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Time varying and asymmetric effect between sovereign credit market and financial market: the asymmetric DCC model

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Abstract

This study examines the interdependence between the daily euro zone sovereign CDS index and four financial market sectors such as, banking CDS market (CDSb), underlying sovereign market (BONDs), stock market (BMI) and future interest rate benchmark of the bunds obligation (EUROBOBL). Focusing on different phases of the sovereign debt crises, the aim of this paper is to examine how the dynamics of correlations between the CDSs and financial market indicators evolved from September 20, 2011 to February 12, 2016. To this end, the A-DCC model allowing for conditional asymmetries in covariance and correlation dynamics has been adopted to examine the presence of asymmetric responses in correlations during periods of negative shocks. The empirical findings indicate a general pattern increase in correlations during the phase of the sovereign debt crisis, suggesting the spillover effect of the CDS index and financial market indicators.

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Keywords A-DCC model; EGARCH; asymmetries; CDSs and financial market indicators

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1. Introduction

Unlike past crises, such as the 1997 Asian financial crisis, the 1998 Russian crisis and the 1999 Brazilian crisis, the recent 2007-2009 global financial crisis originated from the largest and most influential economy, the US market, and was spreading over other countries' financial markets worldwide. Global financial crisis resulted in sharp declines in asset prices, stock and foreign exchange markets, and skyrocketing risk premiums on interbank loans. It also disrupted country's financial system and threatened real economy with huge contractions.

After the Subprime Crisis in 2007, the sovereign crisis in the Euro zone emerged and has highlighted the link existing between the sovereign credit risk, the country's indebtedness level and the macroeconomic fundamentals. In fact, studies found that investors do not evaluate the sovereign default probability objectively and that the market psychology plays an important role in the sovereign spreads evolutions. Generally, markets unnoticed the economic fundamentals deteriorations during the phase of financial euphoria and investors tend to ignore default probability during tranquil periods. They under estimate and do not incorporate effectively credit risk in the sovereign prices. After a specific event, there will be a reevaluation of the sovereign credit default risk, markets become irrational and the global and specific fundamentals became under observation. Investors run to purchase credit insurance derivatives, sovereign Credit Default Swaps (CDS), for protection and spreads will widen.

The increasing number of studies that treated CDS spreads during the European sovereign crisis had find relatively similar results: the local macroeconomic fundamentals and especially fiscal variables (Aizenman and al.; 2013) are the main determinants of sovereign CDS spreads and global factors related to contagion during an eventual crisis (Groba and al.; 2013). Gibson and al. (2014) show that the sovereign rating downgrades and the political instability are the main drivers of the sovereign Greek spreads during the period 2008-2009. These results are valuables for developed and deeply rooted democratic countries.

Some papers have similarly treated the developed and developing countries like Beirne and Frantzscher (2013) how find that the sovereign rating and the sovereign risk market price are related and that sovereign rating reflects the country's fundamentals. However, the study of some emerging countries CDS spreads determinants shows some different characteristic results from developed countries. Wang and al. (2013) find that the Latin American sovereign CDS price movement, after Lehman Brothers bankruptcy, depends principally on American financial markets volatility, regional contagion and little on specific factors (see also Fender and al. (2012)) . For Zinna (2013), generally, emerging economies risk premium co-move with advanced economies global factors and especially with US macro variables during tranquil periods. Gibson and al. (2012) thought that sovereign spreads determinants differ in developed and developing countries: in developed countries, macroeconomic and financial economics are the principal determinants while in developing countries economic fundamentals and global markets conditions are most significant. There is generally some dependence of developing countries from developed one especially American market.

In crisis period, emerging economies are decoupled from advanced economies and specific factors become more predictive of risk premium. Kabir Hassan and al. (2015) find that common external factors are the main causes of sovereign credit risk and bond yields changes rather than specific factors for a set of emerging countries. Siklos (2011) says that emerging markets should not have been easily studied as a single block. He also suggests the use of institutional variables on specific factors for emerging market bond yield spreads like the central bank transparency indicator.

The main objective for this paper is to employ the asymmetric DCC to analyze the co-movement between sovereign credit market and other financial markets. Empirically, we study the co-movement (similar movement) between return series. Specifically we analyze the presence or absence of asymmetric effect between pairs of series. We adopt the short memory effect (short persistence of shocks) (exponential GARCH model). However in the article entitled "Long Memory and Asymmetric Effects between Exchange Rates and Stock Returns" (see El Abed and Maktouf (2015)), the long memory effect and asymmetric effect (the A-DCC model and the FIAPARCH model) have been used to analyze the persistence of shocks. Specifically we study the comportment of correlations during the different phases of crises.

