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COMPARING SPILLOVER EFFECTS AMONG EMERGING MARKETS WITH A HIGHER (LOWER) SHARE OF COMMODITY EXPORTS: EVIDENCE FROM THE TWO MAJOR CRISES

Abstract. *The paper empirically analyses the spillover into emerging markets with a higher (lower) share of commodity exports during the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis (ESDC). To investigate such spillover effects, a group of rapidly growing emerging economies collectively known as BRICS (Brazil, Russia, India, China, and South Africa) is selected. The findings of the paper are as follows. First, a substantial increase in the average conditional correlation is noticed within all BRICS stock markets during the GFC. When considering the ESDC period, we also observed an increase in all markets, except for Brazil. Furthermore, the dynamic evaluation significantly increased from 2007 and it remained high during the ESDC. Second, trade profiles can help in explaining the spillover and correlation levels between emerging and developed markets. Among the BRICS countries, Brazil, Russia and South Africa heavily depend on commodity exports and the results show that these economies have a higher correlation with the developed economies. Further, Brazil and Russia are the most volatile when compared to the other BRICS countries, since these countries' commodities are dominated by food and agricultural exports and fuel and agricultural exports, respectively.*

***Keywords**: Commodity exports, stock market co-movements, volatility transmission, DCC-GARCH, Crisis.*

JEL Classification: G01, G15, F30, C22

1. Introduction

Uncertainty about the future course of action on the part of the US Federal Reserve Bank (the Fed) in terms of quantitative easing (QE) as well as the recent introduction of QE by the European Central Bank (ECB) continue to dominate the headlines. It is worth remembering that the Fed introduced QE to stimulate the economy after it was severely affected by the Global Financial Crisis (GFC). If the Fed chooses to end QE, it may boost capital inflow to the USA, which has already begun due to the high expectations of investors that interest rates will increase from their currently level of zero.[1] Alongside this, the ECB launched QE to try and fully recover from the impact of the European Sovereign Debt Crisis (ESDC), which resulted from high debt and budget deficits in peripheral economies and quickly spread to other member states. Therefore, the consequences of such QE policies in developed economies (USA and the EU) increase the vulnerability and risk of emerging markets, especially those economies that have strong trade and financial linkages with the developed economies.

BRICS is the acronym used to describe certain emerging economies (Brazil, Russia, India, China and South Africa) that have close economic ties with the developed economies. Over the last few decades, the BRICS economies have been growing faster when compared to many developing and developed economies (see Table 1). They also seem to attract considerable inflows of capital into their growing financial markets. On the other hand, the BRICS countries face some challenges that cannot be ignored. For example, they are highly dependent on high-income economies for their exports. Table 1 demonstrates that merchandise exports to high-income economies are well above 50% for all the BRICS countries, with the highest export level being that of China. It can also be observed from Table 1 that during both the GFC and the ESDC, exports to high-income economies declined. In addition, most of the BRICS economies have greater volatility in exchange markets that respond quickly to policy changes in developed economies.

There have been several studies that support dynamic interrelationships between trade and the exchange rate with the stock market. For example, on the linkage between trade and the stock market, see Forbes (2002), who argued that international trade linkages transmit country-specific crises through stock markets to other countries worldwide. There have also been studies that examine the interaction between the stock price and the exchange rate (Ning, 2010; Ulku and Demirci, 2012). Given these relationships, it is necessity to investigate equity markets' behaviour during both

[1] However, some financial analysts and media commentators such as Peter Schiff (CEO and Chief Global Strategist for Euro Pacific Capital Inc.) have argued that if the Fed decides to raise the interest rate, it will cause an even greater financial collapse since the USA now holds huge debt. Schiff did in fact predicate the global financial crisis and is the author of several books as well as regularly appearing on several TV channels.

tranquil and turbulent periods. Indeed, it is critical to understand whether there is greater interdependence and higher correlation among stock markets for individual investors and corporate managers for the purpose of portfolio diversification, since the benefits of diversification can only be achieved by investing in markets with lower correlation (Watson, 1978).

Based on the above, this paper aims to address three important issues. First, to what degree have the BRICS countries been affected by the GFC and the ESDC? Did the correlation change from that of the pre-crisis period? Which of the two crises had a greater impact on the emerging markets? Second, do economies with a higher (lower) share of commodity exports to total merchandise have a higher (lower) level of correlation and more (less) volatile markets? In other words, does the trade profile help to explain the level of correlation and spillover? Third, do the BRICS countries provide the opportunity for international diversification during periods of turmoil in developed markets?

The study contributes to the existent literature in several ways. First, we show that a country's trade profile is significant in explaining the levels of correlation and volatility between emerging and developed economies. Second, previous studies that investigated the spillover to emerging economies mostly failed to take into account the role of the EU in the emerging economies. We believe that the EU's role should be considered because some of the member states felt the GFC severely and experienced a crisis. Third, unlike previous studies that assumed the whole sample in investigating the impact of the GFC on emerging economies, this study divides the sample into three subsamples (pre-crises, global crisis and Europe crisis) and compares the spillover. Fourth, the study employs a DCC model that has several advantages as compared to conventional methodologies such as long run cointegration and the error correction model.

