Dynamic Interdependence of Sovereign Credit Default Swaps in BRICS and MIST Countries

Abstract

This paper examines the lead-lag relationships and volatility interactions of emerging markets sovereign credit default swaps (CDS). Using a multivariate VAR-EGARCH model and principal component analysis, we find significant volatility spillover effects within the two groups of emerging markets under study. Our evidence indicates that global financial market factors are dominant drivers of BRICS and MIST sovereign CDS spreads variability with the European debt crisis showing significant influence on emerging markets sovereign spreads.

1. Introduction

Events such as the Asian financial crisis, the Argentinian and Russian debt defaults, the collapse of Lehman Brothers, the deteriorating sentiment in European sovereign debt markets and the Greek debt crisis, among others, have served as precursors to studies regarding sovereign debt markets. Of special attention in this area of study has been the sovereign credit default swaps (CDS), instruments that are considered to be some of the most liquid credit derivative instruments in emerging markets and which are widely used for hedging country default risk, as well as for speculative positions, relative value trading, government bond vs. CDS arbitrage (Fontana and Scheicher, 2011). This area of study is of interest due to major concerns regarding the destabilizing effect that speculation through the use of sovereign CDS could have in the financial markets.

A number of studies investigate the determinants of emerging markets sovereign credit defaults swaps. Studies have placed special attention in these markets for two reasons: (1) financial integration and growth in these markets as well as (2) investor's perception of higher credit risk and variability in emerging rather than developed markets. Longstaff et al. (2011) use a sample of

26 developed and less developed sovereign CDS and show that the majority of sovereign credit risk is explained by global macroeconomic forces. They also perform a principal components analysis and find that the first principal component accounts for a large portion of the variation within the data and is highly correlated with US stock market returns and volatility. Pan and Singleton (2008) also look at the relationship between currency options volatility, risk premiums in sovereign CDS markets and the VIX. Employing a sample of CDS for three of the MIST countries (Mexico, Turkey and South Korea), they show that sovereign CDS risk is significantly related to changes in the volatility index (VIX). A different study on the determinants of sovereign CDS pricing is by Fender et al. (2012). They focus on 12 emerging markets before and during the 2008 financial crisis and show that sovereign spread changes experience substantial spillover effects during the crisis period. Wang and Moore (2012) examine the dynamic correlation between 38 emerging and developed sovereign CDS markets and find that stronger integration after the Lehman collapse.

Within the emerging markets, BRICS countries (Brazil Russia, India, China and South Africa) have become synonymous with high growth and significant influence on regional and global affairs. Yet, few studies examine BRICS sovereign CDS dynamics. Sujithan and Avouyi-Dovi (2013) use a Markov-switching model to model the behavior of BRICS sovereign spreads and find that euro area financial market factors are significant factors in BRICS spreads dynamics. Stolbov (2014) studies the causal links between BRICS and European sovereign CDS, and show that BRICS CDS prices Granger-cause France, Italy, Spain and the UK CDS prices during the

European debt crisis[1]. Causal relationships are also researched by Wang et al. (2013), but their focus is on Latin American sovereign CDS and global financial variables.

As the BRICS economies have started to slow down, investment opportunities in the MIST countries (Mexico, Indonesia, South Korea and Turkey) have become more attractive based on expectations for high growth due to their favorable demographics and fast-paced economies.

Our paper expands on the existing literature by studying the interactions of the sovereign credit spreads of two groups of countries: BRICS and MIST, as well as the relations of these countries sovereign spreads with global factors. The analysis focuses specifically on the market interaction between the groups' participants as well as the relation between these countries and the European CDS markets. This last relationship is studied to determine whether any crisis in Europe could affect these markets, as was the case of Brazil and Russia in the 1990s. The analysis is achieved through the use of Koutmos and Booth's (1995) methodology which analyzes the first and second moment interdependence of different markets as well principal component analysis, two methodologies well established in the literature. Better understanding of cross-market linkages and interactions is important for both speculators and hedgers in sovereign debt markets, as well as for policy-makers.

Our main findings confirm the notion of increased global CDS markets integration. We find significant volatility spillover effects within the two groups of emerging markets under study. In line with earlier studies on emerging market sovereign CDS, we show that global financial market variables are dominant factors in BRICS and MIST sovereign CDS spreads variability, with the European debt crisis having significant influence on emerging markets sovereign spreads.

[1] Other studies on the European debt crisis and European sovereign CDS include Tamakoshi and Hamori (2013), Hui and Chung (2011), Calice et al. (2013).

The rest of the paper is organized as follows. Sections 2 and 3 present the data and methodology. The empirical results are discussed in section 4, while section 5 offers concluding remarks.

2. Data

Sovereign CDS

Sovereign CDS contracts functions as insurance against credit events on the debt of a sovereign entity. The buyer of credit protection pays basis points as a premium and if there is no default, the buyer will pay the premiums as an annuity for the horizon of the contract. In case of a credit event, the protection buyer can sell the debt to the seller at par value. The CDS contract specifies the list of events triggering protection payments, the notional principal, the term of the CDS contract, the debt issuer (reference entity) and the specific reference obligations. Some of the events which could be selected to trigger payments are bankruptcy, failure to make interest or principal payments, debt restructuring, etc.

