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Assessing the extent of contagion of sovereign credit risk among BRICS countries

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This paper conducts an ex ante analysis to assess how sovereign credit risk is transmitted among BRICS countries. To this end, the conditional value-at-risk (CoVaR) methodology is used. Moreover, the paper makes use of the generalised forecast error decomposition to assess the contribution of key economic and financial variables of each of the BRICS countries to credit risk transmitted from China, the biggest economy among the BRICS. The findings of this paper show the existence of cross-transmission of credit risk shocks among BRICS countries, with China affecting the most other BRICS countries. However, the channel through which credit risk distress in China is transmitted to the other BRICS countries is not homogenous.

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Abstract

This paper conducts an *ex ante* analysis to assess how sovereign credit risk is transmitted among BRICS countries. To this end, the conditional value-at-risk (CoVaR) methodology is used. Moreover, the paper makes use of the generalised forecast error decomposition to assess the contribution of key economic and financial variables of each of the BRICS countries to credit risk transmitted from China, the biggest economy among the BRICS. The findings of this paper show the existence of cross-transmission of credit risk shocks among BRICS countries, with China affecting the most other BRICS countries. However, the channel through which credit risk distress in China is transmitted to the other BRICS countries is not homogenous.

1. INTRODUCTION

Following the collapse of Iceland's banking system in 2008, which triggered the European sovereign debt crisis, there has been an increase in academic work on sovereign credit risk spillovers (see Arghyrou and Kontonikas, 2012; Galariotis et al., 2016; Mink and De Haan, 2013). Several studies have attempted to assess the extent of contagion of the European sovereign debt crisis in Eurozone and worldwide. For example, Galariotis et al. (2016) examine the drivers of credit default swap (CDs) spreads and potential spillover effects in Eurozone countries during the crisis. The authors make use of a panel vector autoregressive (PVAR) model and find that the determinants of CDs variances are neither the same nor stable at different periods.

While most literature on sovereign debt crisis contagion has focused mainly on developed economies, especially by considering developed economies as the source of contagion, very few of these studies have given consideration to emerging markets in this regard. For example, Kaminski and Schmukler (2002) show that changes in sovereign debt rating in emerging economies directly impact on the markets of the countries rated among emerging economies and engender cross-country contagion. Moreover, existing papers on sovereign credit risk contagion are often conducted *a posteriori*, i.e., assessed the extent of contagion after the crisis has occurred (see Galariotis et al., 2016; Mink and De Haan, 2013; Kalbaska and Gatkowski, 2012). In order to fill this gap in literature, this paper uses the CoVaR model to conducts an *ex* *ante* analysis on the possible effects of credit risk spillovers among BRICS countries. In addition, the paper makes use of the generalised forecast error decomposition to assess the contribution of state variables in the CoVaR of the BRICS countries conditioned by China, the biggest economy among the BRICS. The findings of this paper provide useful information on how a distressed country within the BRICS grouping adds to the risk of peer countries, an important insight to asset managers who intend to diversify their portfolio among the BRICS countries.

The remainder of the paper is organised as follows; section 2 presents the methodology used in the paper, section 3 discusses the data issues, the model as well as while Section 4 concludes the paper.

2. METHODOLOGY

This section presents the main methodology of the paper. It shows how the CoVaR is modelled, mainly by making use of the quantile regression when estimating the value-at-risk related to sovereign credit risk.

2.1. CoVaR Definition

Given Y_t , the returns of a bond for example, we can statistically define the VaR of a bond as the q quantile of the distribution of its returns over the confidence level *1-q*. This can be represented as follows

$$\Pr\left(Y_t^i \leq VaR_{t,q}^i\right) = q \tag{1}$$

Where Y_t^i represents the returns of a bond in country i and $VaR_{t,q}^i$ is the q percent value at risk for country *i*.

Adrian and Brunnermeier (2016) define CoVaR as the Value-at-Risk of the system given that one institution is already at its VaR. In the context of this study, CoVaR represents the extent of the exposure to credit risk by some of the BRICS countries when one of the BRICS countries is in distress (exposed to credit risk). Hence, the concept of CoVaR is statistically defined as the *qth* quantile of a country's returns distribution on condition that the returns of another individual country are equal to the VaR. This can be represented as follows:

$$\Pr\left(Y_t^j \leq CoVaR_{t,q}^{j|i} | Y_t^i = VaR_{t,q}^i\right) = q \tag{2}$$

Where Y_t^j are the returns of the country *j* at time t and Y_t^i are the returns of country *i* at time t.

