Physica A 466 (2017) 310–324

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Interdependence and contagion among industry-level US credit markets: An application of wavelet and VMD based copula approaches

Syed Jawad Hussain Shahzad [a,b,*], Safwan Mohd Nor [a,c], Ronald Ravinesh Kumar [d,e], Walid Mensi [f,g]

[a] University of Malaysia Terengganu, Malaysia
[b] Montpellier Business School, France
[c] Victoria Institute of Strategic Economic Studies, Victoria University, Australia
[d] School of Accounting & Finance, The University of the South Pacific, Suva, Fiji
[e] School of Business, Queensland University of Technology, Gardens Point, Brisbane, QLD 4001, Australia
[f] Department of Finance and Accounting, University of Tunis El Manar, Tunis, Tunisia
[g] Department of Finance and Investment College of Economics and Administrative Sciences, Al Imam Mohammad Ibn Saud Islamic University (IMSIU), P.O Box 5701, Riyadh, Saudi Arabia

HIGHLIGHTS

- The interdependence between US credit markets is examined through wavelet squared coherence.
- The little "shift-contagion" is analyzed using elliptical and Archimedean copulas on the short-run decomposed series through Variational Mode Decomposition (VMD).
- The Basic Material (Utilities) industry credit market has the highest (lowest) interdependence with other industries.
- Basic Materials credit market passes cyclical effects to the other industries.
- Contagion effect between US industry-level credit markets occurred during the global financial crisis of 2007–08.

ARTICLE INFO

Article history:
Received 12 July 2016
Received in revised form 5 September 2016
Available online 23 September 2016

Keywords:
Credit default swap
Contagion
Wavelet squared coherence
Variational mode decomposition
Copula

ABSTRACT

This study examines the interdependence and contagion among US industry-level credit markets. We use daily data of 11 industries from 17 December 2007 to 31 December 2014 for the time–frequency, namely, wavelet squared coherence analysis. The empirical analysis reveals that Basic Materials (Utilities) industry credit market has the highest (lowest) interdependence with other industries. Basic Materials credit market passes cyclical effect to all other industries. The little "shift-contagion" as defined by Forbes and Rigobon (2002) is examined using elliptical and Archimedean copulas on the short-run decomposed series obtained through Variational Mode Decomposition (VMD). The contagion effects between US industry-level credit markets mainly occurred during the global financial crisis of 2007–08.

* Corresponding author at: Montpellier Business School, France.
E-mail addresses: jawad.kazmi5@gmail.com (S.J.H. Shahzad), safwan@umt.edu.my (S.M. Nor), kumar_RN@usp.ac.fj, ronaldkmr15@gmail.com (R.R. Kumar), walid.mensi@fsegt.rnu.tn (W. Mensi).

http://dx.doi.org/10.1016/j.physa.2016.09.008
0378-4371/

1. Introduction

The financial markets contagion and interdependence is a widely studied topic in empirical finance.[1] The integration of financial markets is of particular importance for academics, investors and policy makers. Financial markets' interdependence and contagion is important due to many reasons. First, the higher co-movement between the markets implies less (high) diversification (hedging) benefits. Low correlation between the markets may provide higher risk dispersion and lesser hedging opportunities. Second, the correlation between financial markets also provides information on the spillover effects. The shock transmission among the markets increases during the periods of financial turmoil [3]. The information regarding the spillover effect between the financial markets also helps in effective risk management. Finally, the comovement and contagion among financial markets provide useful information to undertake rescue measures and hence is important for regulators and international financial institutions [2].

Credit Default Swaps (CDSs) are derivative instruments that enable market participants to manage transfer or redistribute credit risk. The substantial growth of the CDS market highlights the usefulness and the effectiveness of the CDS as a crucial tool for hedging on credit risk. Market participants find credit derivatives to be useful for risk management. In fact, CDS contracts play a vital role in inferring eventual defaults for traders, practitioners and regulators. Credit derivatives are more flexible at transferring risks than are other. However, the size, structural opacity, and interconnectedness of the CDS market may pose the systemic risk to financial intuitions and markets stability. The question that whether CDS markets are vulnerable to contagion has got importance in the recent literature especially aftermath of US subprime and Greece crises. The comparison of banks and no-banks show that the there is a persistent difference between their CDS premia during normal times; however, it disappears during the crisis [4].

Literature identifies four main channels of contagion in CDS markets. The first channel suggests liquidity issue arising during the financial crises. The investor's reaction when faced with heavy losses on their investment in a diversified portfolio justifies this channel. The portfolio diversification across markets open-up "common creditor effect". A sharp fall in one market causes a reduction in investors wealth and thereby withdrawal from risky assets [5,6]. This phenomenon can arise even if the investors are rational and the markets are perfect. The intermediaries specifically the banks' liabilities overlapping across countries may also add vulnerability [7]. The role of financial intermediaries in risk management systems tends to feedback with asset prices and spreads contagion [8]. Illiquidity during a financial crises effects money managers to simultaneously sell their assets and hence this fire sale spreads across the markets. Convergence traders [9,10] and arbitrageurs [11] are forced to sell and this pressure gets intensified due to margins calls specially in leveraged positions [12]. The efforts to reduce value-at-risk and marked to market requirement may also incite financial institutions to liquidate the assets ([13]; Shin, 2008).

The second channel through which contagion grows is the updating of judgments and preferences. As soon as a crisis bursts, investors suddenly start to realize the riskiness of other assets and revise (upward) their risk assessments. Change in risk assessments trigger an increase in risk premia due to fall in risky assets prices. The rise in uncertainty drives investments from risky to safe assets, a phenomenon known as "flight to quality". Caballero and Krishnamurthy [14,15] models describe that financial intermediaries provide the necessary mechanism and facilitate this process. Kumar and Persaud [16] argue that investors' risk appetite suddenly drops and thus they require higher excess returns for all risky assets. Coudert and Gex, [17] empirical confirmed the change in risk aversion indicators around a crisis episode. Notably, as risky assets are also the ones with less liquidity, it is somewhat difficult to disentangle between "flight to liquidity" and "flight to quality" [18]. Annaert et al., [19] highlight that risk aversion level of investors is sensitive and varies with business cycle and thereby affects credit spreads.

The behavioral finance suggests that contagion arise due to herding behavior [20]. The herding behavior stems from the inherent emotional biases of investors. Agents and their investment decisions in a financial system are influenced by the investment choices of others. Market participants may start to believe that trading behavior reflects the private information and cascades through market prices. Herding may also influence the rational agents due to high information costs [21]. Kodres and Pritsker [22] argue that asymmetric information increase the markets' vulnerability to crises due to cross-market rebalancing. Portfolio manager's compensation is usually linked with performance which imitates their behavior towards herding [23]. Finally, mimetic behavior is an intrinsic feature of human nature shared by financial market participants.

The fourth channel through which contagion may arise is the counterparty risk. The contagion within CDS market is mainly driven by increase in counterparty credit risk. The business relations between the firms effect non-distressed firms when other firms are in financial distress. The interdependence among the firms (suppliers or consumers of the products) transmits the firm's financial distress signal to other depending firms. The default intensities of these firms are also interlinked and hence push their credit spreads to co-move during financial distress. Market participants may anticipate these difficulties and therefore may bid down a whole range of CDS prices after the bankruptcy announcement. Jarrow and Yu [24] have studies this type of counterparty risk in the bonds and CDS markets. The negative impact of Chapter 11

[1] Following Forbes and Rigobon [1], the contagion is a significant increase in cross-market linkages after a shock to one country (or group of countries). Based on this definition, contagion does not occur if two markets show a high degree of comovement during both stability and crisis periods. The interdependence is used instead if strong linkages between the two economies exist in all states of the world. Ahmad et al. [2] define the contagion is defined as significant increases in cross market correlations during the turmoil period, while any continued increase in cross market correlation at high levels is referred as interdependence.

Table 1
Summaries of some contagion papers.

Study	Time period	Markets	Methodology	Contagion findings
Hwang & Kang [38]	1/1/2006–31/7/2008	Asia, Europe, Latin America, North America, and Oceania (Bank's CDS)	Regression & DCC	No
Longstaff [39]	19/1/2006–31/12/2008	CDO & stock markets in US	Correlation test & VAR	Yes
Kim et al. [40]	1/2005–1/2009	10 Asian countries	Regression	Yes
Grammatikos & Vermeulen [41]	1/1/2003–31/8/2010	15 EMU countries (Government bond CDS)	GARCH	Yes
Fong & Wong [42]	14/12/2007–30/9/2011	11 Euro area & three IFC (US, UK and Japan) countries (sovereign bond)	CoVaR–Value at Risk	Yes
Metiu [33]	1/2008–2/2012	10 European countries (10-year sovereign bond)	Canonical model of contagion proposed by Pesaran and Pick [47]	Yes
Kalbaska & Gatkowski [34]	8/2005–8/2010	Nine European countries	EWMA correlation analysis and GC	Yes
Arghyrou & Kontonikas [35]	1/1999–8/2011	10 Euro area countries	Principle component analysis	Yes
Fender et al., [43]	4/2002–12/2011	12 Emerging markets	GARCH	Yes
Alter & Schüler [44]	1/6/2007–31/5/2010	Seven European countries	VAR & VEC	Mixed
Beirne & Fratzscher [45]	1999–2011	31 advanced and emerging economies	Regression analysis	Yes
Mink & Haan [37]	2010	48 European banks	Regression analysis, Event study	Yes
Sensoy et al., [32]	2/9/2004–11/4/2013	Turkey and 13 European countries	DCC	Yes
Gómez-Puig & Sosvilla-Rivero [46]	1/1/1999–31/12/2012	EMU sovereign debt markets	GC and endogenous breakpoint test	Yes
Broto & Pérez-Quirós [36]	1/1/2007–12/3/2012	US, UK and 10 European countries	Dynamic factor model	Yes

Abbreviations are as follows: CDO = Collateralized debt obligation; DCC = Dynamic Conditional Correlation; EWMA = Exponential Weighted Moving Average; GARCH = Generalized Auto Regressive Conditional Heteroscedasticity; VAR = Vector Auto Regressive; VEC = Vector Error Correction.

bankruptcy on intra-industry firms and thereafter contagion has been concluded by Jorion and Zhang [25]. Coudert and Gex [26] empirically examined the contagion effect in the CDS market using General Motors (GM) and Ford crisis of 2005. They used 226 CDSs on major US and European firms and studied the dynamic correlation by Exponentially Weighted Moving Average (EWMA) and dynamic conditional correlation (DCC-GARCH) models. Their findings suggest significant increase in correlations within CDS markets during the crisis. The risk of CDS sellers' failure got importance since the bankruptcy of Lehman Brothers in 2008. Jorion and Zhang [27] studied the contagion in CDS market resulting from the bankruptcy announcements.

