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Full Length Article

Dynamic model for hedging of the European stock sector with credit default swaps and EURO STOXX 50 volatility index futures

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Abstract

In this paper, the time-varying correlations are estimated for the purpose of examining whether CDS can act as a hedge and safe haven for the European stock sectors. Similarly, the implications for portfolio design are also evaluated on daily and weekly data span bases, concerning the period ranging from December 2007 to September 2017. Overall, the empirical results appear to reveal that the safe haven roles associated with the CDS and the portfolio design prove to differ noticeably across the time horizons as well as from one model to another. Likewise, choosing CDS or VSTOXX futures as hedging instrument seem to depend heavily on data frequency and the models applied. The interest lying behind the conduction of such a study is twofold: on the one hand, it should serve as a guide to investors through enabling them to opt for the most effective strategies useful for hedging the stock sectors' relating risks and, on the other hand, to highlight the models' specifications associated impacts.

JEL classification: C32; C58; G11; G15

Keywords: CDS index; VSTOXX futures; Stock sector; DCC; ADCC; Hedge-safe haven; Optimal hedge ratios; Portfolio variance

1. Introduction

It is worth stating that the global financial crisis of 2007−2008 along with the European debt crisis of 2010−2011 have culminated in a significant increased in stock market volatility and portfolio investment associated risk. Triggered by the Lehman Brother collapse in September 2008, the stream of shocks went on to involve several European markets including the equity markets. In fact, a sovereign credit rating downgrade has proved to remarkably affect stock markets through negatively impacting securities' prices and investor related confidence. Consequently, managed portfolio performances have turned out to be seriously affected by both of the equity and bond markets' associated falls, with negative influences on the investor being perceived throughout the financial crisis period (Kaminsky and Schmukler (2002)). As a result, investors turned out to look for effective ways whereby the investment related risks could be minimized in a bid to find defensive diversification strategy likely to help them invest in safe haven assets.

In this respect, some studies have been conducted to examine the dynamic correlations binding two distinct assets, such as gold and equity, in order to evaluate the role of gold as a hedging asset against equity risk. Other studies have undertaken to test the hypothesis stipulating that gold is a safe haven for financial assets. Hence, safe havens turnout to be the most sought after portfolio assets by investors, who seek to protect their portfolios through abandoning their risky assets and targeting the risk-free assets or safe havens. In this regard, a clear distinction should be made between the hedge and safe haven types of assets. Following Baur and Lucey (2010), an asset is considered to stand as an effective hedge once it proves to be uncorrelated or negatively correlated to stock price movements

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on average, where as a safe haven asset is that which is consistently uncorrelated or negatively correlated to stock price movements during times of market turmoil. In the literature, several studies have been noted to consider gold to stand as an effective means to hedge against stocks on average and as a safe haven during times of stress. Worth citing among these studies are those conducting by Baur and Lucey (2010), Baur and McDermott (2010), Coudert and Raymond (2011), Ratner and Chiu (2013), Kumar (2014), etc. In a more recent study conducted by Arouri, Lahiani, and Nguyen (2015), the authors have undertaken to explore both of the return and volatility spillovers persistent between the stock market and gold prices within the Chinese context, through implementation of the VAR-GARCH model. Their reached results appear to reveal the persistence of a significant return and volatility transmission between the gold prices and stock market in China. They have also discovered that on adding gold to that stocks' portfolio of stocks decreases in portfolio risk and improvements in hedging against stock risk appear to be perceived.

Following the same line of thought, the present work is dedicated to check whether the CDS could well stand as a potentially useful hedging tool providing a safe haven for the stock sector market. In this context, investigating of the links persisting between the CDS and the European stock markets is necessary in terms of hedging and portfolio risk management. This necessity stems actually from the negative correlations prevailing between these both modes of investment. Indeed, risk managers, investors and portfolio managers consider that the portfolio associated risk would be diversified if a portfolio of negatively correlated assets could be assembled. For this reason, a combination of CDS and European stock market assets in the management of portfolio risk turns out to be beneficial in terms of portfolio risk reduction. In this study, we consider that credit default swap (CDS) may well stand as a insurance against default risk, whereby, a positive correlation between stock returns and default risk implies that CDS would provide potential insurance benefits to stock investors. In this regard, Calice, Chen, and Williams (2013) document that the CDS represents in itself a hedge against stock risk. In turn, Caporin (2013) add that the CDS can be used as a hedging strategy against stock sector related risk as stemming from the bond markets associated crisis. Consequently, an individual or company exposed to a high degree of credit risk can shift some of that risk by buying protection in a CDS type of contract. This option may well stand as a preferable solution to selling the security outright should the investor apt for reducing exposure rather than eliminating it, or just eliminating exposure for a certain time of period.

Nevertheless, hedging the stock sector related risk might not represent an optimal, or entirely efficient solution, especially during the stock market extreme period, since CDS indices can be considered as monitors of bond or credit risks, likely to react to the bond market attached turbulences. Hence, it is plausible to look for a rather efficient instrument whereby the stock sector related risk can be hedged once the turbulence appears to emerge from the equity market. Indeed, the volatility index stands as the most effective indicator available helping to capture the equity markets pulse. In principle, the VSTOXX index helps to capture the equity risk as a whole, since it relies heavily on equity based options. Noteworthy, however, is that the VSTOXX refers to the entire market level, with no reference being available at the sectoral level. Furthermore, it is most often characterized with a non-quick response to shocks of non-equity market origin. In so far as the present work is concerned, however, the focus of interest is laid on the sectoral indices, for the major reason that they allow for a finer comparison of the CDS related hedging properties across economic sectors. Indeed, one might well postulate that default and credit risks appear to be more remarkably relevant to the financial, insurance, and banking sectors in respect of their potential effect on the consumer-related sectors (e.g., retail and travel). Moreover, the sector-level based analysis could also further confirm, through indirectly, the systemic effect of market turbulences as observed over the recent years. Actually, the volatility index relating trends are widely known to be negatively correlated with the equity index returns (Whaley (1993)). The implication of this specifically unique relationship lies in the fact that the volatility index turns out to provide enhanced capabilities for risk diversification and protection against downside risk (see: Bowler, Ebens, Davi, and Kolanovic (2003); Black (2006); Moran and Dash (2007)). Nevertheless, the VSTOXX is, in itself, not directly tradable, for only derivatives on the VSTOXX can be traded. As part of this study, also, is a proposal to add the VSTOXX futures as a further dimension for designing a hedging strategy concerning the case in which the turbulence prove to stem from the stock market, as an alternative to the CDS. Actually, the established comparison rests on the potential benefits associated with the application of the CDS indices and/or VSTOXX futures as attached to each separate stock sector. In effect, the major significant benefit likely to be drawn from implementing the CDS indices, as compared to the VSTOXX futures, resides in the fact that they not only involve sector-specific features, but can also act as indicators of the global impact of the bond and interest markets' shocks on the equity market. The latter's choice has its justification in the nature of the relationship binding both indices. As volatility tends to rise with the decline in equities, a long volatile future position could well be taken for a hedge.

The objective targeted by the present study is three fold. In a first place, an investigation of the dynamic correlation between the CDS and stock sectors is undertaken in order to assess the CDS role in acting as a potential tool for hedging or maintaining a safe haven in the European stock sectors. In this context, a particular attention is paid to the 2008 financial crisis. Above all, a particular interest is placed on checking whether the cited financial crisis has contributed in consolidating or disrupting the association binding both markets. In a second place, the focus of interest is placed on the implications of this dynamic correlation on portfolio hedge and its role in decreasing portfolio risk. In a third place, a comparison is established between CDS and VSTOXX futures in terms of portfolio variance minimization. Overall, such a study is of great use for the equity investors intending to hedge the equity associated risk by enabling them to take positions either in favor of the CDS indices or favoring the VSTOXX futures. The remainder of this paper is organized as follows. Section 2 is dedicated to provide a review of the relevant literature. As for section 3, it depicts the applied methodology and implemented models' specifications. Regarding section 4, it displays the applied data, while section 5 encloses the empirical analysis. Finally, section 6 is devoted to conclude the conducted study.

2. Literature review

This paper's contribution to the existing literature is twofold. In a first stage, we propose to investigate the recently conducted literature documenting the link binding default risk and stock returns. In a second stage, we undertake to review the relevant papers focusing directly on the equity market's hedging role. Actually, the initial investigation studies dealing with credit risk and stocks has been conducted by Black and Scholes (1973). The contingent-claims analysis model originally introduced by Merton (1974) has later been expanded by Black and Cox (1976), Leland (1994), Longstaff and Schwartz (1995), and Collin-Dufresne and Goldstein (2001). As for the present, and primarily motivated by the recently elaborated literature dealing with the linkage associating default risk and stock returns, it has been discovered that several authors appear to investigate

Table 1
Previous research on studies of the relationships between default risk and stock return.

Authors	Objective	Methodology	Main findings
Longstaff, Longstaff, Mithal, and Neis (2003)	The authors investigate the lead-lag relationship between changes in single-name CDS spreads, changes in bond spreads and stock returns.	Period: 2000 to 2001 Model: closed-form model for credit-default swap premia	The results indicate that stock markets and CDS markets led corporate bond markets.
Zhu (2006)	The authors examine the relationship between CDS markets, stock markets and bond markets.	Period: 1999 to 2002 Model: Cointegration test, Granger causality test, VECM and panel data regression.	This paper finds that CDS markets lead bond markets in the long-term, but the short-term relationship shows substantial deviation from theory.
Fung, Sierra, Yau, and Zhang (2008)	The authors analyze the link between stock (S&P 500) and CDS markets.	Period: 2001 to 2007 Model: Vector Autoregression	This paper proves that the CDS market plays a more significant role in volatility spillover than the stock market.
Alexander and Kaeck (2008)	This paper examines the empirical influence of a wider set of theoretical determinants of CDS spreads on the daily changes in iTraxx Europe.	Period: 2004 to 2007 Model: Linear regression, Markov switching	The authors find that the theoretical determinants of structural credit risk models, i.e. interest rates, stock returns and implied volatility each has a significant effect on CDS spreads. However, only about 20−30% of the variation in credit spreads can be explained and most of the unexplained variation is due to a systematic factor.
Carr and Wu (2009)	The authors examine the link between stock return and CDS.	Period: 2002 to 2004 Model: Marcov process	This paper confirms the link between market risk, as measured by stock return variance, and credit risk indicated by default arrival in their pricing model of stock options and CDS.
Norden and Weber (2009)	This paper examines the lead/lag relationships between CDS markets, bond markets, and stock markets.	Period: 2002 to 2002 Model: Vector autoregressive	The authors demonstrate that stocks lead both CDS and bonds. They reveal also that CDS Granger-cause bonds more than bonds Granger-cause CDS.
Avramov, Chordia, Jostova, and Philipov (2009)	This paper examines the link between CDS and stock prices.	Period: 2000 to 2007 Model: CAPM	This paper proves that the effects of rating downgrades on stock prices and CDS spreads are higher amid financially distressed firms.
Zhang, Zhou, and Zhu (2009)	The author examines the relationship between CDS market and stock market.	Period: 2001 to 2003 Model: OLS regressions	The findings indicate that CDS spreads anticipate credit quality deterioration before stock markets.
Wang and Bhar (2014)	This paper focuses on the information spillover between the Credit protection returns and Equity returns for US firm.	Period: 2004 to 2010 Model: Panel regression	These results show that credit protection returns are more sensitive to contemporaneous equity return if credit deterioration is detected in the CDS market on the previous day.
Narayan (2015)	This paper test for spillover effects from the CDS spread and sectoral returns.	Period: 2004 to 2012 Model: VAR	The authors find that CDS return shocks are important in explaining the forecast error variance of sectoral equity returns for the USA.
Kiesel, Kolaric, and Schiereck (2016)	This paper tests the market integration and efficiency of CDS and equity markets.	Period: 2010 to 2013 Model: Panel regression	These results indicate that stock markets react prior to CDS markets, anticipating credit events to a certain extent.

