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Examining the efficiency and interdependence of US credit and stock markets through MF-DFA and MF-DXA approaches

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HIGHLIGHTS

- Relative efficiency of 11 industry-level US credit and stock markets is examined through MF-DFA.
- Mutual interdependence between CDS-stock market pairs is investigated using MF-DXA.
- Both credit and stock markets exhibit multifractal behavior.
- Industry-level credit markets are relatively more inefficient compared to their equity counterparts except the Banks and Financial sectors.
- Materials has the highest dependence with the other credit market industries.

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ABSTRACT

This study examines the power law properties of 11 US credit and stock markets at the industry level. We use multifractal detrended fluctuation analysis (MF-DFA) and multifractal detrended cross-correlation analysis (MF-DXA) to first investigate the relative efficiency of credit and stock markets and then evaluate the mutual interdependence between CDS-equity market pairs. The scaling exponents of the MF-DFA approach suggest that CDS markets are relatively more inefficient than their equity counterparts. However, Banks and Financial credit markets are relatively more efficient. Basic Materials (both CDS and equity indices) is the most inefficient sector of the US economy. The cross-correlation exponents obtained through MF-DXA also suggest that the relationship of the CDS and equity sectors within and across markets is multifractal for all pairs. Within the CDS market, Basic Materials is the most dependent sector, whereas equity market sectors can be divided into two distinct groups based on interdependence. The pair-wise dependence between Basic Materials sector CDSs and the equity index is also the highest. The degree of cross-correlation shows that the sectoral pairs of CDS

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and equity markets belong to a persistent cross-correlated series within selected time intervals.

1. Introduction

The analysis of time series dependence is a key research area in finance, economics and physics. Time series dependence in the financial markets, whether temporal or sectional, may lead to the prediction of a time series and the possibility of violating the efficient markets assumption. The efficient markets hypothesis (EMH) is of great importance in financial literature for understanding and promoting the quality of financial markets. A market is qualified weak-form efficient if all available and relevant information (historical price information) is immediately and fully reflected in the asset prices [1]. Thus, the validity of the EMH implies that market price forecasts are impossible to make because there are no accurate patterns to asset prices and that no investor can take advantage of the available information to make abnormal profits through arbitrage. However, in financial literature, studying the EMH remains the key to identifying possible gains.

The lack of consensus on the theoretical background and the inconsistency of the empirical evidence constitute additional reasons to study financial market dynamics.[1] Recent literature supports the stock market efficiency premise (see [8–18]; among others), while other studies reject the EMH (see [19–24]; among others).

Despite many studies that research the efficiency of the stock markets, there has been less focus on the credit default swap (CDS, hereafter)[2] market, which has experienced phenomenal growth. In fact, the CDS market began growing in the late 1990s; by the end of 1997, its size was approximately $180 billion in nominal terms. The notional amount doubled each year from 2004 to 2007, achieving a peak of $58 trillion by the end of 2007; this nearly surpassed foreign exchange derivatives as the second largest segment in the global OTC derivatives market [25]. This remarkable growth in the CDS market has made it an active venue for credit risk transfers and has made it one of the most important financial innovations in recent times. It is worth noting that CDSs were blamed for exacerbating the 2008 financial crisis. The notional amount of outstanding credit derivatives contracts decreased from $16 trillion at December-end 2014 to $15 trillion at June-end 2015; this represented only a quarter of the market's 2007 year-end peak of $58 trillion [25].[3] Concurrently, CDSs have been subjected to intense policy debates that include discussions of their role in the recent financial crisis [26], their effect on the debtor and creditor relation [27,28] and the cost of capital, credit risk and financial choices of firms [29,30].

A growing body of empirical literature examined CDS market efficiency. Norden and Weber [31] and Zhang [32] investigated the impact of adverse credit events and credit rating announcements on the informational efficiency of CDS and stock markets. Hull et al. [33] analyzed the relationship between bond yields, CDS spreads and credit rating announcements. Acharya and Johnson [34] examine the effects of insider trading on credit derivatives. Forte and Pena [35] analyze the informational content of stocks, bonds and CDS spreads. Ismailescu and Kazemi [36] document the reaction of emerging market CDS spreads to sovereign credit rating changes. Jenkins et al., [37] study the informational efficiency of the CDS market using post-earnings announcement returns. Schweikhard and Tsesmelidakis [38] show how the CDS and equity markets are impacted by government interventions. In a recent study, Zhang and Zhang [39] analyze the impact of earnings surprises on the information efficiency of the US CDS market. However, these studies have mainly focused on country-level credit markets and have examined the impact of different events on credit market efficiency.

Many factors, including higher trading costs, bad quality of information systems, disintermediation, and lack of competition due to investment barriers can cause the information inefficiency in the financial markets [18]. Other stylized facts that may contribute to the rejection of an asset return's normality include the leverage effect (the negative relation between volatility and profitability), volatility clustering, the existence of asymmetries in gains and losses (loss movements are more pronounced) and autocorrelation in return variance. These factors result in serial dependence, both linear and nonlinear, and thus require focus to identify the possibility of autocorrelation in a financial time series.

The most important development to identify long-range dependence behavior and its implications for financial market efficiency is the adoption of Detrended Fluctuation Analysis (DFA) proposed by Peng et al., [40], which was first applied in

[1] In early studies, Bachelier [2] notes that share prices have a Gaussian distribution and [3] reports that share prices are determined randomly. Other studies that support the random walk hypothesis include Osborne [4], Granger and Morgenstern [5] and Fama [6], among others. The Bachelier's theory (1964) of random walk was accepted and used in many financial applications, including the EMH [1]. However, fat-tailed behavior [4], the presence of asymmetries in gains and losses where the movements of loss are more pronounced, the leverage effects implied by the negative association between volatility and profitability, the trading volumes and volatility correlation, and the presence of autocorrelation in variance [7] were identified as some stylized fact of assets distributions.

[2] A credit default swap (CDS) is a financial swap contract where periodic payments, called CDS premiums, are made by a buyer for being protected against default or any other credit event stated in the contract. The credit events may include non-payment of debt, bankruptcy and debt restructuring.

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

econophysics. The initial work on financial market efficiency [41–43] through the DFA approach assumed a monofractal[4] structure in a financial time series. However, Fisher et al. [44], Pasquini and Serva [45], Kwapień et al. [46] and Oświęcimka et al. [47], among others, empirically identified that financial markets exhibit multifractal behavior; thus, a single scaling exponent is insufficient because it can provide spurious results. Considering this fact, Grech and Mazur [48] and Cajueiro and Tabak [49–51] proposed the time-varying Hurst exponent to study long-range serial correlation in a financial time series. Thereafter, many empirical studies [52–54] have utilized the time-varying Hurst exponent to test the EMH in different stock markets.

We contribute to this literature by examining the relative efficiency of credit and stock markets using MF-DFA on an industry-wide basis; the consideration of the aggregate markets may induce bias and hide useful information regarding the behavior of the individual industries. The CDS index spreads of different industries may exhibit heterogeneous responses to different economic and financial conditions depending on the type of business, the perceived risk of the industry, the cyclical or counter-cyclical nature, the balance sheet structure and the typical position of firms in an industry's CDS market [55].

It should also be noted that the CDS and equity markets are interlinked [56,57]. Theoretically, the stock price of a firm impacts its CDS spread. The structural model proposed by Merton [58] suggests that CDS spreads and stock prices have a negative relationship. Deterioration in the financial conditions of a firm increases the probability of its default on underlying debt obligations. Therefore, financial distress conditions result in a decrease in the value of a firm's stock and an increase in the CDS spread. Empirical works by Collin-Dufresne et al. [59], Blanco et al. [60] and Kapadia and Pu [61] suggest a weak correlation between stock returns and credit spread changes. However, the capital structure arbitrage that exploits the relationships between CDS and stock prices may enhance the integration and information flows between these markets (Fung et al., 2008).

Like DFA, Detrended Cross-Correlation Analysis (DCCA) [62–64] and its generalized form, MF-DXA [65], are used to examine the dependence between financial time series and is capable of capturing global as well as linear dependence. The main advantage of this method is that it considers the whole structure of a time series, both linear and nonlinear [66], which linear models may fail to reflect fully. Podobnik et al. [63] examined the dependence behavior between price and volume change in several indices and found a cross-correlation between these variables. Zebende [67] proposed a DCCA cross-correlation coefficient defined in terms of the DFA method and the DCCA method to quantify the level of cross-correlation between non-stationary time series.