In this study, we use sovereign credit default swaps spreads of contracts with five years to maturity (full restructure) obtained from Thomson Reuters for the BRICS (Brazil Russia, India, China, South Africa) and MIST (Mexico, Indonesia, South Korea and Turkey) countries. Sovereign CDS for India is not available and we use the State Bank of India CDS five year CDS as a proxy. The sample starts on January 4, 2010 and ends on July 11, 2014. Our choice of sample period is dictated mainly by two considerations – exclusion of the 2008 financial crisis period and market liquidity. Prior to 2010 fewer changes are observed in CDS spreads, particularly for India. As such, we start the sample in 2010. The exact distributions of days with changes in spreads for each country is as follows: Mexico 97% , Indonesia 89%, South Korea 89%, Turkey 94%, Brazil 98%, Russia 93%, India 76%, China 88%, South Africa: 92%. To address the issue of infrequent trading and larger number of zero changes in spread in the case of India, we linearly interpolate the differenced series and use the new series in the empirical analysis.[2]

Financial Market Variables

U.S., European and global financial market variables are incorporated as explanatory variables in our analysis. The data is daily and gathered from Datastream. We use the S&P 500 index returns, as well as changes in the CBOE VIX volatility index to account for US stock market conditions. To proxy for changes in US government bond markets we include changes in the 3-month Treasury bill rate and change in the slope of the yield curve. The yield curve is calculated as the difference between the ten-year Treasury rate and the 3-month Treasury bill rate. We also include changes in the Merrill Lynch 1-motnh MOVE index (Merrill Option Volatility Expectations), which is an estimate of near-future Treasury market volatility using implied volatility of outstanding options on Treasury securities. Stock market conditions in European markets are proxied by daily returns on the Dow Jones Eurostoxx 50 and the first difference of the Euro Stocks 50 Volatility (VStoxx) index. Market conditions in corporate bond and government bond European markets are covered by Barclays Euro Aggregate Bond Market Index and Barclays Euro Aggregate Government Bond Market Index.

3. Methodology

To model the dynamic relation among the CDS spread changes and volatility a VAR-EGARCH model as presented by Koutmos and Booth (1995) and Koutmos (1996) was utilized.

$$Y_{i,t} = \beta_{i,o} + \sum_{j=1}^{n} \beta_{ij} Y_{j,t-1} + \epsilon_{i,t} \quad for\ i,j = 1, \dots, n \tag{1}$$

$$\sigma_{i,t}^2 = exp\left\{\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j\left(z_{j,t-1}\right) + \gamma_i \ln(\sigma_{i,t-1}^2)\right\} \quad for\ i,j = 1, \dots, n \tag{2}$$

[2] Our main results are qualitatively similar with or without interpolation. All tables without interpolating the changes of the State Bank of India CDS are available upon request from the corresponding author.

$$f_j(z_{j,t-1}) = (|z_{j,t-1}| - E(|z_{j,t-1}|) + \delta_j z_{j,t-1}) \ \ for\ i,j = 1,\dots,n \tag{3}$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \quad for\ i,j = 1,\dots,n\ and\ i \neq j \tag{4}$$

Equation (1) describes the dynamic relation between variables as a vector autoregression (VAR) such that the conditional mean of each variable is a function of its own lagged values, as well as the lagged values of the other variables. The variable $Y_{i,t}$ represents a time series vector of returns/changes at time *t* for variable *i*,. For example, $i = 1, 2$ denotes 1 = the returns of the first country's CDS, and 2 = the returns of the second country's CDS. The β_{ij} coefficients represent the lead-lag relationships in the model (for $i \neq j$). To test the causality from one CDS to the other, restrictions on the coefficients are imposed as follows:

$$H_{0,1}: \beta_{ij} = 0\ for\ i,j = 1,\dots,n\ and\ i \neq j \tag{5}$$

The conditional variance and the volatility spillover effect is modeled via equation (2). In this instance, the conditional variance is an exponential function of its own lagged and other market lagged standardized innovations. The variables $\sigma_{i,t}^2$ and $\sigma_{i,j,t}$ denote the conditional variance and covariance, respectively, $\epsilon_{i,t}$ is the innovation at time *t*, and $z_{i,t} = \epsilon_{i,t}\ /\sigma_{i,t}^2$ is the standardized innovation. In equation (2) both the lagged value of the conditional variance and cross-market standardized innovations are allowed to impact the volatility of a given market. For volatility to spill over from one market/country to another, $\alpha_{i,j}$, for i≠j must be significantly different from zero. The persistence of volatility is measured by γ_i, where a γ_i equal to one can be interpreted as the non-existence of an unconditional variances and a conditional variance that follows an I(1) process.

Equation (3), representing the functional form of $f_j(z_{j,t-1})$, allows the standardized innovation and the other market innovations to affect the conditional variance asymmetrically with $|z_{j,t-1}| - E(|z_{j,t-1}|)$ measuring the magnitude (size) effect and $\delta_j z_{j,t-1}$ the sign effect. The asymmetric impact on the volatility of the market under study is thus measured by δ_j as:

$$\partial f_j(z_{j,t})/\partial z_t = 1 + \gamma, \quad for\ z_t > 0$$
$$\partial f_j(z_{j,t})/\partial z_t = -1 + \gamma, \quad for\ z_t < 0 \qquad (6)$$

where a negative δ_j, combined with a positive and significant $\alpha_{i,j}$, would imply that a negative return shocks in one market increases volatility more than positive returns in the other market; while a negative z_t accompanied by a negative δ_j is to represent an increase in the magnitude effect. Volatility spillovers across the markets are measured by $\alpha_{i,j}$ for $i, j = 1, \dots, n\ and\ i \neq j$. The conditional covariance specification is presented in equation (4), where $\rho_{i,j}$ represents the cross-market correlation coefficients between volatility of returns and $\sigma_{i,t}$ and $\sigma_{j,t}$ represent the conditional covariance between the markets, and suggests that the correlations between markets are constant. The log likelihood for the VAR-EGARCH model, assuming normality, is represented in equation (7) as:

$$L(\Theta) = -0.5(NT)\ln(2\pi) - 0.5\sum_{t=1}^{T}(ln|S_t| + \epsilon_t' S_t^{-1}\epsilon_t) \qquad (7)$$

where *N* is the number of equations, *T* is the number of observations, Θ is the parameter vector of the model, ϵ_t' is the vector of innovations at time *t*, S_t is the time-varying conditional variance-covariance matrix. For the estimation procedure we follow Koutmos (1996).

