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Distribution specific dependence and causality between industry-level U.S. credit and stock markets

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ABSTRACT

This paper examines the dependence and causal nexuses between ten U.S. credit default swaps and their corresponding stock sectoral markets, using the Quantile-on-Quantile (QQ) approach and the nonparametric causality-in-quantiles tests. The results, using the QQ approach, show asymmetric negative association between credit and markets for all industries and that the link depends on both the sign and size of the stock market shocks (i.e., bullish or bearish conditions in the CDS and/or stock markets). The sensitivity of CDS returns to stock markets shocks is higher in the extreme quantiles. Using the nonparametric causality-in-quantile tests, we find evidence of causality-in-mean from stock to CDS only for the Financial (in average and upper quantiles), Consumer Services and Oil & Gas sectors (only for the middle quantile i.e., 0.5). In addition, the causality-in-mean from the CDS to stock markets is only found for the Financial and Telecommunication sectors in the extreme lower quantiles. Finally, we find a bidirectional Granger causality-in-variance for all the CDS-equity sector pairs.

1. Introduction

The dependence between stock markets and credit default swap (CDS) spreads has re-emerged as a more challenging and interesting area of research in the wake of the global financial crisis (GFC) of 2008–2009 and the European sovereign debt crisis (ESDC) of 2010–2012. During this period, the CDSs are called weapons of mass destruction due to their associations with those grave crises.[1] These concerns had caused a steady reduction in the size of the global credit derivatives market, which started in 2007, and continued in the first half of 2015. This reflects a contraction in inter-dealer activity. The notional amount of the outstanding credit derivatives contracts fell from \$16 trillion at the end of December 2014 to \$15 trillion at the end of June

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[1] Warren Buffett, the legendary U.S. investor, called the CDSs financial weapons of mass destruction.

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2015, which constitutes only a quarter of its peak of $58 trillion at the end of 2007 (BIS, 2015).[2] The widening of sovereign and corporate CDS spreads to unprecedented levels during the GFC had stoked the heightened concerns over default risk, particularly in the financial industry and for countries with gloomy macroeconomic outlooks and serious fiscal imbalances.

Considered as the most controversial financial instruments created over the past two decades, the CDSs are strongly supported by some market participants, while blamed by others including researchers.[3] On the positive side, some researchers view them as efficient instruments that have processed information rapidly before and after the recent credit crisis. On the other side, researchers such as Subrahmanyam et al. (2014) argue that CDSs have played a leading role in the bankruptcy of Lehman Brothers on September 15, 2008 and in the Eurozone sovereign debt crisis (ESDC) that started in Greece in late 2009 and spread into Europe. To others, those derivatives had shown under-reaction during the GFC but in the latter stages of this crisis they overreacted although the overreaction was shorted lived. Thus, researchers call the efficiency of those credit derivatives into question during less stable economic periods (Jenkins et al., 2016).

Theoretically, the structural model of credit risk proposed by Merton (1974) offers a theoretical framework that supports the link between CDS and stock markets. According to this model, default occurs when a firm's value, which is perceived to follow a stochastic process, goes below a certain threshold. This value is unobserved and its changes cannot be measured directly, but changes in the firm's stock value are widely accepted as good proxies for changes in the firm's value. The Merton model asserts that that a drop in stock returns is accompanied by an increase in the firm's CDS spread. Thus, this structural model suggests that CDS spreads and stock prices have a negative relationship with each other and co-move to prevent arbitrage from taking place. The deterioration in the financial conditions of a firm increases the probability of its default on the underlying debt obligations, and that financial distress conditions result in a decrease in the value of firms' stocks and an increase in 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 credit spread changes. However, Fung et al. (2008) argue that the exploitation of capital structure arbitrage enhances the integration and information flows between CDSs and stock prices.

It is also argued that an informed trader may prefer CDSs over equity shares to take a hedge (i.e., insure against default) or a speculative position (i.e., bet on the likelihood of default) due to the market opacity and the entrenched leverage advantage of CDSs. Additionally, CDS contracts trade based on the notional amount, and thus the physical size of the market does not impact the trading volume which is the case in stock markets. A CDS contract can be created whenever the other side (i.e., market maker) is willing to buy and sell but a bespoke CDS contract can also be very different having different degrees of liquidity and embedded leverage. Based on these advantages, the informed traders on aggregate may prefer to trade in the CDS market than in the stock market. This trading preference between these two markets may result in a price discovery advantage for the CDS market.

This paper aims to study the extreme dependence and nonparametric asymmetric causalities between CDS spreads and stock markets in the U.S. at the industry level. To achieve this objective, we apply two novel methods which are the quantile-on-quantile approach and the nonparametric causality-in-quantiles method to the daily data covering the period December 14, 2007 to September 30, 2015. While the nonparametric causality in quantiles has recently been applied to foreign exchange and stock markets, to our knowledge it has not been used in the CDS markets.

The current study contributes to the related literature in at least two major ways. First, it extends the previous literature to the CDS-equity nexus at sector level. More specifically, we consider stock indices and their corresponding 5-year industry CDS spreads denominated in U.S. dollars for ten U.S. industries. The 5 year contracts is the most liquid and constitutes about 85% of the trades in the CDS market. The industries are Oil & Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Utilities, Financials and Technology. Second, it follows the two quantile methods for different reasons. The quantile-on-quantile (QQ) regression is an extension of the quantile regression approach by allowing one to estimate how the quantile of a CDS return is dependent with the quantile of a stock shock. Given the different distributions, the QQ regression provides informative results on how well or how poorly the U.S. equity sectors perform. Moreover, the QQ approach outperforms the OLS or quantile regression in its ability to uncover some characteristics which are not apparent in the conventional frameworks (e.g., OLS or quantile regressions). As for the nonparametric causality-in-quantile method, the analytical framework is flexible since it allows one to test the nonlinear causality of the kth order across all quantiles (or markets conditions) of the distribution of CDS-equity indices' movements. We test not only the CDS-equity causality in the first order moments (or returns) but also in the second order moments (variance).

We decide to use these methods because previous studies posit that CDS and equity return series are marked by nonlinearity and structural breaks (see Section 4) and that the comovements between these markets are sensitive to different market conditions. The QQ and nonparametric causality-in-quantile methods used in this study are robust to misspecification errors, structural breaks and frequent outliers which are commonly found in the financial time series.

By doing so, we have found quite interesting results from using the QQ approach and the nonparametric causality in quantile test. The relationship between the U.S. CDS returns and stock market at the sector level is negative and asymmetric

[2] http://www.bis.org/publ/otc_hy1511.pdf.

[3] 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 which existed twenty-five years ago. In contrast, financier George Soros called for an outright ban on the naked credit default swaps, viewing them as "toxic". Noble prize winning economist Myron Scholes, who developed a good part of the pricing structure used in CDSs, considered these over-the-counter instruments to be so dangerous that they should be "blown up or burned".

across the quantiles of both variables for all industries, underpinning the results of the Merton (1974) model. More specifically, the sensitivity of CDS returns to stock market shocks is higher in the extreme quantiles that is during bull and bear markets. The reactions of CDS markets to their respective stock counterparts are higher and lower for the bullish and bearish stock market conditions, respectively. Using the nonparametric causality-in-quantile tests, we find supportive evidence of the causality-in-mean from the stock to CDS only for the Financial sector during normal and bull market periods, and for the Consumer Services and Oil & Gas sectors only for the middle quantile (i.e., 0.5). In addition, the causality-in-mean from the CDS to stock markets is only found for the Financial and Telecommunication sectors, particularly in bearish conditions. Finally, we find a bidirectional Granger causality in variance for all the CDS-equity sectoral pairs. These results at the sector level are in sharp contrast with the traditional CDS-stock literature which claims that the causality runs from stocks to CDSs.

The remainder of the paper is organized as follows: Section 2 presents a brief review of the literature. Section 3 discusses the econometric framework. Section 4 presents the data and their stochastic properties. Section 5 analyzes the results and discusses the implications, while Section 6 concludes.

2. Brief review of the literature

The empirical literature that dealt with the CDSs has applied traditional time series models to investigate average results without paying much attention to different market conditions (e.g., the bull, normal and bear markets) and diverse investment horizons (short, medium and long horizons) which are needed to accommodate the diverse behavior of speculators, arbitragers and long term investors. For example, Byström (2006), 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. This literature has concentrated exclusively on traditional econometric techniques utilizing a wide range of traditional time series methods including the Vector Autoregressive (VAR) model, the Vector Error Correction Model, the Granger causality tests, among others. Specifically, Chan-Lau and Kim (2004), Longstaff et al. (2003), Norden and Weber (2009), and Trutwein and Schiereck (2011) use the Vector Autoregressive (VAR) model, while da Silva (2014), Forte and Lovreta (2015), Forte and Peña (2009), Schweikhard and Tsesmelidakis (2012) employ the VECM to ascertain cointegration among the CDS and stock markets. Others such as Chan et al. (2009), Coronado et al. (2012), da Silva (2014) and Fung et al. (2008) base their conclusions on the presence of causal flows between the CDS and stock markets through Granger causality tests.

Considering that tranquil and turbulent periods may play an important role in driving the relationship between the CDS and stock markets, recent attempts have been made to address the shortcomings of the conventional econometric frameworks by employing the copula approach (da Silva et al., 2014; Fei et al., 2013; Fenech et al., 2014) or by utilizing Markov regime-switching models (Castellano and Scaccia, 2014; Da Fonseca and Wang, 2016; Guo et al., 2011). These previous empirical studies on the lead-lag relationship between the CDS and stock markets mostly suggest that the stock markets tend to lead the CDS market (Forte and Peña, 2009; Fung et al., 2008; Norden and Weber, 2009; Trutwein and Schiereck, 2011, among others), supporting the view that stock markets more quickly incorporate new information than the CDS market. There are two notable findings in this vein. (i) The CDS-stock nexus depends on the credit quality of the underlying debt obligation, where 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 case of better credit worthiness. (ii) The volatile market conditions enhance the degree of association between the CDS and stock markets (see e.g., Coronado et al., 2012; Fei et al., 2013; Trutwein and Schiereck, 2011).

Most of the previous works on the CDS-stock connection have either concentrated on sovereign CDSs (Corzo et al., 2014; Ngene et al., 2014) or utilized firm-level CDSs (e.g., Forte and Lovreta, 2015; Forte and Peña, 2009). Few studies have examined the linkages between the CDS spreads and stock returns at the industry-level (Byström, 2006; Narayan, 2015; Narayan et al., 2014). By proposing panel cointegration and panel vector-error correction models in their pioneering study, Narayan et al. (2014), investigate the price discovery in the U.S. CDSs and the stock markets at the industry level. They find that with significant heterogeneity across industries, there is a dominant lead of stock markets in the price discovery process for nine sectors except the Telecommunication. They also find that the recent global financial crisis affects the price discovery process in all sectors. More recently, Narayan (2015) finds that for the ten U.S. sectors, both stock and CDS market shocks explain the forecast error variance (FEV) of each other and the impact of these shocks is more profound during the post-Lehman crisis period.

