SFB 649 Discussion Paper 2014-038

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This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

http://sfb649.wiwi.hu-berlin.de
ISSN 1860-5664

SFB 649, Humboldt-Universität zu Berlin
Spandauer Straße 1, D-10178 Berlin

SFB 649 ECONOMIC RISK BERLIN

The integration of credit default swap markets in the pre and post-subprime crisis in common stochastic trends

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Abstract

It was evident that credit default swap (CDS) spreads have been highly correlated during the recent financial crisis. Motivated by this evidence, this study attempts to investigate the extent to which CDS markets across regions, maturities and credit ratings have integrated more in crisis. By applying the Panel Analysis of Non-stationarity in Idiosyncratic and Common components method (*PANIC)* developed by Bai and Ng (2004), we observe a potential shift in CDS integration between the pre- and post-Lehman collapse period, indicating that the system of CDS spreads is tied to a long-run equilibrium path. This finding contributes to a credit risk management task and also coincides with the missions of Basel III since the more integrated CDS markets could result in correlated default, credit contagion and simultaneous downgrading in the future.

JEL classification: *C38; G32; E43*

Keywords: Credit default swaps; cointegration; common stochastic trend; correlated default

The authors gratefully acknowledge financial support from the Deutsche Forschungsgemeinschaft through SFB 649 ”Economic Risk” and IRTG 1792 ”High Dimensional Non Stationary Time Series”.

1. Introduction

The recent US subprime crisis has brought illiquidity and credit risk in the financial market into focus. These two risk types are often very difficult to differentiate especially in the banking sector. When do we know that a financial institution is insolvent because of its own failed business strategy (e.g. wrong investment decisions) or because of the illiquid market which leads to price slumps and value adjustments of its trading book? In the recent financial crisis it was observed that illiquidity was not caused by bank runs but by collateral runs through the increase in margin requirements as modern financial institutions finance themselves through wholesale funding markets and securitized lending (e.g. repo). These runs can cause spillover and contagion effects because changes in prices lead to losses which decrease the net worth of financial institutions, the so called liquidity spiral (Brunnermeier and Oehmke (2013), Gorton and Metrick (2011), Krishnamurthy, Nagel, and Orlov (2011), and Copeland, Martin, and Waler (2010)). As a consequence, fire sales occur which further depresses the prices on the market. Financial institutions' net worth reduction will affect their credit risk which embodies another source of credit risk co-integration besides the price effect. Fig. 1 displays the loss spiral triggered by a shock on capital on the market.

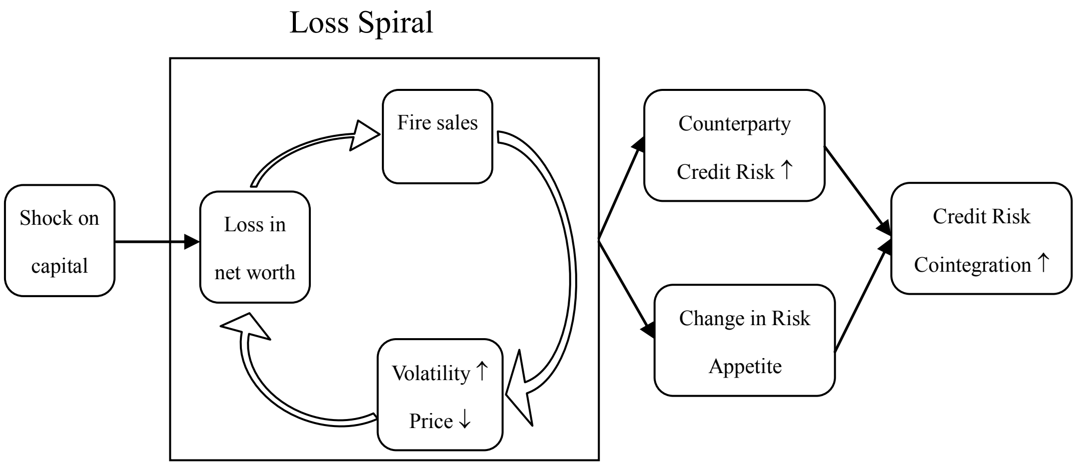

Fig. 1. Credit Risk Cointegration triggered by shock event.

Liquidity spiral illustration according to Brunnermeier and Oehmke (2013)

Accompanied by recent research, Credit Default Swap (CDS) spreads are used as a proxy for credit risk as CDS soreads are liquid and react quickly to changes on the market (Longstaff et al. 2007). Coudert and Gex (2010) find that an apparent credit contagion might be due to the strong interdependence and integration of the CDS markets. Further, Wang and Moore (2011) find that Lehman's default has strengthened the integration of the sovereign CDS markets, especially for the developed market. In integrated credit markets, CDS spreads across different regions, maturities and credit ratings are expected to have a common stochastic trend. CDS spreads are linked closely in an integrated market that movements in prices in one reference entity immediately impact CDS prices of other reference entities in the local market or the foreign markets. The comovements imply their common tie to a long-run equilibrium path. This study attempts to investigate the existence of common stochastic trends in a system of CDS spreads between the pre- and post-Lehman collapse period. Dooley and Hutchison (2009) and Wang and Moore (2012) find that sovereign CDS spreads have higher correlations and comovement during the US subprime crisis, implying a greater integration. Their studies, however, are limited to the sovereign entities without covering the corporate or institution entities. It's accepted by the empirical evidence that when the crisis reached its peak, the comovements in CDS spreads across different maturities, and credit ratings and regions were more profound. Wang and Moore (2012) argued that the higher correlations are generally more associated with global risk premia and capital flows, implying susceptibility to global economic conditions. During the outbreak of the crisis, the common factors seem to play a major role in the comovement of CDS markets. Chen and Härdle (2014) and Eichengreen et al. (2009) investigate the influence of common factors by using the technique of principal component analysis. After the outbreak of the crisis, they found a higher comovement in CDS markets caused by a higher systematic credit risk that is measured by the significant common factors.

This study investigates the extent to which CDS markets across regions, maturities and credit ratings are more integrated during the U.S. subprime crisis. We conduct a closer assessment of the potential shift in CDS integration between the pre- and post-Lehman collapse period. Our research provides an approach to investigate the long-run relationship and co-integration in credit markets by exploring the integration of CDS markets across regions, maturities and credit rating. We apply the panel data analysis on CDS spreads due to the availability of panel data with a long time span, and the growing use of cross-region, cross-maturity and cross-rating data in academia and industry. A panel of unit root test and cointegration test developed by Bai and Ng (2004) is applied. They develop the Panel Analysis of Non-stationarity in Idiosyncratic and Common components (hereafter PANIC) methodology that uses the factor structure of large dimensional panels to understand the nature of nonstationarity in the data. If one of the common factors is unit root, then this I(1) common factor represents an unobservable common stochastic trend. Many CDS series might contain the same stochastic trends so that they are cointegrated. We infer that they may have long-run co-integrating relations in the panel as long as the pooled idiosyncratic errors are stationary. In sum, the presence of cointegration across cross-sectional units introduces *long-run cross-sectional dependencies*, implying that the system of CDS spreads is tied to one long-run equilibrium path. As a result, correlated default, credit contagion and concurrent downgrading caused by more integrated CDS markets would incur higher challenges in credit risk management.