Naifar [28] argues that CDS indices are a higher-risk indicator and hence they are more sensitive to stock market conditions and macroeconomic variables during the financial crises. Due to this higher sensitivity, CDS markets lead the stock markets [29]. Hence, the CDS markets impact the financial markets' stability [30]. Fang et al., [31] studied the impact of CDX-US index spreads on the stock markets in high-risk and low-risk countries. The CDS market shows a significant contagion effects towards the stock indices of high-risk countries. More recently, Sensoy et al., [32] have examined the relationship between time-varying risk perceptions of investors towards major European countries and Turkey. Their results suggest increased correlation among the markets and conclude that financial crises increase the markets integration in terms of risk perception.

Notably, previous empirical work has mainly focused on the increased interdependence and contagion among European countries. Table 1 summarizes previous studies. Using Canonical model of contagion, Metiu [33] find a strong evidence of contagion in ten European countries (10-year sovereign bond). Similar results are found by Kalbaska and Gątkowski [34], Arghyrou and Kontonikas [35], Sensoy et al. [32], and Broto and Pérez-Quirós [36], among others. In the context of financial sector, Mink and Haan [37] use regression analysis and event study and show evidence of contagion for 48 European banks. In contrast, Hwang and Kang [38] fail to support contagion effect for Bank's CDS for Asia, Europe, Latin America, North America, and Oceania.

The present study extends the debate on the role of CDS markets during financial crises by analyzing the interdependence and contagion among US sectoral indices. First, we examine the dynamic dependence between CDS markets using time and frequency analysis namely wavelet squared coherence (WSC) approach. The method is appropriate for useful insight on the comovements[2] among the financial markets [49]. However, to investigate contagions effect among US CDS sectoral indices we follow Gallegati [50] and Dewandaru et al. [51]. The sudden increase in short-term interdependence is hence considered as contagion effect. For this purpose, we use an advance multi-resolution technique known as the Variational Mode Decomposition (VMD) to decompose the CDS series. The non-recursive VMD of Dragomiretskiy and Zosso [52]

[2] See e.g. Graham et al., (2012), Ranta [48] and Albulescu et al., [49].

decomposes a time series into different modes that collectively reproduce the input signal. Notably, the Discrete Wavelet Transform (DWT) is also widely used to identify the contagion among stock markets (see e.g. Gallegati [50] and Dewandaru et al. [51]). However, Lahmiri [53] highlights at least three advantages of VMD over DWT approach: (1) DWT is not adaptive as the VMD technique; (2) DWT requires a pre-determined wavelet function and scale of decomposition; and (3) the number of observations decreases with level of decomposition and thus negatively affects the linear estimates. More recently, Lahmiri [54] compares the forecasting results of VMD-general regression neural network (GRNN) with three competing prediction models (the Empirical Model Decomposition (EMD)-GRNN model, feedforward neural networks (FFNN), and auto regressive moving average (ARMA) process). Using mean absolute error (MAE), mean absolute percentage error (MAPE), and the root mean of squared errors (RMSE), the author shows the superiority of the VMD-based method over the three competing prediction approaches, suggesting that VMD is an effective and promising technique for analysis and prediction of economic and financial time series. Shahzad et al., [55] have compared the properties of VMD and wavelet decomposition while examining the interdependence of Greece and other European stock markets. They show that variations in VMD modes are relatively stable over time, compared to wavelet decomposition where the variations captured by each decomposition level decrease as the levels increase. In what follows, we examine the symmetric and asymmetric tail dependence using elliptical and Archimedean copulas [56], with a special focus on the change in dependence regime for short-term variational mode series during and after the global financial crisis of 2008–2009 and the Eurozone sovereign debt crisis of 2011–2013.

Rest of the study is organized as follows; Section 2 provides the econometric framework. Section 3 describes the data used and results of empirical analysis. Final section concludes the study.

2. Methodology

2.1. Wavelet squared coherence

The wavelet analysis can be performed using either the continuous wavelet transform (CWT) or the discrete wavelet transform (DWT). The former has many advantages over DWT. It provides freedom to select wavelets according to the length of data. The redundancy in CWT makes interpretation and discovery of patterns or hidden information easier [63].

The Continuous Wavelet Transformation (CWT) can distribute a time series into wavelets based on different frequencies over the time period. Aguiar-Conraria and Soares [63, p. 2872] defined wavelet squared coherence (WSC) as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series". The detailed description of the CWT and WSC can be seen in Grinsted et al., [64]; however, we provide a simplistic representation with brief description. The wavelet transform converts the time-series using wavelet functions. This wavelet function is a small wave and can be manipulated (stretching or squeezing over time) to extract the frequency components from a complex and non-stationary signal. The mother wavelet that is used to produce these small waves is expressed as a function of time positions and scales and can be specified as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right). \tag{1}$$

Notably, the wavelet is a real-value or a complex value function $\psi(.)$ that is defined over the real axis. The wavelet is also assumed to be a square integrable function $\psi(.) \in L^2(\mathbb{R})$. In Eq. (1), τ, s and $\frac{1}{\sqrt{s}}$ represent time position (translation parameter), scale (dilation parameter related with frequencies) and normalization factor, respectively. The normalization factor ensures that the transformation remain comparable across scales and over time. The mother, $\psi(t)$, should also have certain properties so that it can utilized for decomposition. It must have zero mean, $\int_{-\infty}^{+\infty}\psi(t)\,\mathrm{d}t = 0$; its square integrates to unity, $\int_{-\infty}^{+\infty}\psi^2(t)\,\mathrm{d}t = 1$, which means that $\psi(t)$ is limited to an interval of time; and it should also satisfy the so-called admissibility condition, $0 < C_\psi = \int_0^{+\infty}\frac{|\hat{\psi}(\omega)|^2}{\omega}\,\mathrm{d}\omega < +\infty$ where $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$, that is, $\hat{\psi}(\omega) = \int_{-\infty}^{+\infty}\psi(t)\,\mathrm{e}^{-\mathrm{i}\omega\tau}\mathrm{d}t$.

The literature provides different types of wavelets for the decomposition of time series depending on the research topics. We use Morlet wavelet to examine the wavelet coherence among the stock markets because it provides the best balance between time and frequency localization [65]. Grinsted et al. [64] show that Fourier period for the Morlet wavelet is almost equal to the scale used is given as:

$$\psi^M(t) = \frac{1}{\pi^{1/4}}\mathrm{e}^{\mathrm{i}\omega_0 t}\mathrm{e}^{-t^2/2}. \tag{2}$$

In Eq. (2), ω_0 indicates the central frequency of the wavelet. Following the previous work by Grinsted et al. [64], Rua and Nunes [66] and Vacha and Barunik [67], we used $\omega_0 = 6$. Morlet wavelet with $\omega_0 = 6$ provides a better localization between time and frequency. A continuous wavelet transform W_x of a discrete time series $(x(t), t = 0, 1, \ldots, n)$ with respect to $\psi(t)$, can then be written as:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\,\psi^*_{\tau,s}(t)\,\mathrm{d}t = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\,\psi^*\left(\frac{t-\tau}{s}\right)\mathrm{d}t \tag{3}$$

where * denotes the complex conjugate. Notably, wavelet transform preserves the energy of a time series that can be used to analyze the power spectra. Thus, the variance can be seen as follows:

$$\|x\|^2 = \frac{1}{C_\psi} \int_0^\infty \left[\int_{-\infty}^{+\infty} \left| W_x(\tau, s)^2 \right| d\tau \right] \frac{ds}{s^2}. \tag{4}$$

Torrence and Compo [68] define the cross wavelet transform $|W_{xy}(\tau, s)|$ of two time series $x(t)$ and $y(t)$ with the continuous transforms $W_x(\tau, s)$ and $W_y(\tau, s)$ as follows:

$$W_{xy}(\tau, s) = W_x(\tau, s) . W_y^*(\tau, s) . \tag{5}$$

The cross wavelet power shows the areas of high common power between two time series in the time-scale space. Similarly, the WSC for the CWT of two time series $W_x(\tau, s)$ and $W_x(\tau, s)$ can be presented as:

$$R^2(\tau, s) = \frac{\left| S\left(s^{-1} W_{xy}(\tau, s)\right) \right|^2}{S\left(s^{-1} |W_x(\tau, s)|^2\right) .S\left(s^{-1} \left|W_y(\tau, s)\right|^2\right)}. \tag{6}$$

In Eq. (6), $S(.)$ and R^2 represent wavelet squared coherency and smoothing operator, respectively. Torrence and Webster [69] defined WSC as the squared absolute value of the smoothed cross wavelet spectra that is normalized by the product of the smoothed individual wavelet power spectra. The values of squared coherence $R^2(\tau, s)$ range from zero (low comovement) to one (high comovement). The WSC when plotted as an image provide a clear picture of comovement over time and different frequencies.