In this article, we focus on interrelations between the returns of the euro zone sovereign CDS index and four financial market sectors such as, banking CDS market (CDSb), underlying sovereign market (BONDs), stock market (BMI) and future interest rate benchmark of the bunds obligation (EUROBOBL) in the period during the sovereign debt crises. We empirically investigate the time-varying linkages of the CDSs and four financial market indicators during the period spam from September 20, 2011 until February 12, 2016. We investigate the asymmetric behavior of dynamic correlations among sovereign CDS and financial market indicators by employing the multivariate asymmetric DCC (A-DCC) model put forward by Cappiello et al. (2006). The A-DCC model allows for conditional asymmetries in covariance and correlation dynamics, thereby enabling to examine the presence of asymmetric responses in correlations during periods of negative shocks. Second, we evaluate how the European sovereign debt crises influenced the estimated DCCs among the CDSs and financial market indicators.

The rest of the paper is organized as follows. Section 2 presents the econometric methodology. Section 3 provides the data and a preliminary analysis. Section 4 displays and discusses the empirical findings and their interpretation, while Section 5 provides our conclusions.

2. Econometric methodology: The A-DCC-EGARCH model

To investigate the dynamics of the correlations between the Euro zone sovereign CDS index and four financial market indicators such as, banking CDS market (CDSb), underlying sovereign market (BONDs), stock market (BMI) and future interest rate benchmark of the bunds obligation (EUROBOBL), we use the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello et al. (2006).

This approach generalizes the DCC model of Engle (2002) by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation dynamics. In this paper, we adopt the following three step approach (see also Kenourgios et al., 2011; Toyoshima et al., 2012; Samitas and Tsakalos, 2013; Toyoshima and Hamori, 2013). In the first step, we estimate the conditional variances of sovereign CDS returns and financial market indicator returns using an autoregressive- asymmetric exponential generalized autoregressive conditional heteroscedasticity ($AR(m)-EGARCH(p,q)$) model[1]. For a more detailed analysis, we use the following equations:

$$r_t = \mu_0 + \sum_{i=1}^{m} \mu_i r_{t-i} + \varepsilon_t \tag{1}$$

$$ln(h_t) = \omega + \sum_{i=1}^{q} [\alpha_i |z_{t-i}| + \gamma_i z_{t-i}] + \sum_{i=1}^{p} \beta_i ln(h_{t-i}) \tag{2}$$

Where r_t indicates sovereign CDS and financial market indicators returns, ε_t is the error term, h_t is the conditional volatility, and $z_t = \varepsilon_t/\sqrt{h_t}$ is the standardized residual.

[1] See Nelson (1991).

The EGARCH model has several advantages over the pure GARCH specification. First, since $ln(h_t)$ is modelled, and then even if the parameters are negative, $h_t$will be positive. Thus, there is no need to artificially impose non-negativity constraints on the models parameters. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ_i will be negative. Note that a negative value of γ_i means that negative residuals tend to produce higher variances in the immediate future.

Furthermore, we assume that the random variable z_t has a student distribution (see Bollerslev, 1987) with $\upsilon > 2$ degrees of freedom with a density given by:

$$D(z_t, \upsilon) = \frac{\Gamma(\upsilon+\frac{1}{2})}{\Gamma(\frac{\upsilon}{2})\sqrt{\pi(\upsilon-2)}}(1+\frac{z_t^2}{\upsilon-2})^{\frac{1}{2}-\upsilon} \quad (3)$$

Where $\Gamma(\upsilon)$ is the gamma function and υ is the parameter that describes the thickness of the distribution tails. The Student distribution is symmetric around zero and, for $\upsilon > 4$, the conditional kurtosis equals $3(\upsilon - 2)/(\upsilon - 4)$, which exceeds the normal value of three. For large values of υ, it density converges to that of the standard normal.

The log form of the EGARCH (p, q) model ensures the positivity of the conditional variance, without the need to constrain the parameters of the model. The term z_{t-i} indicates the asymmetric effect of positive and negative shocks. If $\gamma_i > 0$, then $z_{t-i} = \varepsilon_{t-i}/\sigma_{t-i}$ is positive. The term $\sum_{i=1}^{p} \beta_i$ measures the persistence of shocks to the conditional variance.