The recent studies on the investigation of the cointegration of CDS markets are concentrated on the univariate approach such as Dooley and Hutchison (2009), Coudert and Gex (2010), and Wang and Moore (2012). They tend to estimate the cross-correlation coefficients or variance-covariance matrices to claim the evidence of cointegration. In the study of Wang and Moore (2012), the higher cointegration is claimed based on the higher pairwise correlations between US and non-US CDS spreads. Instead, multivariate analysis such as the PANIC method is likely to overcome the size and power constraints associated with the use of a univariate time series. The pooled tests that exploit cross-section information are supposed to be more powerful than univariate unit root tests. On the other hand, the factor structure in the panel unit root test can accommodate the problem of cross-section dependence. We note this in CDS markets not only because it creates a severer statistical problem in testing the unit roots, but also because the banking industry and bond portfolio management need to be concerned with correlated defaults caused by cross-sectional cointegrated relations.

One of the main proposals regarding counterparty credit risk (CCR) in the Basel III regulation is to increase the correlation assumptions by increasing the risk weighting of systematically important financial institutions (BIS, 2014). This proposal is made based on the assumption of the regulators that correlations among systemically important financial institutions increase during a crisis and are higher than correlations among non-financial institutions. In our research we have proved that the integration of CDS indices behave differently in normal periods than in comparison to distressed periods. This has also been observed by CDS indices across regions and in different rating classes. In general, we approved the assumption made by Basel III as one of our main finding is the overall increase in correlation in the crisis period. Our research contributes in explaining the related behavior of CDS indices as there is not much known about the relationship between CDS indices of the US and Europe until now.

The remainder of this study is organized as follows. The next section discusses the possible sources of cointegration in CDS markets. Section 3 describes the data we used and examines their correlations. Section 4 introduces the PANIC method to estimate the numbers of common stochastic trends and to perform a panel cointegration test. In section 5, we examine the underlying determinants that have driven an increase in cointegration, followed by a conclusion.

2. Sources of cointegration

The main sources that have contributed to the integration of CDS markets include (1) concentrated counterparty credit risk; (2) a closer interdealer relationship; (3) a closer business relationship between suppliers or consumers (4) the change in the risk appetite of investors; (5) an increased transparency in the CDS markets. The first main source, the concentrated ***counterparty credit risk*****,** emerges through the CDS seller's default risk, and it has become more serious since the bankruptcy of Lehman Brothers in Sep. 2008. As Lehman Brothers had been a major counterparty on CDS markets, its failure has immediately raised the concern about the value of CDS contracts, and the possibility of other CDS sellers not to honor their contracts. CDS buyers recognized that creditworthiness of counterparties is highly important. On the other hand, the CDS market was concentrated on a very limited amount of dealers, a dozen as at the end 2009. The European central bank (2009) documented that the 10 largest dealers account for a significant portion of gross notional trading volume. The CDS market becomes more integrated in terms of this concentration.

Recently, a closer interdealer relationship has been organized through interdealer brokers (IDBs) who match buy and sell side dealers (Avellaneda and Cont, 2010). In this trading mechanism, the dealers tend to form a small, highly interconnected network, so that a large proportion of transactions are done between dealers themselves for hedging trades with their clients or for risk management purposes. A higher interaction between major players in the CDS markets during the post-crisis period may increase comovement and integration.

A firm's financial distress usually has adverse effects on other firms as supplier or consumer. As financial markets have become more integrated during the crisis, default intensities of interdependent firms are better linked together, pushing a higher comovement in their CDS spreads. The change in the risk appetite of investors due to risk re-assessment is another source of cointegrated CDS markets. Under the distress, investors are urged to re-evaluate the asset risk and adjust their investments subsequently. Kumar and Persaud (2002) argued that a sudden drop in investors' risk appetite will spread the crisis. Pan and Singleton (2008) pointed out that a substantial portion of the comovement of CDS spreads across countries was induced by changes in investors' appetites for credit exposure at a global level, rather than at a country level. In this regard, a simultaneous risk adjustment for all credit assets across countries, maturities and credit ratings may lead to a higher comovement and a more cointegrated market.

The transparency of CDS markets has gradually improved since the default of Lehman (Avellaneda and Cont, 2010). Central clearing and increased reporting of CDS trades to data repositories are important steps towards increased transparency, which regulators intend to use for monitoring and enhancing market stability. The CDS market has attracted considerable concerns from regulators after a number of large scale incidents from 2007 to 2009. It's argued that transparency is necessary for proper functioning and stability of markets, and more transparency leads to more liquidity. Transparency is supposed to encourage greater participation in the CDS markets, and then enhance liquidity and market efficiency. By providing better information for pricing different CDS contracts, regulatory transparency and market transparency will benefit the integration of CDS markets.

In summary, an increased integration of CDS markets that may be induced by higher counterparty credit risk, change in investors' risk appetite on a global level, and an increased transparency would lead to (1) ***correlated default*** (2) ***credit contagion*** and (3) ***simultaneous downgrading*** between market participants. As observed in the recent financial crisis, main losses were not caused by default of a counterparty but by valuation adjustments resulting from downgrades of counterparty credit rating (Brunnermeier and Oehmke (2013)). This is associated with the interconnectedness between market members. Therefore, regulators have to account for the correlation in the counterparty credit risk in their regulation proposal. Understanding how and why corporate defaults are correlated is particularly important for the risk management of debt portfolios, since banks have to retain greater capital to survive default losses if defaults are heavily clustered in time. Credit loss in reality may be higher than expected as CDS markets have become highly integrated. There is no doubt that an increased market integration would diminish the benefits of risk diversification of credit asset portfolios. An issue of integration is also crucial for the rating and risk analysis of structured credit products, such as collateralized debt obligations (CDOs) and options on portfolios of credit default swaps, that are exposed to correlated default.

3. CDS spreads correlations

3.1. Data

Synthetic credit indices have become increasingly popular in recent years. This is mostly driven by the higher tradability in comparison to a basket of bond indices or single name CDS contract. Credit indices are highly liquid, and traded by banks and institutional investors. For our panel data analysis we apply CDS indices data provided by Markit. The Markit CDX family of indices includes the most liquid baskets covering North American investment-grade, high-yield, and also emerging markets single name credit default swaps. In addition, Markit also owes and manages the Markit iTraxx family including iTraxx Europe and Asia among others. The Markit CDS indices are rolled semi-annually in March and September. Similarly to CDS single name, there are defined credit events that trigger a close-out for individual constituents such as bankruptcy or failure to pay. For iTraxx indices a modified restructuring is also included in the set of credit events.