the relationships binding both sectors, as illustrated through Table 1.

Subsequently, and as depicted on Table 2, a review of relevant papers dealing directly with the issue of hedging in the equity market is outlined.

Very few, however, are those studies which have been interested in investigating the CDS market relating aspects, either as a hedge and/or as a safe haven against stock sector returns in Europe. In this regard, Calice et al. (2013) conducted work stands as the single academic research paper elaborated to investigate the CDS as a potential stock hedge, in which a single name corporate CDS data is applied as a sample representing the U.S context. The study concludes that an effective holding of basket of CDS helps greatly in reducing both of the default and capital associated risks. The authors also highlighted that CDS are not priced as a linear combination of alternative assets and that they stand as unique financial assets bearing strong and persistent negative correlations with stocks. They have ultimately reached the conclusion that holding CDS without exposure to the actual reference entity (a naked CDS) constitutes a significant partial hedge against stocks, commodities, and foreign exchange investments.

Table 2
Previous research on studies that focus on hedging in the equity market.

Authors	Objective	Methodology	Main findings
Arouri, Jouini, and Nguyen (2011a)	This paper investigate volatility spillovers between oil and stock market sectors in the US and Europe.	Period: 1998 to 2009 Model: bivariate GARCH	The authors find evidence of a spillover effect from oil to stock markets in Europe and a bidirectional spillover effect between oil and US stock market sectors.
Arouri, Lahiani, and Nguyen (2011b)	The authors determine return and volatility transmission between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries.	Period: 2005 to 2010 Model: bivariate GARCH	This work finds evidence of spillovers between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries.
Arouri, Jouini, and Nguyen (2012)	The authors model volatility dynamics between European equity markets and oil.	Period: 1998 to 2009 Model: VAR-GARCH	This paper finds evidence of volatility spillovers between oil prices and sector stock returns.
Sadorsky (2012)	This paper investigates volatility dynamics between the stock prices of clean energy companies, technology companies and oil prices.	Period: 2001 to 2010 Model: multivariate GARCH(1,1)	The author finds that the stock prices of clean energy companies correlates more highly with technology stock prices than with oil prices.
Lin, Wesseh, and Appiah (2014)	The authors investigate the dynamic volatility and volatility transmission between oil and Ghanaian stock market returns in a multivariate setting.	Period: 2000 to 2013 Model: VAR-GARCH, VAR-AGARCH and DCC-GARCH	The findings point to the existence of significant volatility spillover and interdependence between oil and the stock markets returns. Also, the spillover effects are stronger for Nigeria, the transmission of volatility is much more apparent from oil to stock than from stock to oil in the case of Ghana.
Sadorsky (2014a)	The authors study the volatility dynamics between emerging market stock prices, oil prices, copper prices, and wheat prices.	Period: 2000 to 2012 Model: multivariate GARCH	The findings indicate that, on average, oil provides the cheapest hedge for emerging market stock prices while copper is the most expensive but since the hedge ratios display considerable variability, these hedges should be routinely monitored and updated is necessary.
Sadorsky (2014b)	The authors model volatility and conditional correlations between the Dow Jones socially responsible investment (SRI) equity portfolio, gold and oil.	Period: 2000 to 2012 Model: DCC and CCC GARCH	This work proves that the SRI share similar statistical properties with the S&P 500 and as a result, SRI investors can expect to pay a similar amount to hedge their investment with oil or gold as investors in the S&P 500.
Basher and Sadorsky (2016)	This paper model volatilities and conditional correlations between emerging market stock prices, oil prices, VIX, gold prices and bond prices.	Period: 2000 to 2014 Model: DCC, ADCC and GO-GARCH	The authors find that the oil is the best as set to hedge emerging market stock prices. Hedge ratios from the ADCC model are preferred (most effective) for hedging emerging market stock prices with oil, VIX, or bonds. Hedge ratios estimated from the GO-GARCH are most effective for hedging emerging market stock prices with gold in some instances.

3. Methodology

3.1. The dynamic conditional correlation (DCC) model

In this context, appeal is made to the multivariate Dynamic Conditional Correlation (DCC) model, as introduced by Engle (2002), as it helps remarkably in capturing the time-varying and dynamic relationships via return series with minimum computational sophistications. In this sense, the DCC model is used for a direct parameterization of the conditional correlation, as it helps maintain the flexibility of a univariate GARCH model (Engle, 2002). In this context, and given the large number of return series, the DCC model is implemented for the purpose of separately estimating the return series' pairs, rather than a simultaneous estimation of the return series.

Accordingly, modeling the dynamics correlations and volatilities could be achieved through decomposing the conditional covariance matrix as follows:

Let r_t be an $n\ x\ 1$ vector of asset returns. An AR (1) process for r_t , as conditional on the information set I_{t-1}can be written as:

$$r_t = \mu + ar_{t-1} + \varepsilon_t \tag{1}$$

The residuals are modeled in the form of:

$$\varepsilon_t = H_t^{1/2} z_t \tag{2}$$

H_t is the conditional covariance matrix of r_t and z_t is a $n\ x\ 1$ i.i.d random vector of errors.

The estimation of the Engle (2002) dynamic conditional correlation (DCC) model involves two main steps. In the first step, the GARCH parameters are estimated, while the second step involves estimating the conditional correlations such as:

$$H_t = D_t R_t D_t \tag{3}$$

H_t is a $n\ x\ n$ conditional covariance matrix, R_t is the conditional correlation matrix, and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag\left(H_t^{1/2}\right) \tag{4}$$

The expressions of h are univariate GARCH models (with H is a diagonal matrix). Concerning the GARCH (1,1) model, the elements of H_t can be written as:

$$h_t = \omega + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}^2 \tag{5}$$

With Q_t is a symmetric positive definite matrix.

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1} z_{t-1}' + \theta_2 Q_{t-1} \tag{6}$$

where $\overline{Q}$ is the nxn unconditional correlation matrix of the standardized residuals $z_{i,t}$.where

$$z_{i,t} = \varepsilon_{i,t} \Big/ \sqrt{h_{i,t}} \tag{7}$$

The parameters θ_1 and θ_2 are non-negative, and are associated with the exponential smoothing process as used to construct the dynamic conditional correlations. The DCC model is mean reverting as long as $\theta_1 + \theta_2 < 1$. The correlation estimator turns out to be:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,jt}}} \tag{8}$$

3.2. The asymmetric dynamic conditional correlation (ADCC) model

More generally, the Asymmetric DCC-GARCH model serves to assume both sets of negative and positive news bearing symmetric effects on the variance and conditional correlations. As for, Cappiello, Engle, and Sheppard (2006), the presence of asymmetric responses has been perceived to persist in variances conditional to negative returns. For the purpose of achieving accurate conditional correlations of stock returns, the asymmetry effect need be carefully accounted for. Consequently, we consider opting for the Asymmetric DCC-GARCH model. For the purpose of investigating the conditional correlations between the stock sector and CDS indices.

Reeling on the DCC model and the asymmetric GARCH model of Glosten, Jagannathan, and Runkle (1993), Cappiello et al. (2006) have farther extended this models by inserting an asymmetric term, thus, devising the Asymmetric DCC (ADCC) model such as:

$$h_{i,t} = \omega_i + a_1 \varepsilon_{i,t-1}^2 + b_1 h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1}) \tag{9}$$

The indicator function $I(\varepsilon_{i,t-1})$is equal to one if $\varepsilon_{i,t-1} < 0$, and to 0 otherwise. In terms of this specification, a positive value for d should denote that negative residuals tend to increase the variance more than the positive ones do. The asymmetric effect or "leverage effect" is designed to capture an often observed characteristic of financial assets, namely, that an unexpected drop in asset prices tends to increase volatility more than an unexpected increase in asset prices of the same magnitude. This fact could well denote that bad news increasing volatility more than the good news do.

Concerning the ADCC model, the Q associated dynamics are given by:

$$Q_t = \left(\overline{Q} - A'^{\overline{Q}}A - B'^{\overline{Q}}B - G'^{\overline{Q}^-}G\right) + A'^{z_{t-1}z_{t-1}'}A + B'^{Q_{t-1}}B + G' z_t^- z_t'^- G \tag{10}$$

In the above equation A, B and G are $n\ x\ n$ parameter matrices, and z_t^- are zero-threshold standardized errors which are equal to z_t when less than zero, and zero otherwise. $\overline{Q}$ and $\overline{Q}^-$ are the unconditional matrices of z_t and z_t^- , respectively.