2.2. Variational mode decomposition

Following, Gallegati [50] and Dewandaru et al. [51], we consider a sudden increase in short-term (long-term) dependence after a shock as contagion (interdependency) effect. To distinguish between short- and long-term variations of CDS indices, we use an advance multi-resolution technique known as the Variational Mode Decomposition (VMD) for the decomposition of CDS index returns. The non-recursive VMD of Dragomiretskiy and Zosso [52] decomposes a time series into different modes that collectively reproduce the input signal. These decomposed time series are compact around a center pulsation with a limited bandwidth and is updated by Wiener filtering in Fourier domain; and a Lagrangian multiplier is used to enforce exact signal reconstruction. Hence, the low (high) frequency modes obtained through VMD present the long (short) term dynamics of the original signal. This mode-by-mode decomposition enables to examine the change in CDS markets dependence on different scales.

The fundamental concept of VMD is to decompose a time series f into discrete k number of sub-series (known as modes), u_k, and the bandwidth of each mode is limited in spectral domain [52]. Each decomposed variational mode k is assumed to be compressed around a center pulsation, ω_k, which is determined along with the decomposition [52]. The algorithm to determine the bandwidth of a time series requires: (1) a unilateral frequency spectrum to be obtained for each mode u_k by computing the associated analytic signal by means of the Hilbert transform; (2) for each mode, the mode's frequency spectrum is then shifted to baseband by mixing with an exponential tuned to the respective estimated center frequency; and (3) the bandwidth is estimated through Gaussian smoothness of the demodulated signal (cf. Dragomiretskiy and Zosso [52]). Thus, the resulting constrained variational problem can be given as follows:

$$\min_{\{u_k\},\{\omega_k\}} = \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad \text{s.t.} \sum_k u_k = f \tag{7}$$

where, k indicates the set (number) of modes u of the original signal f; ω, δ and * represent frequency, the Dirac distribution, and convolution, respectively. Thus, $\{u_k\} := \{u_1, \ldots, u_k\}$ and $\{\omega_k\} := \{\omega_1, \ldots, \omega_k\}$ are the sets of all variational modes and their central frequency, respectively. The Eq. (1) decomposes the original signal into a set of modes with a limited bandwidth in Fourier domain. The solution to the original minimization problem is the saddle point of the following augmented Lagrange ($\mathcal{L}$) expression:

$$\mathcal{L}(u_k, \omega_k, \lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] \right\|_2^2 + \left\| f - \sum u_k \right\|_2^2 + \left\langle \lambda, f - \sum u_k \right\rangle \tag{8}$$

where, λ is the Lagrange multiplier and $\|\bullet\|_p$ denotes the usual vector ℓp norm where $p = 2$. The solution to Eq. (8) is found in a sequence of k iterative sub-optimizations. Finally, the solutions for u and ω are found in Fourier domain and are given by:

$$u_n^{n+1} = \left(f - \sum_{i \neq k} u_i + \frac{\lambda}{2} \right) \frac{1}{1 + 2\alpha(\omega - \omega_k)^2} \tag{9}$$

$$\omega_n^{n+1} = \frac{\int_0^\infty \omega |u_k(\omega)|^2 d_\omega}{\int_0^\infty |u_k(\omega)|^2 d_\omega} \tag{10}$$

where, n is the number of iterations. To examine contagion effect during the global financial crises (2007–09) and European debt crisis (2011–13) we use the variational mode representing the short-term dynamics.

2.3. Elliptical and Archimedean copulas

Since correlation measure only provides linear relationship between the time series and does not capture tail dependence i.e. the likelihood that extreme events occur jointly, the copulas approach is utilized to examine the tail dependence between financial time series [56]. The copula approach which is based on the theorem of Sklar [57]: Let $x_1, \ldots, x_n$ be the random variables, $F_1, \ldots, F_n$ are the corresponding marginal distributions and H is the joint distribution, then copula $C : [0, 1]^n \rightarrow [0, 1]$ exists such that $H(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n))$. On the other hand, if C is a copula and $F_1, \ldots, F_n$ are distribution functions, then H is a joint distribution with margins $F_1, \ldots, F_n$. If the $F_1, \ldots, F_n$ marginal distributions are elliptically contoured then the tail dependence of joint distribution H can be examined through elliptical (implicit) copulas. The applicability of elliptical copulas as a multivariate dependence measure gives its widely applicability while analyzing financial time series (cf. Embrechts et al. [58]; Berger and Missong [59]; among others). The t-copula is a measure of symmetric tail dependence and belongs to the family of elliptical copulas. It represents the dependence structure implicit in a multivariate t-distribution. The setup of the t-copula is as follows:

$$\begin{aligned} C^t(x_1, \ldots, x_n) &= t_{\rho,\nu}\left(t_\nu^{-1}(x_1), \ldots, t_\nu^{-1}(x_n)\right), \\ &= \int_{-\infty}^{t^{-1}(x_1)} \cdots \int_{-\infty}^{t^{-1}(x_n)} \frac{\Gamma\left(\frac{\nu+n}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)(\nu\pi)^{\frac{n}{2}}|\rho|^{\frac{1}{2}}} \left(1 + \frac{1}{\nu} z^t \rho^{-1} z\right)^{-\frac{\nu+n}{2}} \mathrm{d}z_1 \ldots \mathrm{d}z_n \end{aligned} \tag{11}$$

where, $t_{\rho,\nu}$ represents the multivariate t-distribution having a correlation matrix ρ with ν degrees of freedom, t_ν^{-1} indicates the inverse of the univariate t distribution, and symmetric tail dependence is presented by ν. As $\nu \rightarrow \infty$ the t-distribution approximates to the Gaussian.

Notably, the elliptical copula family can only assess symmetric tail dependence and thus Archimedean (explicit) copulas are used to examine the asymmetric tail dependence. The first of Archimedean copulas class is the Clayton copula which exhibiting greater dependence in the negative tail than in the positive and is specified as:

$$C^{Clayton}(x_1, x_2) = \left(\max\left\{x_1^\theta + x_2^\theta - 1, 0\right\}\right)^{\frac{1}{\theta}}, \quad \theta \in [-1, 8) \setminus \{0\}. \tag{12}$$

The Clayton copula implies co-monotonicity as $\theta \rightarrow \infty$, and independence as $\theta \rightarrow 0$. Since the Clayton copula exhibits higher dependence in negative tails, to examine the dependence in positive tail, the Gumbel copula (higher dependence in the positive tail) can be used and is specified as:

$$C^{Gumbel}(x_1, x_2) = \exp\left(-\left[(-\ln x_1)^\theta + (-\ln x_2)^\theta\right]^{\frac{1}{\theta}}\right), \quad \theta \in [1, \infty). \tag{13}$$

The Gumbel copula implies tail dependence as $\theta \rightarrow \infty$ and independence as $\theta \rightarrow 1$. Notably, the estimation of parameters for the higher order copulas are computationally cumbersome and hence the parameters are estimated in a two step maximum likelihood method (also known as inference for the margins) introduced by Joe [60].

We first apply three copula functions on the raw time series to examine the tail dependence among the industry-level CDS indices and then to explore the contagion effect, we apply elliptical and Archimedean copulas on the short-run variational mode obtained through VMD approach.

3. Data and findings

The study examines the co-movement and contagion among CDS markets of US using sector indices. The sectors include Banking, financial, Telecommunication, Healthcare, Oil and Gas, Materials, Consumer Goods, Utilities, Industrial, Consumer Services and technology. This daily data is extracted from DataStream International (Thomson Financial) for the period December 17, 2007 to December 31, 2014 as the sector level CDS indices were launched by DataStream in December 2007. The time period is not only recent but is large enough for empirical analysis to indicate long-run relationship between the markets. It also covers the impact of various international events (e.g., global financial crisis and European sovereign debt crisis).

We treat banking and financial sectors as two because earlier empirical work suggests that CDS premia of these sectors react differently to market conditions [61,4]. Banks have unique characteristics that distinguish them from the non-financial or industrial firms. The balance sheet composition, their central role in an economy and different regulatory framework are few of the reasons. The sector level CDS indices (denominated in basis points so that 100 basis points equates to 1 percentage point) are based on 5-year tenor series contracts because the five year credits instruments are considered adequate based on liquidity and are widely used in empirical analysis [62]. The final data comprises of 1838 observations for each index. The CDS index returns are calculated by natural logarithmic of differenced daily closing premia as $r_t = \ln(\text{Spread}_t/\text{Spread}_{t-1}) \times 100$.

Table 2
Statistical properties of the CDS returns.