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

More recently, Kinateder et al. (2017) examine the predictability of the out-of-sample yield spread in the European Monetary Union. The authors show evidence of the usefulness of economic models in predicting sovereign spreads during crisis periods. Dufour et al. (2017) examine the determinants of European sovereign bond returns. The results show that the sign of the equity beta crucially depends on country risk. More importantly, government bonds are a safe asset of low risk countries.

In contrast, government bonds of high-risk countries lose their safe haven status and exhibit more equity-like behavior during the sovereign debt crisis, with strongly significant and positive co-movements relative to the corresponding stock market. Narayan et al. (2017) analyze how bond, equity, gold, oil markets, as well as market volatility and inflation interact. Their results show a negative reaction between equity prices and shocks in uncertainty, thereby building a positive risk premium. In addition, the authors find a significant cross-market pricing transmission from gold to bonds and to oil.

3. Methodology

3.1. Quantile-on-quantile approach

We briefly describe the key features of the quantile-on-quantile approach proposed by Sim and Zhou (2015) and the model specification used to investigate the sector-level relationship between CDS and stock markets. The QQ approach, as a generalization of the standard quantile regression, is a combination of quantile regression and nonparametric estimation enabling one to examine how the quantiles of a variable affect the conditional quantiles of another variable. In the framework of the present study, the QQ approach proposed to investigate the effect of the quantiles of stock market returns on the quantiles of CDSs of an industry has its starting point in the following nonparametric quantile regression model:

$$CDS_t = \beta^{\theta}(SP_t) + u_t^{\theta} \tag{1}$$

where CDS_t represents the CDS returns of a given industry in period t, SP_t denotes the stock market returns of that industry in period t, θ is the θth quantile of the conditional distribution of the CDS returns and u_t^{θ} is a quantile error term whose conditional θth quantile is equal to zero. The $\beta^{\theta}(\cdot)$ is an unknown function as we have no prior information on how the CDS and stock markets are linked.

This standard quantile regression model allows the effect of stock returns to vary across different quantiles of CDS returns; however, it is unable to capture the dependence in its entirety. We posit that large or small positive/negative stock market shocks may have a differential influence on the CDS markets, and that the CDSs may also react asymmetrically to the negative and positive stock market shocks.

Therefore, to examine the relationship between the θth quantile of CDS returns and the τth quantile of stock returns, denoted by SP^{τ}, Eq. (1) is examined in the neighborhood of SP^{τ} using a local linear regression. As $\beta^{\theta}(\cdot)$ is unknown, this function can be approximated through a first order Taylor expansion around a quantile SP^{τ}, such that:

$$\beta^{\theta}(SP_t) \approx \beta^{\theta}(SP^{\tau}) + \beta^{\theta'}(SP^{\tau})(SP_t - SP^{\tau}) \tag{2}$$

where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}(SP_t)$ with respect to SP, also called the marginal effect or response and is similar in interpretation to the coefficient (slope) in a linear regression model. Now, $\beta^{\theta}(SP^{\tau})$ and $\beta^{\theta'}(SP^{\tau})$ can be renamed as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$, respectively, and Eq. (2) can be rewritten as:

$$\beta^{\theta}(SP_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(SP_t - SP^{\tau}) \tag{3}$$

By substituting Eq. (3) in Eq. (1), the following equation is obtained:

$$CDS_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(SP_t - SP^{\tau})}_{(*)} + u_t^{\theta} \tag{4}$$

The term $(*)$ of Eq. (4) is the θth conditional quantile of the CDS returns. Unlike the standard conditional quantile function, Eq. (4) captures the overall dependence structure between the θth quantile of the CDS returns and the τth quantile of the stock market returns as the parameters β_0 and β_1 are doubly indexed in θ and τ. To estimate Eq. (4), it is necessary to replace SP_t and SP^{τ} by their empirical counterparts $\widehat{SP}_t$ and $\widehat{SP}^{\tau}$, respectively. The local linear regression estimates of the parameters b_0 and b_1 are obtained by solving the following minimization problem:

$$\min_{b_0,b_1} \sum_{i=1}^{n} \rho_{\theta}[CDS_t - b_0 - b_1(\widehat{SP}_t - \widehat{SP}^{\tau})] K\left(\frac{F_n(\widehat{SP}_t) - \tau}{h}\right) \tag{5}$$

where $\rho_{\theta}(u)$ is the quantile loss function, defined as $\rho_{\theta}(u) = u(\theta - I(u < 0))$ and I is the usual indicator function. $K(\cdot)$ denotes the kernel function and h is the bandwidth parameter of the kernel. The Gaussian kernel, because of its computational simplicity and efficiency, is used to weight the observations in the neighborhood of SP^{τ}. Specifically, in our analysis these weights are inversely related to the distance between the empirical distribution function of $\widehat{SP}_t$, denoted by $F_n(\widehat{SP}_t) = \frac{1}{n}\sum_{k=1}^{n} I\left(\widehat{SP}_k < \widehat{SP}_t\right)$, and the value of the distribution function that corresponds with the quantile SP^{τ}, denoted by τ. A bandwidth parameter $h = 0.05$ is used following Sim and Zhou (2015).

3.2. Causality in quantile approach

We use the novel nonlinear causality method proposed by Balcilar et al. (2016, forthcoming) to examine the causality-in-quantiles between sector-level CDS (y_t) and corresponding sector stock returns (x_t). This hybrid nonparametric quantile causality approach is an extension of the earlier work by Nishiyama et al. (2011) and Jeong et al. (2012). Following Jeong et al. (2012),[4] we test that x_t does not cause y_t in the θ-quantile with regards to the lag-vector of

$$\{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\} \quad \text{if} \quad Q_\theta(y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}) = Q_\theta(y_t|y_{t-1},\ldots,y_{t-p}) \tag{6}$$

However, x_t presumably causes y_t in the θ-th quantile with regards to

$$\{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\} \quad \text{if} \quad Q_\theta(y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}) \neq Q_\theta(y_t|y_{t-1},\ldots,y_{t-p}) \tag{7}$$

where $Q_\theta(y_t|\cdot)$ is the θ -th quantile of y_t. The conditional quantiles of y_t, $Q_\theta(y_t|\cdot)$ depends on t and the quantiles are restricted between zero and one, i.e., $0 < \theta < 1$.

Let us define the vectors $Y_{t-1} \equiv (y_{t-1},\ldots,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},\ldots,x_{t-p})$, and $Z_t = (X_t, Y_t)$. The functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$, be the conditional distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1}, respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is presumed to be completely continuous in y_t for nearly all Z_{t-1}. By defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we can see that $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds with a probability equal to one. Accordingly, the causality-in-quantiles hypothesis based on the Eqs. (1) and (2) can be represented as:

$$H_0: \ P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \tag{8}$$

$$H_1: \ P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \tag{9}$$

In order to define a measurable metric for the practical implementation of the causality-in-quantiles tests, Jeong et al. (2012) make use of the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1})f_Z(Z_{t-1})\}$, where ε_t denotes the regression error and $f_Z(Z_{t-1})$ denotes the marginal density function of Z_{t-1}. In our particular case, the estimator of the unknown regression error is defined as:

$$\widehat{\varepsilon}_t = \mathbf{1}\{y_t \leqslant \widehat{Q}_\theta(Y_{t-1})\} - \theta \tag{10}$$

In Eq. (10), the quantile estimator $\widehat{Q}_\theta(Y_{t-1})$ yields an estimate of the θ -th conditional quantile of y_t given Y_{t-1}. We estimate $\widehat{Q}_\theta(Y_{t-1})$ by employing the nonparametric kernel approach as:

$$\widehat{Q}_\theta(Y_{t-1}) = \widehat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{11}$$

where $\widehat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the *Nadarya-Watson* kernel estimator given by:

$$\widehat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)1\{y_s \leqslant y_t\}}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{12}$$

with $L(\cdot)$ denotes a known kernel function and h is the bandwidth used in the kernel estimation.

Next, we examine the causality in variance (2nd moment) because the rejection of causality in the moment m does not imply non-causality in the moment k for $m < k$, from stock market returns to volatility of CDS returns. We can illustrate this by utilizing the following model:

$$y_t = g(X_{t-1}, Y_{t-1}) + \varepsilon_t \tag{13}$$

where the higher order causality-in-quantiles can be tested as:

$$H_0: \ P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad \text{for} \quad k = 1,2,\ldots,K \tag{14}$$

$$H_1: \ P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad \text{for} \quad k = 1,2,\ldots,K \tag{15}$$

We test that x_t Granger causes y_t in quantile θ up to K -th moment using Eq. (14) to formulate the feasible kernel-based test statistic following Jeong et al. (2012), for each k. For the joint density-weighted nonparametric tests for all $k = 1,2,\ldots,K$, we follow the sequential testing approach as in Nishiyama et al. (2011). The lag order of 1 is chosen based on the Schwarz Information Criterion (SIC) in a VAR involving stock and CDS market returns. The bandwidth value is selected by using the least squares cross-validation techniques. Finally, for $K(\cdot)$ and $L(\cdot)$ we employ Gaussian-type kernels.

[4] The exposition in this section closely follows Nishiyama et al. (2011) and Jeong et al. (2012).

4. Data and stochastic properties

4.1. Data overview

We use daily closing values for the stock indices and their corresponding 5-year industry CDS spreads denominated in U. S. dollars for the U.S. ten industries. Based on the most liquid term contract (the 5-year CDSs), the industry CDS indices are equally weighted and reflect the price performance of a basket of 5-year CDSs of firms within a given industry. These indices are rebalanced every six months to better represent liquidity in the CDS market.[5] The industry breakdown closely follows the Industry Classification Benchmark (ICB) developed by Dow Jones and FTSE, which is the most widely used global standard for company classification. Thus, the industries covered are: Oil & Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Utilities, Financials and Technology.

All the data are collected from the Thomson Reuters Datastream and the sample period ranges from December 14, 2007 to September 30, 2015, which includes both the recent global financial crisis and the euro area sovereign debt crisis. The beginning of the sample is dictated by the availability of liquid data of the CDS industry indices. Figs. 1 and 2 plot the trend of the CDS spreads and stock market prices, respectively. The increase (decrease) in CDS spread (stock prices) is evident following some significant market events, and the industry-level behavior of both CDS and stock markets is different, and hence an industry level analysis is valid for an in-depth evaluation of the CDS-stock dependence.

Figs. 3 and 4 illustrate the dynamic returns of the U.S. CDS and equity sectors, respectively. As shown in these figures, all returns series show volatility clustering and structural breaks. The impacts of the 2008–09 GFC on these markets is evident in the figures. More importantly, we find a presence of several structural breaks in all return series. These results explain the importance of applying nonparametric methods.