The key findings of this paper are as follows. First, a substantial increase in conditional correlation is noticed within all BRICS stock markets during the GFC and, considering the ESDC period, we also observed an increase in all markets except for Brazil. Furthermore, the dynamic evaluation of most of the BRICS countries significantly increased from 2007 and remained high during the ESDC. Second, trade profiles can help in explaining the spillover and correlation levels between emerging and developed markets. Among the BRICS countries, Brazil, Russia and South Africa are highly dependent on commodity exports and the results show that these economies have a higher level of correlation with the developed economies. Further, Brazil and Russia are the most volatile when compared to the other BRICS economies, since these countries' commodities are dominated by food and agricultural exports and fuel and agricultural exports, respectively.

The remainder of this paper is organised as follows. The next section will summarise the empirical literature on spillovers. Section three discusses the data and the methodology of the study. The empirical findings are presented in section four and, finally, section five concludes the study.

Table 1. Macroeconomic profile of BRICS

GDP growth (annual %)					
Period	Brazil	China	India	Russia	SA
2002-2004	3.17	9.73	6.53	6.41	3.72
2005-2007	4.40	12.72	9.45	7.69	5.48
2008-2010	4.12	9.77	7.54	0.64	1.75
2011-2013	3.90	10.74	7.84	4.91	3.65
Merchandise exports to high-income economies (% of total merchandise exports)					
2002-2004	63.67	85.55	70.56	65.67	61.47
2005-2007	59.96	82.45	67.48	66.59	70.67
2008-2010	53.11	77.11	65.33	60.58	62.36
2011-2013	49.84	74.23	63.05	61.52	49.71

South Africa=SA

2. Literature Review

A reasonable number of studies have been conducted that examine the spillover and volatility transmission that resulted from the GFC, particularly in the context from developed economies (USA, UK, Germany, France, and Japan) to emerging markets (Dajčman and Alenka, 2011; Syllignakis and Kouretas, 2011). There have also been studies that investigated the specific impact of the GFC on the BRICS economies. For example, Alou et al. (2011) as well as Dimitriou et al. (2013) observed substantial spillover to the BRICS economies from the USA during the GFC, especially after the collapse of Lehman Brothers in 2008. However, these studies did not investigate the impact of the ESDC, and most of them failed to take into account the role of the EU. Given that most of the BRICS economies are regionally close and have strong economic (trade and financial) ties to Europe, it is necessary to consider the role of EU index in the BRICS countries. Regarding the ESDC, there have been studies that investigated spillover within the European stock markets. For example, Dajčman (2013) noted contagion during the Greek debt crisis from the Irish, Italian and Spanish stock markets to the stock markets of France and Germany. Along the same lines, Tamakoshi and Hamori (2013) argued that the stock returns of the five major European financial institutions under study were highly affected by the Greek debt crisis. Furthermore, Harmann (2014) examined contagion from western European countries to eight emerging European economies and observed an increase in correlation during the ESDC. Employing daily data that covered the ESDC period, Popa el al. (2015) investigated spillover among emerging European stock markets (including Russia) and two developed stock markets, namely the USA and Germany. In their analysis, Popa el al. (2015) documented that there is no significant relationship between Russian stock returns and any other equity market. There have also been studies that examine spillover effects from peripheral countries (Greece, Ireland, Portugal, Spain and Italy; GIPSI) to emerging European markets. For instance, Bein and Tuna (2015) argued that the dynamic condition correlations between Poland and Hungary and the GIPSI countries increased substantially during the sovereign debt crisis. Further, they demonstrated that the Czech Republic remained the most volatile stock market, although they did not observe an increase in the dynamic evaluation correlation.

However, to best of our knowledge, studies that examine the spillover effects into the BRICS countries and other non-European emerging economies are rare. Only Ahmed el al. (2013) have investigated the spillover from the GIPSI countries to the BRIICKS (BRICS plus Indonesia and South Korea) markets. Nevertheless, Ahmed et al. (2013) did not take into account the impacts of the GFC on the BRICS economies, nor did they compare the two crises. In addition, their data stops in January 2012, which does not adequately cover the entire ESDC since the crisis persisted for a longer period.

3. Data and Methodology

3.1 Data

The weekly stock indices for five emerging and two developed stock markets are used from 6 January 2003 to 23 March 2015. We used weekly price indexes in order to minimise both the cross-country differences and the end-of-week effect. The emerging market indexes are the BOVESPA for Brazil, the SSE Composite Index for China, the

CNX for India, the MICEX for Russia, and the FTSE/JSE All Share for South Africa. The developed stock price indexes are the S&P500 for the USA and the EUROSTOXX50 (from now on EU index) stock price index for the Eurozone. We prefer the EU (EUROSTOXX50) index as a proxy for the Eurozone because its represents 50 blue-chip companies that operates in twelve Eurozone countries.[2] All of the stock price indexes are obtained from DataStream and they are all US dollar-denominated. The reason for choosing a common currency is to account for the local inflation rate.

