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The lead-lag relationship between US industry-level credit and stock markets

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Abstract
Purpose – The purpose of this paper is to identify the arbitrage opportunities between US industry-level credit and stock markets with a focus on dynamic lead-lag relationships given that these markets involve heterogeneous agents operating over various time horizons.

Design/methodology/approach – The authors use daily data of 11 US industries stock markets and their credit counterparts to model the dynamic dependence and casual nexuses using time-frequency approach, namely, wavelet squared coherence (WTC).

Findings – The WTC estimation results show that credit and stock markets are out of phase (counter cyclical) and stock markets lead their credit counterparts. The coherence between two markets increases during financial crises. The banks (utilities) industry credit and stock markets have relatively high (low) dependence.

Research limitations/implications – The casual nexuses between stock and credit markets have multilateral dimensions. Greater interest in examining the relationship between stock markets and credit default swap (CDS) spreads emerged as an important albeit a complex area of research, and gained prominence especially at the onset and following the global financial crises of 2007-2008 which clearly showed that the positive views of CDSs contribution in creating a resilient and efficient financial sector was nothing further from the truth.

Practical implications – The arbitrage and hedging opportunities between stock and credit markets are industry dependent and vary over investment time horizons. The utilities industry seems attractive for the investment with the objective to exploit arbitrage, but not for hedging.

Originality/value – The paper, for the first time, employs time-frequency approach to assess the arbitrage opportunities between US industry-level credit and stock markets.

Keywords Granger causality, Arbitrage, Credit default swap, Wavelet squared coherence

1. Introduction
The casual nexuses between stock and credit markets have multilateral dimensions. Greater interest in examining the relationship between stock markets and credit default swap (CDS) spreads emerged as an important albeit a complex area of research, and gained prominence especially at the onset and following the global financial crises of 2007-2008 (Narayan, 2015)
which clearly showed that the positive views of CDSs contribution in creating a resilient and efficient financial sector cannot be further from the truth\[1\]. Notably, during the financial crises, the sovereign and corporate CDS spreads widened to unprecedented levels, putting financial industry and the countries with pessimistic macroeconomic outlooks and serious fiscal imbalances under intense pressure and risk of default (Subrahmanyam et al., 2014).

In theory, the stock price of a firm impacts its CDS spread. The structural model of Merton (1974) suggests that CDS spreads and stock prices have a negative relationship with each other and they must co-move to prevent arbitrage. The deterioration in the financial conditions of a firm increases the probability of its default on underlying debt obligations. Therefore, financial distress conditions result in a decrease in the value of firms’ stocks and increase the CDS spread.

Furthermore, an informed trader may prefer CDS over equity shares to take a hedge (insure against default) or speculative (bet on the likelihood of default) position due to the market opacity and entrenched leverage advantage of CDSs. Additionally, CDS contracts trade based on the notional amounts, and hence the physical size of the market does not impact the trading volume. A CDS contract can be created whenever the other side (market maker) is willing to buy and sell. Based on these advantages, the informed traders, on aggregate, may prefer to trade in the CDS market compared to the stocks. This trading preference between the two markets would result in a price discovery advantage to the CDS market.

Galindo et al. (2014) argue that the financial integration leads to credit contraction in case of adverse financial shocks and also help the credit markets to deepen. Therefore, the answers to a question like whether the CDS market leads and/or lags the stock market in terms of both pricing and efficiency has implications for hedging, speculation and arbitrage. The answers can provide an early warning of large shocks in asset prices. Moreover, the information of the transmission channels of credit risk across different markets and over time will help to understand the relative efficiency of these markets, and provide answers on how the functioning of these markets may change under different market conditions (Avino et al., 2013).

The extant literature has concentrated on similar issues; however, mainly applying the traditional econometric techniques. The empirical works by Byström (2008), Castellano and Scaccia (2014), Coronado et al. (2012) and Ngene et al. (2014), among others, have focused on a bivariate framework consisting of CDS and stock markets. Other studies such as Chan-Lau and Kim (2004), Longstaff et al. (2005), Norden and Weber (2009), Trutwein and Schiereck (2011) used the vector autoregressive (VAR) model while Da Silva (2014), Forte and Lovreta (2015), Forte and Peña (2009) and Schweikhard and Tsesmelidakis (2012) employed vector error correction model (VECM) to ascertain the cointegration among CDS and stock markets; and others such as Chan et al. (2009), Coronado et al. (2012), Da Silva (2014) and Fung et al. (2008) applied Granger causality tests to conclude the presence of causal flows between CDS and stock markets.

The recent wave of studies considered the fact that markets do not behave consistently during tranquil and turbulent periods and applied copula approach to examine the relationship between CDS and stocks (Da Silva et al., 2014; Fei et al., 2013; Fenech et al., 2014; Naifar, 2011) or by utilizing Markov regime-switching models (Castellano and Scaccia, 2014; Da Fonseca and Wang, 2015; Guo et al., 2011). According to these studies, the general finding is that the stock markets tend to lead the CDS market (cf. Forte and Peña, 2009; Fung et al., 2008; Norden and Weber, 2009; Trutwein and Schiereck, 2011) thus supporting the view that the stock markets incorporate new information relatively quickly. Furthermore, these studies show that the CDS-stock nexus depends on the credit quality of the underlying debt obligation – a higher CDS-stock dependence was noted by Corzo et al. (2014), Forte and Lovreta (2015), Fung et al. (2008) and Norden and Weber (2009) in the presence of better credit worthiness and
volatile market conditions enhance the degree of association between CDS and stock markets (cf. Coronado et al., 2012; Fei et al., 2013; Naifar, 2011; Trutwein and Schiereck, 2011).

Another observation from the related literature on CDS-stock link is that most studies have concentrated on sovereign CDSs (Corzo et al., 2014; Ngene et al., 2014), utilized the firm-level CDSs (e.g. Forte and Lovreta, 2015; Forte and Peña, 2009), or examined the linkages between CDS spreads and stock returns at the industry level (Byström, 2008; Narayan, 2015; Narayan et al., 2014). Narayan et al. (2014) use panel cointegration and panel VECMs to investigate the price discovery in the US CDSs and stock markets at the industry level. Among other things, they find the presence of heterogeneity across industries; stock markets lead their CDS counterparts in the price discovery process; and price discovery process is stronger during the recent global financial crisis. Narayan (2015) finds that the CDS shocks of US industry explain the forecast error variance of sectoral equity returns and have different effects on equity returns and return volatility; and the CDS return shocks are most dominant in the post-Lehman crisis period.