In sum, this paper's objective is to investigate the multifractal properties of eleven US CDS and equity sectoral markets using daily data covering the December 14, 2007 to December 31, 2014 period. Further, we examine the cross-correlation between the considered sectoral markets. This study contributes to the existing literature in the following aspects. First, we provide an analysis of the efficiency of US CDS and equity markets at the sectoral level using the MF-DFA method developed by Kantelhardt et al. [68]. Second, we examine the linkages between the markets considered using the MF-DXA method. To the authors' knowledge, no study to date has examined the efficiency and cross-correlation between the CDS and equity sectoral markets. It is worth noting that many types of financial time series, most notably market returns, illustrate multifractal behaviors and mainly attribute the multifractality to different long-range temporal correlations for small and large fluctuations or to the fat-tailed probability distributions of variations [69]. Over the past few decades, econophysics methods (e.g., MF-DFA and MF-DXA) have shown their ability to examine the weak-form efficiency hypothesis. One of the main advantages of the MF-DFA method is its ability to analyze the multifractality (long-range memory) in nonstationary time series. The method allows one to measure the long-range dependence, the level of persistency, and the efficiency in financial markets. The MF-DFA method is sufficiently flexible to measure the long-range correlation behavior of non-stationary time series and avoid the misjudgment of correlation [70]. These methods are more flexible than rescaled range analysis (R/S), which is sensitive to the short-term auto-correlation and non-stationary series and is likely to lead to a biased estimation of long memory parameters [71]. The MF-DFA and MF-DXA methods are robust against these issues and have been widely used to detect long-range auto-correlations in financial markets. We assume that the strengths of multifractality between the sector CDS market and the sector stock markets are different; these can be regarded as an indicator to reflect how close the linkage between these markets is. This new method can solve the complex relationship between sector stock markets and sector CDS markets.

Our results from the scaling exponents of the MF-DFA method suggest that CDS markets are relatively more inefficient than their equity counterparts. Moreover, the Banking and Financial sector CDS indices are relatively more efficient, while the Basic Materials sector for both CDS and equity markets is the most inefficient. The cross-correlation exponents from the MF-DXA approach show that the relationship between the CDS and equity sectors within and across markets is multifractal for all pairs. Within the CDS market, the Basic Materials sector is the most dependent sector, whereas the equity market sectors can be divided into two distinct groups based on interdependence. Using the cross-correlation method, we support evidence that CDS-equity sectoral pairs belong to a persistent cross-correlated series within selected time intervals.

The remainder of the paper is organized as follows. Section 2 presents the methodology. In Section 3, we report the data used and discuss the results of the empirical study. Section 4 concludes the paper.

[4] The fractal is a natural phenomenon or a mathematical set that shows repletion in pattern at different scales. A monofractal structure is defined by a single power law exponent, i.e., independent of time and scale or scale invariant. The multifractal time series exhibits changing behavior with the change in scale and over time.

2. Methodology

2.1. Multifractal detrended fluctuation analysis (MF-DFA)

The MF-DFA method characterizes the multifractal properties of the financial time series. This method can measure and rank stock market efficiency. The method provides a spectrum of generalized Hurst exponents that can be used to determine the stationarity or random walk nature of the given time series. Furthermore, the qth order Hurst exponents can be used to rank the stock markets based on their relative inefficiency. The method comprises the following five steps:

First, the integration is used to determine the corresponding profile of a correlated time series $\{x(t), t = 1, \ldots, N\}$:

$$dfX\,(t) = \sum_{k=1}^{t} [x_t - (x)], \quad t = 1, \ldots, N \tag{1}$$

where N and (x) represent the length and mean of the series, respectively. Second, the profile $X(t)$ is divided into $N \equiv int(N/s)$, which are non-overlapping intervals (windows) of equal length s. In cases where the length of the time series is not a multiple of the considered time scale s, a portion of the series may not be captured by the intervals. Therefore, to avoid the loss of data, the procedure may be repeated beginning from the opposite end [72]. Finally, 2Ns sub-intervals are obtained.

Next, for each sub-interval $\{v = 1, \ldots, 2Ns\}$, the local trend is examined. The least square fit for each sub-interval is determined, and the difference $(Xs(t))$ between the original and the de-trended time series is obtained as:

$$X_s\,(t) = X\,[(v - N_s)\,s + 1] - x_v\,(t) \quad \text{for } v = 1, \ldots, Ns, \quad \text{and} \tag{2}$$

$$X_s\,(t) = X\,[N - (v - N_s)\,s + 1] - x_v\,(t) \quad \text{for } v = Ns + 1, \ldots, 2Ns \tag{3}$$

where x_v indicates the polynomial fit for the vth sub-interval. Then, the variance is determined as:

$$F_{xx}^2\,(s, v) = \frac{1}{s} \sum_{t=1}^{s} \{X\,[(v-1)\,s + t] - x_v(t)\}^2 \quad \text{for } v = 1, \ldots, Ns, \quad \text{and} \tag{4}$$

$$F_{xx}^2\,(s, v) = \frac{1}{s} \sum_{t=1}^{s} \{X\,[N - (v-1)\,s + t] - x_v(t)\}^2 \quad \text{for } v = Ns + 1, \ldots 2Ns. \tag{5}$$

Next, the qth order fluctuations are obtained by averaging the variance over all sub-intervals as:

$$F_q\,(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2\,(s, v)]^{q/2} \right\}^{1/q}. \tag{6}$$

Here, the qth order can have any real value except one since, for $q = 0$, it is not possible to obtain the scaling exponent value for $h(0)$. Finally, the scaling behavior of the functions can be determined by analyzing the log–log plot of $Fq(s)$ versus s for each value of q. The time series $x(t)$ is said to be a long-range power-law multifractality correlated if the $Fq(s)$ increases with the scale (s):

$$F_q(s) \sim s^{h(q)}. \tag{7}$$

The slope of the log–log plot of $Fq(s)$ versus s can provide a family of scaling exponents $h(q)$. These scaling exponents $h(q)$ are the generalizations of the Hurst exponent $H(\equiv h(2))$. The Hurst exponent provides information on time series behavior (power-law correlated) over time; a $0.5 < H < 1$ ($0 < H < 0.5$) indicates a positive/persistence (negative/anti-persistence) correlation indicating the level of inefficiency of the stock markets. However, a $H = 0.5$ suggests the time series follows an uncorrelated Brownian process, i.e., stock markets are efficient.

The $h(q)$ obtained from the MF-DFA is directly related to the classical multifractal scaling exponent given by:

$$\tau\,(q) = qh\,(q) - 1. \tag{8}$$

Using the spectrum of generalized Hurst exponents $h(q)$, the singularity strength α and the singularity spectrum $f\,(\alpha)$ can be calculated by using:

$$\alpha = h\,(q) + qh'\,(q) \quad \text{and} \quad f\,(\alpha) = q\,[\alpha - h\,(q)] + 1. \tag{9}$$

In the multifractal case, the different parts of the structure are characterized by different values of α leading to the existence of the spectrum $f(\alpha)$.

2.2. Multifractal detrended cross-correlation analysis (MF-DXA)

To measure the relationship between the CDS and equity indices of the US at the sector level, we employ the MF-DXA methodology. Assume that there are two series $x(t)$ and $y(t)$ ($t = 1, 2, \ldots, N$). The first steps (Eqs. (1)–(5)) are similar to

MF-DFA analysis. However, the detrended covariance is determined by:

$$F_{xy}^{2}(s,v)=\frac{1}{s}\sum_{t=1}^{s}\left|X\left((v-1)s+t\right)-x_{v}(t)\right|.\left|Y\left((v-1)s+t\right)-y_{v}(t)\right| \tag{10}$$

for $v = 1, \ldots, Ns$, and

$$F_{xy}^{2}(s,v)=\frac{1}{s}\sum_{t=1}^{s}\left|X\left(N-(v-N_{s})s+t\right)-x_{v}(t)\right|.\left|Y\left(N-(v-N_{s})s+t\right)-y_{v}(t)\right| \tag{11}$$

for $v = Ns + 1, \ldots 2Ns$

Now, the remainder of the definitions are the same as in the MF-DFA section; in addition, the log–log plot of $Fq(s)$ versus s, the classical multifractal scaling exponent (τ) and the singularity strength α can be obtained using Eqs. (7)–(9). The following bivariate scaling exponents are in order: if $H_{XY}\ (q = 2) > 0.5$, the cross-correlations between X and Y are long-range persistent; if $H_{XY}\ (q = 2) < 0.5$, the cross-correlations between X and Y are anti-persistent; and if $H_{XY}\ (q = 2) = 0.5$, there is no cross-correlation between the two times series. Furthermore, for positive (negative) values of q, the generalized Hurst exponents $H_{XY}\ (q)$ describe the scaling properties of large (small) fluctuations. Conversely, for negative values of q, exponents $H_{XY}\ (q)$ describe the scaling properties of small fluctuations.

