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The Causal Linkages between Sovereign CDS Prices for the BRICS and Major European Economies

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Abstract
The article examines causal relationships between sovereign credit default swaps (CDS) prices for the BRICS and most important EU economies (Germany, France, the UK, Italy, Spain) during the European debt crisis. The cross-correlation function (CCF) approach that distinguishes between causality-in-mean and causality-in-variance and the Breitung–Candelon causality test in the frequency domain are used in the research. Both tests reveal limited dependence of the BRICS CDS (especially, in the case of Brazil, China and South Africa) on the EU CDS prices. Thus, the paper underscores the signs of decoupling in the sovereign CDS market and also supports the view that the European debt crisis has so far had a limited non-EU impact in this market.

JEL C50 G10 G15
Keywords BRICS; sovereign credit default swaps (CDS); causality-in-mean; causality-in-variance; decoupling; European debt crisis; Breitung–Candelon test

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1 Introduction

The European debt crisis has reignited the public and scientific debate on financial contagion and spillovers. In this context, one of the central issues is whether the affected EU countries have been contagious for emerging market (EM) economies, in particular, for the BRICS. The BRICS have fared relatively well during the EU financial turmoil but, obviously, have not been insulated from the negative shocks generated within the EU. For example, Ahmad et al. (2013) find that the BRICS stock markets have been hit strongly during the Eurozone crisis period, with Italy, Spain and Ireland being the most contagious for the BRICS. However, the overall degree of the BRICS exposure to the EU shocks remains insufficiently examined as other potentially important venues of instability propagation, e.g. sovereign debt market or interbank lending linkages have not received necessary attention. Meanwhile, such an analysis would be beneficial and timely due to an increasing systemic financial importance of emerging economies, in particular, that of China (Armijo et al. 2014).

This study attempts to partly fill in this gap by testing for causalities between the most important EU economies (Germany, France, the UK, Italy and Spain) and the BRICS in the sovereign credit default swaps (CDS) market. Studying CDS prices appears to be instrumental in analyzing sovereign credit risks as CDS markets tend to be more liquid than those of the referenced sovereign bonds and disseminate market-wide information more rapidly (Forte and Peña 2009; Delis and Mylonidis 2011). These features of sovereign CDS are valid for advanced and EM economies (Longstaff et al. 2011; Li and Huang 2011; Dieckmann and Plank 2012). In addition, Rodriguez-Moreno and Peña (2013) emphasize an important role of CDS prices as a basis of robust systemic risk measures.

The novelty of the paper lies in the use of the cross-correlation function (CCF) approach which allows to examine the presence of two types of causality (causality-in-mean and causality-in-variance)[1] between the major EU economies

[1] This approach to testing causal linkages is in the vein of the Granger–Sims concept of causality which is data-based and without direct reference to economic theory (Hoover 2008). It builds on the notion of predictability when *Y* is said to Granger cause *X* if lagged *Y* values help predict *X*. Though criticized from the methodological viewpoint, this approach is legitimized by probabilistic theory of causality (Eells 1991) and is widely recognized in econometrics. Moreover, recent studies show that

and the BRICS on country-to-country basis. I find that the major EU economies' CDS prices are largely dependent on the performance of the BRICS CDS with the exception of Germany. Italian and Spanish CDS experience the greatest number of incoming causal linkages from the BRICS. Meanwhile, India is the only BRICS sovereign to have a clear-cut negative balance of outgoing and incoming causality among the BRICS.

The results make case for the decoupling hypothesis[2] in the sovereign CDS market and for a limited magnitude of the non-EU contagion in sovereign bond markets triggered by the developments within the EU. Limited dependence of the BRICS CDS prices on the EU CDS prices generally holds when causal relations between the pair-wise series are examined in the frequency rather than time domain, based on Breitung and Candelon (2006) test. This dependence tends to be the lowest when tested on weekly data.

The remainder of the paper is organized as follows. Section 2 reviews relevant literature, Section 3 presents the data, Section 4 describes econometric methodology with respect to the CCF approach. Section 5 discusses the results, Section 6 presents the robustness checks, and Section 7 concludes.

2 Relevant Literature Review

The paper is related to several strands of literature. Its bulkiest body focuses on intra–EU linkages in the sovereign CDS market.[3] The analysis of the papers enables to distill several stylized facts.

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this reduced approach to testing causality can be embedded into structural models that imply deterministic relations between variables (White and Lu 2010; White and Petenuzzo 2014).

[2] Decoupling stands for a delinking of economic and financial variable trajectories of advanced and developing economies. Most often it is examined in the context of business cycle asymmetry (or synchronization) between the two groups of countries. Here I resort to this concept in a narrow sense. Decoupling is defined as a relatively small number of Granger causalities running from the major EU CDS series to the BRICS CDS prices, when the impact of a BRICS economy on the EU countries (the number of outgoing causal relations) is more profound than the influence exerted by the EU (in terms of incoming causalities).

[3] It is also worth mentioning the literature on the credit risk transfer from the banking sector to sovereigns prior to the European debt crisis and mutually reinforcing linkages between banks and

First, there has been substantial co-movement of the EU sovereign CDS prices. The leading EU economies, such as Germany, have also witnessed a notable rise in their CDS spreads. However, this has been a reflection of interdependence rather than contagion. It was first fueled by Greece and then by Ireland and Portugal in a relay-race manner (Caporin et al. 2013; Broto and Perez-Quiros 2013).

Second, in regard to contagion, the EU sovereign CDS market has been split into two segments—peripheral (Greece, Portugal, Ireland) and core economies (Germany, the UK, France). There was certain risk transmission between them but prior to 2010, and by now it has almost vanished (Groba et al. 2013). The core economies have more capacity to trigger contagion internationally (Kalbaska and Gatkowski 2012), whilst within the EU the intensity of risk spillovers is higher for the peripheral economies which have a long–run volatility memory, but their overall impact is relatively low (Gunduz and Kaya 2013).

Third, though often referred to as peripheral, Italy and Spain should rather be considered core economies. They play a pivotal role for the dynamics of German CDS prices, and vice versa. Consequently, any credit risk event on Italian or Spanish CDS will have catastrophic implications for the entire EU (Gonsalez-Hermosillo and Johnson 2012).

Fourth, the global non-EU factors (the VIX index or TED spread) do not influence significantly the EU core economies' CDS prices but these economies are sensitive to changes in intra-EU financial market variables such as the dynamics of the DAX index (Ang and Longstaff 2013; Zoli 2013).

Unlike their EU counterparts, EM sovereign CDS spreads are linked to global indicators more tightly. For example, the VIX index and TED spread are important predictors for Latin American CDS prices, including those of Brazil and Mexico (Wang et al. 2013). Similarly, based on a wider sample of EM sovereign CDS, Fender et al. (2012) assert that global and regional risk premia contribute to EM sovereign CDS dynamics more than country-specific determinants like credit ratings or macroeconomic variables. They enlarge the list of useful international predictors by adding S&P 500 index and US Treasury 3-month bill rate. China CDS prices are also heavily dependent on global indicators and this dependence has become more pronounced over the past years relative to the role of domestic

sovereigns during the subsequent crisis period. See, for example, Acharya et al. (2011), Ejsing and Lemke (2011), Alter and Schuler (2012).

factors such as the China stock market index and the real interest rate (Eyssell et al. 2013).

The importance attached to China CDS as a potential predictor of other countries' credit risk has been on the rise as well. Analyzing linkages among 11 Asian sovereign CDS spreads, Wong and Fong (2011) emphasize the systemic role of China and South Korea. Ang and Longstaff (2013) and Kalotychou et al. (2013) find that China CDS price dynamics is a reliable predictor of the EU credit risk. However, they do not focus on country-to-country linkages, considering the EU as an integration block.

The literature studying the EU impact on EM CDS prices is very scarce. To the best of my knowledge, the only paper that addresses this issue in regard to the BRICS is Sujithan and Avouyi–Dovi (2013). They find that EU financial indicators exerted major influence over the BRICS sovereign CDS prices in the long-run—from 2002 to 2012. Nevertheless, their analysis was not carried out on country-to-country basis either, as aggregate indicators (Dow Jones Eurostoxx 50 and Eurozone corporate benchmark 5-year yield for AAA issuers) were used as predictors of the BRICS CDS prices. Sujithan and Avouyi–Dovi also find that the EU financial factors remain robust when global indicators (the VIX and S&P 500 indices) are taken into account.

Neither of the papers, however, explicitly tackles causality issues as risk spillovers were quantified based on VAR/VECM models and econometric techniques derived from them. The paper which directly addresses the issue via the cross-correlation function (CCF) approach and, thus, is closest in methodology to my research, is Yoshizaki et al. (2013). They study causal linkages between major EU economies' CDS (Germany, France, the UK, Italy, Spain, Greece and Portugal) and Japan in two sub-samples—before the start of the European debt crisis (January 2009–April 2010) and afterwards (May 2010–March 2012). They conclude that the causal linkages strengthened in terms of causality-in-mean after the beginning of the European debt crisis. Their direction also experienced a reversal: Japan began to trigger transmission to all the EU economies but the UK, whereas before the crisis it had been subject to incoming linkages from them.

3 Data

Daily 5-year sovereign CDS prices[4] are used to conduct the research. The data are sourced from *Bloomberg* and contain 975 observations from January 2010 to September 2013. Thus, the time span encompasses the developments related to the European debt crisis.

CDS prices for the BRICS exhibit a high degree of co-movement. In particular, the first principal component accounts for 79 percent of the variation in the BRICS CDS prices. On pairwise basis, correlations between the BRICS range from 0.60 (between India and Brazil) to 0.92 (between China and Russia) (Fig. 1).

There is also a high level of commonality in the major EU countries' CDS prices. The first principal component explains 77 percent of the variation in these countries' CDS prices, though the disparity in pairwise correlations is more significant than for the BRICS. The lowest correlation is observed between the UK and Spain (0.14), whereas the highest is between Germany and France (0.96) (Fig. 2).

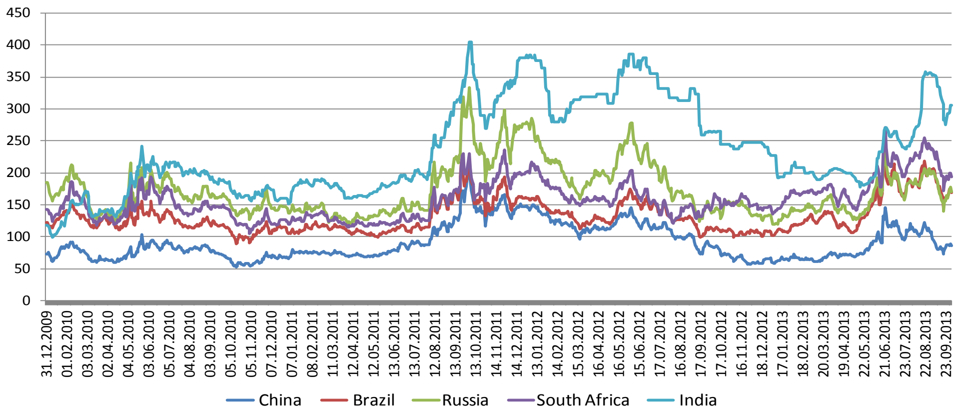

Figure 1: Daily Sovereign CDS Price Dynamics for the BRICS Countries, January 2010–September 2013

[4] State Bank of India (SBI) CDS prices are used as a proxy of sovereign credit risk as India has not issued Eurobonds. This is the largest commercial bank in India and the only one featuring in Global Fortune 500 among Indian financial institutions. The indicators of SBI economic performance are often referred to as proxies for the Indian economy by international investors.