From the above studies, it becomes clear that the lead-lag relationship measured using index-level data can avoid idiosyncrasies (Fung et al., 2008); the relationship between CDS and stock market is time dependent (Forte and Peña, 2009; Lenciauskaitė, 2012) and hence conventional econometric technique cannot fully capture the dynamics; and the industry-wise nature (spread and volatility) of the CDS market is different and thus have varying speed of adjustment in comparison with its equity counterparts (Narayan et al., 2014).

Subsequently, in understanding the relationship between CDS and stock markets, this study contributes to the existing literature in the following ways. We examine the co-movement along with the lead-lag relationship between CDS and stock markets at the industry level. To do this, we utilize wavelet squared coherence (WTC) analysis which is considered a promising method for an in-depth examination of the instantaneous interactive relationship between the time series. The advantages of this technique are that it overcomes the problems of non-stationarity in the time series and it is an appropriate method for examining the co-movement particularly when the short- and long-term investment horizons are jointly considered (Madaleno and Pinho, 2010).

The credit and stock markets are well known to be complex systems which involve heterogeneous agents that include speculators, hedge funds, institutional investors, banks and insurance companies operating over various time horizons (from minutes to years) and thus collectively determine the markets' behaviors (both on aggregate and at the industry level). Therefore, the degree of association between credit and stock markets may vary over time and over different investment horizons for the market participants who differ in terms of expectations, trading strategies, risk profiles, informational sets, etc. Furthermore, we examine the cause and effect relationship and present robust findings from the wavelet analysis through frequency domain Granger causality technique (Lemmens et al., 2008).

The balance of the paper is organized as follows. In Section 2, we briefly survey further related studies that examined the relationship between CDS and stock markets. In Section 3, we present the empirical approach. In Section 4, we describe the data used and reports the key empirical findings. Finally, in Section 5, we conclude the paper.

2. A brief literature survey

Longstaff et al. (2005) analyze the CDS market’s lead-lag relationship with corporate bond spreads and stock returns of US firms. Although they find that CDS and stock markets lead the bond market, the lead-lag relationship between CDS and stock markets was not clear. Norden and Weber (2004) investigate the European CDS markets and note a negative correlation between CDS spread change and stock returns; and suggest that stock returns lead CDS spread changes.
In another study, Norden and Weber (2009) investigate 58 international firms using daily data over three years time period and re-affirm that individual stock returns significantly lead CDS spread changes for most of the firms in their sample. Norden and Weber (2009) find a definite lead of the stock market relative to the CDS market and suggest that, the co-movement between the markets is affected by the credit quality of the sample firms, and co-movement increases with the decrease in credit quality. Similarly, Forte and Peña (2009) use North American and European firm-level data and suggest that price discovery process of CDS and stock prices depends on the financial situation of a firm. Stock market turnover, firm’s credit quality and negative shocks significantly contribute toward the stock market’s price discovery. Additionally, while the stock markets has led both bond and CDS markets, this relationship is time dependent and decrease over time.

The empirical works by Collin-Dufresne et al. (2001), Blanco et al. (2005) and Kapadia and Pu (2012) suggest a weak correlation between stock returns and credit spreads change. However, Fung et al. (2008) argue that the exploitation of capital structure arbitrage enhances the integration and information flows between CDSs and stock prices.

On the contrary, Blanco et al. (2005) find that the price discovery occurs in the CDS markets and that CDS markets anticipate deterioration in credit quality earlier than the stock markets (Zhang, 2008). Coudert and Gex (2010) find that the CDS markets lead the bond markets and the current financial crisis has increased this leading role of CDS markets.

Byström (2008) analyze the relationship between CDS and stock markets using index-level data. He confirms the importance of stock market volatility within the Merton model and concludes that stock markets Granger cause changes in CDS spread. Fung et al. (2008) argue that the information flow between the CDS and stock markets is driven by both the market-wide systemic risk (e.g. wars and economic recessions) and/or idiosyncratic risk (e.g. corporate events such as corporate restructuring or insider trading). Because the firm-level data may affect the co-movement and lead-lag relationship between the two markets, they diversify the idiosyncrasies using CDS and stock market indices and make a distinction between investment grade and high-yield CDS. Their results show that the CDS markets provide additional information for the detection of default probability beyond stock market, and the two-way interaction between these markets is evident especially when the stock market is on a downturn. More recently, Coronado et al. (2012) and Lenciauskaitė (2012) examine the lead-lag relationship between European CDS and stock markets and confirm that stock markets lead sovereign CDSs. However, prior to the 2007-2008 financial crises, the CDS market took a lead over stock market.

One puzzling finding in the existing literature on CDS spreads and stock links is the variability of outcomes which is dependent on sample periods, sample sizes and model specification. Hence, to gain a better and thorough understanding of the links between CDS spreads and stock prices, it is of interest and importance to study the dynamics of these variables using sophisticated econometric tools.

3. Methodology

3.1 Toda and Yamamoto’s (1995) Granger non-causality test

When the first variable Granger causes the second variable, this implies that including the first variable in the information set improves the forecast of the second variable over and above its own information (Granger, 1969). The causality tests are typically performed by examining the joint significance of the lagged values for the first variable in a predictive model for the second variable. The Toda and Yamamoto’s (1995) Granger non-causality procedure is often used to examine causal relationships because it can be applied irrespective of the order of integration of the variables. For the bootstrap, Toda and Yamamoto’s (1995) dynamic lag (TYDL) Granger causality test, the following bivariate VAR(p) process is considered:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-(p+1)} + \epsilon_t$$  (1)
where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a white noise process with 0 mean and non-singular covariance matrix $\Sigma$ and $p$ denotes the optimal lag length of the VAR system. The above representation is simplified by partitioning the vector $y_t$ into two sub-vectors, CDS premia ($CDS_t$) and stock prices ($SP_t$). Hence, Equation (1) is written as:

$$
\begin{pmatrix}
CDS_t \\
SP_t
\end{pmatrix}
= \begin{pmatrix}
\phi_{10} \\
\phi_{20}
\end{pmatrix} + \begin{pmatrix}
\phi_{11}(L) & \phi_{12}(L) \\
\phi_{21}(L) & \phi_{22}(L)
\end{pmatrix}
\begin{pmatrix}
CDS_t \\
SP_t
\end{pmatrix}
+ \begin{pmatrix}
\varepsilon_{1t} \\
\varepsilon_{2t}
\end{pmatrix}
$$

(2)

$$
\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij,k}L^k, \ i,j = 1, 2 \text{ and } L \text{ is the lag operator such that } L^k x_t = x_{t-k}.
$$

Using Equation (2), the null hypothesis that stock prices does not Granger cause CDS premia is tested by imposing the zero restriction $\phi_{12,k} = 0$ for $k = 1, 2, \ldots, p$. Similarly, by imposing the restriction $\phi_{21,k} = 0$ for $k = 1, 2, \ldots, p$, the null hypothesis that CDS premia does not Granger cause stock prices is tested.