3.3. The regression models

Two models are implemented to test the CDS as a hedge and safe haven against stock sector risk, following the same methodology as applied by Baur and McDermott (2010). While, the first model is used to examine the hedging and safe haven characteristics of CDS over stock market volatility periods, the second model is focused on the CDS hedging and safe haven properties throughout the U.S. financial crisis. Retracing the steps undertaken by Baur and McDermott (2010), we consider estimating of the correlation coefficient $\rho_t$via an autoregressive two-step model in a bid to test whether the CDS indices would act as a hedge and/or safe haven against stock market risks. Thus, the first model will serve to examine the CDS hedging and safe haven characteristics during periods of extreme stock market volatility in the following way:

$$\rho_t = \gamma_0 + \gamma_1 D(r_{action} q_{10}) + \gamma_2 D(r_{action} q_5) + \gamma_3 D(r_{action} q_1) \tag{11}$$

where D represents the dummy variables helping to capture the extreme movements in the underlying stock sectors at the 10%, 5%, and 1% quantiles of the most negative stock returns.

In effect, the CDS would act as a weak hedge if γ_0 is zero and as a strong hedge in case γ_0 proves to be negative, thus, standing as significant for the individual sector. Still, the CDS turns out to be a weak safe haven once the γ_1, γ_2, or γ_3 coefficients appear to be negative and non significant and a strong safe haven in case they prove to be negative and significant. Accordingly, the CDS should not represent a safe haven in case the γ_1, γ_2, or γ_3 coefficients turn out to be positive.

As for the second model, it serves to deal with the CDS hedging and safe haven properties with respect to the U.S. financial crisis, according to the following formula:

$$\rho_t = \gamma_0 + \gamma_1 D(\textit{financial crisis}) \tag{12}$$

where a dummy variable is set to one to represent the U.S. financial crisis during the period starting on September the 9th, 2008 and continues over 20 trading days.[1]

Indeed, the CDS will represent a weak hedge if γ_0 appears to be statistically insignificant from zero, and a strong hedge once γ_0 turns out to be negative and significant with respect to the individual sectors. So, the CDS will prove to be a weak safe haven if γ_1 appears to be statistically negative and non significant, and a strong safe haven in case γ_1 proves to be negative and significant with regard to the individual sectors. Besides, the CDS will not stand as a safe haven once γ_1 turns out to be positive.

4. Data description

Concerning the present study, eleven European activity sectors have been selected to form the study sample, as illustrated on Table 3, below.

Table 3
List of selected industrial sectors.

Oil & Gas	Basic materials	Industrial	Bank
Consumer goods	Telecom	Technology	Other financial services
Utilities	Consumer services	Insurance	

The CDS related index data are matched with the corresponding stock sector index data on the basis of market sector. Daily and weekly data concerning the entirety of series are derived from Datastream concerning the period ranging from December 14, 2007 and September 11, 2017 making up a total of 2542 observations. As for, the CDS index data, they consist of midmarket prices concerning the five-year contracts relevant to each single sector. The five-year CDS indices have been opted for given the fact that they are the most frequently traded in the indices' markets, with maturities ranging from one to ten years. Additionally, the VSTOXX futures have also been downloaded for they represent a major possible hedging instrument most often applied to offset equity volatility. Table 4, below, depicts a summary of the return series statistics relevant to the variables under review.

As indicated by in Panel A of Table 4, the CDS appears to bear the highest daily mean and volatility levels. The entirety of the return series are discovered to be leptokurtic, characterized with an asymmetrical type of distribution, as skewness appears to be either positive or negative. In consistence with the findings published by Black and Cox (1976), all CDS and stock returns prove to display a fat or heavy distribution tail (leptokurtic), since kurtosis is discovered to be positive (greater than 3). As for the weekly returns summary statistics, Panel B of Table 4 appears to reveal well that the CDS prove to maintain the highest levels of weekly mean and volatility. Moreover, the entirety of the assets associated kurtosis prove to be significantly decreased. Additionally, as can be noted on the basis of Table 4, the asymmetry marking the return distribution is also sustained by the Jacque−Berra statistics, which helps test the nullity of normal distribution. This nullity is decisively rejected due mainly to the high value significance associated with the JB statistics (All P-values are equal to zero). Moreover, as postulated by Merton (1974), along with Campbell and Taskler (2003), the CDS related premium and equity prices appear to display a negative correlation, denoting that as credit risk increases, equity prices appear to decline. These preliminary results partly justify the need for a nonlinear modeling, highlighting that a stationary condition approves to be imposed with respect to the entirety of the variables. This could be verified by the unit root test (ADF), as all the variables appear to be stationary in 1.

5. Empirical results

5.1. Extraction of residues from the ARMA (1,1) -TGARCH (1,1) model

The ARMA model is the tool applied to highlight the financial return series' tendencies and behavior, and predicting possible future values. As for the AR section is focused on regressing the variable (daily returns) on its own historical values. Then, the MA part is modeled after the standard deviation (error) in the form of a linear combination

[1] Baur and McDermott (2010) identify the start of the U.S. financial crisis with the collapse of Lehman Brothers in September 2008, and maintain an "effect" window of 20 trading days.

Table 4
Summary statistics.

	Mean	Min	Max	St.dev.	Skewness	kurtosis
Panel A: Daily returns						
Oil & Gas:						
CDS	0.0001	−0.5915	0.6978	0.0364	1.0535	90.0195
Equity	−0.0002	−0.1143	0.1466	0.01744	−0.0460	7.5045
Consumer services:						
CDS	−0.0002	−0.8235	0.7083	0.0327	−1.9481	252.7790
Equity	$-1.789.10^{-5}$	$-1.024.10^{-1}$	$8.746.10^{-2}$	0.0136	−0.2993	16.34260
Basic materials:						
CDS	−0.0002	−0.32906	0.3341	0.0292	0.0248	21.0455
Equity	$-1.085.10^{-4}$	$-1.372.10^{-1}$	$1.504.10^{-1}$	0.0209	−0.1527	7.0620
Telecom:						
CDS	−0.0001	−0.5070	0.6088	0.0508	0.5589	52.1960
Equity	$-1.085.10^{-4}$	$-1.118.10^{-1}$	$1.504.10^{-1}$	0.0144	−0.1049	7.8898
Industrial:						
CDS	0.0001	−0.6721	0.6703	0.0351	−0.1436	201.0667
Equity	$5.328.10^{-5}$	$-1.004.10^{-1}$	$1.022.10^{-1}$	0.0161	−0.2261	5.5213
Utilities:						
CDS	0.0001	−0.2816	0.1830	0.0304	−0.1141	7.8086
Equity	−0.00032	0.1440	0.1440	0.0150	−0.0514	9.3118
Consumer goods:						
CDS	$3.030.10^{-6}$	$-2.170.10^{-1}$	$2.612.10^{-1}$	0.0215	0.6907	25.2795
Equity	0.0002	−0.0813	0.1985	0.0141	−0.8529	18.7522
Technology:						
CDS	−0.0001	−0.2527	0.4214	0.0285	1.0222	25.1028
Equity	0.0001	−0.1211	0.1040	0.0159	−0.3178	6.1726
Insurance:						
CDS	−0.0001	−0.7932	0.2615	0.0393	−3.2337	69.2242
Equity	$-6.745.10^{-5}$	$-1.463.10^{-1}$	$1.286.10^{-1}$	0.0193	−0.0629	7.4476
Bank:						
CDS	0.0002	−0.7144	0.7071	0.0528	−0.2500	48.2917
Equity	$-4.149.10^{-4}$	$-1.739.10^{-1}$	$1.503.10^{-1}$	0.0217	−0.0823	7.1929
Other financial services:						
CDS	−0.0002	−1.3227	1.4083	0.0911	0.5201	136.0265
Equity	$-1.139.10^{-5}$	$-1.034.10^{-1}$	$1.071.10^{-1}$	0.0151	−0.3610	67.4263
Panel B: Weekly returns						
Oil & Gas:						
CDS	0.0005	−0.3607	0.3822	0.0784	0.1735	5.4755
Equity	−0.0010	−0.2699	0.1607	0.0379	−0.8210	6.8929
Consumer services:						
CDS	−0.0008	−0.8797	0.6828	0.0730	−1.7276	55.3615
Equity	−0.0001	−0.2203	0.1071	0.0296	−1.1904	7.4282
Basic materials:						
CDS	−0.0007	−0.3965	0.3527	0.0661	0.2444	5.6384
Equity	−0.0005	−0.2798	0.1875	0.0452	−0.7050	5.0397
Telecom:						
CDS	−0.0003	−0.5590	0.4593	0.0795	−0.0016	9.8116
Equity	−0.0009	−0.2414	0.1124	0.0303	−1.3413	9.1868
Industrial:						
CDS	0.0006	−0.6197	0.6794	0.0715	0.4668	28.5812
Equity	0.0002	−0.2146	0.1397	0.0352	−0.9161	4.8950
Utilities:						
CDS	−0.3277	0.0005	0.4418	0.0776	0.4350	4.9846
Equity	−0.0016	−0.3049	0.1114	0.0335	−1.7194	13.664
Consumer goods:						
CDS	$4.502.10^{-5}$	$-2.146.10^{-1}$	$2.686.10^{-1}$	0.0467	0.7753	6.0701
Equity	0.0009	−0.1936	0.1859	0.0305	−0.8024	7.9541
Technology:						
CDS	−0.0002	−0.3038	0.4460	0.0680	0.8784	5.1904
Equity	0.0004	−0.2432	0.1206	0.0338	−1.1378	6.5766
Insurance:						
CDS	0.0001	−0.7244	0.4052	0.0920	−0.7680	7.8845
Equity	−0.0003	−0.2827	0.1660	0.0426	−1.0127	6.0035

Table 4 (*continued*)

	Mean	Min	Max	St.dev.	Skewness	kurtosis
Bank:						
CDS	0.0011	−0.4304	0.4453	0.0820	0.1235	6.8352
Equity	−0.0020	−0.3211	0.1743	0.0492	−0.9875	5.6838
Other financial services:						
CDS	−0.0010	−1.2148	1.2175	0.1105	−0.0272	59.1789
Equity	$-7.931.10^{-5}$	$-2.533.10^{-1}$	$1.083.10^{-1}$	0.0333	−1.4308	8.0703

of standard deviations (errors) happening contemporaneously and at various past times.

The notation ARMA (p, q) refers to the model with p designating the autoregressive terms and q the moving-average terms. This model simultaneously incorporates both of the AR (p) and MA (q) models.

$$d_t = C + \sum_{i=1}^{P} \varphi_i d_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{13}$$

Regarding the financial returns' series, a preferable choice to model the marginal lies in applying the TGARCH (Threshold Generalized Autoregressive Conditional Heteroskedasticity). The latter allows for capturing asymmetries in terms of negative and positive shocks (Zakoian (1994), Glosten et al. (1993)). It is worth noting that the non-stationary TGARCH models helps in simultaneously capturing the non-stationarity and asymmetry of the time series' data volatility. This motivates us to study the estimation of the TGARCH models related problem of non-stationary, once the errors turn out to be either skewed or leptokurtic.

