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Directional and bidirectional causality between U.S. industry credit and stock markets and their determinants

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Abstract

We examine the causal links between U.S. industry-wise credits and stock markets. The full sample bootstrap Granger causality results show that all stock markets Granger cause their CDS counterparts and there is also bidirectional causality for the banking, healthcare and material industries. The short-run parametric stability tests highlight that the full sample parameters are not stable and hence less reliable. The bootstrap rolling window estimations confirm the inconsistency in the CDS-stock causality relationships where bidirectional causalities are also found between the credit and stock markets that vary over different sub-samples. Finally, we analyze the impact of different financial and macroeconomic determinants on the CDS-stock causality through a probit model. Overall, the business conditions, stock market volatility, default premiums, Treasury bond rate and the slope of the yield curve are major drivers of the CDS-stock nexus. Our findings provide possible explanation for varying and mixed previous empirical findings in the existing literature, and hence have useful investment implications.

JEL Classification: C32, G20, G32

Keyword: Credit default swap; stock; bootstrap rolling windows; Granger non-causality; Probit.

1. Introduction

The new literature in empirical finance that uses nonlinear models and techniques that may fit better subperiods is faulting the old literature that uses linear models and applies the estimation to full sample periods when the results are time-dependent and difficult to capture with linear techniques. Some authors now say that empirical finance is in crisis (De Prado, 2015). Others assert that a possible solution to false empirical findings lies in multiple trials and peer p-values (Harvey and Liu, 2015).

The financial and credit markets have economic and financial interconnections that are multilateral in dimension and having various feedback loops. Causal linkages among the financial markets in particular are multisided and may be multidirectional and difficult to capture with old techniques. They are of theoretical, practical and policy importance. The results are important because they have implications for portfolio diversification, hedging, speculation, arbitrage, market integration, contagion risk, market efficiency, among others. This narrative applies to the link between the CDS and stock markets particularly when the investigation of the link is conducted at the industry level. The substantial use of CDSs as a tool to hedge and speculate credit risk by short-term traders like speculators and long term investors such as institutional investors has increased their importance as tools for risk management practices and requires better methods to obtain more accurate results.

The price of CDS contract is determined by the credit risk of the underlying entity, and market practitioners rigorously evaluate the value of CDS contracts for credit risk management decisions. Thus, the CDS price reflects the market view on the credit risk and plays an important role for credit risk assessment. The deterioration (increase) in credit quality (risk) leads to widening of credit spreads, whereas the CDS spread decreases (tightens) with the improvement in credit quality. Thus, it is worth examining the connections of the CDS markets with the stock markets using new nonlinear techniques and rolling the window bootstrap causality estimation over subsamples.

Fung et al. (2008) suggest that due to the very nature of these contracts, the CDS market responds quickly to the credit events and leads the stock market when exposed to a shock. Similar findings are reported by Blanco et al. (2005), Zhang (2008) and Coudert and Gex (2010). However, Narayan et al. (2014) find that the stock market contributes to the price discovery in comparison with the CDS markets[1]. Previously, Norden and Weber (2004 & 2009) also empirically confirm the definite lead of stock markets in the price discovery process. Finally, the literature on the relationship between the CDS and stock markets is not only mixed but also inconclusive (Narayan et al., 2014).

The linkage between the CDS spreads and stock markets does not necessarily have to be the same over the sample period, but it may be time-varying and subject to regime shifts resulting from unexpected changes in economic and financial market conditions. For instance, the global financial crisis of 2008-2009 and the Eurozone sovereign debt crisis of 2010-2013 had increased the fear and risk aversion in the stock markets and amplified stress and spillover effects in financial markets in general. In those circumstances, market participants whether they are speculators such as hedge funds and market makers or long-term investors such as pension funds and other institutional investors alter their expectations, risk tolerance, risk aversion and beliefs. The nature of the relationship between the CDS spreads and stock markets in the aggregate or at

[1] Hassan et al., (2015) found that sovereign CDS and bond markets of emerging countries are cointegrated and 29% times, price discovery occurs in CDS markets.

the industry level may also have changed during such extreme financial conditions. The participants in the credit and stock markets who have heterogeneous preferences and diverse risk tolerance may become particularly active under different economic and market conditions, especially during the periods of high financial turmoil and in different industries. Furthermore, the findings of previous works have underscored that the relationship between the CDS and stock markets is time-dependent and, hence, may be sensitive to the sample period but they have not done our work (e.g., Forte and Pena, 2009; Lenciauskaitė, 2012; Tabak et al., 2016). Therefore, the conclusions drawn by assuming in the literature that the relationship between the two types of markets is permanent or linear may be misleading.

In this paper, we take part in the stream of research concerning the lead-lag relationship between the CDS and stock markets in the United States in two ways. First, we examine this relationship at the industry level as the industry dynamics of both markets are different (Narayan et al., 2014). The findings may suggest some investment implications (e.g., arbitrage opportunities may exist when the individual industry is considered). Second, the causal nexus between the CDS and stock markets is examined through a rolling window bootstrap causality test[2]. As discussed above, the literature on the relationship between CDS and stock markets not only provides mixed findings, it also differs in the sample and methodology used for the analysis. Moreover, the previous studies utilize the approach where the full sample period is used for analysis. We argue that the causal relationship may vary over time[3] and may radically differ during volatile periods (e.g., the global financial crises of 2008-2009). This has motivated us to adopt a different approach to examine the relationship between the CDS and stock markets in the aggregate and at the industry level and in a time-varying fashion, which should also allow us to explore the determinants of the causal links for the two markets. Finally, we examine the possible determinants of the CDS-Stock nexus at the industry level, using the probit model and evaluate the forecasting of causality using fitted vs. observed casualty estimates for the industries.

The rest of the paper is organized as follows. Section 2 presents the relevant literature on the CDS and stock market relationship. Section 3 discusses the econometric framework. Section 4 details the data and empirical results, and Section 5 concludes the paper and offers some policy implications.

2. Related Literature

Similar to the stock market indices, those of CDSs were launched during 2004 in an effort to assist the credit risk traders to manage and diversify the portfolio credit risk. These CDS indices provide liquidity, efficiency and lower the cost of trading credit risk (Fung et al., 2008). The standardization of CDS contracts in terms of an index provides liquidity to the CDS market and hence decreases the bid-ask spread. From a portfolio perspective, the cost to replicate a credit risk portfolio through CDS indices is also lower than buying and selling individual CDS contracts. Each CDS index serves as a standard benchmark to evaluate the specific underlying exposure. For example, the CDX.NA.IG (CDX.NA.HY) index may be seen as the benchmark credit risk exposure of investment grade (high yield) bonds issued by the North American firms.

[2] The causality is in the Granger sense (Granger, 1969).

[3] The stock markets may Granger-cause the CDS markets during some sub-periods and not in others, or there might be bidirectional causality in some sub-periods.

The significant growth and understandability of credit markets is considered a result of the development of CDS indices (Bank for International Settlements, 2005).

The CDS price/spread depends on the credit risk of associated/underlying reference; therefore, a trader can evaluate the CDS price through three different methods. One way of quantifying the credit risk is to follow the credit ratings assigned by rating agencies (Moody's and Standard & Poor's are the two well-known raters among the others) because these agencies substantially review the firms' ability to serve and repay their future obligations. This approach is also known as the reduced form credit risk modeling. The second method relies on the structural modeling approach where the price of default is determined based on the firms' fundamentals. The accounting ratios such as return on assets and leverage along with earning volatility can be used to measure the probability of default and hence the price of default risk. The third and more simplistic approach considers that the market (stock) provides the general view on the credit quality and hence the market price, in case of many informed trades, reflects the amount of credit risk associated with the underlying assets. Therefore, change in the stock price of an entity can be used as a quantitative measure of its credit risk.

Theoretically, the stock price of a firm impacts its CDS spread. The structural model proposed by Merton (1974) suggests that CDS spreads and stock prices have a negative relationship with each other. The deterioration in the financial conditions of a firm increases the probability of default on its underlying debt obligations. Therefore, financial distress conditions may result in a decrease in the value of firms' stocks and increase the CDS spread. 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 changes in credit spreads. However, the capital structure arbitrage that exploits the relationships between the CDS and stock prices may enhance the integration and information flows between these markets (Fung et al., 2008).

It is also argued that an informed trader may prefer CDSs over stock shares in order 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; therefore, 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 trading the stocks. This trading preference between the two markets would result in a price discovery advantage to the CDS market. On the empirical side, Longstaff et al. (2005) found mixed result on the lead-lag relationship between CDS and stock price using individual firms' data. Using CDS and stock market indices, Fung et al. (2008) concluded that the lead-lag relationship between these markets is rather complex in nature. They also made a distinction between high yield and investment grade CDS indices and argued that the high yield CDS index due to low credit quality of the companies is more vulnerable to credit events. In general, buying insurance against default has more (less) value and frequency when the underlying is issued by the low (high) credit quality firms. Therefore, it is more likely that high yield CDS index may lead the stock prices than the investment-grade CDS spreads.