4.2. Stochastic properties

In line with previous studies in this area (Acharya and Johnson, 2007; Hammoudeh and Sari, 2011; Hammoudeh et al., 2013; Narayan, 2015), stock and CDS returns are calculated as first log differences of the stock indices and CDS spreads, respectively, in order to obtain stationarity.[6] Table 1 presents the descriptive statistics for the CDS (Panel A) and the stock (Panel B) returns. The CDS return series are positive for all the sectors with the exception of Industrials, Consumer Goods, Telecommunications and Utilities. The Oil & Gas CDS yields the highest mean returns followed by the Technology and Financial CDS markets. Furthermore, the Utilities sector has the highest risk, as is evident by its standard deviation which amounts to 8.768%, followed by Oil & Gas (7.433%) and Financial (5.677%). As for the U.S. stock market sectoral indexes, four out of the ten stock sectoral indexes (Oil &Gas, Basic Materials, Financial and Telecommunication) yield negative mean returns. In addition, the Financial and Oil &Gas (Consumer Goods and Health Care) stock returns are more (less) volatile among the remaining stock sectoral returns.

All the return series are asymmetric and fat tailed as indicated by the skewness and Kurtosis tests. The Jarque-Bera normality test also indicates that the returns for both the CDS and stock markets are not normally distributed. Also, the results of the Ljung-Box test statistics of the residuals (Q(1) and Q(5)) fail to support the null hypothesis of a white noise process (i.e., an *i.i.d* process), underlying the presence of temporal dependence for all the return series. In addition, we find strong evidence of the ARCH effects for all series. To initially establish that we are dealing with nonstationary time series, we implement two types of unit root tests and one type of stationary tests. The two unit root tests are the augmented Dickey and Fuller (ADF; 1979) and the Phillips and Perron (PP; 1988) tests, and the stationary test is the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS; 1992) test. The results of the unit root and the stationarity test (not reported in the text but are available upon request) strongly suggest that all the return series are stationary processes at the conventional levels.

5. Empirical results

5.1. Preliminary analysis

To justify the use of the nonparametric causality in quantile methods, we start our analysis by examining the linear Granger causality between the industry-level CDS and stock markets. Table 2 reports the linear Granger causality test and the

[5] The sector level CDS indices are usually based on the 5-year tenor series contracts because the five year credit instruments are considered adequate in terms of liquidity and hedging, and are commonly used in empirical analyses (see Narayan et al., 2014). They are the most frequently traded and most researched in the academic literature. The 5-year CDS spread is a potentially important component of the spread of a CDS. The CDS market is quite liquid, at least for the 5-year maturity contract, with low transaction costs to initiate a contract with a market maker on a short notice (see Blanco et al., 2005). Moreover, analysing the 5-year CDS spread allows one to extract relevant information particularly during turbulence times. During the period spanning from June to December 2010, a total of 11,196 contracts were concluded and approximately 86% of them involved the 5-year maturity (http://creditmatch.gfigroup.com/). Also, the number of contracts with expiry dates of less than 5 years are more limited. Finally, the literature also may not be receptive to research on the 10-year CDS contracts.

[6] The use of CDS change as opposed to percentage change have only a minor impact on the main results. To conserve space, we do not include these results, however, are available upon request.

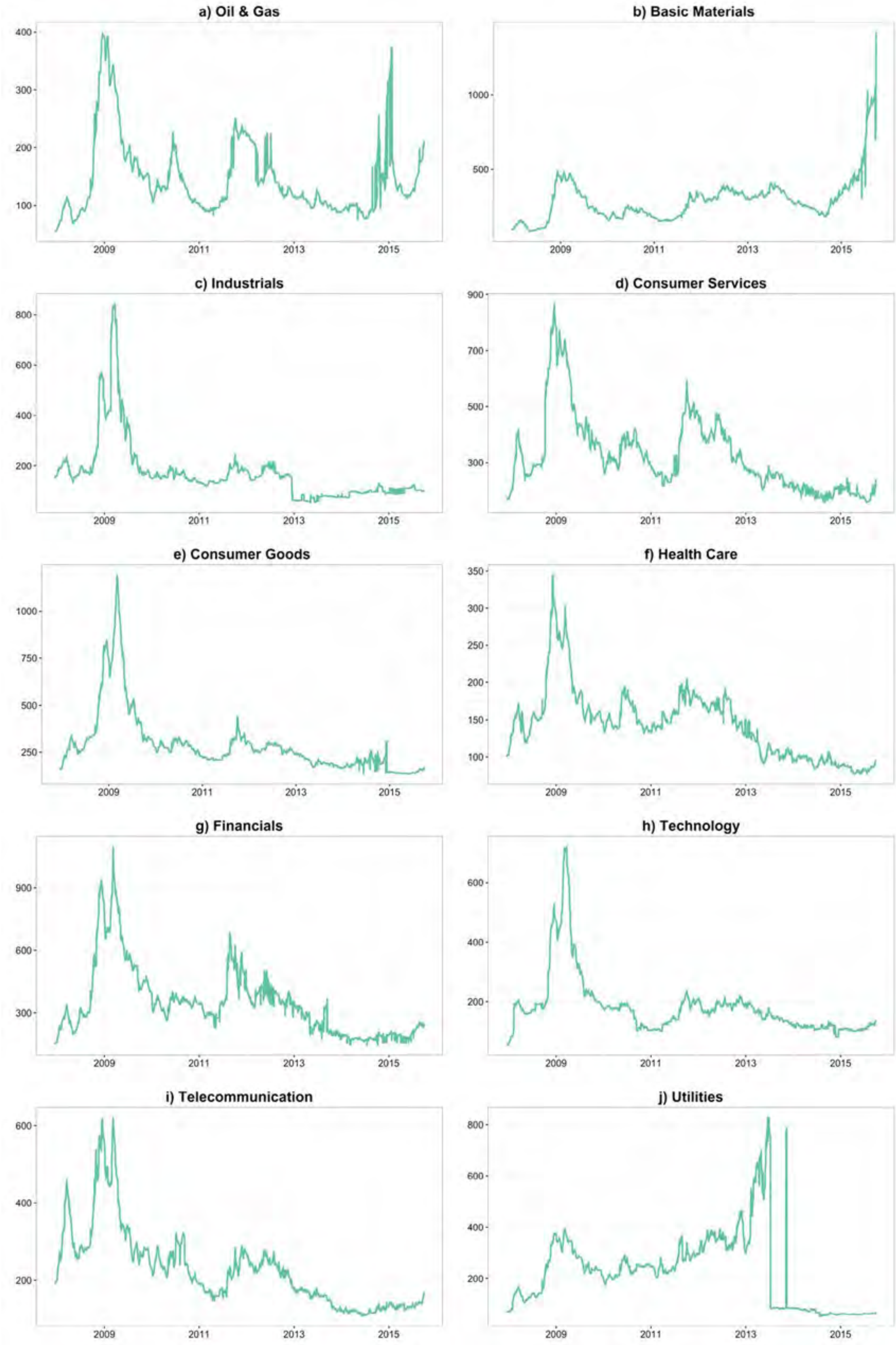

Fig. 1. Time series plots of industry-level CDS indices (December 14, 2007 to September 30, 2015).

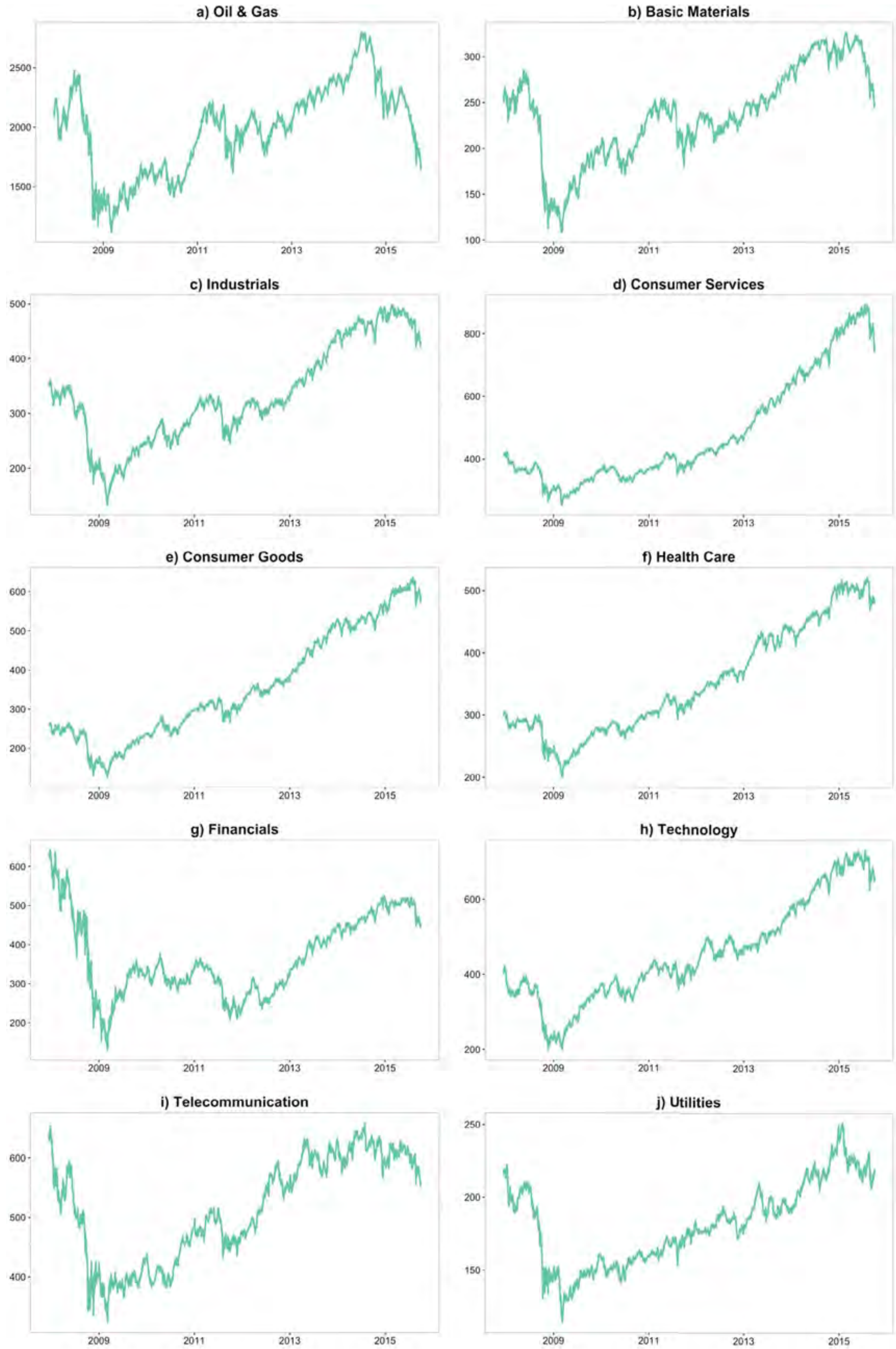

Fig. 2. Time series plots of industry-level stock market indices (December 14, 2007 to September 30, 2015).