Let us consider the TGARCH (m,s) model as defined by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s} (\alpha_i + \gamma_i N_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2 \tag{14}$$

Based on Table 5, the estimated parameters of the equation of ARMA (1,1)-TGARCH (1,1) and asymmetry are significant at the 5% level with respect to all series, confirming the existence of a continuous volatility throughout the entire period. Furthermore, the Ljung-Box statistics are used to test the non-autocorrelation hypothesis of order 12. Actually, the gains statistics of Ljung-Box (Q (12) and Q^2 (12)) are discovered to be greater than 0.05, thus, rejecting the null hypothesis concerning the presence of auto-correlation in the first and second order at a confidence level of 95%. To note, the number of lags relevant to each series mean and variance equations has been determined in conformity with the Akaike information criteria[2] (AIC). Accordingly, the minimum AIC value appears to indicate well that the ARMA (1,1)-GARCH (1,1) model turn out to be the most appropriately fit for our study case.

5.2. The CDS hedge and safe haven properties

Two models are actually implanted to test the CDS properties as a hedge and/or safe haven against stock sector risk, following the same methodology applied by Baur and McDermott (2010). The first model serves to examine the CDS hedging and safe haven characteristics during the periods of extreme stock-market volatility. As for the second model, it helps to determine the CDS hedging and safe haven properties over the U.S. financial crisis.

Table 6 depicts the regression estimates as based on model (12), whereby the DCC and ADCC coefficients ρ_t are regressed on a constant and on three dummy variables, representing levels of extreme stock volatility quantiles of 10%, 5% and 1% of the most negative stock returns associated with each sector. The "hedge" column, which represents the model constant(γ_0), proves to reveal the predominance of a negative relationship between CDS and stock returns with respect to each sector with a noticeable significance being perceived at the 1% level. The persistence of a significant negative value appears to indicate well that the CDS prove to stand as a strong hedge against the stock sector related risk. Even though strong hedging properties are demonstrated across the entirety of sectors, the CDS relating benefits appear to vary in terms of sectors, data frequency and method. Panel A of Table 6 presents the coefficient estimates relevant to the daily data concerning the DCC and ADCC models. As for the Panel B, it illustrates the same estimates and models with respect to weekly data. Relying on the definitions of a hedge and safe haven, the following daily and weekly analyses' pertaining results are reported with respect to both of the DCC and ADCC models.

5.2.1. Daily analysis

The "hedge" column figuring on Panel A of Table 6 represents the model's constant $(\boldsymbol{\gamma}_0)$, which highlights the persistence of a negative relationship between the CDS and the European stock indexes concerning each sector and with respect to the DCC and ADCC models, with a noticeable significance being perceived at the 1% level. Despite the strong hedging properties perceived across all the sectors, the CDS attached benefits appear to vary among the sectors. For instance, at the level of the Oil&Gas sector, the CDS proves to record the value of (−0.4592) marking the most negative hedge value as compared to the CDS value scored for the Basic materials sector (−0.3582), registering the least negative value. Such a finding indicates well that investors take advantage in hedging their portfolio by means of CDS during the periods of extreme stock market volatility.

With respect to the stock quantile regression coefficients $(\gamma_1,\gamma_2\ \gamma_3)$, they prove to represent the CDS safe haven characteristics in regard of the stock sector related risk. The negative and significant coefficients associated with the

[2] The AIC criterion measures the relative goodness of fit of the estimated model.

Table 5
Estimation of ARMA (1,1)-TGARCH (1, 1) model parameters.

	φ_0	φ_1	θ_1	w	α_1	β_1	AIC	Q(12)	$Q^2(12)$
Panel A: Daily returns									
Oil & Gas:									
CDS	−0.0002	0.1725	0.0040	1.0000	0.6627	−0.2621	−5.0338	13.4350	6.3734
Equity	−0.0002	0.0013	0.0001	0.0484	0.9543	0.9069	−5.6981	10.2713	17.3624
Consumer services:									
CDS	−0.0002	0.2069	0.0048	0.8633	0.6971	−0.1990	−5.4942	9.2377	0.3179
Equity	−0.0001	0.0166	0.0002	0.0721	0.9267	0.8685	−6.1543	8.0261	9.6985
Basic materials:									
CDS	−0.0005	0.1057	0.0041	0.6652	0.7775	−0.2563	−5.0396	15.1987	4.2154
Equity	−0.0002	−0.0009	0.0001	0.0427	0.9632	0.9237	−5.3993	8.2685	18.9593
Telecom:									
CDS	−0.0001	0.1667	0.0075	1.0000	0.6515	−0.1906	−4.8936	26.6369	6.8673
Equity	−0.0002	0.0039	0.0004	0.0815	0.9067	0.7083	−5.9744	14.1749	12.6955
Industrial:									
CDS	−0.0002	0.1748	0.0023	0.2969	0.7286	−0.2014	−5.2263	7.8937	2.554
Equity	0.0001	0.0108	0.0001	0.0793	0.9261	0.7212	−5.8828	9.749	9.9468
Utilities:									
CDS	−0.0006	0.1767	0.0007	0.1643	0.8522	−0.1825	−4.6732	11.1632	27.4031
Equity	−0.0002	0.0040	0.0002	0.0676	0.9274	0.7844	−5.9831	13.0964	9.4005
Consumer goods:									
CDS	−0.0002	0.0980	0.0019	1.0000	0.7587	−0.1301	−5.8753	9.2459	1.3244
Equity	0.0001	−0.0164	0.0002	0.0778	0.9247	0.7296	−6.1131	9.1763	9.8346
Technology:									
CDS	−0.0002	0.0980	0.0019	1.0000	0.7587	−0.1301	−4.7565	11.5021	5.3898
Equity	0.0001	−0.0185	0.0002	0.0657	0.9340	0.7730	−5.8408	11.7046	13.6053
Insurance:									
CDS	0.0001	0.1723	0.0032	0.1596	0.7882	−0.2932	−4.0826	4.8489	0.1413
Equity	−0.0002	0.0314	0.0002	0.0785	0.9285	0.8170	−5.6009	5.9465	9.9877
Bank:									
CDS	−0.0010	0.0574	0.0101	1.0000	0.7460	−0.1391	−4.5950	28.4975	4.1322
Equity	−0.0004	0.0513	0.0001	0.0641	0.9413	0.7824	−5.2939	3.1893	9.4737
Other financial services:									
CDS	−0.0010	0.1300	0.0072	0.7421	0.6707	−0.2386	−4.8585	10.9821	0.1314
Equity	0.0001	0.0229	0.0002	0.0872	0.9154	0.6654	−6.0235	6.8004	7.3983
Panel B: Weekly returns									
Oil & Gas:									
CDS	0.0017	0.0759	0.0048	−0.5987	0.1438	0.8343	−6.6836	10.3484	7.9378
Equity	−0.0015	0.0369	0.0013	1.0000	0.0917	0.8912	−4.1027	10.8716	12.0703
Consumer services:									
CDS	−0.0035	0.0240	0.0019	−0.9999	0.0672	0.9155	−5.6560	11.3995	1.7496
Equity	−0.0003	−0.0228	0.0008	0.7816	0.0784	0.9049	−4.5936	7.9188	8.5514
Basic materials:									
CDS	−0.0040	0.0628	0.0052	−0.2446	0.1695	0.8000	−4.4033	12.5126	4.0933
Equity	−0.0004	−0.0554	0.0004	1.0000	0.0617	0.9388	−3.7799	10.3452	15.6533
Telecom:									
CDS	−0.0011	0.0466	0.0055	−0.4830	0.1966	0.7869	−2.6696	22.6314	5.8733
Equity	−0.0007	−0.0171	0.0030	0.7961	0.0854	0.8238	−4.3917	15.8145	10.2891
Industrial:									
CDS	−0.0039	0.1157	0.0153	−0.1209	0.3324	0.5196	−3.0651	7.0137	2.8126
Equity	0.0005	−0.0568	0.0005	1.0000	0.0545	0.9376	−4.2887	7.8150	8.410 8
Utilities:									
CDS	−0.0011	−0.0055	0.0041	−0.3725	0.1691	0.8160	−2.6296	12.7122	27.4031
Equity	−0.0013	0.0083	0.0020	1.0000	0.0876	0.8617	−4.3483	10.8715	9.4005
Consumer goods:									
CDS	−0.0023	0.0728	0.0051	−0.2589	0.3006	0.6972	−3.7022	8.7225	2.6613
Equity	0.0005	−0.0101	0.0017	1.0000	0.1016	0.8573	−4.5516	7.9812	6.8133
Technology:									
CDS	−0.0017	0.0367	0.0010	−0.3205	0.1246	0.8946	−2.8032	12.7155	6.8015
Equity	0.0006	0.0123	0.0007	1.0000	0.0551	0.9329	−4.2760	11.3249	10.0619
Insurance:									
CDS	0.0003	0.0058	0.0051	−0.5894	0.0844	0.8772	−2.0930	4.9145	3.7188
Equity	−0.0005	−0.0061	0.0005	1.0000	0.0616	0.9351	−3.9301	5.5378	9.8197

Table 5 (*continued*)

	φ_0	φ_1	θ_1	w	α_1	β_1	AIC	Q(12)	$Q^2(12)$
Bank:									
CDS	−0.0026	0.0399	0.0045	−0.3806	0.1352	0.8422	−2.5544	23.7189	5.1955
Equity	−0.0019	0.0324	0.0007	1.0000	0.0646	0.9311	−3.5948	5.8150	7.1984
Other financial services:									
CDS	−0.0056	−0.0280	0.0081	−0.2737	0.2518	0.7556	−2.7155	11.8160	2.1891
Equity	0.0008	0.0036	0.0007	1.0000	0.0595	0.9258	−4.3866	5.7881	5.9184

Table 6
Results of regression model estimation.

