428	-2.915	-0.885	-3.081	0.052	0.17
		(-0.85)	(-0.09)	(1.51)	(-1.02)	(-1.97)	(-1.64)	(-2.51)	(0.11)	
	FRP4	0.053	-0.030	-0.964	0.334	-0.941	-0.145	-0.415	-0.447	0.43
		(0.10)	(-0.12)	(-1.07)	(1.72)	(-1.25)	(-0.58)	(-0.44)	(-2.06)	

Notes: the regression analysis in (6) can be conducted in the three subperiods. We have 134 weekly observations in the pre-crisis period (from Oct. 2004 to May. 2007), 104 observations in the crisis period (from Jun. 2007 to Jul. 2009) and 76 observations in the post-crisis period (from Aug. 2009 to Jun. 2011). The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported.

Table 6. Estimation of factor risk prices

	Four-factor model	Five-factor model
Factor 1	-10.746 (-10.462)	-13.565 (3.483)
Factor 2	-2.722 (-10.902)	-3.385 (-3.833)
Factor 3	0.450 (5.472)	0.366 (2.521)
Factor 4	0.492 (2.575)	0.495 (2.256)
Factor 5		0.115 (0.982)
J-statistic	1.206 (0.876)	0.828 (0.842)
R^2 of GLS	95.42%	95.89%

Notes: the market price of factor risk is estimated using the GMM and the value in parentheses is *t*-statistic. The GMM *J*-statistics and the associated *p*-values are also presented to test the overidentifying restrictions. The R^2 of GLS regression evaluates the goodness-of-fit of the factor models.

Table 7. Forecasting performance

	MSE	MAE	MCP	TraceR^2	IC_{p1}	IC_{p2}	IC_{p3}
A. Static Factor Model							
k=1	837.196	14.479	4.184	0.079	7.014	7.041	6.989
k=2	935.015	15.225	4.113	0.090	7.409	7.464	7.360
k =3	980.284	15.649	4.113	0.095	7.741	7.823	7.667
k =4	994.165	15.797	4.067	0.096	8.040	8.149	7.941
k =5	1011.411	15.915	4.166	0.098	8.341	8.478	8.218
k =6	1011.353	16.002	4.083	0.098	8.626	8.790	8.478
k =7	1014.162	16.074	4.067	0.098	8.913	9.105	8.741
B. Dynamic Factor Model							
k=1	512.226	11.061	4.127	0.123	6.523	6.550	6.498
k=2	515.263	11.387	4.109	0.108	6.813	6.876	6.812
k =3	521.053	11.530	4.072	0.106	7.109	7.191	7.035
k =4	527.623	11.547	3.949	0.105	7.406	7.516	7.308
k =5	518.325	11.604	4.040	0.109	7.673	7.810	7.550
k =6	521.404	11.634	4.149	0.112	7.963	8.128	7.816
k =7	521.863	11.618	4.189	0.110	8.249	8.440	8.076
C. Dynamic Factor with Dependent Errors model							
k=1	725.655	13.458	4.069	0.082	6.871	6.898	6.847
k=2	540.526	12.439	4.125	0.098	6.861	6.876	6.812
k =3	534.201	11.844	4.127	0.110	7.134	7.721	7.060
k =4	526.395	11.672	4.109	0.115	7.404	7.513	7.305
k =5	524.747	11.628	4.021	0.113	7.685	7.822	7.562
k =6	527.945	11.575	4.076	0.105	7.976	8.140	7.828
k =7	521.499	11.568	4.123	0.110	8.248	8.440	8.076
D. Time-varying Factor Loading							
k=1	784.773	13.293	3.985	0.036	6.949	6.977	6.925
k=2	509.891	12.079	4.101	0.129	6.803	6.858	6.754
k =3	493.244	11.744	4.090	0.114	7.054	7.136	6.980
k =4	479.815	11.443	4.105	0.151	7.311	7.421	7.213
k =5	479.944	11.415	4.061	0.155	7.596	7.733	7.473
k =6	481.839	11.384	4.130	0.148	7.885	8.049	7.737
k =7	479.683	11.383	4.185	0.156	8.165	8.356	7.992

Note: the information criteria function IC_{p1} , IC_{p2} and IC_{p3} can be referred to (19), (20) and (21) in the text.