The conditional mean equation (Eq. 1) is specified as an autoregressive process of order m. The optimal lag length m for each return series is given by the Schwartz-Bayesian Information Criterion (SBIC). Eq. (2) representing the conditional variance and is specified as and EGARCH (p, q) process. The optimal lag lengths p and q are determined by employing the SBIC criterion. From Eq. 2, we first obtain the conditional volatilities and then recover the conditional correlations. The conditional covariance matrix is then defined as follows:

$$H_t = D_t R_t D_t \quad (4)$$

Where the diagonal matrix D_t is the conditional standard deviation obtained from Eq. (2). The matrix of the standardized residuals Z_t is used to estimate the parameters of the asymmetric dynamic conditional correlation (A-DCC) model developed by Cappiello et al. (2006). The AG-DCC model is given as:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) + A'Z_{t-1}Z'_{t-1}A + B'Q_{t-1}B + G'\eta_{t-1}\eta'_{t-1}G \quad (5)$$

Where $\bar{Q}$ and $\bar{N} = E(\eta_t\eta'_t)$ are the unconditional correlation matrices of Z_t and η_t. $\eta_t = I[Z_t < 0] \circ Z_t$. $I[.]$ is an indicator function such that $I = 1$ if $Z_t < 0$ and $I = 0$ if $Z_t \geq 0$, while " $\circ$ " is the Hadamard product.

The A-DCC (1, 1) model is identified as a special case of the AG-DCC(1,1) model if the matrices A, B and G are replaced by the scalars a_1, b_1 and g_1. Cappiello et al. (2006) show that Q_t is positive definite with a probability of one if $(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G)$ is positive definite. The next step consists in computing the correlation matrix R_t from the following equation:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (6)$$

Where $Q_t^* = \sqrt{q_{ii,t}}$ is a diagonal matrix with a square root of the ith diagonal element of Q_t on its ith diagonal position.

3. Data and preliminary analyses

In this article, we use daily data for the euro zone sovereign CDS index and four financial market indicators such as, banking CDS market (CDSb), underlying sovereign market (BONDs), stock market (BMI) and future interest rate benchmark of the bunds obligation (EUROBOBL) over the period spam from 20 September, 2011 to 26 February, 2016. The major indexes are constructed by Standards and Poor's (http//us.spindices.com). For each series, the continuously compounded return is computed as $\mathrm{r_t} = 100 \times \ln(\mathrm{p_t}/\mathrm{p_{t-1}})$ for $\mathrm{t} = 1,2, \ldots, \mathrm{T}$, where $\mathrm{p_t}$is the price on day t.

Summary statistics for returns are displayed in Table 1(Panel A). From these tables, (CDSb) is the most volatile, as measured by the standard deviation of 3.0723%, while (EUROBOBL) is the least volatile with a standard deviation of 0.1718%. Besides, we observe that CDSs has the highest level of excess kurtosis, indicating that extreme changes tend to occur more frequently for the series. In addition, all series returns exhibit high values of excess kurtosis. To accommodate the existence of "fat tails", we assume student-t distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality at the 1% level for all series. Moreover, all returns are stationary, I (0). Finally, they exhibit volatility clustering, revealing the presence of heteroskedasticity and strong ARCH effects.

Fig. 1 illustrates the evolution of all series (raw series and returns) during the period from September 20, 2011 until February 26, 2016. The figure shows significant variations in the levels during the turmoil, especially at the time of the sovereign debt crises. Specifically, when the global financial crisis triggered, there is a decline for all prices. Moreover, **Fig. 1** plots the evolution of CDSs returns and financial market indicators over time. The figure shows that all series trembled since 2012 with different intensity during the European sovereign debt crises. Moreover, the plot shows a clustering of larger return volatility around and after 2012. This means that markets are characterized by volatility clustering, i.e., large (small) volatility tends to be followed by large (small) volatility, revealing the presence of heteroskedasticity. This market phenomenon has been widely recognized and successfully captured by ARCH/GARCH family models to adequately describe CDSs and financial market returns dynamics. This is important because the econometric model will be based on the interdependence of the markets in the form of second moments by modeling the time varying variance-covariance matrix for the sample.

Table 1
Summary statistics and long memory test's results.