	γ_0		γ_1		γ_2		γ_3	
	DCC	ADCC	DCC	ADCC	DCC	ADCC	DCC	ADCC
Panel A: Daily returns								
Oil & Gas	−0.5100***	−0.4592***	0.3682	0.6468	0.3090	0.3182	−0.4029	−0.4210
Consumer services	−0.4524***	−0.4231***	−0.1100	0.0533	0.3266	0.6820	−0.8469*	−0.3340*
Basic materials	−0.3385***	−0.3582***	−0.3017	0.8468	−0.5183	0.1092	0.0983	−0.7819
Telecom	−0.3720***	−0.3752***	−0.5111	−0.2841*	−0.0060	0.3957	0.1407	−0.3256
Industrial	−0.5001***	−0.4384***	−0.6191	−0.3389	0.4867	0.5436	−0.0833	−0.0612
Utilities	−0.4976***	−0.3673***	−0.1346	0.4739	0.3094	−0.2076	−0.4033	−0.0076
Consumer goods	−0.4014***	−0.4015***	−0.1805	0.0270	−0.5920	−0.0587	1.1484*	0.2401
Technology	−0.4983***	−0.3908***	−0.2376	0.1082	0.1552	−0.1385	−0.3119	−0.1387
Insurance	−0.5124***	−0.4381***	0.0302	−0.5989	1.3653*	0.2251*	−0.4813	0.1073
Bank	−0.4339***	−0.4409***	−0.2007	−0.2397	1.1244*	0.0099*	−0.2279	0.1534
Other financial services	−0.4864***	−0.4560***	0.9278	0.5530	0.6056	−0.2687	−0.9057	0.2959
Panel B: Weekly returns								
Oil & Gas	−0.4457***	−0.4444***	0.3250	0.0474	−0.3782	−0.1357	0.0953	−0.0337
Consumer services	−0.4994***	−0.5033***	−0.0401	−0.0673	−0.1203	0.1949	0.2357	−0.1137
Basic materials	−0.4203***	−0.4230***	−0.0602	−0.0936	0.0244	0.0757	−0.0474	−0.1395
Telecom	−0.4565***	−0.4323***	0.2607	0.2815	−0.0299	0.0411	−0.1307	−0.2065
Industrial	−0.5928***	−0.5817***	−0.2900	−0.4436	−0.1060	0.0653	−0.0480	−0.0914
Utilities	−0.5101***	−0.5154***	−0.7603*	−0.7657*	−0.1906	−0.1786	0.3284	0.3225
Consumer goods	−0.4719***	−0.4682***	−0.1847	−0.2403	−0.0234	0.1773	0.2636	0.1187
Technology	−0.5409***	−0.5422***	−0.4256*	−0.4711*	0.1958	0.2504	0.2261	0.2085
Insurance	−0.5767***	−0.5626***	0.0932	0.2619	−0.6990	−0.7493	0.1649	0.0424
Bank	−0.4905***	−0.4805***	−0.4266	−0.3385	0.2819	0.2877	0.0491	−0.00017
Other financial services	−0.5058***	−0.4955***	−0.2210	−0.2099	0.3860	0.3287	−0.0603	−0.0537

Note: ***, **,* indicates significance at the 1%, 5%, and 10% levels, respectively.

ADCC model indicate well that the CDS stand strongly as a safe haven at the 10% quantile level concerning the Telecom sector (−0.2841) at the 10% significance level. At the 1% stock quantile level, the Consumer services' sector relating CDS (−0.3340) marks the only strong safe haven. Inversely, however, the DCC model related CDS cannot be regarded to stand as a strongly safe haven against extreme movements with regard to any stock sector under study, except for the Consumer services' sector at the 1% stock quantile level. Accordingly, a safe haven attached to these sectors may well provide an additional benefit to stock investors beyond a long-term hedge, as the CDS appear to contribute remarkably in reducing risk, especially during the periods of extreme stock market volatility.

As for the insignificant and negative coefficients they help indicate well that the CDS prove to represent a weak safe haven in regard of the entire remaining sectors and with respect to all quantiles, except for the insurance and Banking sectors concerning both of the DCC and ADCC model cases, regarding the Consumer goods' sector concerning the DCC model's case. A significant and positive coefficient has been recorded concerning the Insurance and Banking sectors' relevant CDS at the 5% stock quantile level with respect to the ADCC model, and concerning the Consumer goods' sector relevant CDS at the 1% quantile level regarding the DCC model which makes them represent more than an effective diversifier.

The results concerning the second model, which serves to test the CDS role as a hedge or safe haven during the U.S. financial, as crisis based on model (21), are presented on Table 7.

The model constant γ_0 as figuring on Panel A of Table 7, proves to reveal a negative relationship binding the CDS and the stock sectors' indices which respect to each sector and concerning both of the DCC and ADCC model cases with significance being perceived at the 1% level. This finding suggests well that the CDS prove to stand as a strong hedge against stock sector risk throughout the U.S. financial crisis. In addition, the significant negative coefficients (γ_1) appears to indicate well that the CDS appear to stand as a strong safe haven with respect to only two sectors for the ADCC model's case (Insurance and Bank), and with respect to three sectors

Table 7
Results of regression model estimation during the U.S. financial crisis.

	γ_0		γ_1	
	DCC	ADCC	DCC	ADCC
Panel A: Daily returns				
Oil & Gas	−0.5091***	−0.4262***	−0.0519**	0.1039
Consumer services	−0.4508***	−0.3658***	0.0220	0.1182***
Basic materials	−0.3378***	−0.3499***	0.0637*	0.0967***
Telecom	−0.3718***	−0.4002***	−0.0291*	−0.0432
Industrial	−0.5006***	−0.4250***	0.0152	−0.1551
Utilities	−0.4969***	−0.4881***	0.0025	0.7653***
Consumer goods	−0.4031***	−0.3925***	−0.0302	−0.1427
Technology	−0.4981***	−0.4975***	0.0622***	0.0178***
Insurance	−0.5133***	−0.4824***	−0.0754*	−0.2654*
Bank	−0.4349***	−0.5140***	−0.0997***	−0.0134***
Other financial services	−0.4846***	−0.5326***	−0.1006***	−0.2678
Panel B: Weekly returns				
Oil & Gas	−0.4450***	−0.4438***	−0.0272	0.0295
Consumer services	−0.5001***	−0.5033***	−0.0263	0.0047
Basic materials	−0.4200***	−0.4224***	0.0206*	0.0387*
Telecom	−0.4554***	−0.4312***	−0.0890*	−0.0632
Industrial	−0.5921***	−0.5812***	0.0816*	0.0732*
Utilities	−0.5112***	−0.5164***	0.1220*	0.1181*
Consumer goods	−0.4727***	−0.4689***	−0.0462*	−0.0349
Technology	−0.5421***	−0.5434***	−0.0612*	−0.0577*
Insurance	−0.5750***	−0.5599***	0.0905*	0.0896*
Bank	−0.4924***	−0.4820***	0.0841	0.0648
Other financial services	−0.5066***	−0.4962***	−0.0193	−0.0012

Note: ***, **,* indicates significance at the 1%, 5%, and 10% levels, respectively.

concerning the DCC model's case (Insurance, Bank and Other Financial Services). Such a result indicates well that the investors intending to hedge their portfolios, involving Insurance, Bank and stock sector relating Other Financial Services turn out to be more secure with CDS despite the disruptions noted in regard of the 2008 financial crisis.

5.2.2. Weekly analysis

The Panel B of Table 6 displayed results show that the CDSs represent a strong hedge against all the stock sectors' related trends, as the hedge column coefficients (γ_0) turn out to be significantly negative. For the market participants, such a result indicates well that CDs hedging capacities prove to be very fruitful for the investors in European stock sectors. Regarding the CDSs safe haven role, statistical evidence at the 10% level indicates clearly that the CDSs can be considered as a strong safe haven against extreme movements in Utilities and Technology stock sectors at the 10% quantile level with respect to both of the DCC and ADCC models. This finding implies well that the CDSs market is most responsive to extreme shocks' downturns and may prove to reduce portfolio volatility related to these sectors. As for the remaining sectors, they function largely as weak safe havens, except for the Oil&Gas, Telecom and Insurance sectors at the 10% stock quantile level, with respect to both of the DCC and ADCC models. Noteworthy, also, is that the CDSs do not seem to provide either a strong or weak safe haven against extreme movements, at the 5% quantile level, with regard to three sectors concerning the DCC model (the Basic materials, Utilities and Insurance sectors), and except for the Oil&Gas, Utilities and Insurance stock sectors in regard of the ADCC model. At the 1% stock quantile level, however, the CDSs appear to provide a weak safe haven for such sectors as the Basic materials, Telecom, Industrial and Other financial services in the case of the DCC model, while neither a weak nor a strong safe haven has been observed for the CDSs against extreme movements with regard to the Utilities, Consumer goods, Technology and Insurance sectors in regard of the ADCC model's case. Thereby, investors in sectors providing a weak safe haven should not expect much protection to be provided by the CDSs during the crisis periods.

The results appearing on Panel B of Table 7 display well that, during the U.S financial crisis, the CDSs stand as a strong hedge against the entirety of the stock sectors witnessed trends, as the hedge column figuring coefficients (γ_0) appear to be significantly negative. More specifically, the CDSs prove to provide a strong safe haven with respect to three sectors concerning the DCC model (Telecom, Consumer goods and Technology) and with respect to the Technology sector only regarding the ADCC model. Actually, safe haven for these sectors may provide an additional benefit to stock investors beyond a long-term hedge, as the CDSs help greatly in reducing risk over the financial crisis period. As for the insignificant coefficients, they indicate that the CDSs appear to display a weak safe haven for all the remaining sectors except for the Basic materials, Industrial, Utilities and Insurance sectors, with respect to both of the DCC and ADCC models. The significant and positive coefficient indicates that CDSs relevant to these sectors do not represent a safe haven asset. As a highly regulated industry, the probability of default is relatively low for the Basic materials, Industrial, Utilities and Insurance sectors as compared to the other sectors, but they still remain potentially useful as both a hedge and diversifier.

