Uncovering equity market contagion among BRICS countries: an application of the multivariate GARCH model

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by

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Abstract

This paper assesses the extent of the transmission of financial shocks between South Africa and other members of the BRICS grouping in order to infer the degree of contagion during the period 1996-2012. The paper makes use of a multivariate VAR-DCC-GARCH model for this end. The paper finds evidence of cross-transmission and dependence between South Africa and Brazil. However, the empirical results show that South Africa is more affected by crises originating from China, India and Russia than these countries are by crises originating from South Africa. The findings of this paper should be of interest to policy makers in the BRICS grouping should they be considering the possibility of full capital market liberalization and to the international investor who is looking at diversifying portfolios in the BRICS grouping.

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1. Introduction[1]

In the past two to three decades, various countries have been beset by severe financial crises: the Mexican peso collapse of 1994, the East Asian crisis of 1997, the Russian collapse of 1998, the Argentinean crisis of 2002, the US (United States) subprime, also referred to as the housing market crisis of 2007, and the European sovereign debt crisis of 2010, just to name a few. Although these financial crises started in a specific country and region of the globe, their effects spread to other countries and regions. For example, the East Asian currency crisis that started in Thailand spread within a short period of time to Indonesia, Malaysia, Korea, Taiwan, and the Philippines (Chancharoenchai and Dibooglu, 2006). Such transmission of shocks is dubbed *contagion* in the financial economics literature.

The term contagion generally refers to the international transmission of shocks during financial crises. Although there is no concise definition of the concept, financial economists nonetheless widely use the term to describe the extent and magnitude of the transmission of shocks from one region or market to others. For example, Bekaert, Harvey, and Ng (2005) refer to contagion as the excess correlation between markets over and above what one would expect from economic fundamentals. Dornhbusch, Park and Claessens (2000) define contagion as a significant increase in cross-market linkages after a shock to an individual or group of countries.

The literature divides the concept of contagion into two broad categories (Dornbusch et al., 2000; Forbes & Rigobon, 2001; Masson, 1998), namely, *fundamental-based* and *investor-behaviour* contagions. *Fundamental-based* contagion refers to the transmission of shocks that is due to real and financial linkages or fundamental relationship of any kind, such as trade or macroeconomic policy, between countries. *Investor-behaviour* contagion refers to a change in investor behavior which alters the flow of international portfolio investments in such a manner that it cannot be explained by economic fundamentals. For example, a crisis in one emerging market country can trigger investors to withdraw funds from many emerging markets without taking into account the fundamental economic differences between them.

[1] We acknowledge the contribution of Natacha Brink.

Studying the effect of contagion of financial crises between BRICS countries is important given the magnitude of interaction between member countries and what the BRICS countries represent globally. The BRICS countries, consisting of Brazil, Russia, India, China, and – since December 2010 – South Africa (SA), represent the world's leading emerging market economies (EME), distinguished by their large, fast-growing economies. The growth potentials in those culturally and geographically disparate countries are based on diverse attributes. Brazil is a resource-rich country, with resources such as coffee, soybean, sugar cane, iron ore and crude oil. Russia is well known for its massive deposits of oil, natural gas and minerals. India has a rising manufacturing base and is a strong service provider. China has a highly skilled workforce at low wage cost and is seen as the manufacturing workshop of the world. SA, the smallest of the five BRICS countries by land mass and world GDP contribution, is the world's largest producer of platinum and chromium, and holds the world's largest known reserves of manganese, platinum group metals, chromium, vanadium and alumino-silicates (New Delhi, 2012). BRICS financial indicators are outstanding in that equity indices more than doubled between 1999 and 2009, and BRICS market capitalisation in equity markets grew from US$1.2 trillion to US$6.4 trillion between 2000 and 2010 (New Delhi, 2012). Nonetheless, in terms of mutual influence and interaction between BRICS member countries, a number of authors have questioned the importance and influence of South Africa (SA) within this prospectively powerful grouping. For example, Naidoo (2012) contends that SA does not fit into BRICS given the size of its economy. The author sees the presence of SA as weakening the group for three reasons. Firstly, because of SA's GDP growth lags compared to the rest of the BRICS countries and other EMEs. Secondly, SA doesn't feature within the top 20 largest world economies in US dollar terms. Thirdly, SA has a population of 50 million compared to the second smallest BRICS country (Russia) with a population of 140 million, and is therefore a small country in comparison.

The questioning by critics of the importance and influence of SA within the BRICS grouping prompted this paper, which endeavours to assess the extent of South Africa's financial influence on other BRICS countries, and also the degree and magnitude of the transmission of financial shocks between South Africa and each of the other BRICS countries during periods of financial crises. In other words, the paper endeavours to assess the extent of contagion between South Africa and each of the BRICS countries during the period 1996-2012.

The financial influence of South Africa on emerging-market economies is well documented. For example, Flvin and O'connor (2010) show that South Africa has one of the most liberalized stock exchange and financial systems among emerging-market economies. However, the extent of its financial influence in the BRICS grouping is a matter of empirical analysis. The hypothesis of this paper is that if it can be found that a crisis that originates in SA spreads to other BRICS countries to the same extent as shocks from other BRICS countries transmit to South Africa, then one could infer the possibility of mutual financial interdependence between South Africa and other BRICS economies, proving wrong the view that South Africa is of little financial influence in the BRICS grouping. The paper assesses the transmission of shocks in the context of the equity market given its importance as a significant financial sector in BRICS countries. A number of studies have made use of stock exchange data to assess the degree of financial dependence and integration of countries (Bonga-Bonga, 2009; Singh, 1997).