We collect these indices from Oct. 2004 to Jun. 2011. The indices are selected by its region: North American (CDX NA), Europe (iTraxx EU), by maturity: 5- and 10-year, and by credit rating: investment-grade (IG) and high-yield grade (HY). Therefore, eight indices with different regions, maturities and credit ratings will be analyzed in the subsequent sections. We choose the indices that are quoted on the spread basis, and each index has 315 weekly observations. Since Lehman Brother filed for bankruptcy in Sep. 2008, we split the sample into the pre-crisis period (pre-Lehman-default period from Oct. 2004 to Aug. 2008) and the post-crisis period (post-Lehman-default period from Sep. 2008 to Jun. 2011). In addition to a complete panel, we have also constructed some relatively smaller panels that group units by only one specific criteria. So we have the high-yield (HY) panel that groups all high-yield CDS spread series across regions and maturities, and the investment-grade (IG) panel that groups all investment-grade CDS spread series. The US or EU panels are constructed by grouping the units across maturities and ratings in the US or Europe, respectively. Across regions and ratings, the 5Y and 10Y panels collect 5-year maturity units and 10-year maturity units, respectively.

Table 1 summarizes the descriptive statistics for the entire sample period, pre-crisis period, and post-crisis period. During the post-crisis period, the mean level and standard deviation in each CDS spread is higher than those during the pre-crisis period to signal a higher credit risk perceived after Lehman defaulted. It is obvious that for a given region or rating, a 5-year CDS index is more volatile than a 10-year one. A higher volatility in short-term CDS contracts could possibly be induced as the term structure occasionally inverts, especially during the financial crisis (Pan and Singleton, 2008). For the 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. In that period, a higher bid-ask spread indicates a higher hedging cost faced by the protection sellers.

The time-variations of CDS indices as displayed in Fig. 2 exhibit a changing dynamic. One noticeable feature is a high level of comovement across various maturities and credit ratings. The presence of higher comovement between CDS indices motivates the study of common factors. Obviously, in Fig. 2 the peak during the outbreak of the U.S. subprime crisis shows an inversion of the risk structure. For a given maturity, a HY index should be higher than an IG one in response to 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 panic, higher default risk premiums demanded by risk-averse investors are required to compensate for the higher 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.

3.2. Statistical significance of comovement

The *Uniform Spacings* method developed by Ng (2006) allows us to summarize the "overall" statistical significance of comovement in our CDS panels across various maturities, regions and credit ratings. Instead of jointly or individually testing the sample correlations, this approach tests whether the probability integral transformation of the ordered correlations are uniformly distributed. In this sense, testing cross-section correlation is turned into testing uniformity and nonstationarity. This method starts with splitting the entire sample into two groups, small-correlation and large-correlation group, by estimating the break fraction. Ng (2006) derived a standardized spacing variance ratio (SVR) test statistic to these two subsamples ($q = 2$), which is asymptotically normally distributed $\sqrt{\eta}SVR(\eta) \sim N(0, \omega_q^2)$

$$svr(\eta) = \frac{\sqrt{\eta}SVR(\eta)}{\sqrt{\omega_q^2}} \tag{1}$$

where η is a subset of $n = N(N-1)/2$ correlations for *N* cross-sectional units, and $\omega_q^2 = \frac{2(2q-1)(q-1)}{3q}$. $SVR(\eta)$ is derived based on the second moment of spacings.

Now we apply the standardized *svr* test statistic to two subsamples, Small and Large. If the *svr* test statistic of small-correlation group is significantly different from zero, then the pairs in this small group are significantly correlated even though they have relatively smaller correlations. Given that these correlations are quantitatively smaller than those in large-correlation group, the statistics of large-correlation group should significantly differ from zero. Table 2 shows the proportion of small correlation, and the *svr* statistics from both small and large subsamples. The proportion of small correlation is around 42.85% during the pre-crisis period, which is much higher than that during the post-crisis period (10.71%) and the entire period (14.28%). A decreased proportion of small subsample from 42.85% to 10.71% implies a rising proportion in large subsample from 57.15% to 89.29%. The *svr* statistic indicates that small subsample is insignificantly different from zero during the pre-crisis period, whereas it turns to be significant during the post-crisis period. In general, there is no doubt to confirm a significant correlation in a large subsample, and it's highly possible that the overall comovements are statistically significant during the post-crisis period, even for those in a small subsample.

The groups of large- and small-correlation for the entire, pre-crisis and post-crisis period are reported in Table A. The correlations are calculated for the entire period, pre- and post-crisis period. By applying the estimated proportion of small correlation, we are able to classify the cross-sectional correlations into small and large subsamples. More interestingly, during the pre-crisis period both the 5-year and 10-year Europe HY indices are less correlated with Europe IG indices, CDX IG and HY indices, as all their correlations belong to the small-correlation group. During the crisis period, the linkage increases as the correlations have switched to large-correlation group. This evidence has attracted our attention to closely look at the fragility of European sovereign bonds since they have become more integrated after the US subprime crisis. However, Europe HY index and 10-year CDX IG index seem to be less integrated together as their correlation remains in the small-correlation group in both periods. We assume that this is driven by the fact that in general high-yield bonds have historically low correlation with other asset classes. In addition, high-yield bonds behave cyclically and they have limited sensitivity to the rising interest rate environment (Phillips (2012)). This behavior especially results in a low correlation between high-yield bonds and investment-grade bonds. Further, we observe that correlation between 10-year IG CDX and 5-year IG EU index also have switched from large-correlation group to small-correlation group. This unusual switch may be attributed to an inverted term structure of CDS curves during the financial crisis (Pan and Singleton, 2008). Overall, the majority of cross-sectional correlations has belonged to large-correlation group since the crisis, indicating that a tighter comovement and higher cointegration are likely to be experienced in CDS markets.

4. The PANIC method

The CDS spreads panels are believed to have unit roots, and this belief has led to cointegration which is useful in the modeling of a potential long-run relationship of variables. The presence of cointegration across cross-sectional units introduces *long-run cross-sectional dependencies*, implying that the European and American CDS markets are tied to a long-run dependence. Long-run cointegrated relations can be empirically investigated by the PANIC method developed by Bai and Ng (2004). The PANIC utilizes the factor structure of large dimensional panels to understand the nature of nonstationarity in the data. Instead of directly testing unit root on the observed data, this method efficiently distinguishes the source of nonstationarity between the common factor and idiosyncratic errors. By applying this approach, we may realize whether a set of CDS spreads are determined by some common driving fundamentals or whether each series reacts to its own particular fundamentals. The common factors capture the comovement or common shocks in economic time series, in this sense, they provide a way of modeling cross-sectional dependence. If one of the common factors is unit root, then this I(1) common factor represents unobservable common stochastic trend. By evidence, CDS series might share common stochastic trends so that they are cointegrated. Given that, we infer that a long-run cointegrated relation may exist as long as the pooled idiosyncratic errors are stationary.

Individually testing each of the factors for the presence of a unit root will, in general, overstate the number of common trends (Bai & Ng, 2004). The PANIC method is successful in determining the number of common stochastic trends (i.e., for the order of cointegration). We allow the common factors to be non-stationary I(1) processes, stationary I(0) processes, or a combination of both. I(0) common factors are regarded as common shocks, while I(1) common factors represent unobservable common stochastic trends. The application of this method in the first step is to specify whether there is a common stochastic trend in the common factors, and then to perform the valid pooled tests for panel data when the units are correlated. Stationarity property in the idiosyncratic errors needs to be examined to claim their panel cointegration relation.