3.2 Wavelet analysis

The analysis of financial and economic time series using wavelet approach has become a common practice in economics and finance literature (Karlsson et al., 2016; Torrence and Compo, 1998; Rua and Nunes, 2009; Aloui and Hkiri, 2014). Wavelet analysis provides useful information regarding the behavior of time series utilizing both frequency and time domains. The method is well suited for processing a non-stationary time series like financial markets data in which the frequencies change over time. The two interesting features of the wavelet approach specific for analyzing the co-movement between the CDS and stock markets analysis are: it can decompose a time series into different time-scaled components, and it represents the variability and structure of the stochastic processes on scale-by-scale basis. The wavelet transform converts the time series using wavelet functions. This wavelet function is a small wave and can be manipulated (stretched or squeezed 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 is specified as:

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

(3)

notably, the wavelet is a real- 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 Equation (3), $\tau, s$ and $\frac{1}{s}$ represent time position (translation parameter), scale (dilation parameter related with frequencies) and normalization factor, respectively. The normalization factor ensures that the transformation remains comparable across scales and over time. The mother, $\psi(t)$, should also have certain properties so that it can be utilized for decomposition. It must have zero mean, $\int_{-\infty}^{+\infty} \psi(t) dt = 0$; its square integrates to unity, $\int_{-\infty}^{+\infty} \psi^2(t) dt = 1$, which means that $\psi(t)$ is limited to an interval of time; it should also satisfy the so-called admissibility condition, $0 < C_\psi = \int_{0}^{+\infty} \left| \hat{\psi}(\omega) \right|^2 d\omega < +\infty$ where $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$, that is, $\hat{\psi}(\omega) = \int_{-\infty}^{+\infty} \psi(t) e^{-i\omega t} dt$.

The literature provides different types of wavelets for the decomposition of time series. For our purpose, we use Morlet wavelet to examine the wavelet coherence among the CDS and stock markets because it provides the best balance between time and frequency localization (Addison, 2002). Grinsted et al. (2004) show that Fourier period for the Morlet
The wavelet is almost equal to the scale used and is given as:

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

In Equation (4), \( \omega_0 \) indicates the central frequency of the wavelet.

Following the previous works by Grinsted et al. (2004), Rua and Nunes (2009), Vacha and Barunik (2012) and Aloui and Hkiri (2014), we used \( \omega_0 = 6 \). Morlet wavelet with \( \omega_0 = 6 \) provides a better localization between time and frequency. The wavelet analysis can be performed using either the continuous wavelet transform (CWT) or the discrete wavelet transform (DWT). The former advantages over DWT in that it provides freedom to select wavelets according to the length of data, and the redundancy in CWT makes interpretation and discovery of patterns or hidden information easier (Aguiar-Conraria and Soares, 2011). A CWT \( W_x \) of a discrete time series \( (x(t), t = 0, 1, \ldots, n) \) with respect to \( c(t) \), can be written as:

\[ W_x(t, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi^{*}_{\frac{t-\tau}{s}}(t) \, dt \tag{5} \]

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

\[ \| x^2 \| = \frac{1}{C_\psi} \int_{0}^{\infty} \left[ \int_{-\infty}^{+\infty} |W_x(\tau, s)|^2 \, d\tau \right] \frac{ds}{s^2} \tag{6} \]

Torrence and Compo (1998) 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:

\[ W_{xy}(\tau, s) = W_x(\tau, s) \cdot W_y^{*}(\tau, s) \tag{7} \]

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

\[ R^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau, s))|^2}{S(s^{-1}|W_x(\tau, s)|^2) \cdot S(s^{-1}|W_y(\tau, s)|^2)} \tag{8} \]

In Equation (8), \( S(.) \) and \( R^2 \) represent wavelet squared coherency and smoothing operator, respectively. Torrence and Webster (1999) define WTC 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 wavelet coherency can be seen as the correlation coefficient at each moment in time and for different frequency. Therefore, it can be used to gauge the co-movement between the two time series over time and frequency domains. The values of squared correlation coefficients \( R^2(\tau, s) \) range from 0 (low co-movement) to 1 (high co-movement). The WTC when plotted as an image provides a clearer picture (dense regions) of the co-movement over time and different frequencies.

The mean and confidence interval of the phase difference of two time series are estimated, the Monte Carlo methods are used to find the statistical level of significance of the wavelet coherence, and for input data, a large ensemble of surrogate data set pairs are generated with the same AR(1) coefficients. As in Grinsted et al. (2004), the number of lags in
phase for wavelets is defined as:

$$\varphi_{xy} = \tan^{-1} \frac{I\{ W_n^y \}}{R\{ W_n^x \}}, \quad \varphi_{xy} \in [-\pi, \pi].$$

(9)

where, $I$ and $R$ indicate the real and imaginary parts of the smooth power spectrum, respectively. The time series move together with specified frequency when the value of phase difference ranges to 0. The series move in phase if $\varphi_{xy} \in [0, \pi/2]$ and series $y$ leads $x$. On the contrary, if $\varphi_{xy} \in [-\pi/2, 0]$, then $x$ leads $y$. The relation is anti-phase relation (negative covariance) when phase difference is $\pi$ (or $-\pi$) implying that $\varphi_{xy} \in [-\pi/2, \pi] \cup [-\pi, \pi/2]$. Now, if $\varphi_{xy} \in [\pi/2, 0]$ then $x$ leads why and otherwise if $\varphi_{xy} \in [-\pi, -\pi/2]$.

4. Data and findings

The study examines the co-movement and causality in time and frequency domain between CDS and equity markets of the USA using industrial indices. The industries include banking, financial, telecommunication, healthcare, oil and gas, materials, consumer goods, utilities, industrial, consumer services and technology. The daily data are extracted from DataSteam International (Thomson Financial) for the period December 14, 2007 to December 31, 2014 because the industry-level CDS indices were launched by DataSteam in December 2007. The time period is recent and sufficiently large enough to conduct empirical analysis to examine the lead-lag relationship between the markets. The sample also covers the impact of various international events.