	Banks	Financial	Telecom	Healthcare	Oil and Gas	Basic materials	Consumer goods	Utilities	Industrial	Consumer services	Technology
Mean	−0.0204	0.0145	−0.0201	0.0062	0.0933	0.0499	−0.0078	0.0020	−0.0202	−0.0060	0.0558
Minimum	−51.115	−55.759	−26.397	−17.113	−64.416	−10.136	−16.031	−148.108	−50.920	−75.553	−19.874
Maximum	37.935	52.432	20.417	26.379	66.430	12.712	22.296	146.620	52.374	76.045	42.696
Std. Dev.	3.9709	5.6192	2.4908	2.3310	6.6109	1.7198	2.1932	6.6729	3.9005	4.4729	2.5429
Skewness	−0.8277	−0.1036	0.1405	1.2193	0.6829	1.3584	0.9438	−5.9873	−0.3656	−0.7703	4.6569
Kurtosis	32.136	22.888	20.953	25.356	52.933	12.663	23.121	390.000	67.164	134.328	82.976
J–B	65 223.0***	30 295.3***	24 690.0***	38 731.0***	191 089.8***	7716.1***	31 276.4***	1148.0***	3150.1***	13 210.0***	4964.3***
ADF	−35.344***	−42.137***	−28.254***	−42.377***	−47.418***	−23.738***	−28.827***	−27.528***	−38.012***	−18.173***	−26.486***
PP	−34.698***	−60.371***	−43.081***	−42.653***	−60.330***	−36.565***	−44.530***	−46.372***	−51.742***	−47.797***	−40.795***
KPSS	0.1321	0.2537	0.1459	0.3939	0.0622	0.2363	0.2608	0.2354	0.2432	0.2684	0.3949
Q(12)	129.43***	229.49***	23.07**	15.06	174.79***	258.27***	22.57**	132.07***	134.11***	187.62***	65.88***
$Q^2(12)$	123.83***	564.28***	25.51**	38.66***	1110.89***	197.00***	183.95***	201.77***	488.12***	365.26***	1.3200
ARCH(12)	412.81***	793.32***	663.44***	489.60***	745.94***	287.89***	625.67***	996.82***	486.55***	625.56***	685.30***

Notes: ADF, PP and KPSS are the empirical statistics of the Augmented Dickey–Fuller (1979), and the Phillips–Perron (1988) unit root tests, and the Kwiatkowski et al. [70] stationarity test, respectively. Q(12) and $Q^2(12)$ refer to the Ljung–Box test for autocorrelation in residuals and squared residuals, respectively. ARCH(12) test of Engle [71] is to check the presence of ARCH effects up to 12 lags.
** Denote the rejection of the null hypotheses of normality, no autocorrelation, unit root, and conditional homoscedasticity at the 5% significance level.
*** Denote the rejection of the null hypotheses of normality, no autocorrelation, unit root, and conditional homoscedasticity at the 1% significance level.

The statistics properties of the industry-level CDS index returns are reported in Table 2. The average returns of Oil and Gas, Technology and Basic Material industries are respectively higher than other industries. Banking sector CDS daily average returns are most negative. The standard deviation is highest for the Utility industry. All the time series are non-normal as the null hypothesis of Jarque Bera test is rejected. Notably, the non-normality stems due to leptokurtic behavior of return distributions. Again, the excess kurtosis value is highest for the Utility industry. The fat tailed behavior identified through fourth (kurtosis) statistical movement justifies the tail dependence measures adopted for the analysis of contagion effect. The Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) unit root tests as well as the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test are also performed. The results of these tests indicate that all the return series are stationary at the 1% level. The results of the Ljung–Box test statistics of the residuals, Q(12), and the squared residuals, $Q^2(12)$, reject the null hypothesis of no serial correlation. Finally, the Engle [71] test for conditional heteroscedasticity shows that ARCH effects are significantly present in all the return series.

The correlation values between the industry-level CDS returns are provided in Table 3. The correlation values various across sectors; however, all are positive and significant at conventional levels. The positive correlation suggests that either the credit quality of all sectors deteriorate together or may have some common factors driving the CDS premia. Notably, the Utility industry CDS index has the lowest (positive) correlation with all other sector. The lowest four correlation of Utility industry (underlined value) are with Financials, Oil and Gas, Industrial and Consumer Services industries. Low correlation coupled with higher fat tailed behavior makes Utility industry stand apart from all other CDS indices. It is worth noting that the Utility sector is regulated by state governments and is considered as defensive sector during a recession or economic downturn. Further, the stable demand for utilities can make this sector less sensitive to changes in the economy. Basic Material industry shows the highest correlations with all other industries where the highest four values (bold values) are found with Technology, Banks, Consumer Goods and Health Care industries, respectively.

3.1. Interdependence through WSC and copula

To analyze the comovement (interdependence) between industry-level CDS markets, we utilize the WSC approach. The method provides a better understanding of dynamic (evolution of association over time and across frequencies) linkage between the time series. Notably, the Monte Carlo simulations are used to assess statistical significance of co-movement following previous relevant studies [67].

The pair-wise wavelet coherence for all eleven industries results in 55 images which is implausible[3] to show here, thus we divide the industry pairs into two major groups based on wavelet coherence. The WSC plots of CDS indices with high and low coherence (four each, see Table 3) are shown in the Panel A and B of Fig. 1, respectively. The horizontal axis of these plots indicates time intervals whereas the vertical axis shows the scale (i.e. frequency band). The frequency in these plots can be referred as the daily time units. The scale on the vertical axis doubles from the previous point and range between 2–512 days and 2–64 days are associated with short-run dynamics and long-term afterwards. The dense black outline indicates the 5% significance level against the red noise. The lighter shade cone shows the edge effect also named as cone of influence (COI). The color code presented on the right end of each image varies between blue (low power) and red (high power). Arrows

3 All other squared wavelet coherence plots are available on request. Notably, all the industry-level CDS pairs posit cyclical (positive) co-movements where the long-run coherence is dominant and statistically significant.

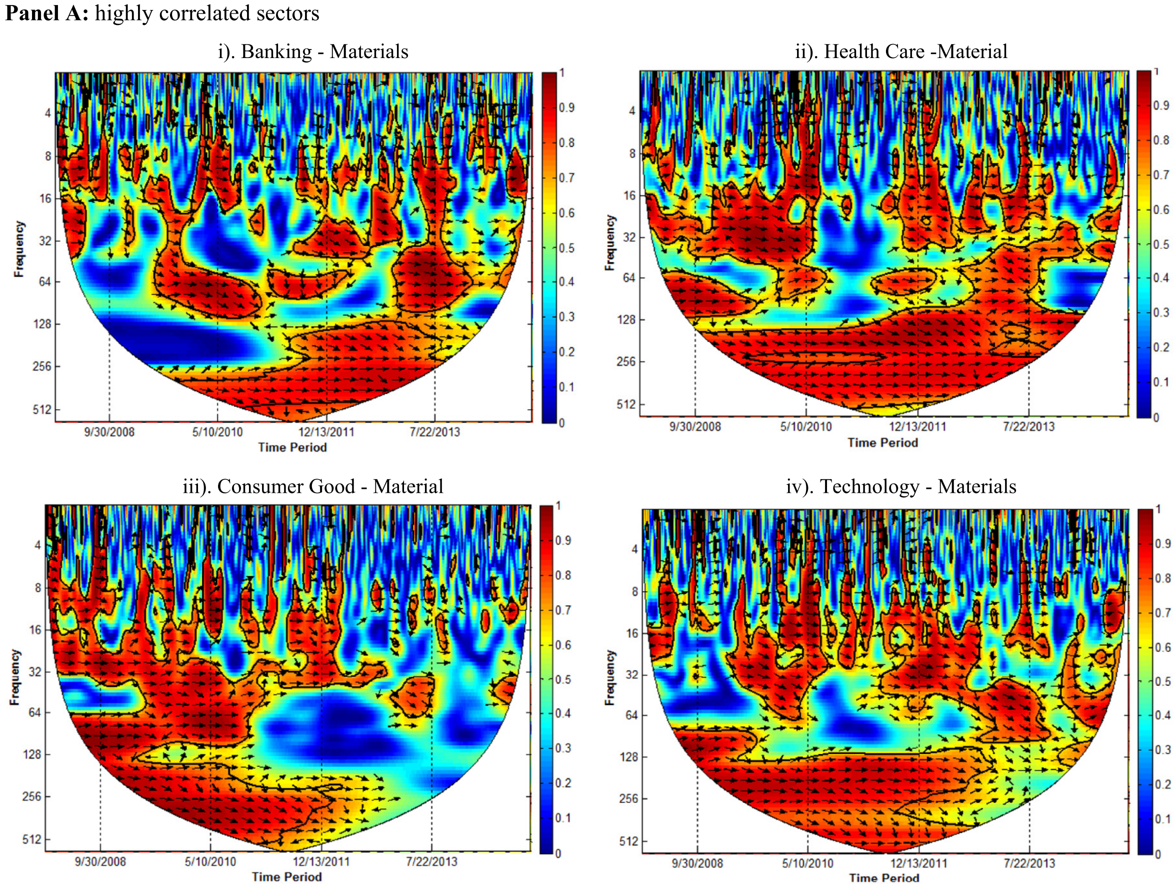


Fig. 1. Wavelet squared coherence. Note: This figure shows the Wavelet squared coherence between the industry-level CDS pairs. Time and frequency (in days) are on the horizontal and the vertical axis, respectively. The colourbar on the right side shows the coherence (strength of relationship), the warmer the color of a region, the greater the coherence between the pairs. The lighter shade cone shows the edge effect also named as cone of influence (COI). The black solid line isolates the statistical significant area at the 5% significance level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

indicate the phase difference between the two series. → & ← indicate that the CDS markets are in phase and out of phase i.e. cyclical or counter cyclical effect on each other, respectively. ↗ & ↙ indicate first CDS index leading. ↘ & ↖ indicate first CDS index is lagging. For interpretation purpose, red color at the bottom (top) of the graph indicates high interdependence at higher (low) frequencies.