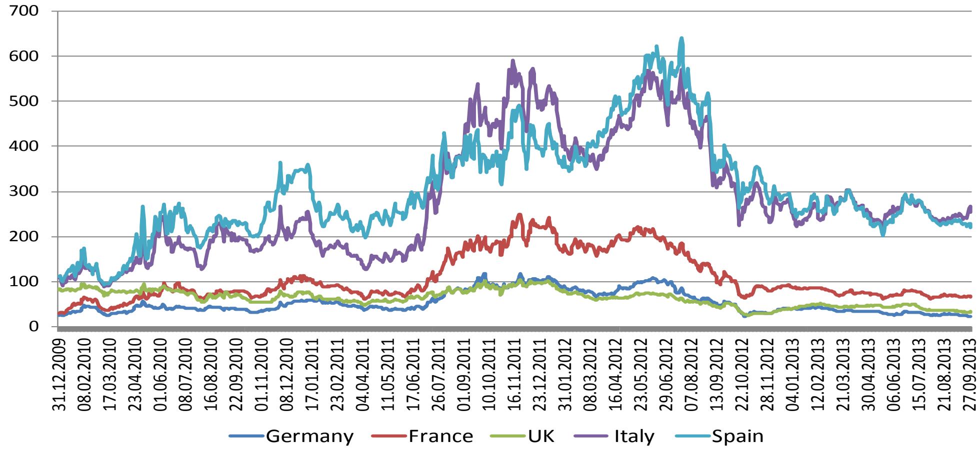

Figure 2: Daily Sovereign CDS Price Dynamics for Major EU Economies, January 2010–September 2013

The first principal component for the joint BRICS–EU sample accounts for 67 percent of the variation in CDS prices, also unveiling a strong co-movement of credit risk between the BRICS countries and leading EU economies. The degree of commonality appears to be only slightly lower than for the BRICS and the five EU economies examined separately. This preliminary result additionally motivates search for possible causality between the BRICS and major EU sovereigns' CDS prices. Pairwise correlations are reported below (Table 1).

The descriptive statistics for the BRICS CDS series are presented in Table 2. The daily mean varies from 91.50 for China to 237.62 for India. The series show

Table 1: Ordinary Correlations between the BRICS and Major EU Economies' CDS Prices, January 2010–September 2013

	CHINA	BRAZIL	RUSSIA	SAFRICA	INDIA
GERMANY	0.82	0.35	0.77	0.24	0.72
FRANCE	0.83	0.38	0.76	0.32	0.81
UK	0.49	0.21	0.59	0.02	0.10
ITALY	0.81	0.47	0.73	0.45	0.88
SPAIN	0.65	0.26	0.54	0.21	0.79

Table 2. Descriptive statistics for the BRICS CDS prices

	LEVELS					1st DIFFERENCES				
	CHINA	BRAZIL	RUSSIA	SOUTH AFRICA	INDIA	CHINA	BRAZIL	RUSSIA	SOUTH AFRICA	INDIA
N obs.	975	975	975	975	975	974	974	974	974	974
Mean	91.50	131.98	172.55	157.50	237.62	0.01	0.05	-0.02	0.05	0.19
Median	81.81	124.53	161.55	153.18	210.33	-0.06	-0.01	-0.10	-0.04	0.00
Maximum	199.22	219.09	333.06	270.62	405.00	29.94	23.88	44.00	37.86	46.14
Minimum	53.26	89.54	119.61	104.96	99.75	-20.88	-25.62	-54.79	-46.41	-48.35
Std. Dev.	27.68	25.72	40.32	30.02	72.64	3.86	4.73	7.01	5.98	6.06
Skewness	0.95	1.10	1.15	0.81	0.46	0.72	0.10	-0.15	-0.30	-0.39
Kurtosis	3.20	3.68	3.88	3.24	2.07	12.11	8.20	12.12	12.42	16.46
Jarque-Bera	148.03 [0.000]	214.86[0.000]	247.38 [0.000]	108.96 [0.000]	69.35 [0.000]	3453.25 [0.000]	1097.15 [0.000]	3381.35 [0.000]	3615.75 [0.000]	7377.56 [0.000]
ADF	-2.24	-2.60*	-2.98**	-3.00**	-1.94	-18.87***	-17.83***	-18.16***	-19.40***	-18.17***
PP	-2.24	-2.67*	-2.88**	-2.79*	-2.02	-30.58***	-27.91***	-28.51***	-31.36***	-29.35***
DF-GLS	-1.84*	-2.35**	-2.86***	-2.61***	-0.37	-18.88***	-17.83***	-18.16***	-19.39***	-18.16***
KPSS	0.65**	0.63**	0.36*	1.35***	1.55***	0.07	0.05	0.04	0.04	0.07
Q-stat(20)	16113 [0.000]	13581 [0.000]	14008 [0.000]	13588 [0.000]	16602 [0.000]	70.81 [0.000]	66.47 [0.000]	58.40 [0.000]	49.39 [0.000]	70.30 [0.000]
Qsq-stat(20)	14990 [0.000]	12939 [0.000]	13157 [0.000]	13086 [0.000]	16227 [0.000]	429.72 [0.000]	521.45 [0.000]	265.01 [0.000]	281.61 [0.000]	32.59 [0.000]
ARCH-LM test (5)	32.26 [0.000]	26.54 [0.000]	23.26 [0.000]	27.22 [0.000]	3.81 [0.002]	33.78 [0.000]	26.66 [0.000]	20.39 [0.000]	24.67 [0.000]	3.89 [0.002]

Note: The figures in square brackets show the probability (p-values) of rejecting the null hypothesis. For ADF, PP and DF–GLS tests the null hypothesis is that the series has a unit root, for KPSS it is that the series is stationary. *, **, *** indicate that the null hypothesis is rejected at 10, 5 and 1% significance level respectively.

signs of positive skewness and excess kurtosis. The Jarque-Bera test strongly rejects the normality of the CDS price series. Thus, their empirical distributions must be characterized by heavy tails.

In case of India and China unit root tests suggest that the series are not stationary, whilst for Brazil, South Africa and especially Russia they yield conflicting results.[5] To ensure stationarity of the series, they are first-differenced. The baseline (levels) and first-differenced series and their squares (both levels and 1st differences) exhibit serial correlation (up to 20 lags) and ARCH effects (up to 5 lags) judging by Ljung-Box Q-statistic and LM conditional variance test.

The descriptive statistics for the leading EU sovereigns' CDS series are presented in Table 3.

The daily mean ranges from 53.79 for Germany to 305.44 for Spain. Thus, mean Spanish and Italian CDS prices exceed the corresponding indicators for the BRICS. The Jarque-Bera test shows that the EU CDS price series are non-normal. Unlike the BRICS series, unit root is present in all the EU sovereigns' series, so, they are first-differenced. Ljung-Box Q-statistic and LM conditional variance test indicate the existence of serial correlation and ARCH effect in levels and 1st differences and in the respective squared series.

4 Econometric Methodology

The two-stage cross–correlation function (CCF) approach proposed by Cheung and Ng (1996) and modified by Hong (2001) is used. It has become widespread in analyzing causality between stock market returns (Xu and Hamori 2012; Korkmaz et al. 2012), sovereign bond yields (Tamakoshi 2011) and different segments of the financial sector (Tamakoshi and Hamori 2012).

At the first stage GARCH models should be fitted to univariate series in question. Usually Autoregressive, Generalized Autoregressive Conditional Heterodoskedasticity (AR–GARCH) or Autoregressive, Exponential Generalized

[5] Most widespread unit root tests (Augmented Dickey-Fuller test (ADF) and Phillips-Perron test (PP) and Dickey-Fuller–GLS (DF–GLS)) reject the null hypothesis that the CDS prices of Brazil, Russia and South Africa have a unit root at least at 10% level. However, the result contradicts Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test that has more power in comparison with the above–mentioned tests.

Table 3. Descriptive statistics for the leading EU sovereigns' CDS prices

	LEVELS					1st DIFFERENCES				
	GERMANY	**FRANCE**	**UK**	**ITALY**	**SPAIN**	**GERMANY**	**FRANCE**	**UK**	**ITALY**	**SPAIN**
N obs.	975	975	975	975	975	974	974	974	974	974
Mean	53.79	108.94	63.58	284.03	305.44	0.00	0.04	-0.05	0.15	0.11
Median	43.62	84.84	64.33	251.50	274.87	0.00	0.00	0.00	-0.08	0.12
Maximum	119.17	249.63	104.92	591.54	641.98	11.00	22.76	10.61	64.08	55.29
Minimum	24.00	29.69	26.20	89.74	93.81	-14.67	-30.03	-12.69	-80.83	-73.89
Std. Dev.	24.31	53.09	17.78	129.26	114.55	2.19	4.76	2.13	12.59	13.47
Skewness	0.90	0.90	-0.04	0.63	0.68	-0.18	-0.28	-0.15	0.05	-0.47
Kurtosis	2.51	2.46	2.19	2.26	3.11	8.76	8.51	7.79	8.58	6.84
Jarque-Bera	140.36 [0.000]	143.28[0.000]	26.91 [0.000]	87.48 [0.000]	75.56 [0.000]	1350.79 [0.000]	1247.02 [0.000]	933.00 [0.000]	1263.89 [0.000]	635.03 [0.000]
ADF	-1.46	-1.70	-1.61	-1.95	-2.02	-19.20***	-19.31***	-29.56***	-21.99***	-18.61***
PP	-1.50	-1.64	-1.49	-1.84	-1.97	-25.23***	-26.94***	-29.65***	-24.21***	-26.96***
DF-GLS	-1.01	-0.79	-0.57	-0.93	-0.78	-7.52***	-26.51***	-2.44**	-21.97***	-18.56***
KPSS	0.73**	0.90***	1.94***	1.42***	1.28***	0.25	0.32	0.06	0.16	0.26
Q-stat(20)	17254 [0.000]	17673 [0.000]	16479 [0.000]	17465 [0.000]	16914 [0.000]	81.04 [0.000]	56.46 [0.000]	42.62 [0.000]	83.78 [0.000]	70.59 [0.000]
Qsq-stat(20)	16909 [0.000]	17347 [0.000]	16170 [0.000]	17015 [0.000]	16858 [0.000]	771.56 [0.000]	536.12 [0.000]	245.98 [0.000]	192.49 [0.000]	266.80 [0.000]
ARCH-LM test (5)	36.70 [0.000]	22.33 [0.000]	17.08 [0.000]	11.06 [0.000]	17.05 [0.000]	37.17 [0.000]	21.42 [0.000]	16.44 [0.000]	10.78 [0.000]	18.73 [0.000]

Note: The figures in square brackets show the probability (p-values) of rejecting the null hypothesis. For ADF, PP and DF–GLS tests the null hypothesis is that the series has a unit root, for KPSS it is that the series is stationary. *, **, *** indicate that the null hypothesis is rejected at 10, 5 and 1% significance level respectively.

Autoregressive Conditional Heterodoskedasticity (AR–EGARCH) specifications are considered. Autoregressive-moving-average (ARMA) models for mean equations can also be applied.