4.1. Consider a factor model

Let S_{it} be the observed 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:

$$S_{it} = c_i + \mathbf{F}_t \lambda_i + e_{it}$$
$$\mathbf{A}(L)\mathbf{F}_t = \boldsymbol{C}(L)\boldsymbol{u}_t$$
$$(1 - \rho_i L)e_{it} = \boldsymbol{D}_{\boldsymbol{i}}(L)\epsilon_t \quad (2)$$

where $\boldsymbol{C}(L) = \sum_{j=0}^{\infty} C_j L^j$, $\boldsymbol{D_i}(L) = \sum_{j=0}^{\infty} D_{ij} L^j$, $\mathbf{F}_t$ is a vector of k 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 $E(F_t, e_{it}) = 0$. $\boldsymbol{u}_t$ and ϵ_t are mutually independent *i.i.d.* *N*(0,1) random variables. The factor is obtained by first differencing the raw data, extracting the principal component from the differenced data and re-cumulating the principal component. Assume that $\mathbf{F}_t$ is a VAR process of order *p* such that $\mathbf{A}(L) = \mathrm{I} - \mathrm{A}_1\mathrm{L} - \cdots - \mathrm{A}_p L^p$. The common factors, $\mathbf{F}_t$, may be nonstationary processes, stationary processes or a combination of both. I(0) common factors are usually seen as common shocks, while I(1) common factors represent unobservable global stochastic trends. We test whether the roots of $\mathbf{A}(L) = 0$ all lie outside of the unit circle. We allow *m* common stochastic trends (unit roots) and *r* stationary factors, with $k = m + r$. The idiosyncratic errors is I(1) if $\rho_i = 1$, and is stationary if $|\rho_i| < 1$. Here we pursue an objective for determining *m* and testing if $\rho_i = 1$.

4.2. Estimating the factors and the number of factors

The validity of PANIC hinges on the ability to obtain estimates of $\mathbf{F}_t$ and e_{it} that preserve their orders of integration, both when e_{it} is I(1) or I(0). The asymptotic principal components technique (Bai and Ng, 2002) is implemented here to estimate the factors and obtain idiosyncratic errors. The asymptotic principal components technique starts with an arbitrary number of factors $k(k < min\{N, T\})$ and estimates λ^k and F^k by solving :

$$(\lambda^k, F^k) = \arg \min_{\Lambda^k, F^k} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(S_{it} - \boldsymbol{F}_t^k \lambda_i^k\right)^2 \tag{3}$$

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 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 $\widehat{\boldsymbol{F}}^{\boldsymbol{k}} = \boldsymbol{S}\widehat{\boldsymbol{\Lambda}}^k / N$. Since the optimal number of factor is unknown, we estimate the number of factor by an information criteria function (*IC*) proposed by Bai and Ng, (2002) :

$$k = \arg \min_{0 \le k \le kmax} IC(k) \tag{4}$$

where $IC(k) = log\{V(k, \hat{\boldsymbol{F}}^k)\} + kg(N,T)$. $V(k, \hat{\boldsymbol{F}}^k) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(S_{it} - \hat{\boldsymbol{F}}_t^k \lambda_i^k)^2$ 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 $k \leq kmax$. Bai and Ng (2002) have proposed three specific formulations of $g(N,T)$ that depend on both *N* and *T*. The value of IC function suggests 5 factors in the complete panel with N=8, while it suggests 3 factors for each subsample panels.

4.3. Testing the number of common stochastic trends

The issue of nonstationarity is highly related to the concept of cointegration. If a linear combination of nonstationary variable is stationary, a set of variables is said to be cointegrated or has a long-run equilibrium relationship. We are concerned with how many stochastic trends are responsible for driving the CDS panels, and how these common trends contribute to the nonstationary property in univariate CDS spreads series. This issue also sheds some lights onto the empirical analysis of the CDS spreads. For instance, the determinants of CDS spreads by panel regression have been broadly examined in the existing literature (Collin-Dufresne, et al., 2001; Cremers et al., 2008; Tang and Yan, 2009; Cao et al., 2010;). However, rarely has recent research checked the panel unit root before conducting a regression analysis, which may cause a spurious regression induced by the inherent non-stationarity in CDS spreads.

The $\mathbf{F}_t$, a vector of k common factors, is presumed to comprise *m* integrated components (common stochastic trend, I(1)) and *r* nonintegrated components (distinct stationary linear combinations, I(0)). Following Stock and Watson (1998), the number of common trend, *m*, can be estimated by testing *k* versus *m* common stochastic trends and *m* is set to be smaller than *k (m<k)*. In their testing strategy, testing *k* versus *m* common stochastic trends is equivalent to examining the first-order serial correlation matrix of $\mathbf{F}_t$. Since $\mathbf{F}_t$ is composed of both integrated and nonintegrated components, its estimated first-order serial correlation matrix has a nonstandard limiting distribution that generally depends on nuisance parameters. A linear transformation of $\mathbf{F}_t$ mitigates this difficulty. Let $\boldsymbol{Y}_t$ denotes the final *k* integrated elements of linear transformation expressed as:

$$\boldsymbol{Y}_t = \boldsymbol{\beta}^{\mathrm{T}}\hat{\mathbf{F}}_t \tag{5}$$

where $\boldsymbol{\beta}$ is the *k* eigenvectors associated with *k* largest eigenvalues of $\mathrm{T}^{-2}\sum \hat{\mathbf{F}}_t{}^{\mathrm{T}}\hat{\mathbf{F}}_t$. $\hat{\mathbf{F}}_t$ is a k-dimensional matrix that comprises k demean factors. In terms of $\boldsymbol{Y}_t$, a test of *k* versus *m* common stochastic trends can be done by testing the rank of first-order serial correlation matrix of $\boldsymbol{Y}_t$, rank k versus rank m. Examining first-order serial correlation matrix of $\boldsymbol{Y}_t$ is conducted by regressing $\boldsymbol{Y}_t$ on $\boldsymbol{Y}_{t-1}$, therefore

$$\boldsymbol{\Phi} = [\sum \boldsymbol{Y}_t \boldsymbol{Y}_{t-1}^{\mathrm{T}}][\sum \boldsymbol{Y}_{t-1} \boldsymbol{Y}^{\mathrm{T}}{}_{t-1}]^{-1} \quad (6)$$

has k real unit roots under the null. Under the alternative, $\boldsymbol{Y}_t$ includes m integrated variables and k-m nonintegrated variables. The testing hypothesis is also equivalent to

$$\mathrm{H}_0: \lambda_{m+1} = 1, \mathrm{H}_1: \lambda_{m+1} < 1$$

where $\lambda_{\mathrm{m+1}}$ denotes the eigenvalue of $\boldsymbol{\Phi}$ with the (m+1)th-largest real part.