	CDSs	BONDs	CDSb	BMI	EUROBOBL
Panel A: descriptive statistics					
Mean	-1.05E-01	0.0218	-0.0388	1.14E-02	1.11E-02
Maximum	18.2321	1.2635	14.483	5.6752	0.9087
Minimum	-14.4249	-1.3708	-12.419	-6.3385	-0.8236
Std. Deviation	2.9034	0.2306	3.0723	1.1517	0.1718
Skewness	0.3558***	-0.4455**	0.52493*	-0.1127*	-0.2690**
	0.0005	0.0292	0.0806	0.0648	0.0104
Excess Kurtosis	7.6218***	7.2461***	3.5723**	5.7402***	4.8638***
	0.0000	0.0000	0.0206	0.0000	0.0000
Jarque-Bera	3923.6***	3568.9***	928.26***	2209.7***	1603.4***
	0.0000	0.0000	0.0269	0.0000	0.0000
Panel B: Serial correlation and LM-ARCH tests					
$LB(20)$	40.999***	52.6804***	55.0122***	35.3893**	43.5573***
	0.0037	0.0000	0.0000	0.0181	0.0017
$LB^2(20)$	60.6531***	282.194***	123.97***	293.584***	386.492***
	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH 1-10	4.8367***	12.0150***	9.0950***	12.373***	15.799***
	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: Unit Root tests					
ADF test statistic	-22.0736*	-23.7391*	-21.4600*	-23.8451*	-24.9288*
	-1.9409	-1.9409	-1.9409	-1.9409	-1.9409

Notes: Observations for all series in the whole sample period are 1607. The numbers in brackets are t-statistics and numbers in parentheses are p-values. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively. $\boldsymbol{LB(20)}$and$\boldsymbol{LB^2(20)}$ are the 20th order Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively.

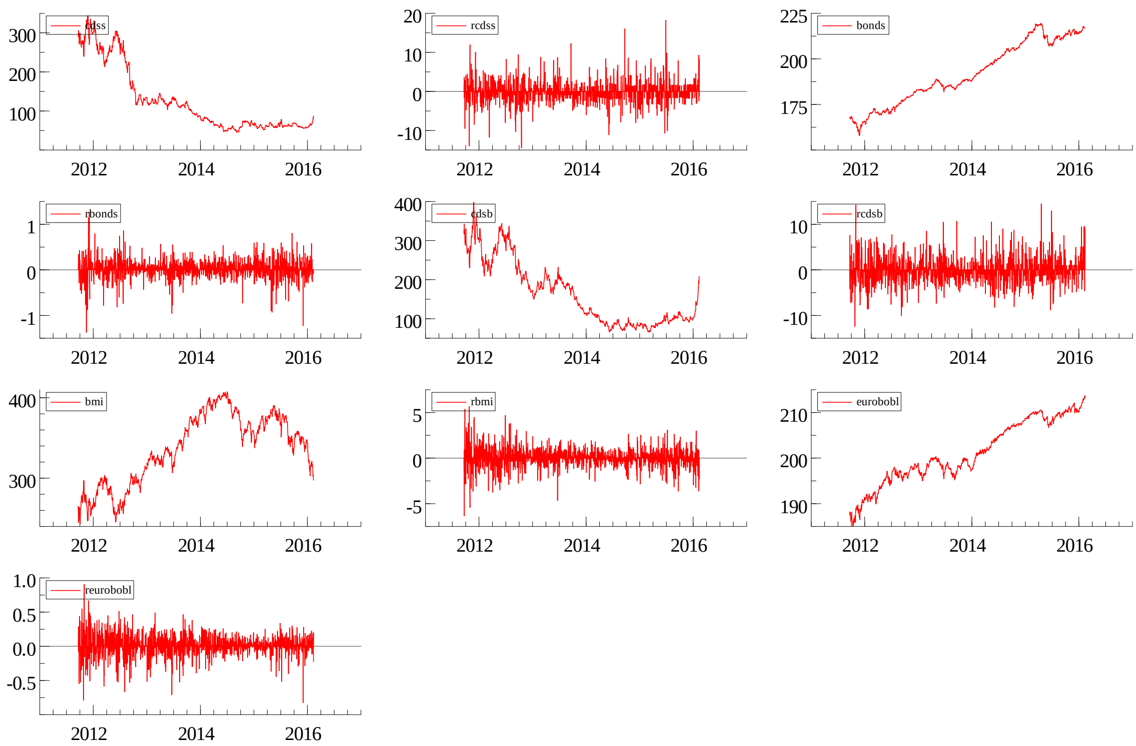


Fig.1. CDSs and financial market indicators behavior over time.

4. Empirical results

4.1. Tests for sign and size bias

Engle and Ng (1993) propose a set of tests for asymmetry in volatility, known as sign and size bias tests. The Engle and Ng tests should thus be used to determine whether an asymmetric model is required for a given series, or whether the symmetric GARCH model can be deemed adequate. In practice, the Engle-Ng tests are usually applied to the residuals of a GARCH fit to the returns data.