At the second stage special statistics to study causality-in-mean and causality-in-variance are computed on the basis of standardized residuals and squared standardized residuals derived from the fitted AR/ARMA–GARCH model. The standardized residuals ν and squared standardized residuals u are represented respectively as follows:

$$\nu = \frac{\varphi_t - \mu}{\sqrt{h_t}} \qquad (1)$$

$$u = \frac{(\varphi_t - \mu)^2}{h_t} \qquad (2)$$

where φ_t are residuals, μ —mean of the residuals and h_t—conditional variance of the AR/ARMA–GARCH model. Let η and ρ be standardized residuals and squared standardized residuals for another AR/ARMA–GARCH model fitted to the series that presumably has causal linkages with the series in question. In order to test the null hypothesis of no causality-in-mean between the two series during the first k lags, an S-statistic proposed by Cheung and Ng (1996) following a null asymptotic $\chi^2(k)$ distribution is computed:

$$S_1 = T\sum_{i=1}^{k} r_{\nu\eta}^2(i) \qquad (3)$$

where T is the sample size of the residual series, k—the number of lags and $r_{\nu\eta}^2(i)$—squared cross-correlation ratio between the standardized residuals ν and η at lag i. In case of causality-in-variance this statistic is calculated in the same way, the standardized residuals being replaced with squared standardized residuals u and ρ:

$$S_2 = T\sum_{i=1}^{k} r_{u\rho}^2(i) \quad (4).$$

The shortcoming of this S-statistic is that each lag is weighted uniformly, making no difference between recent and distant cross-correlations. It is inconsistent with an intuitive expectation that more recent information should play a primary role, with cross-correlations decreasing to 0 as the lag order increases. Hong (2001) proposed a new Q-statistic to overcome this weakness of the S-statistic. The Q-statistics to test causality-in-mean and causality-in-variance are given as follows:

$$Q_1 = \frac{S_1 - k}{\sqrt{2k}} \xrightarrow{L} N(0,1) \quad (5)$$

$$Q_2 = \frac{S_2 - k}{\sqrt{2k}} \xrightarrow{L} N(0,1) \, (6).$$

Q-statistic is designed to test one-sided causality; upper-tailed standard normal distribution critical values must be used. If the Q-statistic is larger than the critical value of the normal distribution, the null hypothesis of no causality during the first k lags is rejected.

The correct application of the CCF approach depends on the adequate specification of AR/ARMA–GARCH models and the unbiased estimation of their parameters. The key problem that might arise and seriously affect the results of the causality tests based on the CCF approach is the presence of structural breaks in the variances of the series. Van Dijk et al. (2005) and Rodriguez and Rubia (2007) find that severe size distortions in causality-in-variance tests occur when these breaks are observed. Thus, prior to testing for causality-in-variance, the presence of the structural breaks in the variances of the series should be examined.

The “iterative cumulative sum of squares (ICSS)” test procedure proposed in Inclan and Tiao (1994) and its modified versions (for example, Sanso et al. 2004) have been used to detect structural breaks in the variances. Nevertheless, the usefulness of the procedures has been questioned as they are not well suited to identify multiple structural breaks.[6]

This paper proposes an approach based on Bai–Perron (2003a, 2003b) structural break tests which may be a viable alternative to the methods enlisted above. Like the competing procedures, Bai–Perron tests are aimed at determining structural breaks endogenously, without any a priori information on their dates, but they are more flexible and instrumental in case of multiple breaks. This approach has been applied to detect volatility in sovereign bond markets (Tamakoshi and Hamori 2013), but to the best of my knowledge, this is the first attempt to use Bai–Perron tests to achieve superior GARCH estimation results as a prerequisite for further multiple causality analysis in the sovereign CDS market. After AR/ARMA–GARCH models have been estimated, GARCH variances are subject to Bai–Perron structural break test. To this end, the variances are regressed on a constant and then Bai–Perron sequential subset testing procedure is implemented. If a structural break is identified, a dummy variable corresponding to its date is constructed and considered as a variance regressor. Then the variance equation of the initial AR/ARMA–GARCH model is re-estimated to account for shifts in volatility. Based on the re-estimated model, the S- and Q-statistics are computed.

5 Results and Discussion

At the first stage of the CCF approach adequate GARCH models have been fitted to the first-differenced CDS price series of the BRICS and leading EU economies. The baseline model specification for all the series is ARMA(k,m)–EGARCH(p,q) which is represented as follows:

$$x_t = a_0 + \sum_{i=1}^{k} a_i x_{t-i} + \sum_{i=1}^{m} b_i \varepsilon_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \text{GED} \qquad (7)$$

$$\ln(\sigma_t^2) = w + \sum_{i=1}^{p} (\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}) + \sum_{i=1}^{q} \beta_i \ln(\sigma_{t-i}^2) \quad (8)$$

6 See Korkmaz et al. (2012) for a detailed discussion of these statistical techniques and problems with their application.

Generalized error distribution (GED) is assumed in the baseline model.[7] $k(1,2,...10)$, $m(0,1,2,...10)$ as well as $p(1,2)$ and $q(1,2)$ are determined by means of Schwartz means of Schwartz Bayesian information criterion (SBIC) whilst conducting residual diagnostics to avoid autocorrelation. The EGARCH (1,1) model has been selected for all variance equations[8] whereas the order of AR/ARMA models fitted to mean equations differs.

After the preliminary estimation of the ARMA(k,m)–EGARCH(p,q) models, GARCH variances have been generated and examined for potential structural breaks. The results of Bai–Perron test indicate that the number of potential breaks does not exceed four dates, except for Russia and South Africa (Table 4).

These countries did not experience any shifts in their CDS prices within the period in question. For the rest of the BRICS and EU countries break dates constitute four "time clusters"—late July 2010, summer 2011, January–February 2012 and early November 2012. The break dates that occurred in summer 2011 and early 2012 can be treated as common for the BRICS and major EU economies. In late July 2010 they largely concentrate in the BRICS and, on the contrary, in January–February 2012 the potential break dates refer to the EU countries.

Then, as stated in Section 4, dummy variables corresponding to the potential break dates have been constructed. The initial ARMA(k,m)–EGARCH(p,q) specifications are re-estimated, with the dummy variables entering variance equations. Tables 5 and 6 present the parameter estimates for the models of the BRICS and major EU sovereigns' CDS prices.

[7] GED distribution is argued to be more flexible than normal and Student's–t distributions in modeling time series with heavy tails and, thus can be considered a generalization of both. However, in case of the UK and India EGARCH(1,1)–normal distributional assumption is found to fit the model better than GED.

[8] ARMA(k, m)–EGARCH(1,1) specifications proposed by Nelson (1991) that account for a possible asymmetry in volatility dynamics outperform standard GARCH (1,1) by their statistical quality, namely, by the values of maximum likelihood estimators of the equations and Schwartz Bayesian information criterion (SBIC).

Table 4: Variance Break Tests for the BRICS and Major EU Economies

Country	No. of potential breaks	Break dates
CHINA	3	27.07.2010 10.08.2011 29.02.2012
BRAZIL	4	28.07.2010 08.08.2011 27.02.2012 12.03.2013
RUSSIA	—	—
SOUTH AFRICA	—	—
INDIA	3	27.07.2010 22.06.2011 16.07.2012
GERMANY	3	12.07.2011 03.02.2012 13.11.2012
FRANCE	3	19.07.2011 07.02.2012 15.11.2012
UK	4	28.09.2010 06.06.2011 26.12.2011 01.11.2012
ITALY	3	07.07.2011 26.01.2012 15.11.2012
SPAIN	4	26.07.2010 18.07.2011 06.02.2012 14.11.2012

Table 5: Empirical Results of ARMA(k,m)–GARCH(1,1) Models for the BRICS

	CHINA AR(2)-EGARCH(1,1)		BRAZIL ARMA(3,3)-EGARCH(1,1)		RUSSIA AR(2)-EGARCH(1,1)		SOUTH AFRICA AR(1)-EGARCH(1,1)		INDIA (SBI) AR(2)-EGARCH(1,1)	
Mean Equation	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
a0	-0.04	0.08	0.07	0.10	-0.08	0.15	0.002	0.10	0.25***	0.01
a1	-0.004	0.03	-0.29***	0.03	0.08***	0.03	0.06**	0.03	0.07***	0.02
a2	0.07**	0.03	-0.26***	0.02	0.07***	0.02			0.13***	0.02
a3			-0.91***	0.02						
b1			0.32***	0.02						
b2			0.32***	0.02						
b3			0.94***	0.02						
Variance equation										
w	-0.11***	0.02	-0.12***	0.02	-0.07**	0.03	0.08***	0.03	0.04***	0.00
α1	0.21***	0.03	0.24***	0.03	0.20***	0.03	0.21***	0.03	-0.03***	0.00
γ1	0.08***	0.02	0.08***	0.02	0.09***	0.02	0.10***	0.03	0.10***	0.01
β1	0.98***	0.01	0.97***	0.01	0.98***	0.01	0.98***	0.01	0.99***	0.01
GED parameter	1.21***	0.07	1.44***	0.07	1.14***	0.05	1.07***	0.06		
Log Likelihood	-2422.46		-2633.19		-3002.93		-2840.16		-2977.28	
Q-stat(20)	8.54		11.16		14.02		13.53		17.53	
p-value	0.14		0.67		0.73		0.81		0.49	
Qsq-stat(20)	18.76		29.89		12.48		12.38		8.71	
p-value	0.54		0.11		0.89		0.90		0.99	

Table 6: Empirical Results of ARMA(k,m)–GARCH(1,1) Models for Major EU Economies

	GERMANY AR(1)-EGARCH(1,1)		FRANCE AR(1)-EGARCH(1,1)		UK ARMA(2,2)-EGARCH(1,1)		ITALY AR(1)-EGARCH(1,1)		SPAIN AR(1)-EGARCH(1,1)	
Mean Equation	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
a0	0.00	0.04	-0.08	0.07	-0.04	0.05	0.02	0.25	0.08	0.28
a1	0.13***	0.03	0.11***	0.03	-1.38***	0.01	0.18***	0.03	0.13***	0.03
a2					-0.96***	0.01				
a3										
b1					1.40***	0.00				
b2					1.00***	0.00				
b3										
Variance equation										
w	-0.23***	0.03	-0.16***	0.03	-0.10***	0.01	-0.09***	0.03	-0.11**	0.04
α1	0.36***	0.05	0.24***	0.04	0.17***	0.02	0.20***	0.04	0.27***	0.04
γ1	0.03	0.03	0.01	0.03	0.05***	0.01	0.09***	0.02	0.06**	0.03
β1	0.97***	0.01	0.99***	0.00	0.98***	0.00	0.99***	0.01	0.98***	0.01
Structural break dummy	-1.50**	0.65			-0.38*	0.23				
GED parameter	1.09***	0.06	1.11***	0.07			1.10***	0.07	1.26***	0.08
Log Likelihood	-1825.49		-2546.97		-1958.69		-3568.49		-3685.04	
Q-stat(20)	17.5		12.81		21.18		18.11		23.77	
p-value	0.56		0.85		0.17		0.52		0.21	
Qsq-stat(20)	10.22		20.12		19.66		21.89		23.89	
p-value	0.96		0.45		0.48		0.35		0.25	

It appears that the use of the dummy variables has improved the quality of only two models—those of Germany and the UK. The initial and re-estimated GARCH specifications have been compared based on the values of maximum likelihood estimators of the equations and Schwartz Bayesian information criterion. Thus, structural shifts in volatility over January 2010–September 2013 mattered more for the EU economies than for the BRICS.