2.2. Estimation Procedure

CoVaR makes use of value-at-risk (VaR) as the basic measure for risk. It is often used to assess the extent of risk contagion between countries or institutions. Given that VaR is often obtained by making use of the quantile regression (see Gaglianone, et al., 2011 ; Taylor, 2008) , it is understandable that the first step in estimating CoVaR requires the use of quantile regression to determine the lowest quantile, which represents situations of distress. Thus, in this paper, we estimate sovereign credit risk for each of the BRICS country, proxied by the change in the sovereign yields, *at q= 5%* quantile thus:

$$Y_{t,q}^{i} = \beta_{0,q}^{i} + \beta_{1,q}^{i} M_t + \varepsilon_t^{i} \tag{3}$$

Where M_t represents a set of a country's variables or possible determinants of sovereign credit risk.

In the second step, we calculate the VaR of the individual countries from the predicted values of Equation (3).

After estimating the VaR of country *i* we then estimate the CoVaR of country *j* , which is obtained by controlling for each of the VaR of country *j* with different state variables and the VaR of country *i*. The expression is represented as:

$$CoVaR_{t,q}^{j|i} = \widehat{\beta_{0,q}^{J}} + \widehat{\beta_{1,q}^{J}} VaR_{t,q}^{i} + \widehat{\beta_{2,q}^{J}} M_t \tag{4}$$

where $VaR_{t,q}^{i}$ is the value-at-risk of country *i* .

It is worth noting that Equation (4) makes use of the predicted values or out-of-sample estimation of the estimated CoVaR of country *j* to substantiate an ex ante analysis of sovereign credit risk contagion.

The extent of contagion of sovereign credit risk among BRICS countries is then achieved by estimating Delta CoVaR ($\Delta CoVaR$), which is the difference between the CoVaR of country *j* when country *i* is in distress and the CoVaR of country *j* when country *i* is in a normal state. $\Delta CoVaR$ provides a tool to assess how a risk of an institution or country changes when a particular institution or country becomes financially stressed. It is then used to measure the extent of risk contagion between countries or institutions. $\Delta COVaR$ is represented as follows:

$$\Delta CoVaR_{t,q}^{s|i} = CoVaR_{t,q}^{s|i=VaR} - CoVaR_{t,q}^{s|i=normal} \quad (5)$$

3. DATA, ESTIMATION AND RESULTS

3.1. Data

In analysing the extent of contagion of sovereign credit risk between BRICS countries, this paper considers daily benchmark yields of ten-year government bonds for Brazil, Russia, India, China and South Africa from March 2008 to May 2017. The sample includes periods of major financial crises such as the global financial crisis and European debt crisis, thus, providing a valuable opportunity to assess sovereign risk contagion among BRICS countries in these tumultuous periods.

Typically, credit default swaps (CDS) data are used in literature to measure credit risk. Because of data unavailability for some of the BRICS countries we opt to use bonds yields, which may also be used to proxy credit risk and have been proven to produce the same results as the CDs spreads (see Lange, Lucas and Siegmann, 2016).