Table 8. Comparing predictive accuracy

	Static factor v.s. dynamic factor	Static Factor v.s. dynamic factor & dependent errors	Static factor v.s. time-varying factor loading	Dynamic factor v.s. dynamic factor & dependent errors	Dynamic factor v.s. time-varying tactor loading	Dynamic factor & dependent errors v.s. time-varying factor loading
CDX.IG.5Y	1.345	26.337	7.588	29.714	9.135	37.224
	(0.089)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CDX.IG.10Y	3.985	6.801	13.870	5.669	17.019	11.719
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CDX.HY.5Y	2.479	3.118	6.188	1.930	6.887	5.568
	(0.006)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)
CDX.HY.10Y	1.567	8.736	7.136	16.304	14.266	3.399
	(0.058)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EU.IG.5Y	2.175	9.721	10.397	16.590	16.910	2.490
	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
EU.IG.10Y	8.376	7.283	17.643	1.625	23.472	24.876
	(0.000)	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)
EU.HY.5Y	1.808	4.587	0.892	15.280	7.392	13.696
	(0.035)	(0.000)	(0.186)	(0.000)	(0.000)	(0.000)
EU.HY.10Y	5.070	7.032	12.389	6.983	14.079	8.240
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: this table reports the statistics and p-values of the Diebold and Mariano (1995) test of equal predictive ability.

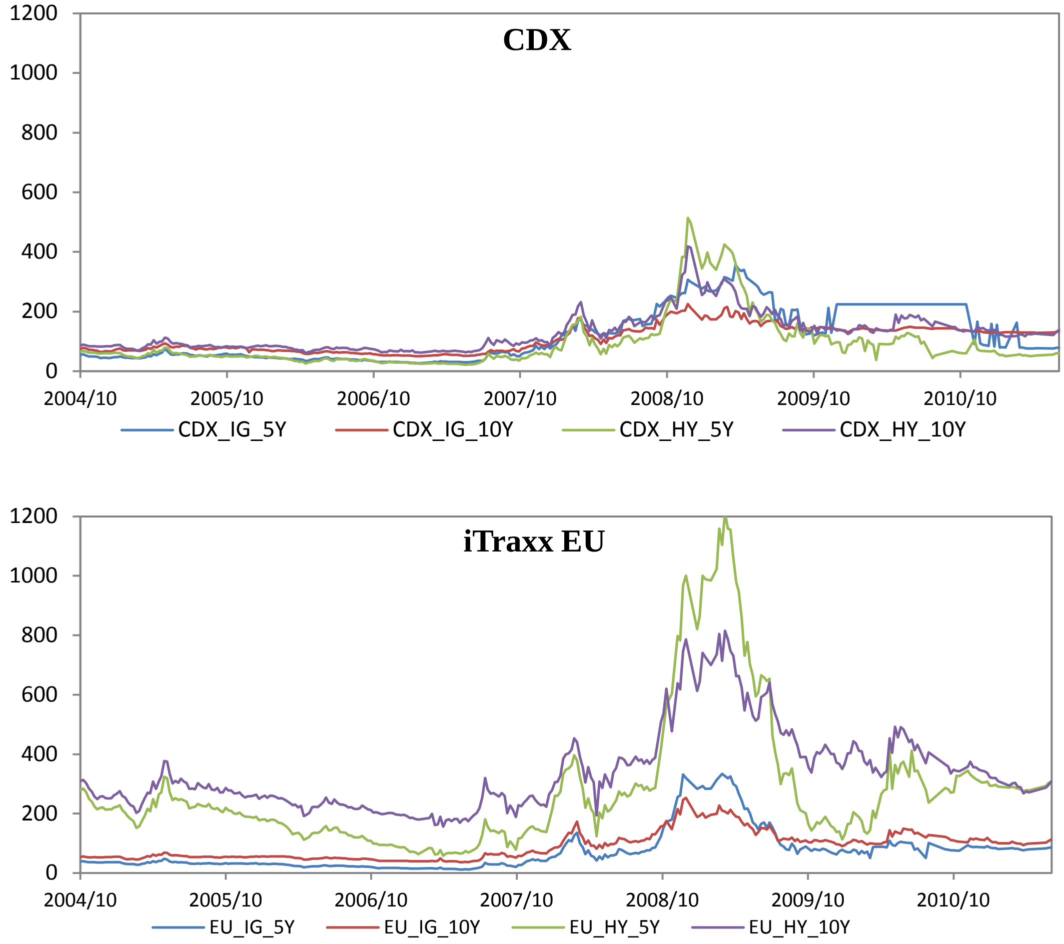

Fig. 1. Time series plots of CDX index and iTraxx EU index.