All the high correlation pairs indicate that CDS markets are in-phase i.e. pass cyclical effect on each other. It can also be interpreted as strength of relationship is strong and there exists a positive correlation between the CDS indices. In Panel A, first two pairs (Figs. A-b) show that the interdependence between these pairs gradually increases towards the end of sample period. While the other two pairs (Figs. C-and d) show that association between these pairs decrease during the last two years. The interdependence between CDS indices is higher and significant over the long-run (128–512 frequencies). Notably, the arrows are pointing right and downward which implies that Basic Material industry is not only the highly correlated industry, it also passes the cyclical effects to the other industries. As the interdependence between these industries varies across time and frequency, therefore, it is difficult to make a precise conclusion regarding the impact of financial crises.

To gauge the impact of financial crises on the interdependence between different CDS markets, we next plot (Panel B) the WSC between the CDS industry pairs where the coherence is relatively low. It is clear from the figures that although the Utility industry has the lowest interdependence with other industries, the financial crises impact this relationship as the small high coherence (red) regions emerge during financial crises. Putting all together, we can conclude that interdependence among the credit markets is a dynamic phenomenon. Basic Material and Utility industry CDS indices show high and low interdependence with other industries, respectively. Furthermore, the coherence (interdependence) between the CDS indices is impacted by the financial crises.

As highlighted in the methodology section, linear dependence measures i.e. correlation or coherence may fail to accurately capture the dependence structure especially when the return distributions exhibit a fat tailed behavior (see

Panel B: low correlated sectors

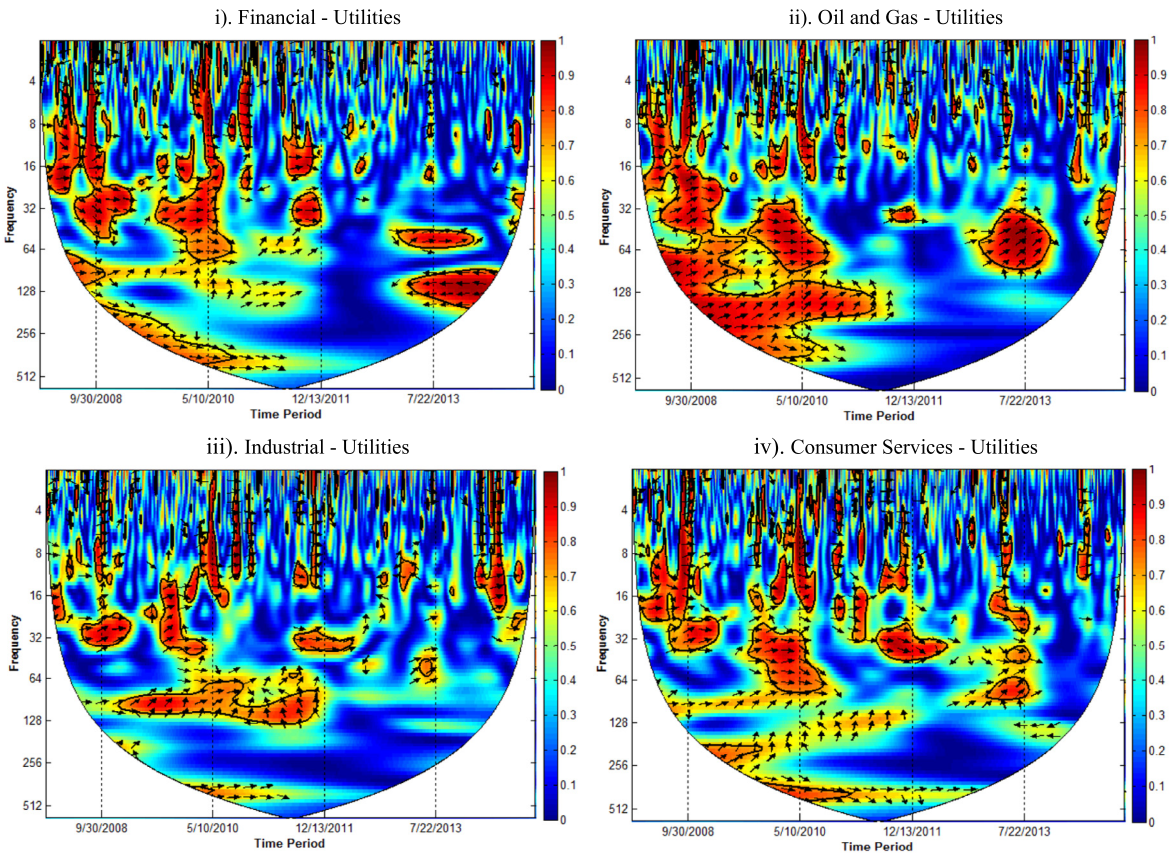
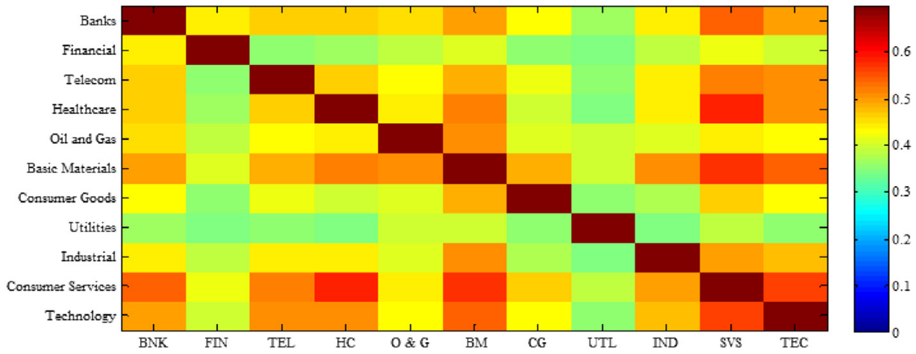


Fig. 1. (*continued*)

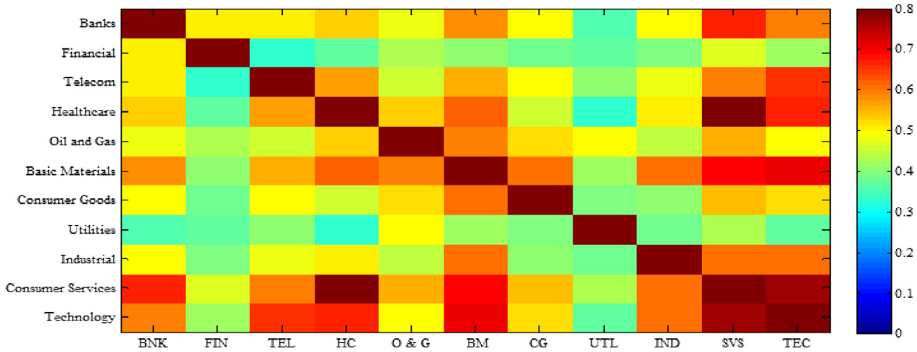
Table 3
Correlation metrics between industry-level CDS returns.

	Banks	Financial	Telecom	Healthcare	Oil and Gas	Basic materials	Consumer goods	Utilities	Industrial	Consumer services	Technology
Banks	1.0000										
Financial	0.1917*** (8.3687)	1.0000									
Telecom	0.3627*** (16.676)	0.0970*** (4.1760)	1.0000								
Healthcare	0.3386*** (15.421)	0.1549*** (6.7190)	0.3636*** (16.723)	1.0000							
Oil and Gas	0.1172*** (5.0581)	0.1002*** (4.3130)	0.1069*** (4.6052)	0.1539*** (6.6753)	1.0000						
Basic Materials	**0.4212***** (**19.899**)	0.2054*** (8.9947)	0.3734*** (17.244)	**0.4014***** (**18.777**)	0.2372*** (10.460)	1.0000					
Consumer goods	0.2845*** (12.716)	0.1363*** (5.8933)	0.2632*** (11.690)	0.2134*** (9.3572)	0.2127*** (9.3295)	**0.4130***** (**19.431**)	1.0000				
Utilities	0.1025*** (4.4140)	0.0442* (1.8950)	0.0902*** (3.8795)	0.0840*** (3.6101)	0.0534** (2.2900)	0.0949*** (4.0838)	0.1054*** (4.5404)	1.0000			
Industrial	0.1693*** (7.3596)	0.0851*** (3.6589)	0.1380*** (5.9692)	0.1328*** (5.7410)	0.0938*** (4.0375)	0.2273*** (10.000)	0.1163*** (5.0159)	0.0606** (2.6009)	1.0000		
Consumer services	0.1904*** (8.3114)	0.0750*** (3.2247)	0.1875*** (8.1788)	0.2232*** (9.8120)	0.0841*** (3.6156)	0.2034*** (8.8996)	0.1438*** (6.2267)	0.0610** (2.6188)	0.0572** (2.4563)	1.0000	
Technology	0.3249*** (14.720)	0.2083*** (9.1273)	0.2736*** (12.187)	0.3380*** (15.388)	0.1701*** (7.3944)	**0.5028***** (**24.923**)	0.3018*** (13.565)	0.0701*** (3.0119)	0.1526*** (6.6174)	0.1863*** (8.1253)	1.0000

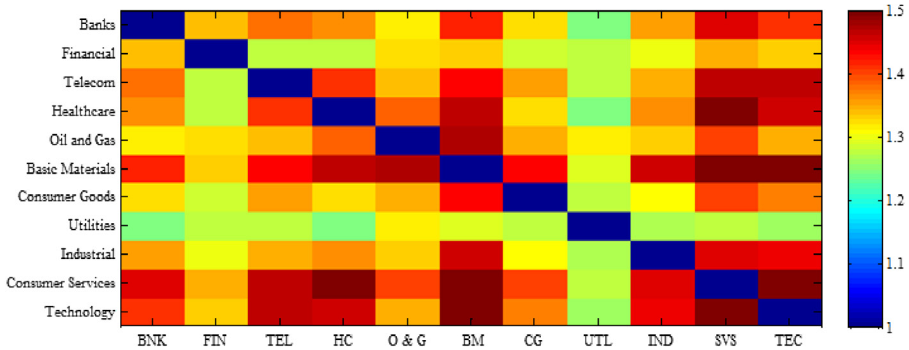
Note: The *t*-statistics are in brackets.
* Indicate significance at 10% level.
** Indicate significance at 5% level.
*** Indicate significance at 1% level.