In the current literature, there is no precise date given for when the GFC started. In deciding on the start of the crisis, researchers generally follow either an econometric or an economic approach, although there are also studies that consider both approaches. In this study, we follow the economics approach, so the starting date for the global financial crisis is determined as 6 August 2007, which is in line with the approach of the Federal Reserve Bank St. Louis (2009). In determining the start of the ESDC, we consider the date when the Greek government first officially requested a bailout from an international organisation, which is 23 April 2010. However, since the study makes use of weekly data, the start date for the crisis is determined as 26 April 2010, which is the closest practical option to the requested date. Finally, yearly trade profiles from 2002-2013 are all obtained from the World Bank.

3.2 Methodology

Following the work of Forbes and Rigobon (2002), researchers have been using more advanced techniques, including regime-switching models, dynamic copulas with and without regime-switching, dynamic conditional correlation (DCC), and nonparametric approaches. To avoid several restrictions, such as the heteroskedasticity problem, the contagion must involve evidence of a dynamic increment in the regressions, affecting at least the second moment correlations and covariances. In this study, to overcome several problems involved in measuring correlation and volatility, a multivariate DCC-GARCH model of (Engle 2002) is used. Engle's (2002) model has many advantages over other models, for example, unlike constant correlation dynamic conditional correlations (DCC) allow the detection of possible changes in conditional correlations over time, which is very important since stock returns are negative during turbulent periods and positive during tranquil periods. In addition, the model estimates

[2] Including Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

the correlation coefficients of the standardised residuals and accounts for heteroscedasticity directly (Chiang et al. 2007).

The estimation of Engle's (2002) DCC-GARCH model comprises two steps: first, the estimation of the univariate GARCH model for the stock returns and second, the estimation of the conditional correlations that vary over time. The DDC model of Engle (2002) can be expressed as

$$H_t = D_t R_t D_t \tag{1}$$

where H_t is the conditional covariance matrix that is decomposed into conditional standard deviations, $D_t = diag(h_{1,1,t}^{1/2},.....,h_{N,N,t}^{1/2})$ in which $h_{i,i,t}$ is any univariate GARCH process and R_t is the time dependent conditional correlations matrix, which defined as: $R_t = diag(q_{11,t}^{-1/2},....,q_{NN,t}^{-1/2})Q_t(q_{11,t}^{-1/2},.....,q_{NN,t}^{-1/2})$ (2)

where Q_t is a symmetrical positive definite matrix that defines the dynamic correlation structure as $Q_t = (1-a-b)\overline{Q} + au_{t-1}u_{t-1}^{'} + bQ_{t-1}$ (3)

where u_t is a vector of the standardised residuals, $\overline{Q}$ is an unconditional variance matrix of u_t, and 'a' and 'b' are non-negative one-period lagged autoregressive and correlation coefficients satisfying a+b<1. Therefore, the conditional correlation between the two stock returns (1 and 2) can be expressed as

$$\rho_{12,t} = \frac{(1-a-b)\overline{q}_{12} + au_{1,t-1}u_{2,t-1} + b_{12,t-1}}{\sqrt{\left[(1-a-b)\overline{q}_{11} + u_{1,t-1}^2 + bq_{11,t-1}\right]\left[(1-a-b)\overline{q}_{22} + au_{2,t-1}^2 + bq_{22,t-1}\right]}} \tag{4}$$

Where ρ_{12} is the element on the 1^{th} line and 2^{th} column of the matrix Q_t. The quasi-maximum likelihood method (QMLE) is used to estimate the parameters. Distribution used is the Student's *t*-distribution.

4. Empirical Results

Table 2 panels A-D show descriptive statistics for the whole sample (6 January 2003 - 23 March 2015), pre-crisis (6 January 2003 - 30 July 2007), global financial crisis/post (6 August 2007 - 19 April 2010) and European debt crisis/post (26 April 2010 - 23 March 2015) periods, respectively. In general, the emerging economies have higher returns as measured by mean and also have more volatile stock markets as measured by standard deviation when compared to the developed economies (USA and EU). Among the emerging economies, the highest return is observed for India (0.30), followed by Brazil (0.23) (in panel A), Brazil (0.87) and Russia (0.79) (in panel B), and Brazil (0.24) and South Africa (0.01) (in panel C). However, in panel D (European debt crisis/post period), the highest return is observed in the USA (0.21), which can be interpreted as meaning that the USA stock market became less volatile during the ESDC. Considering the volatility of the stock markets shown in Table 2, the emerging economies display higher volatility in all of the subsamples (panel A-D), with Russia and Brazil being the most volatile. For example, for the whole sample Russia was 5.68 and Brazil was 5.53; for the pre-crisis period Brazil was 5.00 and Russia was 4.56; for the global financial crisis/post period Russia was 8.52 and Brazil was 7.70; and during the European debt crisis/post period Russia was 4.54 and Brazil was 4.44. Table 2 also shows that the returns are negatively skewed for all the markets, with the exception of South Africa and USA in panel C and China in panel D. All of the returns are also leptokurtic distributions and they confirm the financial series characteristics. The Jarque-Bera test statistics indicate the non-normality of the return series. An autoregressive conditional heteroskedasticity (ARCH) test at lag (5) on the return series reveals that the generalised autoregressive conditional heteroskedasticity (GARCH) is consistent and appropriate for modelling the return. The Ljung-Box (LB) Q-statistics are also presented on the return, and the squared returns (Q^2) at lag (20) indicate the presence of autocorrelation on the return. Finally, the Augmented Dickey-Fuller (ADF) test on the level series failed to reject the null hypothesis that the series unit root against the alternative hypothesis series is stationary (not reported in the table). However, the ADF test on the return series rejects the null of a unit root. The return series is obtained as follow: $r= [\log (P_t) - \log (P_{t-1})]*100$, where P_t is the stock market index on day t.