4. Empirical Results

Descriptive Statistics and Correlations

Table 1 reports descriptive statistics for the daily sovereign CDS spreads. Panel A presents summary statistics per country for the spreads in levels. Among the BRICS countries the highest CDS spreads in basis points are noted in the case of India, followed by Russia and Brazil. Among the MIST countries, Indonesia and Mexico have the highest spreads. Looking at the changes in the spreads in panel B, we notice that the mean change is negative for all MIST countries and also for Russia (from the BRICS group). Some of the CDS spreads in first difference are negatively skewed (India, South Africa and Turkey), while the rest are positively skewed. All series are highly leptokurtic. Panel B also reports Kolmogorov-Smirnov test for normality. The test results reject the null of normally distributed returns. The Ljung-Box (LB) statistic for 12 lags are also significant and show linear dependence in the case of return (LB(12) for R_t) and non-linear dependence in the case of squared returns (LB(12) for R_t^2).

The correlation structure of the BRICS countries is based on the assumption of a stationary mean and variance. The matrix reveals high correlation between Brazil, Russia and South Africa in the BRICS group and also for all countries in the MIST group. Our results are in line with Stolbov (2014) who also reports high degree of co-movement among BRICS CDS prices. We also perform stationary tests to determine whether the analysis should be in levels or first differences of the series. Results from augmented Dickey-Fuller and Phillips-Perron tests are reported in Table 2. We cannot reject the null hypothesis of unit root in the case of India, China, Mexico, South Korea and Indonesia (Brazil CDS spread levels also appears non-stationary using Philips-Perron's test). Even though, the rest of the series appear stationary in levels, we use first differences for all series our VAR-EGARCH analyses to be consistent.

Figure 1 presents the five-year sovereign CDS spreads in basis points for all the countries over time. Panel A shows the BRICS spreads increase in the second half of 2011, which coincides with the deepening of the crisis in Europe. The Russian spread experience a spike during the late 2011 – early 2012 period due to the close links of Russia with the European countries.[3] The higher levels of CDS premia for the BRICS also reflect the expectations for slowing economic growth in the group. The State Bank of India spreads appear highest, especially after 2012 when the country outlook was downgraded to negative over the widening fiscal deficit. Within the MIST countries (Panel B of Figure 1), Turkey and Indonesia have the highest spreads. The spikes in the end of 2011 could be related to the European debt crisis evolving, while the increases in Turkish sovereign spreads reflect also the anti-government protests and political unease in the country spanning from June to August 2013.

Causality

Table 3 reports the causal relations between the sovereign CDS for each group of countries. Granger (1969) causality tests in a VAR model are used to establish the causal relations between the variables under study. With regards to causality directions, Brazil CDS spreads granger cause all other BRICS sovereign spreads. Feedback is also detected from South Africa to Russia and Brazil, whereas, Indian and Chinese CDS changes appear to be influenced by changes in Russian spreads. Bi-directional causality is documented between Brazil and India and Brazil and South Africa.

Among the MIST countries, bi-directional feedback is detected between South Korea and Mexico, South Korea and Indonesia, Turkey and South Korea. Focusing on single country interactions, Mexico and South Korea spreads influence all other MIST sovereign spreads.

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[3] Russia also experienced bombings and terrorist attacks during this period (the 2010 Moscow subway, 2011 Minsk subway and the 2011 Moscow airport bombing).

Volatility Spillover

Koutmos and Booth's (1995) multivariate VAR-EGARCH model for volatility spillover is used to detect linkages between sovereign CDS spreads of BRICS and MIST countries. Tables 4 and 5 report the maximum likelihood estimates for BRICS and MIST spreads, respectively. In terms of conditional means interdependence (β), Brazil appears to influence the conditional means of all other BRICS countries. Russia has substantially less influence (only on India and China), while South Africa spread's lagged values affect India and China. India's spreads are influenced by all the other countries. Overall, Brazil plays a major role as an information player in the BRICS group, which is consistent with the Granger's test results.

In terms of second moment interactions (volatility spillover, α) reported in Table 4, changes in spreads for each country are affected by their own past innovations and to some extent by innovations generated in other markets. For example, Russia's conditional volatility is impacted by innovations in Brazil and South Africa, while India is affected by all other markets. The coefficient for asymmetry (δ) is statistically significant for all countries and negative for China. The degree of volatility persistence is highest for Russia and South Africa.

We also consider the impact of one percent innovation in market i at time t-1 on the conditional variance of market j at time t. An innovation in Brazil is mostly felt in India and China, while the impact of an innovation in volatility in Russian spreads have highest impact on India. Innovations from Russia and South Africa impact mostly Indian volatility as well. Furthermore, positive innovations have larger impact in the case of Brazil, Russia, India and South Africa, i.e., positive innovations increase volatility more than negative innovations. The opposite is mostly true for China.