A simple comparison between the daily and weekly results relevant to the first regression model reveals well that frequency does actually matter to investors in the CDS market, as the CDS safe haven properties appeared to differ across time horizons and models. In this respect, the CDS safe haven property against the Telecom sector, as shown with regard to daily data, proves to vanish with weekly data. Similarly, the CDS safe haven role with regard to the consumer goods services' daily data proves to fade away on using weekly data. On comparing the ADCC and DCC models, one can well notice that the CDS safe haven potential as related to the ADCC model regarding the 10% stock quantile for the Telecom sector, turns out to vanish with respect to the DCC model. Inversely, however, the consumer goods' sector relevant CDS has proved to gain a greater safe haven role with respect to the two econometric methods at the 1% stock level. Regarding the weekly data, the Utilities and Technology sectors' relating CDSs have gained greater safe haven properties at the 10% stock quantile level, which is not the case for the daily data. These CDSs attached properties do not appear to undergo noticeable changes across the applied econometric models. Additionally, and with respect to the second regression model, the frequency factor appears to matter greatly to the CDS market investors, as the CDSs safe haven roles prove to differ across the time horizons throughout the U.S. financial crisis. In fact, the CDSs constitute a safe haven against the Insurance and Bank stock sectors related risks concerning the daily data, and against Bank and Other financial services' stock sectors with respect to the weekly data. Furthermore, the econometric method proves to have an impact on the CDSs relating safe haven role. In fact, and in regard of the ADCC model, the daily results appears to show that the CDSs constitute a safe haven with respect to the Insurance and Bank sectors, while in the DCC model's case, the CDS prove to constitute a safe haven for the Insurance, Bank and Other financial service sectors over the U.S. financial crisis. Yet, the weekly based results appear to indicate that the CDSs safe haven role turns out to be mostly apparent with regard to the technology related sectors on applying the ADCC model, and with respect to the Telecom, Consumer goods and Technology sectors concerning the DCC model. Overall, one might well note that the daily price fluctuations attached to the CDS and its speculative nature seem to undermine CDS relating daily safe haven property to the detriment of its weekly safe haven property.

5.3. Dynamic conditional correlation between CDS and stock sector: implication of portfolio design

The reached findings appear to suggest that the dynamic correlation between the CDS and stock sectors stands as a crucial element for effective diversified portfolios and risk management to take place. In a first place, we undertake to present the estimation results relevant to the DCC and ADCC models as used to compute the dynamic correlation. In a second place, we propose to examine the optimal portfolio weights concerning the CDS and stock sector to account for the dynamic correlation persisting between both types of assets. In this context, an appeal is made to the Kroner and Ng (1998) methodology in addition to the DCC and ADCC models' associated estimates. The aim is to build the optimal weights of a CDS/Stock portfolio that an investor can hold in order to minimize the risk without reducing the portfolio returns. The CDS/Stock sector portfolio optimal weight construction is given by:

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} + h_{22,t} - 2h_{12,t}} \tag{15}$$

Under the condition that $w_{12,t} = \begin{cases} 1 & if \quad w_{12,t} > 0 \\ w_{12,t} & if \quad 0 \le w_{12,t} \le 1 \\ 0 & if \quad w_{12,t} < 0 \end{cases}$

where $h_{11,t}$ and, $h_{22,t}$ are the conditional variances of the CDSs indices and the stock index sector, respectively, while $h_{12,t}$ designates the conditional covariance between CDS and stock sector at time t. The optimal weight of the stock index sector in the considered portfolio, is obtained by computing the amount $(1 - w_{12,t})$.

As for the hedge ratios, Kroner and Sultan (1993) propose to consider the conditional volatility estimates. For the purpose of minimizing the portfolio relating risk (CDS and stock markets sector), we undertake to measure the amount whereby a long position (buy) of one Dollar in the stock index sector should be hedged by a short position (sell) of $\beta_{12,t}$ Dollar in the CDS market, that is:

$$\beta_{12,t} = \frac{h_{22,t}}{h_{11,t}} \tag{16}$$

Table 8 illustrates the estimation results concerning the dynamic correlation between the CDS and stock sector, along with the average values of realized optimal weights $w_{12,t}$ and hedge ratios $\beta_{12,t}$.

5.3.1. Daily analysis

Based on Panel A of Table 8, one could note that the correlation proves to be negative with respect to all the stock sectors and to both of the DCC and ADCC models. This correlation turns out to be more negative with regard to the Telecom sector (−0.6578) concerning the ADCC model, and (−0.5141) regarding the Insurance sector with respect to the DCC model. Such a finding implies well that investors who intend to decrease their risk exposures tend to integrate both of the Telecom stock sector and CDS within the same sector into their portfolios via the ADCC model, and to integrate the

Table 8
Dynamic correlations, optimal portfolio weights and hedge ratios of CDS-stock portfolio.

	ρ_t		$w_{12,t}$		$\beta_{12,t}$	
	DCC	ADCC	DCC	ADCC	DCC	ADCC
Panel A: Daily returns						
Oil & Gas	−0.5097	−0.5160	0.6632	0.7140	−0.3157	−0.2036
Consumer services	−0.4507	−0.4547	0.7010	0.6803	−0.2455	−0.2677
Basic materials	−0.3372	−0.3369	0.6226	0.6253	−0.2639	−0.2600
Telecom	−0.3722	−0.6578	0.7260	0.7384	−0.1965	−0.1886
Industrial	−0.5005	−0.4959	0.6742	0.6530	−0.3026	−0.3267
Utilities	−0.4970	−0.5027	0.7086	0.7058	−0.2610	−0.2651
Consumer goods	−0.4034	−0.4028	0.6100	0.5813	−0.3110	−0.2677
Technology	−0.4975	−0.4966	0.6918	0.6847	−0.2733	−0.2787
Insurance	−0.5141	−0.5136	0.6309	0.6922	−0.3667	−0.2936
Bank	−0.4359	−0.4352	0.6251	0.6470	−0.3519	−0.3334
Other financial services	−0.4856	−0.4739	0.7151	0.7224	−0.2574	−0.2451
Panel B: Weekly returns						
Oil & Gas	−0.4452	−0.4437	0.7310	0.7447	−0.2165	−0.2043
Consumer services	−0.5003	−0.5033	0.6402	0.7346	−0.3349	−0.2344
Basic materials	−0.4199	−0.4221	0.6619	0.6746	−0.2668	−0.2599
Telecom	−0.4561	−0.4317	0.7578	0.7737	−0.1993	−0.1785
Industrial	−0.5915	−0.5806	0.7200	0.7001	−0.2857	−0.3073
Utilities	−0.5102	−0.5155	0.7475	0.7556	−0.2250	−0.2184
Consumer goods	−0.4731	−0.4692	0.6422	0.6804	−0.3143	−0.2748
Technology	−0.5426	−0.5439	0.7380	0.7303	−0.2444	−0.2512
Insurance	−0.5743	−0.5593	0.7576	0.7585	−0.2394	−0.2338
Bank	−0.4918	−0.4815	0.6550	0.6778	−0.3550	−0.3187
Other financial services	−0.5068	−0.4963	0.7584	0.8051	−0.2220	−0.1755

Insurance stock sector and CDS within the same sector into their portfolio via the DCC model, in a bid to reduce the overall volatility attached with such portfolios.

Furthermore, one may also note that the average portfolio weight proves to vary substantially across sectors, ranging between 58.13% for the Consumer Goods sector and 73.84% for the Telecom sector concerning the ADCC model. These results suggest that, in regard of the Consumer Goods' sector, the optimal allocation of CDS in a one Dollar CDS/stock portfolio is 58.13%, while only 41.87% should be invested in the stock market. Concerning the Telecom sector, the optimal investments' weights turn out to be 73.84% and 26.16%, respectively. This finding indicates well that for 1 Dollar portfolio, on average, 73.84% should be invested in CDS and the remaining 26.16% should be invested in the Telecom stock sector. Concerning the DCC model case, one could note that the average portfolio weight range between 61%, for Consumer goods' sector, and 72.60% concerning the Telecom sector. These results suggest that in regard of the Consumer Goods' sector, the optimal allocation of the CDS for a one Dollar CDS/stock portfolio is of a rate of 61%, while only 39% should be invested in the stock market. Regarding the Telecom sector, these optimal investments' weights are of the rates of 72.60% and 27.40%, respectively. This indicates that for a one Dollar portfolio, an average of 72.60% should be invested in CDS, and the remaining 27.40% should be invested in the Telecom stock sector. In addition, the results also indicate that the hedge ratios turn out to be negative with respect to all pairs (CDS-stock sector). Such negative values indicate well that the investor should take the same position (long position) with regard to the entirety of sectors. For instance, concerning the Oil&Gas stock sector, investors should take a long position in the CDS market with the rate of 20.36% on applying the ADCC model. The dynamic conditional correlation between the stock and CDS regarding each sector is illustrated through the figure below.

As the Fig. 1 indicates, one may note a significant drop in conditional correlations which take negative values, especially during the 2008 financial crisis and the European debt crisis of 2010−2011. In fact, the correlations appear to decrease significantly at times of falling stock prices, thus, enhancing the CDS relating safe haven property. These findings prove to corroborate the previously published results, regarding the use of CDS as a safe haven during periods of extreme volatility, as documented by Ratner and Chiu (2013). It is actually the negative values associated with the dynamic correlation which have motivated our analysis to examine the benefits of stock/CDS portfolio diversification.

5.3.2. Weekly analysis

Panel B of Table 8 illustrate well that the dynamic correlation between the CDS and stock sectors is widely perceived by investors as a potential hedging opportunity, given the fact that the coefficients (ρ_t) are discovered to be negative with respect the entirety of stock sectors. This correlation appears to be more negative in respect of the Industrial sector with regard to both of the ADCC and DCC models. Moreover, statistical evidence proves to reveal well that the average portfolio weight turns out to vary remarkably across sectors, through differing slightly different across the models applied. By means of examplification, the average optimal weight appears to range between 67.46% regarding the Basic materials sector and 80.51% in regard of the Other financial services' sector on using the ADCC model, while ranging between 64.02% concerning the Consumer services sector and 75.84% concerning the Other financial services when the DCC model is being used. Such results suggest well that, in regard of the ADCC model, the optimal allocation of CDS relevant to the Basic materials sector in a one Dollar CDS/stock portfolio is of a rate of 67.46%, while only 32.54% should be invested in the stock market. Besides, and regarding the Other financial services' sector, these optimal investments' weights turn out to be of the rates of 80.51% and 19.49%, respectively. This fact indicates that for a one Dollar portfolio, an average of 80.51% should be invested in CDS and the remaining 19.49% should be invested in the Other financial services' stock sector.

Regarding the DCC model, the average portfolio weight is discovered to range between 64.02% concerning the Consumer services' sector and 75.84% concerning the Other financial services' sector. These results suggest that for the Consumer services sector, the optimal allocation reserved to the CDS in a one Dollar CDS/stock portfolio is of a rate of 64.02%, while only 35.98% should be invested in the stock market. In regard of the Other financial services' sector, these optimal investments' weights associated rates are 75.84% and 24.16%, respectively. This finding indicates that for a one Dollar portfolio, an average 75.84% should be invested in CDS, while the remaining 24.61% should be invested in the Other financial services' stock sector. Besides, the negative values figuring on the hedge ratio column highlight that investors should take a long position in the CDS market with regard to the entirety of stock sectors. For instance, investors in the Bank stock sectors should opt for a long position in the CDS market set at a percentage of 35.50%.