Define S_{t-1}^{-} as an indicator dummy variable such as:

$$S_{t-1}^{-} = \begin{cases} 1 \ \ if \ \ \hat{z}_{t-1} < 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{7}$$

The test for sign bias is based on the significance or otherwise of ϕ_1 in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^{-} + \nu_t \tag{8}$$

Where $\nu_t$is an independent and identically distributed error term. If positive and negative shocks to $\hat{z}_{t-1}$ impact differently upon the conditional variance, then ϕ_1 will be statistically significant.

It could also be the case that the magnitude or size of the shock will affect whether the response of volatility to shocks is symmetric or not. In this case, a negative size bias test would be conducted, based on a regression where S_{t-1}^{-} is used as a slope dummy variable. Negative size bias is argued to be present if ϕ_1 is statistically significant in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^{-} z_{t-1} + \nu_t \tag{9}$$

Finally, we define $S_{t-1}^{+} = 1 - S_{t-1}^{-}$, so that S_{t-1}^{+}picks out the observations with positive innovations. Engle and Ng (1993) propose a joint test for sign and size bias based on the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^{-} + \phi_2 S_{t-1}^{-} z_{t-1} + \phi_3 S_{t-1}^{+} z_{t-1} + \nu_t \tag{10}$$

Significance of ϕ_1 indicates the presence of sign bias, where positive and negative shocks have variable impacts upon future volatility, compared to the symmetric response required by the standard GARCH formulation. However, the significance of ϕ_2 or ϕ_3 would suggest the presence of size bias, where not only the sign but the magnitude of the shock is important. A joint test statistic is formulated in the standard fashion by calculating TR^2 from regression (10), which will asymptotically follow aχ^2 distribution with 3 degree of freedom under the null hypothesis of no asymmetric effects.

Table 2
Tests for sign and size bias for sovereign CDS and financial market return series.

	CDSs			BONDs			CDSb			BMI			EUROBOBL		
Variables	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif
ϕ_0	1.0347***	0.1219	0.0000	0.7549***	0.1499	0.0000	0.9185***	0.1065	0.0000	0.9264***	0.1379	0.0000	0.9021***	0.1606	0.0000
ϕ_1	-0.0600	0.2314	0.7952	0.4546**	0.2050	0.0267	0.0884	0.1816	0.6262	0.2866	0.1848	0.1211	0.3144**	0.2109	0.0454
ϕ_2	-0.0201	0.1801	0.9111	0.0950	0.1315	0.4702	-0.0341	0.1497	0.8197	-0.0064	0.1165	0.9557	-0.2085	0.1273	0.1019
ϕ_3	-0.0351	0.1298	0.7864	0.1626	0.1599	0.3096	0.0896	0.1043	0.3904	-0.5479**	0.2431	0.0518	0.0724	0.1721	0.6737
$\chi^2(3)$	10.1080*	_	0.0908	15.2311**	_	0.0556	11.010**	_	0.0388	11.7587***	_	0.0082	13.564**	_	0.0125

Note: The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively.

Table 2 reports the results of Engle-Ng tests. First, the individual regression results show that the residuals of the symmetric GARCH model for the CDSs and CDSb series do not suffer from sign bias, negative and positive size bias. Second, for the BONDs and EUROBOBL series, the individual regression results show that the residuals of the symmetric GARCH model do not suffer from negative and positive size bias. Third, the individual regression results show that the residuals of the symmetric GARCH model for the BMI series exhibit positive size bias. Finally, the $\chi^2(3)$ joint test statistics have p-values of 0.0908, 0.0556, 0.0388, 0.0082 and 0.0125, respectively, demonstrating a total rejection of the null of no asymmetries. The results overall would thus suggest motivation for estimating an asymmetric volatility model for these particular series.

4.2. AR-EGARCH specification

The first step of this specification is to estimate the univariate $AR(m) - EGARCH(p,q)$ models for each sovereign CDS and financial market return series (see Table 3). This paper considers the asymmetric effect, while Tamakoshi and Hamori (2014) did not. The AR(0)-EGARCH (1,1) model is chosen for all return series. The estimated parameters of the EGARCH (1, 1) model are statistically significant at the 1% significance level or better for the four variables, except the γ parameter for the CDSb variable. Table 3 also reports the estimates of the parameter β, which measures the degree of volatility persistence.We find that β for sovereign CDS returns, and major financial market returns are 0.9656, 0.9701, 0.9722, 0.9730 and 0.9924, respectively. From these estimates, we could infer that the persistence in shocks to volatility is relatively large.