While other studies have assessed contagion between BRICS and other developed economics (Nikkinen, et al., 2013; Berikos, 2014; Morales and Gassie, 2011; Sheu and Liao, 2011), to the best of our knowledge there is no study that assesses contagion within BRICS countries, especially since the time of South Africa's inclusion in the BRICS grouping. The finding of this paper should inform policy makers in BRICS countries on the benefit that each member can derive from further liberalizing its capital markets. It is important to note that capital market liberalization in the presence of asymmetric contagion may lead to portfolio re-allocation and capital flight at the detriment of the most vulnerable or reliant country, especially during the periods of financial crisis (Stiglitz, 2004; Borjas and Ramy, 1995). Thus, the finding of this paper should also be of great interest to international investors and asset managers.

In order to assess the extent of contagion between South Africa and each of the BRICS countries, this paper identifies periods of major crises in each of the BRICS countries and assesses how conditional correlation of equity market returns between South Africa and each of the BRICS country fared during these periods. For example, the dynamic conditional correlation of equity market returns between South Africa and each of the BRIC countries will be assessed during the 2001 South African currency crisis. It is important to note that during the 2001 currency crisis in South Africa, the nominal rand depreciated 26% against the US dollar, especially between September 2001 and December 2001 (Bhundia & Ricci, 2005). Bhundai and Gottschalk (2003) as well as Pretorius and de Beer (2004) attribute the sharp depreciation of the rand during those periods to the nominal disturbance that originated from the US, the September 11, 2001 attack and the political unrest in Zimbabwe. Moreover, the impact of crises emanating from other BRICS countries on the South African economy will also be assessed.

The empirical literature on contagion is vast, mostly prompted by the attempt of a number of studies to understand the widespread effects of the financial crises in the 1990s. Different empirical approaches emerged, which could be classified in four different categories (Forbes & Rigobon, 2001): the analysis of cross-market correlation coefficients; GARCH frameworks; cointegration and probit models. The cross-market correlation test measures the correlation in returns between two markets at two distinctly different time periods, the tranquil and turmoil periods. A significant increase in the correlation coefficient during the turmoil period would suggest a transmission mechanism or the occurrence of contagion (King and Wadhwani, 1990; Kim, 1993; Rengasamy, 2012). Nonetheless, cross-correlation models for the analysis of contagion have been criticised for their inability to account for heteroscedasticity in the variables used. To remedy this criticism, Forbes and Rigobon (2001) and Bouaziz, Selmi, and Boujelbene (2012) suggest the use of the generalised autoregressive conditional heteroscedasticity (GARCH) model as per Bollerslev (1986).

The GARCH frameworks use high-frequency data to assess the transmission of volatility across markets (Kalkberg, Liu, & Pasquariello 2005). Morales and Gassie (2011) use a standard univariate GARCH, TGARCH and structural breakpoint identification algorithms to analyse the co-movement of the BRICS and US energy markets (oil, natural gas and electricity). Moreover, in the context of multivariate GARCH, Bouaziz et al. (2012) used Markov Switching in conjunction with a DCC-GARCH model to determine the worldwide contagion effect of the US subprime crisis of 2007.

A number of studies make use of the cointegration technique to test for contagion by determining the long-run relationship between markets in the presence of financial crises (Longin and Solnik, 1995; Fahami, 2011). For example, Fahami (2011) used this method to test the structure of linkages and the causal relationships between BRIC and other developed countries during the 2007 US subprime crisis. The author shows that BRIC equity markets correlated more closely with the US equity market than with UK and Japanese equity markets. Gupta (2011) undertook similar tests on equity markets by comparing BRIC countries' interdependence during the US subprime crisis of 2007 and the European sovereign debt crisis of 2010. The author found long-term correlation between the BRIC countries, and that bi-directional causality exists between China, India and Russia.

The fourth group of empirical analysis assesses financial contagion by making use of exogenous events and microeconomic rather than macroeconomic data (Forbes and Rigobon, 2001). The advantage of microeconomic data is that it provides a more concise and clear identification of the channels through which contagion can occur. For example, Forbes and Rigobon (2001) examined how different types of firms were globally affected by the Russian and Asian Crises and how these crises affected other firms worldwide. The authors showed that firms that transact with countries that are affected by economic crisis are also significantly affected; this therefore suggests that trade channels are important in transmitting contagion.

In order to assess the magnitude of the transmission of financial shocks in the context of contagion, this paper applies the GARCH framework by making use of a multivariate vector autoregressive dynamic conditional correlation GARCH (VAR-DCC GARCH) model, whereby attention will be given to the transmission of equity market volatility shocks and time-varying conditional correlation to assess the evolution of the correlation between the South African and other BRICS equity markets. Contrary to studies that made use of the DCC GARCH model in assessing contagion between different countries (Celik, 2012; Chao and Parhizgani, 2008), this paper makes use of the VAR framework in the mean equation to account for possible endogeneity and interdependence of equity returns of BRICS economies. In addition, as stated earlier, this paper is the first to deal with the issue of contagion among the BRICS countries.

The remainder of this paper is organised as follows: Section 2 deals with the methodology of multivariate VAR-DCC GARCH model, the results will be discussed in Section 3. This paper concludes with a presentation of the findings in Section 4.

2. Methodology

In order to examine financial contagion between SA and its BRICS counterparts during the different crisis periods a VAR DCC GARCH model is estimated. The estimation of the VAR DCC GARCH model is broken down into three stages. In the first stage, a vector autoregressive (VAR) model is estimated as the mean equation. This estimation informs of the interaction between stock returns of

BRICS countries and brings up to date the possible spillover between the stock exchanges of those countries. In the second stage, the residuals obtained from the first stage are used to model the GARCH equations. In this paper use of the GARCH (1,1) model is made, which is suitable for equity returns (Engle & Patton, 2001).[2] Lastly, the covariance matrix obtained in the second stage is used to calculate the time-varying correlation matrix.