Table 3 panels A-B show the unconditional correlation for the three subsamples (pre-crisis, global financial crisis, and European sovereign debt crisis) between the BRICS economies and the developed economies (USA and EU). Looking at panel A, the unconditional correlation with the USA, a higher correlation is noticed with Brazil and South Africa in the three subsamples (pre-crisis, GFC, and EDSC). Similarly, in the panel B correlations with the EU, the same countries (Brazil and South Africa) have a higher correlation. In addition, Russia also has a higher correlation with the USA and the EU during both the GFC and the EDSC, which means that the stock market became vulnerable to the crises. Interestingly, China, the largest emerging economy, is the country with the lowest unconditional correlation with the EU and the USA in all three subsamples. Comparing the unconditional correlation increase during the GFC and the EDSC, it is observed that there is a greater increase during the GFC.

Table 2. Descriptive statistics of weekly stock returns

Full sample Panel A							
	BRAZIL	CHINA	INDIA	RUSSIA	SA	EU	USA
Mean	0.2387	0.2050	0.3052	0.1572	0.2184	0.0662	0.1284
Std. Dev.	5.5358	3.7962	4.4413	5.6811	4.1082	3.608	2.5372
Skewness	-0.6420	-0.2891	-0.7108	-0.507	-0.2772	-0.519	-0.362
Kurtosis	7.76	4.52	8.26	11.34	7.20	6.25	8.76
J-Bera	645^{***}	70^{***}	788^{***}	1874^{***}	477^{***}	309^{***}	895^{***}
ARCH	31.09^{***}	8.40^{***}	12.29^{***}	31.47^{***}	29.49^{***}	27.76^{***}	33.99^{***}
Q(20)	35.76^{**}	53.12^{***}	33.60^{**}	41.86^{***}	43.38^{***}	42.90^{***}	48.29^{***}
$Q^{)2}$ (20)	157.2^{***}	225.1^{***}	127.5^{***}	267.8^{***}	381.6^{***}	368.3^{***}	521.3^{***}
ADF(5)	-9.29^{***}	-9.62^{***}	-9.42^{***}	-9.00^{***}	-9.76^{***}	-9.50^{***}	-9.96^{***}
Panel B Pre crisis (sable period)							
Mean	0.8771	0.5444	0.7305	0.7958	0.5368	0.3289	0.1939
Std. Dev.	5.0074	3.6118	4.0890	4.5609	3.3066	2.4882	1.6609
Skewness	-0.7744	-0.0437	-1.680	-0.906	-0.905	-0.595	-0.364
Kurtosis	3.94	5.33	12.62	5.92	5.22	5.41	4.46
Panel C Global Financial crisis/post							
Mean	0.2452	-0.2402	0.0443	-0.2003	0.0128	-0.2705	-0.144
Std. Dev.	7.7023	5.2350	6.5063	8.5275	6.2185	5.0048	3.8582
Skewness	-0.6683	-0.4157	-0.214	-0.0976	0.0185	-0.3485	0.0343
Kurtosis	7.36	2.79	4.61	8.48	5.00	5.19	5.12
Panel D European debt crisis/post							
Mean	-0.3427	0.1212	0.0505	-0.2443	0.0400	0.0113	0.2155
Std. Dev.	4.4461	2.9126	3.178	4.5401	3.2307	3.582	2.2937
Skewness	-0.2819	0.1928	-0.320	-0.9492	-0.321	-0.368	-0.789
Kurtosis	4.637	3.788	3.325	5.953	4.358	3.863	9.271

Note: The Jarque-Bera (J-Bera), ARCH, and Ljung-Box statistics for serial correlation in the standardised return at lag (20) and the squared standardised return at lag (20) and the ADF test at lag (5) for the three subsamples are not reported to save space but are available on request.

Table 3. Unconditional correlations with the US

Country	Pre-crisis	GFC/post	EU crisis/post
BRAZIL	0.684513	0.812074	0.671212
CHINA	0.057292	0.323736	0.318361
INDIA	0.410207	0.680898	0.474739
RUSSIA	0.390017	0.71233	0.6138
SA	0.546411	0.793966	0.759505
Unconditional correlation with the EU			
BRAZIL	0.664732	0.824872	0.629378
CHINA	0.098462	0.345104	0.264842
INDIA	0.450755	0.733294	0.507579
RUSSIA	0.446033	0.810486	0.608009
SA	0.664635	0.908525	0.76529

Author's calculation.