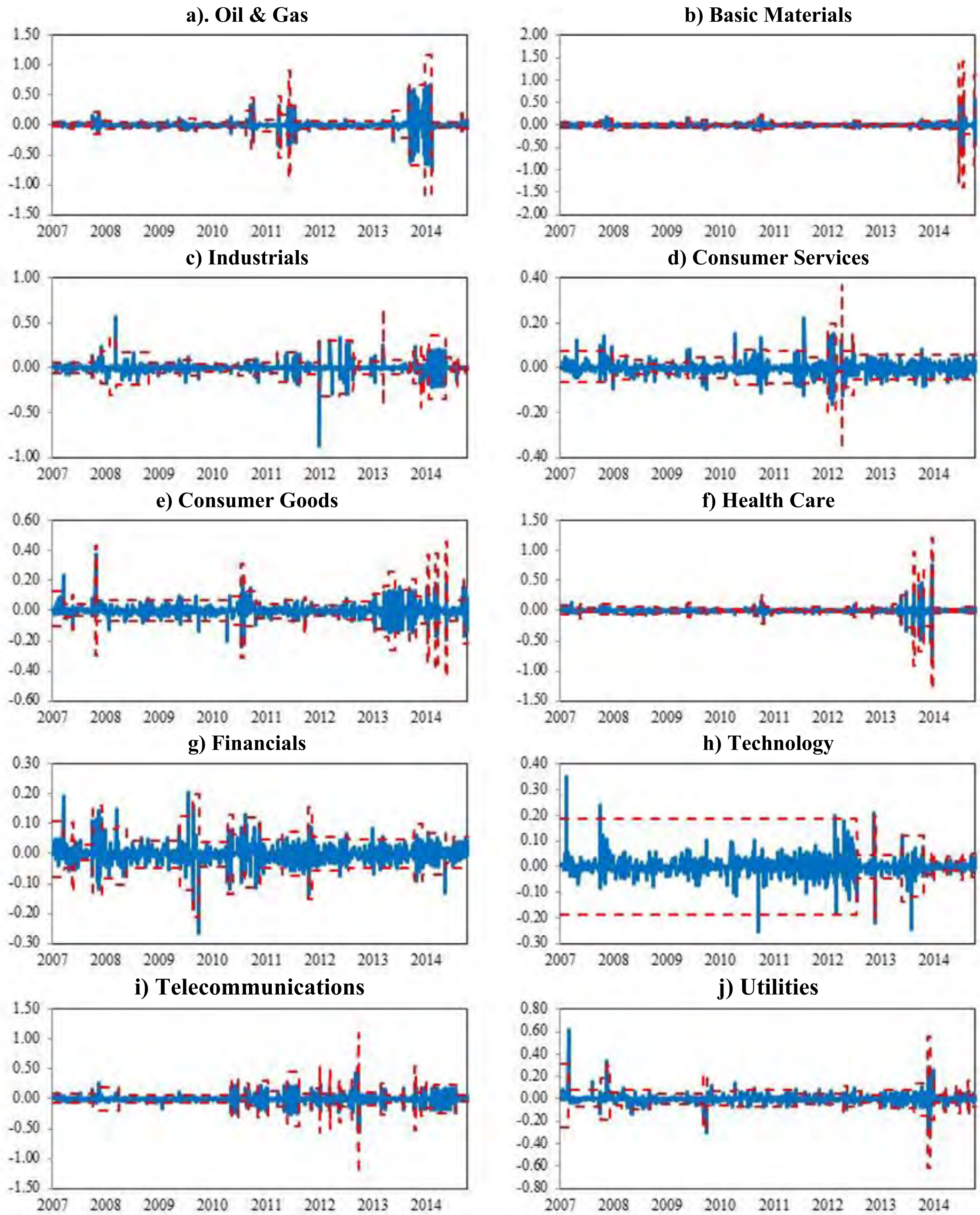

Fig. 3. Time-variations of the daily CDS returns behavior for the U.S. industries (December 14, 2007 to September 30, 2015). **Note:** The dotted red lines define the ± 3 standard deviation bands around the structural break points estimated by the modified ICSS algorithm of Sansó et al. (2004).

results show that CDSs do not Granger cause their stock counterparts except the Financial industry. In contrast, the stock market returns Granger cause their respective industry's CDS returns with the exception of Basic Materials sector.

To further explain the choice of the nonparametric methods, we test the presence of nonlinearity in the CDS-stock relationship using the BDS (Brock, Dechert, Scheinkman and Le Baron, 1996) test. The results are reported in Table 3 and show strong evidence of nonlinearity for both the U.S. CDS and stock returns equations for different embedding dimensions (m) of

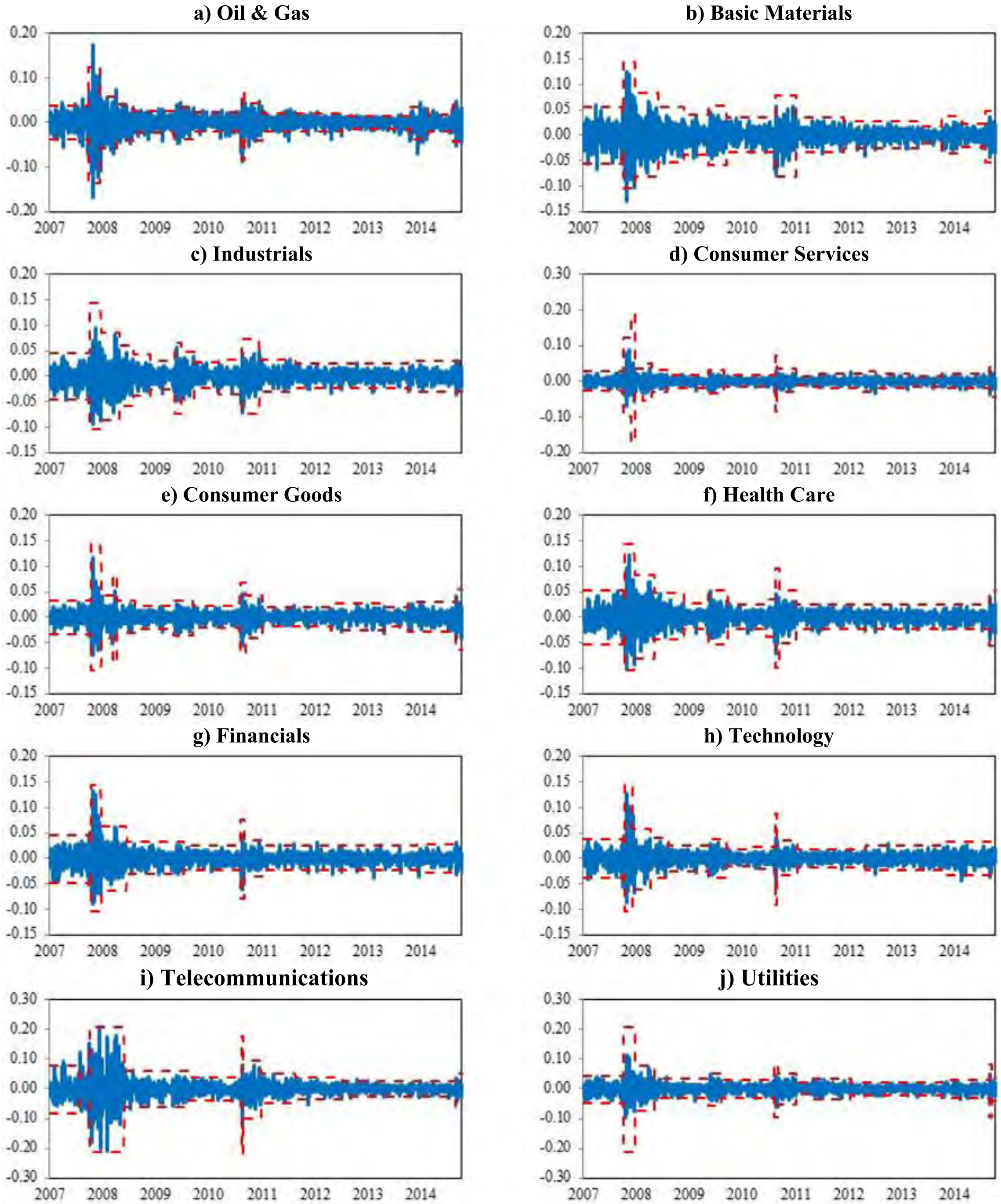

Fig. 4. Time-variations of the daily stock return behavior for the U.S. industries (December 14, 2007 to September 30, 2015). **Note:** see the notes of Fig. 3.

the BDS test. As motivated by the results of the BDS test, it is legitimate to use both the quantile-on-quantile and nonparametric causality-in-quantiles tests.

5.2. The estimates of Quantile-on-quantile regression

This subsection presents the empirical results of the QQ analysis between the industry-level CDS and stock market returns. Fig. 5 shows the estimates of the slope coefficient $\beta_1(\theta, \tau)$, which captures the effect of the τth quantile of stock market on the θth quantile of CDS returns, at different values of θ and τ for the ten U.S industries.

Table 1
Descriptive statistics for the CDS and stock returns.

	Panel A: CDS returns									
Mean	0.0667	0.131	−0.0198	0.0172	0.004	−0.0035	0.025	0.0447	−0.006	−0.0008
S.D.	7.4331	3.7791	4.8066	3.3969	4.2671	2.1501	5.6773	3.1641	2.4451	8.7687
Min	−74.1157	−64.9616	−86.7568	−23.9735	−75.5531	−16.0307	−55.7587	−33.3078	−26.3971	−221.5297
Max	69.1874	59.5101	56.6654	37.8654	76.0454	22.2962	52.4318	61.3798	20.4167	220.6571
Skewness	0.0214	1.3388	−1.6866	0.7458	−0.8063	0.9034	−0.0759	3.4461	0.0797	−7.1058
Kurtosis	49.6059	158.2428	72.4968	19.0996	143.4768	19.8023	17.8715	99.4556	17.887	565.9864
JB	208881.46***	2126029.01***	447087.05***	31160.46***	1747499.44***	33568.99***	27119.20***	843615.52***	27166.40***	27206396.23***
Q(1)	220.8588***	14.1066***	42.3256***	30.0932***	8.3405***	6.7897***	167.9170***	23.1604***	0.0822	0.005
Q(5)	239.4132***	45.9343***	81.2967***	33.2170***	139.0559***	17.2369***	200.0524***	55.8704***	20.3911***	197.2976***
ARCH(1)	362.8820***	106.3469***	2.1664	67.9980***	4.8970**	88.5030***	36.4235***	18.6358***	0.5629	0.0039
ARCH(5)	544.0136***	148.9868***	39.9934***	89.1464***	342.4413***	133.8898***	392.7473***	19.8632***	20.3409***	246.0321***
	Panel B: Stock returns									
Mean	−0.0112	−0.0016	0.0095	0.0301	0.0399	0.0233	−0.0168	0.0235	−0.0069	0.0003
S.D.	1.8476	1.7635	1.5206	1.1588	1.529	0.9468	2.6858	1.4594	1.3763	1.2277
Min	−16.5922	−12.9339	−9.215	−7.4152	−10.0992	−6.6485	−20.7984	−9.6701	−8.8011	−8.5299
Max	17.3266	12.473	9.5164	11.7131	12.3131	8.8353	20.8869	11.461	13.2607	12.684
Skewness	−0.4195	−0.401	−0.3863	−0.0739	−0.0864	0.0446	−0.0346	−0.0345	0.338	0.424
Kurtosis	13.3971	7.1591	5.4554	10.3326	7.4939	10.9557	13.0182	7.0079	12.8511	13.5897
JB	15299.98***	4408.27***	2579.39***	9068.60***	4772.69***	10193.44***	14390.94***	4172.19***	14062.49***	15742.65***
Q(1)	18.1889***	3.6209*	5.2769**	9.0989***	2.0613	22.7705***	25.1885***	13.2878***	2.8238*	30.2671***
Q(5)	38.1940***	10.0892*	7.4003	34.6421***	8.2002	45.0241***	50.6836***	15.8737***	29.0423***	41.5157***
ARCH(1)	136.8828***	94.6697***	78.8648***	93.3356***	74.7667***	96.3033***	148.2967***	102.1644***	47.6379***	104.7860***
ARCH(5)	584.9667***	513.8295***	391.1000***	522.0310***	452.0541***	483.1202***	360.2951***	348.7803***	521.5321***	507.4868***

Notes: This table reports the descriptive statistics for the Oil & Gas (OG), Basic Materials (MAT), Industrials (INDT), Consumer Services (SVS), Consumer Goods (CSMG), Health Care (HC), Financials (FIN), Technology (TECH), Telecommunication (TCOM), and Utilities (UTL) sectors. Panel A reports the descriptive statistics for the Credit Default Swap (CDS) returns while Panel B reports the descriptive statistics for the stock returns. The sample period covers 12/17/2007–9/23/2015 at the daily frequency, totaling 2033 observations for each series. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [$Q(1)$] and the fifth [$Q(5)$] autocorrelation tests, and the first [ARCH(1)] and the fifth-order [ARCH (5)] of the Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH).