The mean equation is represented by the following VAR equation of order n:

$$Y_t = \phi_0 + \sum_{i=1}^{n} \phi_i Y_{t-i} + \theta Z_t + \varepsilon_t \qquad (1)$$

with $\varepsilon_t = \nu_t \sigma_t$ and Y_t is a 5-variable vector containing the following equity market variables in order: Russia, South Africa, India, Brazil and China. Z_t. represents the vectors of deterministic and exogenous variables and the residual ε_t combines the white noise process ν_t and the heteroscedastic component σ_t. Parameters ϕ_0, ϕ_i and θ need to be estimated. The advantage of using the VAR framework in the mean equation is to account for the interdependence of returns between BRICS countries and the influence of the deterministic and/or exogenous variable Z_t (here we account for the influence of the S$P 500 returns on BRICS equity returns).

The second stage uses the residuals obtained from Equation 1 in the first stage to input them into the univariate conditional-variance model specified for each BRICS equity return. To account for equity-market asymmetry, we use the Glosten, Jagannathan and Runkle (GJR) (1993) GARCH model, which accounts for the asymmetric effect of equity-market returns. The GJR GARCH (1,1)[3] model is represented as follows:

$$\sigma_t^2 = \omega + \alpha \sigma_{t-1}^2 + \beta \varepsilon_{t-1}^2 + d\varepsilon_{t-1}^2 \, I\,(\varepsilon_{t-1} < 0) \qquad (2)$$

[2] Mis-specification tests are conducted to ascertain the validity of the model used.

[3] The order of the EGARCH is determined by the log likelihood of the model estimation.

where the parameter ω refers to the long-term conditional variance and α is the lag coefficient. $I()$ is an indicator variable that takes the value of 1 when if $\varepsilon_{t-1} < 0$ and zero otherwise. Thus, the impact of ε_{t-1}^2 on σ_t^2 is $\beta + d$ for negative shocks and β for positive shocks.

The last stage in a DCC GARCH model consists of determining the time-variant conditional correlation matrix from the conditional variance expressed as:

$$H_t = D_t R_t D_t \tag{3}$$

$R_t = (1 - a - b)\overline{R} + a\Psi_{t-1} + bR_{t-1}$ Where D_t is the diagonal matrix of conditional variances such as D_t =diag $\left(h_{11t}^{1/2} .. h_{nnt}^{1/2}\right)$. R_t is a positive definite N x N correlation matrix and is defined as follows: (4)

Where a, b >0 and $a + b < 1$. $\overline{R}$ is a scalar for constant conditional correlation in that R= $\overline{R}$ if a=b=0. Ψ_{t-1} is expressed as:

$$\Psi_{ij,t-1} = \frac{\sum_{m=1}^{M} u_{1,t-m} u_{j,t-m}}{\sqrt{(\sum_{m=1}^{M} u_{i,t-m}^2)(\sum_{h=1}^{M} u_{j,t-h}^2)}} \tag{5}$$

and $u_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$

The logarithm of the likelihood function of the DCC GARCH model is represented as:

$$\ln L = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|D_t R_t D_t| + \ln|R_t| + \varepsilon_t^{'}(R_t)^{-1}\varepsilon_t\right) \tag{6}$$

3. Data, estimations, results and discussion

The paper makes use of weekly data that covers the period December 1996 to May 2012. The initial period corresponds with the liberalization of a number of BRICS equity markets. BRICS equity returns are computed from the following equity indices: the Johannesburg Stock Exchange (JSE) All Share Index for South Africa, the Bovespa Index for Brazil, Shanghai A Share Index for China, the RTS

Index for Russia and the S&P CNX500 Index for India. The S&P 500 returns are used as an exogenous variable in the VAR model to control for the influence of the US on the BRICS equity markets.

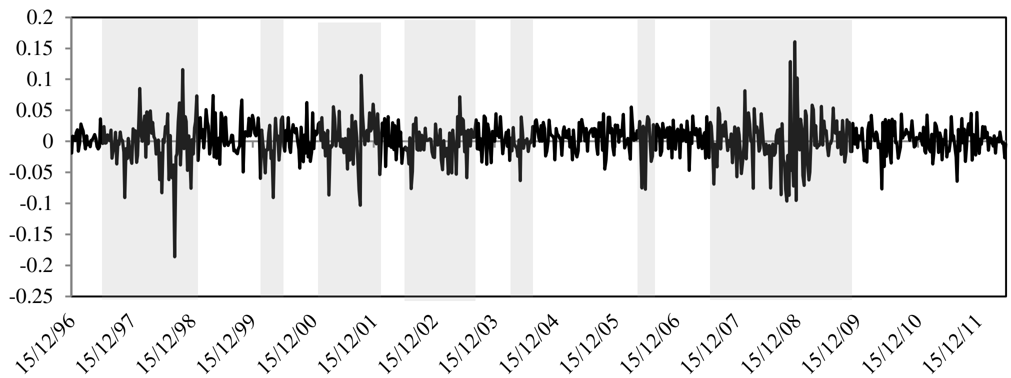
Table 1 reports the summary statistics for the weekly equity returns of the five BRICS countries. The mean returns range from 0.27 % for Brazil to 0.08% for China. Russia has the highest standard deviation for the full sample observation followed by Brazil and India. The high kurtosis and negative skewness for all the BRICS countries indicate that their equity returns are characterized by fat tails and extremely negative returns, respectively. This might explain the vulnerability of BRICS countries to global crises. The Jarque-Bera statistics show that BRICS returns exhibit substantial non-normality; thus quasi-maximum likelihood is considered for GARCH estimation.