All ARCH (α_1) and GARCH (β_1) coefficients of the equations presented in Tables 5 and 6 are statistically significant at least at the 5% level. The Ljung–Box statistics, Q-stat(20) and Qsq-stat(20), show that the null hypothesis of no autocorrelation up to lag 20 for the standardized and squared standardized residuals holds at the 1% percent significance. It enables to argue that the overall quality of the suggested model specifications is reasonably good and they can be used at the second stage of the CCF approach.

The appendix reports empirical results of the CCF analysis to test for the null hypothesis of no causality up to lag k (1, 2,.., 15), measured in days, for each combination of the BRICS–EU series. To generalize the results in a convenient way, a causality table is filled in (Table 7).

The density of causal linkages between the BRICS and major EU sovereigns is quite moderate. It is equal to 24 and 30 per cent of potential linkages in regard to causality-in-variance and causality-in-mean respectively. Moreover, unidirectional causality is predominant. The result is in line with Peltonen et al. (2013) who study bilateral exposures within a big CDS network encompassing 642 sovereigns and financial institutions and find that it is heterogeneous and of low concentration. These properties make it resemble big interbank lending and payment system networks.

In regard to causality directions, Germany is the only sovereign to have a positive balance of outgoing and incoming causal linkages with the BRICS. Within the time span in question, German CDS prices Granger caused those of Brazil and India with respect to causality-in-variance and that of India regarding causality-in-mean. It experienced no feedback from the BRICS. The rest of the EU sovereigns are mostly Granger caused by the BRICS counterparts. This direction of causality becomes more pronounced from the UK and France to Italy and Spain.

Among the BRICS, Brazil has the greatest number of outgoing linkages, both in terms of causality-in-variance and causality-in-mean. China, Russia and South Africa are completely decoupled from the EU influence in any type of causality.

Table 7: Causality-in-Mean and Causality-in-Variance between the BRICS and Major EU Sovereigns' CDS Daily Prices, January 2010–September 2013

	Causality-in-variance		Causality-in-mean	
	EU country→BRICS country	*BRICS country→EU country*	*EU country→BRICS country*	*BRICS country→EU country*
CHINA				
GERMANY				
FRANCE				
UK				
ITALY		+		+
SPAIN		+		+
BRAZIL				
GERMANY	+			
FRANCE		+		+
UK		+		+
ITALY		+		+
SPAIN		+		+
RUSSIA				
GERMANY				
FRANCE		+		
UK				
ITALY				+
SPAIN				+
SOUTH AFRICA				
GERMANY				
FRANCE		+		
UK				
ITALY		+		
SPAIN		+		+
INDIA (SBI)				
GERMANY	+		+	
FRANCE			+	
UK			+	
ITALY			+	+
SPAIN			+	

Note: Only causal linkages significant at least at the 5% level are taken in account and denoted as "+".

Their influence is largely concentrated on Italy and Spain and to a less extent on France. On the contrary, India appears to be the most vulnerable to the EU influence, though it is entirely channeled via causality-in-mean.

Overall, the findings indicate that there was no significant dependence of the BRCS sovereign credit risk on the developments in the EU. Rather, the major EU economies were affected by the changes in the credit risk of the BRCS. In case of Italy and Spain this conclusion is especially true.

The result meshes well with the studies that emphasize a quite satisfactory performance of EM sovereign bonds during 2009–2012 when many of them were reckoned as a safe haven by international investors. EM sovereign bonds denominated in local currencies and US dollars fared best of all (Miyajima et al. 2012). This interest in EM public debt was motivated by the relative shortage of global safe assets and resulted in generally stable EM bond yields during the European debt crisis. The revealed causality-in-mean from the major EU economies to Indian CDS may reflect the difficulties with external financing which the State Bank of India faced in the international interbank market rather than any dramatic deterioration of the Indian macro-fundamentals.

Given the substantial and still growing importance of the BRICS in international economics and finance, the paper provides supportive evidence for a limited magnitude of the non-EU contagion in sovereign bond markets triggered by the developments in the EU. This finding is consonant with Beirne and Fratzscher (2013) who argue that intra- and cross-regional contagion and spillovers in the sovereign CDS market have not increased systematically during the crisis but have become much more dependent on the countries' fundamentals. More fragile economies have experienced stronger and more durable shocks than resilient countries which only faced transitory rises in CDS prices. This type of financial relationships between countries has been dubbed "wake-up call" contagion (Giordano et al. 2013) which is to be contrasted with the "pure" contagion when interrelations are not based on the indicators of economic performance.

These findings of the paper can also be linked with the changing profile of the sovereign CDS market where the net notional amount[9] of the 5 EU CDS contracts has declined considerably since late 2011 whereas the same indicator for the BRICS has remained relatively stable. As a result, by the end of September 2013 the net notional amount of the BRICS CDS contracts totaled 55.3% of the EU–5, compared with 30.6% in late December 2010. Besides, it is noteworthy that the net notional amount of Brazil CDS contracts is close to the top EU levels (Table 8).

[9] Net notional positions in the CDS market are proxies for the maximum possible net funds transfers between sellers and buyers of CDS contracts that could be required upon the occurrence of a credit event.

Table 8: Net Notional amounts of the BRICS and Major EU Sovereigns' CDS Contracts, in bln. US Dollars, December 2010–September 2013

	December 2010	**December 2011**	**December 2012**	**September 2013**
Germany	15.1	19.4	15.3	13.1
France	17.5	21.8	15.7	11.7
UK	11.9	12.2	8.2	5.8
Italy	26.4	20.5	21.3	16.9
Spain	16.9	15.8	12.7	9.3
Total EU-5	*87.8*	*89.7*	*73.2*	*56.8*
China	4.7	9.2	8.1	7.1
Brazil	15.3	18.4	17.3	14.5
Russia	4.0	4.1	4.7	5.5
South Africa	2.1	2.2	2.8	3.6
India (SBI)	0.8	0.8	1.0	0.7
Total BRICS	*26.9*	*34.7*	*33.9*	*31.4*
Total BRICS/Total EU-5, %	***30.6***	***38.7***	***46.3***	***55.3***

Source: Deposit Trust Clearing Corporation data.

6 Robustness Checks

The findings presented above are subject to two robustness checks. The first one is the CCF approach applied to weekly data. This shift in time scale is legitimized due to contemporaneous information flows (e.g. from the EU to Brazil and from India and China to the EU) which are inherent to daily prices. These flows, however, may produce a masking effect. The econometric procedures (including Bai–Perron structural break tests) to conduct Granger causality tests on weekly data are the same as described in Section 4. The results are presented in Table 9.

Table 9: Causality-in-Mean and Causality-in-Variance between the BRICS and Major EU Sovereigns' CDS Weekly Prices, January 2010–September 2013

	Causality-in-variance		**Causality-in-mean**	
	EU country→BRICS country	*BRICS country→EU country*	*EU country→BRICS country*	*BRICS country→EU country*
CHINA				
GERMANY				
FRANCE	+			
UK			+	
ITALY				
SPAIN	+		+	
BRAZIL				
GERMANY				
FRANCE	+			
UK			+	
ITALY				
SPAIN	+		+	
RUSSIA				
GERMANY	+		+	
FRANCE	+		+	
UK	+		+	
ITALY				
SPAIN	+	+	+	
SOUTH AFRICA				
GERMANY				
FRANCE	+			
UK				
ITALY				
SPAIN	+		+	
INDIA (SBI)				
GERMANY				
FRANCE				+
UK				+
ITALY			+	
SPAIN	+		+	

The picture based on weekly data is significantly different as the direction of causalities between the EU and BRICS CDS prices has reversed. Spain and France have become the most influential countries for the BRICS CDS prices. The relative roles among the BRICS have also been reallocated, with Russia becoming the most vulnerable to the changes in the EU CDS prices whereas India is moderately affected. This reversal shows that the causal relations between the EU and BRICS CDS prices are sensitive to changes in time scale. At longer time horizons, the EU countries largely Granger cause the BRICS, though the opposite is observed on daily data.

Notwithstanding the result of the first robustness check, it is too early to disregard the findings presented in Section 5. Causal relations may vary not only along the time scale but in the frequency domain. It means that causalities may appear and vanish with certain periodicities. They may hold over 3-day intervals but disappear when examined, for example, over 6-day periods. The same logic is applicable with regard to weekly or any other time-scale data. To gauge the frequency dimension of causality, Breitung and Candelon (2006) proposed a specific test of (no) causality at a given frequency $\omega \in (0; \pi]$. The frequency ω can be converted into the time-scale as follows $P = \frac{2\pi}{\omega}$, where P—period on the time-scale (in days, weeks, etc.).

The causality test in the frequency domain builds on bivariate VAR models and Fourier transform of the data. Though this test does not disentangle causality-in-mean and causality-in-variance, it possesses two attractive properties which make it a plausible extension to the CCF approach which is at the core of this paper. First, it allows the identification of causality even if the true interdependence between the two variables is non-linear; second, the Breiting–Candelon test is valid in terms of volatility clusters. Besides these general advantages of testing for causal linkages between the EU and BRICS sovereign CDS prices in the frequency domain, the implementation of this test is motivated by the fact that the null hypothesis in the Hong test cannot be tested at all possible lags. Thus, the null hypothesis of no causality is accepted if it holds at all the lags under examination (p-value>0.05 at all the lags from 1 to N, where N normally is between 1 and 15). This cannot exclude the situation that the null may be violated at a more distant lag length.

Below the results of the Breitung–Candelon test conducted on daily and weekly data are presented[10] (Table 10).

India appears to be the only BRICS country that it is persistently influenced by the major EU economies both at high and low frequencies. For example, the causality runs from Germany and France to Indian CDS if 2-day and longer fre-

[10] For theoretical basis and technical details of the test see the original Breitung and Candelon paper (2006). The corresponding GRETL routines are available as supplementary materials to the paper but only final results are presented for brevity.