The test statistic for the common stochastic trend has been constructed either by the parametric or by the nonparametric method. Both test statistics are designed to test if the real part of the eigenvalue of an autoregressive coefficient matrix is unity. As suggested by Stock and Watson (1988), Bai and Ng (2004), we conduct the analysis in a nonparametric way since it is more general and only requires the weakly dependent errors, whereas the parametric test is valid only when the common trends can be represented as finite order AR(p) processes. By excluding the estimated bias term $\widehat{\boldsymbol{\eta}}$, the nonparametric-form of first sample autocorrelation matrix is:

$$\boldsymbol{\Phi}_c = [\sum \boldsymbol{Y}_t \boldsymbol{Y}_{t-1}^{\mathrm{T}} - \mathrm{T}\widehat{\boldsymbol{\eta}}^{\mathrm{T}}][\sum \boldsymbol{Y}_{t-1} \boldsymbol{Y}^{\mathrm{T}}{}_{t-1}]^{-1} \quad (7)$$

where $\widehat{\boldsymbol{\eta}} = \sum_{j=1}^{J} K(j)\left(T^{-1} \sum \hat{u}_{t-j}\, \hat{u}_t^{\mathrm{T}}\right)$. $\hat{u}_t$ is the residuals from estimating a first-order VAR in $\boldsymbol{Y}_t$ and $K(j) = 1 - \frac{j}{J+1}$, $j = 0,1, \ldots, J$. $K(j)$ is a time domain kernel. Hence, the nonparametric test statistic, $Q_c(k, m)$, for k versus m unit roots in $\boldsymbol{\Phi}_c$ is:

$$Q_c(k, m) = T\left[\hat{v}_{c,m+1} - 1\right] \quad (8)$$

where $\hat{v}_c$ is the vector of ordered eigenvalues of $\boldsymbol{\Phi}_c$ and $\hat{v}_{c,m+1}$ is the (m+1)th element of $\hat{v}_c$. By averaging the autocovariance of $\boldsymbol{Y}_t$, the modified version of $\boldsymbol{\Phi}_c$, namely $\mathrm{M}\boldsymbol{\Phi}_c$:

$$\mathrm{M}\boldsymbol{\Phi}_c = 0.5[\sum \boldsymbol{Y}_t \boldsymbol{Y}_{t-1}^{\mathrm{T}} + \boldsymbol{Y}_{t-1} \boldsymbol{Y}_t^{\mathrm{T}}) - T(\widehat{\boldsymbol{\eta}} + \widehat{\boldsymbol{\eta}}^{\mathrm{T}})][\sum \boldsymbol{Y}_{t-1} \boldsymbol{Y}^{\mathrm{T}}{}_{t-1}]^{-1} \quad (9)$$

The modified test statistic, $\mathrm{M}Q_c(k, m)$, for k versus m unit roots in $\mathrm{M}\boldsymbol{\Phi}_c$ is :

$$MQ_c(k, m) = T\left[\widehat{\omega}_{c,m+1} - 1\right] \quad (10)$$

where $\widehat{\omega}_c$ is the vector of ordered eigenvalues of $\mathrm{M}\boldsymbol{\Phi}_{\mathbf{c}}$ and $\widehat{\omega}_{c,m+1}$ is the (m+1)th element of $\widehat{\omega}_c$.

Table 3 reports the results from the PANIC method. The values of $\hat{v}_{c,1}$, denoted as the eigenvalue of $\mathbf{\Phi}_c$ in Eq. (7) with the first-largest real part, are generally larger than one. Likewise, the value of $\widehat{\omega}_{c,1}$, the first-largest real part in the eigenvalues of $\mathrm{M}\mathbf{\Phi_c}$ in Eq. (9) is never less than one. The 5% critical values for Q_c and MQ_c are -6.8 and -32.296, respectively. The test statistics of common stochastic trend either in Q_c or MQ_c fail to reject the null because they are never more negative than its corresponding critical values, implying that the CDS spreads indices across regions, maturities and credit ratings share at least one common stochastic trend. A common stochastic trend is evident by various subsample panels such as the HY and the IG panels, the 5Y and the 10Y panels, or different region groups in the U.S. or Europe. This common stochastic trend already existed in CDS markets from the pre-crisis period to post-crisis period.

The evidence of a common stochastic trend seems to indicate a potential cointegration across the units. However, the cointegrated relationship cannot yet be confirmed unless their idiosyncratic components are stationary. The following subsection tests the stationarity of idiosyncratic components.

4.4. Panel cointegration test for CDS spreads

Recently, panel cointegration tests have been developed with the goal of increase statistical power by pooling information across units and allowing for cross-sectional dependency (Chang and Nguyen, 2012; Westerlund and Edgerton, 2008; Gengenbach et al, 2006). Given the fact that the CDS indices are contemporaneously correlated as shown in Fig.2., assuming that they are independent may be inappropriate. Representing cross-sectional dependency by a common factor structure, the PANIC method tests the panel cointegration through the pooled residuals that gather information across units. In this regard, a pooled test of the idiosyncratic errors can be seen as a panel test of no cointegration (Bai and CIS, 2009). It begins to conduct augmented Dickey-Fuller (ADF) tests in each residuals, and then pool all individual *p*-values obtained from individual ADF tests. Hence, consider testing

$\mathrm{H}_0\colon \rho_i = 1$ against $\mathrm{H}_1\colon \rho_i < 1$ for some $i = 1, \dots, \mathrm{N}$.

The idiosyncratic errors are assumed to be independent. By pooling the *p*-values of the individual ADF tests across *i* unit, the test statistics for idiosyncratic errors are:

$$P_e = \frac{-2\sum_{i=1}^{N} \log p_e(i) - 2N}{\sqrt{4N}} \rightarrow \mathrm{N}(0,1) \tag{11}$$

where $p_e(i)$ is the p-value associated with ADF test for each i. A larger value of P_e tends to reject the null. If $\mathrm{H}_0: \rho_i = 1$ holds, it means that no stationary combination of data series can be formed, that is, no cointegration can be found.

The cross-cointegrated relations are examined and reported in Table 4. For the entire sample period from 2004 to 2011, the CDS panel generally exhibits a long-run cross dependency, except for the IG panel. The IG panel seems to have disjunctive behavior, as it does not show a long-run cross dependency for the entire period but it has become more cointegrated during the post-crisis period. This could result from the flight-to-quality effect in distressed time when financial institutions are forced to invest in assets with good quality. As a result, investment-grade bonds benefit a higher liquidity than other markets even thought they are still suffering from spread widening. In addition, the change in investor's risk-appetite may increase the cointegration within the IG unit due to flight to quality. Investors intend to reallocate their investment in crisis period and invest in higher quality assets.

In general, the cointegrations in the designed panels are distinctive between the pre and post-crisis period. The pooled idiosyncratic errors are not able to reject the null during the pre-crisis period but significantly reject the null during the post-crisis period. It seems that during the pre-crisis period the CDS markets are less integrated but they turn to integrate together after the bankruptcy of Lehman Brother. Apparently, the bankruptcy event has altered the integration of CDS markets, implying that CDS spreads appear to comove and spill over to others than before. This fact subsequently brings correlated default, and decreases the benefits of risk diversification in credit asset portfolios.