Figure 1. BRICS' sovereign bond yields

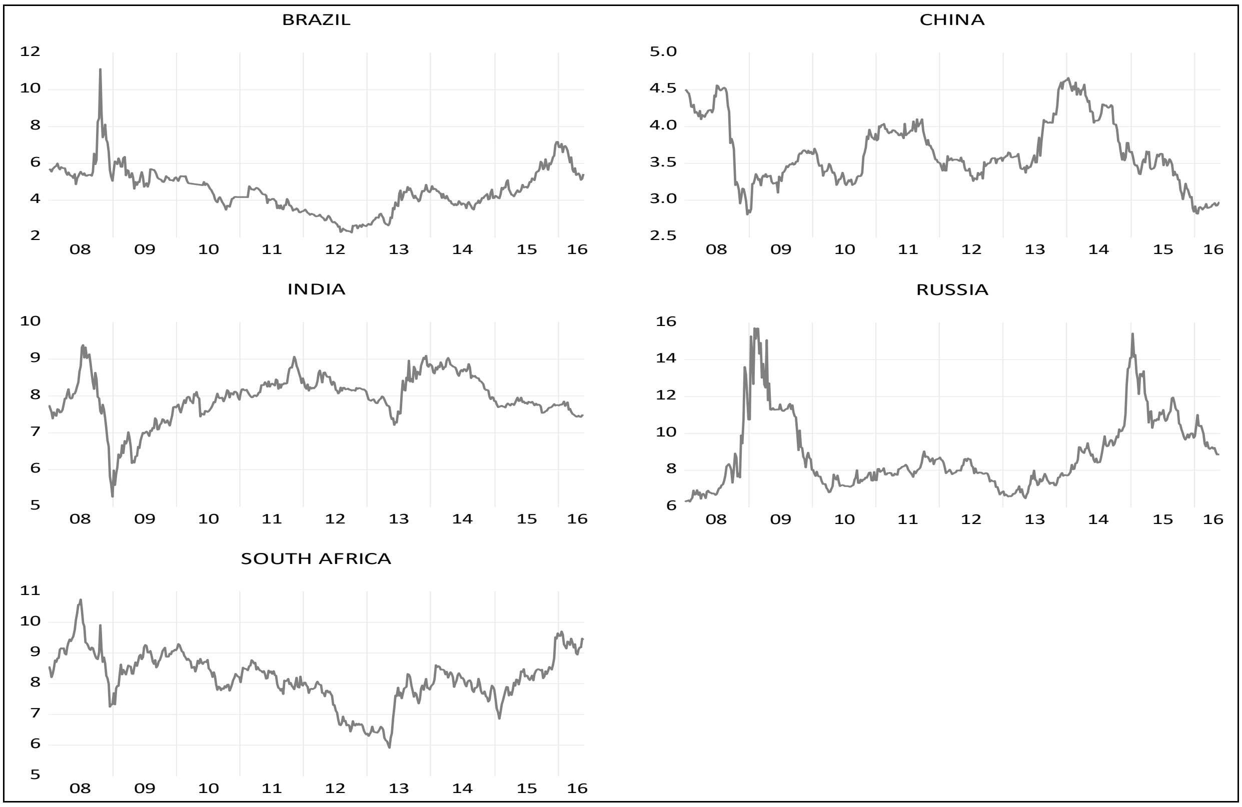

Figure 1 presents the display of the sovereign bond yields for the five BRICS countries. There is clear evidence of co-movement between the different sovereign bond yields, especially during the 2008 global financial crisis when all the yields in increasing considerably with the Russian sovereign bond yield reaching a high of 16% at the end of 2008. This reality shows the vulnerability of BRICS sovereign bond markets to global crises. There is also evidence of contagion or spillover of sovereign credit risk among BRICS countries. For example, Figure 1 shows an increase in sovereign bond yields of most of the BRICS countries in 2014.This is attributed to credit risk contagion that emanated from Russia. In 2014, Russia was a victim of sanctions imposed by the international community following its military intervention in Ukraine with the yield in government bond reaching 16.05% in January 2015 from a low of 8.46% in June 2014. Likewise, crisis in Brazil around 2015 affected other BRICS countries. Figure 1 shows a spike in government bond yield in 2015 in Brazil as a result of the economic crisis in the country augmented by political crisis that culminated in the impeachment of President Roussef. The economic crisis affected investors' confidence and led to the increase in the yield in government bond reaching 16.85% in September 2015. However, not all BRICS countries are affected to the same extent from crisis from other member countries. China has a relatively stable sovereign bond market with low sovereign bond yields that vary between 3% and 4.5% while in Russia, sovereign bond yields vary between 6% and 16.5%.

Table I presents the summary statistics for the change in sovereign bond yields of BRICS countries. It is worth noting that the change in bond yield should approximate the returns of government bonds given the negative relationship between bond yields and bond prices.

Table I: Summary Statistics for Bond Yield Changes

	Brazil	China	India	RSA	Russia
Mean	-0,0058	-0,0026	-0,0046	-0,0013	-0,0012
St. dv	0,5974	0,5537	0,3677	0,4164	1,2607
Kurtosis	15,9417	7,4359	29,0783	13,4258	34,403
Skewness	0,3571	-0,4185	1,1388	1,2818	1,6048
Minimum	-5,3070	-3,3334	-2,5858	-2,4230	-10,073
Maximum	6,8430	3,1671	5,3145	4,9209	16,452

Note: own calculation

The results reported in Table I show that the means of the yield changes of government bonds is negative for all the BRICS countries. Given the negative relationship between bond yields and bond prices, the negative sign reflects the increase in bond prices and positive returns for all the BRICS countries bonds during the period 2008 – 2017. Russia and Brazil have the highest standard deviation of government bond yields. This is confirmed with the display in Figure 1 showing higher volatility of the yields of the two countries.