In Figures 1 and 2, we present the CDS premia (in basis points) and equity index levels, respectively. We plot the mean and standard deviations (SD) of the CDS spread and their equity counterparts by industry, respectively. The figures highlight that CDS premia differs for each industry. It is evident that some industries, such as financial, industrial and consumer services have relatively high CDS spreads, suggesting that these industries are most risky compared to Banks, oil and gas, and consumer goods industries for which the CDS premia is nearly half of the most risky industries. The volatility of the CDS spreads measured by the SD show a clear industrial pattern and in some industries, the volatility is high while in others it is low.

In our sample, we treat banks and financial industries separately because CDS premia of these sectors react differently to the market conditions (Raunig and Scheicher, 2009; Raunig, 2015). Moreover, banks have unique characteristics in terms of balance sheet.

Figure 1.
Mean and standard deviation of CDS premia for US industrial indices

![Figure 1](image-url)
composition, their central role in an economy and different regulatory framework, among other things, that distinguish them from the non-financial or industrial firms. The industry-level CDS indices (denominated in basis points so that 100 basis points equates to 1 percentage point) are based on five-year tenor series contracts because the five-year credits instruments are considered adequate based on liquidity (Narayan et al., 2014). The trend of CDS and stock indices are shown in Figure 3.

The descriptive statistics and correlation between CDS and equity index pairs are reported in Table I. Financial industry CDS premia is highest (364.14 basis points) among the 11 industries. Similarly, other statistics such as minimum, maximum and SD are also higher than other industries. The oil and gas industry has the lowest average CDS premium (146.40). The last column of the table presents the correlation between the CDS and equity index of each industry. All the correlation values are significant and negative. The preliminary analysis indicates that both markets are not only related, but the stock markets have a negative impact on the CDS premia (Merton’s model). The correlation between financial industry CDS and equity indices is also highest (−0.8312) and significant at 1 percent level of significance. The banks industry CDS and equity index show relatively low correlation (−0.4301) with each other. All the time series are non-normal as the null hypothesis of Jarque-Bera test is rejected. For econometric analysis, all the series were transformed into natural logarithmic form to reduce the sharpness in data and to increase the reliability of results.

The issue of spurious regression can arise when statistical inferences are drawn from non-stationary time series. Therefore, it is necessary to first examine the unit root properties of the data (Granger and Newbold, 1974; Phillips, 1987). The Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) unit root test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test are used to determine the order of integration of the variables. Moreover, it can be shown that using a combination of ADF, PP and KPSS tests, the possibility of wrong conclusions on stationarity is minimized (Amano and van Norden, 1992; Schlitzer, 1995). The unit root results are presented in Table II. The three tests (ADF, PP and KPSS) fail to reject (reject) the null hypothesis of no unit root (stationarity) in the levels for all series at the usual levels of significance. However, the tests clearly indicate that the series are stationary in first differences.

The TYDL causality test is utilized to examine the causality relationship between industry-level CDS spread and stock prices. The selection of the optimal lag length of the VAR model for each industry is based on the Akaike information criterion (AIC).
Figure 3.
Trend of industry-level CDS and equity index series.
<table>
<thead>
<tr>
<th>Industry(s)</th>
<th>Index</th>
<th>Mean</th>
<th>Maximum</th>
<th>Minimum</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jorke-Bera test</th>
<th>Corr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>CDS</td>
<td>152.34</td>
<td>511.96</td>
<td>56.217</td>
<td>75.565</td>
<td>1.5054</td>
<td>5.9595</td>
<td>1,307.7*</td>
<td>-0.4301**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>820.03</td>
<td>1,499.6</td>
<td>282.86</td>
<td>209.09</td>
<td>0.5580</td>
<td>2.9802</td>
<td>91.460*</td>
<td>(-19.982)</td>
</tr>
<tr>
<td>Financial</td>
<td>CDS</td>
<td>362.15</td>
<td>1,099.7</td>
<td>144.66</td>
<td>169.57</td>
<td>1.4279</td>
<td>5.1433</td>
<td>935.50*</td>
<td>-0.8312**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>1,800.0</td>
<td>2,946.8</td>
<td>743.42</td>
<td>512.07</td>
<td>0.4503</td>
<td>2.1688</td>
<td>110.07*</td>
<td>(-62.653)</td>
</tr>
<tr>
<td>Telecommunication</td>
<td>CDS</td>
<td>237.44</td>
<td>621.30</td>
<td>107.09</td>
<td>102.23</td>
<td>1.3465</td>
<td>5.0200</td>
<td>831.51*</td>
<td>-0.6953**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>505.18</td>
<td>659.54</td>
<td>323.12</td>
<td>86.070</td>
<td>-0.0393</td>
<td>1.6922</td>
<td>125.95*</td>
<td>(-40.582)</td>
</tr>
<tr>
<td>Healthcare</td>
<td>CDS</td>
<td>170.68</td>
<td>400.01</td>
<td>82.996</td>
<td>63.32</td>
<td>1.2166</td>
<td>4.5829</td>
<td>621.83*</td>
<td>-0.7182**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>2,564.2</td>
<td>4,789.2</td>
<td>1,425.2</td>
<td>811.67</td>
<td>1.0186</td>
<td>2.8988</td>
<td>305.25*</td>
<td>(-43.288)</td>
</tr>
<tr>
<td>Oil and Gas</td>
<td>CDS</td>
<td>145.25</td>
<td>399.00</td>
<td>54.650</td>
<td>67.760</td>
<td>1.6387</td>
<td>5.5399</td>
<td>1286.9*</td>
<td>-0.6922**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>2,063.7</td>
<td>2,929.0</td>
<td>1,246.5</td>
<td>378.89</td>
<td>0.0294</td>
<td>2.1506</td>
<td>53.189*</td>
<td>(-32.219)</td>
</tr>
<tr>
<td>Materials</td>
<td>CDS</td>
<td>229.35</td>
<td>612.22</td>
<td>87.722</td>
<td>98.072</td>
<td>2.0067</td>
<td>7.6433</td>
<td>2783.9*</td>
<td>-0.7433**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>1,216.83</td>
<td>1,643.2</td>
<td>501.83</td>
<td>252.63</td>
<td>-0.7260</td>
<td>3.0509</td>
<td>154.87*</td>
<td>(-46.687)</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>CDS</td>
<td>149.90</td>
<td>345.10</td>
<td>83.023</td>
<td>44.737</td>
<td>1.1612</td>
<td>5.1627</td>
<td>736.94*</td>
<td>-0.7915**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>454.81</td>
<td>694.55</td>
<td>245.36</td>
<td>108.90</td>
<td>0.4308</td>
<td>2.1997</td>
<td>101.45*</td>
<td>(-54.318)</td>
</tr>
<tr>
<td>Utilities</td>
<td>CDS</td>
<td>211.61</td>
<td>465.52</td>
<td>74.284</td>
<td>87.683</td>
<td>0.0492</td>
<td>2.2574</td>
<td>41.177*</td>
<td>-0.6331**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>330.14</td>
<td>464.14</td>
<td>204.35</td>
<td>50.701</td>
<td>0.0638</td>
<td>2.2457</td>
<td>42.940*</td>
<td>(-34.302)</td>
</tr>
<tr>
<td>Industrial</td>
<td>CDS</td>
<td>296.35</td>
<td>903.43</td>
<td>108.56</td>
<td>158.97</td>
<td>1.4807</td>
<td>4.8092</td>
<td>889.63*</td>
<td>-0.8120**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>1,720.0</td>
<td>2,696.0</td>
<td>720.22</td>
<td>460.12</td>
<td>0.3227</td>
<td>2.4353</td>
<td>53.960*</td>
<td>(-58.739)</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>CDS</td>
<td>305.84</td>
<td>1,194.5</td>
<td>135.85</td>
<td>169.20</td>
<td>2.6577</td>
<td>10.5998</td>
<td>6323.5*</td>
<td>-0.6351**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>1,355.74</td>
<td>2,391.7</td>
<td>606.80</td>
<td>435.50</td>
<td>0.5726</td>
<td>2.1716</td>
<td>146.60*</td>
<td>(-34.488)</td>
</tr>
<tr>
<td>Technology</td>
<td>CDS</td>
<td>184.71</td>
<td>511.45</td>
<td>50.254</td>
<td>75.990</td>
<td>1.9176</td>
<td>7.5456</td>
<td>2595.3*</td>
<td>-0.6145**</td>
</tr>
<tr>
<td></td>
<td>Stock</td>
<td>1,527.0</td>
<td>2,461.4</td>
<td>703.23</td>
<td>388.33</td>
<td>0.2068</td>
<td>2.7488</td>
<td>30.478*</td>
<td>(-32.671)</td>
</tr>
</tbody>
</table>