Table 10: Breitung–Candelon Test for Causality in the Frequency Domain between the BRICS and Major EU Sovereigns' CDS Daily and Weekly Prices, January 2010–September 2013

	daily		weekly	
	EU country→BRICS country	*BRICS country→EU country*	*EU country→BRICS country*	*BRICS country→EU country*
CHINA				
GERMANY	**l.o.=3, [2;∞)**	**l.o.=3**	**l.o.=4**	**l.o.=4, [3.3; 4.7]U[7.9; ∞)**
FRANCE	**l.o.=3, [2.7;∞)**	**l.o.=3, [2; 4]**	**l.o.=4, [2; 3.5]**	**l.o.=4, [2; 4.8]U[14; ∞)**
UK	**l.o.=3**	**l.o.=3, [2;∞)**	**l.o.=4**	**l.o.=4, [2; 6]**
ITALY	**l.o.=3**	**l.o.=3**	**l.o.=4, [2; 3.9]U[9.4; ∞)**	**l.o.=4**
SPAIN	**l.o.=9**	**l.o.=9**	**l.o.=4**	**l.o.=4**
BRAZIL				
GERMANY	**l.o.=5, [2.5;6]**	**l.o.=5, [2.9;8.2]**	**l.o.=3**	**l.o.=3, [2; 3.3]**
FRANCE	**l.o.=6, [2; 2.7]U[24.2; ∞)**	**l.o.=6, [2.7; 3.4]U[6; ∞)**	**l.o.=2**	**l.o.=2, [2;∞)**
UK	**l.o.=2**	**l.o.=2, [2.8;8.5]**	**l.o.=2**	**l.o.=2**
ITALY	**l.o.=6, [62.8; ∞)**	**l.o.=6, [8.2; ∞)**	**l.o.=2, [2;∞)**	**l.o.=2, [2;∞)**
SPAIN	**l.o.=6**	**l.o.=6, [13.1; ∞)**	**l.o.=4**	**l.o.=4**
RUSSIA				
GERMANY	**l.o.=5, [2;∞)**	**l.o.=5, [4.7; 24.2]**	**l.o.=2**	**l.o.=2**
FRANCE	**l.o.=3, [2;∞)**	**l.o.=3, [7.9; ∞)**	**l.o.=4, [2; 3.3]U[14; ∞)**	**l.o.=4, [2; 4.7]**
UK	**l.o.=3**	**l.o.=3, [2;∞)**	**l.o.=2**	**l.o.=2, [2;∞)**
ITALY	**l.o.=3, [2;3.3]**	**l.o.=3, [13.1; ∞)**	**l.o.=4, [2; 3.3]U[6.8; ∞)**	**l.o.=4**
SPAIN	**l.o.=4, [2;3.2]**	**l.o.=4, [7.6; ∞)**	**l.o.=4**	**l.o.=4, [2.5; 2.7]**
SOUTH AFRICA				
GERMANY	**l.o.=6, [2; 3.2]U[3.9; 8.8]U[17.4; ∞)**	**l.o.=6**	**l.o.=2**	**l.o.=2**
FRANCE	**l.o.=6, [2; 3.1]U[5.6; 6.3]U[6.3; ∞)**	**l.o.=6**	**l.o.=2**	**l.o.=2, [2;∞)**
UK	**l.o.=6, [2; 2.5]U[4.3; 6.3]**	**l.o.=6**	**l.o.=2**	**l.o.=2, [2;∞)**
ITALY	**l.o.=3, [2; 3.2]**	**l.o.=3, [6.5;∞)**	**l.o.=2**	**l.o.=2, [2;∞)**
SPAIN	**l.o.=6, [2; 3]U[5.2; 6]**	**l.o.=6, [3.5; 5.8]U[11.4; ∞)**	**l.o.=2**	**l.o.=2**
INDIA (SBI)				
GERMANY	**l.o.=8, [2; 2.6]U[2.9; ∞)**	**l.o.=8**	**l.o.=3, [3.1;∞)**	**l.o.=3, [2.4; 3.6]**
FRANCE	**l.o.=4, [2;∞)**	**l.o.=4**	**l.o.=3, [3.2;∞)**	**l.o.=3, [2; 4]**
UK	**l.o.=4, [2; 2.6]U[3.2; 10.3]U[14; ∞)**	**l.o.=4**	**l.o.=3**	**l.o.=3, [2; 4.1]**
ITALY	**l.o.=2, [2;∞)**	**l.o.=2**	**l.o.=2, [2;∞)**	**l.o.=2**
SPAIN	**l.o.=6, [2; 2.6]U[3.2; ∞)**	**l.o.=6**	**l.o.=2, [2;∞)**	**l.o.=2**

Note: l.o. – lag order in a corresponding bivariate VAR model selected on the basis of the Akaike information criterion (AIC).

quency bands are taken into account. On weekly data, this causal direction is observed from 3-week frequency band and further. South Africa experiences incoming causalities from the EU countries on daily data but gets completely decoupled from them if weekly data are considered. Russia is involved into a dense causal network with the EU on daily data. The causality runs from Germany and France to Russia along the entire frequency spectrum (from 2-day frequency band and further) while Russian CDS prices influence the EU at lower frequencies (e.g. from 4.7-day frequency band in case of Germany) except the UK. On weekly data the density of causal relations between Russia and the EU is less pronounced. The shrinkage of causal densities on weekly data is remarkable for Brazil. The EU countries' CDS prices have a limited dependence on China on both daily and weekly data.

If the aggregate results are examined, the BRICS CDS prices are strongly influenced by the EU countries on daily data (19 out of possible 25 causal relations). The influence in the opposite direction is exerted by Russia, Brazil and China, and to a less extent, by South Africa. It is entirely absent in case of India. Totally, only 14 out of possible 25 causalities running from the BRICS CDS prices to the EU are found. However, on weekly data the situation is in favor of the BRICS which have 15 outgoing and only 9 incoming causal linkages. The transfer from daily to weekly data results in the overall shrinkage of causal density between the EU and the BRICS and brings about clear-cut signs of decoupling in case of South Africa and Brazil. For Russia and China the dependence on the EU is also moderate. Thus, based on the Breitung–Candelon test one can conclude that there are indeed signs of decoupling of the BRICS CDS prices from the EU CDS series, which are not only found at very short time horizons but are also observed in the frequency domain, especially when weekly data are considered.

7 Conclusions

In this paper, based on the CCF approach causal linkages between the BRICS and major EU economies in the sovereign CDS market are investigated after the outbreak of the European debt crisis. As these linkages approximate the transmission of sovereign credit risks, this analysis is intended to empirically assess the bilateral impact of the most important EU and EM economies.

Although ordinary correlations and principal component analysis indicate a high degree of co-movement in the EU and BRICS CDS prices during January 2010–September 2013, the density of linkages in terms of causality-in-mean and causality-in-variance is quite moderate. The balance of outgoing and incoming causalities is in favor of the BRICS economies. The only exception is India but this result may be due to the idiosyncratic deterioration of the financial conditions of the State Bank of India which is a conventional proxy for India in the CDS market rather than reflect a dramatic worsening of its macro-fundamentals. Of the major EU economies, Germany is the only sovereign to have a positive balance of outgoing and incoming causal linkages with the BRICS, whilst Italian and Spanish CDS prices are strongly driven by their BRICS counterparts.

These are the findings based on daily data. They are not corroborated if the transfer from daily to weekly data occurs. This analysis is incomplete as it does not account for variation in causal relations in the frequency domain. To verify the presence of causalities, the estimations based on the CCF approach have been complemented by the Breitung–Candelon causality test in the frequency domain. The test reveals that the dependence of the BRICS CDS prices on the EU CDS series significantly diminishes when the transfer from daily to weekly data happens, i.e. at lower frequencies. In the frequency domain Brazil exhibits the least dependence on the EU CDS prices among the BRICS while India appears to be the most susceptible to their influence. The result is consonant with the baseline CCF estimations.

Thus, the paper underscores the signs of decoupling effects in the sovereign CDS market and also supports the view that the European debt crisis has so far had a limited non-EU impact in this market. The statement is still made with caution as the contagion associated with the EU sovereign credit risk can be transmitted to the BRICS via other financial markets (e.g. stock exchange panics) and/or cumulative effect of global risk aversion. Being more sensitive to global indicators in comparison with the major EU sovereigns' CDS, the BRICS CDS prices may also cause a pass-through effect on them. These two hypotheses are to be examined in the course of future research which may also require more advanced statistical techniques (e.g. spectral analysis of time series and wavelet decompositions) to shed more light on causal relations between the BRICS and the EU in the sovereign CDS market.

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Appendix

Table A1. China–Germany Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Germany doesn't cause China	p-value	China doesn't cause Germany	p-value	Germany doesn't cause China	p-value	China doesn't cause Germany	p-value
1	-0.705	0.760	-0.639	0.739	-0.294	0.616	-0.563	0.713
2	-0.998	0.841	-0.904	0.817	-0.417	0.662	-0.797	0.787
3	-1.222	0.889	-1.105	0.865	-0.512	0.696	-0.968	0.834
4	-1.410	0.921	-1.273	0.898	-0.562	0.713	-1.106	0.866
5	-1.577	0.943	-1.426	0.923	-0.628	0.735	-1.244	0.893
6	-1.727	0.958	-1.564	0.941	-0.697	0.757	-1.370	0.915
7	-1.866	0.969	-1.692	0.955	-0.744	0.772	-1.485	0.931
8	-1.994	0.977	-1.811	0.965	-0.772	0.780	-1.597	0.945
9	-2.116	0.983	-1.922	0.973	-0.815	0.792	-1.701	0.956
10	-2.230	0.987	-2.011	0.978	-0.860	0.805	-1.771	0.962
11	-2.339	0.990	-2.096	0.982	-0.869	0.808	-1.841	0.967
12	-2.442	0.993	-2.179	0.985	-0.873	0.809	-1.917	0.972
13	-2.541	0.994	-2.256	0.988	-0.867	0.807	-1.981	0.976
14	-2.636	0.996	-2.330	0.990	-0.867	0.807	-2.045	0.980
15	-2.727	0.997	-2.403	0.992	-0.852	0.803	-2.111	0.983

Table A2. China–France Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	France doesn't cause China	p-value	China doesn't cause France	p-value	France doesn't cause China	p-value	China doesn't cause France	p-value
1	-0.667	0.748	0.190	0.425	-0.685	0.753	-0.187	0.574
2	-0.944	0.828	0.274	0.392	-0.969	0.834	-0.241	0.595
3	-1.158	0.877	0.334	0.369	-1.187	0.882	-0.293	0.615
4	-1.340	0.910	0.377	0.353	-1.371	0.915	-0.353	0.638
5	-1.501	0.933	0.415	0.339	-1.537	0.938	-0.403	0.656
6	-1.647	0.950	0.451	0.326	-1.687	0.954	-0.435	0.668
7	-1.781	0.963	0.479	0.316	-1.826	0.966	-0.470	0.681
8	-1.902	0.971	0.507	0.306	-1.954	0.975	-0.504	0.693
9	-2.019	0.978	0.554	0.290	-2.077	0.981	-0.527	0.701
10	-2.130	0.983	0.540	0.294	-2.193	0.986	-0.611	0.729
11	-2.232	0.987	0.528	0.299	-2.301	0.989	-0.690	0.755
12	-2.330	0.990	0.523	0.300	-2.404	0.992	-0.750	0.774
13	-2.423	0.992	0.505	0.307	-2.502	0.994	-0.825	0.795
14	-2.511	0.994	0.488	0.313	-2.595	0.995	-0.897	0.815
15	-2.596	0.995	0.472	0.319	-2.686	0.996	-0.966	0.833

Table A3. China–UK Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	UK doesn't cause China	p-value	China doesn't cause UK	p-value	UK doesn't cause China	p-value	China doesn't cause UK	p-value
1	-0.507	0.694	-0.707	0.760	-0.463	0.678	-0.600	0.726
2	-0.705	0.760	-1.000	0.841	-0.667	0.748	-0.856	0.804
3	-0.857	0.804	-1.224	0.889	-0.819	0.794	-1.075	0.859
4	-0.987	0.838	-1.411	0.921	-0.946	0.828	-1.266	0.897
5	-1.101	0.865	-1.577	0.943	-1.052	0.854	-1.432	0.924
6	-1.206	0.886	-1.727	0.958	-1.145	0.874	-1.579	0.943
7	-1.304	0.904	-1.865	0.969	-1.240	0.892	-1.714	0.957
8	-1.395	0.918	-1.995	0.977	-1.325	0.907	-1.830	0.966
9	-1.480	0.931	-2.116	0.983	-1.399	0.919	-1.935	0.974
10	-1.558	0.940	-2.230	0.987	-1.461	0.928	-2.046	0.980
11	-1.625	0.948	-2.339	0.990	-1.497	0.933	-2.150	0.984
12	-1.689	0.954	-2.442	0.993	-1.531	0.937	-2.255	0.988
13	-1.753	0.960	-2.541	0.994	-1.584	0.943	-2.358	0.991
14	-1.816	0.965	-2.636	0.996	-1.637	0.949	-2.458	0.993
15	-1.876	0.970	-2.728	0.997	-1.684	0.954	-2.555	0.995