The studies on the relationship between CDS spread and stock prices can be divided into two distinct groups. The first group utilizes the micro approach where the interconnectedness between the markets has been studied using firm level data. Longstaff et al. (2005) are the first of those who analyzed the CDS markets' lead-lag relationship with corporate bond spreads and stock returns of U.S. firms. They find that both CDS and stock markets lead bond market but the lead-lag relationship between CDS and stock markets is unclear. Norden and Weber (2004) investigate the European CDS markets and find a negative correlation between CDS spread change and stock returns. Furthermore, their analysis suggests that stock returns lead CDS spread changes.

Norden and Weber (2009) investigate 58 international firms using daily data over a three-year time period and re-affirm that individual stock returns significantly lead CDS spread changes for most of their sample firms. Moreover, a definite lead of the stock market relative to the CDS market is found. However, those authors also suggest that the co-movement between the markets is affected by the credit quality of the sample firms, and the co-movement increases with the decrease in credit quality. Similar findings are also reported by Forte and Pena (2009) using North American and European firms' data. Moreover, Forte and Pena (2009) 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 towards the stock markets' price discovery. Stock markets lead both bond and CDS markets but this information leadership is time dependent and has decreased over time.

Contrary to these studies, Blanco et al. (2005) find that the price discovery occurs in the CDS market and it anticipates deterioration in credit quality before the stock markets do (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. That said, the firm-level evidence predominantly indicates that the stock markets lead CDS market with few exceptions.

Byström (2005) is the first to analyze the relationship between CDS and stock markets, using index level data. He empirically confirms the importance of stock market volatility within the Merton model and concludes that stock market Granger-cause CDS spread changes. Fung et al. (2008) argue that the information flow between the CDS and stock markets is driven by both the market-wide systematic risk (e.g., wars and economic recessions) and/or idiosyncratic risk (e.g., corporate events such as corporate restructuring or insider trading). Thus, the firms' level data may affect the co-movement and the lead-lag relationship between the two markets, and hence authors diversify the idiosyncrasies by using CDS and stock market indices. Fung et al. (2008) also made a distinction between investment grade and high yield CDSs and find that the CDS markets provide additional information for the detection of default probability beyond the stock market. 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, the CDS market took a lead over stock market before the global financial crises of 2007-2008.

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

Moreover, the industry-wise nature (spread and volatility) of the CDS markets is different, and thus they have varying speeds of adjustment, in comparison with the equity counterparts (Narayan et al., 2014). For instance, Hammoudeh et al. (2013) investigate the banking, financial services and insurance sectors' CDS movements, in the short- and long-run over the period 2004-2009 and report that the individual dynamic adjustments to the equilibrium are different for those sectors. Finally, the lead-lag relationship between CDS and equity markets is time dependent (Forte and Pena, 2009; Lenciauskaitė, 2012), and hence it is difficult to be captured through traditional econometric techniques.

3. Econometric methodology

The equity index is said to be Granger non-causal for the associated CDS index if the inclusion of an equity variable in the information set does not improve the forecast of the CDS spread. In this paper, we use bootstrap[4] version of Toda and Yamamoto (1995) causality tests due to the following advantages. The method is simple to implement, can be implemented irrespectively of the order of integration and shows better asymptotic distribution (Zapata and Rambaldi, 1997). Hacker and Hatemi-J (2006) used Monte Carlo simulations and suggested that the modified Wald test with a bootstrap distribution show much smaller size distortions. They further show that the test results are less sensitive to sample size, integration orders, and error term processes, i.e., homoscedastic or ARCH. To illustrate the Granger causality test in a bivariate VAR(p) process, we consider the following equation:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \dots + \Phi_p y_{t-p} + \varepsilon_t, \qquad t = 1,2,3, \dots, T \tag{1}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a zero mean independent white noise process with the nonsingular covariance matrix $\sum$. The lag length p is determined through the Akaike Information Criterion (AIC). For a simplistic representation, we separate y_t into two sub vectors, the first one is related to the CDS spread (y_{1t}) and the second one is related to counter the stock index (y_{2t}) and write equation (1) in the following form:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{2}$$

where $\phi_{ij}(L) = \sum_{k=1}^{p} \phi_{ij,k} L^k, i, j = 1,2$ and L is the lag operator defined as $L^k x_t = x_{t-k}$. In this setting, the null hypothesis that the equity index does not Granger-cause the CDS market can be tested by imposing zero the restrictions $\phi_{12,i} = 0$ for $i = 1,2, \dots, p$. Analogously, the null hypothesis that CDS market does not Granger cause equity market can be tested by imposing the restriction $\phi_{21,i} = 0$ for $i = 1,2, \dots, p$.

Granger (1969) suggests that the structural instability is the most important problem faced by the researchers. Notably, the structural changes may result in a shift in the parameters and hence the causal relationship may change over time. To examine the change in the causal relationship due to structural changes, we utilize rolling window approach based on the modified bootstrap test. The rolling window MWALD causality test procedure initially estimates the MWALD statistics for a predefined beginning subsample. For the next estimation, the first (next) observation is removed (added) from the beginning (end) of first estimation subsample. The relationship is subsequently re-estimated. In this study, we estimate the MWALD statistics using a subsample of 52 weeks so that T= 52. The first MWALD causality test statistics are obtained using a subsample from 2007:W50 (the start of our study period) to 2008:W49 (i.e., T= 52

[4] The technical details of the bootstrap procedure can be found in Balcilar et al. (2010).

observations). Then the second test statistic is obtained by using the data from 2007:W51 to 2008:W50[5]. This rolling procedure continues until the last observation is employed to examine the causal relationship.

4. Data and findings

4.1. Data overview

The study examines lead-lag relationship between the CDSs and their equity counterparts for 11 industries, using the bootstrap rolling window Granger causality. For overall completion, we also analyze the CDS market index representing all industries along with the S&P 500 stock index. The industries include Banks, Financial, Telecommunication, Healthcare, Oil and Gas, Materials, Consumer Goods, Utilities, Industrial, Consumer Services and Technology. This weekly data is extracted from DataStream International (Thomson Financial - 2015) for the period December 14, 2007 to December 31, 2014 as the industry level CDS indices were launched by DataStream on the start data of our sample. We use weekly data to avoid the problems of "day of the week" effect and to reduce the noise present in daily data[6].

Figures 1 and 2 show the industry-wise weekly average CDS premiums (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 the CDS premium differs for each industry. It is evident that some industries such as Financials, Industrial and Consumer Services have relatively high CDS spreads, suggesting that these industries are the most risky. The CDS premiums for Banks, Oil & Gas, and Consumer Goods are nearly as half as for the most risky industries. The volatility of the CDS spread as measured by the SD also shows a clear industry-wise pattern and in some industries the volatility is high, while in others it is low[7].

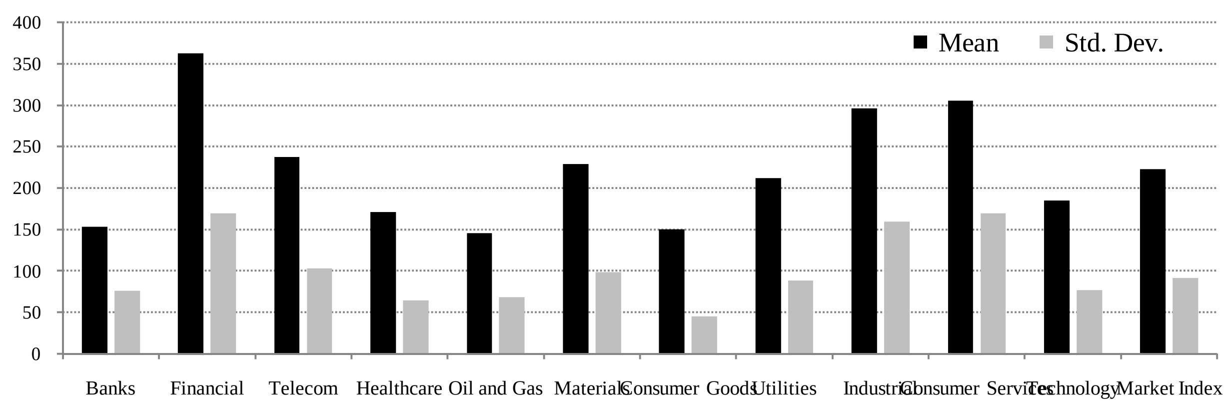

Fig. 1. Weekly averages and standard deviations of US industry-wise CDS premia (basis points).

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[5] For the robustness check on the selection of rolling window size, we re-estimated the Granger non-causality test using window sizes of 36, 48 and 60 weekly observations. The estimates are consistent under three different window lengths and are available from the authors on request.

[6] We also use the monthly data as a robustness check and results are available on request from the authors.

[7] The correlation between all industry-level CDS and stock markets is significant and negative. The correlation results are not presented for the brevity of space; however, are available from the authors on request.