Notes: The number in the parenthesis are $t$-values of correlation test. *Indicates that null hypothesis of normality is rejected at 1 percent significance level; **Significance of correlation at 1 percent level
The causality results are reported in Table III. As noted, the null hypothesis that CDS premia does not Granger cause stock prices is rejected for banks, telecommunication, healthcare and materials industries. In contrast, the null hypothesis that stock prices do not Granger cause CDS spread is rejected for the 11 industries.

While the aforementioned results provide some insights into the causality dynamics, it is important to highlight that the causal inference on the full sample can be seriously biased in the presence of structural changes such as the global financial crises, among other things. The structural changes can produce non-linearities, shifts in the parameters and hence alter the pattern of causality over time. Noting this, we examine the presence of non-linearity in the CDS-Stock relationship using the Broock-Dechert-Scheinkman (BDS) (Broock et al., 1996) test. As shown in Table IV, the null hypothesis of independent and identically distributed (iid) residuals is rejected at 5 percent significance level across various dimensions for all the 11 industries, which suggests strong evidence of nonlinear relationship between stock prices and CDS spread and implies that the results from the standard linear Granger causality test are biased.

Furthermore, we conduct the tests for short-run and long-run parameter stability to ascertain the reliability of statistical inference based on TYDL. In practice, a number of tests can be utilized to examine the temporal stability of VAR models (Andrews, 1993; Andrews and Ploberger, 1994). Although it is straightforward to apply these tests to stationary systems, the variables in our model are non-stationary and cointegrated and hence this integration-cointegration property

### Table II

Unit root properties of the time series

<table>
<thead>
<tr>
<th>Industries</th>
<th>Level ADF First difference</th>
<th>Level PP First difference</th>
<th>Level KPSS First difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: CDS series</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Banks</td>
<td>45.407*** 2.5085*** 0.2666</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financials</td>
<td>44.182*** 4.2180*** 0.2431</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telecommunications</td>
<td>45.168*** 1.1426*** 0.2365</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare</td>
<td>46.111*** 4.5699*** 0.3628</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oil and gas</td>
<td>46.140*** 4.5407*** 0.5042</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basic materials</td>
<td>48.277*** 2.6706*** 0.4048</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer goods</td>
<td>44.719*** 3.6693*** 0.3051</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utilities</td>
<td>48.277*** 2.6706*** 0.4048</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrials</td>
<td>47.379*** 0.8231*** 0.2798</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer services</td>
<td>46.181*** 4.2180*** 0.2431</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology</td>
<td>47.379*** 0.8231*** 0.2798</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table presents the results of the standard ADF, PP and KPSS unit root tests. Level and first difference denote the statistics of the tests applied on the level and the first differences of the time series, respectively. For the ADF and PP tests, the critical values are based on the work of MacKinnon (1996). The null hypothesis in the ADF and PP (KPSS) tests is that the time series has a unit root (is stationary). ***Significant at the 1 percent level
should be taken into account. In a cointegrated VAR, the variables form a VECM and the stability of both the long-run and short-run parameters needs to be investigated. If the long-run or cointegration parameters are stable, the model exhibits long-run stability. Moreover, if the short-run parameters are also stable, the model has full structural stability. Since the estimators of

\[
\begin{align*}
\text{CDS} \rightarrow & \text{Stock} \\
\text{Stock} \rightarrow & \text{CDS}
\end{align*}
\]

\[\chi^2 \quad p\text{-value} \quad \chi^2 \quad p\text{-value}\]

<table>
<thead>
<tr>
<th>Industries</th>
<th>Lag order</th>
<th>(\chi^2)</th>
<th>(p)-value</th>
<th>(\chi^2)</th>
<th>(p)-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>8</td>
<td>31.2588***</td>
<td>(0.0001)</td>
<td>82.808***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Financials</td>
<td>8</td>
<td>2.4514</td>
<td>(0.2931)</td>
<td>66.345***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Telecommunication</td>
<td>5</td>
<td>31.827***</td>
<td>(0.0000)</td>
<td>91.802***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Healthcare</td>
<td>7</td>
<td>35.9841***</td>
<td>(0.0000)</td>
<td>65.9657***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Oil and gas</td>
<td>8</td>
<td>6.5359</td>
<td>(0.2680)</td>
<td>60.7830***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Basic materials</td>
<td>9</td>
<td>20.4442***</td>
<td>(0.0154)</td>
<td>148.652***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Consumer goods</td>
<td>7</td>
<td>10.1972</td>
<td>(0.1777)</td>
<td>84.8266***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Utilities</td>
<td>8</td>
<td>3.0329</td>
<td>(0.9323)</td>
<td>14.373***</td>
<td>(0.0725)</td>
</tr>
<tr>
<td>Industrial</td>
<td>9</td>
<td>7.2336</td>
<td>(0.6128)</td>
<td>88.848***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Consumer services</td>
<td>9</td>
<td>5.6102</td>
<td>(0.7782)</td>
<td>96.0883***</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Technology</td>
<td>7</td>
<td>21.0871</td>
<td>(0.0036)</td>
<td>70.0185***</td>
<td>(0.0000)</td>
</tr>
</tbody>
</table>