Table A4. China–Italy Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Italy doesn't cause China	p-value	China doesn't cause Italy	p-value	Italy doesn't cause China	p-value	China doesn't cause Italy	p-value
1	-0.694	0.756	1.304	0.096	-0.502	0.692	1.090	0.138
2	-0.983	0.837	1.874	0.030	-0.727	0.766	1.557	0.060
3	-1.204	0.886	2.303	0.011	-0.896	0.815	1.909	0.028
4	-1.385	0.917	2.668	0.004	-1.007	0.843	2.236	0.013
5	-1.547	0.939	3.047	0.001	-1.120	0.869	2.604	0.005
6	-1.694	0.955	3.384	0.000	-1.227	0.890	2.945	0.002
7	-1.828	0.966	3.684	0.000	-1.318	0.906	3.247	0.001
8	-1.955	0.975	3.969	0.000	-1.405	0.920	3.545	0.000
9	-2.072	0.981	4.229	0.000	-1.480	0.931	3.807	0.000
10	-2.184	0.986	4.490	0.000	-1.549	0.939	4.063	0.000
11	-2.291	0.989	4.738	0.000	-1.627	0.948	4.317	0.000
12	-2.393	0.992	4.972	0.000	-1.694	0.955	4.549	0.000
13	-2.491	0.994	5.203	0.000	-1.765	0.961	4.797	0.000
14	-2.585	0.995	5.427	0.000	-1.831	0.966	5.048	0.000
15	-2.676	0.996	5.640	0.000	-1.897	0.971	5.280	0.000

Table A5. China–Spain Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Spain doesn't cause China	p-value	China doesn't cause Spain	p-value	Spain doesn't cause China	p-value	China doesn't cause Spain	p-value
1	-0.706	0.760	4.992	0.000	-0.701	0.758	1.876	0.030
2	-0.997	0.841	7.131	0.000	-0.994	0.840	2.719	0.003
3	-1.221	0.889	8.754	0.000	-1.219	0.888	3.348	0.000
4	-1.410	0.921	10.102	0.000	-1.407	0.920	3.863	0.000
5	-1.575	0.942	11.293	0.000	-1.574	0.942	4.332	0.000
6	-1.725	0.958	12.363	0.000	-1.724	0.958	4.746	0.000
7	-1.863	0.969	13.339	0.000	-1.862	0.969	5.124	0.000
8	-1.991	0.977	14.262	0.000	-1.990	0.977	5.498	0.000
9	-2.111	0.983	15.120	0.000	-2.109	0.983	5.835	0.000
10	-2.225	0.987	15.977	0.000	-2.222	0.987	6.190	0.000
11	-2.331	0.990	16.789	0.000	-2.332	0.990	6.529	0.000
12	-2.432	0.992	17.552	0.000	-2.437	0.993	6.824	0.000
13	-2.529	0.994	18.291	0.000	-2.537	0.994	7.116	0.000
14	-2.623	0.996	18.995	0.000	-2.634	0.996	7.381	0.000
15	-2.713	0.997	19.668	0.000	-2.727	0.997	7.622	0.000

Table A6. Brazil–Germany Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Germany doesn't cause Brazil	p-value	Brazil doesn't cause Germany	p-value	Germany doesn't cause Brazil	p-value	Brazil doesn't cause Germany	p-value
1	1.047	0.148	-0.495	0.690	0.078	0.469	-0.030	0.512
2	1.475	0.070	-0.703	0.759	0.119	0.453	-0.062	0.525
3	1.791	0.037	-0.864	0.806	0.129	0.449	-0.078	0.531
4	2.038	0.021	-0.998	0.841	0.095	0.462	-0.072	0.529
5	2.266	0.012	-1.107	0.866	0.062	0.475	-0.022	0.509
6	2.467	0.007	-1.233	0.891	0.022	0.491	-0.076	0.530
7	2.652	0.004	-1.349	0.911	-0.030	0.512	-0.143	0.557
8	2.818	0.002	-1.455	0.927	-0.097	0.539	-0.191	0.576
9	2.967	0.002	-1.555	0.940	-0.173	0.569	-0.239	0.594
10	3.110	0.001	-1.686	0.954	-0.230	0.591	-0.368	0.644
11	3.307	0.000	-1.809	0.965	-0.228	0.590	-0.490	0.688
12	3.487	0.000	-1.924	0.973	-0.235	0.593	-0.594	0.724
13	3.658	0.000	-2.033	0.979	-0.248	0.598	-0.681	0.752
14	3.812	0.000	-2.137	0.984	-0.279	0.610	-0.762	0.777
15	3.965	0.000	-2.237	0.987	-0.308	0.621	-0.847	0.802

Table A7. Brazil–France Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	France doesn't cause Brazil	p-value	Brazil doesn't cause France	p-value	France doesn't cause Brazil	p-value	Brazil doesn't cause France	p-value
1	-0.699	0.758	2.982	0.001	-0.019	0.508	1.693	0.045
2	-0.987	0.838	4.211	0.000	-0.042	0.517	2.414	0.008
3	-1.207	0.886	5.158	0.000	-0.093	0.537	3.009	0.001
4	-1.393	0.918	5.969	0.000	-0.131	0.552	3.568	0.000
5	-1.555	0.940	6.676	0.000	-0.189	0.575	4.056	0.000
6	-1.701	0.955	7.361	0.000	-0.257	0.601	4.491	0.000
7	-1.834	0.967	7.979	0.000	-0.311	0.622	4.856	0.000
8	-1.963	0.975	8.552	0.000	-0.299	0.618	5.191	0.000
9	-2.083	0.981	9.112	0.000	-0.311	0.622	5.509	0.000
10	-2.196	0.986	9.412	0.000	-0.327	0.628	5.616	0.000
11	-2.306	0.989	9.701	0.000	-0.280	0.610	5.721	0.000
12	-2.411	0.992	10.004	0.000	-0.245	0.597	5.861	0.000
13	-2.512	0.994	10.307	0.000	-0.224	0.588	6.030	0.000
14	-2.608	0.995	10.599	0.000	-0.204	0.581	6.189	0.000
15	-2.702	0.997	10.885	0.000	-0.180	0.571	6.339	0.000

Table A8. Brazil–UK Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	UK doesn't cause Brazil	p-value	Brazil doesn't cause UK	p-value	UK doesn't cause Brazil	p-value	Brazil doesn't cause UK	p-value
1	-0.481	0.685	1.245	0.107	-0.243	0.596	4.209	0.000
2	-0.673	0.749	1.769	0.038	-0.391	0.652	6.035	0.000
3	-0.824	0.795	2.148	0.016	-0.497	0.690	7.356	0.000
4	-0.953	0.830	2.457	0.007	-0.584	0.720	8.382	0.000
5	-1.079	0.860	2.727	0.003	-0.625	0.734	9.304	0.000
6	-1.193	0.884	2.998	0.001	-0.651	0.742	10.176	0.000
7	-1.303	0.904	3.246	0.001	-0.641	0.739	11.015	0.000
8	-1.409	0.921	3.466	0.000	-0.608	0.728	11.740	0.000
9	-1.506	0.934	3.675	0.000	-0.575	0.717	12.403	0.000
10	-1.598	0.945	3.943	0.000	-0.547	0.708	13.226	0.000
11	-1.697	0.955	4.200	0.000	-0.452	0.674	14.051	0.000
12	-1.793	0.963	4.439	0.000	-0.356	0.639	14.825	0.000
13	-1.884	0.970	4.661	0.000	-0.264	0.604	15.532	0.000
14	-1.968	0.975	4.877	0.000	-0.201	0.580	16.219	0.000
15	-2.049	0.980	5.077	0.000	-0.144	0.557	16.838	0.000

Table A9. Brazil–Italy Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Italy doesn't cause Brazil	p-value	Brazil doesn't cause Italy	p-value	Italy doesn't cause Brazil	p-value	Brazil doesn't cause Italy	p-value
1	-0.546	0.708	2.116	0.017	-0.466	0.680	4.554	0.000
2	-0.772	0.780	3.036	0.001	-0.663	0.746	6.577	0.000
3	-0.945	0.828	3.732	0.000	-0.822	0.794	8.090	0.000
4	-1.078	0.859	4.307	0.000	-0.916	0.820	9.277	0.000
5	-1.209	0.887	4.887	0.000	-1.042	0.851	10.534	0.000
6	-1.326	0.908	5.440	0.000	-1.151	0.875	11.656	0.000
7	-1.431	0.924	5.937	0.000	-1.242	0.893	12.656	0.000
8	-1.528	0.937	6.398	0.000	-1.320	0.907	13.617	0.000
9	-1.618	0.947	6.837	0.000	-1.394	0.918	14.533	0.000
10	-1.703	0.956	7.315	0.000	-1.465	0.929	15.451	0.000
11	-1.776	0.962	7.763	0.000	-1.502	0.933	16.328	0.000
12	-1.846	0.968	8.183	0.000	-1.539	0.938	17.138	0.000
13	-1.913	0.972	8.587	0.000	-1.580	0.943	17.921	0.000
14	-1.979	0.976	8.971	0.000	-1.621	0.947	18.655	0.000
15	-2.043	0.979	9.343	0.000	-1.669	0.952	19.368	0.000

Table A10. Brazil–Spain Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Spain doesn't cause Brazil	p-value	Brazil doesn't cause Spain	p-value	Spain doesn't cause Brazil	p-value	Brazil doesn't cause Spain	p-value
1	-0.169	0.567	1.409	0.079	0.142	0.444	2.058	0.020
2	-0.233	0.592	2.031	0.021	0.227	0.410	3.001	0.001
3	-0.276	0.609	2.501	0.006	0.297	0.383	3.704	0.000
4	-0.311	0.622	2.899	0.002	0.367	0.357	4.326	0.000
5	-0.340	0.633	3.244	0.001	0.459	0.323	4.878	0.000
6	-0.363	0.642	3.593	0.000	0.533	0.297	5.410	0.000
7	-0.382	0.649	3.907	0.000	0.612	0.270	5.895	0.000
8	-0.402	0.656	4.199	0.000	0.673	0.250	6.360	0.000
9	-0.420	0.663	4.477	0.000	0.729	0.233	6.789	0.000
10	-0.437	0.669	4.807	0.000	0.773	0.220	7.258	0.000
11	-0.388	0.651	5.118	0.000	0.922	0.178	7.710	0.000
12	-0.344	0.635	5.411	0.000	1.059	0.145	8.128	0.000
13	-0.304	0.619	5.698	0.000	1.185	0.118	8.542	0.000
14	-0.273	0.608	5.970	0.000	1.280	0.100	8.931	0.000
15	-0.244	0.596	6.242	0.000	1.362	0.087	9.345	0.000