On comparing the daily results and the weekly ones, one could well note that the frequency factors appears to matter the most for the CDS market investors, as the dynamic correlation, the optimal portfolio weight and hedge ratio of the CDS-stock sector portfolio prove to differ across the time horizons. Indeed, statistical evidence indicates well that the estimation results as associated with dynamic correlation appears to vary noticeably across the time horizons. They seem to be rather negative with respect to the Oil&Gas, Consumer services, Telecom and Other financial services' sectors regarding the daily data side. Besides, the correlations appears to decrease significantly with regard to the Basic materials, Utilities and Technology sectors with respect to the weekly data. As for the optimal portfolio weights, the statistical evidence reveal well that the average weekly portfolio's weight turns out to be higher than the average daily portfolio weight. This fact is also valid and applies for the implemented models, whereby it has been discovered that the average weekly portfolio's weights prove to exceed the average daily portfolio's weights.

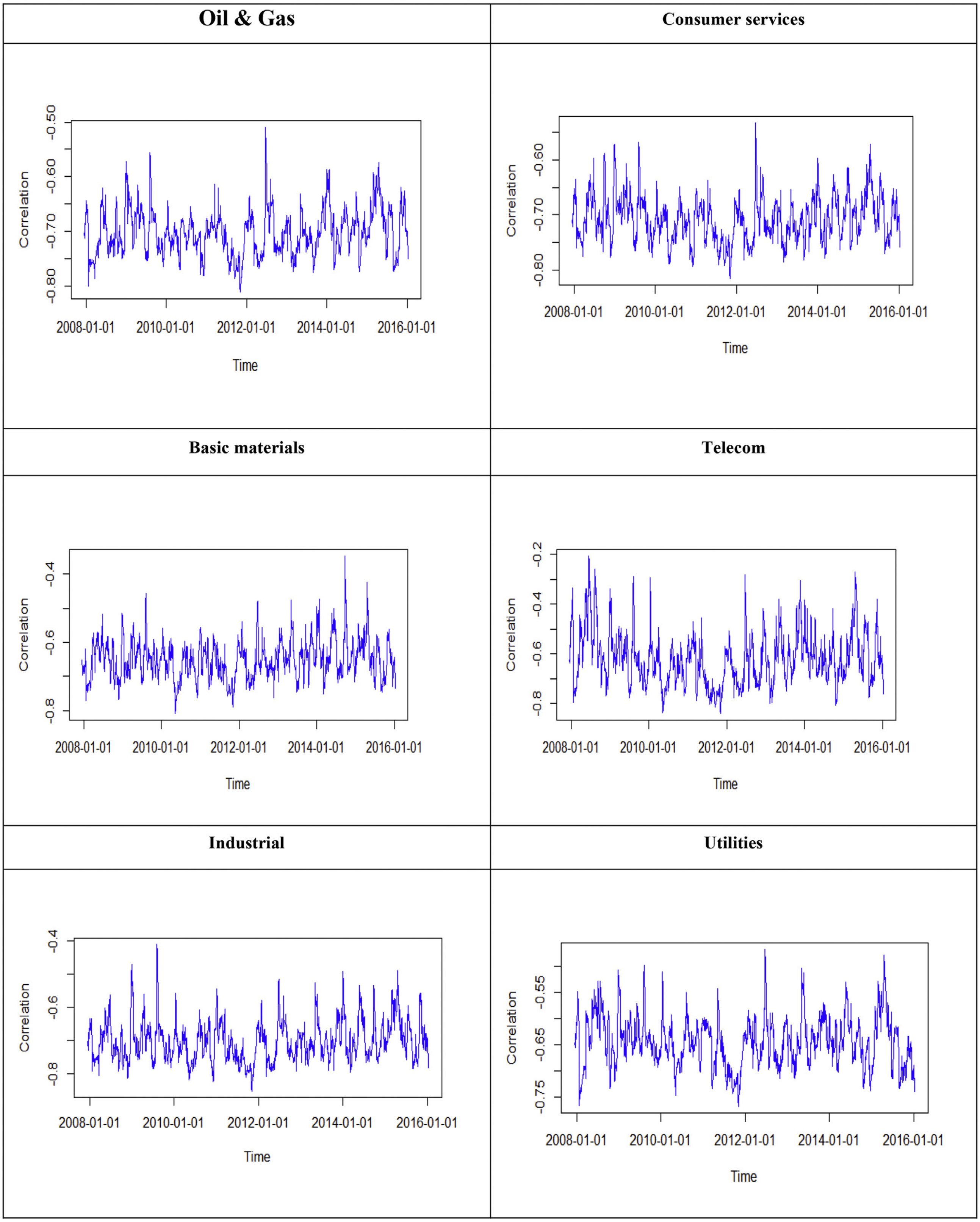

Fig. 1. Dynamic conditional correlations between stock sector and CDS.

5.4. Comparison between the CDS and VSTOXX futures

Our applied methodology also involves the incorporation of an extra index closely related to the stock sector indices, namely the VSTOXX futures. The aim lies in selecting the most optimum hedging strategy in terms of portfolio variance reduction among the stock sector/CDS and the stock sector/VSTOXX futures. Table 9 illustrates the optimal portfolio

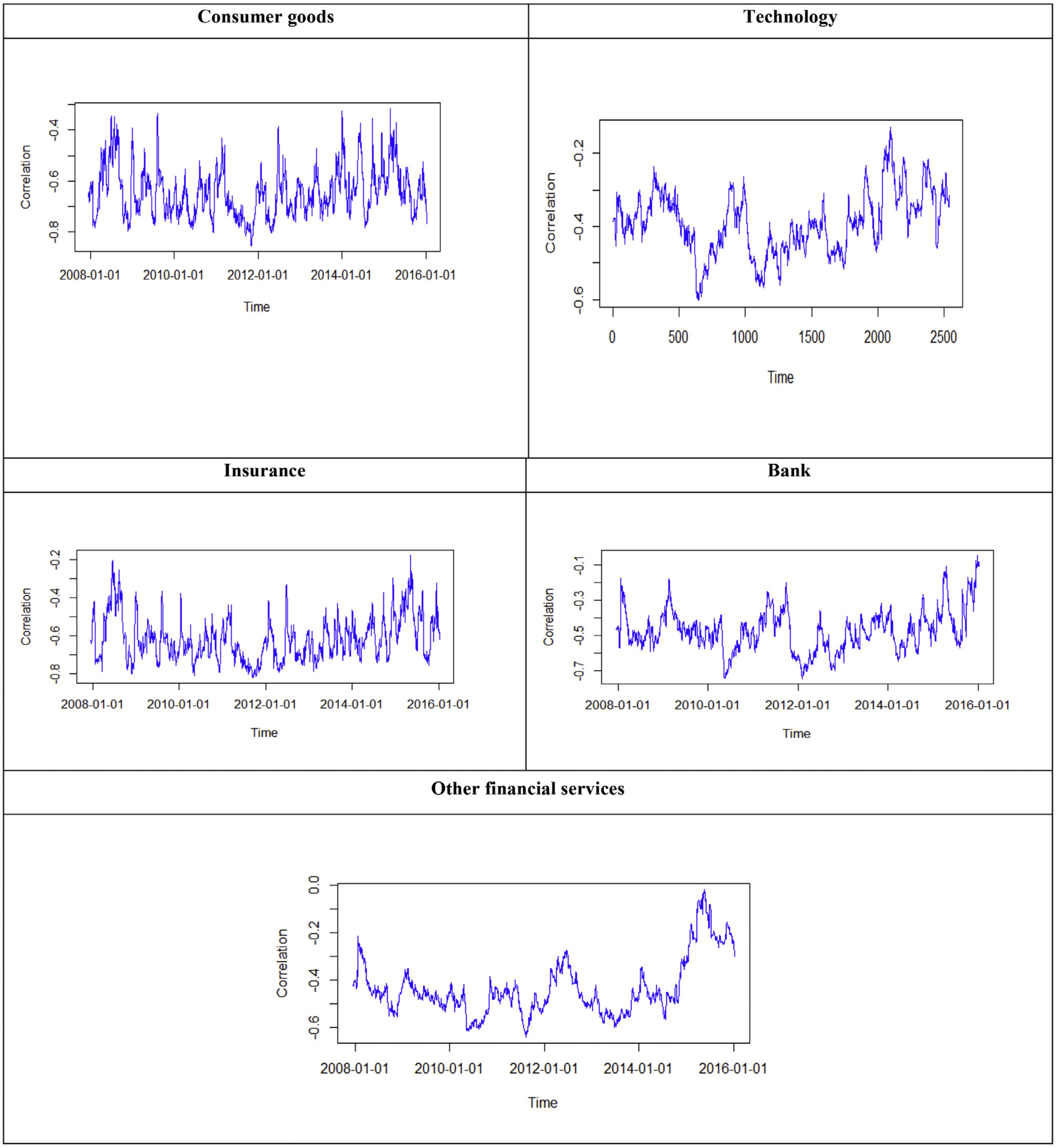

Fig. 1. (*continued*)

associated variance concerning the cases in which each stock sector is covered, either by CDS or by VSTOXX futures.

5.4.1. Daily analysis

On the basis of Panel A of Table 9, one might well note that the variances marking the portfolio, as provided by the ADCC model, touch the Oil & Gas, Utilities, Consumer Good, Technology as well as the Other financial services' sectors as covered by the CDS. These variances appear to be lower than the variances portfolios concerning the same areas as covered by the VSTOXX futures. Inversely, however, the variances characterizing the portfolios, following implementation of the ADCC model, affecting the Basic materials, Telecom, Consumer Services, Industry, Insurance and Bank sectors, as covered by the VSTOXX futures, are discovered to be lower than the portfolio variances concerning the same areas as covered by the CDS. This finding implies that for the investor who intends to take position in the CDS or VSTOXX futures, it would be better to hedge a portfolio enclosing the Oil & Gas, Utilities, Consumer good and Technology by means of

Table 9
Portfolio variance.