Table 4 panels A-C show the univariate estimation for each country index as well as the generated dynamic conditional correlation (DCC) with the US and EU stock markets, respectively. The univariate estimation in Table 1 panel A shows that the ARCH and GARCH coefficients are statistically significant at 1% for all the countries and so confirm that GARCH (1;1) is appropriate for modelling the stock markets. In other words, a significant ARCH coefficient means that the previous day's information on the return reflects in today's volatility, whereas a significant GARCH means that the previous day's return volatility reflects on today's volatility. The significance of the two coefficients means that the stock return volatility is influenced by its own shock. Considering the derived multivariate DCC equation, the condition a+b<1 is satisfied between the developed markets (EU and USA). In addition, the coefficients (a and b) are non-negative. Furthermore, Table 3 shows that the t-student distributions for all of the stock markets are statistically significant at 1%, confirming that the t-student is an appropriate distribution. The portmanteau multivariate statistics reported as multivariate Q(20), and $Q^2(20)$ are due to Li and McLeod's (1981) testing of serial correlation in the mean and variance equations, respectively. The results in panels A and B confirm the successful elimination of serial correlation in the mean and variance equations.

Table 4. Estimation results from GARCH-DCC using weekly return data

Panel A Conditional mean and variance equations for each market					
Countries	Mean equation	Variance equation			
	μ	ω	α	β	
Brazil	0.2664	1.5847**	0.1366***	0.8131***	
	(0.1837)	(0.6906)	(0.0367)	(0.0385)	
China	0.1335	0.3331	0.0863***	0.8922***	
	(0.1388)	(0.2336)	(0.0328)	(0.0434)	
India	0.4059**	0.6922	0.1610***	0.8160***	
	(0.1434)	(0.4611)	(0.0566)	(0.0626)	
Russia	0.2845	2.4587**	0.1359***	0.7782***	
	(0.1871)	(1.078)	(0.0487)	(0.0686)	
SA	0.2543***	0.5529	0.1084***	0.8589***	
	(0.1343)	(0.3746)	(0.0367)	(0.0551)	
US	0.2588***	0.3143***	0.2049***	0.7415***	
	(0.0734)	(0.1181)	(0.0763)	(0.07)	
EU	0.1644	0.4706**	0.1274***	0.8346***	
	(0.1127)	(0.2257)	(0.0382)	(0.0446)	
Panel B Multivariate DCC with the US					
	Brazil	China	India	Russia	SA
a	0.1328**	0.0066	0.0456	0.0165**	0.0579***
	(0.0589)	(0.0077)	(0.0408)	(0.0069)	(0.0156)
b	0.7497***	0.9798***	0.7498***	0.9820***	0.9184***
	(0.1612)	(0.015)	(0.279)	(0.0085)	(0.0239)
df	11.311***	9.142***	7.426***	6.3062***	7.0161***
	(3.007)	(1.683)	(1.183)	(0.772)	(1.031)
Diagnostic checking					
Log-L	-3074	-3031	-3008	-3122	-2858
MQ(20)	185.5	225.8	201.8	205.7	179.9

	[0.4790]	[0.1012]	[0.4501]	[0.3763]	[0.8421]
$MQ^2(20)$	149.7	155.5	131.8	192.2	200.4
	[0.9956]	[0.9886]	[0.9999]	[0.6020]	[0.4375]
Panel C Multivariate DCC with the EU					
	Brazil	China	India	Russia	SA
a	0.0374^{**}	0.0058	0.0629	0.0487	0.0653^{***}
	(0.0186)	(0.0072)	(0.0485)	(0.037)	(0.0181)
b	0.9402^{***}	0.9775^{***}	0.3044	0.9126^{***}	0.9045^{***}
	(0.0425)	(0.017)	(0.3053)	(0.0954)	(0.0267)
df	8.500^{***}	8.020^{***}	7.112^{***}	5.236^{***}	6.867^{***}
	(1.634)	(1.352)	(1.129)	(0.5328)	(1.077)
Diagnostic checking					
Log-L	-3351	-3289	-3248	-3339	-3037
MQ (20)	190.1	231.3	205.5	203.3	175.8
	[0.6799]	[0.0641]	[0.3798]	[0.4221]	[0.8901]
MQ^2 20)	190	171.2	169.1	194.7	255.9
	[0.6454]	[0.9159]	[0.9324]	[0.5520]	[0.9948]

Note: Log-L (Log-likelihood) ,the numbers given in ( ) are standard error while the numbers given in [ ] are the p-values. ***, **, and * donate statistical significance at 1%, 5%, and 10% respectively.