Notes: The optimal lag order \((k)\) is determined by the Akaike information criteria (AIC). The relationship \(Y \rightarrow \text{X}\) implies that \(Y\) does not Granger cause \(X\). **, ***Significant at the 5 and 1 percent levels, respectively.

Panel A: CDS equation residuals

<table>
<thead>
<tr>
<th>面板A：CDS方程残差</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industries</td>
</tr>
<tr>
<td>Banks</td>
</tr>
<tr>
<td>Financials</td>
</tr>
<tr>
<td>Telecommunication</td>
</tr>
<tr>
<td>Healthcare</td>
</tr>
<tr>
<td>Oil and gas</td>
</tr>
<tr>
<td>Consumer goods</td>
</tr>
<tr>
<td>Consumer services</td>
</tr>
<tr>
<td>Technology</td>
</tr>
</tbody>
</table>

Panel B: Stock price equation residuals

<table>
<thead>
<tr>
<th>面板B：股票价格方程残差</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industries</td>
</tr>
<tr>
<td>Banks</td>
</tr>
<tr>
<td>Financials</td>
</tr>
<tr>
<td>Healthcare</td>
</tr>
<tr>
<td>Oil and gas</td>
</tr>
<tr>
<td>Basic materials</td>
</tr>
<tr>
<td>Consumer goods</td>
</tr>
<tr>
<td>Industrial</td>
</tr>
<tr>
<td>Consumer services</td>
</tr>
</tbody>
</table>

Notes: The entries indicate the BDS test based on the residuals of CDS and stock prices in a VAR for various sectors. \(m\) denotes the embedding dimension of the BDS test. ***, **Significant at the 5 and 1 percent levels, respectively.

Source: Broock et al. (1996)
cointegration parameters are super consistent, stability testing can be split into two steps. First, the stability of the cointegration parameters is checked and second, the stability of the short-run parameters of the VAR model is tested. To evaluate the stability of long-run parameters, the $L_c$ test of Nyblom (1989) and Hansen (1992) is used. The $L_c$ test is an LM test for parameter constancy against the alternative hypothesis that the parameters follow a random walk process and hence, are time-varying. When the series are I(1), the Nyblom-Hansen $L_c$ test serves as a test of cointegration. In the second step, the Sup-LR, Mean-LR and Exp-LR (Andrews, 1993; Andrews and Ploberger, 1994) are used to investigate the stability of the short-run parameters. All the tests are computed from the sequence of LR statistics that test the null hypothesis of constant parameters against the alternative of a one-time structural change at each possible time in the sample. These tests have non-standard asymptotic distributions and the critical values are available from the works of Andrews (1993) and Andrews and Ploberger (1994). In order to avoid the use of asymptotic distributions, the critical values and $p$-values for all stability tests are obtained from a parametric bootstrap approximation to the null distribution of the test statistics, constructed by means of Monte Carlo simulation using 2,000 samples generated from a VAR model with constant parameters.

Table V reports the outcome of these tests of parameter constancy for both CDS and stock price equations along with the associated $p$-values. The $L_c$ test is calculated for each equation separately and the entire VAR system using the fully modified OLS estimator of Phillips and Hansen (1990). Unlike the $L_c$ test, the Sup-LR, Mean-LR and Exp-LR tests require trimming at the ends of the sample. Following the works of Andrews (1993), Balcilar and Ozdemir (2013) and Balcilar et al. (2010), among others, we trim 15 percent from both ends and calculate these test statistics for the fraction of the sample in the interval (0.15, 0.85). The results for the $L_c$ test of stability of cointegration parameters indicate that both CDS and stock price equations do not have constant long-run parameters at the usual levels. Moreover, the system $L_c$ test statistics show that the VAR model as a whole turns out to be unstable at the 1 percent level of significance for all industries. In addition, the Sup-LR, Mean-LR and Exp-LR test statistics reject the null hypothesis of short-run parameter constancy at the conventional (1-10 percent) levels of significance in both CDS and stock price equations in a large number of cases for almost all the industries. In sum, the evidence from the parameter stability tests suggests that the estimated VAR models do not have constant long-run and short-run parameters and hence support the presence of structural changes. Consequently, any statistical inference based on the assumption of parameter constancy is likely to be biased.

Our analysis of non-linearity and parametric stability tests provide necessary ground to analyze the dependence and causality of CDS markets vis-à-vis stock markets in a time and frequency space using WTC approach. This method provides a better understanding of dynamics (evolution of association over time and across frequencies) between CDS spread and stock prices for the selected industries. The graphs of WTC between the industry-level CDS and equity pairs are shown pair-wise in Figures 4(a)-(j). 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 0 and 256 where 2-32 scale is associated with short-run dynamics and long-term afterwards. The WTC range between 0 (no co-movement) to 1 (strong co-movement). The strength of co-movement between any pair of CDS and stock index is shown through color code (shown on the right side of each plot). The red color at the bottom (top) of the graph indicates high co-movement at low (high) frequencies. The thick black contour designates the 5 percent significance level against red noise which is estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line.
### Table V. The results of parameter stability tests