3. Empirical study

3.1. Data

The study uses the daily closing prices of 11 US CDS and equity sectoral indices. The sectors include Banks, Financial, Telecommunication, Healthcare, Oil and Gas, Basic Materials, Consumer Goods, Utilities, Industrials, Consumer Services and Technology. The industry classification is in accordance with the Industry Classification Benchmark (ICB) developed by Dow Jones and FTSE, which is the most widely used global standard for company classification. We use 5-year industry CDS index spreads, as these represent the most frequently traded term, are equally weighted and reflect the average mid-spread calculation of the 5-year CDS of the firms within each industry. To better reflect the liquidity in the CDS market, these indices are rebalanced every six months. The daily data is extracted from DataStream International (Thomson Financial) for the December 14, 2007–December 31, 2014 period, and the start of this period is dictated by the availability of CDS data on the Thomson Reuters DataStream. The study period covers several global and regional events (high levels of volatility and an upward trend in commodity prices, the Lehman Brother collapse in September 15, 2008, the GFC, the Eurozone sovereign debt crisis in 2009–2012 and the gradual recovery of global markets in 2011) and is sufficiently large for empirical analysis to indicate a long-run relationship between the markets.

We have treated Banks and Financial sectors separately because earlier empirical works suggest that the CDS premia of these sectors react differently to market conditions (Raunig and Scheicher, 2009; Raunig, 2015). Specifically, unique characteristics that distinguish Banks from the non-financial or industrial firms include the balance sheet composition, their central role in an economy, and the differences in the regulatory framework. The sector level CDS indices (denominated in basis points so that 100 basis points equates to 1 percentage point) are based on 5-year tenor series contracts because the five-year credit instruments are considered adequate by liquidity standards (Narayan et al., 2014). From the closing values (p_t on day t) of the CDS and equity indices, the natural logarithmic returns, $r_t = \ln(p_{t+1}/p_t) \times 100$, are calculated, and a total of 1838 observations for each index are used in the current analysis.

The daily CDS spread (in basis points) of all sectoral indices is transformed into natural logarithmic form, and the trend is shown in Fig. 1; this illustrates significant abrupt changes during the onset of the GFC 2008–2009 for all indexes. The descriptive statistics and the correlation between the CDS and equity index pairs are reported in Table 1. The Technology sector CDS spread returns are highest (0.0558%) among the 11 sectors, and the Utilities sector standard deviation is highest (6.6729%) among the others. The Banks sector has the lowest average CDS premium returns (−0.0204%). The last column of the table presents the correlation between the CDS and equity index of each sector. All the correlation values are negative and statistically significant at the conventional levels. A preliminary indication is that both markets are related, and the stock markets have a negative relationship with the CDS premia (Merton's model). The correlation between the Banks sector CDS and equity indices is also highest (−0.3539) and significant at the 1% level. The Oil and Gas sector CDS and equity index show a relatively low correlation (−0.0510) with each other. All the time return series are non-normal, as the null hypothesis of Jarque–Bera test is rejected.

3.2. Results and discussions

The MF-DFA can be applied when the time series exhibits a fractal structure over time and the equity market returns exhibit power law long dependence (see, e.g., [18,73]). However, this study is the first to examine the multifractal nature of CDS indices by analyzing the scaling behavior of the fluctuation functions.

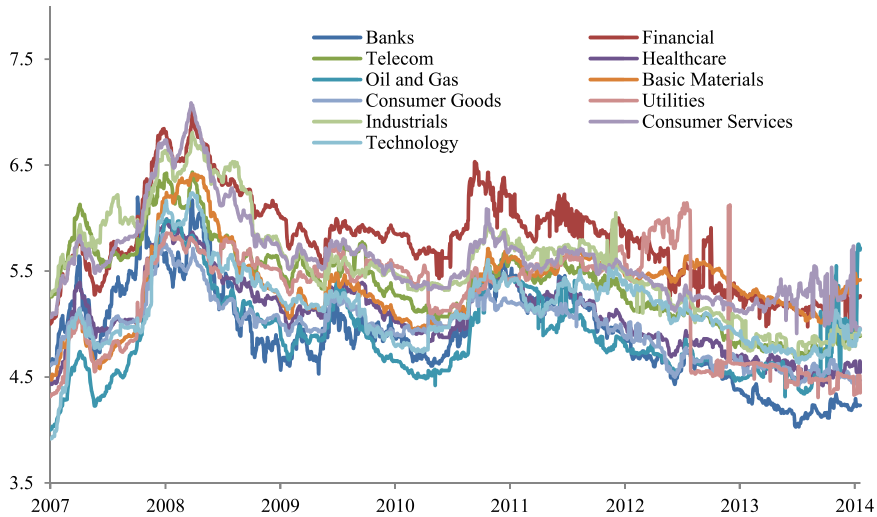


Fig. 1. Time evolution of daily CDS sectoral indices.

Table 1
Sector-wise descriptive statistics of CDS and equity indices.

Sector(s)	Index	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	JB stats	Correlation
Banks	CDS	−0.0204	37.935	−51.114	3.9709	−0.8277	32.136	65 223***	−0.3539*
	Equity	−0.0121	19.340	−21.678	2.9040	0.1145	14.437	10 021.9***	(−16.214)
Financial	CDS	0.0145	52.431	−55.758	5.6192	−0.1036	22.888	30 295.3***	−0.1045*
	Equity	0.0062	15.446	−17.212	2.3361	−0.1988	13.573	8573.42***	(−4.5036)
Telecommunication	CDS	−0.0201	20.416	−26.397	2.4908	0.1405	20.953	24 690.0***	−0.1687*
	Equity	−0.0047	13.260	−8.8011	1.4168	0.3379	15.547	12 091.6***	(−7.3317)
Healthcare	CDS	0.0062	26.378	−17.112	2.3310	1.2193	25.356	38 730.9***	−0.1774*
	Equity	0.0389	11.436	−7.0681	1.1471	−0.1272	13.338	8191.17***	(−7.7230)
Oil and Gas	CDS	0.0933	66.429	−64.415	6.6109	0.6829	52.933	191 089.***	−0.0510**
	Equity	0.0031	17.308	−16.504	1.8710	−0.2844	17.024	15 086.7***	(−2.1901)
Materials	CDS	0.0499	12.711	−10.135	1.7198	1.3584	12.663	7716.10***	−0.2544*
	Equity	0.0063	14.493	−14.458	2.0884	−0.5524	10.288	4161.61***	(−11.269)
Consumer Goods	CDS	−0.0078	22.296	−16.030	2.1932	0.9438	23.120	31 276.4***	−0.1477*
	Equity	0.0254	9.0169	−7.4776	1.0723	−0.1396	12.721	7242.93***	(−6.3973)
Utilities	CDS	0.0020	146.61	−148.10	6.6729	−5.9873	389.99	1 148 076***	−0.0662**
	Equity	0.0059	13.392	−8.6492	1.2440	0.4612	18.676	18 884.8***	(−2.8447)
Industrial	CDS	−0.0202	52.373	−50.920	3.9005	−0.3656	67.164	315 340***	−0.1397*
	Equity	0.0205	9.4296	−9.3548	1.5423	−0.4212	8.4116	2297.12***	(−6.0458)
Consumer Services	CDS	−0.0060	76.045	−75.553	4.4729	−0.7703	134.32	1 321 020***	−0.1284*
	Equity	0.0403	10.971	−9.4502	1.3546	−0.1252	10.874	4753.30***	(−5.5486)
Technology	CDS	0.0558	42.696	−19.874	2.5429	4.6569	82.975	496 478.3***	−0.1593*
	Equity	0.0271	11.609	−9.8399	1.5006	−0.0566	9.7191	3458.41***	(−6.9143)

Note: Max., Min., Std. Dev., Skew, Kurt and JB denote maximum, minimum, standard deviation, skewness, kurtosis and Jarque–Bera test, respectively. The number in the brackets are t-statistics of correlation test.
* Indicates significance of correlation at 1% level.
** Indicates significance of correlation at 5% level.
*** Indicates that null hypothesis of normality is rejected at 1% significance level.