(a) Student t copula.



(b) Clayton copula.



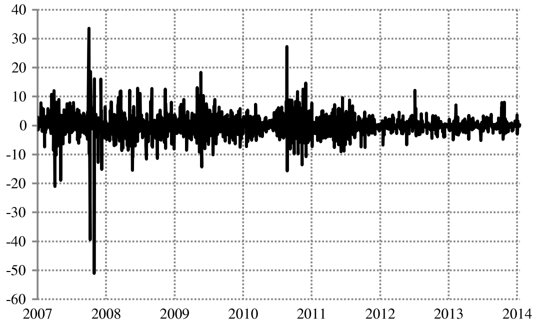
(c) Gumbel copula.

Fig. 2. Tail dependence coefficients. Note: This figure shows the copula based tail-dependence between the industry-level CDS pairs. The colourbar on the right side shows the degree of tail-dependence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

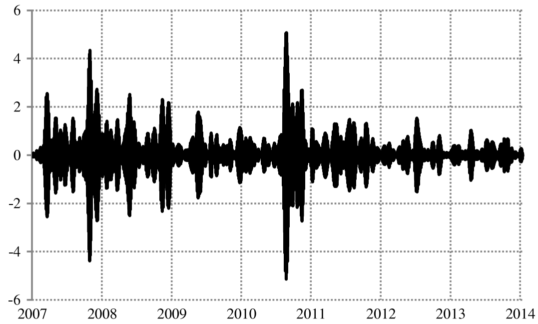
Table 1). Thus, we turn our attention to tail dependence measures[4]. We use student t-copula to estimate the symmetric tail dependence while the asymmetric tail behavior is captured through Clayton and Gumbel copula. The Clayton and Gumbel copula capture the positive and negative asymmetric tail dependence, respectively. The pair-wise estimated copula co-efficients matrix is presented in pictorial form, for consistency with wavelet images. The copula co-efficient matrix heat maps for student t, Clayton and Gumbel copula are shown in Fig. 2, respectively.

The overall message of tail dependence measures coincide with wavelet findings. Utilities and Financial industries show the least dependence (both symmetric and asymmetric dependence) with all other industries. Financial industry CDS index has relatively higher interdependence with Banking industry as both sectors mainly operate in similar businesses. Utilities industry has relatively higher dependence with Oil & Gas and Basic Material industries. The Basic Material industry's CDS

[4] The estimation of tail dependence based on copula models is done in a two-step procedure [72]. First, the marginal distribution of each time series is obtained through univariate GJR-GARCH (1, 1) model proposed by Glosten et al. [73]. The standardized residuals for each index returns are then used for copula estimates.



(a) Raw series.



(b) Variational mode 1.

Fig. 3. Variational modes of Banking sector CDS index.

index show highest tail dependence with all other industries. It is worth noting that majority of the previous work to measure credit risk have concentrated on estimating the default probabilities (dynamics of the term structure of credit spreads) using corporate bond data. The assessment of tail dependence among CDS indices can be utilized by the market participants to gauge the probability of simultaneous extreme losses. Naifar [28] highlight that ignoring the tail dependence would lead to under-estimation of the default risk premium. Our findings of three different dependence measures highlight that Utilities and Financial industries stand apart in terms of tail dependence form all other CDS industries and Basic Material industry can be viewed as most dependent industry.

3.2. Contagion effects through VMD and copula

Next, we apply VMD approach to extract ten different variational modes of the standardized residuals obtained through marginal models fitting on each CDS index return series. We arbitrarily set the number of modes k to ten for faster data processing. Forbes and Rigobon [1] suggest that the short time period associated with higher volatilities in asset prices should be used to examine the contagion effect hence we utilize the variational mode (VMD#10) representing the short-run dynamics of the CDS returns to identify the contagion effect[5]. Fig. 3 plots the original signal along with the variational mode representing the short-run dynamics of Banks CDS return series.

Notably, the Banking sector CDS returns exhibit higher variations during the crises episodes i.e. the global financial crisis of 2008–2009 and the Eurozone sovereign debt crisis of 2011–2013.[6] Therefore, we split the short-run time series into four sub-periods to examine the contagion effects. We identify the different sub-samples is as follows. We extract specific dates of the global financial crisis of 2008–2009 and the Eurozone sovereign debt crisis of 2011–2013 from the National Bureau of Economic Research (NBER) and Centre for Economic Policy Research (CEPR), respectively. Therefore our first sub-sample, from 17 December 2007 to 30 June 2009, is what we call the crisis period and the second sub-sample, from 1 July 2009 to 31 March 2011, is a post-global financial crisis sub-sample. We compare the tail dependence measures for these two sub-samples to examine the contagion effects among the industry-level credit markets during global financial crisis. Similarly, our third sub-sample, from 1 April 2011 till 31 March 2013, is the Eurozone sovereign debt crisis period while from 1 April 2013 to 30 December 2014 is regarded as the post-Eurozone sovereign debt crisis period. We compare the tail dependence among the industry-level credit markets for these two sub-samples to examine the contagion effects during Eurozone sovereign debt crisis.

The decomposed tail dependence analyses (Fig. 4), both during and after the global financial crises, show that dependence between a large number of industrial pairs increased during the crisis. This increase in tail dependence is evident for all three copula functions i.e., symmetric and asymmetric tail dependence. The copula estimates comparing the Eurozone sovereign debt crisis and post-crisis periods are shown in Fig. 4. Banks and Telecommunication and Health Care and Consumer Services pairs only show an increase in tail dependence (both symmetric and asymmetric tail dependence) during the crisis period as compared to post-crises period. These findings suggest that contagion effect among the US industry-level mainly took place during the global financial crises. This is not surprising as the crisis was originated from US sub-prime mortgage market with the collapse of Lehman brothers on 15 September 2008. It was primarily caused by a combination of under-pricing of credit risk and innovation in derivative products which allowed an explosive growth of leverage and hence affected the credit risk of different US industries. It is worth noting that Greece's credit rating was downgraded by Fitch from B+ to CCC on July 13, 2011 and there were also concerns about worsening credit conditions from the start of 2011.

---

5 Forbes and Rigobon [1] suggest that the contagion and interdependence must be differentiated when analyzing the pre- and post-crises scenarios. Contagion can be characterized as a sudden increase in short term correlation between the markets of interest, whereas, the increase in long term correlation portrays the higher interdependence that may occur due to bi-lateral ties or economic linkages among the markets. Further, the contagion effect does not only result in an increase in short term correlation but the increased turbulence (variations) may also result in lower dependence.

6 The VMDs of other CDS indices show similar patterns and for brevity of space we do not show figures for other industries; however, those are available from the authors on request.

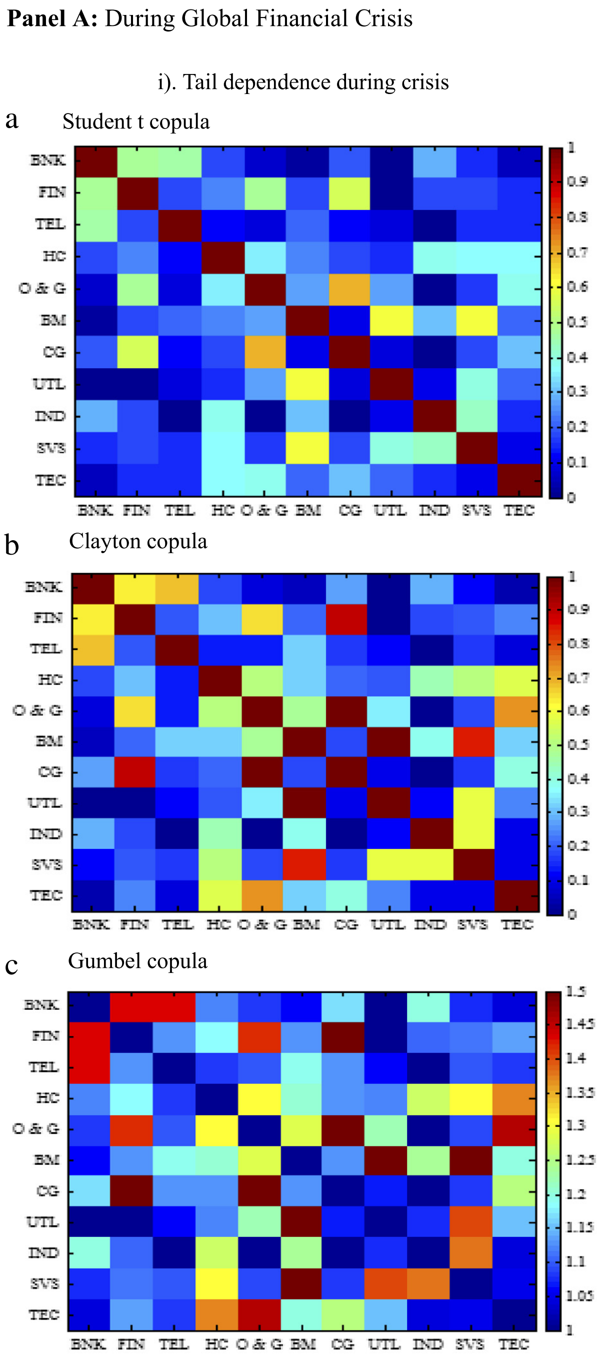


Fig. 4. Contagion effect. Note: See notes to Fig. 2.