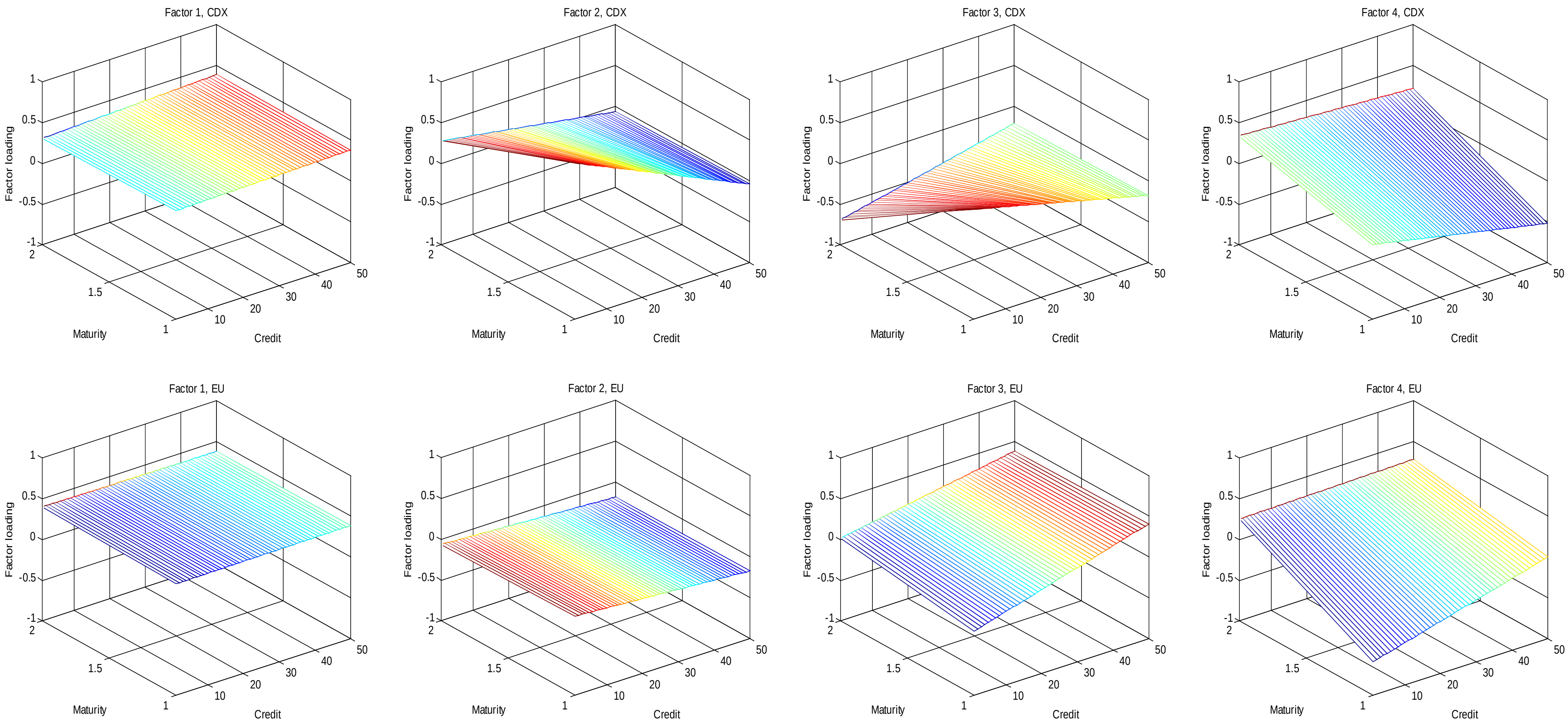

Fig. 2. The relationship between Factor loadings, credit ratings and maturities.

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