Table 5 reports the maximum likelihood estimates for the first and second moment interactions of MIST sovereign CDS. While Indonesia and South Korea are significantly affected by the lagged changes in spreads in all other countries in the group, Mexico appears influenced only by Indonesia and Turkey by Mexico. Overall, Mexico plays a major role as an information producer in the group. With respect to volatility interactions, from Table 5 we can see that they are extensive and each country's conditional volatility is influenced by its own past innovations as well as innovations of some of the other countries in the group. Again, innovations in volatility of Mexican sovereign spreads influence all other conditional volatilities. The coefficient for asymmetry (δ) is statistically significant for all countries and negative for South Korea and Turkey. The conditional correlation coefficients are slightly lower than the coefficients reported in table, but still confirm the conclusions of close co-movement of the series.

The impact of a one percent innovation in market i at time t-1 on the conditional variance of market j at time t for the MIST countries is also reported in Table 5. Innovations in Mexican CDS spreads are mostly felt in Indonesia and Korea, while Korean CDS spread changes are have highest impact on Turkey. Furthermore, negative innovations have smaller impact than positive innovations throughout, i.e., positive innovations in all countries increases volatility more than negative innovations. Since sovereign CDS spreads increase when affected by sovereign and global risk factors, this is consistent with the leverage hypothesis - negative news imply higher spreads and higher volatility.

To sum up, we find significant first and second moment interactions between sovereign CDS spreads in BRICS and MIST countries. Changes in sovereign CDS spreads of Brazil and Mexico, the two Latin American countries spreads under study, are the major information producers in their respective groups.

Principal Components Analysis

As we find significant conditional mean and volatility interactions a month the sovereign CDS of BRICS and MIST countries, we further investigate whether the interdependencies are driven in part by common factors affecting spreads. Principal component (PC) analysis can help in identifying the common factors determining sovereign spreads in each group. Table 6 reports the maximum likelihood results from principal component analysis and in particular the proportion of the variation explained by the first three principal components, as well as the cumulative percentage of the variation explained. For both groups, we find a high level of commonality. The first principal component explains about 69 percent of the variation in BRICS sovereign spreads and almost 64 percent of the variation in MIST spreads. Cumulatively, the first three principal components account for 92 and 94 percent of the variation in BRICS and MIST sovereign spreads, respectively.

We next study the relationship between the common factors extracted from the principal component analysis and other financial market variables. In table 7, we report the correlation between the time series of the first principal component for the BRICS and MIST spreads and market variables. The highest correlations of the first PC for both BRICS and MIST is with stock market variables, such as S&P 500 returns, changes in the VIX, EuroStoxx returns and changes in VStoxx. The correlation with stock market returns is negative, while with volatility indices is positive. The highest correlation is with the Eurostoxx returns, which is -60 percent with the first BRICS PC and -54 percent with the first MIST PC. Interest rate variables such as the Treasury rate level and slope of the yield curve have low and negative correlation with the first principal component for both groups, while the MOVE bond volatility and Barclays Euro aggregate corporate and government bond indices have a little higher correlation with the first principal component for each group. These findings are in line with Longstaff et al. (2011), who show that sovereign credit spreads are more related to global than to local factors. Our results, and in particular the high significance of European stock markets variables, may also be influenced by Greek debt crisis which partly evolved during our sample period.

Spillover with European CDS

After establishing that most of the variation in BRICS and MIST sovereign CDS is driven by US and European market factors, we examine in more detail the dynamics between the sovereign CDS of the two groups of emerging markets and European CDS markets. To gain more insight, we use Thomson Datastream sovereign CDS index. The equally-weighted index is based on the most liquid 5-year sovereign CDS and reflects the average mid-spread of the constituents. The index is rebalanced every six months based on the CDS liquidity in the sector.

Table 8 reports the volatility spillover coefficients from the multivariate EGARCH model. Significant spillover is documented from European sovereign spreads to all BRICS CDS, with the exception of China. The highest coefficients are for Russia, followed by Brazil and South Africa. Similarly, the MIST countries experience significant spillover effect, albeit smaller compared to their BRICS counterparts. The conditional correlation reported in Table 8 indicate that even after accounting for conditional heteroscedasticity, the highest degree of relatedness with European sovereign debt markets is documented with Russia and Turkey. Brazil, South Africa and Mexico have conditional correlation coefficients above 30 percent as well.

Conclusion

Given that the markets of BRICS and MIST countries have been developing faster than those of developed economies and are expected to surpass the largest six economies based on GDP volume

(Wilson and Purushothaman, 2003), the study of their returns and volatilities is important not only to researchers and investor but to policy makers as well. Of special interest is the area of sovereign CDS due to their speculative nature and possible destabilizing effect. As such, this study estimates the spillover effect for these nine countries using Koutmos and Booth's (1995) VAR-GARCH model.

A surprising result found in this study is that the two Latin American countries under study dominate the spillover effects within their respective group, namely Brazil and Mexico. Based on VAR-GARCH model, Brazil plays a major role as an information producer in the case of India, China and South Africa while Mexico plays this role in the case of Indonesia South Korea and Africa. In addition, in the case of the BRICS and MIST countries, positive innovations tend to be are larger than negative ones (except in the case of China), suggesting that positive innovations in these countries increase volatility more than negative innovations.

Further analysis performed using principal components further shows that there is a strong relationship between the European markets and the countries that form part of the BRICS' and MIST's groups, once again with the exception of China. This is further supported by the results of the VAR-GARCH model.