In implementing quantile regression for VaR and CoVaR estimation[1], we follow Afonso et al., (2011)and Wong and Fong (2011) by making use of a set of important variables that influence sovereign bond yields, namely the business cycle (YSPRE), liquidity squeeze (LIQS), global risk premium (RISKP)and currency fluctuation (CURR). The business cycle is proxied by the yield spread between each country's 10-year government bond and the three - month Treasury bill. Liquidity squeeze is calculated by taking the difference between the repo rate and 3-month Treasury bill. The difference between the MSCI world index return and 3 month US Treasury bill proxies the global risk premium and the change in the exchange rate between the countries in question's currency and the US dollar represents the currency appreciation/depreciation.

3.2. CoVaR estimation and Results

Using quantile regression, we estimate the CoVaR at the 5 percent quantile for each BRICS country's sovereign debt market by making use of Equation (4). The results of the delta CoVaR for the period March 2008 to May 2017, as in Equation (5), are reported in Table II for all BRICS countries. As stated earlier, Delta CoVaR measures how much a distressed country adds to the risk of a peer country when it moves form operating normally to being in a state of distress. In Table II, column 1 indicates how much Brazil adds to the credit risk of the other four countries. For example, when Brazil enters a state of distress it increases the risk in Russia by 16.4 percent (0.164), whilst it adds 7, 8 and 13 percent to China, India and South Africa respectively. The findings imply that Brazil will be the most and China the least, affected when Russia's sovereign debt markets malfunctions. A look at column 2 shows that the results are not symmetric as a distressed Russia only adds 1.4 percent to the credit risk of Brazil, making Brazil the least vulnerable country to a distressed Russia. South Africa, the smallest economy in the BRICS grouping, is on average the most affected country by credit risk contagion from other BRICS countries. For example, the results of the net mutual contagion show that Brazil increases the credit risk contagion of South Africa by close to 14%, while credit risk in Brazil increase by 4.4% when South Africa is in distress. A distress in China has the largest impact

[1] See Equations 3 and 4.

on all countries in the BRICS grouping. For example, distress in China increases sovereign credit risk in India by close to 23.5% while distress in India changes credit risk in China by 19%.

In the last row of Table II, it is shown how much on average the risk of the other economies increases when one economy is in distress. On average China increases the risk of other BRICS countries by 18 percent when in distress. This percentage is the largest among the five countries' averages indicating that China has the largest significant effect on the other economies. South Africa influences the least other BRICS countries

Table II. Delta CoVaR for the full sample period

	Brazil	Russia	India	China	South Africa
Brazil		0.014076	0.02044	0.188607	0.044437
Russia	0.164796		0.141655	0.179624	0.048243
India	0.086232	0.04786		0.235327	0.107268
China	0.078128	0.079715	0.178661		0.04868
South Africa	0.139177	0.227491	0.189192	0.124221	
Average	**0.117083**	**0.092286**	**0.132487**	**0.181945**	**0.0062157**

Note: estimated from Equations 4 and 5

The finding that China is the most influential country in the BRICS grouping in terms of sovereign credit risk contagion is supported by many studies. For example, Bonga-Bonga (2017) finds that there is an asymmetric influence among BRICS countries in terms of the cross transmission of shocks with China being the most influential BRICS country. Moreover, the author shows that the vulnerability of South Africa to shocks from other countries within the BRICS grouping should imply that the country must be cautious to approve any legislation that supports capital market liberalisation among BRICS countries. With such legislation China may become the safe haven of BRICS grouping and net beneficiary of inflows of risky assets from other BRICS countries, especially in crisis periods.

While Table II presents the results for the full sample periods, from March 2008 to May 2017, it is important to assess the effects of sovereign credit risk spillover among the BRICS in three sub periods: the global financial crisis, European sovereign debt crisis and post crisis periods. Following Bonga-Bonga and Umoetok (2016), the effects of global financial crisis are analysed during the period 2008-2010. The effects of the European sovereign debt crisis are assessed during the period 2010-2012, corresponding to the peak of the crisis. The sample period 2013-2017 is used to analyse the post crisis period. Tables III, IV and V present the results of the delta CoVaR of the global financial crisis, European sovereign debt crisis and post crisis periods, respectively.