4. Conclusion

The CDS indices are considered a higher-risk indicator and hence they are more sensitive to stock market conditions and macroeconomic variables during the financial crises. They play leading role in a financial system and impact the stability of financial system. Due to their vital role in an economy, this paper investigates the interdependence and contagion among the US industry-level credit markets. We utilize both wavelet squared coherence (WSC) and copula approaches for linear and non-linear dependence analysis. Daily data from 17 December, 2007 to 31 December 2014 is utilized and decomposition was done using variational mode decomposition (VMD) framework.

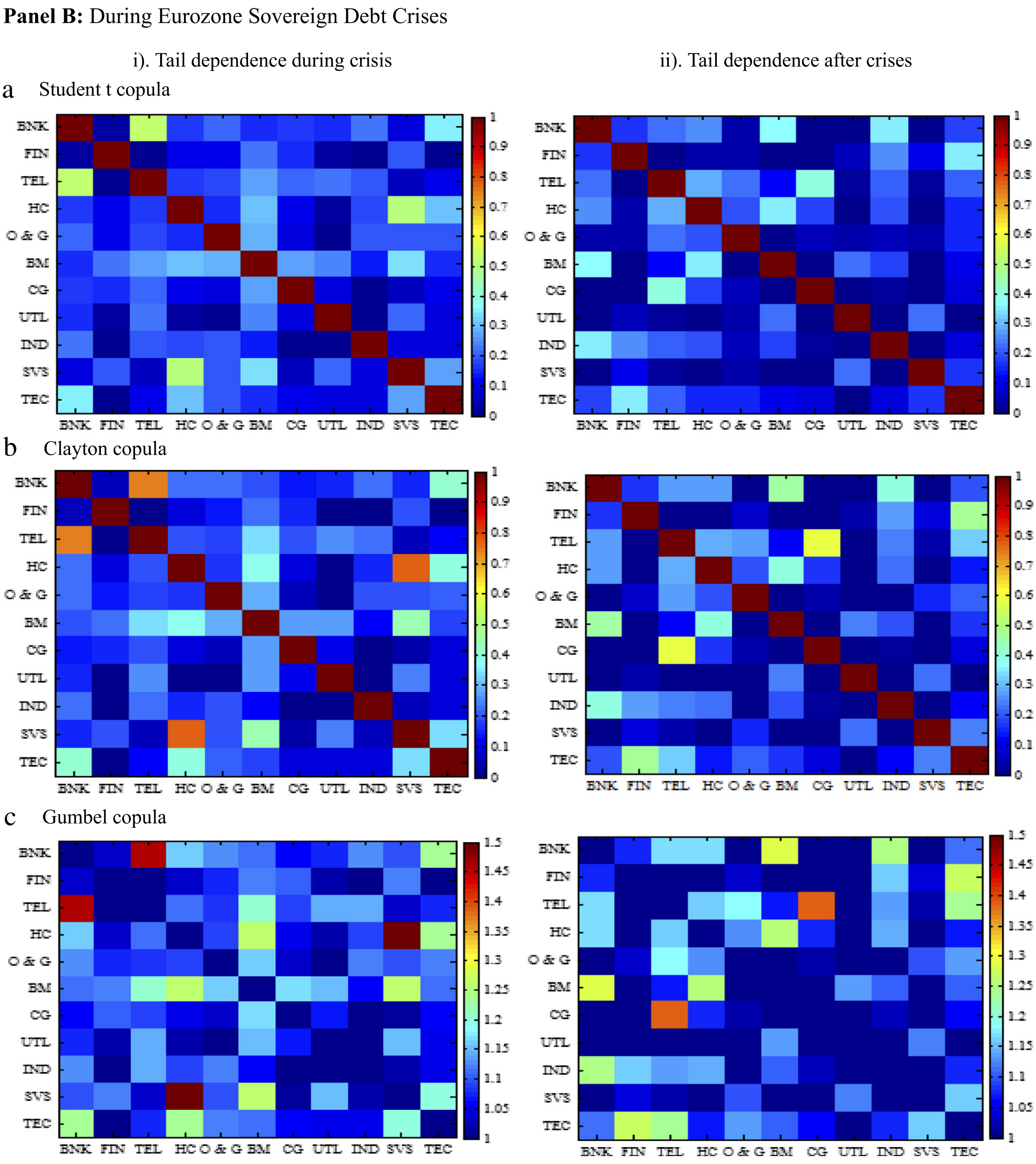


Fig. 4. (*continued*)

The empirical analysis reveals that Basic Material (Utilities) industry credit market has the highest (lowest) interdependence with the other industries. The dependence dynamics of these two industries provide arbitrage and hedging prospects for the credit market investors. The Utilities industry is a natural monopoly that is regulated by policy makers and due to low dependence with the other credit markets it can be exploited for possible arbitrage opportunities. Furthermore, Utilities is a counter-cyclical industry and its lower dependence with other industries may also be seen as a possible credit risk diversifier. On the other hand, Basic Materials industry is sensitive to changes in the business cycle and its higher dependence with the other industries stems from the fact that the credits risk of most of the industries dependence on the state of economy. The resulting higher comovement with the other industries can be useful to hedge the credit risk across industries. On the whole, the low dependence between Utility sector and others CDS sectors implies the emergence of diversification opportunities while the high dependence between Basic Materials economic sector, which is sensitive by the volatility of the price in metals, nonmetallic and construction materials, with the remaining CDS sectors indicates evidence of contagion.

Our findings that the interdependence among the credit markets varies across investment time horizons also have implications for the institutional investors. The investors with specific investment time horizons must consider the coherence among the industries for that particular time and frequency while formulating their investment strategies. Finally, we argue that dependence between the credit markets is subject to change during turbulence market conditions, more specifically, we find that most of the US credit markets experienced little "shift-contagion" as defined by Forbes and Rigobon [1].

Kapar and Olmo [74] argue that inventors' risk perceptions differ towards the risk of financial and non-financial CDS contracts. We suggest that the investor does not only distinguish between financial and non-financial contracts, they also differentiate between the non-financial sectors. We posit that contagion among CDS markets may arise through both economic channels and contractual links. The CDS markets are highly interdependent and hence the regulatory framework should also focus on the management of risk arising from co-movement between the assets, namely the operational risk or second-order risks of financial institutions. The second-order risks arise from the investment characteristics such as illiquidity, leverage, concentration and market structure, among others.