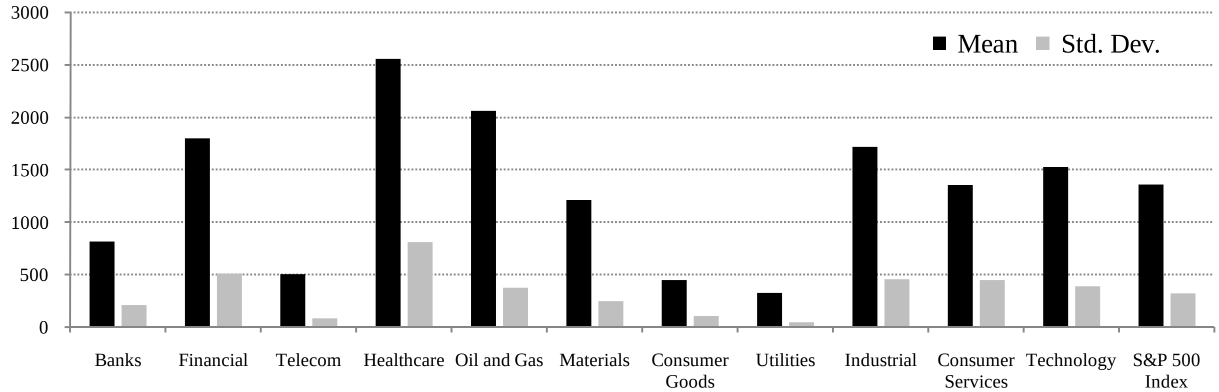


Fig. 2. Weekly averages and standard deviations of US industry-wise equity indices (in level form).

Notably, we treat banks and other financial firms separately because earlier empirical works suggest that the CDS premiums of these industries react differently to market conditions (Raunig, 2015)[8]. The CDS indices (denominated in basis points so that 100 basis points equate to one percentage point) are based on 5-year contracts because the five year credit instruments are considered adequate based on liquidity and are widely used in empirical analyses (Narayan et al., 2014; Hammoudeh et al., 2013). Moreover, senior debt 5-year CDSs are the most liquid contracts and represent over 85% of the single-name CDS traded volume (Trutwein et al., 2011). The trends of the banking CDS index and the CDS market index along with their equity counterparts are shown in Figures 3a and 3b, respectively. A notable increase (decrease) is evident in the CDS premium (equity index) during the recent global financial crisis of 2008-2009.

a). Banks **b).** Overall CDS market and S&P 500

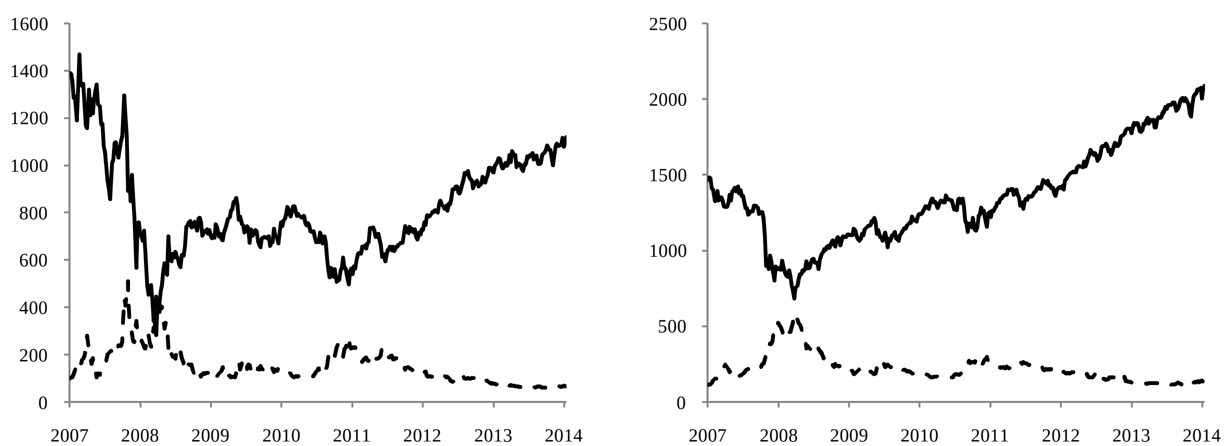


Fig. 3. Trends of the CDS market spread (black dotted line) (in basis points) and the equity indices (in solid black line).

[8] 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 descriptive statistics of both the CDSs (Panel A) and stocks (Panel B) are reported in Table 1. The financial CDS premium is the highest (362.82 basis points) among the 11 industries and similarly its other statistics i.e. minimum, maximum and standard deviation are also higher than those of the other industries. Oil and gas has the lowest average CDS premium (145.32). All of the time series are non-normal as the null hypothesis of Jarque-Bera (JB) test is rejected at the 1% level. For the econometric analysis, all the series were converted into natural logarithmic form to reduce the sharpness in data and to increase the reliability of results.

Table 1

Descriptive statistics of the CDS and stock indices at the industry level

Industry	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J-B stats
Panel A: CDS Indices							
Banks	152.86	511.96	56.964	76.143	1.555	6.191	304.43***
Financials	362.82	984.76	145.10	169.78	1.377	4.943	174.16***
Telecommunication	237.45	597.59	107.09	102.59	1.337	4.954	168.20***
Healthcare	171.15	391.63	83.786	64.000	1.227	4.570	130.14***
Oil and Gas	145.32	393.68	54.654	68.173	1.638	5.548	264.09***
Basic Materials	229.30	607.48	90.049	98.064	1.994	7.598	568.00***
Consumer Goods	149.98	343.91	84.624	44.934	1.166	5.183	156.43***
Utilities	211.85	465.53	74.869	88.005	0.051	2.276	8.2020***
Industrial	296.61	866.13	108.58	159.38	1.476	4.787	182.61***
Consumer Services	305.65	1186.4	140.49	169.74	2.636	10.42	1271.1***
Technology	184.79	509.95	50.254	76.290	1.875	7.356	506.64***
Market Index	222.52	589.01	113.42	91.107	1.715	6.234	340.68***
Panel B: Stock Indices							
Banks	821.22	1469.6	282.86	211.05	0.576	3.023	20.390***
Financials	1801.8	2943.1	748.83	513.20	0.446	2.164	22.941***
Telecommunication	505.29	649.81	334.93	86.650	-0.038	1.700	25.988***
Healthcare	2562.7	4778.1	1452.0	811.67	1.023	2.916	64.322***
Oil and Gas	2063.6	2915.5	1266.4	379.72	0.021	2.141	11.332***
Basic Materials	1217.3	1643.2	542.92	252.61	-0.719	3.019	31.741***
Consumer Goods	454.79	694.55	248.40	109.10	0.436	2.200	21.486***
Utilities	330.20	458.54	209.48	50.791	0.064	2.241	9.0910***
Industrial	1720.3	2696.0	726.76	460.92	0.327	2.431	11.515***
Consumer Services	1355.7	2380.5	624.45	454.48	0.576	2.174	30.797***
Technology	1525.9	2461.4	730.27	388.40	0.304	2.762	6.5170***
S&P 500 Index	1361.5	2088.7	683.38	321.94	0.418	2.494	14.656***

Note: Max., min., std. dev., skew, kurt and JB stand for maximum, minimum, standard deviation, skewness, kurtosis and the Jarque-Bera normality test, respectively. *** indicates that the null hypothesis of normality is rejected at the 1% significance level.

4.2. Unit root test results

The unit root analysis using the Fourier and traditional ADF tests is performed in three steps. In the first step, we determine the optimal frequency ($\tilde{k}$) and the optimal lag length ($\tilde{l}$). Then, the F-test is utilized to test the null hypothesis of linearity. If the F-test rejects the null hypothesis, then the trigonometric terms are incorporated into the traditional ADF model and the nonlinear FADF test is thus appropriate to examine the unit root properties of a time series. In the case the F-test fails to reject the null, a standard linear ADF test is then used to draw conclusion (Enders and Lee, 2012).

The results of the unit root tests for all the time series are reported in Table 2. The upper panel (A) shows the results for the CDS indices and the lower panel (B) presents the results for the equity indices. These results show that the F-statistic fails to reject the null hypothesis of linearity for all the time series, except for the CDS index series of the technology industry. As the F-statistic shows non-linearity in the technology CDS time series, we utilize the non-linear FADF (τ_{DF}) test to draw a conclusion on stationarity. The FADF test rejects the null of non-stationarity and hence the technology CDS index is stationary in levels, i.e., I(0). For all other series, we revert to the traditional ADF test statistics and conclude that basic materials CDS index is stationary in level, while all the other series are stationary in first difference, i.e., I(I).