Table 5 panels A-B show the weighted conditional correlation between the BRICS economies and the developed markets (US and EU) for the three subsamples (pre-crisis period, GFC/post period, and ESDC/post period). The weighted conditionals are all derived using DCC-GARCH (1;1). As can be observed from the table, most of the weighted correlations are higher with the EU than with the US, which is also the case in Table 3 (unconditional correlations). In addition, the weighted correlations between the BRICS economies and the developed market substantially increased during the GFC (column 2) and during the ESDC, expect with Brazil in column 3. Therefore, the Brazilian stock market is the least affected by the ESDC. Comparing the level (magnitude) of the weighted correlations in penal A, Brazil has the highest correlation in a stable period while Russia and South Africa have the highest during the GFC/post and ESDC/post period, respectively. In panel B (correlation with the EU), the highest correlation is observed with South Africa during the three subsamples. Interestingly, the Chinese stock market has the lowest correlation with both the EU and the USA during tranquil and turbulent periods (in the three subsamples). In general, economies that have a higher commodity export share have a higher correlation with the developed markets (see Table 6).

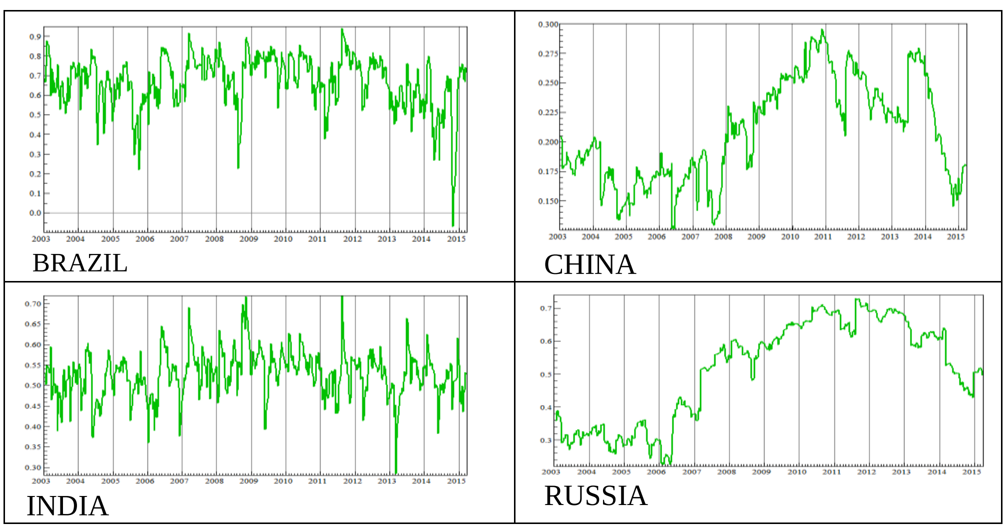
Table 5. Conditional correlation during for three subsamples using GARCH (1;1)

Panel A with the USA			
Country	Pre-crisis	GFC/post	EU crisis/post
Brazil	0.6831***	0.7935***	0.6471***
	(0.0451)	(0.0674)	(0.0497)
China	0.0884	0.3673***	0.2322**
	(0.0720)	(0.0762)	(0.1046)
India	0.4505***	0.6914***	0.4984***
	(0.0723)	(0.0484)	(0.0440)
Russia	0.4070***	0.8957***	0.5938***
	(0.0723)	(0.2877)	(0.0708)
SA	0.5411***	0.7180***	0.7052***
	(0.0826)	(0.1230)	(0.0627)
Panel B with the EU			
Brazil	0.6534***	0.7944***	0.6005***
	(0.0415)	(0.0365)	(0.0774)
China	0.1843**	0.4184***	0.2239**
	(0.0807)	(0.0616)	(0.0941)
India	0.5058***	0.7233***	0.5149***
	(0.0545)	(0.0463)	(0.0425)
Russia	0.4694***	0.7884***	0.6240**
	(0.0755)	(0.0532)	(0.0411)
SA	0.6601***	0.9002***	0.7295***
	(0.0513)	(0.025731)	(0.036807)

The numbers given in ( ) are standard errors. ***, **, and * donate statistical significance at 1%, 5%, and 10% respectively.

Figure 1 shows the evolution of the conditional correlation between the USA and the BRICS economies. A sudden sharp increase in the conditional correlation is noticed starting from 2007 and 2008, especially for China, Russia, and South Africa. These markets stayed higher during both the GFC and the ESDC. Starting from 2014, the correlations fall gradually for Russia and South Africa, whereas China experienced a sharp decline during the same year. A sharp increase in the correlation is regarded as a change in investors' appetite for risk and their herding behaviours. Investors' appetite for risky investments falls during the crisis, since they experience loss in some markets. Therefore, to offset their losses they may decide to sell their shares in another market, which will lead to a decline in the stock price. Regarding the volatility of the correlation, it is observable that India remains the most volatile as compared to the other emerging economies. The highest correlation is observed with Brazil, varying between 60-80%. In general, the conditional correlations are higher with Brazil, South Africa and Russia and the lowest with the Chinese stock market, which reached its highest point in 2011 at around 30%.

Figure 2 shows the evaluation correlation between the BRICS economies and the EU for the full sample. The correlation shows almost the same trend as with the USA. The highest correlation is noticed with South Africa, reaching approximately 90%, and the lowest with China. Similarly, the correlation with India remains very volatile throughout the sample, unlike the other emerging stock markets, which display herding behaviours and changes in the risk appetites of investors.