*** The asterisks represent significance at the 1% levels.

** The asterisks represent significance at the 5% levels.

* The asterisks represent significance at the 10% levels.

Table 2
Linear Granger causality tests.

	H_0: CDS dos not Granger cause stock returns	H_0: Stock returns dos not Granger cause CDS
Oil & Gas	0.0624	18.5208***
Basic Materials	0.0956	0.2482
Industrials	0.0005	4.1986**
Consumer Services	0.0251	3.8297*
Consumer Goods	0.3266	4.0906**
Health Care	0.0005	9.2164***
Financials	5.6089**	5.7750**
Technology	1.2071	6.2923**
Telecommunication	0.3136	5.0705**
Utilities	0.0005	5.2628**

Notes: This table reports the *F*-statistic for the no Granger causality restrictions imposed on a linear vector autoregressive (VAR) model under the null hypotheses H_0. The sample period ranges from December 14, 2007 to September 30, 2015.
*** The asterisks indicate a rejection of the null of no Granger causality at the 1% levels of significance.
** The asterisks indicate a rejection of the null of no Granger causality at the 5% levels of significance.
* The asterisks indicate a rejection of the null of no Granger causality at the 10% levels of significance.

Table 3
[Brock et al. (1996)] BDS test for nonlinearity.

	$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$
	Panel A: CDS equation residuals				
Oil & Gas	20.8135***	23.8842***	25.1621***	25.9440***	26.5585***
Basic Materials	16.0120***	17.6897***	18.0469***	18.9945***	19.6144***
Industrials	13.7272***	16.3541***	18.2154***	19.6198***	21.2631***
Consumer Services	9.8595***	11.7736***	13.1195***	15.1144***	17.0566***
Consumer Goods	20.4962***	24.5861***	28.4856***	32.8902***	37.9852***
Health Care	12.7891***	14.8607***	17.0677***	18.9169***	21.1814***
Financials	16.5365***	19.8415***	21.2816***	22.9077***	25.1206***
Technology	12.5882***	14.5579***	16.3711***	17.7860***	19.2888***
Telecommunication	14.5003***	17.3775***	20.4956***	24.3606***	29.2654***
Utilities	16.9762***	18.3762***	19.2964***	19.9950***	20.5967***
	Panel B: Stock returns equation residuals				
Oil & Gas	7.2079***	10.5534***	13.4834***	16.7002***	19.7063***
Basic Materials	5.0236***	7.1690***	9.4236***	12.0532***	15.0308***
Industrials	3.4158***	5.8634***	9.0657***	12.0290***	14.8595***
Consumer Services	7.5126***	10.6117***	12.5844***	15.2861***	19.2572***
Consumer Goods	5.3054***	8.4987***	11.9829***	15.8294***	20.2988***
Health Care	7.2823***	11.0971***	13.7033***	16.4729***	19.9321***
Financials	12.0964***	17.2856***	21.5523***	25.9410***	31.0585***
Technology	4.9268***	7.3552***	9.7358***	12.2040***	14.7492***
Telecommunication	6.6271***	9.2834***	11.4315***	13.4737***	15.9143***
Utilities	8.2348***	10.7278***	13.4571***	15.9104***	18.7011***

Notes: This table reports the results of nonlinearity test over the period December 14, 2007 to September 30, 2015. The null hypothesis is linearity and the alternative is nonlinearity. The entries indicate the BDS test based on the residuals of the CDS returns and stock returns in a VAR for various sectors. *m* denotes the embedding dimension of the BDS test.
*** The asterisk indicates a rejection of the null of residuals being *iid* at 1% level of significance.

These graphs (Fig. 5) provide several interesting results. First, the relationship between the stock market returns and CDS returns is primarily negative across the quantiles of both variables for all industries. An increase in the stock price of a firm generally brings about an improvement in business and financial conditions of the underlying firm, which lowers the probability that the firm will default on its debt, and consequently leads to a decline in the firm's CDS spread. Second, the connection between the CDS and stock markets is consistent with the outcome of the structural model of credit risk of Merton (1974). In fact, in the Merton model, equity and debt are viewed as contingent claims on the firm's asset value and both debt and equity prices are determined by the firm's fundamental data such as the value of its assets, asset volatility and leverage ratio, etc. A key implication of the Merton model is that changes in stock prices and in credit spreads must be negatively and closely related to ensure the absence of arbitrage opportunities, suggesting an inverse relationship between equity prices and CDS spreads.

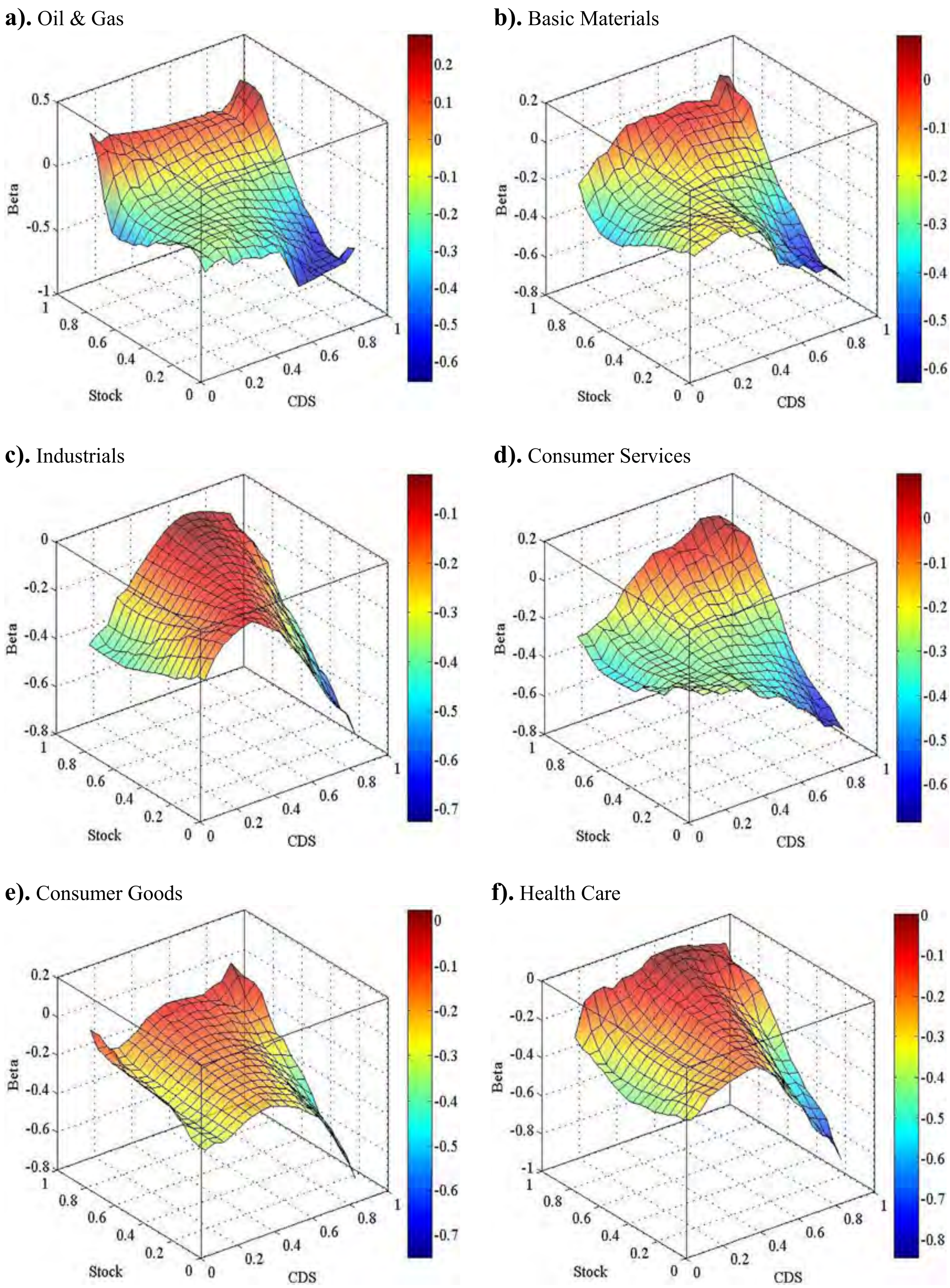

Fig. 5. Quantile-on-Quantile (QQ) estimates of the slope coefficient, $\widehat{\beta}_1(\theta, \tau)$. **Note:** The graphs depict the estimates of the slope coefficient, $\beta_1(\theta, \tau)$, which is placed on the *z*-axis against the quantiles of the CDS returns (θ) on the *x*-axis and the quantiles of stock market returns (τ) on the *y*-axis. The sample period ranges from December 14, 2007 to September 30, 2015. The colors in the colors bar measure the degree of the association or the comovement between the two assets. The red color corresponds to a positive and growing value of slope coefficient while the blue color corresponds to the negative slope coefficients.