Table 1. BRICS returns descriptive statistics

	Brazil	**China**	**India**	**South Africa**	**Russia**
Mean	0.271188	0.084571	0.185604	0.217194	0.194894
Median	0.598903	0	0.550784	0.330402	0.648624
Std. Dev.	4.613913	3.583381	4.084939	2.995959	7.376514
Skewness	-0.593755	-0.382265	-0.279117	-0.373522	-0.15564
Kurtosis	6.575494	7.120415	4.39699	6.999358	11.1266
Jarque-Bera	475.5104	588.3379	75.81741	554.5234	2215.639
Probability	0	0	0	0	0
Observations	804	804	804	804	804

Figures 1 to 5 display the equity returns of the five BRICS countries superimposed on periods of major financial and economic crises. Figure 1 shows that the South African equity returns, the JSE All Share Index returns, were highly volatile during 1997, 1998, 2001, and 2002 and during the 2007 to 2009 period (as indicated by the shaded areas), which correspond to the Asian crisis in 1997, the Russian crisis in 1998, the Argentinean crisis in 2002, and the US subprime crisis and European sovereign debt crises during 2007 and 2009, respectively. This suggests that South Africa has been vulnerable to contagion from both emerging and developed markets. In addition, high volatility clustering – though to a lesser extent – is also visible during 2000, 2004 and 2006. It is worth noting that the observed high volatility in 2006 was due to a balance of payments problem in emerging markets triggered by a strong signal by the US Federal Reserve Bank that there would be a hike in the Fed Fund rate in May 2006, which led to massive capital flows from emerging markets (Bonga-Bonga, 2014).

Figure 1. Returns on the South African JSE All Share Index



A similar picture is evident for Brazil's Bovespa Index returns. Figure 2 shows that Brazils Bovespa Index returns experienced high levels of volatility during 1997, 1998, 2000, 2001, 2002, and between 2008 and 2009, just like the South African equity returns. Nonetheless, the Brazilian equity returns were more volatile during the crisis periods than South Africa's were, as evidenced by high returns spikes during those periods.

Figure 3 displays the equity returns of Russia's RTS index. Russian equity returns portray a different picture from those of SA and Brazil. Periods of high volatility are few and far between, but much more pronounced than those of both SA and Brazil. Periods in which high volatility is evident are between 1997 and 1998, the latter part of 2008, the beginning of 2009 and during 2011. This explains Russia's susceptibility to the Asian crisis and its own (Russian) crisis as well as to the US subprime crisis and the 2010-2011 European sovereign debt crisis.

India's S&P CNX500 returns, displayed in Figure 4, resembles SA's more closely. However, high volatility clustering is more frequent compared to periods of low volatility. Periods of high volatility in India's S&P CNX500 Index returns are during 1998 to 2001, the beginning of 2004 and 2006, and between 2007 and 2009. High volatility during 2001, however, can be explained by either the currency crisis that originated in SA or the 9/11 terror attacks in the US. Similarly, the high volatility evident in both 2004 and 2006 also does not coincide with periods of known crises. The period from 2007 to 2009 corresponds to both the US subprime crisis and the European sovereign debt crisis.