For all the CDS returns, we compute the fluctuation function, $Fxx(q; s)$, as a function of scale, s, for different values of q. A plot of the $Fq(s)$ versus scale for CDS indices is provided in Fig. 2. The figure shows that the fluctuations function for all CDS indices increase with the scale. It can be inferred that the sector level CDS indices return series are power law correlated with respect to scale; thus, MF-DFA analysis can be applied to further examine the levels of efficiency.

Following the verification of the scaling function, we calculate the important exponents to further examine the statistical properties of the CDS and equity index return series. The generalized Hurst exponent ($h_{xx}(q)$), multifractal scaling exponent ($\tau_{xx}(q)$) and singularity spectrum (α_{xx}) are the well-known scaling exponents used to classify the stochastic fluctuation of a multifractal time series. We have calculated these three scaling exponents on the sector level for both CDS and equity indices.

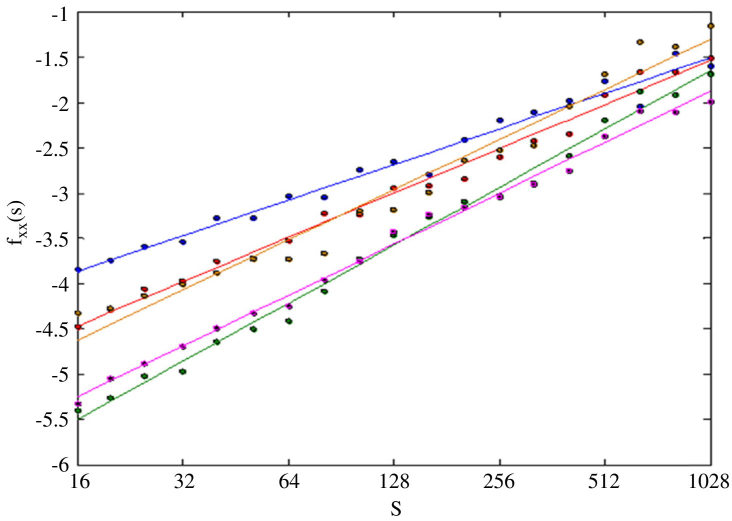


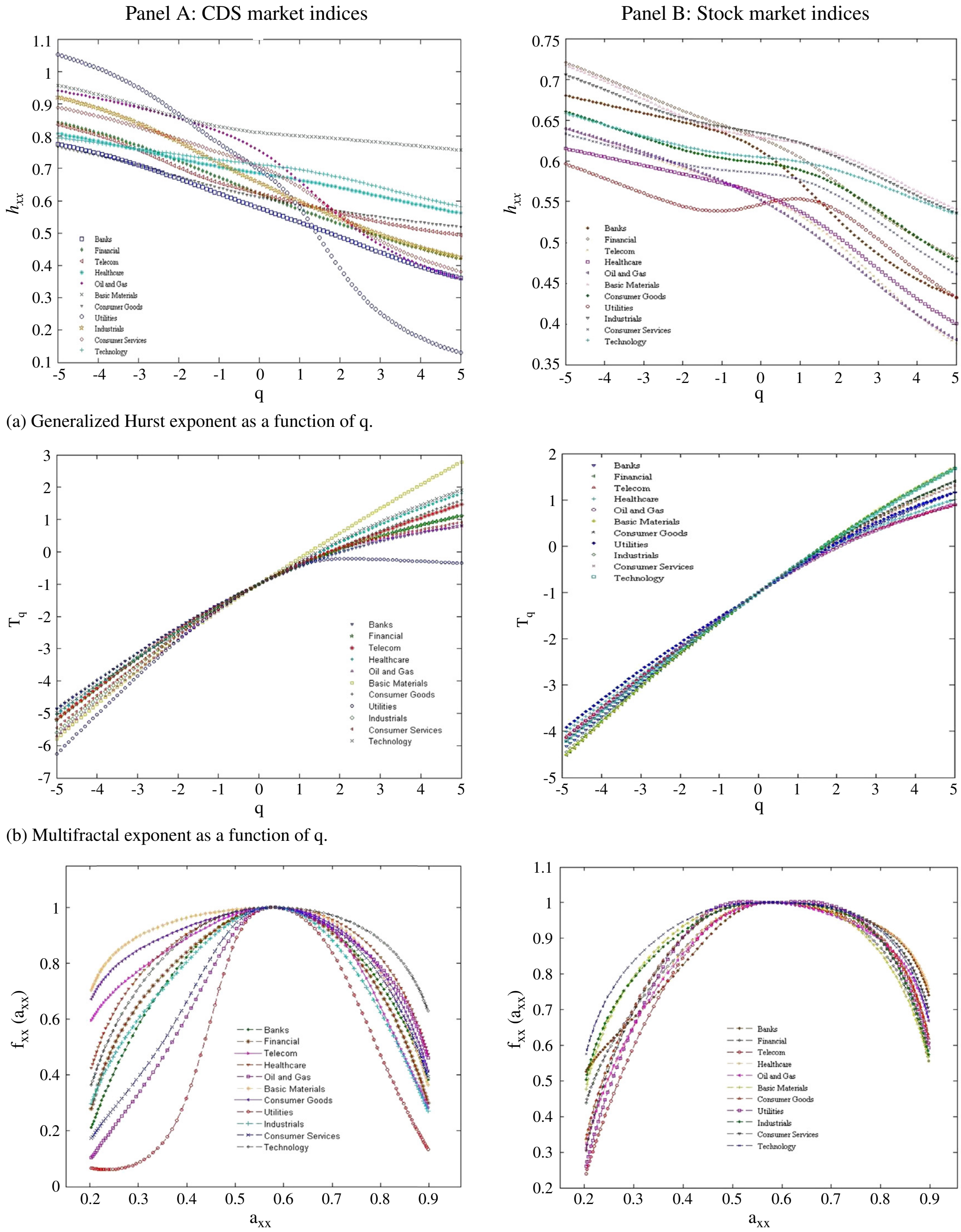
Fig. 2. Fluctuation function for some CDS indices as a function of scale. Note: the vertical axis plots f_{xx} values again the scales (16–1028) on the horizontal axis.

The upper left (right) plot of Fig. 3 indicates the $h_{xx}(q)$ as a function of q for all CDS (equity) indices. Similarly, the behavior of $\tau_{xx}(q)$ and the singularity spectrum $f_{xx}(\alpha xx)$ of all CDS (equity) sector return series are shown in the middle and lower left (right) panels of Fig. 3, respectively. All the return series demonstrate a multifractal nature, as shown by the q-dependency of generalized $h(q)$, indicating the presence of long-range memory. The strength of the multifractality is shown through $\Delta\alpha xx = \alpha_{xx}^{\max} - \alpha_{xx}^{\min}$. These figures collectively show that both the CDS and the equity time series exhibit a multifractal nature and the sector-wise fluctuation functions are different; this supports the need for out sector-level comparison.

After confirmation of the multifractal nature of both CDS and equity indices, the value of the Hurst exponent $H(\equiv h(2))$ for the CDS and the equity indices are displayed in Figs. 4 and 5, respectively. Notably, except for the Banks and Financial sectors, all remaining CDS markets appear to be relatively more inefficient than their equity counterpart. The Banks and Financial sector CDS indices are more efficient than their equity counterparts. This result suggests that the CDS Banks and Financial sectors are more liquid than their equity counterparts. Within the CDS markets, except for the Utility sector (anti-persistence process), all the other indices show persistence in autocorrelation (long memory process). This result may be explained by a contraction in inter-dealer activity. Specifically, the notional amount for contracts between reporting dealers decreased from $7.7 trillion at December-end 2014 to $6.5 trillion at June-end 2015. The Basic Materials sector appears to be the most inefficient CDS sector in the US economy, followed by the Technology and Healthcare sectors. Regarding the equity sectoral markets, the Basic Materials and the Industrials sectors are relatively more inefficient than the remaining equity sectors. The Telecom, Healthcare and Oil and Gas equity sectors are relatively efficient, as their coefficient is close to 0.5.