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Table 1. Sovereign CDS Descriptive Statistics and Correlations

	BRICS countries					MIST countries			
	Brazil	Russia	India	China	South Africa	Mexico	Indonesia	South Korea	Turkey
A. Level									
Mean	138.18	162.69	239.77	89.41	150.74	115.29	175.72	96.81	174.09
Std. dev.	28.93	37.58	66.51	25.54	28.86	23.31	37.28	31.19	41.59
Skewness	0.72	1.10	0.33	1.13	0.36	0.61	0.85	0.82	0.36
Kurtosis	-0.42	0.94	-0.85	0.93	-0.57	0.63	0.22	0.46	-0.52
K-S	25.88	29.46	15.32	37.85	5.94	8.76	22.31	18.17	6.63
LB(12) for R_t	11998.13	11032.58	13211.15	12504.83	11667.11	11680.52	11324.43	12646.60	12388.35
LB(12) for R_t^2	11639.00	10321.33	12721.83	11853.68	11293.29	11003.59	10544.64	11693.23	11928.37
Panel B. First difference									
Mean	0.03	-0.01	-0.02	0.00	0.02	-0.05	-0.04	-0.03	-0.02
Std. dev.	4.52	7.94	6.63	3.51	5.43	3.86	6.56	4.13	6.24
Skewness	0.29	0.00	-0.39	0.52	-0.71	0.28	0.30	0.29	-0.30
Kurtosis	6.16	15.26	8.55	8.20	13.28	7.51	9.59	9.30	8.61
K-S	19.26	44.19	62.78	35.67	30.06	22.92	49.92	47.85	24.55
LB(12) for R_t	80.44	17.89	505.48	66.75	35.09	64.34	56.56	71.59	33.59
LB(12) for R_t^2	356.16	427.31	259.43	583.27	193.21	375.97	366.23	1016.36	169.66

Panel C. Correlations

	Brazil	Russia	India	China		Mexico	Indonesia	South Korea	Turkey
Russia	0.58								
India	0.26	0.27			Indonesia	0.40			
China	0.40	0.44	0.51		South Korea	0.38	0.76		
South Africa	0.68	0.69	0.31	0.48	Turkey	0.68	0.48	0.41	

The tables report descriptive statistics individual countries' CDS. The Kolmogorov-Smirnov (K-S) test is a test for normality. The Ljung-Box (LB) statistic for 12 lags is distributed as χ^2.

Table 2. Unit Root Test

Panel A. BRICS Countries

	Level (in bps)		First Difference	
	Augmented Dickey Fuller	Phillip-Perron	Augmented Dickey Fuller	Phillip-Perron
Brazil	-3.1985*	-2.7085	-29.3053*	-29.1297*
Russia	-3.6717*	-3.6717*	-35.2608*	-35.4318*
India	-2.2359	-2.3554	-20.1923*	-32.6123*
China	-2.4904	-2.4032	-20.4851*	-32.2752*
South Africa	-3.8616*	-33.7248*	-21.7916*	-37.7428*

Panel B. MIST Countries

	Level (in bps)		First Difference	
	Augmented Dickey Fuller	Phillip-Perron	Augmented Dickey Fuller	Phillip-Perron
Mexico	-2.6203	-2.7151	-18.9118*	-30.3377*
Indonesia	-3.3591*	-3.1785**	-31.0011*	-30.9133*
South Korea	-2.0590	-2.1266	-23.3119*	-31.7473*
Turkey	-2.7986	-2.4161	-31.6619*	-31.9047*

* Reject the null of unit root at the 1% significance level using both an intercept and trend in the case Korea and South Africa but only an intercept in the case of Brazil, Mexico, Indonesia, Russia, and India.

** Reject null hypothesis at the 5% level.

Table 3. VAR Granger Causality
Panel A. BRICS Countries

	df	Brazil	Russia	India	China	South Africa
Brazil	7		5.3042	14.4878	7.2204	14.0755
			(0.3799)	(0.0128)	(0.2048)	(0.0151)
Russia	7	34.5830		5.7689	3.4704	11.3145
		(0.0000)		(0.3294)	(0.6279)	(0.0455)
India	7	34.5218	11.8763		3.4704	1.4672
		(0.0000)	(0.0305)		(0.6279)	(0.9168)
China	7	70.6670	23.2634	6.7281		8.6462
		(0.0000)	(0.0003)	(0.2417)		(0.1240)
South Africa	7	89.3536	5.5222	7.1943	1.7845	
		(0.0000)	(0.3555)	(0.02066)	(0.8781)	

Panel B. MIST Countries

	df	Mexico	Indonesia	South Korea	Turkey
Mexico	5		7.8817	15.0861	4.2143
			(0.1629)	(0.0100)	(0.5190)
Indonesia	5	185.1338		12.0171	9.9158
		(0.000)		(0.0346)	(0.0777)
South Korea	5	166.5787	16.3604		18.3410
		(0.0000)	(0.0059)		(0.0025)
Turkey	5	53.1340	14.4645	30.5262	
		(0.0000)	(0.0129)	(0.0000)	

Values presented are the χ^2 (Wald) statistics for the joint significance of each of the other lagged endogenous variables in that equation. Values in parentheses refer to the p-values. All represents the χ^2 statistic for joint significance of all other lagged endogenous variables in the equation.