Table III. Delta CoVaR during the global financial crisis

	Brazil	Russia	India	China	South Africa
Brazil		0.14444	0.29676	0.62460	0.48601
Russia	0.02186		0.27531	0.77587	0.03782
India	0.07720	0.06378		0.36268	0.38519
China	0.10323	0.06681	0.22810		0.16014
South Africa	0.17110	0.59905	0.34324	0.52032	
Average	**0.09335**	**0.21852**	**0.28585**	**0.57087**	**0.26729**

Note: estimated from Equations 4 and 5

Table IV. Delta CoVaR during the European sovereign crisis

	Brazil	Russia	India	China	South Africa
Brazil		0.3463	0.3311	0.3689	0.1647
Russia	0.2650		0.2436	0.1845	0.1363
India	0.2094	0.1430		0.0647	0.1683
China	0.2317	0.1596	0.4503		0.1511
South Africa	0.2067	0.1253	0.0331	0.2122	
Average	**0.2282**	**0.1936**	**0.2645**	**0.2076**	**0.1551**

Note: estimated from Equations 4 and 5

Table V. Delta CoVaR during the post crisis period

	Brazil	Russia	India	China	South Africa
Brazil		0.2388	0.1581	0.4162	0.3083
Russia	0.0739		0.1632	0.6084	0.0575
India	0.2175	0.3018		0.2591	0.0815
China	0.0101	0.2336	0.1284		0.0302
South Africa	0.1790	0.1971	0.1861	0.0611	
Average	**0.12012**	**0.24282**	**0.15895**	**0.33622**	**0.11937**

Note: estimated from Equations 4 and 5

The results reported in Tables III and V show that, similar to the full sample period, distress in China has the largest impact on all countries in the BRICS grouping, showing the influence of China on other BRICS countries during the global financial crisis and after the crisis. However, the results reported in Table IV show that sovereign credit risk in India affected the most other BRICS countries during the European debt crisis, with the largest effect on China. This finding should be explained by the negative effect the European debt crisis had on India. Given that Europe is the most important destination of India's exports, the European debt crisis affected greatly the country exports and its industrial growth (see Dua and Tuteja, 2017). The decline in India's exports led to a substantial current account deficit, which puts pressure on the Indian currency, the Rupee. The devaluation of the Rupee during the European debt crisis affected negatively India's sovereign debt repayment, especially for government bonds denominated in foreign currency. This development led an increase in government bond yields, as shown in Figure 1. From the same figure, one can observe a conspicuous increase in China's government bond yields during the same period, showing the similar responses of both china and India to the European sovereign debt crisis. Thus the spillover of sovereign credit risk between India and china may be triggered by global risk premium and business cycle synchronisation, given that India is among the largest China's top trading partners.

3.3. Variance Decomposition

The results reported in Tables II, III and V show that China has the largest potential to transmit sovereign credit risk to other BRICS countries. However, it is important to assess the extent to which each variable[2] contributes to this contagion. Hence, this sub-section intends to analyse the impact of the innovation to each variable on the credit risks transmitted by China to other BRICS countries. To this end, the paper makes use of the generalised forecast error variance decomposition (see Pesaran and Shin, 1998). The results of the generalised forecast error variance decomposition are reported in Tables 1A to 4A in the appendix and summarised in Figures 2 to 5.

Figure 2 shows that in the short-term 18 percent of the variance of conditional credit risk transmitted by China to South Africa is attributed to shocks to liquidity squeeze whereas shock to risk premium accounts for around 11 percent in explaining the variation of the conditional risk transmitted by China. This finding implies that liquidity squeeze accounts for the most of the fluctuation of the conditional credit risk contagion in South Africa. Over the long horizon liquidity squeeze continues to dominate as an important contributor to the conditional credit risk transmitted from China to South Africa. This finding shows that when China's sovereign credit market is in turmoil, there is a likelihood that other emerging markets such as South Africa would be impacted negatively through sharp sell-offs in their equity and bond markets. The dollar liquidity squeeze that ensues is often due to massive foreign capital outflow from these markets.