The strong evidence of long-range dependence in both the CDS and equity sectors motivates us to investigate the cross-correlation between the CDS indices followed by the equity indices. It is argued that market inefficiency may also result from the higher interdependence between the markets. For this objective, we use the MF-DXA approach and the bivariate scaling exponent H_{XY} $(q = 2)$ for both the CDS and the equity indices; the graphical trajectories are shown in Figs. 6 and 7, respectively. Within the CDS sectors, the Basic Materials and Technology sectors appear to be the most correlated sectors with all other sectors, indicating increasing integration of both CDS sectors with the remaining sectors. The individual and institutional investors should be cautious in the use of these CDS sectors as a means to speculate on the future direction of the market. The banking CDS index shows the least cross-dependence with the remainder of the CDS markets. Fig. 7 illustrates the MF-DXA cross-correlation matrix of equity sectoral indices. As shown in this figure, we divide the sectoral indices into two distinct groups. The Banks, Financial, Basic Materials, Consumer Goods, Industrials, Consumer Services and Technology are the most interdependent US equity sectors, while the Telecommunication, Healthcare, Oil and Gas and Utilities sectors show a low bivariate scaling exponent H_{XY} $(q = 2)$ and hence low dependence on the other sectors. These equity sectors are less integrated with the remaining sectors and can be useful to effectively manage an equity portfolio. The results support the outcomes noted by the MF-DFA efficiency analysis and provide the portfolio perspective on both the CDS and equity investments. Arguably, the least dependent sectors can provide maximum portfolio diversification benefits and vice versa.

The question of whether and why the equity price and CDS spreads are related and have a long-run relationship are important (Narayan et al., 2014). Merton's [58] model implies that changes in credit spread and stock price must co-move to prevent arbitrage. The deterioration in the financial conditions of a firm increases the probability of its default on underlying debt obligations. In other words, financial distress conditions result in a decrease in the value of a firm's stock and increase the CDS spread [61]. To examine the long-range dependence between equity and CDS markets, we again utilize the MF-DXA method on the sector-wise pairs of CDS and equity indices.



(a) Generalized Hurst exponent as a function of q.

(b) Multifractal exponent as a function of q.

(c) Singularity spectrums.

Fig. 3. MF-DFA analysis of CDS and equity indices.

Fig. 8 displays the plot of the fluctuation function (H_{XY}) using the MF-DXA for 11 pairs of CDS and equity indices. The Basic Materials and Industrials sector CDS markets react more in response to both a small and a large fluctuation in their equity counterparts. The Technology sector's CDS index responds to large fluctuations of its equity sector. Moreover, the Bank and Utility sector CDS indices have the least response to large fluctuations in respective equity markets. The above cross-correlation results are further confirmed by examining the detrended cross-correlations analysis (ρDCCA) of Podobnik

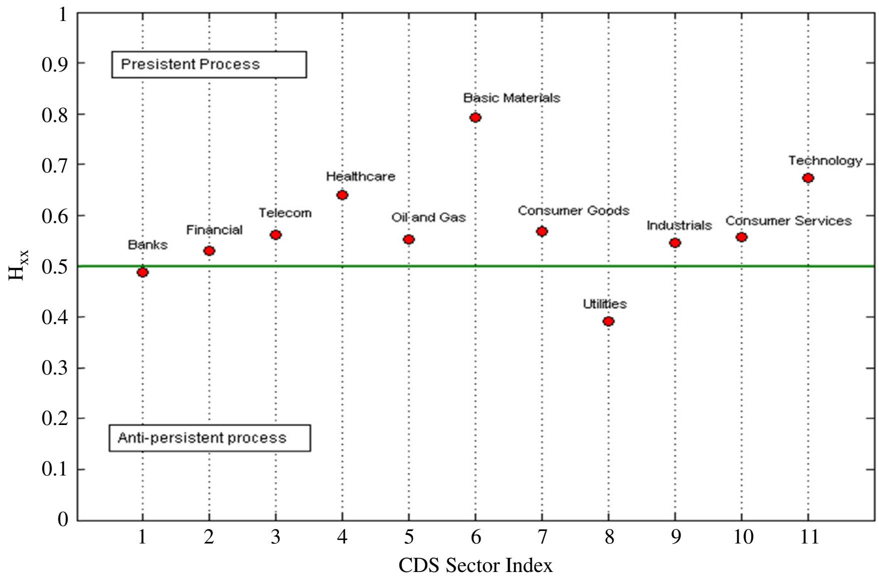


Fig. 4. CDS sectoral indices efficiency index.

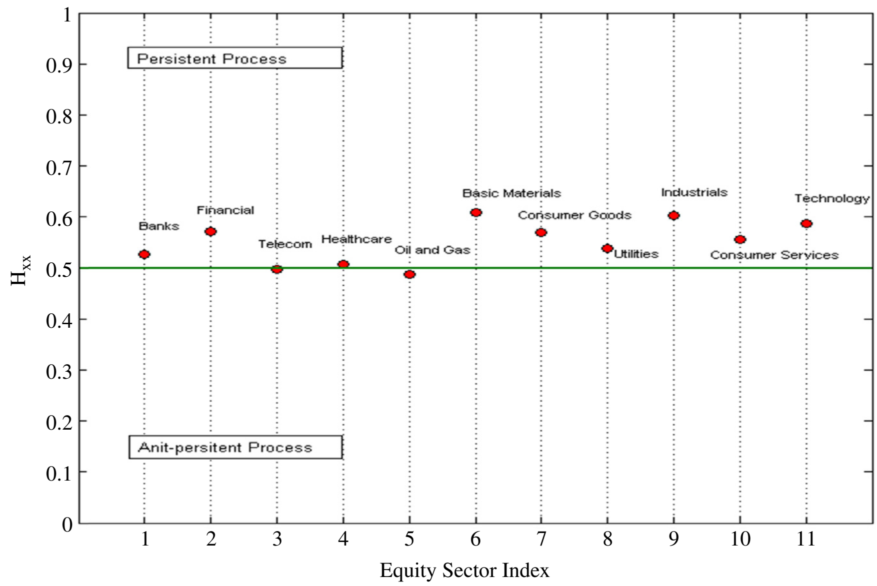


Fig. 5. Equity sectoral indices efficiency index.

et al. [74]. The ρDCCA is the ratio between the detrended covariance function and the variances functions given as:

$$\rho_{DCCA} = \frac{F^2_{DCCA}(n)}{F_{DFA1\{n\}} \cdot F_{DFA2\{n\}}} \tag{12}$$

where the $|\rho DCCA| \leq 1$. A $\rho DCCA = 0$ implies no cross-correlation between the CDS and the equity index, and the zero is regarded as the split point for cross-correlation in the positive and the negative case. The positive and negative values are viewed as the cross-correlation between the two time series as persistent and anti-persistent, respectively.

For ease of interpretation, the plotted values of ρDCCA for different window sizes ($n = 16, 32, 64, 128, 256, 512, 1024$ days) for all the sectoral pairs are provided in Fig. 9. Notably, the DCCA cross-correlation coefficients quantify the level of cross-correlation. Except for the Bank sector CDS and equity pair, we observe from Fig. 9 that the DCCA cross-correlation coefficient is very close to zero for all the remaining sectoral pairs. At lower scales $16 < s > 256$, we note that the Bank sector pair of the CDS and the equity index shows a relatively higher positive cross-correlation coefficient (0.05–0.2) than other sectors. However, at higher scales $256 < s > 1024$, there is a significantly higher positive cross-correlation between

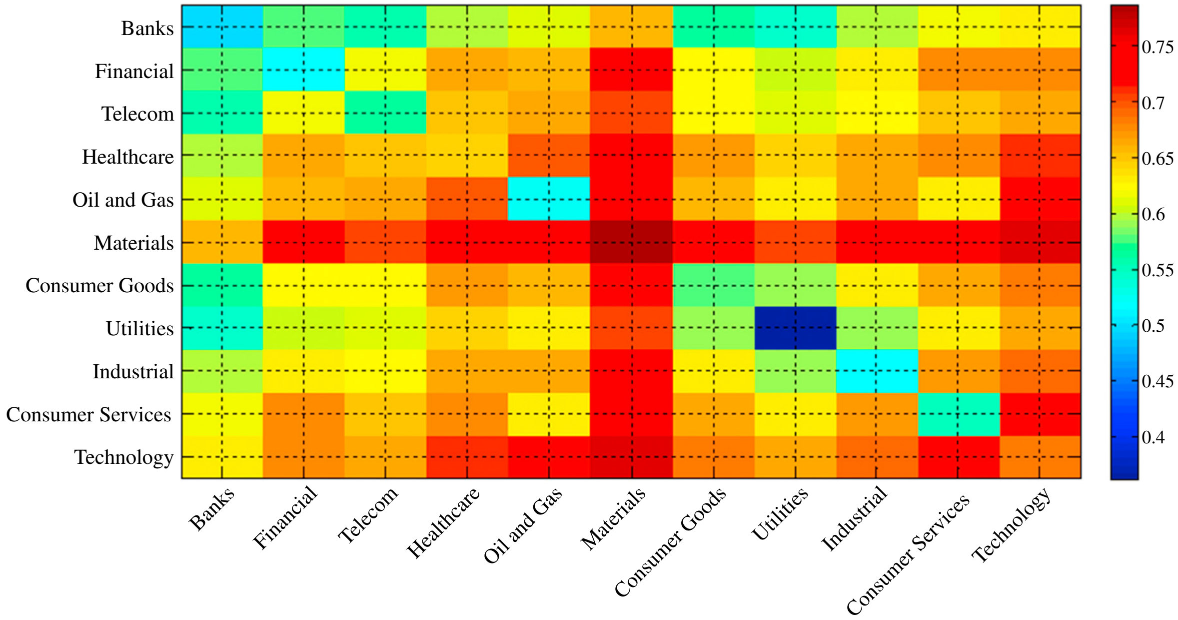


Fig. 6. MF-DXA cross-correlation matrix of CDS sectoral indices.