5. Further investigation for increased market cointegration

5.1. Determinants of market cointegration

Having found long-run cross-dependency during the post-crisis period, this section examines the extent to which the driving determinants are behind the increased cointegration. Eichengreen et al. (2012) and Chen and Härdle (2014) found that common factors play a major role during and after the crisis. They further found that the eigenstructures are distinct for the pre, during and post-crisis periods, and the essences of latent factors are distinctive in three sub-periods. The degree of market integration changes corresponding to the change of the factor structure which is measured by the change of underlying determinants of latent factors. The factors, however, are latent; they are unobservable. Our strategy is to apply "observable" economic variables to represent these "unobservable" factors, and judge their changes between the pre and post-crisis period. In this regard, the changed underlying determinants of latent factors, measured by observable economic variables, may lead to a change of market integration. This investigation can be strategically performed by examining what are the underlying determinants of latent factors during the pre and post-crisis period, respectively, and then comparing their difference across two sub-periods.

The method developed by Bai and Ng (2006) is employed to determine the underlying determinants of latent factors by assessing the associations between the latent factors with the observed economic variables. A higher association indicates a higher potential to be the underlying determinants. The candidate series can be represented as a linear combination of the latent factors by permitting a limited degree of noise in this association, thus

$$G_{j,t} = \beta_j^{\mathrm{T}} \mathrm{F}_t + \varsigma_{j,t} \tag{12}$$

where G_t is an *J*-dimentional vector of observed economic variables. β_j is estimated by the OLS regression, and $\varsigma_{j,t}$ is denoted as the error term. The above equation yields the predicted value $\hat{G}_{j,t} = \hat{\beta}_j^{\mathrm{T}} \hat{\mathrm{F}}_t$. $R^2(j)$ is designed to measure the association between $G_{j,t}$ and $\hat{G}_{j,t}$ and defined as:

$$R^2(j) = \frac{\widehat{\mathrm{var}}(\widehat{G_j})}{\widehat{\mathrm{var}}(G_j)} \tag{13}$$

where $\widehat{\mathrm{var}}(\cdot)$ denotes the sample variance and $\widehat{\mathrm{var}}(\hat{G})$ is computed by using the sample analog of the factors' asymptotic covariance matrix. $R^2(j)$, bounded between zero and one, is used to examine whether any of the candidate economic series yields the same information that is contained in the factors. It is equal to one if they have a high association, and is close to zero in the absence of correlation.

As suggested by Collin-Dufresen, et al. (2001), Benkert (2004) and Ericsson, et al. (2009), we choose the *change of interest rate level, change of credit spread, change of interest rate term structure and the change of stock index volatility* as observed economic variables because they are important determinants of credit assets. The one-year Treasury bond rate represents the level of risk-free interest rate in the US. 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 the US. The credit spread is the difference between the average Moody's Baa yield and the average Moody's Aaa yield of US corporate bonds. We also employ CBOE VIX index to measure the generalized risk aversion.

Table 5 shows the association of latent factors with the chosen economic variables. During the pre-crisis period, the R^2 criterions are on a relatively high level for the term structure of interest rate. However, the analysis during post-crisis period shows that credit spread and VIX are intensively associated with latent factors. This finding is in accordance with Kumar and Persaud (2002), Pan and Singleton (2008), Cremers, et al., (2008), Cao et al. (2010) and Collin-Dufresne et al, (2001). The perceptions of credit risk were shaped by the common factors that are best summarized by credit spread and a generalized risk aversion, especially during the crisis period. The main underlying determinants of latent factors after the crisis have switched from interest rate variables to credit spread and VIX. It's understandable that under distressed market condition, higher volatility leads to a decrease in liquidity and asset price, but a rise in investor's risk aversion. More importantly, the finding suggests that either a higher perceived credit risk or generalized risk aversion could possibly induce an increased integration and a higher transmission toward systematic credit risk.

To examine the co-integrated relationship between the latent factors and the observed economic variables, Table 5 also reports the statistics of ADF unit root test for the error term. If the error term, $\varsigma_{j,t}$, is stationary, then the latent factor and the observed economic variable is cointegrated. Not surprisingly, the chosen economic variables are all cointegrated with the latent factors.

5.2. CDS spreads convergence

CDS spreads across regions, maturities and ratings may gradually converge, given the evidence that CDS spreads have cointegrated during the post-crisis period. The convergence of CDS spreads may be driven by the fact that they share at least one common stochastic trend and several stationary common factors. The PANIC method is also capable of testing the convergence properties. By examining 28 pairwise CDS spreads differentials, the stationarity of idiosyncratic error terms can be viewed as an indication of convergence. The pairwise CDS spreads differentials not only share common factors but also allow economy-specific idiosyncratic variations in the error terms. Testing the convergence is equivalent to testing whether the pooled idiosyncratic errors are stationary. A stationarity indicates a convergence, whereas a unit root implies a divergence.

Table 6 shows that the convergences between the pre and post-crisis period are dissimilar. For a complete panel, the test statistics based on 28 pairwise CDS spreads differentials can (cannot) reject the unit root after (before) the bankruptcy of Lehman Brothers. The credit market has achieved convergence during post-crisis period, caused by the concentrated CDS sellers, a closer interdealer relationship, consensus of risk assessment and an increased transparency in the CDS markets.

The convergence property for subsample panels can also be found in Table 6. The regional panels, US and Europe, have converged during the post-crisis period, implying that the convergence of CDS spreads can be achieved within the specific regions. The 10-year panel has converged, but we cannot make this statement for the 5-year panel. The longer-term CDS spreads seem to have better comovement compared with the short-term CDS spreads. In general, the CDS panels on the basis of credit ratings fail to converge, suggesting that the CDS panels converge in the region rather than in the credit rating. Economically, the comovement of CDS spreads is more possible on the basis of geography, but not for the rating basis.

6. Conclusion

This study investigates the integration of CDS markets between the pre-crisis and post-crisis period to explain why correlated default, credit contagion and simultaneous downgrading became evident during and after the US subprime crisis. By applying the PANIC method to trace where the nonstationarity comes from, the common factors or idiosyncratic error terms. We find a common stochastic trend existing on the entire sample period, but the pooled test of the idiosyncratic errors only rejects the unit root after the crisis, indicating that the cointegration can only be achieved after the crisis. Accordingly, the system of CDS spreads is tied to a long-run equilibrium path, and shares more systematic credit risk than before. We also examine which the driving determinants are behind an increased cointegration. The empirical results point out that either a higher perceived credit risk or generalized risk aversion are potentially driving forces. The credit market also converged during post-crisis period, caused by the concentrated CDS sellers, a closer interdealer relationship, consensus of risk assessment and an increased transparency in the CDS markets. The integration of CDS markets draws regulators', portfolio managers' and investors' attentions to correlated default, credit contagion issues, which supports the necessity of upcoming Basel III accord.

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Table 1. Summary statistics for entire sample period, pre, and post-crisis period.