In addition, Table 3 depicts the diagnostics of the empirical findings of the AR (0)-EGARCH (1,1) model. $LB - Q(20)$ and $LB - Q^2(20)$ are the Ljung-Box test statistics for the null hypothesis that there is no serial correlation up to order 20 for standardized and squared standardized residuals, respectively. The null hypothesis of no autocorrelation up to order 20 for squared standardized residuals is also accepted at the 1% level of significance.

Since our analysis focused on the dynamics of the correlations among the sovereign CDS and financial market returns, the well-fitted variance equations described above led us to conclude that our AR-EGARCH models fit the data rationally well.

Table 3
AR(0)-EGARCH(1,1) estimation results.

	CDSs			BONDs			CDSb			BMI			EUROBOBL		
	Coefficient	StdError	p-value	Coefficient	StdError	p-value	Coefficient	StdError	p-value	Coefficient	StdError	p-value	Coefficient	StdError	p-value
μ_0	-0.1829**	0.0621	0.0032	0.0317***	0.0049	0.0000	-0.2023***	0.0761	0.0079	0.0097	0.0224	0.6631	0.0127***	0.0032	0.0001
ω	-0.0088	0.0356	0.8037	-0.2181***	0.0692	0.0016	-0.0339	0.0297	0.2527	-0.1062***	0.0212	0.0000	-0.1142***	0.0428	0.0076
α	0.1281***	0.0415	0.0020	0.1728***	0.05	0.0005	0.1277***	0.0417	0.0022	0.1415***	0.0283	0.0000	0.1115***	0.0368	0.0024
β	0.9656***	0.0196	0.0000	0.9701***	0.0138	0.0000	0.9722***	0.017	0.0000	0.9730***	0.0101	0.0000	0.9924***	0.0055	0.0000
γ	-0.1173**	0.0228	0.0475	-0.0448*	0.0274	0.0921	0.0245	0.0193	0.2044	-0.1439***	0.0271	0.0000	-0.0625***	0.0189	0.0009
Student-t parameter (υ)	3.3887***	0.3736	0.0000	4.4456***	0.5929	0.0000	5.5579***	0.9031	0.0000	5.9233***	0.9751	0.0000	5.6895***	0.8858	0.0000
Log likelihood	-2730.98	_	_	210.2901	_	_	-2856.2924	_	_	-1631.13	_	_	551.8317	_	_
$LB-Q(20)$	77.9577***	_	0.0069	61.7943	_	0.1223	64.1816*	_	0.0715	91.4535***	_	0.0003	57.6622	_	0.2129
$LB-Q^2(20)$	53.8243	_	0.2612	78.9434***	_	0.0032	198.378***	_	0.0000	515.354***	_	0.0000	125.447***	_	0.0000

Notes: $\boldsymbol{r_t = \mu_0 + \varepsilon_t}$and $\boldsymbol{ln(h_t) = \omega + \alpha|z_{t-1}| + \gamma z_{t-1} + \beta ln(h_{t-1}}$, where $\boldsymbol{r_t}$ represents sovereign CDS returns and financial market returns, $\boldsymbol{\varepsilon_t}$ is the error term, $\boldsymbol{h_t}$ is the conditional volatility and$\boldsymbol{z_t = \varepsilon_t/\sigma_t}$ is the standardized residual. $\boldsymbol{LB - Q(20)}$and$\boldsymbol{LB - Q^2(20)}$ are the Ljung-Box statistics with 20 lags for the standardized and squared standardized residuals, respectively. The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively.

4.3. Multivariate Asymmetric DCC results

The second step of our analysis is to estimate the multivariate A-DCC model developed by Cappiello et al. (2006). The estimation results of the DCC and A-DCC models are reported in Table 4. We use this methodology to test the correlation among the selected sovereign CDS and financial market returns. Generally, we find that the A-DCC model seems to be specified reasonably well. Indeed, the estimates of the parameter of standardized residuals (a_1) and of innovations in the dynamics of the conditional correlation matrix (b_1) are significant at the 1% level or better. Most remarkably, the estimate of the parameter of the asymmetric term (g_1) is significant at the 10% level or better, thus providing evidence of an asymmetric response in correlations. In other words, when driven by negative innovations to changes, the conditional correlation among the CDSs and financial market indicators exhibits higher dependency than when driven by positive innovations. This result is rather interesting because it suggests that the reasons for the identified asymmetric correlation differ from the theoretical explanation of the "currency portfolio rebalancing" hypothesis.

Table 4
Empirical results of the DCC model (whole sample analysis).