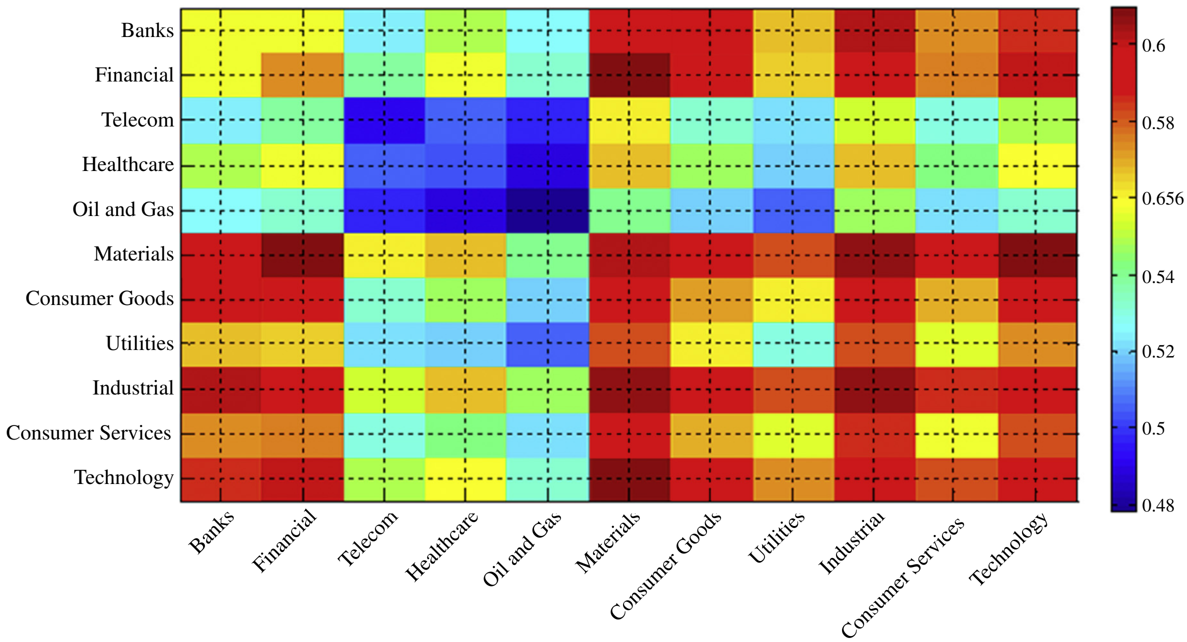


Fig. 7. MF-DXA cross-correlation matrix of equity sectoral indices.

the Basic Materials sector CDS and equity markets. Moreover, it is noted that the ρDCCA between the Utility sector CDS and the equity index pair is the lowest among all scales. In sum, the CDS markets are dependent on their equity counterparts. The evidence of cross-correlation between the CDS and equity markets are in accordance with Kiesel et al. [56] who found integration between the CDS and equity markets.

4. Conclusions

This study provides an analysis of the power law auto- and cross-correlation properties of US CDS and equity sectoral indices using daily data covering the December 17, 2007–December 31, 2014 period. The relative efficiency/inefficiency of the CDS and equity markets within the US is examined using the MF-DFA approach. In addition, we investigate the

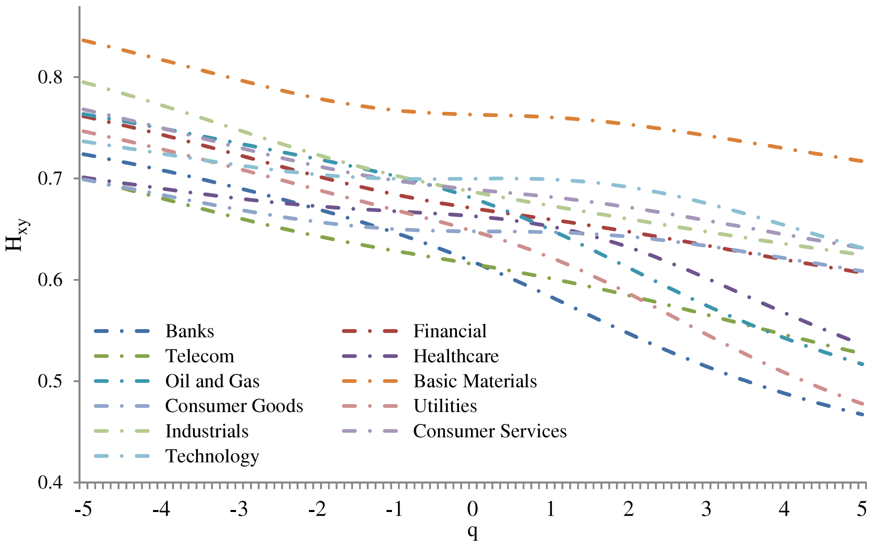


Fig. 8. Generalized Hurst exponent for industry-level CDS and stock index pairs. Note: The calculated (H_{XY}) values depend on q, which implies the existence of MF-DXA behavior for 11 CDS-equity sectoral pairs.

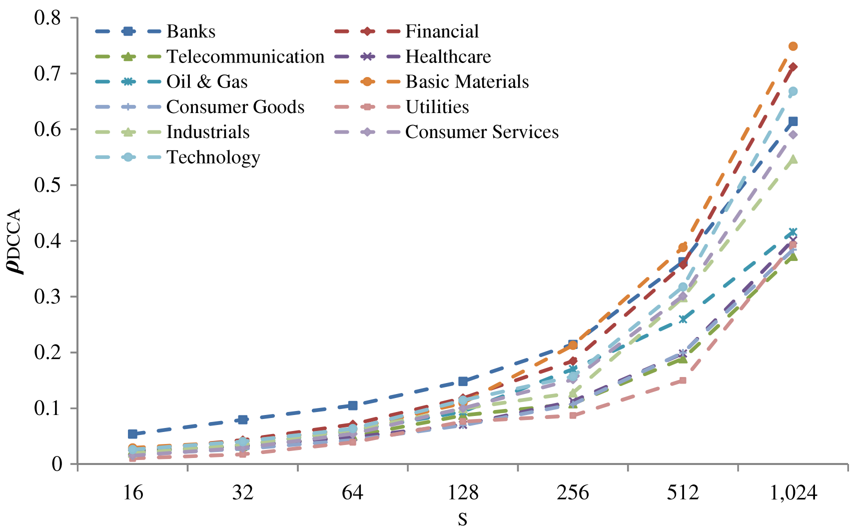


Fig. 9. Cross-correlation coefficients between industry-level CDS and stock index pairs. Note: This figure shows the variations of Multifractal cross-correlation exponents for CDS-equity sectoral pairs. We quantify the ρDCCA for different window sizes ($s = 16, 32, 64, 128, 256, 512, 1024$ days).

multifractal cross-correlations within and across the CDS and equity markets using both the MF-DXA and MF-DCCA methods. The scaling and fluctuation exponents suggest that all the individual CDS and equity series are multifractal in nature. The evidence of the multifractality is mainly attributed to long-range dependence, which affects the asset allocation, as the informing investors can beat the markets and obtain excess returns. The equity sectoral indices are more efficient than their CDS counterparts. However, the Bank and Financial CDS sectors are relatively efficient, while the Basic Materials sector is the most inefficient sector in terms of CDS and the equity index. The inefficiency indicates the deviations of the market price from the true value; hence, informed investors can consistently find under- or over-valued assets using any investment strategy. It is worth noting that financial institutions are major participants in the CDS markets, which allow them to hedge and diversify their exposure to illiquid bonds and/or loans/receivables. CDSs can stimulate financial stability through their ability to improve credit risk allocation because of a more liquid and diversified market for credit risk transfers. Banks use credit derivatives for hedging, securitizing the credit risk and/or credit risk sharing. Banks have unique characteristics that distinguish them from non-financial or industrial firms. These characteristics include balance sheet composition, their central role in an economy and a different regulatory framework. Bank assets are mainly composed of loans and retail deposits. Higher leverage with an inherent mismatch of maturities creates valuation and agency problems that are difficult to resolve alone through market discipline. Hence, these deposit-taking financial institutions are normally under rigorous regulatory controls. Further, government public safety nets and/or deposit guarantee programs also distinguish between banks and other sectors in an economy, and rigorous regulatory control results in better information efficiency.