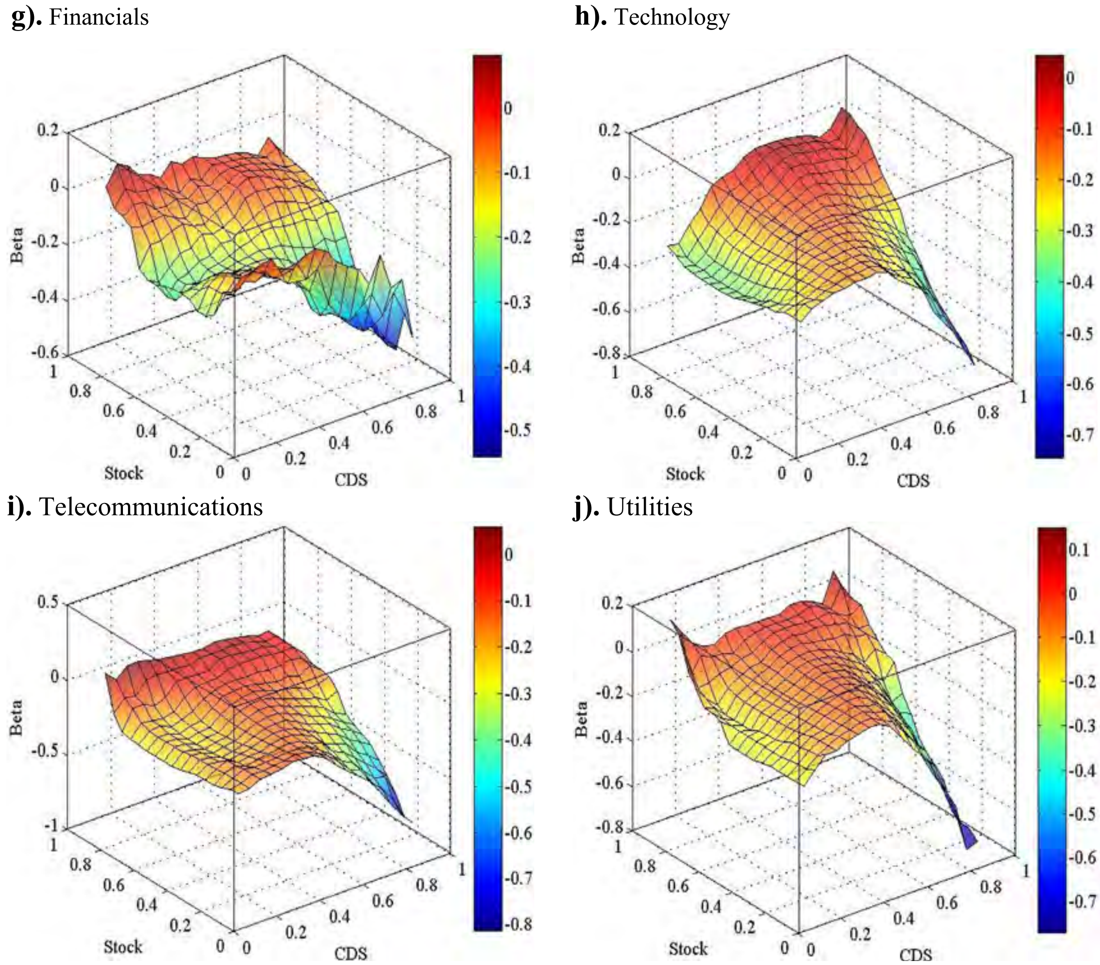

Fig. 5 (*continued*)

Third, despite the existing negative association, there is a considerable heterogeneity across industries in terms of the CDS-stock nexus.[7] This result is probably due to the business nature of these industries i.e., cyclical or non-cyclical nature. Fourth, within each industry, a marked variation in the slope coefficient is observed across the different quantiles of the CDS and stock market returns. This suggests that the link between the two markets is not uniform (but asymmetric) across the quantiles and that this link depends on both the sign and size of the stock market shocks i.e., whether there are bullish, normal or bearish conditions in the CDS and/or stock markets.

In the middle quantile (0.4–0.6), there are fewer variations in the negative impact of stock markets on CDS markets for most of the industries. A striking finding of the QQ approach is that sensitivity of the CDS returns to the stock markets shocks is higher in the extreme quantiles. The reactions of the CDS markets to their respective stock counterparts are higher for the bullish (the stock market quantiles from 0.7 to 0.90) and lower for bearish (the stock market quantiles from 0.10 to 0.30) stock market conditions. This finding is only possible through using the QQ approach and also has some investment implications for the arbitragers, hedgers and speculators. There are three implications in this regard. (i) The Merton model implies that credit and stock markets must co-move to prevent arbitrage opportunities. We posit that the stronger association during improved market conditions may decrease the arbitrage opportunities but these opportunities may exit during normal market conditions. Moreover, they may further increase during crisis periods where we associate the lower stock market quantiles with the bad or crisis situations in the markets. (ii) The portfolio weights of the hedged portfolios or the speculative bets may be adjusted during the changing market conditions.

The QQ approach decomposes the estimates of a standard quantile regression where regression regresses the θth quantile of the stock market returns on the CDS return and vice versa. However, the QQ approach regresses the θth quantile of the

[7] We are thankful to the referee for highlighting that our estimates may be sensitive to different market states i.e. global financial crisis and tranquil periods thereafter as our sample starts during the crisis period. The results of GFC sub-sample estimations, not reported here for brevity and available from the authors on request, confirm that our methods are not sensitive to the market conditions.

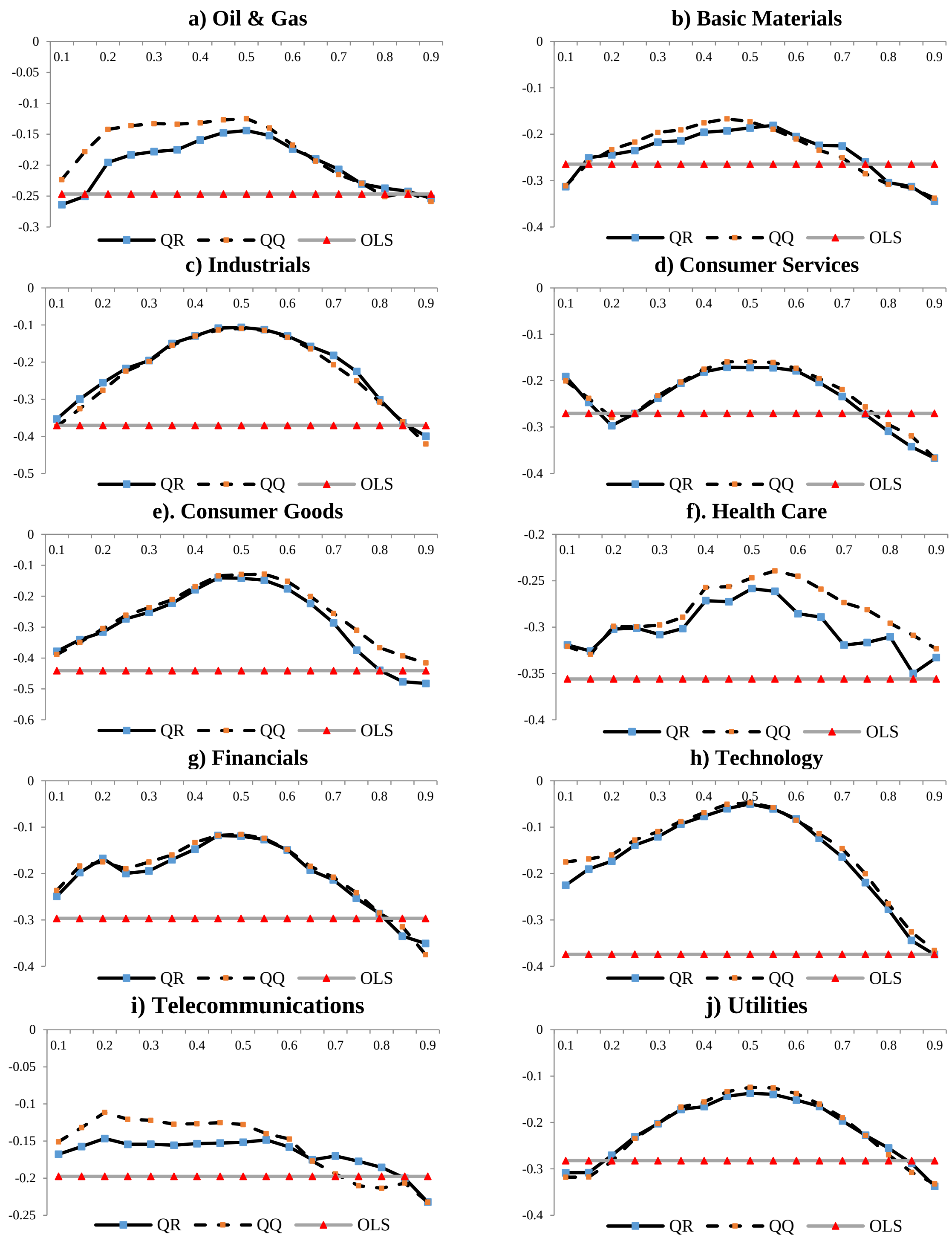

Fig. 6. Comparison of OLS, quantile regression and average QQ estimates. **Note:** The graphs display the estimates of the OLS parameter (the continuous grey- red dotted- line), the standard quantile regression parameters, denoted by QR (the continuous black curved line), and the averaged QQ parameters, denoted by QQ (the dashed black curved line), at the different quantiles of the CDS returns for all the industries examined. The sample period ranges from December 14, 2007 to September 30, 2015.

stock markets returns on the τth quantile of the CDS returns and, therefore, its parameters will be indexed by both θ and τ. Given this inherent property of decomposition, it is possible to use the QQ estimates to recover the estimates of a standard quantile regression. Specifically, the quantile regression parameters, which are only indexed by θ, can be generated by averaging the QQ parameters along τ. For instance, the slope coefficient of the quantile regression model, which measures the effect of stock market returns on the distribution of CDS returns, denoted by $\gamma_1(\theta)$, can be obtained as follows:

$$\gamma_1(\theta) \equiv \overline{\widehat{\beta}_1}(\theta) = \frac{1}{S}\sum_{\tau}\widehat{\beta}_1(\theta,\tau) \tag{16}$$

where S = 17 is the number of considered quantiles $\tau = [0.10, 0.15, \ldots, 0.90]$.

In this context, a simple way of checking the validity of the QQ approach is to compare the estimated quantile regression parameters with the τ-averaged estimated QQ parameters. Fig. 6 plots the OLS, quantile regression and the averaged QQ estimates of the slope coefficient that measures the impact of the stock returns on the CDS returns for all the industries under study. As shown in this figure, the averaged QQ estimates of the slope coefficient are very similar to the quantile regression estimates regardless of the quantile considered for the different industries. This graphical evidence provides a simple validation of the QQ methodology by showing that the main features of the quantile regression model can be recovered by summarizing the more detailed information contained in the QQ estimates. Furthermore, Fig. 6 largely confirms the results of the QQ analysis reported earlier and also shows that the OLS only provides an approximation of the relationship between the two markets.

However, for robustness purposes, we formally test the heterogeneity of the estimated quantile regression coefficients across the entire range of the quantiles using the Khmaladze test adapted to the quantile regression methodology by Koenker and Xiao (2002). This test is based on the idea that the covariates exert a pure location shift effect on the distribution of the dependent variable. The results of the Khmaladze test reported in Table 4 reject the null hypothesis of equal coefficient estimates at the usual significance levels regardless of the industry. This significant heterogeneity across quantiles means that the quantile regression approach provides a better framework than the OLS to examine the relationship between industry-level CDS-stock links.