	Whole sample period (September 20, 2011-February 02, 2016)					
	Symmetric DCC			Asymmetric DCC		
	Coefficient	StdError	p-value	Coefficient	StdError	p-value
a_1	0.1793***	0.0089	0.0000	0.1793***	0.0085	0.0000
b_1	0.9725***	0.0031	0.0000	0.9725***	0.0030	0.0000
g_1	-	-	-	0.0468***	0.0634	0.0000
Log Likelihood	-5493.9619	-	-	-5493.9619	-	-
BIC	11213.3886	-	-	11220.4343	-	-

Notes: The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively. $\boldsymbol{Q_t = (1 - a_1 - b_1)\bar{Q} - g_1\bar{N} + a_1 Z_{t-1}Z'_{t-1} + b_1 Q_{t-1} + g_1\eta_{t-1}\eta'_{t-1}}$ where $\boldsymbol{Q_t}$ is the conditional covariance matrix between the standardized residuals; $\boldsymbol{Z_t}$ is the matrix of the standardized residuals; $\boldsymbol{\bar{Q}}$ and $\boldsymbol{\bar{N}}$ are the unconditional correlation matrices of $\boldsymbol{Z_t}$; $\boldsymbol{\eta_t = I[Z_t < 0] \circ Z_t}$ and $\boldsymbol{I}[.]$ is a $\boldsymbol{k \times 1}$ indicator function such as $\boldsymbol{I = 1}$ if $\boldsymbol{Z_t < 0}$ and $\boldsymbol{I = 0}$ if $\boldsymbol{Z_t \geq 0}$, while " $\circ$ " is the Hadamard product.

Fig. 2 plots the estimated DCCs between each pair of the sovereign CDS and major financial market indicators. First, the time path of the DCC series fluctuates over the whole sample period for all pairs, thereby suggesting that the assumption of constant correlations may not be appropriate. This result is generally in line with empirical studies such as Perez-Rodriguez (2006) and Tamakoshi and Hamori (2014). Second, the estimated DCCs between all pairs remain at a relatively high level before 2012. This implies the development of a considerable degree of market integration, which has occurred since the inception of the euro. Third, the DCC series between all pairs of CDSs and financial market have shown sharp increases during the sovereign debt crisis since 2011.

5. Conclusion and policy implications

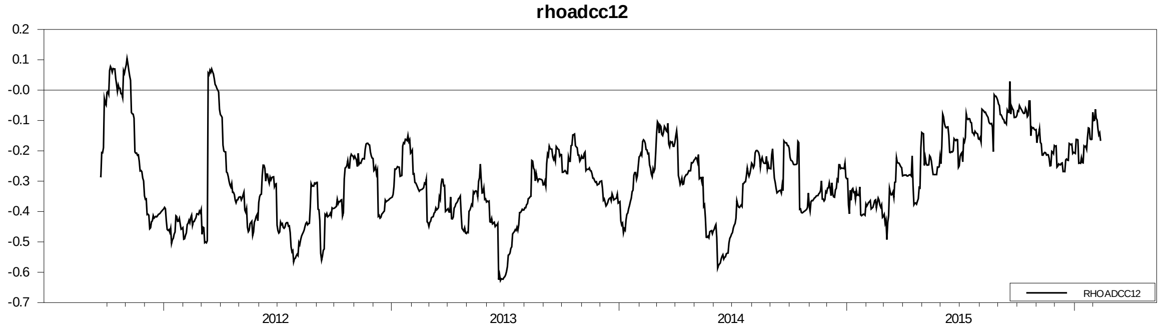
While time varying correlations of sovereign CDS and financial market returns have yielded voluminous research, relatively little attention has been given to the dynamics of correlations within a market.

In this paper, we analyze the dynamic conditional correlation between the sovereign CDS and financial market using the Asymmetric Dynamic Conditional Correlation (A-DCC) model developed by Cappiello et al. (2006). We also use an AR-GARCH model for statistical analysis of the time-varying correlations by considering the major financial and economic events relative to the sovereign debt crisis. Our empirical results indicate that sovereign CDS and financial market indicators exhibit asymmetry in the conditional variances. Therefore, the results point to the importance of applying an appropriately flexible modeling framework to accurately evaluate the interaction between CDSs and financial market co-movements.