Table 2

Results of the Nonlinear FADF and ADF unit root tests

Industry	Nonlinear FADF						ADF	
	$\tilde{k}$	SSR	$\tilde{l}$	AIC	F($\tilde{k}$)	τ_{DF}	Level	First diff.
Panel A: CDS Indices								
Banks	2	3.166	2	-1.876	3.990	-2.714	-1.190[0]	-20.66[0]***
Financials	2	2.673	5	-2.026	3.348	-2.126	-1.982[0]	-21.51[1]***
Telecommunication	2	1.178	1	-2.872	3.271	-1.765	-1.113[0]	-17.18[0]***
Healthcare	2	1.048	3	-2.973	3.042	-2.752	-1.725[0]	-18.28[0]***
Oil & Gas	2	3.429	4	-1.779	2.997	-2.537	-2.398[2]	-12.64[1]***
Basic Materials	2	0.809	5	-3.215	2.650	-2.941	-2.708[2]**	-9.887[1]***
Consumer Goods	2	0.919	0	-3.130	2.906	-1.925	-1.487[0]	-19.16[0]***
Utilities	2	7.233	1	-1.058	2.831	-3.048	-2.509[1]	-23.80[0]***
Industrial	2	1.782	1	-2.459	6.056	-1.534	-0.953[1]	-21.22[0]***
Consumer Services	2	2.361	6	-2.208	2.361	-1.723	-1.470[0]	-5.236[11]***
Technology	2	1.320	3	-2.742	6.983[B]	-4.519***	-3.477[2]***	-10.56[1]***
Market Index	2	0.936	2	-3.094	5.688	-2.606	-1.752[0]	-17.44[0]***
Panel B: Stock Indices								
Banks	1	1.246	1	-2.803	2.264	-3.043	-2.310[1]	-22.62[0]***
Financials	2	0.723	1	-3.355	2.917	-1.369	-1.054[1]	-22.21[0]***
Telecommunication	1	0.283	5	-4.258	5.600	-3.019	-1.752[0]	-21.38[0]***
Healthcare	1	0.206	6	-4.568	0.871	0.722	0.703[0]	-21.03[0]***
Oil & Gas	1	0.473	0	-3.787	4.340	-3.186	-1.815[0]	-20.10[0]***
Basic Materials	2	0.666	0	-3.445	3.213	-2.173	-1.620[0]	-19.66[0]***
Consumer Goods	2	0.169	5	-4.772	1.836	-0.251	0.098[0]	-20.64[0]***
Utilities	1	0.241	0	-4.462	3.285	-2.541	-1.127[0]	-19.70[0]***
Industrial	2	0.391	0	-3.978	2.938	-1.010	-0.492[0]	-18.91[0]***
Consumer Services	2	0.287	3	-4.260	1.503	-0.200	0.183[0]	-19.54[0]***
Technology	2	0.331	3	-4.118	1.791	-0.847	-0.268[0]	-19.36[0]***
S&P 500 index	2	0.284	5	-4.254	1.979	-0.686	-0.403[0]	-20.16[0]***

Note: In the nonlinear FADF unit root test, the optimal frequency ($\tilde{k}$) is selected by using the data-driven grid-search method in which the frequency minimizes the Sum of Squared Residual (SSR). τ_{DF} and F($\tilde{k}$) are the test statistic and the F-test of the FADF unit root test, respectively. The optimal lag ($\tilde{l}$) is the lag length that minimizes the Akaike Information Criterion (AIC). The critical values are obtained from Table 1b in Enders and Lee. (2012). For the traditional ADF unit root test, the critical values are based on MacKinnon (1996). The optimal lag lengths of the ADF test in the squared brackets are chosen on the basis of the Schwarz Information Criterion (SIC) and (Newey-West Criterion), using the Bartlett kernel. All the variables assume the intercept specification.

*** and ** indicate significance at the 1% and 5% levels, respectively.

4.3. Granger causality results

Next, we use the residual-based modified-LR tests (see e.g., Mantalos, 2000; Hacker and Hatemi-J, 2006) to examine the causal nexus between the industry CDSs and their equity counterparts. The optimal lag length is first determined through the VAR model using the AIC. This model's optimal lag order for each industry pair is reported in the second column of Table 3. Then the null hypothesis that the CDS market does not Granger-cause the corresponding stock market or vice versa is tested using the full sample bootstrap LR statistics and their respective bootstrap p-values.

Columns (3)–(6) of Table 3 display the full sample bootstrap LR statistics and their bootstrap p-values for the both non-causality hypotheses. The null hypothesis stating that the CDS market does not Granger-cause its stock market counterpart (i.e., CDS $-/\rightarrow$ Stock) is rejected for Banks, Health Care and Materials. The null hypothesis that stock market does not Granger-cause its CDS counterpart (i.e., Stock $-/\rightarrow$ CDS) is rejected for all industries based on the LR statistic and the bootstrap p-values. The overall results using the full sample bootstrap Granger causality tests show that the equity counterparts appear to have a predictive power of their corresponding CDSs for all industry indices, while also there are industry CDSs that have a predictive power for the Banks, Health Care and Material equity counterparts. The findings based on the full sample estimates are in line with Narayan et al. (2014) where they find that equity markets lead CDS markets in the price discovery in most of the industries. Notably, Narayan et al provide the first and only industry evidence on the CDS-equity markets relationships; however; they use the panel data framework with self-constructed industry panels using firm level data.

Table 3
Full sample bootstrap Granger non-causality results

(1)	(2)	(3)	(4)	(5)	(6)
Industry	***k***	**CDS $-/\rightarrow$ Stock**		**Stock $-/\rightarrow$ CDS**	
		LR-statistic	**p-value**	**LR-statistic**	**p-value**
Banks	8	32.007***	[0.0040]	20.332**	[0.0240]
Financials	4	6.8194	[0.1780]	46.548***	[0.0000]
Telecommunication	3	2.0467	[0.6820]	29.662***	[0.0000]
Healthcare	6	13.041*	[0.0759]	57.294***	[0.0000]
Oil & Gas	5	7.1574	[0.2680]	34.850***	[0.0000]
Basic Materials	5	20.990***	[0.0040]	87.452***	[0.0000]
Consumer Goods	4	0.3158	[0.9840]	56.131***	[0.0000]
Utilities	2	0.5802	[0.7960]	9.4356**	[0.0160]
Industrial	3	3.1120	[0.4539]	52.183***	[0.0000]
Consumer Services	8	2.6646	[0.9540]	71.248***	[0.0000]
Technology	6	12.609	[0.1020]	55.029***	[0.0000]
Market Index	5	12.830	[0.1820]	61.341***	[0.0000]

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The optimal lag order (k) is determined by the AIC. The relationship CDS $-/\rightarrow$ Stock means the CDS spread does not Granger-cause the respective stock index. The p-values in brackets are the bootstrap probability values calculated using 2000 repetitions.

As discussed in the literature review, previous studies on the causal relationship between CDS and equity markets provide mixed results by using different sample periods and model specifications. It is possible that the mixed findings in those studies are due to the sensitivity of the causality tests to sample periods and model specifications. The inference based on Granger causality tests would be misleading if the assumption of parameter stability (due to structural changes or regime shifts) is violated (Salman and Shukur, 2004). The literature highlights various tests to investigate the temporal stability of the VAR models (see e.g., Andrews, 1993; Andrews and Ploberger, 1994). We examine the stability of short-run parameters using the Supermum Wald test (Sup-Wald) and Supermum Likelihood Ratio (Sup-LR) tests proposed by Andrews (1993) and Andrews and Ploberger (1994). These short-run parameter stability tests require data trimming from both ends of the sample. The test statistics are estimated using a fraction of the data [0.15 0.85] with 15% trimming (Andrews, 1993; Balcilar et al., 2010).

Although it is straightforward to examine the stability of parameters when the variables are stationary, in our case the variables are non-stationary and hence this integration-cointegration property must be taken into consideration. The variables form a VECM in a cointegrated VAR, and therefore it is pertinent to examine the stability of both the long-run and short-run parameters. If the cointegration (long-run) parameters are unstable, the model exhibits long-run instability. Further, the model has full structural instability if the short-run parameters are also unstable. Thus, we can test the consistency of our model, using a two step procedure. In the first step, we test the stability of the cointegration parameters, and then the stability of the short-run parameters. For testing the stability of the long-run parameters, we apply the L_c test proposed by Nyblom (1989) and Hansen (1992). This LM test examines the stability of the parameters against the alternative hypothesis that the parameters follow a random walk process i.e., the parameters are time-varying. In what follows, the Sup-LR and Sup-Wald test statistics are used to examine the swift (the short-run stability) regime shifts.

The estimates of both long- and short-term parametric stability tests along with identified structural break dates are reported in Table 4. The results for the L_c test show that long-run parameters of both the CDS and stock price equations are inconsistent at the usual significance levels. The system L_c test statistics indicate that the VAR models as a whole turn out to be unstable at the 1% level of significance for all industries. The results suggest significant evidence of a short-run parameter instability in both equations for all industries as well. The associated structural break dates mainly correspond to the 2008-2009 global financial crisis and the 2011-2013 Eurozone sovereign debt crisis. Thus, the results show that both CDS and equity markets have undergone structural and regime changes during the financial crises episodes. Therefore, the overall evidence based on the parameter stability tests indicates that the VAR model parameters are not constant over time, and thus the statistical inference based on stable parameter assumption is invalid. Further, the inference drawn using the Granger causality test based on the estimates of the full sample VAR model for the CDS and equity market relationship are not reliable.