References

[1] K. Forbes, R. Rigobon, No contagion, only interdependence: Measuring stock market comovements, J. Finance 57 (2002) 2223–2261.
[2] W. Ahmad, S. Sehgal, N.R. Bhanumurthy, Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? Econ. Modell. 33 (2013) 209–225.
[3] D. Dimitriou, D. Kenourgios, T. Simos, Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach, Int. Rev. Financ. Anal. 30 (2013) 46–56.
[4] B. Raunig, Firm credit risk in normal times and during the crisis: are banks less risky? Appl. Econ. 47 (24) (2015) 2455–2469.
[5] F. Caramazza, L. Ricci, R. Salgado, International financial contagion in currency crises, J. Int. Money Finance 23 (1) (2004) 51–70.
[6] I. Goldstein, A. Pauzner, Contagion of self-fulfilling financial crises due to diversification of investment portfolios, J. Econom. Theory 119 (1) (2004) 151–183.
[7] F. Allen, D. Gale, Financial contagion, J. Polit. Econ. 108 (1) (2000) 1–33.
[8] T. Adrian, H.S. Shin, Financial intermediaries, financial stability, and monetary policy. FRB of New York staff report, (346), 2008.
[9] A.S. Kyle, W. Xiong, Contagion as a wealth effect, J. Finance 56 (4) (2001) 1401–1440.
[10] W. Xiong, Convergence trading with wealth effects: an amplification mechanism in financial markets, J. Financ. Econ. 62 (2) (2001) 247–292.
[11] D. Gromb, D. Vayanos, Limits of arbitrage: The state of the theory (No. w15821). National Bureau of Economic Research, 2010.
[12] G.A. Calvo, Contagion in emerging markets: when Wall Street is a carrier, 1999. http://drum.lib.umd.edu/handle/1903/4036.
[13] I. Schnabel, H.S. Shin, Liquidity and contagion: The crisis of 1763, JEEA (2004) 929–968.
[14] R. Caballero, A. Krishnamurthy, Financial system risk and flight to quality (No. w11834). National Bureau of Economic Research, 2005.
[15] R.J. Caballero, A. Krishnamurthy, Flight to quality and collective risk management (No. w12136). National Bureau of Economic Research, 2006.
[16] M.S. Kumar, A. Persaud, Pure contagion and investors' shifting risk appetite: analytical issues and empirical evidence, Int. Financ. 5 (3) (2002) 401–436.
[17] V. Coudert, M. Gex, Does risk aversion drive financial crises? Testing the predictive power of empirical indicators, J. Empir. Finance 15 (2) (2008) 167–184.
[18] D. Vayanos, Flight to quality, flight to liquidity, and the pricing of risk (No. w10327). National Bureau of Economic Research, 2004.
[19] J. Annaert, M. De Ceuster, P. Van Roy, C. Vespro, What determines euro area bank CDS spreads ? J. Int. Money Finance 32 (2013) 444–461.
[20] S. Bikhchandani, S. Sharma, Herd behavior in financial markets. IMF Staff papers, 2000, pp. 279–310.
[21] G.A. Calvo, E.G. Mendoza, Rational contagion and the globalization of securities markets, J. Int. Econ. 51 (1) (2000) 79–113.
[22] L.E. Kodres, M. Pritsker, A rational expectations model of financial contagion, J. Finance 57 (2) (2002) 769–799.
[23] S. Chakravorti, S. Lall, Managerial incentives and financial contagion. Federal Reserve Bank of Chicago Research Paper Series, 2003.
[24] R.A. Jarrow, F. Yu, Counterparty risk and the pricing of defaultable securities, J. Finance 56 (5) (2001) 1765–1799.
[25] P. Jorion, G. Zhang, Good and bad credit contagion: Evidence from credit default swaps, J. Financ. Econ. 84 (3) (2007) 860–883.
[26] V. Coudert, M. Gex, Contagion inside the credit default swaps market: The case of the GM and Ford crisis in 2005, J. Int. Financ. Markets Inst. Money 20 (2) (2010) 109–134.
[27] P. Jorion, G. Zhang, Credit contagion from counterparty risk, J. Finance 64 (5) (2009) 2053–2087.
[28] N. Naifar, What explains default risk premium during the financial crisis? Evidence from Japan, J. Econ. Bus. 63 (5) (2011) 412–430.
[29] L. Norden, M. Weber, Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements, J. Bank. Finance 28 (11) (2004) 2813–2843.
[30] N. Terzi, K. Ulucay, The role of credit default swaps on financial market stability, Procedia-Soc. Behav. Sci. 24 (2011) 983–990.
[31] H. Fang, Y.H. Lee, C.T. Yu, The impact of the sub-prime financial crisis on stock index returns for high and low risk countries, Investment Manag. Financ. Innov. 8 (4) (2010) 123–137.
[32] A. Sensoy, U. Soytas, I. Yildirim, E. Hacihasanoglu, Dynamic relationship between Turkey and European countries during the global financial crisis, Econ. Modell. 40 (2014) 290–298.
[33] N. Metiu, Sovereign risk contagion in the Eurozone, Econom. Lett. 117 (1) (2012) 35–38.
[34] A. Kalbaska, M. Gątkowski, Eurozone sovereign contagion: Evidence from the CDS market (2005–2010), J. Econ. Behav. Organ. 83 (3) (2012) 657–673.
[35] M.G. Arghyrou, A. Kontonikas, The EMU sovereign-debt crisis: Fundamentals, expectations and contagion, J. Int. Financ. Markets Inst. Money 22 (4) (2012) 658–677.
[36] C. Broto, G. Perez-Quiros, Disentangling contagion among Sovereign CDS spreads during the European debt crisis, J. Empir. Finance 32 (2015) 165–179.
[37] M. Mink, J. De Haan, Contagion during the Greek sovereign debt crisis, J. Int. Money Finance 34 (2013) 102–113.
[38] K. Hwang, J. Kang, Contagion effects in CDS markets. 2008. https://www.researchgate.net/profile/Jangkoo_Kang/publication/228844902_Contagion_effects_in_the_CDS_markets/links/0a85e53b5da81e2483000000.pdf.
[39] F.A. Longstaff, The subprime credit crisis and contagion in financial markets, J. Financ. Econ. 97 (3) (2010) 436–450.
[40] D.H. Kim, M. Loretan, E.M. Remolona, Contagion and risk premia in the amplification of crisis: evidence from Asian names in the global CDS market, J. Asian Econ. 21 (3) (2010) 314–326.
[41] T. Grammatikos, R. Vermeulen, Transmission of the financial and sovereign debt crises to the EMU: Stock prices, CDS spreads and exchange rates, J. Int. Money Finance 31 (3) (2012) 517–533.
[42] T.P.W. Fong, A.Y. Wong, Gauging potential sovereign risk contagion in Europe, Econom. Lett. 115 (3) (2012) 496–499.
[43] I. Fender, B. Hayo, M. Neuenkirch, Daily pricing of emerging market sovereign CDS before and during the global financial crisis, J. Bank. Finance 36 (10) (2012) 2786–2794.

[44] A. Alter, Y.S. Schüler, Credit spread interdependencies of European states and banks during the financial crisis, J. Bank. Finance 36 (12) (2012) 3444–3468.
[45] J. Beirne, M. Fratzscher, The pricing of sovereign risk and contagion during the European sovereign debt crisis, J. Int. Money Finance 34 (2013) 60–82.
[46] M. Gómez-Puig, S. Sosvilla-Rivero, Causality and contagion in EMU sovereign debt markets, Int. Rev. Econ. Finance 33 (2014) 12–27.
[47] M.H. Pesaran, A. Pick, Econometric issues in the analysis of contagion, J. Econom. Dynam. Control 31 (4) (2007) 1245–1277.
[48] M. Ranta, Contagion among major world markets: a wavelet approach, Int. J. Manag. Finance 9 (2) (2013) 133–149.
[49] C.T. Albulescu, D. Goyeau, A.K. Tiwari, Contagion and dynamic correlation of the main European stock index futures markets: a time-frequency approach, Proc. Econ. Finance 20 (2015) 19–27.
[50] M. Gallegati, A wavelet-based approach to test for financial market contagion, Comput. Statist. Data Anal. 56 (11) (2012) 3491–3497.
[51] G. Dewandaru, R. Masih, A.M.M. Masih, Why is no financial crisis a dress rehearsal for the next? Exploring contagious heterogeneities across major Asian stock markets, Physica A 419 (2015) 241–259.
[52] K. Dragomiretskiy, D. Zosso, Variational mode decomposition, IEEE Trans. Signal Process. 62 (3) (2014) 531–544.
[53] S. Lahmiri, Long memory in international financial markets trends and short movements during 2008 financial crisis based on variational mode decomposition and detrended fluctuation analysis, Physica A 437 (2015) 130–138.
[54] S. Lahmiri, A variational mode decompoisition approach for analysis and forecasting of economic and financial time series, Expert Syst. Appl. 55 (2016) 268–273.
[55] S.J.H. Shahzad, R.R. Kumar, S. Ali, S. Ameer, Interdependence between Greece and other European stock markets: A comparison of wavelet and VMD copula, and the portfolio implications, Physica A 457 (2016) 8–33.
[56] H. Boubaker, N. Sghaier, Portfolio optimization in the presence of dependent financial returns with long memory: A copula based approach, J. Bank. Finance 37 (2) (2013) 361–377.
[57] M. Sklar, Fonctions de répartition à n dimensions et leurs marges. Université Paris 8, 1959.
[58] P. Embrechts, A. McNeil, D. Straumann, Correlation and dependence in risk management: properties and pitfalls, in: Risk Management: Value at Risk and Beyond, 2002, pp. 176–223.
[59] T.H.E.O. Berger, M. Missong, Financial crisis, Value-at-Risk forecasts and the puzzle of dependency modeling, Int. Rev. Financ. Anal. 33 (2014) 33–38.
[60] H. Joe, Multivariate Models and Multivariate Dependence Concepts, CRC Press, 1997.
[61] B. Raunig, M. Scheicher, Are banks different?: evidence from the CDS market. Oesterreichische Nationalbank, 2009.
[62] P.K. Narayan, S.S. Sharma, K.S. Thuraisamy, An analysis of price discovery from panel data models of CDS and equity returns, J. Bank. Finance 41 (2014) 167–177.
[63] L. Aguiar-Conraria, M.J. Soares, Oil and the macroeconomy: using wavelets to analyze old issues, Empir. Econom. 40 (3) (2011) 645–655.
[64] A. Grinsted, J.C. Moore, S. Jevrejeva, Application of the cross wavelet transform and wavelet coherence to geophysical time series, Nonlinear Processes Geophys. 11 (5/6) (2004) 561–566.
[65] P.S. Addison, The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science Engineering, Medicine and Finance, Institute of Physics Publishing, Bristol, 2002.
[66] A. Rua, L.C. Nunes, International comovement of stock market returns: A wavelet analysis, J. Empir. Finance 16 (4) (2009) 632–639.
[67] L. Vacha, J. Barunik, Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis, Energy Econ. 34 (1) (2012) 241–247.
[68] C. Torrence, G.P. Compo, A practical guide to wavelet analysis, Bull. Am. Meteorol. Soc. 79 (1) (1998) 61–78.
[69] C. Torrence, P.J. Webster, Interdecadal changes in the ENSO-monsoon system, J. Clim. 12 (8) (1999) 2679–2690.
[70] D. Kwiatkowski, P.C. Phillips, P. Schmidt, Y. Shin, Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?, J. Econometrics 54 (1–3) (1992) 159–178.
[71] R.F. Engle, Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, Econometrica 50 (1982) 987–1007.
[72] R.B. Nelsen, An Introduction to Copulas, in: Lecture Notes in Statistics, vol. 139, 1999.
[73] L.R. Glosten, R. Jagannathan, D.E. Runkle, On the relation between the expected value and the volatility of the nominal excess return on stocks, J. Finance 48 (5) (1993) 1779–1801.
[74] B. Kapar, J. Olmo, The determinants of credit default swap spreads in the presence of structural breaks and counterparty risk (Report No. 11/02). London, UK: Department of Economics, City University London, 2011.