	Entire period			Pre-crisis			Post-crisis		
	mean	std	AR(1)	mean	std	AR(1)	mean	std	AR(1)
CDX.IG.5Y	85.50	50.83	0.976	61.19	34.14	0.964	127.20	47.65	0.942
CDX.IG.10Y	97.81	36.14	0.961	79.23	24.04	0.954	129.69	30.79	0.894
CDX.HY.5Y	654.74	281.44	0.981	545.09	152.23	0.968	842.86	346.23	0.972
CDX.HY.10Y	731.68	208.13	0.956	627.32	109.42	0.941	910.71	215.60	0.906
EU.IG.5Y	70.14	69.12	0.986	35.63	20.94	0.955	129.34	81.83	0.975
EU.IG.10Y	87.45	45.24	0.975	61.48	24.02	0.956	132.01	37.76	0.926
EU.HY.5Y	269.94	221.58	0.984	177.21	73.52	0.956	429.04	290.41	0.977
EU.HY.10Y	333.38	136.37	0.970	260.86	60.15	0.924	457.80	140.84	0.938

Notes: The entire sample period covers from Oct. 2004 to Jun. 2011. The indices are selected by its regions: North American (CDX), Europe (EU), by maturities: 5-year (5Y) and 10-year (10Y), by credit rating: investment-grade (IG) and high-yield grade (HY). We have 199 weekly observations in the pre-crisis period (from Oct. 2004 to Aug. 2008), 116 observations in the post-crisis period (from Aug. 2008 to Jun. 2011). The CDS indices are quoted as the basis point, and their mean, standard deviation (std) and first autocorrelation (AR(1)) are reported.

Table 2. Spacing variance ratio test statistics

	$\hat{\theta}$	Small correlation	Small *svr*	Large *svr*
Entire period	0.1428	4 out of 28	1.997*	5.041*
Pre-crisis	0.4285	12 out of 28	1.625	4.783*
Post-crisis	0.1071	3 out of 28	2.744*	5.130*

Notes: $\hat{\theta}$ is the proportion of correlations that belong to small and estimated by minimizing the total sum of squared residuals between the spacings and its corresponding sample mean values. For more detail, please refer to Ng. (2006). The *svr* test statistic indicates whether overall correlation significantly differs from zero for a given subgroup. The *svr* is distributed as standard normal with critical value at 1.96 (significant at 5% marked with asterisk). N=8, therefore there are $n = N(N-1)/2$ =28 potential correlations. An asterisk indicates that the significance is achieved at the 5% level.

Table 3. PANIC panel unit root test for CDS spreads

This table reports the first-largest real part in the eigenvalues as well as test statistics in an autoregressive coefficient matrix to check its unity. The non-parametric test statistic $\mathrm{Q_c}$ in Eq. (8), and its corresponding eigenvalues, $\hat{v}_{c,1}$, is initiated by Stock and Watson (1998), and they are modified by Bai and Ng (2004) and denoted as $\mathrm{MQ_c}$ in Eq. (10) with the value of $\widehat{\omega}_{c,1}$, the first-largest real part in the eigenvalues of $\mathrm{M}\boldsymbol{\Phi}_{\mathbf{c}}$ in Eq. (9).

		All	HY	IG	10Y	5Y	CDX	EU
Panel A. Pre-crisis								
$\mathrm{Q_c}$	$\hat{v}_{c,1}$	2.553	3.065	1.878	2.095	2.595	2.049	2.062
	Statistic	309	411	174	217	317	208	211
$\mathrm{MQ_c}$	$\widehat{\omega}_{c,1}$	3.015	3.353	2.149	2.213	3.399	2.139	1.934
	Statistic	419	468	238	241	477	226	185
Panel B. Post-crisis								
$\mathrm{Q_c}$	$\hat{v}_{c,1}$	1.395	1.591	1.569	0.942	5.954	3.535	2.965
	Statistic	45	68	66	-6.62	574	294	238
$\mathrm{MQ_c}$	$\widehat{\omega}_{c,1}$	1.443	1.908	2.046	0.910	4.089	3.087	2.149
	Statistic	51	105	121	-10.42	358	242	133
Panel C. Entire period								
$\mathrm{Q_c}$	$\hat{v}_{c,1}$	3.217	2.265	2.026	3.565	4.073	4.193	2.718
	Statistic	698	398	323	808	968	1106	541
$\mathrm{MQ_c}$	$\widehat{\omega}_{c,1}$	3.661	2.216	2.488	3.242	3.577	4.075	2.711
	Statistic	822	383	468	706	811	968	539

Table 4. Panel cointegration test for CDS spreads

By pooling the *p*-values of the individual ADF tests across units, the test statistics for pooled idiosyncratic errors in Eq. (11) determine whether the idiosyncratic errors are unit root (under the null) or stationary. This table reports the test statistics and the corresponding *p*-values in parentheses. An asterisk indicates that the significance is achieved at the 5% level.

	Pre-crisis	Post-crisis	Entire period
All	1.483 (0.138)	3.366* (0.001)	3.036* (0.002)
HY	1.726 (0.084)	2.684* (0.007)	2.809* (0.005)
IG	0.208 (0.835)	3.185* (0.001)	0.993 (0.320)
10Y	1.391 (0.164)	2.728* (0.006)	2.565* (0.010)
5Y	1.007 (0.313)	2.894* (0.003)	2.090* (0.036)
CDX	0.098 (0.921)	1.961* (0.051)	2.482* (0.013)
EU	2.682* (0.007)	3.053* (0.002)	2.841* (0.005)

Table 5. Connecting latent factors with observed variables

This table reports the R^2 criterion as a measure of association. The observed economic variables include the one-year Treasury bond rate that represents level of the risk-free interest rate in the US, the credit spread measured as the difference between the average Moody's Baa yield and the average Moody's Aaa yield of US corporate bonds, the slope of the yield curve as the difference between the ten-year treasury bond rate and the one-year treasury bond rate, CBOE VIX index to measure the generalized risk aversion. To examine the cointegrated relationship between the latent factors and the observed economic variables, we report the statistics of ADF unit root test for the error term in parentheses.

	All	HY	IG	10Y	5Y	CDX	EU
Panel A. Pre-crisis							
Interest rate level	0.962 (-3.384)	0.958 (-1.749)	0.981 (-2.956)	0.614 (-2.050)	0.892 (-3.080)	0.957 (-1.941)	0.953 (-2.793)
Credit spread	0.833 (-2.388)	0.785 (-2.477)	0.833 (-2.428)	0.726 (-1.547)	0.893 (-3.080)	0.850 (-2.612)	0.734 (-2.292)
Term structure	0.853 (-2.284)	0.814 (-2.429)	0.839 (-2.908)	0.294 (-2.146)	0.687 (-2.590)	0.829 (-1.318)	0.789 (-1.927)
VIX	0.500 (-3.132)	0.301 (-3.045)	0.388 (-2.783)	0.527 (-2.715)	0.730 (-2.903)	0.415 (-2.893)	0.310 (-2.852)
Panel B. Post-crisis							
Interest rate level	0.525 (-2.504)	0.139 (-2.620)	0.325 (-2.299)	0.263 (-2.311)	0.307 (-2.774)	0.424 (-2.397)	0.225 (-2.329)
Credit spread	0.988 (-4.697)	0.983 (-4.252)	0.978 (-3.480)	0.813 (-3.528)	0.971 (-3.186)	0.979 (-4.068)	0.984 (-3.237)
Term structure	0.528 (-2.889)	0.261 (-2.226)	0.434 (-2.317)	0.343 (-2.399)	0.687 (-2.620)	0.489 (-2.537)	0.263 (-2.064)
VIX	0.730 (-4.954)	0.742 (-4.682)	0.678 (-3.976)	0.742 (-4.747)	0.892 (-3.891)	0.737 (-4.856)	0.659 (-3.631)

Table 6. Panel cointegration test for the convergence in CDS spreads

By pooling the *p*-values of the individual ADF tests across 28 pairwise CDS spreads differentials, the test statistics for pooled idiosyncratic errors determine whether the idiosyncratic errors are unit root (under the null) or stationary. This table reports the test statistics and the corresponding *p*-values in parentheses. An asterisk indicates that the significance is achieved at the 5% level. Rejecting panel unit root indicates a convergence, whereas panel unit root means a divergence.