Figure 2. Returns on Brazil's Bovespa Index

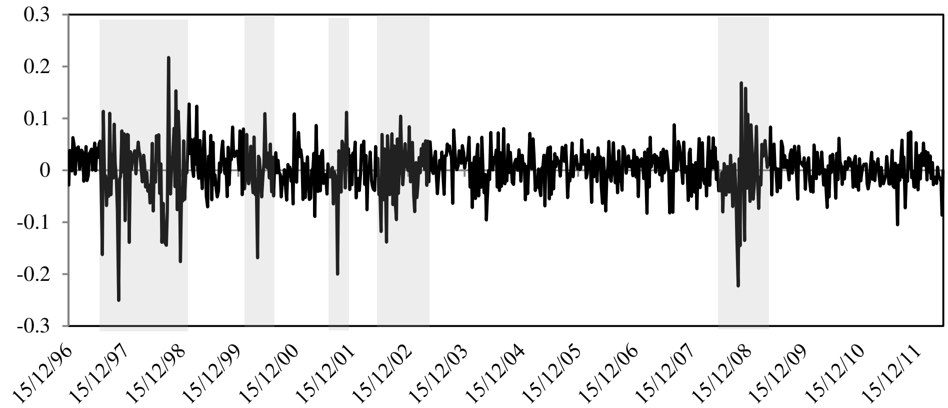


Figure 3. Returns on Russia's RTS Index

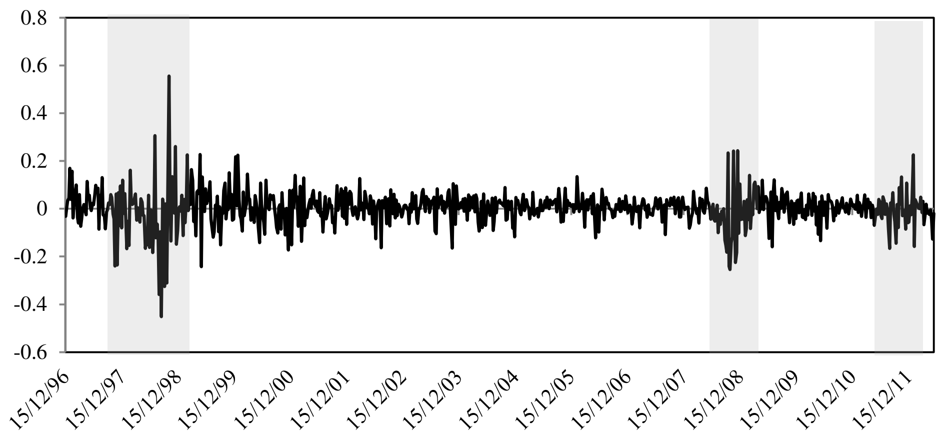


Figure 4. Returns on India's S&P CNX500

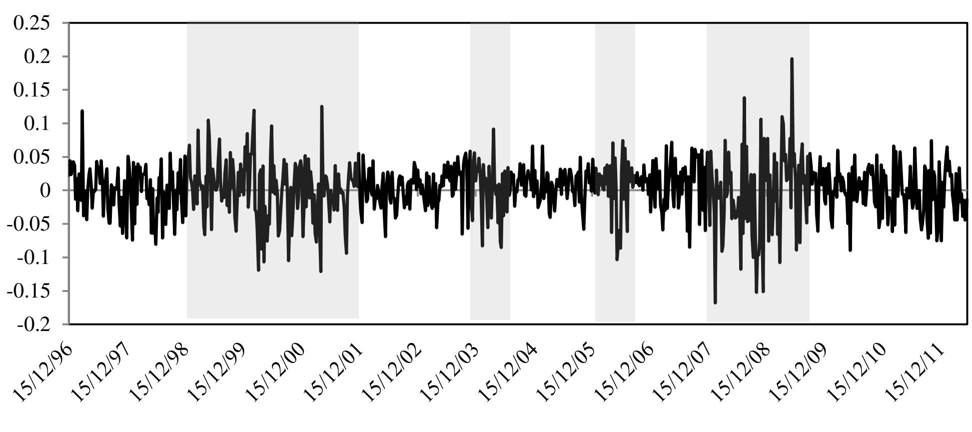
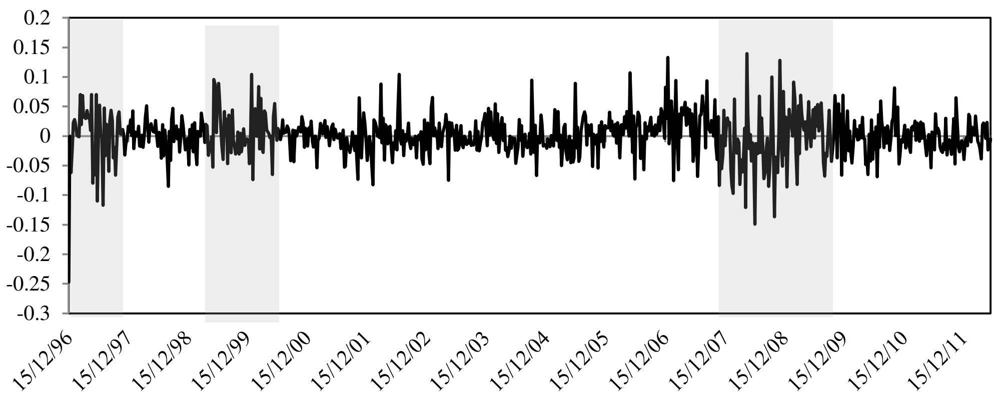


Figure 5 shows that the volatility in China's Shanghai A share is moderate, with the most significant deviations observed during the period 2007-2009.

Figure 5. Returns on China's Shanghai A Share Index



In order to obtain the conditional correlation estimates of the South African equity market and each of the other BRICS equity markets, we first make use the mean equation approximated by a VAR model with one lag,[4] where the endogenous variables consist of equity returns from the different BRICS countries. In addition, we control exogenously for the influence of the S&P 500 equity returns on BRICS countries. Given that there is evidence that the series co-breaks, the VAR model did not include specific dummy variables. Secondly, the residuals obtained from the VAR estimation are used to model the GJR-GARCH(1,1) from the different countries. In the third step, the likelihood function in Equation 6 is used to obtain the parameters of the VAR-DCC-GARCH model. Table 1 presents the results of the estimation of the models represented by Equations 1 to 5.

The results reported in Table 2 show that on average the S&P 500 equity index returns have a positive impact on BRICS equity returns, with the impact being statistically significant for all the BRICS countries. While the Brazilian equity market seems to be the most influenced by the US equity market, with the coefficient θ equals 0.9084, the Chinese equity market is the least influenced by the US equity market among BRICS countries. It is important to note that the positive influence of the US equity market on emerging market equity returns is well documented (see Bonga-Bonga and Mwamba, 2015).

[4] The choice is based on information criteria such as the Akaike Information Criteria and the Bayesian Information Criteria

Moreover, the results reported in Table 2 show that the asymmetric effect is statistically significant in the South African, Brazilian and Russian equity markets and that the sum of coefficient a and b is less than unity, which justifies the stability of the volatility model used.

Table 2. VAR DCC GARCH estimation of BRICS equity markets

	Brazil	South Africa	India	Russia	China
ϕ_0	0.1822***	0.2581***	0.30936	0.38333***	0.05552
ϕ_1	-0.07233	-0.00734***	-0.01638***	-0.02844***	-0.05486
ϕ_2	0.08758	-0.13552***	0.18503***	0.07356***	0.02078
ϕ_3	-0.00887***	0.09501	0.04413*	0.08147	0.03959**
ϕ_4	0.0672*	0.01072**	0.05758	-0.11897***	0.02961
ϕ_5	-0.01113	0.01767	-0.04877	-0.04319	0.06364
θ	0.9084***	0.6318**	0.3940***	0.6154***	0.1052***
ω	0.6775***	1.06505**	0.38769**	2.06785***	0.55817***
β	0.07132***	0.02287***	0.11303***	0.02732***	0.08038***
α	0.8955***	0.85381*	0.86464	0.82166***	0.85606***
d	0.0136***	0.09362***	0.001641	0.1082***	0.0369

DCC Coefficients

	coefficients	**standard error**	**t-stat**	**Probability**
a	0.0082	0.00224	3.673	0.000239
b	0.9872	0.00342	284.71	0.000000

***, ** and * denotes rejection of the null hypothesis at 1%, 5% and 10% respectively. The order of countries is 1 for Russia, 2 for South Africa, 3 for India, 4 for Brazil and 5 for China.