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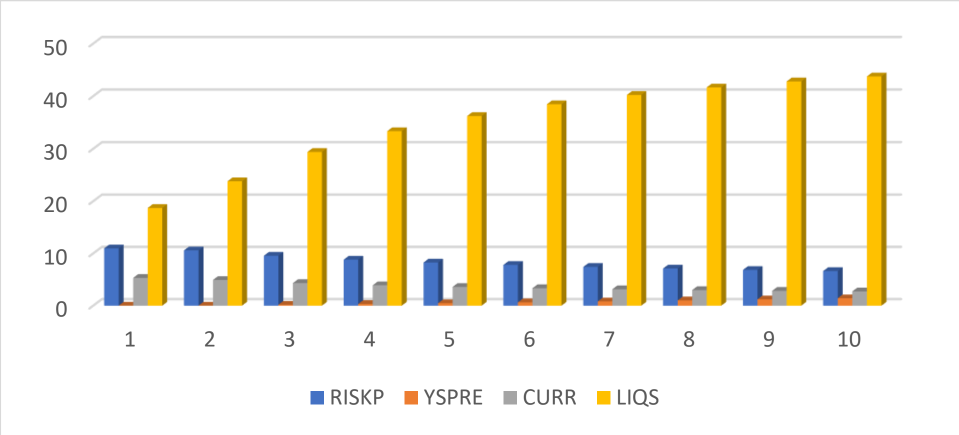
[2] We focus on the states variables that determine the COVAR as in Equation 4, namely, liquidity squeeze, risk premium, credit rating and currency fluctuation

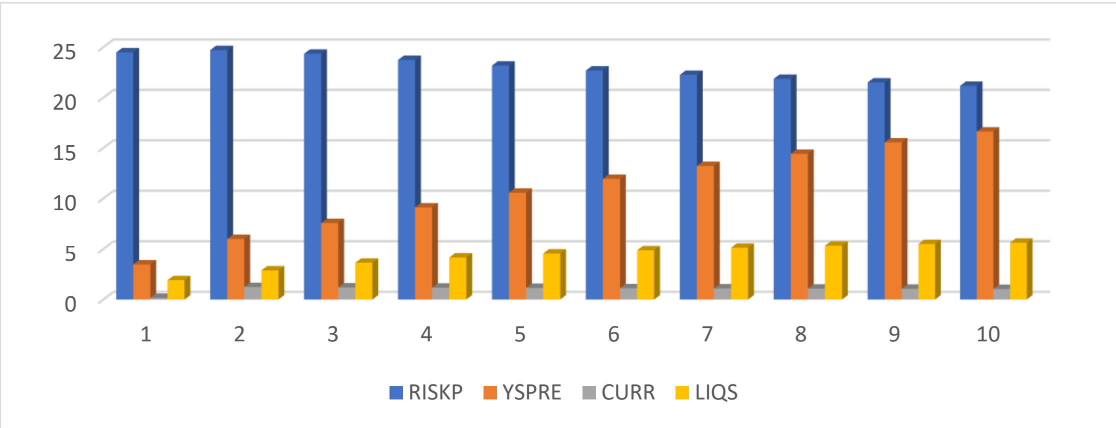
Figure 2. Variance Decomposition of conditional credit risk transmitted from China to South Africa



Source: own estimation. Graphical representation of the results reported in Table 1A

Figure 3 shows that innovation to global risk premium contributes the most to the variation of credit risk transmitted by China to Brazil. The contribution of the business cycle increases over time, although the global risk premium continues to dominate as the largest contributor to shocks to credit. This finding is explained by the fact that sovereign credit risk crises in China should fuel global risk premium and, given the susceptibility of Brazil to global risk premium (see Dungey, et al., 2006), it is likely that an innovation to global risk premium should become an important channel through which sovereign credit crisis in China is transmitted to Brazil.

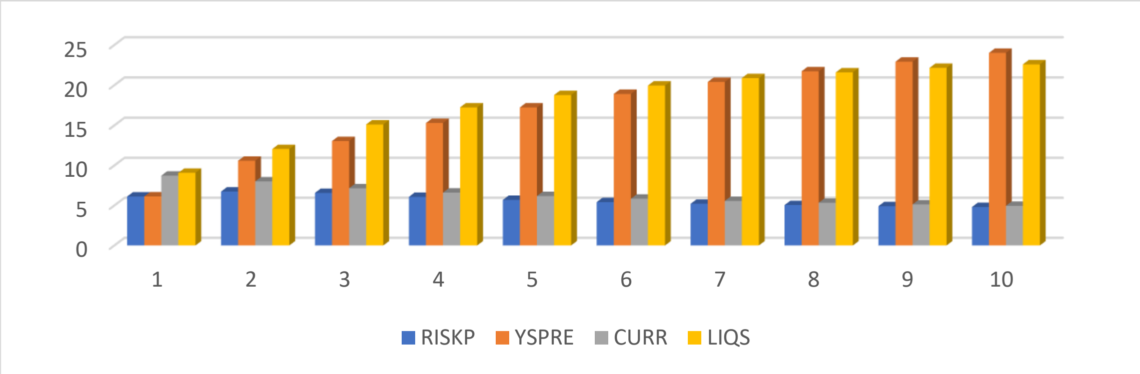
Figure 3. Variance Decomposition of conditional credit risk transmitted from China to Brazil