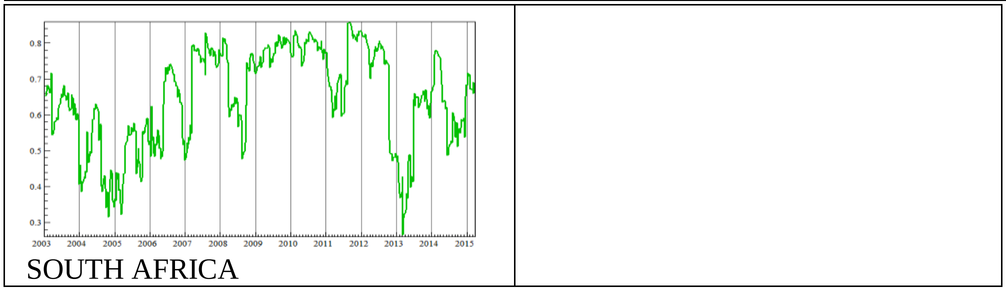


Figure 1. Conditional correlation between the USA and the BRICS economies

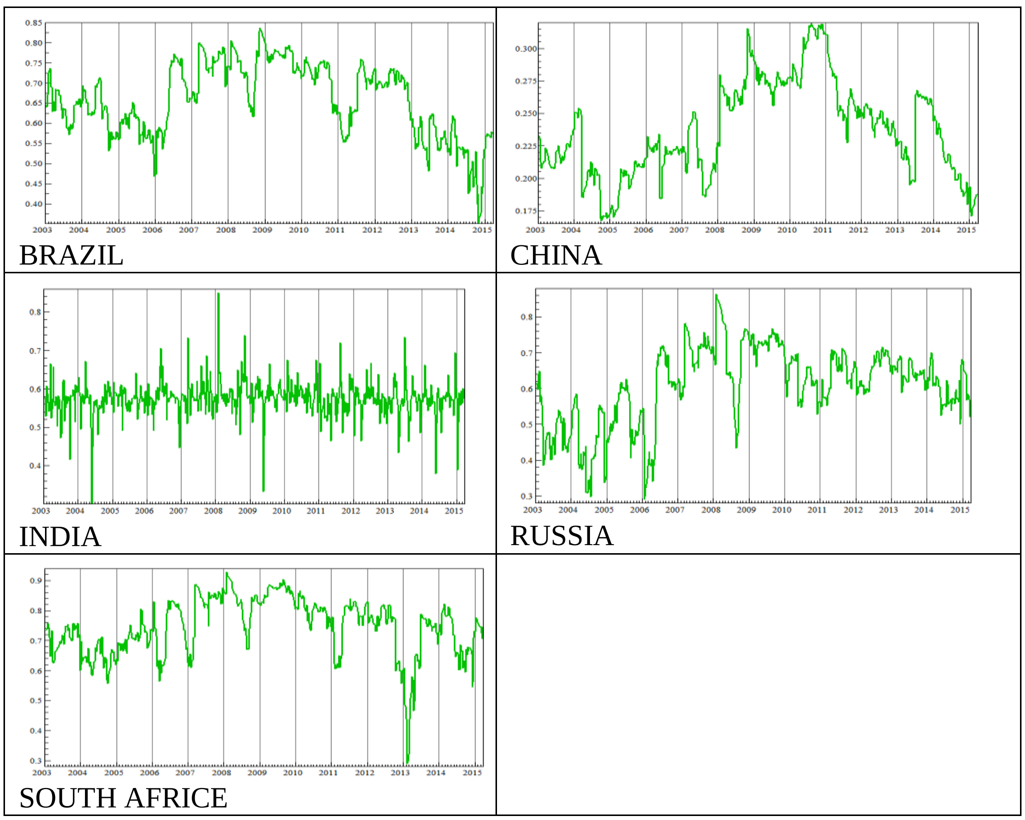


Figure 2. Conditional correlations between the EU and the BRICS economies

Table 6 details the trade profiles for the BRICS economies as constructed using yearly data from 2002-2013. We present it by using three-year averaging to account for the business cycle and the distortion due to the GFC and the EDSC. We define the share of commodity exports as the sum of agricultural raw materials, food exports, fuel exports, and ores and metals exports to the total merchandise exports (all in percentages). Higher commodity exports are observed in Brazil, Russian, and South Africa. It should be recalled that Brazil and Russia have the most volatile markets (as measured by standard deviation; see Table 2) as compared to the rest of the emerging markets, which could be due to the fact that commodity exports for Brazil are dominated by food and agricultural, while for Russia fuel exports and agricultural exports are dominant. In international markets, there is normally greater fluctuation in the price of those two products, and this is expected to reflect in the domestic stock markets through the interaction of the exchange rate and the price of commodities and the stock market. A higher share of manufacturing exports as a percentage of merchandise exports is noted for both China and India. Those two economies do have lower market volatility (see Table 2) and a lower correlation with the developed economies.