The Q-statistics and the LM ARCH tests in Table 3 confirm that the null hypothesis of no serial correlation and no ARCH effect is not rejected for the estimated VAR DCC-GARCH(1,1) model. This confirms the validity of the model used, from which the dynamic conditional correlation graphs displayed in Figures 6 to 9 are obtained.

Table 3. GARCH Q test coefficients

Equity returns	Q	Probability	ARCH	Probability
Russia	6.802059	0.743990	4.188044	0.839771
SA	9.720357	0.465360	3.525700	0.897186
India	16.972717	0.074970	7.409127	0.493201
Brazil	15.792835	0.105718	3.868925	0.868752
China	19.405899	0.035400	9.112442	0.332900

As the focus of this paper is on the dynamic conditional correlation obtained in the third step of the VAR-DCC-GARCH model, Figures 6 to 9 display the dynamic conditional correlation between South Africa and each of the other BRICS countries from 1996 to 2012. From these figures, contagion is inferred when there is evidence of an increasing correlation during particular crisis periods. The periods of crisis identified in this paper are mainly specific BRICS countries crises, such as the South African currency crisis of 2001, the Brazilian currency crisis of 2002, and the Russian currency crisis of 1998. Because no particular crisis emanated from India and China during the sample period of our study, we will use the Asian crisis as the originating crisis for the two countries. Our approach to assessing the financial influence of South Africa on the BRICS grouping is to compare the magnitude of the correlation between the South African equity market returns and each of the BRICS equity market returns during the crisis emanating from South Africa and the crises emanating from each of the other BRICS countries. The identified crisis periods during which possible contagion is assessed include the month of the beginning of the crisis in each BRICS country and the following month in order to account for contemporaneous and possible lag effects in the transmission of shocks. Thus, the identified time period for the South African currency crisis is from December 2001 to January 2002. The period for the Russian financial crisis is from August to September 1998. The Brazilian currency crisis is identified from July to August 2002 and the Asian financial crisis from November to December 1997. These crisis periods are indicated by the dark shades in Figures 6 to 9 with the addition of the subprime crisis.

Figure 6 shows the dynamic correlation between South Africa and Brazil. The display in Figure 6 shows that there is clear evidence of an increasing correlation between South Africa and Brazil during the Brazilian currency crisis, but no such clear evidence during the South African currency crisis.[5] This should indicate that crises from Brazil spill over to South Africa and not the opposite. Another observation from Figure 6 is that the correlation between equity markets in Brazil and South Africa increases during crisis periods emanating from other countries and regions, such as the Russian, Asian and subprime crises. This indicates that the synchronization of the two equity markets is also triggered by external shocks.

Figure 6. Dynamic correlation between South Africa and Brazil

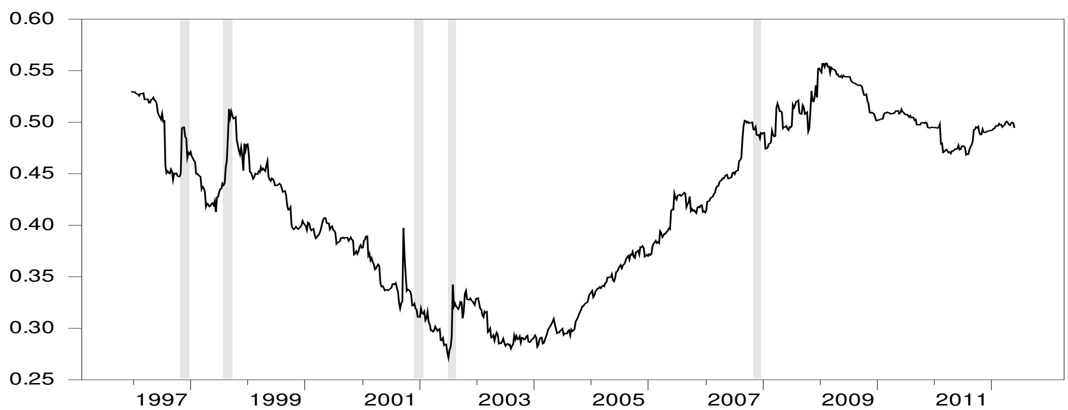


Figure 7 shows the dynamic correlation between South Africa and Russia. While there is a clear evidence of an increase in the correlation between the equity market returns of the two countries during the Russian crisis, there is no such strong evidence during the South African currency crisis. This evidence should indicate that the South African currency crisis had a negligible influence on Russia and, thus, the absence of contagion of the South African equity market to the Russian equity market. As in the case of Brazil, the two equity markets commove to different external shocks.

Figure 8 shows the dynamic correlation between the South African and Indian equity market returns. The increasing correlation between the two equity markets during the Asian financial crisis and the negligible increasing correlation during the South African currency crisis indicate unidirectional contagion from India to South Africa.