Further, we find strong evidence of multifractal cross-correlations among all selected pairs. The presence of multifractal cross-correlations between CDS and equity indices suggests the use of dynamic methods for credit risk hedging and speculation. The results also confirm that CDS and equity markets are cross-correlated and exhibit complex features. Overall, the Basic Materials (Utilities) sector CDS market appears to be the most (least) related to other sectors and to its equity counterpart. The dynamic dependence of these two US industries provides arbitrage and hedging prospects for credit market investors. The CDS Utilities industry regulated by policy makers is a counter-cyclical industry with low dependence on the remaining credit markets. Thus, this industry can be exploited for possible arbitrage opportunities. That the Basic Materials industry sector, which is dependent on variations in the business cycle, is highly linked with the other industries stems from the fact that the credit risks of most of the industries depend on the state of the economy. The resulting higher co-movement with the other industries can be useful for hedging the credit risk across industries. Overall, the low dependence of the Utilities sector and others CDS sectors implies the emergence of diversification investment opportunities, while the high dependence between the Basic Materials economic sector is due to its sensitivity to the volatility of the price of metals and nonmetallic and construction materials. These CDS market dependence results are in accordance with the recent findings of Shahzad et al. [75].

Interestingly, the result of superiority of the efficiency level of the US equity sectoral markets over the CDS sectoral markets is due to the fact that the latter do not process the arrival of the information set immediately, and the latter takes longer to embody this news in the current index. The market depth that results from market size, market development and capital flows is a major determinant for market efficiency and is higher for equity markets than for the CDS markets. From the investor perspective, the stock prices can be reasonably viewed as accurate signals for capital allocation and for pricing of stock-related products and derivatives instruments. The market integration between CDS and US equity markets may be due to US companies remaining under stress because of the aftermath of the 2008–2009 GFC. More importantly, US equity markets appear to lead US CDS markets. Therefore, stock returns can potentially serve to forecast future CDS spread changes, indicating that CDS markets are not yet truly efficient and dependent on equity markets. The highest efficiency degree of bank and financial credit markets is explained by the liquidity of these sectors regarding the other markets. The banking and financial sectors play a crucial role in the financial stability of the economy by providing liquidity.

Finally, the sector level findings on efficiency and interdependence should help investors and portfolio managers to better understand the associated risks and hence contribute to better investment decisions in both markets.

These results are important for bankers, policymakers, regulators, risk managers and investors. The efficiency within CDS and equity sectoral indices are heterogeneous, implying that these indices may be under- or overvalued. In fact, investors can use these sectors to construct a portfolio and to effectively manage their risk and implement a profitable investment strategy based on the market efficiency level difference. Market participants attempt to identify under-evaluated assets, as their price will increase in the future and more will buy the over-evaluated assets. Regarding the empirical results obtained, the violation of EMH may discourage the investment incentives. To improve transparency, automation, regulation and market standardization for the CDS and equity markets, it is crucial to engender greater confidence in this market and better serve market participants in this regard. It will be intriguing in the future to extend this work by examining the determining factors of the weak-form efficiency of CDS and equity sectoral market efficiency.

References

[1] E.F. Fama, Efficient capital markets: A review of theory and empirical work, J. Finance 25 (2) (1970) 383–417.
[2] L. Bachelier, Theory of speculation, in: P. Cootnered (Ed.), The Random Character of Stock Prices, MIT Press, Cambridge, 1964, originally published in 1900.
[3] M.G. Kendall, The analysis of economic time-series-Part I: Prices, J. R. Stat. Soc. Series A (General) 116 (1) (1953) 11–25.
[4] M.M. Osborne, Brownian motion in the stock market, Oper. Res. 7 (2) (1959) 145–173.
[5] C.W. Granger, O. Morgenstern, Spectral analysis of New York stock market prices, Kyklos 16 (1) (1963) 1–27.
[6] E.F. Fama, Mandelbrot and the stable Paretian hypothesis, J. Bus. 36 (4) (1963) 420–429.
[7] R. Cont, Empirical properties of asset returns: stylized facts and statistical issues, Quant. Financ. 1 (2) (2001) 223–236.
[8] V. Alexeev, F. Tapon, Testing weak form efficiency on the toronto stock exchange, J. Empir. Finance 18 (4) (2011) 661–691.
[9] I. Awad, Z. Daraghma, Testing the weak-form efficiency of the Palestinian securities market, Int. Res. J. Financ. Econ. 32 (2009) 7–17.
[10] O. Gozbasi, I. Kucukkaplan, S. Nazlioglu, Re-examining the Turkish stock market efficiency: Evidence from nonlinear unit root tests, Econ. Modell. 38 (2014) 381–384.
[11] M. Hasanov, T. Omay, Are the transition stock markets efficient? Evidence from non-linear unit root tests, Cent. Bank Rev. 7 (2) (2012) 1–12.
[12] H. Marashdeh, M.B. Shrestha, Efficiency in emerging markets-evidence from the Emirates securities market, Eur. J. Econ. Finance Adm. Sci. 12 (2008) 143–150.
[13] P.K. Narayan, R. Smyth, Random walk versus multiple trend breaks in stock prices: evidence from 15 European markets, Appl. Financ. Econ. Lett. 2 (1) (2006) 1–7.
[14] S. Neaime, Are emerging MENA stock markets mean reverting? A Monte Carlo simulation, Finance Res. Lett. 13 (2015) 74–80.
[15] S.A.P. Oskooe, H. Li, A. Shamsavari, The random walk hypothesis in emerging stock market, Int. Res. J. Finance Econ. (50) (2010) 51–61.
[16] Z.A. Ozdemir, Efficient market hypothesis: evidence from a small open-economy, Appl. Econ. 40 (5) (2008) 633–641.
[17] S.A.R. Rizvi, S. Arshad, Investigating the efficiency of East Asian stock markets through booms and busts, Pac. Sci. Rev. 16 (4) (2015) 275–279.
[18] S.A.R. Rizvi, G. Dewandaru, O.I. Bacha, M. Masih, An analysis of stock market efficiency: Developed vs Islamic stock markets using MF-DFA, Physica A 407 (2014) 86–99.
[19] F. Jamaani, E. Roca, Are the regional Gulf stock markets weak-form efficient as single stock markets and as a regional stock market? Res. Int. Bus. Finance 33 (2015) 221–246.
[20] M. Metghalchi, C.P. Chen, L.A. Hayes, History of share prices and market efficiency of the madrid general stock index, Int. Rev. Financ. Anal. (2015).