<table>
<thead>
<tr>
<th>Industry</th>
<th>Sup-LR</th>
<th>Exp-LR</th>
<th>Mean-LR</th>
<th>$L_c$</th>
<th>$L_c$ for system</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: CDS equations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Banks</td>
<td>3.1097***</td>
<td>0.8281*</td>
<td>1.5140 (0.1180)</td>
<td>21.8794*** (0.0000)</td>
<td>95.9465*** (0.0000)</td>
</tr>
<tr>
<td>Financials</td>
<td>11.0553***</td>
<td>4.0164***</td>
<td>7.0534*** (0.0000)</td>
<td>1.6522*** (0.0000)</td>
<td>65.2839*** (0.0000)</td>
</tr>
<tr>
<td>Telecommunication</td>
<td>4.8197***</td>
<td>1.5174***</td>
<td>2.8042*** (0.0000)</td>
<td>8.0193*** (0.0000)</td>
<td>45.8722*** (0.0000)</td>
</tr>
<tr>
<td>Healthcare</td>
<td>9.5743***</td>
<td>3.1427***</td>
<td>5.5525*** (0.0000)</td>
<td>2.4982*** (0.0000)</td>
<td>48.9844*** (0.0000)</td>
</tr>
<tr>
<td>Oil and gas</td>
<td>15.2614***</td>
<td>5.3507***</td>
<td>8.8015*** (0.0000)</td>
<td>9.7266*** (0.0000)</td>
<td>117.6405*** (0.0000)</td>
</tr>
<tr>
<td>Basic materials</td>
<td>8.6363***</td>
<td>3.8385***</td>
<td>15.6058*** (0.0000)</td>
<td>3.5615*** (0.0000)</td>
<td>31.9398*** (0.0000)</td>
</tr>
<tr>
<td>Consumer goods</td>
<td>9.3742***</td>
<td>3.3419***</td>
<td>5.6916*** (0.0000)</td>
<td>3.5615*** (0.0000)</td>
<td>31.9398*** (0.0000)</td>
</tr>
<tr>
<td>Utilities</td>
<td>46.2217***</td>
<td>16.0408***</td>
<td>4.0938*** (0.0000)</td>
<td>4.0938*** (0.0000)</td>
<td>48.6996*** (0.0000)</td>
</tr>
<tr>
<td>Industrial</td>
<td>16.5653***</td>
<td>5.0817***</td>
<td>7.7996*** (0.0000)</td>
<td>2.7393*** (0.0000)</td>
<td>24.4723*** (0.0000)</td>
</tr>
<tr>
<td>Consumer services</td>
<td>12.5247***</td>
<td>4.5443***</td>
<td>7.2880*** (0.0000)</td>
<td>7.4272*** (0.0000)</td>
<td>64.1411*** (0.0000)</td>
</tr>
<tr>
<td>Technology</td>
<td>6.2916***</td>
<td>2.1943***</td>
<td>3.9153*** (0.0010)</td>
<td>4.7943*** (0.0000)</td>
<td>53.3096*** (0.0000)</td>
</tr>
<tr>
<td><strong>Panel B: Stock price equations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Banks</td>
<td>3.9248***</td>
<td>0.4349 (0.7960)</td>
<td>0.7808 (0.8810)</td>
<td>6.3523*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Financials</td>
<td>7.1956***</td>
<td>1.3868***</td>
<td>2.918*** (0.0020)</td>
<td>3.2681*** (0.0000)</td>
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</tr>
<tr>
<td>Telecommunication</td>
<td>7.3293***</td>
<td>2.1435***</td>
<td>3.2808*** (0.0000)</td>
<td>4.8726*** (0.0000)</td>
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</tr>
<tr>
<td>Healthcare</td>
<td>7.8593***</td>
<td>2.4588***</td>
<td>4.0884*** (0.0000)</td>
<td>19.5617*** (0.0000)</td>
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</tr>
<tr>
<td>Oil and gas</td>
<td>7.9219***</td>
<td>2.4768***</td>
<td>3.5035*** (0.0000)</td>
<td>14.0730*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Basic materials</td>
<td>4.8431***</td>
<td>0.9855**</td>
<td>1.6164*** (0.0820)</td>
<td>19.9387*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Consumer goods</td>
<td>8.0968***</td>
<td>1.7145***</td>
<td>2.7000*** (0.0000)</td>
<td>12.1360*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Utilities</td>
<td>8.2016***</td>
<td>2.4491***</td>
<td>3.9754*** (0.0000)</td>
<td>14.9201*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Industrial</td>
<td>6.7844***</td>
<td>1.4030***</td>
<td>2.8066*** (0.0020)</td>
<td>4.9358*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Consumer services</td>
<td>6.5433***</td>
<td>1.6541***</td>
<td>3.0360*** (0.0000)</td>
<td>17.5234*** (0.0000)</td>
<td>–</td>
</tr>
<tr>
<td>Technology</td>
<td>6.0795***</td>
<td>1.3843***</td>
<td>2.9775*** (0.0000)</td>
<td>21.3415*** (0.0000)</td>
<td>–</td>
</tr>
</tbody>
</table>

**Notes:** The null hypothesis for all tests is that the estimated parameters are constant. The Sup-LR test statistics are appropriate to examine a swift regime shift, while the Mean-LR and the Exp-LR tests are the optimal tests to examine whether the model captures a stable relationship over time. The $p$-values for the long-run and short-run parameter stability tests are calculated using 2,000 bootstrap repetitions. The Hansen-Nyblom $L_c$ parameter stability test has been calculated for each equation separately and for the VAR system as a whole. ***,***Indicate rejection of null hypothesis of no causality at the 10, 5, and 1 percent levels of significance, respectively.
Figure 4.
Pair-wise wavelet squared coherence between CDS and equity indices
(continued)
Notes: (a) Banks; (b) financials; (c) telecommunications; (d) healthcare; (e) oil and gas; (f) materials; (g) consumer goods; (h) utilities; (i) industrials; (j) consumer services; (k) technology. The horizontal (vertical) axis in these figures show time period (frequencies). The color bar is shown on the right side of each figure and color code for coherency ranges from blue (low coherency-close to 0) to red (high coherency-close to 1). The thick black contour designates the 5 percent significance level against red noise which is estimated from Monte Carlo simulations using phase-randomized surrogate series. The COI, which indicates the region affected by edge effects, is also shown with a light black line. The phase difference between the two series is indicated by arrows. Arrows pointing to the right (left) mean that the variables are in-phase (out-of-phase). To the left-down (left-up) mean stock price (CDS premia) is leading.
The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase (positively correlated) and the arrows pointing to the left mean that the variables are out of phase (negatively correlated). Since the latter is evident in the CDS and equity relationship, we only discuss the direction of arrow pointing towards left. The arrows pointing to the left and up (down) means the CDS (equity) market is leading. The WTC plots show the dynamic nature of relationship between CDS and equity markets over time-frequency space and hence provide superior picture of lead-lag linkages between these two markets.