Table 4

The results of parameter stability tests

	Long-run stability tests		Short-run stability tests		
Industry	L_c	L_c for system	Sup-LR	Sup-Wald	Break Date
Panel A: CDS equation					
Banks	6.3963***	19.7773***	5.1863***	46.677***	3/13/2009

Financials	0.5273**	1.9636***	5.6051***	50.446***	9/20/2013
Telecommunication	2.2036***	13.8709***	5.2692***	47.423***	3/13/2009
Health Care	0.7197***	10.3748***	3.1259**	28.133**	1/30/2009
Oil & Gas	1.3950***	10.6132***	12.449***	112.04***	11/29/2013
Basic Materials	4.6754***	24.4911***	5.7369***	51.632***	6/12/2009
Consumer Goods	1.0598***	6.6535***	3.3178**	29.860**	4/5/2013
Utilities	1.2333***	9.9683***	44.826***	403.43***	7/12/2013
Industrial	0.7758***	4.9537***	5.9737***	53.764***	11/16/2012
Consumer Services	2.1114***	13.4739***	8.6629***	77.966***	12/13/2013
Technology	1.4477***	11.6444***	8.4356***	75.920***	5/15/2009
Market Index	1.4276***	10.8393***	4.1530***	37.377***	3/13/2009
Panel B: Stock price equation					
Banks	1.7931***	--	5.6828***	51.145***	3/13/2009
Financials	0.8720***	--	6.6293***	59.664***	3/13/2009
Telecommunication	1.3671***	--	3.9278***	35.350***	1/30/2009
Health Care	5.5493***	--	2.2158	19.943	3/13/2009
Oil & Gas	4.0846***	--	2.5391*	22.852*	9/30/2011
Basic Materials	5.6618***	--	7.1236***	21.371***	3/13/2009
Consumer Goods	3.2838***	--	3.8368***	34.531***	3/13/2009
Utilities	4.4552***	--	5.6994***	51.294***	5/15/2009
Industrial	1.2564***	--	3.6253***	32.627***	3/13/2009
Consumer Services	4.9514***	--	4.7667***	42.900***	3/13/2009
Technology	5.8932***	--	2.1026	18.924	3/13/2009
Market Index	3.4189***	--	4.2578***	38.320***	3/13/2009

Note: The Hansen-Nyblom L_c long-run parameter stability test is applied to each equation separately and to the VAR system as a whole. The Sup-LR and Sup-Wald test statistics are appropriate to examine a swift regime shift.
***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

To accommodate the structural shifts and the changes in the CDS-stock causal relationship over time, we estimate the VAR models using a rolling window technique. These rolling window estimates are obtained by sequentially changing the subsample of fixed length from the beginning of the sample to the end. The VAR model and then the bootstrap causality tests are applied for each subsample. This sequential testing of causality has some advantages in comparison to the full sample casualty test. The procedure of fixed window rolling estimation allows the system to evolve over time and accommodate the subsample instability issue in a convenient way, using a sequence of subsamples (Balcilar et al., 2010).

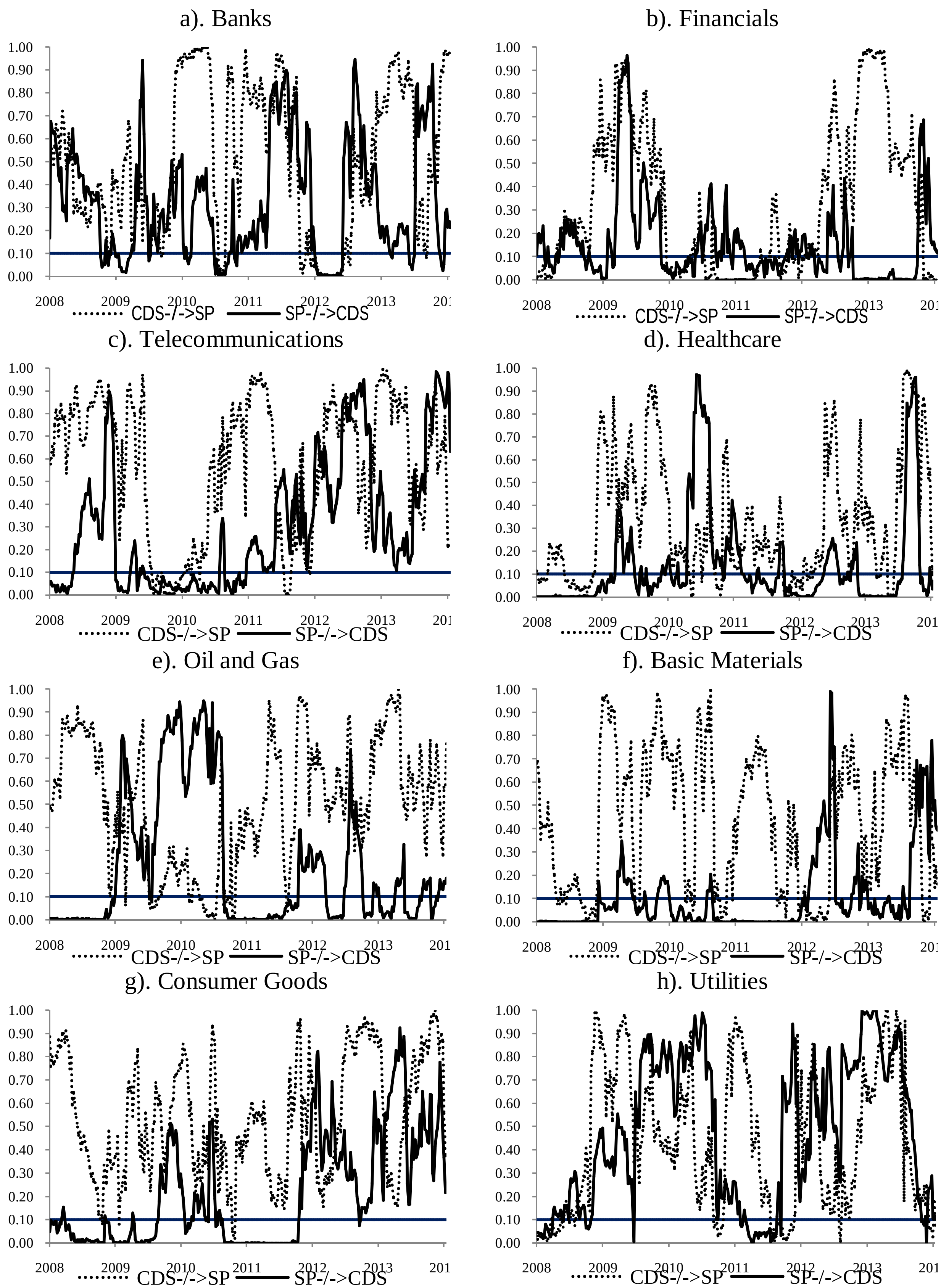
Balcilar et al. (2010) and Tang and Tan (2015) suggest that the rolling window Granger causality estimation require a tradeoff between the window size and the number of estimation windows. The heterogeneity in the data may render the estimates based on a large window size less precise and the latter will also result in fewer windowed estimates. The use of a smaller window may also be imprecise since it may increase the variance of the estimates. However, there is no set criterion for selecting the window size for the rolling window estimation. Pesaran and Timmermann (2005) highlight two conflicting demands, while selecting the optimal window size. The degree of freedom (potential of multiple structural breaks) requires a larger (small) sample size for accurate parameter estimation. Considering the data availability of the CDS spread at the industry level and the above mentioned tradeoff, we arbitrarily select a window size of 52 weeks (a one year time horizon). However, to enhance the precision of rolling estimates, we apply the bootstrap technique (see e.g. Koutris et al., 2008; Balcilar et al., 2010).

The lack of Granger causality from the CDS markets to the equity markets or vice versa is examined by estimating the residuals-based p-values of the LR statistic of the VAR model in Equation (3). The bootstrap p-values for the 11 CDS-Stock nexuses are plotted in Figures (4a-4k). The results of the overall CDS index and the S&P 500 index are shown in Figure 4l. In all the plots, the time period starting from the first rolling window to the end is shown on the horizontal axes. The null hypothesis that *y* does not cause *x* is rejected when the p-values are below the horizontal black line, showing a less than the 10% significance level. For banks, the results in Figure 4a show that the null hypothesis of the CDS does not Granger-cause the stock counterpart is rejected during the years 2012-2013. In 2012, U.S. banks celebrated their second-most-profitable year with a whopping $141 billion in net income, which is barely smaller than the record that was set before the crash in 2006. However, the stock market Granger causes the corresponding CDS during the years 2009, 2011 and 2012–2013. Hence, there is a bi-directional causality between the Banking CDS and stock indices but only during 2012-13.

For the Financial industry CDS-equity nexus, the results reported in Figure 4b indicate that the CDS spreads Granger-cause the corresponding stock index during the years 2011-12, while the Financial stock index Granger-causes the CDS counterpart over most of the time periods. For all the other industries[9], the results plotted in Figures (4b-4k) point to following important findings. The CDS markets Granger-cause the corresponding stock markets for a short time period, particularly during 2011-12, for the Health Care, Oil & Gas, Basic Materials, Utilities, Consumer Services and Technology industries. Moreover, CDSs Granger-cause the stocks for Telecommunication and Industrials during the years 2010 and 2013, respectively. However, there is no significant causality from the CDS to the stock market for the Consumer Goods industry. Further, stock markets Granger-cause the CDS counterparts for the Health Care, Oil & Gas, Basic Materials, Industrial and Technology industries for the majority of the sample period. Similar findings are evident for the Telecommunications, Consumer Goods and Consumer Services industries for most of the sample period. However, there is no causality from the stock to CDS markets towards the end of sample period (i.e., 2012-14) for these industries. 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.