5.3. Causality-in-quantile approach

The results of the nonparametric causality-in-mean and -in-variance using both first (the returns) and second (the variance) order moments respectively from the stock to CDS markets are shown in Fig. 7. The null hypothesis of no Granger causality-in-mean from stock to CDS markets is rejected at the usual levels of significance over the entire conditional distribution of the CDS returns, suggesting a predictability for the stock markets. More precisely, for the causality-in-mean, there is evidence of a causality from the stock to CDS only for the Financial, Consumer Services and Oil & Gas sectors. The Financial sector stock returns Granger cause its respective CDS market in the average and upper quantiles (from 0.35 to 0.95). As for the Consumer Services sector, the causal flow is evident only for the middle quantile i.e., 0.5. The causality from the stock to CDS returns is also evident for the Oil & Gas sector as the t-statistics are marginally higher than the critical values. This result reveals that past stock returns affect the CDS returns for different market conditions (across all quantiles). There is no significant Granger causality for the remaining sectors. Turning to the nonparametric Granger causality in the second moment, the results of the Granger causality-in-variance exhibit a hump-shaped pattern for all cases. These results also suggest that the predictability of industry-level CDSs returns volatility from their respective stock markets is minimal in the tails. This is relevant for speculators such as money managers and hedge funds who are disposed to operate during extreme market conditions.

Table 4
The Khmaladze test of equality of coefficient estimates across the entire range of quantiles.

Sector	Test statistics
Oil & Gas	8.5106***
Basic Materials	9.8047***
Industrials	10.598***
Consumer Goods	5.6888***
HealthCare	7.9058***
Consumer Services	1.9030*
Telecom	6.2149***
Utilities	29.106***
Financials	1.9569*
Technology	4.6594***

Notes: This table contains the statistics of the Khmaladze test introduced by Koenker and Xiao (2002) applied to the quantile regression coefficient estimates from December 14, 2007 to September 30, 2015. The Khmaladze test is a joint test assuming that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across all quantiles. A rejection of this null favors the quantile regression model.

* As usual, denote the statistical significance at the 10% levels.

*** As usual, denote the statistical significance at the 1% levels.

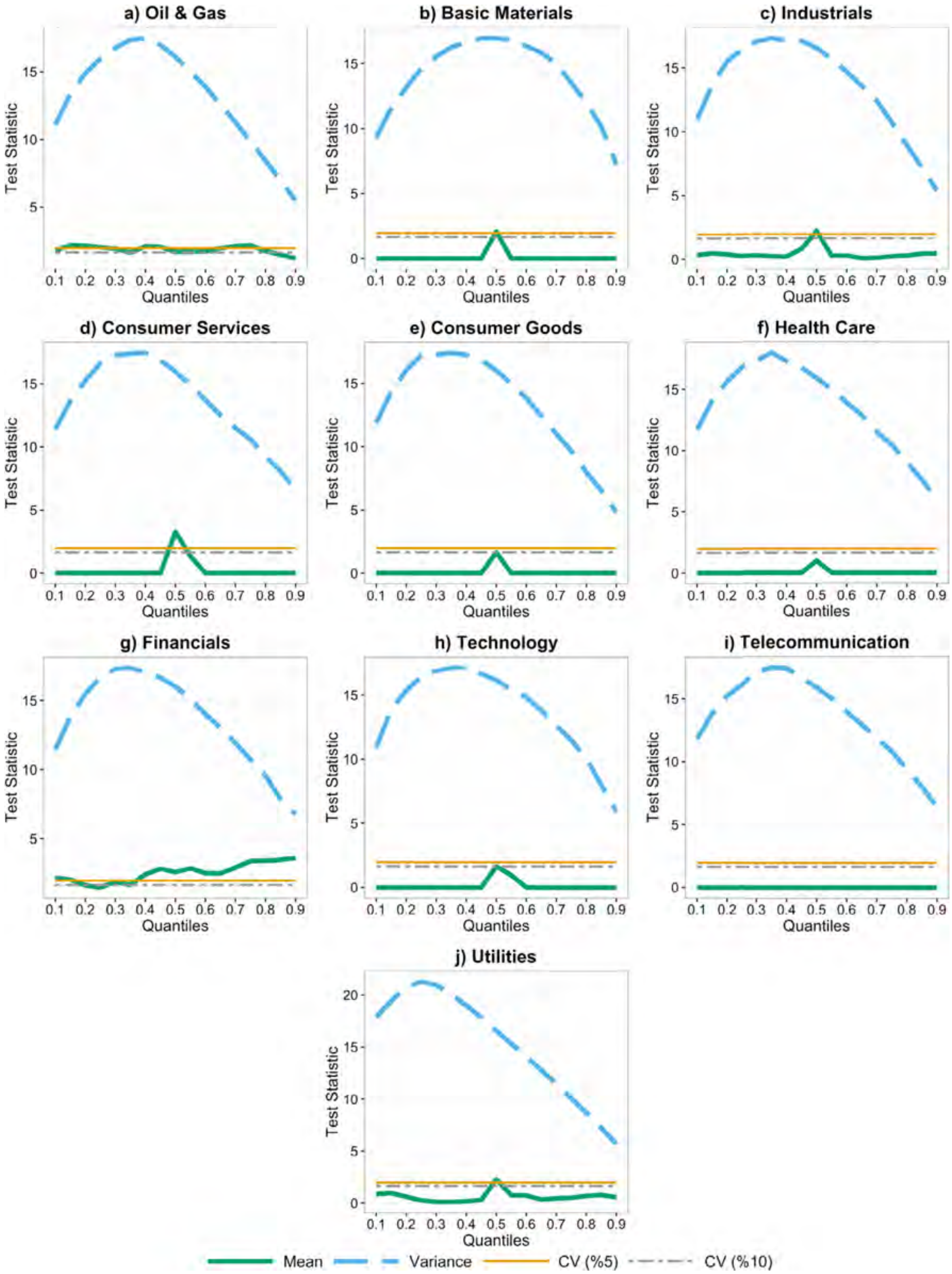

Fig. 7. Non-parametric causality in mean and variance from the stock markets to the CDSs at various quantiles. **Note**: The figure plots the estimates of the nonparametric causality tests of the various quantiles from December 14, 2007 to September 30, 2015. The horizontal thin solid and the thin two-dashed lines represent the 5% and 10% critical values (CV), respectively.

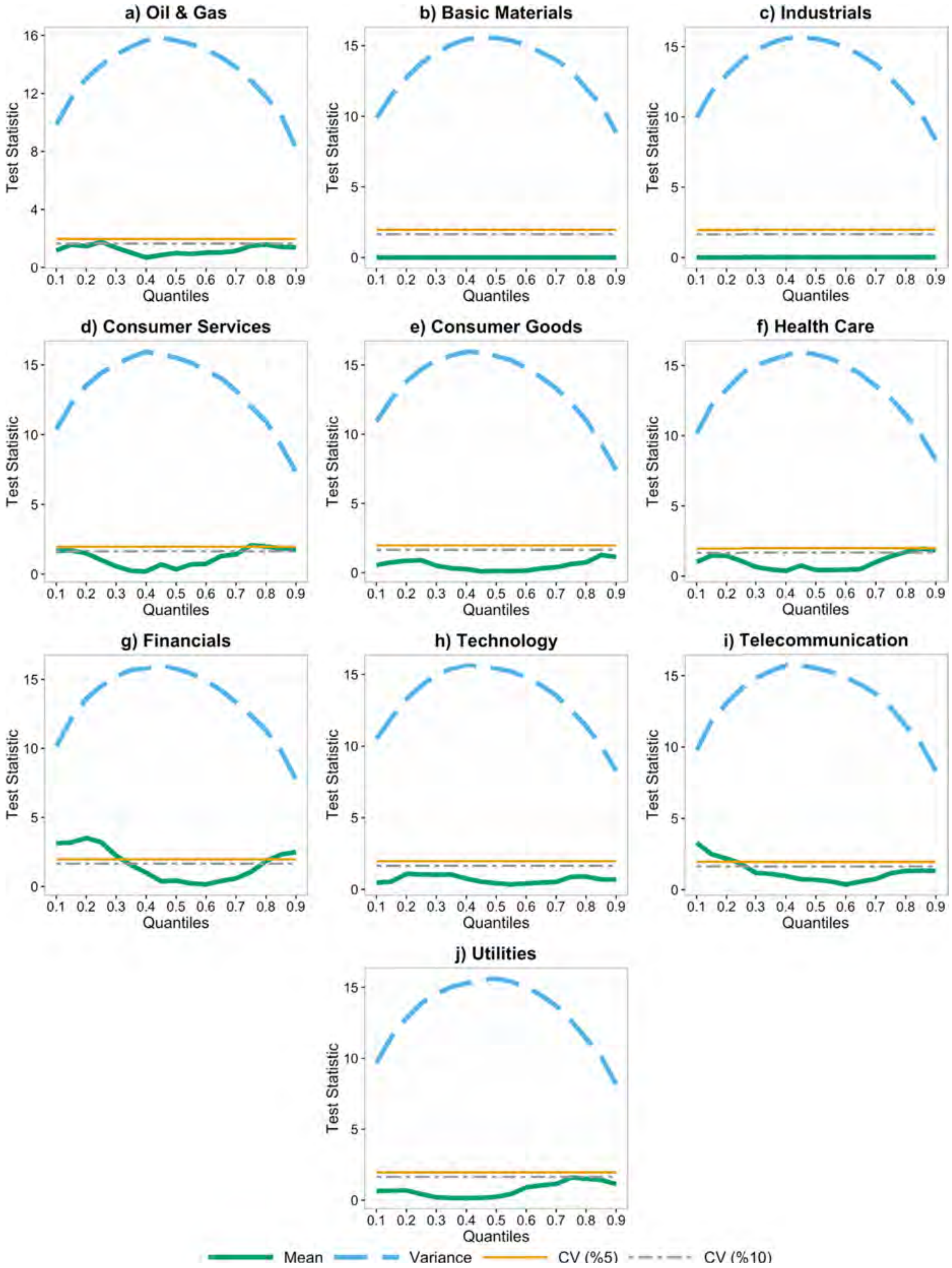

Fig. 8. Non-parametric causality in mean and variance from the CDSs to stock markets at various quantiles. **Note**: This figure plots the estimates of the nonparametric causality tests at the various quantilesv from December 14, 2007 to September 30, 2015. The horizontal thin solid and the thin two-dashed lines represent the 5% and 10% critical values (CV), respectively.

By looking at the trajectories for the causality-in-quantiles from the CDS to stock markets (Fig. 8), one can observe that the CDS markets Granger-cause their equity counterparts for the Financial and Telecommunication sectors which is evident in the extreme lower quantiles. This result reveals that these two CDS sectors are helpful determinants in explaining the return behavior of the corresponding stock sectors, which comes in contrast to the result of the traditional approach that consistently asserts a causality running from stock markets to CDS markets. For the other sectors, there is no Granger causality in the mean from the CDS to stock markets.

The causality-in-variance is evident for all industries. However, we observe a hump-shaped pattern for all the pairs. The causality is asymmetric, indicating that portfolio managers (particularly hedge funds, market makers and money managers) should adjust their portfolios during bearish and bullish markets. The volatility spillover from the credit to stock markets reveals an integration of these markets.