[5] The observed spike in 2001 corresponds to the 11 September event in the United States

Figure 7. Dynamic correlation between South Africa and Russia

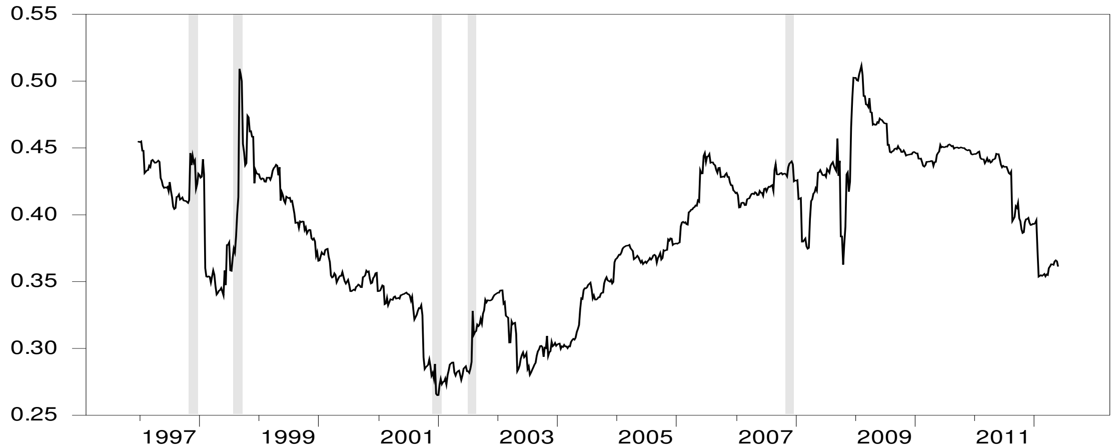


Figure 8: Dynamic correlation between South Africa and India

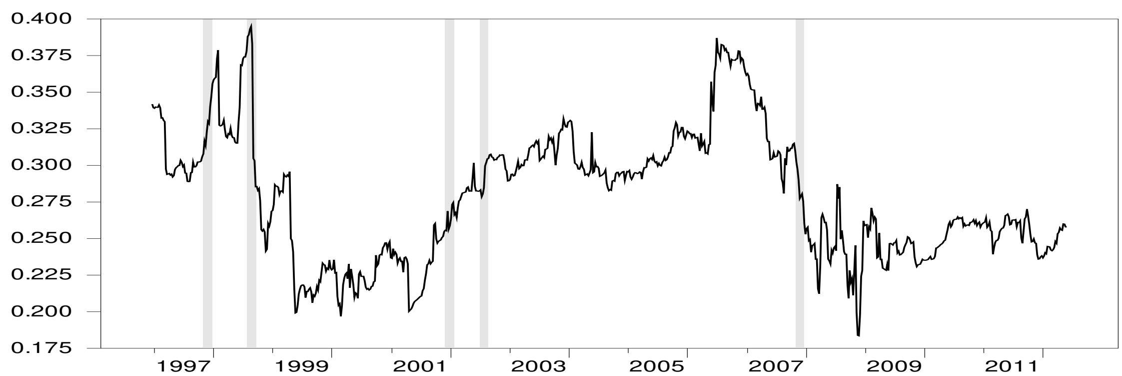
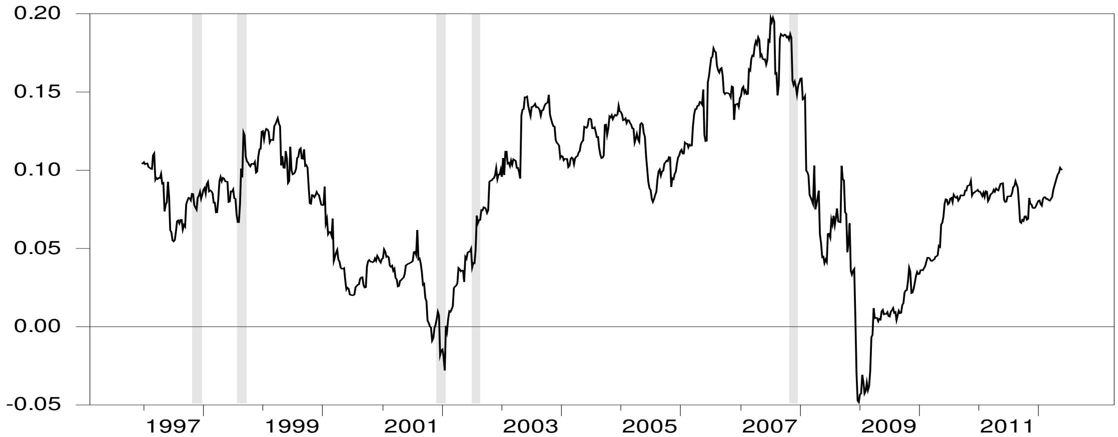


Figure 9 displays the dynamic correlation between the South African and Chinese equity market returns. The correlation between the South African and Chinese equity markets is lower than those between the South African and other BRICS equity markets. Moreover, contrary to other equity markets where the correlation with the South African equity market has remained positive during the sample periods, the correlation between the South African and Chinese equity markets is characterised by periods of negative correlation, indicating that the two markets occasionally decouple.

__Figure 9. Dynamic correlation between South Africa and China__



The results displayed in Figures 6, 7, 8, and 9 show that there seems to be weak evidence of an increasing correlation between South Africa and each of the BRICS countries during a period of crisis that stems from South Africa, which may lead to the conclusion that South Africa is a receiver rather than transmitter of financial shocks to other BRICS countries during periods of financial crisis. Such a conclusion will not be robust without assessing whether the difference in the means dynamic correlation observed during periods of crisis emanating from South Africa and other BRICS countries is statistically different. We use the t-statistics test of means difference to this end whereby the null and alternative hypotheses for the t-statistics test of means difference are defined as:

$$Ho = \mu_\rho^{SAcrisis} = \mu_\rho^{BRICS\ crisis}, \quad Ha = \mu_\rho^{SAcrisis} \neq \mu_\rho^{BRICS\ crisis}$$