	Pre-crisis	Post-crisis
All	0.659 (0.509)	4.097* (0.001)
HY	1.267 (0.205)	1.180 (0.237)
IG	0.221 (0.824)	1.123 (0.261)
10Y	1.889 (0.058)	2.335* (0.019)
5Y	0.440 (0.659)	1.414 (0.157)
CDX	0.540 (0.589)	2.146* (0.031)
EU	0.924 (0.355)	3.018* (0.002)

Table A. Large versus Small subsample correlation

	CDX_IG_5Y	CDX_IG_10Y	CDX_HY_5Y	CDX_HY_10Y	EU_IG_5Y	EU_IG_10Y	EU_HY_5Y	EU_HY_10Y
Entire sample period								
CDX_IG_5Y	1.000	0.958	0.937	0.965	0.891	0.963	**0.825**	0.900
CDX_IG_10Y		1.000	0.880	0.920	**0.840**	0.931	**0.769**	**0.829**
CDX_HY_5Y			1.000	0.935	0.936	0.903	0.906	0.892
CDX_HY_10Y				1.000	0.928	0.968	0.872	0.935
EU_IG_5Y					1.000	0.935	0.967	0.943
EU_IG_10Y						1.000	0.870	0.945
EU_HY_5Y							1.000	0.922
EU_HY_10Y								1.000
Pre-crisis period								
CDX_IG_5Y	1.000	0.987	0.974	0.984	0.950	0.984	**0.707**	**0.840**
CDX_IG_10Y		1.000	0.962	0.978	**0.947**	0.970	**0.744**	**0.870**
CDX_HY_5Y			1.000	0.967	0.931	0.961	**0.686**	**0.814**
CDX_HY_10Y				1.000	0.959	0.987	**0.741**	**0.869**
EU_IG_5Y					1.000	0.975	**0.832**	**0.891**
EU_IG_10Y						1.000	**0.740**	**0.859**
EU_HY_5Y							1.000	0.946
EU_HY_10Y								1.000
Post-crisis period								
CDX_IG_5Y	1.000	0.878	0.931	0.937	0.881	0.938	0.847	0.860
CDX_IG_10Y		1.000	0.826	0.806	**0.754**	0.794	**0.721**	**0.614**
CDX_HY_5Y			1.000	0.911	0.947	0.915	0.928	0.887
CDX_HY_10Y				1.000	0.893	0.945	0.864	0.891
EU_IG_5Y					1.000	0.947	0.976	0.919
EU_IG_10Y						1.000	0.934	0.927
EU_HY_5Y							1.000	0.910
EU_HY_10Y								1.000

Notes: The cut-off points of order correlations, $\hat{\rho}_j$, to separate Small subsample from Large subsample for entire sample, pre-crisis period and post-crisis are respectively $\hat{\rho}_j$ =0.8405, $\hat{\rho}_j$ =0.8914 and $\hat{\rho}_j$ =0.7535, where $\hat{\rho}_j$ is the sample correlation estimated from the ranked correlations within $j = 1,..,\hat{m}$. $\hat{m} = [\hat{\theta} n]$ where $\hat{\theta}$ is the proportion of correlations that are belong to small and n is the number of cross-section correlation. The correlations smaller than the cut-off points are in bold type.

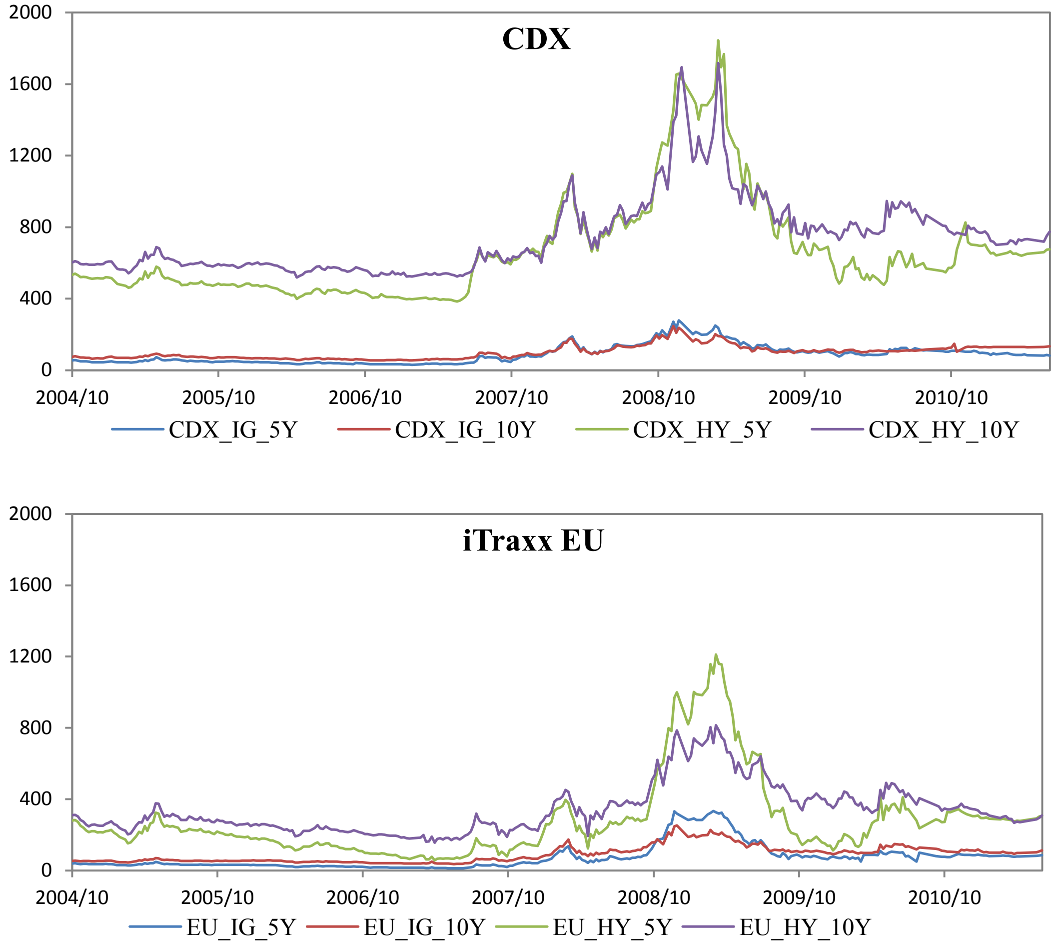

Fig. 2. Time series plots of CDX indices and iTraxx EU indices.

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This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

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This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".