The results of the CDS market index and the S&P 500 index (Figure 4l) show causality from the stocks to CDSs over most of the time period and also a bidirectional causality between the CDS and stock markets during 2012-2013. During this period, Greece downgrades were announced and the markets were uncertain of the future. Thus, during volatile periods we mostly find bi-directional casual links.

[9] To honor space limitation, we only discuss the plots of few industries including the overall CDS and stock relationships as the objective is to highlight the change in relationships, while the industry level investment implications of the CDS-equity nexus are beyond the scope of this study. However, for the interested readers/viewers, we present plots of all industries.



a). Banks
b). Financials
c). Telecommunications
d). Healthcare
e). Oil and Gas
f). Basic Materials
g). Consumer Goods
h). Utilities
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
2008
2009
2010
2011
2012
2013
CDS-/->SP
SP-/->CDS

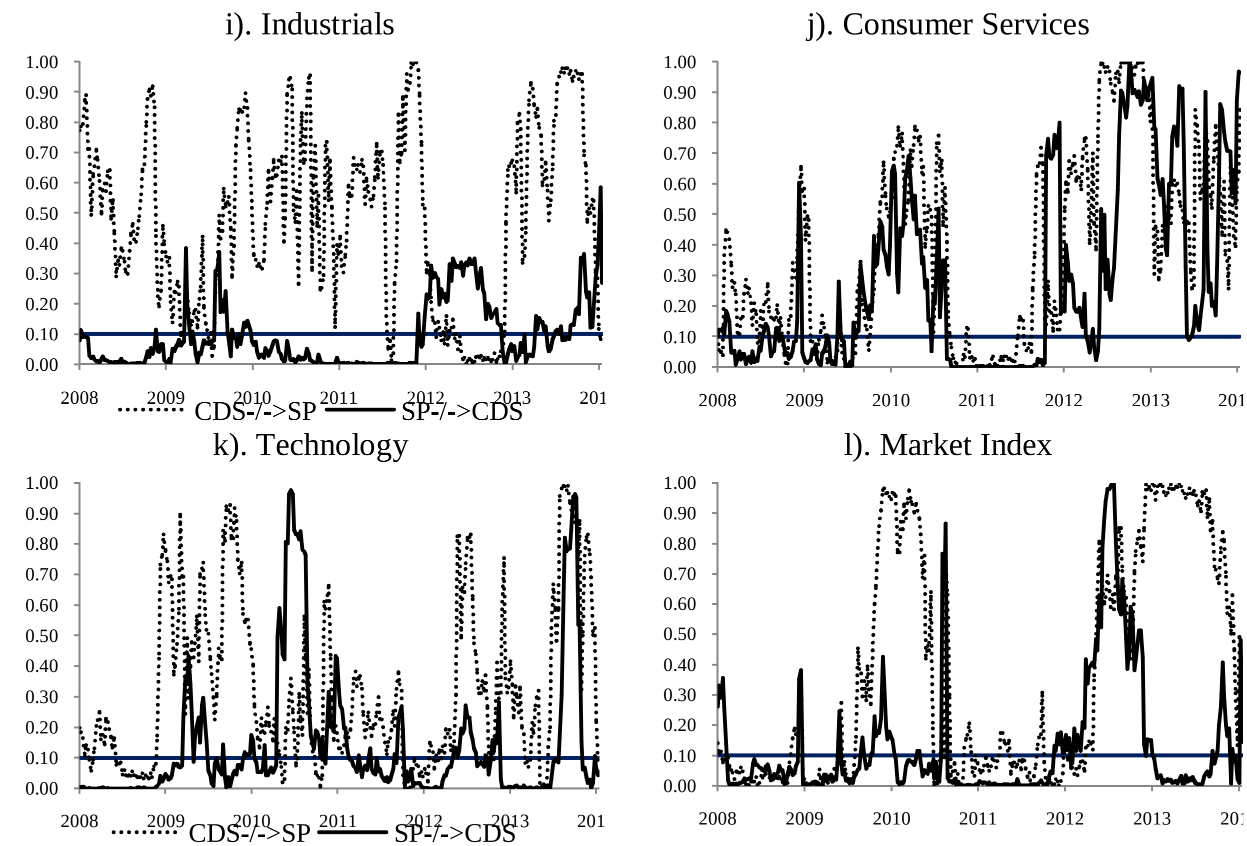


Fig. 4. Industry-level rolling window estimates of Granger non-causality.
Note: The black horizontal line indicates significance at the 10% level. The relationship $y -/\rightarrow x$ implies that *y* does not Granger-cause *x*. The p-value are obtained using a bootstrap procedure with 2000 repetitions.

In sum, the above findings 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 relationships and with due caution that those relationships are subject to change. 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. Our results also reveal that the CDS markets may Granger-cause their stock counterparts during the periods marked with significant credit events, which adds to the existing literature that suggests that the causality comes from the stock market only.

4.4. Determinants of CDS-stock nexuses

After identifying the episodes of significant Granger-causality for the different industries, we use the probit regression models to analyze the determinants of the CDS-stock nexuses of those industries. For this, our dependent variable (*y*) takes the value of one if the Granger casualty is significant at the 10 percent level and zero otherwise. The objective is to examine and quantify a set of instruments (*X*) that may explain the dynamics of Granger causality between the CDS and stock markets for the 11 industries, i.e. the probability of occurrence of this event (*y*). In doing so, we model the probability of observing a value of one as:

$$\Pr(y = 1 | X, \beta) = 1 - \Phi(-X'\beta) = \Phi(X'\beta) \quad (3)$$

where Φ is the cumulative distribution function of the standard normal distribution. We adopt the standard convention by assuming that the index specification is linear in the parameters and takes the form $X'\beta$.

The explanatory variables in our model are known to impact both the CDS and equity markets and hence we hypothesize that these identified variables may explain the interactive relationships between these two markets as well. We include in the model the general business conditions as proxied by the Aruoba-Diebold-Scotti (ADS) business conditions index, the market volatility (VIX), interest rate, the slope of the yield curve, the default risk premium and the Fama-French factors as the explantroy variables. It is evident from the results of short-term stability analysis that both credit and stock markets are impacted by the global financial crisis of 2008-2009 and the Eurozone sovereign debt crisis of 2011-2013. To reflect the impact of these changes we also use dummy variables for these crises periods as explanatory variables in our model. The definitions, sources and related references are provided in Table 5.

Table 5
Explanatory variables used in the probit model

Name	Variables	Source	Reference
ADS	ADS business conditions index	Federal Reserve Bank of Philadelphia	Chan & Marsden (2014)
VIX	Market volatility (VIX) index representing option-implied volatility based on the S&P 500 index options.	DataStream International (Thomson Financial - 2015)	Collin-Dufresne et al., (2001); Galil et al. (2014)
SPOT	Five-year Treasury Constant Maturity Rate (TCMR).	St. Louis Federal Reserve (FRED)	Collin-Dufresne et al., (2001); Galil et al. (2014)
SLOPE	Differences between the 10-year Treasury Constant Maturity Rate and the two-year Treasury Constant Maturity Rate.	St. Louis Federal Reserve (FRED)	Fama & French (1989); Galil et al. (2014)
PREM	Default premium calculated as the yield spread between Moody's Baa and Aaa corporate bonds.	St. Louis Federal Reserve (FRED)	Altman & Kishore (1996); Galil et al. (2014)
SMB	Return on a small capitalization portfolio minus the return on a big capitalization portfolio.	Kenneth French website	Fama & French (1993); Galil et al. (2014)
HML	Return on the portfolio of high book-to-market stocks minus the return on the portfolio of low book-to-market stocks.	Kenneth French website	Fama & French (1993); Galil et al. (2014)
DM1	Dummy Variable for the global financial crisis (2007-09)	Crisis period takes the value 1 and 0 otherwise	National Bureau of Economic Research (NBER)
DM2	Dummy Variable for the Euro Area recession (2011-13)	Crisis period takes the value 1 and 0 otherwise	Centre for Economic Policy Research (CEPR)

Note: The crisis dummy variables (DM1 and DM2) take the value one during crises and zero otherwise. The crises' dates are specified according to the sources mentioned in this table.

The estimation of the probit model is done using the general-to-specific approach based on the theory of reduction (Hendry, 1995, Ch. 9). We initially analyze a general statistical model with all the explanatory variables and then eliminate the statistically insignificant ones. First, we estimate the probit model for the case when the CDS markets Granger cause the stock markets. The results are reported in Table 6. The z-statistics and the robust standard errors are computed using the Huber–White quasi-maximum likelihood method. The coefficients of the probit regressions do not allow a direct interpretation of the impact of an explanatory variable on dependent variable. Therefore, we are interested in the *ceteris paribus* effects of changes in the regressors affecting the probability of causality. We calculate the marginal effects and report them in squared brackets [ ] below the probit regression coefficient for each predicting variable. These marginal effects can be interpreted as the impact of a unit change in a given explanatory variable on the probability that the CDS Granger-causes its corresponding stock or vice versa, keeping all the other variables constant. The results are computed using the average values of the variables[10] and the distinction of the coefficient signs is made by shading the relative columns (i.e., the negative coefficients are shaded with light grey color).