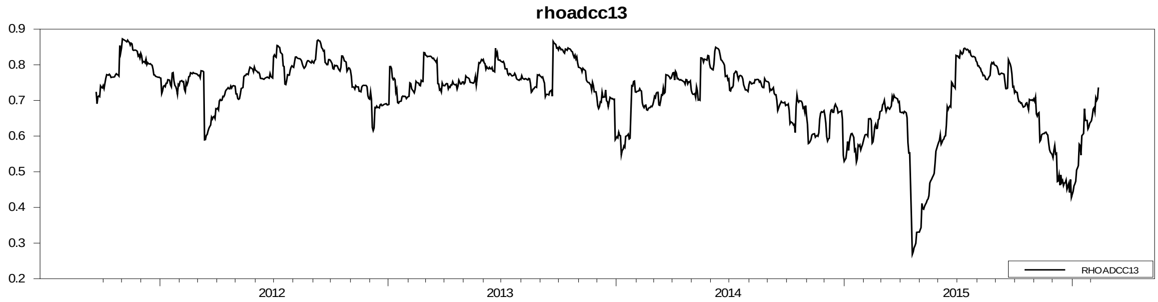
The time path of the DCC series fluctuates over the whole sample period for all pairs, thereby suggesting that the assumption of constant correlations may not be appropriate. Second, the estimated DCCs between all pairs remain at a relatively high level before 2012. This implies the development of a considerable degree of market integration, which has occurred since the inception of the Euro.

The findings lead to important implications from investors’ and policy makers’ perspective. They are of great relevance for financial decisions of international investors on managing their risk exposures to sovereign CDS and financial market fluctuations and on taking advantages of potential diversification opportunities that may arise due to lowered dependence among the sovereign CDS and financial market indicators.

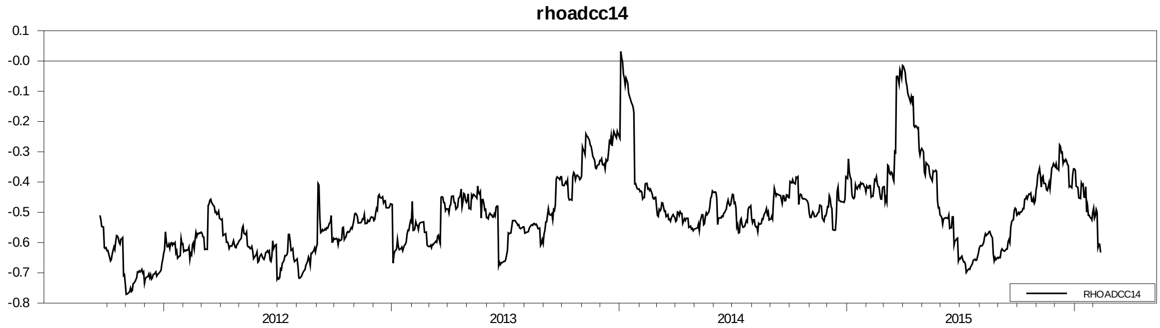
(A) The DCC between the CDSs and BONDs



(B) The DCC between the CDSs and CDSb



(C) The DCC between the CDSs and BMI



(D) The DCC between the CDSs and EUROBOBL

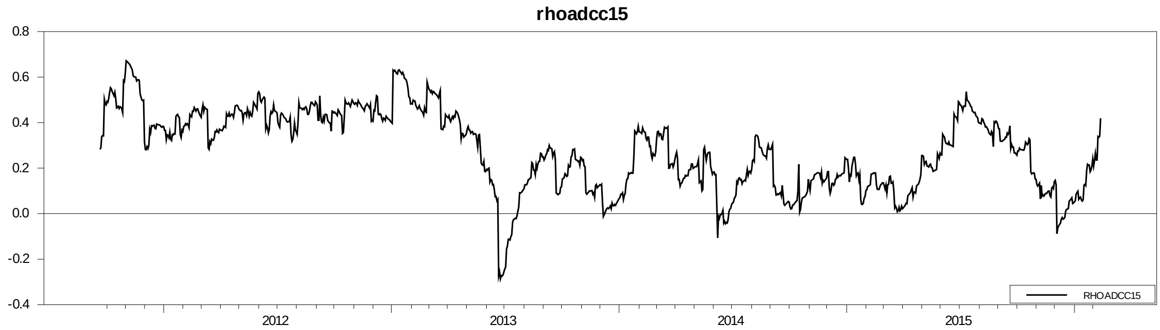


Fig. 2. Dynamic conditional correlations between each sovereign CDS and financial market pair. (a) The DCC between the CDSs and BONDs. (b) The DCC between the CDSs and CDSb. (c) The DCC between the CDSs and BMI. (d) The DCC between the CDSs and EUROBOBL.

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