The purpose of this study is primarily to highlight the industry-level relationship between CDS and equity markets and how this relationship changes over time and across frequencies. The higher coherence between the markets will imply less arbitrage opportunities and vice versa. Therefore, we first discuss some of the highlights of the findings. All the CDS and equity markets which are related (red color) are out of phase (negative correlation), implying that an increase in equity prices results in a decrease in CDS premia. The probability of default increases when the value or the returns to assets and equity decrease. The decrease in firms' value or profitability will increase the chances of hitting the default threshold. The firms' values are considered unobservable or not measurable in the direct sense. Since a firm’s value changes with a decrease or increase in profitability or equity, the structural model suggests that a downward trend in the equity value convey an upward trend in the CDS spread. Chiaramonte and Casu (2013), Galil et al. (2014), Narayan et al. (2014) and Raumig (2015) have empirically confirmed the negative relationship between CDS premia and equity markets. However, most of the previous studies have used the firm-level data and our findings confirm that the relationship also holds at the industry level.

Next, the arrows within the significant regions (strong coherence) mostly point downwards which implies that stock markets lead the CDS markets. The leading role of equity market in CDS-equity markets relationship may be seen as price discovery which mainly occur in the equity counterparts of the CDS industries; and the impact of new information is then transmitted to CDS premia. Interestingly, the lead of equity markets holds for all 11 industries. Similar evidence is noted by the work of Narayan et al. (2014) who use a traditional econometric framework. However, their telecommunication panel was made up of only four firms and produced a statistically not significant error correction term. Our results (Figure 4(c)) clearly show a significant lead of equity index for telecommunication industry at 32-128 days scale. Overall, we also confirm the general view that CDS and equity markets relationship was impacted (increased) by the financial crises of 2008.

By looking at each wavelet coherence plot, we can divide the industry indices into three distinct groups based on CDS-equity relationship. The banks, material, industrial and technology industries show small regions of higher (negative) coherence at low frequencies (short-term scale) especially during financial crises 2008-2009 and during 2011[2]. The relationship gets stronger over longer time period (128-512 days scale). And this relationship also gets stronger towards the end of our sample period (during 2014). Important to highlight is that in the wake of the global financial crisis, a number of new rules and regulations put in place to enhance the functioning of CDS market and tame the volatile and speculative behavior. The second group comprises of financial, healthcare, consumer goods and consumer services. Although we note high coherence regions at higher scales in these industries, the relationship is getting weaker towards the end of 2014. The third and most prominent group comprises of telecommunication, oil and gas and utilities. The CDS and equity markets of these industries have lower coherence and thus give an indication of possible arbitrage opportunities for the investors. Notably, there is very little or no coherence between CDS and equity markets of Utilities industry. Recall, that the traditional correlation of
this industry (Table I) is somewhat comparable to the other industries, however, we argue that simple time domain correlation does not fully reflect the relationship between two variables and the findings based on traditional measures may not accurately portray the true nature of the association. Our findings contradict with Caporin (2013) who suggest that the utilities industry CDS can provide hedging benefits to the equity investors.

Interestingly, the utilities industry’s stock market does not Granger cause its CDS counterpart over most of the sample period. This industry is a natural monopoly that is regulated by policy makers. We note a larger coherence region with CDS leading the stock markets for banks and financial sectors. Recall that a CDS is an insurance contract providing heavy protection against losses emerging from a crisis event. As major participants in CDS market are the banks and the other financial institutions, we should not neglect the important role played by the “implicit” government guarantee (i.e. the value of government subsidy to financial institutions to protect from insolvency) in strengthening the leading role of CDS in turbulent times. Indeed, we note that for banks and financial industries, stock prices are also most reactive to changes in CDS. This predictive performance may also be due to the pro-cyclical nature of financial system (Andersson et al., 2011). Moreover, the CDS market contains a wide number of sophisticated participants and thus, information about the CDS should help in appropriately capturing changes in credit risk and promoting risk sharing among traders and investors.

Regarding portfolio allocation, investors and traders seek to shift the portfolio into sectors that appear less influenced by the business cycle (Wagner and Bode, 2011). Because some of these sectors are cyclical while the others are defensive, one can expect that various industries could respond differently to changes in the economy and as a result, the dynamic relationship between the sector-specific equity market and CDS spreads should exhibit a sharp dissimilarity.

In summary, the findings of WTC approach suggest that the causalities between the stock and credit markets vary with time and are unstable over time. The investment decisions (e.g. hedging, speculative, arbitrage or long-term investing) may be made while considering the dynamics of the industry CDS-stock markets, with due consideration that the relationships are subject to change. Moreover, the existing literature suggests that causality comes from the stock markets only. However, our results reveal that, in addition, the CDS markets may cause their stock counterparts during the periods marked with significant credit events.

5. Conclusion
This study analyzes the lead-lag relationship between US CDS and equity industries. The co-movement between the two markets is examined through wavelet coherence approach, a promising method for an in-depth examination of the instantaneous interactive relationship between the time series. This method is of particular importance when the short- and long-term investment horizons are jointly considered (Madaleno and Pinho, 2010). The daily data of 11 industrial indices are used from December 14, 2007 to December 31, 2014. The Toda-Yamamoto non-causality approach is used to examine the causality relationship between industry-level CDS spread and stock prices. However, the non-linearities and parametric instability provide necessary grounds to analyze the dependence and causality of CDS markets vis-à-vis stock markets in a time and frequency space using WTC approach.

We find that both the markets are out of phase (counter cyclical) and with dynamic association, equity markets lead CDS market over the entire sample period. The coherence between two markets increases during financial crises. The banks (utilities) industry has a relatively higher (lower) coherence. The frequency domain Granger causality results indicate a unidirectional causality running from equity to CDS markets for all industries
except banks and utilities. There is bidirectional (no) causality between the equity and CDS markets for banks (utilities) industry. We argue that arbitrage and hedging opportunities vary over time and utilities industry seems attractive for the investment with the objective to exploit arbitrage, but not for hedging. Furthermore, the significant lead-lag relationship between industry-level equity and CDS markets reflect sharp differences with respect to market participants and liquidity. These differences in turn can influence the level of pricing information they possess. Future research can utilize the findings and extend the analysis in the direction of multivariate coherence and Granger causality frameworks and taking into consideration exogenous variables like spot rate, slope of the yield curve, etc. which are known to impact the CDS-equity nexus.

Notes
1. For instance, Alan Greenspan, the former Federal Reserve Bank Chairman, stated in May 2003 that CDSs had contributed to the development of a far more flexible, efficient and resilient financial system that existed 25 years ago. In contrast, according to the legendary US investor, Warren Buffett, the CDSs are financial weapons of mass destruction.
2. 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 conditions from the start of 2011.

References


Further reading


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