Source: own estimation. Graphical representation of the results reported in Table 2A

Figure 4 shows that innovation to liquidity squeeze and business cycle contribute the most to the variation of credit risk transmitted by china to Russia. A number of studies find that China's business cycle converges with that of a number of emerging markets, especially with Russia, due to their increase in trade (See Calderon et al., 2007 and Cesa-Bianchi et al., 2012). It is evident that the occurrence of credit crisis in China affects the Russia's business cycle. Thus, the business cycle should become an important channel through which credit risk in China is transmitted to Russia.

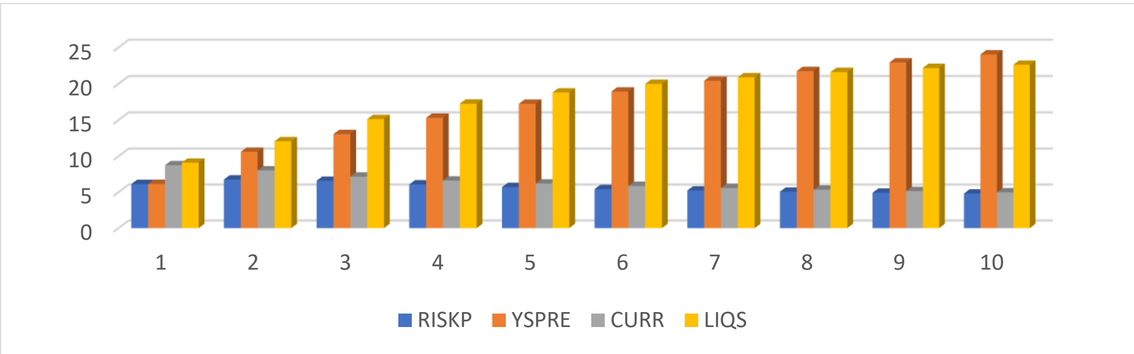
Figure 4. Variance Decomposition of conditional credit risk transmitted from China to Russia



Source: own estimation. Graphical representation of the results reported in Table 3A

Figure 5 shows that, just as with the case of Russia, innovation to liquidity squeeze and business cycle contribute the most to the variation of credit risk transmitted by china to India. This shows that the comovement of the business cycle between China and India is an important source of shock transmission. Moreover, like in the case of South Africa where liquidity squeeze is an important channel of shock transmission to credit risk, it is important to infer that when China's sovereign credit market is in turmoil, there is a likelihood that India will be impacted negatively through sharp sell-offs in their equity and bond markets.

Figure 5. Variance Decomposition of conditional credit risk transmitted from China to India



Source: own estimation. Graphical representation of the results reported in Table 4A

3.4 Robustness test

In order to test the robustness of our results, we re-estimated the CoVaR at the 1% quantile, instead of 5% in the previous analyses, for each BRICS country's sovereign debt market by making use of Equation (4). The results reported in Table VI for the full sample shows that China continues to have the largest influence for sovereign credit risk transmission to other BRICS countries.

Table VI. Delta CoVaR for the full sample period using 1% quantile

	Brazil	Russia	India	China	South Africa
Brazil		0.1410	0.0455	0.1074	0.0563
Russia	0.1624		0.2792	0.1781	0.0144
India	0.0051	0.0056		0.5564	0.0141
China	0.0817	0.0241	0.1571		0.1075
South Africa	0.2193	0.3011	0.2110	0.0870	
Average	**0.1171**	**0.1180**	**0.1732**	**0.2322**	**0.0481**

Note: estimated from Equations 4 and 5

4. CONCLUSION

This paper assesses the extent of sovereign credit risk spillover among BRICS countries by exploring how a sovereign credit risk that emanates in one of the BRICS countries transmits to other BRICS countries. The paper makes use of the CoVaR methodology to this end. The results of the empirical analysis show a degree of cross-transmission of credit risk shocks among BRICS countries, although China has the largest potential to affect the sovereign credit risks of other BRICS countries, especially for the full sample analysis. For example, it is shown that credit risk distress in China increases sovereign credit risk in India by close to 23.5% while a distress in India changes credit risk in China by 19% only. Moreover, the paper analyses the impact of the innovation to each variables on the credit risk transmitted by China to other BRICS countries. The results show that the extent of the contribution of key economic and financial variables of other BRICS countries to sovereign credit risk transmitted by China varies according to specific peer countries. For example, it is shown that innovation to liquidity squeeze and business cycle contribute the most to the variation of credit risk transmitted by china to Russia, while innovation to global risk premium contributes the most to the variation of credit risk transmitted by China to Brazil. The findings of this paper implies that small economies in BRICS must be cautious to approve any legislation that supports full capital market liberalisation among BRICS countries without proper scrutiny. Such legislation may benefit China to become a safe haven of the BRICS grouping.