For banks, an increase in the statistically significant explanatory variables (ADS, SPOT, and SMB) decreases the probability of the CDS Granger causing its stock counterpart. Interestingly, the SMB portfolio returns (size premium) also decrease this probability. The importance of the bank size as a strong determinant of the Banking CDS premium is also highlighted by Raunig (2015) and Bijlsma et al. (2014), among others. Bijlsma et al. (2014) find that large banks have a 67 basis points funding advantage over small banks. Additionally, it can be inferred that deterioration in the business conditions (ADS), and an increase in the interest rate (SPOT), and the size premium (SMB) reduces the probability causality flow from the Banking CDS market to their corresponding stock market. Notably, VIX and DM2 increase the probability of the CDS Granger causing its stock counterpart.

Overall, the business conditions (ADS), the market volatility (VIX), the Treasury bond rate (SPOT), the slope of the yield curve (SLOPE), and Default premium (PREM) are the major drivers of causality from the CDS to the stock markets in most of the industries, but do not serve the same causing role for all the industries. Specifically, an increase in the Treasury bond rate decreases the probability of causality from the CDSs to stocks for the Telecommunication suggesting a calming effect on credit risk of higher interest rates in this industry. On the other hand, an increase in the same Treasury bond rate increases the probability of causal flows from CDSs to stocks for the Oil & Gas, Consumer Goods, Utilities, and Consumer Services industries, underscoring the differential impacts of higher interest rates in the U.S. industries. Therefore, increases in government bond yields are processed differently by the CDS and stock markets depending on the industry. However, increases in the Treasury bond rate and the slope of the yield curve have inverse impacts on the causality flows. If the increase in the Treasury bond rate increases (decreases) the probability of CDS Granger-causing stock for an industry, an increase in the slope of the yield curve decreases (increases) it for that industry. These credit variables thus differentially affect the CDS and stock markets and their causalities as their information does not arrive simultaneously in the CDS and stock markets. An increase in the government bond yields signals more risk for some but not all industries and hence strengthens the causing role of the CDS markets, contributing to greater causality from CDSs to stock markets. On the

[10] Nevertheless, the direction of the effect of a change in any of the explanatory variable depends only on the sign of the coefficient estimated where a positive value implies that an increase in a given instrument will increase the probability of one market causing the other, while a negative value indicates the opposite.

other hand, the slope of the yield curve reflects the strength of the economy and the state of the business cycle, and would thus be reflected more in corporate earnings and the stock markets than in the CDS markets, leading to lower causality flows from CDSs to stocks.

A similar impact on the causality flows is observed with the improvement/increase of the business conditions and default premium. The improvements in business conditions decrease the probability of casual flows from CDS to stock markets whereas increase in default premia increase such probability. The market volatility (VIX) is another important explanatory factor driving the causality flows from the CDS to stock markets and is significant in the majority of the industries. An increase in the market volatility which reflects tightening anxiety in the markets would increase the probability of CDSs causing stocks, except for the Technology industry. Notably, the dummy variable used to reflect European sovereign debt crisis of 2011-13 increases the chances of causal flows from CDS to stock markets. The findings that CDSs Granger-cause their stock counterparts during the years 2011-12 and that VIX increases this probability collectively indicate that under volatile market conditions, the credit markets reflect the market information more quickly than stock markets in comparison with normal market conditions. These findings suggest that CDS markets may not Granger cause stock markets under normal conditions; however, changing market volatility (e.g., VIX) would increase the chances.

Further, increases in the value premium (HML) would decrease the probability of the causal flows from the CDSs to the stocks causal nexus for the Utilities industry. Finally, the reported McFadden R-squared values show the models' goodness of fit for these relationships, where the values range between 0.09 (Banking) and 0.64 (Consumer Goods), suggesting that the industry-wise impacts of business conditions, market volatility, interest rate, slope of the yield curve, default premium and Fama-French factors on the causal flows are different.

Table 6

Probit models: Causal relationships running from CDS to equity markets

Industry	ADS	VIX	SPOT	SLOPE	PREM	SMB	HML	DM1	DM2	R^2
Banks	-0.840	0.035	-0.351		-1.994	-0.121			0.548	0.090
	(-2.710)	(2.200)	(-2.010)	--	(-4.490)	(1.325)	--	--	(2.350)	
	[-0.262]	[0.011]	[-0.109]		[-0.621]	[-0.054]			[0.171]	
Financial	-1.291	0.058			-0.692	-0.158		-1.730		0.154
	(-5.570)	(3.850)	--	--	(-1.910)	(-2.240)	--	(-2.380)	--	
	[-0.515]	[0.023]			[-0.276]	[-0.063]		[-0.690]		
Telecommunication	-1.628	0.149	-2.812	5.896	2.476			-6.468		0.531
	(-4.630)	(6.910)	(-5.810)	(7.150)	(3.370)	--	--	(-5.380)	--	
	[-0.392]	[0.036]	[-0.678]	[1.422]	[0.597]			[-1.560]		
Health Care	-0.699	0.074			1.753				0.663	0.126
	(-2.500)	(4.260)	--	--	(4.050)	--	--	--	(3.540)	
	[-0.262]	[0.028]			[0.656]				[0.248]	
Oil & Gas	-0.540	0.030	0.536	-1.750						0.137
	(-2.070)	(2.230)	(2.080)	(-5.080)	--	--	--	--	--	
	[-0.215]	[0.012]	[0.213]	[-0.696]						
Basic Materials	-0.610			0.842	2.087	-0.131			0.635	0.193
	(-2.180)	--	--	(3.620)	(4.970)	(-1.670)	--	--	(2.740)	
	[-0.198]			[0.274]	[0.678]	[-0.042]			[0.206]	
Consumer Goods	2.009	0.034	2.203		6.680	0.153		-5.679	2.202	0.649
	(4.900)	(1.670)	(7.050)	--	(7.890)	(1.470)	--	(-5.530)	(6.120)	
	[0.765]	[0.013]	[0.839]		[2.544]	[0.058]		[-2.163]	[0.839]	
Utilities			1.886	-2.963	0.901		-0.135	-1.482	1.062	0.352
	--	--	(3.520)	(-4.440)	(2.060)	--	(-2.110)	(-1.960)	(2.570)	
			[0.263]	[-0.413]	[0.126]		[-0.019]	[-0.207]	[0.148]	
Industrial		0.056		1.992	0.653				1.953	0.328

	--	(2.220)	--	(6.170)	(1.810)	--	--	--	(6.450)	
		[0.017]		[0.602]	[0.197]				[0.590]	
Consumer Services	1.283		1.056	-0.869	2.225				1.272	0.313
	(6.010)	--	(3.130)	(-2.030)	(5.720)	--	--	--	(5.300)	
	[0.481]		[0.396]	[-0.326]	[0.835]				[0.477]	
Technology	-0.510	-0.061			1.702				-0.711	0.105
	(-1.870)	(-3.740)	--	--	(4.020)	--	--	--	(-3.830)	
	[-0.192]	[-0.023]			[0.642]				[-0.268]	
Market Index	-0.666		1.373		0.894				1.236	0.214
	(-3.090)	--	(6.660)	--	(2.670)	--	--	--	(5.190)	
	[-0.219]		[0.451]		[0.294]				[0.406]	

Note: The z-statistics are given below the parameter estimates in the parentheses, while the associated marginal effects are given in the squared brackets.
ADS= Business conditions index; VIX= Market volatility index; SPOT= Five-year Treasury Constant Maturity Rate; SLOPE= Difference between the 10-year Treasury Constant Maturity Rate and the two-year Treasury Constant Maturity Rate (i.e., term structure); PREM= Default premium calculated as the yield spread between Moody's Baa and Aaa corporate bonds; SMB= Return on a small capitalization portfolio minus the return on a big capitalization portfolio; HML= Return on the portfolio of high book-to-market stocks minus the return on the portfolio of low book-to-market stocks; DM1= the global financial crisis of 2008-2009 dummy; DM2= the Eurozone sovereign debt crisis of 2011-2013 dummy.
R^2 (McFadden) measures the goodness of fit and mirrors the R-squared in OLS. Values between 0.2-0.4 indicate (in McFadden's words) excellent model fit. For example, values of 0.2 to 0.4 for the rho-squared represent an excellent fit.