Table A11. Russia–Germany Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Germany doesn't cause Russia	p-value	Russia doesn't cause Germany	p-value	Germany doesn't cause Russia	p-value	Russia doesn't cause Germany	p-value
1	-0.662	0.746	-0.703	0.759	-0.259	0.602	-0.622	0.733
2	-0.936	0.825	-0.994	0.840	-0.352	0.638	-0.876	0.810
3	-1.148	0.875	-1.218	0.888	-0.435	0.668	-1.074	0.859
4	-1.326	0.908	-1.406	0.920	-0.518	0.698	-1.236	0.892
5	-1.484	0.931	-1.572	0.942	-0.586	0.721	-1.386	0.917
6	-1.626	0.948	-1.722	0.957	-0.652	0.743	-1.525	0.936
7	-1.758	0.961	-1.860	0.969	-0.710	0.761	-1.643	0.950
8	-1.880	0.970	-1.990	0.977	-0.764	0.778	-1.776	0.962
9	-2.008	0.978	-2.112	0.983	-0.892	0.814	-1.904	0.972
10	-2.128	0.983	-2.227	0.987	-0.988	0.838	-2.026	0.979
11	-2.242	0.988	-2.336	0.990	-1.076	0.859	-2.138	0.984
12	-2.351	0.991	-2.441	0.993	-1.161	0.877	-2.248	0.988
13	-2.455	0.993	-2.541	0.994	-1.233	0.891	-2.349	0.991
14	-2.554	0.995	-2.637	0.996	-1.293	0.902	-2.448	0.993
15	-2.650	0.996	-2.731	0.997	-1.368	0.914	-2.540	0.994

Table A12. Russia–France Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	France doesn't cause Russia	p-value	Russia doesn't cause France	p-value	France doesn't cause Russia	p-value	Russia doesn't cause France	p-value
1	-0.695	0.756	0.718	0.236	0.105	0.458	-0.407	0.658
2	-0.983	0.837	1.028	0.152	0.167	0.434	-0.548	0.708
3	-1.205	0.886	1.259	0.104	0.181	0.428	-0.658	0.745
4	-1.392	0.918	1.449	0.074	0.177	0.430	-0.752	0.774
5	-1.558	0.940	1.618	0.053	0.177	0.430	-0.824	0.795
6	-1.707	0.956	1.771	0.038	0.168	0.433	-0.885	0.812
7	-1.845	0.967	1.909	0.028	0.161	0.436	-0.952	0.829
8	-1.971	0.976	2.060	0.020	0.200	0.421	-1.025	0.847
9	-2.090	0.982	2.092	0.018	0.112	0.456	-1.152	0.875
10	-2.204	0.986	2.131	0.017	0.062	0.475	-1.272	0.898
11	-2.313	0.990	2.167	0.015	0.013	0.495	-1.388	0.917
12	-2.416	0.992	2.208	0.014	-0.036	0.514	-1.489	0.932
13	-2.515	0.994	2.247	0.012	-0.068	0.527	-1.595	0.945
14	-2.611	0.995	2.291	0.011	-0.095	0.538	-1.687	0.954
15	-2.704	0.997	2.341	0.010	-0.120	0.548	-1.774	0.962

Table A13. Russia–UK Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	UK doesn't cause Russia	p-value	Russia doesn't cause UK	p-value	UK doesn't cause Russia	p-value	Russia doesn't cause UK	p-value
1	-0.701	0.758	-0.687	0.754	0.084	0.466	-0.695	0.757
2	-0.992	0.839	-0.973	0.835	0.081	0.468	-0.977	0.836
3	-1.215	0.888	-1.194	0.884	0.092	0.463	-1.197	0.884
4	-1.403	0.920	-1.380	0.916	0.078	0.469	-1.380	0.916
5	-1.568	0.942	-1.544	0.939	0.060	0.476	-1.544	0.939
6	-1.718	0.957	-1.691	0.955	0.057	0.477	-1.691	0.955
7	-1.856	0.968	-1.827	0.966	0.032	0.487	-1.825	0.966
8	-1.984	0.976	-1.908	0.972	0.024	0.490	-1.951	0.974
9	-2.106	0.982	-1.980	0.976	0.089	0.464	-2.061	0.980
10	-2.221	0.987	-2.049	0.980	0.121	0.452	-2.166	0.985
11	-2.331	0.990	-2.116	0.983	0.149	0.441	-2.268	0.988
12	-2.435	0.993	-2.184	0.986	0.179	0.429	-2.369	0.991
13	-2.535	0.994	-2.250	0.988	0.185	0.426	-2.468	0.993
14	-2.632	0.996	-2.312	0.990	0.204	0.419	-2.560	0.995
15	-2.725	0.997	-2.369	0.991	0.210	0.417	-2.643	0.996

Table A14. Russia–Italy Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Italy doesn't cause Russia	p-value	Russia doesn't cause Italy	p-value	Italy doesn't cause Russia	p-value	Russia doesn't cause Italy	p-value
1	-0.652	0.743	0.099	0.461	-0.677	0.751	1.270	0.102
2	-0.926	0.823	0.161	0.436	-0.954	0.830	1.847	0.032
3	-1.135	0.872	0.204	0.419	-1.165	0.878	2.285	0.011
4	-1.312	0.905	0.238	0.406	-1.346	0.911	2.641	0.004
5	-1.468	0.929	0.286	0.387	-1.505	0.934	2.952	0.002
6	-1.609	0.946	0.329	0.371	-1.647	0.950	3.253	0.001
7	-1.737	0.959	0.365	0.357	-1.776	0.962	3.524	0.000
8	-1.856	0.968	0.449	0.327	-1.897	0.971	3.908	0.000
9	-1.974	0.976	0.530	0.298	-2.004	0.977	4.260	0.000
10	-2.087	0.982	0.600	0.274	-2.101	0.982	4.580	0.000
11	-2.193	0.986	0.661	0.254	-2.193	0.986	4.854	0.000
12	-2.295	0.989	0.717	0.237	-2.280	0.989	5.101	0.000
13	-2.392	0.992	0.768	0.221	-2.365	0.991	5.343	0.000
14	-2.485	0.994	0.817	0.207	-2.450	0.993	5.569	0.000
15	-2.575	0.995	0.871	0.192	-2.525	0.994	5.808	0.000

Table A15. Russia–Spain Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Spain doesn't cause Russia	p-value	Russia doesn't cause Spain	p-value	Spain doesn't cause Russia	p-value	Russia doesn't cause Spain	p-value
1	-0.620	0.732	0.192	0.424	-0.707	0.760	0.352	0.363
2	-0.881	0.811	0.303	0.381	-1.000	0.841	0.578	0.282
3	-1.077	0.859	0.382	0.351	-1.224	0.890	0.744	0.228
4	-1.242	0.893	0.442	0.329	-1.414	0.921	0.870	0.192
5	-1.388	0.917	0.495	0.310	-1.581	0.943	0.994	0.160
6	-1.519	0.936	0.543	0.293	-1.731	0.958	1.119	0.132
7	-1.638	0.949	0.587	0.279	-1.870	0.969	1.234	0.109
8	-1.749	0.960	0.679	0.248	-1.999	0.977	1.407	0.080
9	-1.863	0.969	0.762	0.223	-2.120	0.983	1.542	0.061
10	-1.973	0.976	0.835	0.202	-2.233	0.987	1.669	0.048
11	-2.078	0.981	0.898	0.185	-2.340	0.990	1.768	0.038
12	-2.177	0.985	0.951	0.171	-2.442	0.993	1.840	0.033
13	-2.273	0.988	1.000	0.159	-2.540	0.994	1.906	0.028
14	-2.364	0.991	1.051	0.147	-2.636	0.996	1.971	0.024
15	-2.453	0.993	1.109	0.134	-2.727	0.997	2.062	0.020

Table A16. South Africa–Germany Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Germany doesn't cause South Africa	p-value	South Africa doesn't cause Germany	p-value	Germany doesn't cause South Africa	p-value	South Africa doesn't cause Germany	p-value
1	-0.694	0.756	-0.624	0.734	-0.629	0.735	-0.626	0.734
2	-0.980	0.837	-0.885	0.812	-0.899	0.816	-0.878	0.810
3	-1.199	0.885	-1.081	0.860	-1.108	0.866	-1.085	0.861
4	-1.380	0.916	-1.248	0.894	-1.298	0.903	-1.254	0.895
5	-1.538	0.938	-1.391	0.918	-1.467	0.929	-1.408	0.920
6	-1.684	0.954	-1.521	0.936	-1.616	0.947	-1.550	0.939
7	-1.817	0.965	-1.638	0.949	-1.753	0.960	-1.685	0.954
8	-1.940	0.974	-1.743	0.959	-1.883	0.970	-1.814	0.965
9	-2.047	0.980	-1.818	0.965	-2.010	0.978	-1.944	0.974
10	-2.159	0.985	-1.887	0.970	-2.119	0.983	-2.067	0.981
11	-2.265	0.988	-1.954	0.975	-2.225	0.987	-2.183	0.985
12	-2.366	0.991	-2.019	0.978	-2.327	0.990	-2.294	0.989
13	-2.462	0.993	-2.085	0.981	-2.422	0.992	-2.399	0.992
14	-2.556	0.995	-2.145	0.984	-2.511	0.994	-2.500	0.994
15	-2.645	0.996	-2.202	0.986	-2.603	0.995	-2.597	0.995

Table A17. South Africa–France Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	France doesn't cause South Africa	p-value	South Africa doesn't cause France	p-value	France doesn't cause South Africa	p-value	South Africa doesn't cause France	p-value
1	-0.496	0.690	1.664	0.048	-0.567	0.714	-0.531	0.702
2	-0.692	0.756	2.345	0.010	-0.778	0.782	-0.750	0.773
3	-0.840	0.799	2.900	0.002	-0.935	0.825	-0.885	0.812
4	-0.967	0.833	3.352	0.000	-1.074	0.858	-1.011	0.844
5	-1.074	0.859	3.748	0.000	-1.180	0.881	-1.124	0.869
6	-1.173	0.880	4.108	0.000	-1.274	0.899	-1.218	0.888
7	-1.264	0.897	4.438	0.000	-1.355	0.912	-1.316	0.906
8	-1.359	0.913	4.759	0.000	-1.450	0.926	-1.410	0.921
9	-1.420	0.922	4.554	0.000	-1.497	0.933	-1.564	0.941
10	-1.503	0.934	4.394	0.000	-1.583	0.943	-1.706	0.956
11	-1.579	0.943	4.254	0.000	-1.657	0.951	-1.839	0.967
12	-1.649	0.950	4.135	0.000	-1.713	0.957	-1.964	0.975
13	-1.717	0.957	4.030	0.000	-1.775	0.962	-2.083	0.981
14	-1.782	0.963	3.947	0.000	-1.830	0.966	-2.195	0.986
15	-1.847	0.968	3.877	0.000	-1.884	0.970	-2.302	0.989

Table A18. South Africa–UK Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	UK doesn't cause South Africa	p-value	South Africa doesn't cause UK	p-value	UK doesn't cause South Africa	p-value	South Africa doesn't cause UK	p-value
1	-0.623	0.733	-0.586	0.721	0.398	0.345	-0.142	0.557
2	-0.871	0.808	-0.822	0.795	0.577	0.282	-0.155	0.562
3	-1.058	0.855	-1.022	0.847	0.759	0.224	-0.247	0.598
4	-1.219	0.889	-1.185	0.882	0.873	0.191	-0.300	0.618
5	-1.364	0.914	-1.330	0.908	0.937	0.174	-0.355	0.639
6	-1.495	0.932	-1.456	0.927	1.017	0.155	-0.371	0.645
7	-1.614	0.947	-1.571	0.942	1.078	0.141	-0.381	0.648
8	-1.724	0.958	-1.698	0.955	1.150	0.125	-0.463	0.678
9	-1.823	0.966	-1.827	0.966	1.259	0.104	-0.589	0.722
10	-1.918	0.972	-1.949	0.974	1.312	0.095	-0.709	0.761
11	-2.010	0.978	-2.065	0.981	1.351	0.088	-0.814	0.792
12	-2.098	0.982	-2.173	0.985	1.400	0.081	-0.895	0.815
13	-2.185	0.986	-2.276	0.989	1.413	0.079	-0.962	0.832
14	-2.267	0.988	-2.375	0.991	1.443	0.074	-1.035	0.850
15	-2.348	0.991	-2.471	0.993	1.458	0.072	-1.106	0.866