Table 4. Maximum Likelihood Estimates of the multivariate VAR-GARCH Model for BRICS countries

	Brazil		Russia		India		China		South Africa
$\beta_{1,0}$	0.0791 (0.0509)	$\beta_{2,0}$	-0.0468* (0.0034)	$\beta_{3,0}$	-0.2973* (0.0074)	$\beta_{4,0}$	-0.0332 (0.0477)	$\beta_{5,0}$	0.0369 (0.0709)
$\beta_{1,1}$	0.1263* (0.0241)	$\beta_{2,1}$	0.3445* (0.0027)	$\beta_{3,1}$	0.1878* (0.0068)	$\beta_{4,1}$	0.2703* (0.0154)	$\beta_{5,1}$	0.3418* (0.0224)
$\beta_{1,2}$	-0.0109 (0.0060)	$\beta_{2,2}$	-0.1059* (0.0103)	$\beta_{3,2}$	0.0154* (0.0009)	$\beta_{4,2}$	0.0251* (0.0090)	$\beta_{5,2}$	-0.0036 (0.0135)
$\beta_{1,3}$	0.0334* (0.0029)	$\beta_{2,3}$	0.0459* (0.0009)	$\beta_{3,3}$	0.4452* (0.0145)	$\beta_{4,3}$	0.0181 (0.0104)	$\beta_{5,3}$	0.0376* (0.0122)
$\beta_{1,4}$	-0.0002 (0.0201)	$\beta_{2,4}$	-0.0466* (0.0100)	$\beta_{3,4}$	0.0023 (0.0019)	$\beta_{4,4}$	-0.1426* (0.0226)	$\beta_{5,4}$	-0.0360 (0.0271)
$\beta_{1,5}$	-0.0235 (0.0182)	$\beta_{2,5}$	0.0231 (0.0170)	$\beta_{3,5}$	0.0039* (0.0004)	$\beta_{4,5}$	0.0323** (0.0158)	$\beta_{5,5}$	-0.1249* (0.0255)
$\alpha_{1,0}$	0.1081* (0.0164)	$\alpha_{2,0}$	0.1101* (0.0208)	$\alpha_{3,0}$	0.5965* (0.0914)	$\alpha_{4,0}$	0.1147* (0.0143)	$\alpha_{5,0}$	0.0933* (0.0220)
$\alpha_{1,1}$	0.2014* (0.0255)	$\alpha_{2,1}$	0.0644* (0.0231)	$\alpha_{3,1}$	0.2529* (0.0424)	$\alpha_{4,1}$	0.2181* (0.0265)	$\alpha_{5,1}$	0.1030* (0.0216)
$\alpha_{1,2}$	0.0076 (0.0210)	$\alpha_{2,2}$	0.2565* (0.0287)	$\alpha_{3,2}$	-0.2902* (0.0447)	$\alpha_{4,2}$	-0.0218 (0.0212)	$\alpha_{5,2}$	0.0598* (0.0210)
$\alpha_{1,3}$	0.0242 (0.0158)	$\alpha_{2,3}$	0.0010 (0.0199)	$\alpha_{3,3}$	0.3188* (0.0309)	$\alpha_{4,3}$	0.0657* (0.0157)	$\alpha_{5,3}$	-0.0117 (0.0152)
$\alpha_{1,4}$	0.0047 (0.0104)	$\alpha_{2,4}$	-0.0186 (0.0161)	$\alpha_{3,4}$	0.1565* (0.0517)	$\alpha_{4,4}$	0.0289* (0.0145)	$\alpha_{5,4}$	0.0056 (0.0103)
$\alpha_{1,5}$	0.0217 (0.0180)	$\alpha_{2,5}$	-0.0594* (0.0175)	$\alpha_{3,5}$	0.1822* (0.0420)	$\alpha_{4,5}$	0.0499* (0.0177)	$\alpha_{5,5}$	0.0556* (0.0194)
δ_1	0.3396* (0.0706)	δ_2	0.5356* (0.0945)	δ_3	0.1944* (0.0676)	δ_4	-1.1599* (0.4280)	δ_5	0.8048* (0.1864)
γ_1	0.9634* (0.0056)	γ_2	0.9712* (0.0056)	γ_3	0.8273* (0.0278)	γ_4	0.9491* (0.0065)	γ_5	0.9713* (0.0069)

Correlation Matrix

	Brazil	Russia	India	China	South Africa
Russia	0.6121* (0.0141)	1			
India	0.1749* (0.0201)	0.1982* (0.0203)	1		
China	0.3150* (0.0194)	0.3800* (0.0185)	0.3250* (0.0209)	1	
South Africa	0.5962* (0.0147)	0.7300* (0.0105)	0.2093* (0.0207)	0.3585* (0.0181)	1

Model Diagnostics					
	Brazil	Russia	India	China	South Africa
$E(z_{i,t})$	0.0014	0.0159	0.0519	0.0197	0.0112
$E(z_{i,t}^2)$	0.9937	0.9963	1.0004	1.0068	1.0015
LB(12); $z_{i,t}$	12.2182	11.1187	22.1882*	26.9198*	11.2829
LB(12); $z_{i,t}^2$	11.629	17.1271	8.6547	3.7666	25.1177*

Degree of Volatility Persistence		*Degree of Volatility Asymmetric Impacts of Negative and Positive Innovations*	
Brazil	18.5897	Brazil	0.4929
Russia	23.7193	Russia	0.3024
India	3.6561	India	0.6744
China	13.2682	China	-13.50
South Africa	23.8032	South Africa	0.1082