6. Conclusions

The CDS-stock market nexus has attracted a great deal of attention following the GFC and ESDC as this connection between these markets reflects almost all financial and economic activities. Note that the notional value of the global CDS market grew from $6 trillion in 2004 to $24 trillion in 2013--and peaked at a level of $58 trillion just prior to the financial crisis (Bank for International Settlements).[8] Nonetheless, the CDS spreads of the major US and European banks evidently increased after July 2007 when the S&P issued a credit watch alert for mortgage-backed securities (Ballester et al., 2016; Yu, 2017). The collapse of the Lehman Brothers on September 15, 2008, has also drawn the attention of all global financial markets, and the sovereign credit risk in particular has become a serious concern for many countries.

This paper examines the extreme the connection between the U.S. CDS and stock sectoral markets over the daily period 2007–2014. For a deeper analysis, we focus on the connection at the sectoral level in order to provide useful information for portfolio managers and policy makers, using the quantile distributions to serve the interests of all market participants including speculators (money managers, hedge funds, market makers, etc.) and long term investors (institutional investors such as pension funds, banks, etc.) who may be disposed to work under different markets conditions.

Methodologically, we use two novel nonparametric approaches, namely the Quantile on quantile approach and the causality in quantile method. To our knowledge, those methods particularly the second one has not been applied to U.S. CDSs for the ten sectors. This methodology fits the study's objective to capture all types of market participants.

Using the QQ approach, the results underscore the presence of a negative and asymmetric dependence between the stock market and CDS returns across quantiles for all industries. The sensitivity of the CDS returns to the stock markets shocks is higher in the extreme quantiles which fits the behavior of speculators as explained earlier. The reactions of the CDS markets to their respective stock counterparts are higher for the bullish market and lower for the bearish stock market conditions. Overall, market participants should seek information in both markets for all industries when they are about to engage in trading and/or (cross) hedging, and more so during extreme conditions in the stock markets.

By using the nonparametric causality-in-quantile tests, we find evidence of a causality-in-mean from the stock to CDS markets only for the Financial (in the average and upper quantiles), and for the Consumer Services and Oil & Gas sectors only in the middle quantile i.e., 0.5. In addition, the causality-in-mean is only found for the Financial and Telecommunication sectors which is evident in the extreme lower quantiles. Finally, we find a bidirectional Granger causality in variance for all the CDS-equity sector pairs. This causality-in-variance is stronger in the lower quantiles (the downturns or bear markets) than in the higher quantiles (the upturns or bull markets). These results reveal a contagion effect which has important implications for portfolio managers and institutional investors. They come in a sharp contrast to the traditional literature on stocks and CDSs which uses standard techniques and for the most part looks at averages or two regimes at best and find a unidirectional causality from stocks to CDSs. The quantile approach considers multiple regimes

The time-varying comovements and causality during different market and credit episodes imply a temporary adjustment due to risk transfer. The CDSs play a significant role in distributing risk in the global financial system. Policymakers should handle the dynamic information flow between the stock and CDS markets by weighing the costs and benefits of potential effects on the sovereign credit risk. They should monitor both markets more closely particularly during crisis periods and pay more attention to trading and/or hedging during those periods. As one of the major participants in the CDS markets, the financial institutions use these CDS contracts to hedge and diversify their exposure to illiquid bonds and/or loans/receivables which improve the U.S. financial stability.

References

Acharya, V.V., Johnson, T.C., 2007. Insider trading in credit derivatives. J. Financ. Econ. 84 (1), 110–141.
Avino, D., Lazar, E., Varotto, S., 2013. Price discovery of credit spreads in tranquil and crisis periods. Int. Rev. Financ. Anal. 30, 242–253.
Balcilar, M., Bekiros, S., Gupta, R., 2016. The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empir. Econ. 49, 1–11.
Ballester, L., Casu, B., González-Urteaga, A., 2016. Bank fragility and contagion: Evidence from the bank CDS market. J. Empir. Finance 38, 394–416.
BIS, 2015. Statistical release OTC derivatives statistics at end. June 2015.

[8] https://www.federalreserve.gov/econresdata/notes/feds-notes/2014/risk-transfer-across-economic-sectors-using-credit-default-swaps-20140903.html.

Blanco, R., Brennan, S., Marsh, I.W., 2005. An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. J. Finance 60 (5), 2255–2281.
Broock, W.A., Scheinkman, J.A., Dechert, W.D., Le Baron, B., 1996. A test for independence based on the correlation dimension. Economet. Rev. 15 (3), 197–235.
Byström, H., 2006. Credit default swaps and equity prices: The iTraxx CDS index market. Financ. Anal. J. 62, 65–76.
Castellano, R., Scaccia, L., 2014. Can CDS indexes signal future turmoils in the stock market? A Markov switching perspective. CEJOR 22 (2), 285–305.
Chan, K.C., Fung, H.G., Zhang, G., 2009. On the relationship between Asian sovereign credit default swap markets and equity markets. J. Asia Bus. Stud. 4 (1), 3–12.
Chan-Lau, J.A., Kim, Y.S., 2004. Equity prices, credit default swaps, and bond spreads in emerging markets. IMF Working Paper 04-27.
Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001. The determinants of credit spread changes. J. Finance 56 (6), 2177–2207.
Coronado, M., Corzo, M.T., Lazcano, L., 2012. A case for Europe: the relationship between Sovereign CDS and stock indexes. Front. Finance Econ. 9 (2), 32–63.
Corzo, M.T., Gómez, J., Lazcano, L., 2014. Financial crises and the transfer of risk between the private and public sectors: Evidence from European financial markets. Spanish Rev. Financ. Econ. 12 (1), 1–14.
Da Fonseca, J., Wang, P., 2016. A joint analysis of market indexes in credit default swap, volatility and stock markets. Appl. Econ. 48 (19), 1767–1784.
Da Silva, P.P., Rebelo, P.T. & Afonso, C., (2014). Tail dependence of financial stocks and CDS markets–Evidence using copula methods and simulation-based inference. Economics: The Open-Acess, Open-Assessment E-Journal, 8(2014-39), 1-27.**
Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74 (366a), 427–431.
Dufour, A., Stancu, A., Varotto, S., 2017. The equity-like behaviour of sovereign bonds. J. Int. Financ. Markets, Inst. Money 48, 25–46.
Fei, F., Fuertes, A.M., Kalotychou, E., 2013. Modeling dependence in CDS and equity markets: dynamic copula with Markov-switching. Cass Business School Working Paper, City University London.
Fenech, J.P., Vosgha, H., Shafik, S., 2014. Modelling the dependence structures of Australian iTraxx CDS index. Appl. Econ. 46 (4), 420–431.
Forte, S., Lovreta, L., 2015. Time-varying credit risk discovery in the stock and CDS markets: Evidence from quiet and crisis times. Eur. Financ. Manage. 21 (3), 430–461.
Forte, S., Peña, J.I., 2009. Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. J. Bank. Finance 33 (11), 2013–2025.
Fung, H.G., Sierra, G.E., Yau, J., Zhang, G., 2008. Are the US stock market and credit default swap market related? Evidence from the CDX indices. J. Altern. Invest. 11 (1), 43–61.
Galindo, A., Izquierdo, A., Rojas-Suarez, L., 2014. Financial integration and foreign banks in Latin America: how do they impact the transmission of external financial shocks? Glob. Bank. Financ. Markets Crises, Int. Finance Rev. 14, 305–339.
Guo, F., Chen, C.R., Huang, Y.S., 2011. Markets contagion during financial crisis: a regime-switching approach. Int. Rev. Econ. Finance 20 (1), 95–109.
Hammoudeh, S., Sari, R., 2011. Financial CDS, stock market and interest rates: which drives which? N. Am. J. Econ. Finance 22 (3), 257–276.
Hammoudeh, S., Bhar, R., Liu, T., 2013. Relationships between Financial Sectors' CDS spreads and other gauges of risk: did the great recession change them? Financ. Rev. 48 (1), 151–178.
Jenkins, N.T., Kimbrough, M.D., Wang, J., 2016. The extent of informational efficiency in the credit default swap market: evidence from post-earnings announcement returns. Rev. Quant. Financ. Acc. 46 (4), 725–761.
Jeong, K., Härdle, W.K., Song, S., 2012. A consistent nonparametric test for causality in quantile. Economet. Theory 28 (04), 861–887.
Kapadia, N., Pu, X., 2012. Limited arbitrage between equity and credit markets. J. Financ. Econ. 105 (3), 542–564.
Kinateder, H., Hofstetter, B., Wagner, N., 2017. Do Liquidity Variables Improve Out-of-Sample Prediction of Sovereign Spreads during Crisis Periods? Finance Res. Lett. 21, 144–150.
Koenker, R., Xiao, Z., 2002. Inference on the quantile regression process. Econometrica 70 (4), 1583–1612.
Kwiatkowski, D., Phillips, P.C., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? J. Economet. 54 (1–3), 159–178.
Longstaff, F.A., Mithal, S., Neis, E., 2003. The credit-default swap market: is credit protection priced correctly? Working Paper, University of California at Los Angeles.
Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J. Finance 29 (2), 449–470.
Narayan, P.K., Sharma, S.S., Thuraisamy, K.S., 2014. An analysis of price discovery from panel data models of CDS and equity returns. J. Bank. Finance 41, 167–177.
Narayan, P.K., 2015. An analysis of sectoral equity and CDS spreads. J. Int. Financ. Markets, Inst. Money 34, 80–93.
Narayan, P., Thuraisamy, K., Wagner, N., 2017. How do bond, equity and commodity cycles interact? Finance Res. Lett. 21, 151–156.
Ngene, G.M., Hassan, M.K., Alam, N., 2014. Price discovery process in the emerging sovereign CDS and equity markets. Emerg. Markets Rev. 21, 117–132.
Nishiyama, Y., Hitomi, K., Kawasaki, Y., Jeong, K., 2011. A consistent nonparametric test for nonlinear causality—specification in time series regression. J. Economet. 165 (1), 112–127.
Norden, L., Weber, M., 2009. The co-movement of credit default swap, bond and stock markets: an empirical analysis. Eur. Financ. Manage. 15 (3), 529–562.
Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (2), 335–346.
Sansó, A., Arrago, V., Carrion, J.L., 2004. Testing for change in the unconditional variance of financial time series. Revistade Economia Financiera 4, 32–53.
Schweikhard, F.A., Tsesmelidakis, Z., 2012. The impact of government interventions on CDS and equity markets. University of Oxford Working Paper
Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. J. Bank. Finance 55, 1–8.
Subrahmanyam, M.G., Tang, D.Y., Wang, S.Q., 2014. Does the tail wag the dog? The effect of credit default swaps on credit risk. Rev. Financ. Stud. 27 (10), 2927–2960.
Trutwein, P., Schiereck, D., 2011. The fast and the furious–stock returns and CDS of financial institutions under stress. J. Int. Financ. Markets, Inst. Money 21 (2), 157–175.
Yu, S., 2017. Sovereign and bank Interdependencies—evidence from the CDS market. Res. Int. Bus. Finance 39, 68–84.