[21] T. Sunde, J. Zivanomoyo, The random walk hypothesis for the Zimbabwe stock exchange: January 1998-November 2006, J. Soc. Sci. 4 (3) (2008) 216.
[22] B.M. Tabak, The random walk hypothesis and the behaviour of foreign capital portfolio flows: the Brazilian stock market case, Appl. Econ. Lett. 13 (2003) 369–378.
[23] M.G.S. Uddin, A.K.M.N. Khoda, An empirical examination of random walk hypothesis for Dhaka stock exchange: Evidence from pharmaceutical sector of Bangladesh, Int. Res. J. Finance Econ. 33 (2009) 87–100.
[24] J. Wang, D. Zhang, J. Zhang, Mean reversion in stock prices of seven Asian stock markets: Unit root test and stationary test with Fourier functions, Int. Rev. Econ. Finance 37 (2015) 157–164.
[25] Bank for International Settlements (2015). OTC derivatives statistics at end-December 2015. http://www.bis.org/publ/otc_hy1605.htm.
[26] R.M. Stulz, Credit default swaps and the credit crisis (No. w15384). National Bureau of Economic Research, 2009.
[27] P. Bolton, M. Oehmke, Credit default swaps and the empty creditor problem, Rev. Financ. Stud. 24 (8) (2011) 2617–2655.
[28] H.T. Hu, B. Black, Debt, equity and hybrid decoupling: Governance and systemic risk implications, Eur. Financ. Manag. 14 (4) (2008) 663–709.
[29] M.G. Subrahmanyam, D.Y. Tang, S.Q. Wang, Does the tail wag the dog?: The effect of credit default swaps on credit risk, Rev. Financ. Stud. 27 (8) (2014) 2927–2960.
[30] A. Saretto, H. Tookes, Corporate leverage, debt maturity and credit default swaps: The role of credit supply, Working paper, University of Texas at Austin and Yale University, 2011.
[31] L. Norden, M. Weber, Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements, J. Bank. Finance 28 (11) (2004) 2813–2843.
[32] G. Zhang, Informational efficiency of credit default swap and stock markets: The impact of adverse credit events, Int. Rev. Account. Bank. Finance 1 (1) (2009) 1–15.
[33] J. Hull, M. Predescu, A. White, The relationship between credit default swap spreads, bond yields, and credit rating announcements, J. Bank. Finance 28 (11) (2004) 2789–2811.
[34] V.V. Acharya, T.C. Johnson, Insider trading in credit derivatives, J. Financ. Econ. 84 (1) (2007) 110–141.
[35] S. Forte, J.I. Pena, Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS, J. Bank. Finance 33 (11) (2009) 2013–2025.
[36] I. Ismailescu, H. Kazemi, The reaction of emerging market credit default swap spreads to sovereign credit rating changes, J. Bank. Finance 34 (12) (2010) 2861–2873.
[37] N.T. Jenkins, M.D. Kimbrough, J. Wang, The extent of informational efficiency in the credit default swap market: evidence from post-earnings announcement returns, Rev. Quant. Finance Account. 46 (4) (2016) 725–761.
[38] F.A. Schweikhard, Z. Tsesmelidakis, The impact of government interventions on CDS and equity markets, in: Finance Meeting EUROFIDAI-AFFI, Paris, December, 2011, June.
[39] G. Zhang, S. Zhang, Information efficiency of the US credit default swap market: Evidence from earnings surprises, J. Financ. Stab. 9 (4) (2013) 720–730.
[40] C.K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Mosaic organization of DNA nucleotides, Phys. Rev. E 49 (2) (1994) 1685–1689.
[41] T. Di Matteo, T. Aste, M.M. Dacorogna, Scaling behaviors in differently developed markets, Physica A 324 (1) (2003) 183–188.
[42] T. Di Matteo, T. Aste, M.M. Dacorogna, Long-term memories of developed and emerging markets: Using the scaling analysis to characterize their stage of development, J. Bank. Finance 29 (4) (2005) 827–851.
[43] D.O. Cajueiro, B.M. Tabak, Testing for time-varying long-range dependence in volatility for emerging markets, Physica A 346 (3) (2005) 577–588.
[44] A. Fisher, L. Calvet, B. Mandelbrot, Multifractality of Deutschemark/US dollar exchange rates, in: Cowles Foundation Discussion Paper, 2007. http://users.math.yale.edu/users/mandelbrot/web_pdfs/Cowles1166.pdf.
[45] M. Pasquini, M. Serva, Multiscale behaviour of volatility autocorrelations in a financial market, Econom. Lett. 65 (3) (1999) 275–279.
[46] J. Kwapień, P. Oświe, S. Drożdż, Components of multifractality in high-frequency stock returns, Physica A 350 (2) (2005) 466–474.
[47] P. Oświęcimka, J. Kwapień, S. Drożdż, Multifractality in the stock market: price increments versus waiting times, Physica A 347 (2005) 626–638.
[48] D. Grech, Z. Mazur, Can one make any crash prediction in finance using the local Hurst exponent idea? Physica A 336 (1) (2004) 133–145.
[49] D.O. Cajueiro, B.M. Tabak, The Hurst exponent over time: testing the assertion that emerging markets are becoming more efficient, Physica A 336 (2) (2004) 521–537.
[50] D.O. Cajueiro, B.M. Tabak, Evidence of long range dependence in Asian equity markets: the role of liquidity and market restrictions, Physica A 342 (3) (2004) 656–664.
[51] D.O. Cajueiro, B.M. Tabak, Ranking efficiency for emerging markets, Chaos Solitons Fractals 22 (2) (2004) 349–352.
[52] J. Alvarez-Ramirez, J. Alvarez, E. Rodriguez, G. Fernandez-Anaya, Time-varying Hurst exponent for US stock markets, Physica A 387 (24) (2008) 6159–6169.
[53] S.R. Bentes, R. Menezes, D.A. Mendes, Long memory and volatility clustering: Is the empirical evidence consistent across stock markets? Physica A 387 (15) (2008) 3826–3830.
[54] S. Saadi, D. Gandhi, S. Dutta, Testing for nonlinearity & Modeling volatility in emerging capital markets: The case of Tunisia, Int. J. Theor. Appl. Finance 9 (07) (2006) 1021–1050.
[55] S.J.H. Shahzad, S.M. Nor, S. Hammoudeh, M. Shahbaz, Directional and bidirectional causality between US industry credit and stock markets and their determinants, Int. Rev. Econ. Finance 47 (2016) 46–61.
[56] F. Kiesel, S. Kolaric, D. Schiereck, Market integration and efficiency of CDS and equity markets, Quart. Rev. Econ. Finance 61 (2016) 209–229.
[57] B.M. Tabak, R. Miranda, M.M. Junior, Contagion in CDS, banking and equity markets, Econ. Syst. 40 (2016) 120–134.
[58] R.C. Merton, On the pricing of corporate debt: The risk structure of interest rates, J. Finance 29 (2) (1974) 449–470.
[59] P. Collin-Dufresne, R.S. Goldstein, J.S. Martin, The determinants of credit spread changes, J. Finance 56 (6) (2001) 2177–2207.
[60] R. Blanco, S. Brennan, I.W. Marsh, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, J. Finance 60 (5) (2005) 2255–2281.
[61] N. Kapadia, X. Pu, Limited arbitrage between equity and credit markets, J. Financ. Econ. 105 (3) (2012) 542–564.
[62] B. Podobnik, H.E. Stanley, Detrended cross-correlation analysis: a new method for analyzing two nonstationary time series, Phys. Rev. Lett. 100 (8) (2008) 084102.
[63] B. Podobnik, D. Horvatic, A.M. Petersen, H.E. Stanley, Cross-correlations between volume change and price change, Proc. Natl. Acad. Sci. 106 (52) (2009) 22079–22084.
[64] I. Gvozdanovic, B. Podobnik, D. Wang, H.E. Stanley, 1/f behavior in cross-correlations between absolute returns in a US market, Physica A 391 (2012) 2860–2866.
[65] W.X. Zhou, Multifractal detrended cross-correlation analysis for two nonstationary signals, Phys. Rev. E 77 (6) (2008) 066211.
[66] G.A. Darbellay, D. Wuertz, The entropy as a tool for analysing statistical dependences in financial time series, Physica A 287 (2) (2000) 429–439.
[67] G.F. Zebende, DCCA cross-correlation coefficient: quantifying level of cross-correlation, Physica A 390 (4) (2011) 614–618.
[68] J.W. Kantelhardt, S.A. Zschiegner, E. Koscielny-Bunde, S. Havlin, A. Bunde, H.E. Stanley, Multifractal detrended fluctuation analysis of nonstationary time series, Physica A 316 (1) (2002) 87–114.
[69] L. Yang, Y. Zhu, Y. Wang, Multifractal characterization of energy stocks in China: A multifractal detrended fluctuation analysis, Physica A 451 (2016) 357–365.
[70] H. Zhao, S. He, Analysis of speech signals' characteristics based on MF-DFA with moving overlapping windows, Physica A 442 (2016) 343–349.
[71] X. Zhuang, Y. Wei, F. Ma, Multifractality, efficiency analysis of Chinese stock market and its cross-correlation with WTI crude oil price, Physica A 430 (2015) 101–113.
[72] M.Y. Bai, H.B. Zhu, Power law and multiscaling properties of the Chinese stock market, Physica A 389 (9) (2010) 1883–1890.
[73] D.O. Cajueiro, P. Gogas, B.M. Tabak, Does financial market liberalization increase the degree of market efficiency? The case of the Athens stock exchange, Int. Rev. Financ. Anal. 18 (1) (2009) 50–57.
[74] B. Podobnik, Z.Q. Jiang, W.X. Zhou, H.E. Stanley, Statistical tests for power-law cross-correlated processes, Phys. Rev. E 84 (6) (2011) 066118.
[75] S.J.H. Shahzad, S.M. Nor, R.R. Kumar, W. Mensi, Interdependence and contagion among industry-level US credit markets: An application of wavelet and VMD based copula approaches, Physica A 466 (2017) 310–324.