Now, we estimate the probit models to examine the industry-wise determinants of causality from the *stock to CDS* markets. The results are reported in Table 7. For banks, an improvement in the business conditions (ADS), an increase in the interest rate (SPOT) and the size premium (SMB) separately would decrease the probability of causality running from the banking stock market to the corresponding CDS market whereas the default premium (PREM) increase this probability. The changing market conditions (even improvements in business conditions) decrease both directional probabilities (i.e., the causality from stocks to CDSs and CDSs to stocks. The banking industry CDS-stock nexus is strong when the market situation is stable. VIX would increase this probability probably pointing that the source of fear is coming from the banking stock market. However, the magnitude of this effect is very low. The probability of a casual flow from the financial industry stock index to the CDS counterpart increases with an increase in the stock market volatility (VIX), underscoring a tranquility in financial stability. The stock-to-CDS causality also increases (decreases) with the increase (decrease) in the size premium (slope of the yield curve). The causal flows from the financial industry's stock to CDS market are also higher during the Eurozone sovereign debt crisis of 2011-2013, as the coefficient shows a positive value.

All in all, for all industries, PREM, VIX, SPOT, ADS and SLOPE appear to be the significant determinants of causality flows from the stock-to-CDS counterparts. The stock-to-CDS causal flows decrease with the improvement in the business conditions for Oil & Gas, Utilities, Industrials and the overall market index. On the other hand, improvements in the business conditions increase the causality from the stock to CDS markets for the Consumer Services industry. Further, surges in default premium significantly increase the probability of stocks causing CDSs for Telecommunication, Health Care, Oil & Gas, Basic Material, Industrials, Consumer Services and the overall market index. Notably, we find that improvements in the business conditions decrease the causal probability, while the default premium increases it for the Banks, Oil & Gas, Industrials and overall market index, which suggests that the stock-to-CDS causal flows more likely occur during deteriorating market conditions.

Moreover, a spike in the Treasury bond rate (SPOT) increases the probability of the causal flows running from stocks to CDSs for Healthcare, Basic Material, Consumer Goods, Utilities, Consumer Services, Technology and Market Index, while decreases the flows for Telecommunication, Oil & Gas and Industrials. An increase in the slope of the yield curve also reduces the probability of causality from stocks to CDSs for seven out of the nine cases. The probability of equity causing CDS increases with the increase in default premium Telecommunication, Healthcare, Oil & Gas, Basic Materials, Industrial, Consumer Services and overall market index. An increase in the size premium (SMB) also increases the causality probability from stocks to CDSs for Financial. Similarly, the value premium (HML) increases the probability that stock markets Granger cause the corresponding CDS markets for Basic Materials, Utilities and Market Index. Both the 2008-2009 global financial crisis and the 2011-2013 Eurozone sovereign debt crisis impact the causal flows from equity to CDS markets and their impact is industry specific. Again, the model fit is shown through the McFadden R-squared which ranges from 0.08 (for Basic Materials) to 0.48 (for Utilities). The McFadden R-squared measures the goodness of fit and mirrors the R-squared in OLS. Values from 0.2-0.4 indicate (in McFadden's words) an excellent model fit.

Table 7

Probit models: Causal relationships running from equity to CDS markets

Industry	ADS	VIX	SPOT	SLOPE	PREM	SMB	HML	DM1	DM2	R^2
Banks	-0.867		-1.500		2.612	-0.160			0.683	0.320
	(-2.090)	--	(-5.290)	--	(4.540)	(-1.550)	--	--	(2.490)	
	[-0.103]		[-0.179]		[0.311]	[-0.019]			[0.081]	
Financial		0.054		-0.511		0.123			1.009	0.230
	--	(5.460)	--	(-2.580)	--	(1.750)	--	--	(5.160)	
		[0.020]		[-0.185]		[0.044]			[0.364]	
Telecommunication			-5.271	4.352	7.479				-3.487	0.458
	--	--	(-4.720)	(3.700)	(5.790)	--	--	--	(-5.570)	
			[-0.098]	[0.081]	[0.139]				[-0.065]	
Health Care			1.582	-1.671	0.772			1.258	1.043	0.126
	--	--	(4.580)	(-3.840)	(2.160)	--	--	(1.980)	(4.040)	
			[0.440]	[-0.465]	[0.215]			[0.350]	[0.290]	
Oil & Gas	-1.664	0.067	-1.753	4.354	2.257				1.466	0.361
	(-0.003)	(3.490)	(-2.660)	(4.210)	(2.460)	--	--	--	(4.310)	
	[-0.090]	[0.004]	[-0.095]	[0.235]	[0.122]				[0.079]	
Basic Materials			1.090	-1.704	0.466		0.085		0.544	0.083
	--	--	(3.400)	(-4.120)	(2.350)	--	(1.460)	--	(2.390)	
			[0.306]	[-0.479]	[0.131]		[0.024]		[0.153]	
Consumer Goods		0.088	1.592	-2.553						0.293
	--	(2.780)	(1.980)	(-1.900)	--	--	--	--	--	
		[0.001]	[0.011]	[-0.017]						
Utilities	-0.540	0.041	0.685	-3.048			0.190			0.486
	(-2.610)	(2.440)	(1.840)	(-4.870)	--	--	(2.180)	--	--	
	[-0.067]	[0.005]	[0.084]	[-0.376]			[0.023]			
Industrial	-0.767	-0.105	-1.283		2.050				-2.353	0.269
	(-1.760)	(-2.520)	(-4.120)	--	(2.830)	--	--	--	(-5.390)	
	[-0.095]	[-0.013]	[-0.160]		[0.255]				[-0.293]	
Consumer Services	1.315	0.048	0.512		2.868			2.306	1.168	0.348
	(4.770)	(3.100)	(2.160)	--	(6.130)	--	--	(2.830)	(3.420)	
	[0.284]	[0.010]	[0.111]		[0.620]			[0.498]	[0.252]	
Technology			1.581	-1.559	-1.054			1.287	1.068	0.101
	--	--	(4.690)	(-3.670)	(-2.960)	--	--	(2.060)	(4.220)	
			[0.432]	[-0.426]	[-0.288]			[0.352]	[0.292]	
Market Index	-0.909		1.984	-1.493	1.858		0.135		1.979	0.405
	(-4.250)	--	(4.830)	(-3.100)	(4.690)	--	(1.830)	--	(6.970)	

[-0.345]	[0.753]	[-0.566]	[0.705]	[0.051]	[0.751]

Note: The z-statistics are given below the parameter estimates in the parentheses, while the associated marginal effects are given in the squared brackets.
ADS= Business conditions index; VIX= Market volatility index; SPOT= Five-year Treasury Constant Maturity Rate; SLOPE= Difference between the 10-year Treasury Constant Maturity Rate and the two-year Treasury Constant Maturity Rate (i.e., term structure); PREM= Default premium calculated as the yield spread between Moody's Baa and Aaa corporate bonds; SMB= Return on a small capitalization portfolio minus the return on a big capitalization portfolio; HML= Return on the portfolio of high book-to-market stocks minus the return on the portfolio of low book-to-market stocks; DM1= the global financial crisis of 2008-2009 dummy; DM2= the Eurozone sovereign debt crisis of 2011-2013 dummy.
R^2 (McFadden) measures goodness of fit and mirrors the R-squared in OLS. Values between 0.2-0.4 indicate (in McFadden's words) excellent model fit. For example, values of 0.2 to 0.4 for the rho-squared represent an excellent fit.

5. Conclusion

This study examines the CDS-equity nexuses for 11 industries in the United States by employing bootstrap Granger causality tests, using industry level data. We use weekly data that span the period from December 14, 2007 to December 31, 2014. The bootstrap Granger causality tests are conducted using both the full sample and rolling window subsamples. The later is utilized to cater for structural changes and their impacts on the Granger causality estimates.

The findings of the full sample bootstrap tests reveal that the stock markets Granger-cause the CDS counterparts in all cases, and there is also a bi-directional causality for the Banking, Healthcare and Materials industries. The results also show that the full sample short-run parameters are unstable due to structural changes and regime shifts caused mostly by the recent global crises including the 2008-2009 global financial crisis and the 2011-2013 Eurozone sovereign debt crisis. The rolling window approach provides strong empirical evidence that the lead-lag relationship between the stock and credit markets for all industries is dynamic with varying degrees of causalities because of structural breaks. The stock markets at the industry and overall market levels lead their CDS counterparts, except for the Utility industry, over the majority of the time period, using the rolling window approach. However, the industry CDS markets also Granger-cause the corresponding stock markets when being a part of bidirectional causalities during the volatile market conditions. For the overall market index, the causality also runs from the CDS markets to the stock markets during 2009-10 and then 2011-13, which adds a new result to the existing literature that concentrates on the stock-to-CDS causality.

Further, the study analyzes some of the possible determinants of the CDS-stock causal nexuses at the industry level through the probit model. The overall results show that the business conditions, the Treasury bond rate, the slope of the yield curve, and the market volatility (VIX) are the major determinants of the causality from the CDS to stock markets in most of the industries. The findings also suggest that the impacts of the macro-economic determinants on this relationship are industry-dependent and that different market conditions may increase (or decrease) the probability of the Granger causality running from the CDS to the stock markets and vice versa. For example, hikes in VIX would increase the probability of CDSs causing stocks for almost all industries reflecting fear and anxiety in the markets, whereas increase in interest rates enhances the causal flows from stocks to CDSs in majority of cases. Changes in the different macro-economic information may be processed in stock markets but not in the credit markets or both simultaneously. Hence, those changes may affect the CDS-stock interactions and the probabilities of causality for the industries differently.

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