Impact of Innovation on Volatility					
Innovation at t-1 from:	%△ of volatility in Brazil at t	%△ of volatility in Russia at t	%△ of volatility in India at t	%△ of volatility in China at t	%△ of volatility in S Africa at t
+1% in Brazil	-	0.0863	0.3388	0.2922	0.1380
-1% in Brazil	-	0.0425	0.1670	0.1440	0.0680
+1% in Russia	0.0117	-	-0.4456	-0.0335	0.0918
-1% in Russia	0.0035	-	-0.1348	-0.0101	0.0278
+1% in India	0.0289	0.0012	-	0.0785	-0.0140
-1% in India	0.0195	0.0008	-	0.0529	-0.0094
+1% in China	0.0008	-0.0030	0.0250	-	0.0101
-1% in China	0.0102	-0.0402	0.3380	-	0.0011
+1% in S Africa	0.0392	-0.1072	0.3288	0.0901	-
-1% in S Africa	0.0042	-0.0116	0.0356	0.0097	-

Numbers in parentheses are asymptotic standard errors. *,** represents1 and 5 percent significance, respectively. LB(12) is the Ljung-Box statistic for up to 12 lags (distributed as χ^2 with n degrees of freedom). $z_{i,t}$ is the standardized residual for market i at time t. Degree of volatility persistence is based on the half-life of a shock measured as $\ln(0.5)/\ln(\gamma_i)$. The number of times that a negative innovation increases volatility more than a positive innovation (degree of asymmetric impacts) is estimated as $|-1+\delta_i|/(1+\delta_i)$. Values reported are the total impact of innovations defined as $\alpha_{i,j}(1+\delta_j)$ and $\alpha_{i,j}|-1+\delta_j|$ for 1% and -1% innovation, respectively.

Table 5. Maximum Likelihood Estimates of the multivariate VAR-GARCH Model for MIST countries

	Mexico		Indonesia		South Korea		Turkey
$\beta_{1,0}$	-0.1193* (0.0431)	$\beta_{2,0}$	-0.0330 (0.0711)	$\beta_{3,0}$	-0.0239 (0.0472)	$\beta_{4,0}$	-0.0687 (0.1032)
$\beta_{1,1}$	0.0547* (0.006)	$\beta_{2,1}$	0.3868* (0.0292)	$\beta_{3,1}$	0.2138* (0.0194)	$\beta_{4,1}$	0.2046* (0.0416)
$\beta_{1,2}$	-0.0275* (0.0080)	$\beta_{2,2}$	-0.0396* (0.0202)	$\beta_{3,2}$	-0.0384* (0.0117)	$\beta_{4,2}$	-0.0043 (0.0229)
$\beta_{1,3}$	0.0773* (0.0162)	$\beta_{2,3}$	0.0176 (0.0256)	$\beta_{3,3}$	-0.0005 (0.0233)	$\beta_{4,3}$	0.0077 (0.0356)
$\beta_{1,4}$	-0.0130 (0.0105)	$\beta_{2,4}$	0.1069* (0.0214)	$\beta_{3,4}$	0.0645* (0.0119)	$\beta_{4,4}$	-0.0812* (0.0293)
$\alpha_{1,0}$	0.1122* (0.0152)	$\alpha_{2,0}$	0.1089* (0.0327)	$\alpha_{3,0}$	0.0664* (0.0099)	$\alpha_{4,0}$	0.0481* (0.0113)
$\alpha_{1,1}$	0.1484* (0.0197)	$\alpha_{2,1}$	0.1902* (0.0313)	$\alpha_{3,1}$	0.1533* (0.0202)	$\alpha_{4,1}$	0.0727* (0.0167)
$\alpha_{1,2}$	0.0905* (0.0221)	$\alpha_{2,2}$	0.2181* (0.0366)	$\alpha_{3,2}$	-0.0019 (0.0205)	$\alpha_{4,2}$	0.0511* (0.0207)
$\alpha_{1,3}$	0.0361 (0.0209)	$\alpha_{2,3}$	-0.0845* (0.0245)	$\alpha_{3,3}$	0.1517* (0.0214)	$\alpha_{4,3}$	-0.0654* (0.0182)
$\alpha_{1,4}$	0.0278 (0.0172)	$\alpha_{2,4}$	0.0025 (0.0181)	$\alpha_{3,4}$	-0.0032 (0.0145)	$\alpha_{4,4}$	0.0682* (0.0242)
δ_1	0.3889* (0.0779)	δ_2	0.4131* (0.1082)	δ_3	0.3107* (0.0852)	δ_4	0.9819* (0.3003)
γ_1	0.9584* (0.0073)	γ_2	0.9691* (0.0039)	γ_3	0.9737* (0.0030)	γ_4	0.9874* (0.0197)

Correlation Matrix

	Mexico	Indonesia	South Korea	Turkey
Indonesia	0.3480* (0.0139)			
South Korea	0.3348* (0.0154)	0.6928* (0.0094)		
Turkey	0.6312* (0.0097)	0.4036* (0.0148)	0.3952* (0.0158)	

Model Diagnostics

	Mexico	Indonesia	South Korea	Turkey
E($z_{i,t}$)	0.0318	0.0142	0.0067	0.0221
E($z_{i,t}^2$)	0.9859	1.0100	1.0154	0.9972
LB(12); $z_{i,t}$	14.0440	26.3874*	25.7498*	11.7533
LB(12); $z_{i,t}^2$	8.7336	11.4031	16.7474	11.4183

Degree of Volatility Persistence		*Degree of Volatility Asymmetric Impacts of Negative and Positive Innovations*	
Mexico	16.3132	Mexico	0.439988
Indonesia	22.0836	Indonesia	0.415328
South Korea	26.0073	South Korea	0.525902
Turkey	54.6644	Turkey	0.009133