Table 6. Trade profile for the BRICS economies

Agricultural raw materials exports (% of merchandise exports)					
YEAR	BRAZIL	CHINA	INDIA	RUSSIA	SA
2002-2004	4.13	0.65	1.12	3.21	2.67
2005-2007	3.77	0.49	1.66	2.75	1.82
2008-2010	3.75	0.45	1.64	2.15	1.82
2011-2013	3.62	0.48	1.95	1.84	1.86
Food exports (% of merchandise exports)					
2002-2004	28.19	4.28	11.39	1.79	9.77
2005-2007	25.72	2.94	8.90	1.84	7.42
2008-2010	30.95	2.75	8.73	2.30	9.16
2011-2013	32.33	2.77	10.24	2.81	9.81
Fuel exports (% of merchandise exports)					
2002-2004	4.88	2.52	6.21	53.89	10.29
2005-2007	7.33	1.93	13.66	62.03	10.05
2008-2010	9.53	1.86	16.01	65.99	10.38
2011-2013	9.67	1.57	19.12	69.72	11.93
Ores and metals exports (% of merchandise exports)					
2002-2004	8.42	1.74	4.32	7.33	17.53

2005-2007	10.49	1.99	7.49	7.73	26.85
2008-2010	13.88	1.45	6.48	5.62	28.92
2011-2013	17.09	1.33	3.38	4.96	29.46
Commodity export (% of merchandise exports)					
2002-2004	45.62	9.20	23.04	66.21	40.25
2005-2007	47.31	7.34	31.71	74.35	46.14
2008-2010	58.11	6.51	32.86	76.06	50.28
2011-2013	62.70	6.16	34.69	79.34	53.06
Manufacture exports (% of merchandise exports)					
2002-2004	52.60	90.60	75.26	22.30	59.35
2005-2007	50.55	92.44	67.18	17.40	53.70
2008-2010	40.46	93.37	64.45	16.01	49.46
2011-2013	35.18	93.75	62.96	15.36	46.38

Commodity exports defined as the sum of agricultural raw materials, food exports, fuel exports, and ores and metals exports to total merchandise exports (all in percentages).

5. Concluding Remarks

The study empirically compares the spillover during the Global Financial Crisis and the European Sovereign Debt Crisis into emerging economies that have a higher (lower) share of commodity exports. The BRICS countries are emerging economics that not only have good economic ties but have also registered rapid growth as compared to many developed and developing economies over the last decade. In addition, they seem to attract large capital investment to their growing financial markets as a result of this rapid globalisation process. However, one of the greatest disadvantages of the BRICS countries is their reliance on high-income economies to sell their products and for investment inflow, which makes their economies vulnerable and sensitive to policy changes and shocks that may arise in high income countries (see Table 1). This makes it necessary to investigate the degree to which those emerging stock markets have been affected by the crises and to determine whether trade profiles matter in understanding the extent of spillover. We also consider whether the emerging economies provide the benefit of portfolio diversification during turmoil in the developed markets. In order to precisely gauge the impact of the two crises, weekly return data from 6 January 2003 to 23 March 2015 is used after being divided into three subsamples – stable period, GFC/post, and ESDC/post period. We used weekly price indexes to minimise the cross-country differences and the end-of-week effect. A multivariate GARCH framework is used in studying the volatility spillovers among each country with the USA and the EU indexes and to account for the time variability of the conditional correlations. A dynamic structure is included by using the DCC model of Engle (2002). For the trade profiles, we consider yearly data from 2002-2013. We utilise three-year averaging to control for business cycles and to reduce the possible distortions caused by the crises.

The findings of the paper are as follows. First, during the GFC a significant increase in the conditional correlation is noticed with all the BRICS stock markets, while during the ESDC there is also an increase, albeit lower than during the GFC. In addition, we observed an increase in correlation during the ESDC with the Brazilian stock markets. Therefore, among the BRICS stock markets, the Brazilian market is the least affected by ESDC. Furthermore, the dynamic evaluation significantly increased from 2007 and remained high during the ESDC. Second, we found that trade profiles can help in explaining the spillover and conditional correlation between emerging and developed markets. Among the BRICS economies, Brazil, Russia and South Africa highly depend on commodity exports. The results show that these countries are more affected and have a higher level of correlation with the developed economies. Further, Brazil and Russia are the most volatile markets when compared to the other BRICS economies. Manufacturing export-oriented countries such as China and India exhibit a lower correlation with the developed countries. In particular, China has the highest manufacturing exports and the lowest correlation. In addition, even though Russia has a lower correlation than India during the stable period, during the two crises it is observed that the Russian stock markets have a higher correlation. This is because commodity prices such as food, agricultural and oil prices are more volatile in the international market as compared to manufacturing goods.

The results have important implications for both policy makers and investors. First, from foreign investors' point of view, the GFC and the ESDC have substantially reduced the benefits of diversification in the BRICS economies, especially those with a higher share of commodities (Brazil, Russia, and South Africa). In addition, investors who are willing to invest in the BRICS economies should also consider a hedging technique against the adverse effects of exchange rates and stock price changes. Our study also emphasises that policy makers in the BRICS countries should work toward establishing and promoting trade and investment with each other and with other developing economies. This could be one way to avoid being adversely affected by another shock to the developed economies.

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