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Appendix A

Table 1A. Variance Decomposition of conditional credit risk transmitted from China to South Africa (in percent of total variance)

Step	S.E	OWN	RISKP	YSPRE	CURR	LIQS
1	0.03088667	21.618	0.000	3.187	0.002	75.193
2	0.04041777	21.898	0.304	4.581	0.038	73.179
3	0.04789981	22.651	0.628	4.863	0.075	71.782
4	0.05377783	23.053	0.877	4.991	0.103	70.977
5	0.05863686	23.330	1.061	5.028	0.119	70.462
6	0.06274402	23.536	1.201	5.023	0.132	70.108
7	0.06626907	23.698	1.309	4.996	0.141	69.856
8	0.06932757	23.830	1.393	4.955	0.148	69.674
9	0.07200328	23.940	1.459	4.907	0.154	69.540
10	0.07435923	24.035	1.512	4.853	0.159	69.441

Note: OWN denotes effects of own shocks. S.E denotes the standard error of the estimation

Table 2A. Variance Decomposition of conditional credit risk transmitted from China to Brazil (in percent of total variance)

Step	S.E	OWN	RISKP	YSPRE	CURR	LIQS
1	0.02770130	2.555	0.000	3.962	0.003	93.480
2	0.03607618	1.968	0.382	5.751	0.047	91.853
3	0.04247312	1.623	0.799	6.185	0.096	91.297
4	0.04750457	1.388	1.124	6.396	0.132	90.960
5	0.05166022	1.223	1.367	6.477	0.154	90.778
6	0.05517127	1.105	1.554	6.497	0.170	90.674
7	0.05818302	1.016	1.698	6.481	0.183	90.622
8	0.06079481	0.948	1.811	6.444	0.193	90.604
9	0.06307829	0.894	1.901	6.394	0.201	90.611
10	0.06508738	0.850	1.974	6.335	0.207	90.634

Note: OWN denotes effects of own shocks. S.E denotes the standard error of the estimation

Table 3A. Variance Decomposition of conditional credit risk transmitted from China to Russia (in percent of total variance)

Step	S.E	OWN	RISKP	YSPRE	CURR	LIQS
1	0.03085969	21.481	0.000	3.192	0.002	75.325
2	0.04088250	23.663	0.297	4.478	0.037	71.525
3	0.04867251	25.088	0.608	4.710	0.073	69.521
4	0.05481636	25.941	0.844	4.804	0.099	68.313
5	0.05988715	26.498	1.018	4.820	0.114	67.550
6	0.06416658	26.889	1.149	4.803	0.126	67.034
7	0.06783210	27.174	1.249	4.768	0.135	66.674
8	0.07100544	27.387	1.328	4.724	0.141	66.420
9	0.07377521	27.550	1.390	4.674	0.147	66.240
10	0.07620820	27.676	1.440	4.621	0.151	66.112

Note: OWN denotes effects of own shocks. S.E denotes the standard error of the estimation

Table 4A. Variance Decomposition of conditional credit risk transmitted from China to India (in percent of total variance)

Step	S.E	OWN	RISKP	YSPRE	CURR	LIQS
1	0.17315298	69.931	6.116	6.138	8.728	9.088
2	0.18784122	62.584	6.745	10.593	8.017	12.062
3	0.19929211	58.102	6.571	13.054	7.154	15.118
4	0.20743210	54.782	6.073	15.302	6.605	17.238
5	0.21442992	52.112	5.695	17.229	6.185	18.779
6	0.22055421	49.854	5.424	18.915	5.849	19.959
7	0.22606268	47.935	5.217	20.400	5.571	20.876
8	0.23105609	46.290	5.053	21.727	5.336	21.593
9	0.23561340	44.868	4.918	22.926	5.135	22.155
10	0.23979087	43.628	4.801	24.018	4.960	22.592

Note: OWN denotes effects of own shocks. S.E denotes the standard error of the estimation