Impact of Innovation on Volatility

Innovation at t-1 from:	%△ of volatility in Mexico at t	%△ of volatility in Indonesia at t	%△ of volatility in South Korea at t	%△ of volatility in Turkey at t
+1% in Mexico	-	0.2642	0.2129	0.1010
-1% in Mexico	-	0.1162	0.0937	0.0444
+1% in Indonesia	0.1279	-	-0.0027	0.0722
-1% in Indonesia	0.0531	-	-0.0011	0.0300
+1% in South Korea	0.0473	-0.1108	-	1.2453
-1% in South Korea	0.0249	-0.0582	-	0.6239
+1% in Turkey	0.0551	0.0050	-0.0063	-
-1% in Turkey	0.0005	0.0000	-0.0001	-

Numbers in parentheses are asymptotic standard errors. *,** represents1 and 5 percent significance, respectively. LB(12) is the Ljung-Box statistic for up to 12 lags (distributed as χ^2 with n degrees of freedom). $z_{i,t}$ is the standardized residual for market i at time t. Degree of volatility persistence is based on the half-life of a shock measured as $\ln(0.5)/\ln(\gamma_i)$. The number of times that a negative innovation increases volatility more than a positive innovation (degree of asymmetric impacts) is estimated as $|-1+\delta_i|/(1+\delta_i)$. Values reported are the total impact of innovations defined as $\alpha_{i,j}(1+\delta_j)$ and $\alpha_{i,j}|-1+\delta_j|$ for 1% and -1% innovation, respectively.

Table 6. Principal components analysis. Variance explained by the first three factors.

Principal Components	BRICS countries		MIST countries	
	Proportion explained %	Cumulative explained %	Proportion explained %	Cumulative explained %
PC1	68.94	68.94	63.90	63.90
PC2	14.38	83.32	22.37	86.27
PC3	8.53	91.85	8.06	94.33

Table 7. Correlations of the first principal component with financial market variables

Market variable	BRICS countries	MIST countries
S&P 500	-0.42	-0.38
VIX	0.38	0.35
US 3m Treasury Bill	-0.04	-0.02
Slope of the yield curve	-0.23	-0.20
Move 1m Bond Volatility index	0.22	0.24
EURO STOXX	-0.60	-0.54
VSTOXX	0.55	0.51
Barclays Euro agg bond index	-0.15	-0.17
Barclays Euro agg government bond index	-0.16	-0.17

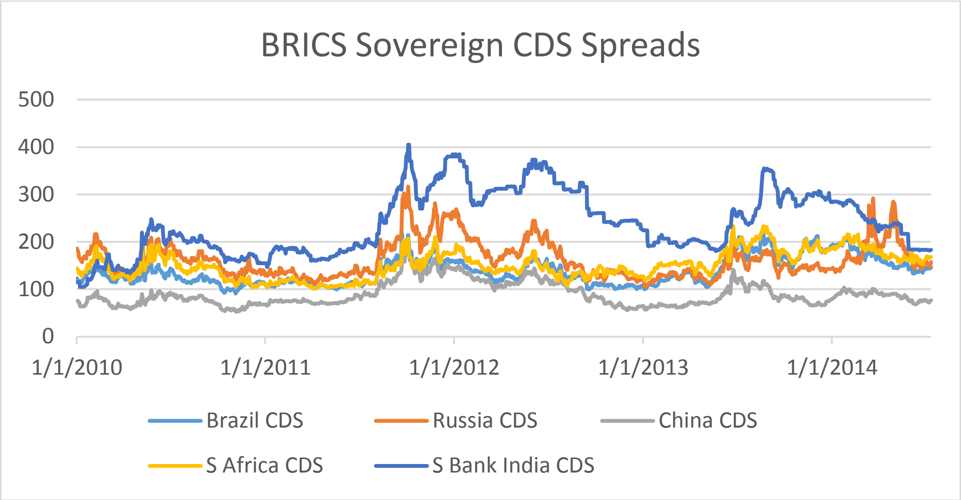
Table 8. Summary Results for Volatility Spillover with European Sovereign CDS

		Europe Sovereign CDS Index	Conditional correlation with Europe Sov CDS Index			Europe Sovereign CDS Index	Conditional correlation with Europe Sov CDS Index
Brazil	$\alpha_{1,6}$	-0.0913*	0.3074	Mexico	$\alpha_{1,5}$	-0.0244*	0.3308
		(0.0175)	(0.0186)			(0.0011)	(0.0158)
Russia	$\alpha_{2,6}$	-0.1211*	0.3595	Indonesia	$\alpha_{2,5}$	-0.0549*	0.2032
		(0.0180)	(0.0187)			(0.0028)	(0.0185)
India	$\alpha_{3,6}$	-0.0772*	0.1263	S Korea	$\alpha_{3,5}$	0.0490*	0.2753
		(0.0307)	(0.0240)			(0.0000)	(0.0180)
China	$\alpha_{4,6}$	-0.0330	0.2512	Turkey	$\alpha_{4,5}$	-0.0232*	0.4015
		(0.0171)	(0.0203)			(0.0000)	(0.0123)
S Africa	$\alpha_{5,6}$	-0.0864*	0.355423				
		(0.0171)	(0.3554)				

Numbers in parentheses are asymptotic standard errors. *,** represents1 and 5 percent significance, respectively.

Figure 1. Sovereign CDS Spreads (in basis points)

Panel A. BRICS Countries



Panel B. MIST Countries