Where $\mu_\rho^{SAcrisis}$ and $\mu_\rho^{BRICS\ crisis}$ are the means of the conditional correlation coefficients during the periods of crisis emanating from South Africa and each of the BRICS countries, respectively. The t-statistics are calculated as follows:

$$t = \frac{(\bar{\rho}_{ij}^{SAcrisis} - \bar{\rho}_{ij}^{BRICS\ crisis})}{\sqrt{\frac{s_{SAcrisis}^2}{n} + \frac{s_{BRICS\ crisis}^2}{n}}}$$

Where $\bar{\rho}_{ij}^{SAcrisis}$ denotes the mean of dynamic correlation coefficients between South Africa () and each of the BRICS country (j) during the crisis emanating from south Africa. $s^2_{SAcrisis}$ is the variance of these coefficients estimated as:

$$s^2 = \frac{1}{n-1}\sum_{t=1}^{n}\left(\rho_{ijt} - \bar{\rho}_{ij}\right)^2$$

Table 4 presents the DCC mean values, the t-statistics for means difference and the outcome of the test of the means difference. While there is a rejection of equal magnitude of contagion between South Africa-China, South Africa-India and South Africa-Russia during the periods of crisis emanating from each of these countries, there is evidence of equal magnitude of contagion between South Africa and Brazil during periods of crisis stemming from each of the two countries. These results show that South Africa is more affected by crises originating from China, India and Russia than the three countries are by crises originating from South Africa. China seems to be decoupled from crises originating from South Africa, with a slightly negative conditional correlation during period of crisis originating from South Africa. Brazil and South Africa are equally affected during crises originating from their respective countries.

Table 4. DCC mean values and t-statistics for means difference

	$\mu_\rho^{SAcrisis}$	$\mu_\rho^{BRICS\ crisis}$	t-statistics	outcome
South Africa - Brazil	0.3157	0.3042	1.22	H0 not rejected
South Africa - India	0.2636	0.3291	-11.15*	H0 rejected
South Africa - Russia	0.274	0.4346	-8.23*	H0 rejected
South Africa - China	-0.008	0.0813	-18.79*	H0 rejected

* denotes rejection at 1% level

These findings should be of interest to policy makers in BRICS as well international investors and portfolio managers who intend to invest in BRICS. Policy makers in South Africa, in particular, should be cautious in attempting to pursue the agenda of full capital market liberalization with other BRICS countries with the possibility of scrapping the existing exchange control. Such a move may result in capital flight from South Africa to other BRICS countries, especially during periods of financial instability in South Africa. However, South Africa may attempt the full capital market liberalization embarked on by Brazil, which is already South Africa's most important trade partner in the BRICS grouping. The two countries are also both members of the IBSA (India, Brazil and South Africa) grouping. For international investors and portfolio managers, these findings should inform on the possibility of portfolio diversification and equity and option pricings when investing in the BRICS bloc. South Africa is shown to be far from a safe haven during crises originating from Russia, India and China.

To determine the validity of our findings, we conducted a robustness test by making use of unconditional correlation measures obtained from adjusting the DCC for heteroscedasticity. Forbes and Rigobon (2002) suggest the use unconditional correlation when inferring for contagion. The authors shows that formal tests for contagion based on conditional correlation may be biased if the latter is not adjusted to unconditional correlation (see discussion in Forbes and Rogobon, 2002).

We adjusted the conditional correlation to unconditional correlation by making use of the relative increase in the variance of the South African returns before and during the 2001 currency crises. Table 5 presents the mean values, the t-statistics for means difference and the outcome of the test of the means difference during the crisis originated from South Africa and the one originated from specific BRICS country by making use of unconditional correlation measures.

Table 5 Unconditional correlation mean values and t-statistics for means difference

	$\mu_\rho^{SAcrisis}$	$\mu_\rho^{BRICS\ crisis}$	t-statistics	outcome
South Africa - Brazil	0.1957	0.1882	1.207	H0 not rejected
South Africa - India	0.1617	0.2046	-7.733*	H0 rejected
South Africa- Russia	0.1684	0.2790	-10.92*	H0 rejected
South Africa - China	-0.0048	0.0488	-18.81*	H0 rejected

* denotes rejection at 1% level

The results reported in Table 5 show that although the magnitude of means of unconditional correlation is less than the mean of the conditional correlation across all the identified crises, the outcome of the test of the means difference is identical to that reported for conditional correlation in Table 4. This indicates that the inference drawn for the extent of contagion between South Africa and other BRICS countries holds across different measures of correlation. South Africa is more contaminated by crises originated from China, India and Russia than those countries are by crises originating from South Africa. Nonetheless, there is evidence of interdependence between South Africa and Brazil.

4. **Conclusion**

This paper assesses the extent of financial contagion between South Africa and other BRICS countries by using the VAR-DCC-GARCH model. The magnitude of the correlation between South Africa and other BRICS countries is analysed during BRICS-specific and global financial crises, such as the 1998 Russian currency crisis, the 2001 South African currency crisis, the 2002 Brazilian currency crisis and the 1997 Asian financial crisis. The findings of the paper indicate that Brazil and South Africa are equally affected during crises emanating from their respective countries. These findings indicate that there is interdependence between South Africa and Brazil. However, the empirical results show that South Africa is more affected by crises originating from China, India and Russia than those countries are by crises originating from South Africa. The findings of this paper should be of interest to policy makers in the BRICS grouping when they consider the possibility of full capital market liberalization. Moreover, the findings of this paper should inform international investors and portfolio managers on the possibility of portfolio diversification and equity and option pricings when investing in BRICS. For further research we suggest that other volatility measures be considered when analysing the possibility of contagion within the BRICS grouping.

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