Table A19. South Africa–Italy Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Italy doesn't cause South Africa	p-value	South Africa doesn't cause Italy	p-value	Italy doesn't cause South Africa	p-value	South Africa doesn't cause Italy	p-value
1	-0.707	0.760	0.608	0.272	-0.579	0.719	0.048	0.481
2	-1.000	0.841	0.912	0.181	-0.806	0.790	0.148	0.441
3	-1.224	0.890	1.149	0.125	-0.973	0.835	0.217	0.414
4	-1.413	0.921	1.348	0.089	-1.150	0.875	0.288	0.387
5	-1.580	0.943	1.559	0.060	-1.308	0.905	0.376	0.353
6	-1.731	0.958	1.739	0.041	-1.444	0.926	0.439	0.330
7	-1.870	0.969	1.913	0.028	-1.562	0.941	0.505	0.307
8	-1.999	0.977	2.097	0.018	-1.673	0.953	0.608	0.271
9	-2.120	0.983	2.328	0.010	-1.774	0.962	0.714	0.238
10	-2.233	0.987	2.536	0.006	-1.840	0.967	0.805	0.210
11	-2.341	0.990	2.724	0.003	-1.902	0.971	0.873	0.191
12	-2.444	0.993	2.897	0.002	-1.967	0.975	0.916	0.180
13	-2.543	0.994	3.059	0.001	-2.030	0.979	0.962	0.168
14	-2.638	0.996	3.214	0.001	-2.098	0.982	1.005	0.157
15	-2.730	0.997	3.368	0.000	-2.156	0.984	1.060	0.145

Table A20. South Africa–Spain Causal Linkages

	Causality-in-variance tests				Causality-in-mean tests			
Lag length	Spain doesn't cause South Africa	p-value	South Africa doesn't cause Spain	p-value	Spain doesn't cause South Africa	p-value	South Africa doesn't cause Spain	p-value
1	-0.288	0.613	0.333	0.370	-0.591	0.723	0.250	0.401
2	-0.413	0.660	0.518	0.302	-0.844	0.801	0.439	0.330
3	-0.510	0.695	0.673	0.251	-1.035	0.850	0.618	0.268
4	-0.591	0.723	0.793	0.214	-1.194	0.884	0.753	0.226
5	-0.658	0.745	0.898	0.185	-1.333	0.909	0.876	0.191
6	-0.727	0.766	0.991	0.161	-1.465	0.928	0.994	0.160
7	-0.788	0.785	1.092	0.137	-1.583	0.943	1.153	0.125
8	-0.843	0.800	1.207	0.114	-1.692	0.955	1.334	0.091
9	-0.901	0.816	1.330	0.092	-1.800	0.964	1.468	0.071
10	-0.987	0.838	1.438	0.075	-1.922	0.973	1.582	0.057
11	-1.068	0.857	1.534	0.063	-2.039	0.979	1.671	0.047
12	-1.143	0.873	1.616	0.053	-2.149	0.984	1.727	0.042
13	-1.213	0.888	1.694	0.045	-2.254	0.988	1.792	0.037
14	-1.277	0.899	1.774	0.038	-2.350	0.991	1.859	0.032
15	-1.340	0.910	1.846	0.032	-2.446	0.993	1.912	0.028

Table A21. India–Germany Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Germany doesn't cause India	p-value	India doesn't cause Germany	p-value	Germany doesn't cause India	p-value	India doesn't cause Germany	p-value
1	0.370	0.356	-0.379	0.648	2.140	0.016	-0.677	0.751
2	0.524	0.300	-0.542	0.706	2.994	0.001	-0.946	0.828
3	0.650	0.258	-0.668	0.748	3.710	0.000	-1.154	0.876
4	0.770	0.221	-0.770	0.779	4.367	0.000	-1.333	0.909
5	0.871	0.192	-0.851	0.802	4.935	0.000	-1.499	0.933
6	0.965	0.167	-0.927	0.823	5.501	0.000	-1.642	0.950
7	1.056	0.145	-1.002	0.842	6.085	0.000	-1.767	0.961
8	1.147	0.126	-1.070	0.858	6.678	0.000	-1.884	0.970
9	1.237	0.108	-1.146	0.874	7.231	0.000	-1.981	0.976
10	1.349	0.089	-1.221	0.889	7.876	0.000	-2.071	0.981
11	1.453	0.073	-1.289	0.901	8.477	0.000	-2.158	0.985
12	1.546	0.061	-1.353	0.912	9.032	0.000	-2.242	0.988
13	1.633	0.051	-1.417	0.922	9.558	0.000	-2.316	0.990
14	1.704	0.044	-1.476	0.930	9.978	0.000	-2.392	0.992
15	1.780	0.038	-1.535	0.938	10.420	0.000	-2.462	0.993

Table A22. India–France Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	France doesn't cause India	p-value	India doesn't cause France	p-value	France doesn't cause India	p-value	India doesn't cause France	p-value
1	0.119	0.453	-0.397	0.654	3.799	0.000	-0.651	0.743
2	0.173	0.431	-0.560	0.712	5.368	0.000	-0.924	0.822
3	0.220	0.413	-0.690	0.755	6.649	0.000	-1.127	0.870
4	0.253	0.400	-0.795	0.787	7.702	0.000	-1.301	0.903
5	0.280	0.390	-0.891	0.813	8.612	0.000	-1.452	0.927
6	0.309	0.379	-0.980	0.836	9.512	0.000	-1.580	0.943
7	0.337	0.368	-1.061	0.856	10.320	0.000	-1.696	0.955
8	0.359	0.360	-1.136	0.872	10.989	0.000	-1.803	0.964
9	0.381	0.352	-1.082	0.860	11.600	0.000	-1.935	0.974
10	0.427	0.335	-1.039	0.851	12.328	0.000	-2.059	0.980
11	0.467	0.320	-1.000	0.841	13.020	0.000	-2.177	0.985
12	0.502	0.308	-0.965	0.833	13.667	0.000	-2.288	0.989
13	0.533	0.297	-0.940	0.826	14.294	0.000	-2.394	0.992
14	0.549	0.292	-0.916	0.820	14.811	0.000	-2.495	0.994
15	0.563	0.287	-0.893	0.814	15.314	0.000	-2.593	0.995

Table A23. India–UK Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	UK doesn't cause India	p-value	India doesn't cause UK	p-value	UK doesn't cause India	p-value	India doesn't cause UK	p-value
1	-0.707	0.760	-0.443	0.671	0.946	0.172	-0.369	0.644
2	-0.999	0.841	-0.618	0.732	1.316	0.094	-0.555	0.710
3	-1.223	0.889	-0.771	0.780	1.503	0.066	-0.632	0.736
4	-1.412	0.921	-0.903	0.817	1.663	0.048	-0.686	0.754
5	-1.578	0.943	-1.017	0.846	1.804	0.036	-0.747	0.773
6	-1.729	0.958	-1.120	0.869	1.913	0.028	-0.802	0.789
7	-1.866	0.969	-1.214	0.888	1.960	0.025	-0.859	0.805
8	-1.993	0.977	-1.302	0.904	1.996	0.023	-0.914	0.820
9	-2.113	0.983	-1.372	0.915	2.033	0.021	-1.006	0.843
10	-2.225	0.987	-1.436	0.925	2.052	0.020	-1.090	0.862
11	-2.332	0.990	-1.498	0.933	2.074	0.019	-1.168	0.879
12	-2.435	0.993	-1.558	0.940	2.101	0.018	-1.242	0.893
13	-2.534	0.994	-1.614	0.947	2.142	0.016	-1.318	0.906
14	-2.629	0.996	-1.668	0.952	2.192	0.014	-1.388	0.917
15	-2.721	0.997	-1.724	0.958	2.251	0.012	-1.448	0.926

Table A24. India–Italy Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Italy doesn't cause India	p-value	India doesn't cause Italy	p-value	Italy doesn't cause India	p-value	India doesn't cause Italy	p-value
1	0.044	0.483	-0.267	0.605	3.934	0.000	0.958	0.169
2	0.025	0.490	-0.404	0.657	5.329	0.000	1.217	0.112
3	0.008	0.497	-0.503	0.692	6.357	0.000	1.435	0.076
4	0.021	0.492	-0.586	0.721	7.356	0.000	1.628	0.052
5	0.028	0.489	-0.674	0.750	8.230	0.000	1.703	0.044
6	0.034	0.486	-0.749	0.773	9.019	0.000	1.817	0.035
7	0.044	0.483	-0.818	0.793	9.805	0.000	1.931	0.027
8	0.051	0.480	-0.882	0.811	10.530	0.000	2.038	0.021
9	0.058	0.477	-0.935	0.825	11.224	0.000	2.137	0.016
10	0.084	0.466	-0.988	0.838	11.995	0.000	2.228	0.013
11	0.108	0.457	-1.039	0.851	12.723	0.000	2.317	0.010
12	0.127	0.449	-1.087	0.861	13.406	0.000	2.403	0.008
13	0.146	0.442	-1.133	0.871	14.071	0.000	2.487	0.006
14	0.169	0.433	-1.179	0.881	14.775	0.000	2.566	0.005
15	0.188	0.425	-1.226	0.890	15.439	0.000	2.616	0.004

Table A25. India–Spain Causal Linkages

Lag length	Causality-in-variance tests				Causality-in-mean tests			
	Spain doesn't cause India	p-value	India doesn't cause Spain	p-value	Spain doesn't cause India	p-value	India doesn't cause Spain	p-value
1	0.322	0.374	-0.675	0.750	2.317	0.010	-0.445	0.672
2	0.412	0.340	-0.946	0.828	3.097	0.001	-0.681	0.752
3	0.491	0.312	-1.155	0.876	3.731	0.000	-0.856	0.804
4	0.558	0.288	-1.331	0.908	4.284	0.000	-1.006	0.843
5	0.616	0.269	-1.485	0.931	4.779	0.000	-1.138	0.872
6	0.670	0.251	-1.626	0.948	5.241	0.000	-1.250	0.894
7	0.726	0.234	-1.756	0.960	5.713	0.000	-1.354	0.912
8	0.775	0.219	-1.876	0.970	6.135	0.000	-1.449	0.926
9	0.820	0.206	-1.988	0.977	6.532	0.000	-1.551	0.940
10	0.890	0.187	-2.093	0.982	7.031	0.000	-1.646	0.950
11	0.959	0.169	-2.193	0.986	7.502	0.000	-1.737	0.959
12	1.020	0.154	-2.289	0.989	7.942	0.000	-1.824	0.966
13	1.079	0.140	-2.382	0.991	8.377	0.000	-1.905	0.972
14	1.142	0.127	-2.471	0.993	8.826	0.000	-1.980	0.976
15	1.199	0.115	-2.556	0.995	9.237	0.000	-2.059	0.980

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