	Hedging with CDS		Hedging with VSTOXX futures	
	DCC	ADCC	DCC	ADCC
Panel A: Daily returns				
Oil & Gas	$2.232.10^{-4}$	**0.0092**	**$1.772.10^{-4}$**	0.0099
Consumer services	$1.550.10^{-4}$	0.0109	**$9.630.10^{-5}$**	**0.0080**
Basic materials	$4.319.10^{-4}$	0.0118	**0.0002**	**0.0112**
Telecom	$1.762.10^{-4}$	0.0096	**$1.199.10^{-4}$**	**0.0092**
Industrial	$2.085.10^{-4}$	0.0091	**$1.359.10^{-4}$**	**0.0089**
Utilities	$1.690.10^{-4}$	**0.0085**	**$1.330.10^{-4}$**	0.0089
Consumer goods	$1.715.10^{-4}$	**0.0074**	**$1.137.10^{-4}$**	0.0107
Technology	$2.046.10^{-4}$	**0.0090**	**$1.514.10^{-4}$**	0.0102
Insurance	$2.759.10^{-4}$	0.0110	**$1.985.10^{-4}$**	**0.0098**
Bank	$3.832.10^{-4}$	0.0112	**$2.462.10^{-4}$**	**0.0107**
Other financial services	$1.404.10^{-4}$	**0.0080**	**$9.847.10^{-5}$**	0.0087
Panel B: Weekly returns				
Oil & Gas	0.0011	0.0015	**0.0009**	**0.0008**
Consumer services	0.0006	0.0024	**0.0005**	**0.0004**
Basic materials	0.0017	0.0030	**0.0013**	**0.0012**
Telecom	0.0006	0.0044	**0.0006**	**0.0005**
Industrial	0.0007	0.0004	**0.0006**	**$6.440.10^{-4}$**
Utilities	0.0008	0.0033	**0.0007**	**0.0006**
Consumer goods	0.0006	**0.0004**	**0.0005**	0.0005
Technology	0.0008	**0.0006**	**0.0007**	0.0007
Insurance	0.0011	**0.0009**	**0.0010**	0.0010
Bank	0.0017	**0.0011**	**0.0014**	0.0013
Other financial services	0.00079	**$5.307.10^{-4}$**	**$6.515.10^{-4}$**	$5.827.10^{-4}$

Bold values indicate minimum portfolio variance obtained after comparing the two hedging strategies (VSTOXX or CDS).

CDS. It is also desirable to hedge the portfolio involving the Consumer services, Basic materials, Telecom, Industrial, Insurance, Bank and Other financial services' sectors by favoring to opt for VSTOXX futures. Moreover, the results also indicate that the hedging strategies which involve the VSTOXX futures make would help greatly in reducing portfolio associated risk (variance) by appealing to the DCC model with respect to the entirety of the stock sectors except for the Basic materials' sector.

5.4.2. Weekly analysis

An examination of Panel B of Table 9 reveals that the CDSs constitute the most convenient instrument to hedge Consumer goods, Technology, Insurance, Bank and Other financial services' sectors on applying the ADCC model. Inversely, however, for all the remaining sectors, the VSTOXX future stands as the most appropriate hedging instrument as the portfolios associated variances turn out to be lower than those related to the CDS covered areas. Moreover, and on using the DCC model, the statistical evidence proves to show that the hedging strategies involving the VSTOXX futures help noticeably in reducing the portfolio variances associated with the entirety of sectors. This finding stresses the fact that the VSTOXX futures related hedging strategy turns to be more efficient than the CDS indices relating strategy.

A comparison established between the daily and weekly data reveals that the frequency factor matters greatly to the portfolio investors, as the most optimal hedging instrument option appears to vary and differ across the time horizons. In fact, the CDS hedging role against the stock sectors, as noticed with respect to the daily data, is limited in regard of five sectors (Oil&Gas, Utilities, Consumer goods, Technology and Other financial services). On the other hand, the CDS hedging properties regarding such sectors as Consumer goods, Technology, Insurance, Bank and Other financial services appears to vanish with regard to weekly data concerning the remaining sectors, in favor of the VSTOXX futures. Noteworthy, however, is that the choice of the most adequate hedging instrument proves to vary across models. For example, the CDS indices based hedging strategy proves to stand as rather efficient with respect to daily data, while the ADCC model displays greater efficiency as to the Oil&Gas, Industrial, Utilities, Consumer goods, Technology and Other financial services, whereas the DCC model associated efficiency appears to exhibit greater effectiveness with regard to the Basic materials' sector. Concerning the weekly data, the VSTOXX futures constitute the best hedging instrument with respect to the entirety of the European stock sectors by means of the DCC model.

Such findings highlight the predominance of significant differences between both of the data frequency and implemented methodology factors when the CDS and VSTOXX futures are being applied by the portfolio investors to cater for the downward trends in persistent among the European stock sectors.

6. Conclusion

In this paper, a thorough investigation of the dynamic relationships persisting between the CDS and various stock sectors is advanced, highlighting the CDS role as a strong hedging mechanism against the stock sectors' fluctuations. Using daily and weekly data treated via DCC and ADCC models, our major striking results reached appear to reveal well that the CDS can serve as a hedge and safe haven with respect to most of the studied cases. Noteworthy, however, is that only with regard to a few cases did the CDS display certain diversifier properties that helped distinguish between horizons and econometric models concerning the periods of extreme stock market trends and the U.S. financial crisis. On extending our analysis to the optimal hedging strategies prevailing between the CDS/stock sectors and VSTOXX futures/stock sectors, evidence proves to highlight that the choice of the most optimum hedging instrument turns out to differ across time horizon, model and especially the investor's targeted objective. Our results might well be of great interest to institutional investors seeking affective hedging strategies fit for shielding against, or else attenuating the stock sector associated risks. Actually, our devised methodology may stand as an effective tool for them whereby they could evaluate the benefits alternative hedging instruments.

Conflict of interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

References

Alexander, C., & Kaeck, A. (2008). Regime dependent determinants of credit default swap spreads. *Journal of Banking and Finance, 32*, 1008−1021.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011a). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance, 30*, 1387−1405.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics, 34*, 611−617.

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2011b). Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Economic Modelling, 28*, 1815−1825.

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2015). World gold prices and stock returns in China: Insights for hedging and diversification strategies. *Economic Modelling, 44*, 273−282.

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2009). Credit ratings and the cross-section of stock returns. *Journal of Financial Markets, 12*, 469−499.

Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics, 54*, 235−247.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review, 45*, 217−229.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance, 34*, 1886−1898.

Black, K. H. (2006). Improving hedge fund risk exposures by hedging equity market volatility, or how the VIX ate my kurtosis. *The Journal of Trading, 1*, 6−15.

Black, F., & Cox, J. C. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *The Journal of Finance, 31*, 351−367.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, 81*, 637−654.

Bowler, B., Ebens, H., Davi, J., & Kolanovic, M. (2003). *Volatility-the perfect asset*. Merill Lynch Global Securities Research and Economics Group. December.

Calice, G., Chen, J., & Williams, J. M. (2013). Are there benefits to being naked? the returns and diversification impact of capital structure arbitrage. *The European Journal of Finance, 19*, 815−840.

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *Journal of Finance, 58*(6), 2321−2350.

Caporin, M. (2013). Equity and CDS sector indices: Dynamic models and risk hedging. *The North American Journal of Economics and Finance, 25*, 261−275.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics, 4*, 537−572.

Carr, P., & Wu, L. (2009). Stock options and credit default swaps: A joint framework for valuation and estimation. *Journal of Financial Econometrics*, nbp010.

Collin-Dufresne, P., & Goldstein, R. S. (2001). Do credit spreads reflect stationary leverage ratios? *The Journal of Finance, 56*, 1929−1957.

Coudert, V., & Raymond, H. (2011). Gold and financial assets: Are there any safe havens in bear markets. *Economics Bulletin, 31*, 1613−1622.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics, 20*, 339−350.

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. *The Journal of Alternative Investments, 11*, 43−61.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*, 1779−1801.

Kaminsky, G., & Schmukler, S. L. (2002). Emerging market instability: Do sovereign ratings affect country risk and stock returns? *The World Bank Economic Review, 16*, 171−195.

Kiesel, F., Kolaric, S., & Schiereck, D. (2016). Market integration and efficiency of CDS and equity markets. *The Quarterly Review of Economics and Finance, 61*, 209−229.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies, 11*, 817−844.

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Finance and Quantitative Analysis, 28*, 535−551. https://doi.org/10.2307/2331164.

Kumar, D. (2014). Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness. *IIMB Management Review, 26*, 5−16.

Leland, H. E. (1994). Corporate debt value, bond covenants, and optimal capital structure. *The Journal of Finance, 49*, 1213−1252.

Lin, B., Wesseh, P. K., & Appiah, M. O. (2014). Oil price fluctuation, volatility spillover and the Ghanaian equity market: Implication for portfolio management and hedging effectiveness. *Energy Economics, 42*, 172−182.

Longstaff, P. F., Longstaff, F. A., Mithal, S., & Neis, E. (2003). *The credit-default swap market: Is credit protection priced correctly?*. Working Paper.

Longstaff, F. A., & Schwartz, E. S. (1995). Valuing credit derivatives. *The Journal of Fixed Income, 5*, 6−12.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance, 29*, 449−470.

Moran, M. T., & Dash, S. (2007). VIX futures and options: Pricing and using volatility products to manage downside risk and improve efficiency in equity portfolios. *The Journal of Trading, 2*, 96−105.

Narayan, P. K. (2015). An analysis of sectoral equity and CDS spreads. *Journal of International Financial Markets, Institutions and Money, 34*, 80−93.

Norden, L., & Weber, M. (2009). The co-movement of credit default swap, bond and stock markets: An empirical analysis. *European Financial Management, 15*, 529−562.

Ratner, M., & Chiu, C.-C. J. (2013). Hedging stock sector risk with credit default swaps. *International Review of Financial Analysis, 30*, 18−25.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics, 34*, 248−255.

Sadorsky, P. (2014a). Modeling volatility and conditional correlations between socially responsible investments, gold and oil. *Economic Modelling, 38*, 609−618.

Sadorsky, P. (2014b). Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. *Energy Economics, 43*, 72−81.

Wang, P., & Bhar, R. (2014). Information content in CDS spreads for equity returns. *Journal of International Financial Markets Institutions and Money, 30*, 55−80.

Whaley, R. E. (1993). Derivatives on market volatility: Hedging tools long overdue. *Journal of Derivatives, 1*, 71−84.

Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control, 18*, 931−955.

Zhang, B. Y., Zhou, H., & Zhu, H. (2009). Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. *Review of Financial Studies, 22*, 5099−5131.

Zhu, H. (2006). An empirical comparison of credit spreads between the bond market and the credit default swap market. *Journal of Financial Services Research, 29*, 211−235.