THE INTERCONNECTION OF THE SOUTH AFRICAN, AFRICAN AND BRICS EQUITIES MARKETS

Master of Commerce in Finance (50% Research)

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Abstract

This study aims to find out whether the South African equities market is integrated with the remainder of the BRICS markets and with other selected African markets (Botswana, Nigeria, and Namibia). The sample period used for this study spans from January 2000 – December 2021 for the BRICS markets and February 2004 – December 2021 for the African markets. These periods were chosen to allow for the same number of years before and after the 2008 global financial crisis to be roughly the same without having to separate the two periods. The study makes use of a Vector Autoregression (VAR) model to see whether lagged values of the dependant variable and other variables have some sort of predictive power. The model is used for all the respective market indices as dependent variables. This is then followed by a Granger Causality test, which is used to see in which direction causality flows, or if indeed it flows in both directions (reverse causality). Results point to the existence of interconnection between BRICS markets as there is significant predictive power, with the Russian market appearing to be the most dominant market as it granger causes the majority of markets within the group. Within Africa, interconnection is also present with the Nigerian market showing to be the leader. This all points to the bigger economies leading the groups while the smaller ones follow, with China being an exception within the BRICS group, as it appears to neither significantly affect nor significantly be affected by other markets.

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1. INTRODUCTION

Recent world events such as the 2008 Global Financial Crisis and the more recent COVID-19 pandemic have made it clear that international financial markets are somewhat linked to each other. The linkages are almost beyond doubt during a crisis or bear market; however, some may argue that this is not the case during a normal or stable market. Conclusions made on the relationships between financial markets during down markets are therefore seen as a biased view. It is therefore suggested that the relationships between financial markets be studied during times of a timeframe that includes both stable and turbulent conditions, as this would be a more neutral representation. For this study, interconnection (used interchangeably with integration) is defined as circumstances in which there is a close regional or global linkage between different financial markets.

Something that often goes hand in hand with the study of equity market interconnection is the issue of diversification and whether such interconnection is favourable to investors. On the one hand, market interconnection is seen as a way to make access to capital and different assets across the globe easier and more efficient, while on the other hand, others may argue that long run diversification benefits are nullified by such interconnection. This study partially explores the issue around the existence of long-term diversification benefits within interconnected markets and goes further by doing so from the perspective of investors from different developed markets.

For the most part, studies on the interconnection of markets have focused on the US, the European Union (EU), the Asian market and Latin America, both at a regional level and how they interact with other developed markets. Very little attention has been given to African markets and how they behave at a regional level, what sort of relationship they share with other emerging markets and lastly, with developed markets. This is the gap that this study tries to fill by bringing more African markets into the conversation regarding interconnection. Piesse and Hearn (2002) is one of very few studies that looked at the interconnection between South Africa and other Southern African markets, they found causality Namibia to South Africa, which is puzzling considering the size of the two markets. This study looks to unpack whether there is interconnection between two groups of markets, being the BRICS and African markets and whether there is causality within the interconnection.

1.2 Research Objectives

The increasing move towards globalization means a lot more things are linked than was previously the case and the financial markets are no different. The interconnection between markets across the globe can be beneficial as it allows relatively easier access to different assets in different geographical locations. There are, however, some negatives to it, particularly to investors as the increase in the interconnection between equity markets can sometimes erase potential gains from diversification. This study focuses on exploring the relationship that is shared between equity markets in different parts of the world. It does this by using a model to see whether returns in one market have some sort of predictive power over other markets. This is then followed by another model to determine from which direction causality flows. The study looks at how the South African market performs in relation to the remaining BRICS (Brazil, Russia, India, China, South Africa) markets and takes it a step further to see how it is possibly interconnected to other African markets, namely, Botswana, Nigeria, and Namibia. The objective of this study is therefore the following:

- To determine whether equity markets are interconnected
- To determine in which direction causality runs if interconnection is present

The hypothesis to be tested:

- H_0 = Variable X does not granger cause variable Y
- H_1 = Variable X granger causes Variable Y

The remainder of the paper goes as follows: Section 2 will be reviewing past literature relating to equity market integration and international diversification. Section 3 will describe the dataset and focus on the empirical framework while Section 4 will discuss the results obtained after applying the methodology to the data. Section 5 will conclude the paper and point out possible directions for further research.

2. LITERATURE REVIEW

2.1 Interconnection and Diversification

A higher degree of financial integration should act as a catalyst for macroeconomic stability through the facilitation of trade and increased capital mobility. This, however, poses problems to investors who seek to diversify their investments as they may be led to believe that there are no long-term benefits to international diversification. Deregulation of the money and capital markets worldwide has increased liberalization and in turn increased the likelihood of correlations between international equity markets. This was not the case before the deregulation of the capital markets as barriers to international capital flows were higher, investors did not have enough information related to foreign securities and as a result, were biased against taking their money offshore (Errunza & Padmanabhan, 1988). Investors must therefore understand some of the forces driving this integration to be aware of the potential risk and rewards. One of the main reasons for an investor going offshore and buying assets in a foreign market is to potentially be able to steer clear of elements contained in market risk.

According to Panda and Nanda (2017), two theories can help explain the concept behind stock market linkages: the integration theory, which states that the pricing of a local portfolio is relative to a global portfolio, and the diversification theory, which as per modern portfolio theory speaks to risk averse market participants seeking efficiency by minimizing risk and maximizing profit through low correlation assets. Gains from international portfolio diversification can therefore be realised if investment returns from stock markets around the world are not perfectly correlated. An example of this can be seen in a study done by DeFusco, Geppert and Tsetsekos (1996) who found no evidence of integration between the US market and thirteen other emerging markets, similar to another study done by Felix, Dufresne and Chatterjee (1998), which therefore suggests that long-term investors can achieve gains from diversifying across these markets. On the other hand, if returns on investments are explained by similar factors, no significant gains from diversification would be possible. Chakrabarti and Roll (2002) study equity market integration between East Asia and Europe after 1997 - 1998 Asian financial crisis and evidence pointed to returns from diversification being wiped out due to increased integration.

Existing literature shows that some emerging markets are more capable of resisting spill overs and providing diversification benefits than others. There is however, so much literature regarding spill over effects and international diversification that results can sometimes be conflicting. This is due to a number of reasons such as change in sample, change in sample period, and change in methodology. For example, De Santis and Gerard (1997) show US investors to have an annual expected gain of 2.11% from international diversification, particularly in emerging markets. Errunza, Hogan and Hung (1999) show that diversification gains for US investors invested in Brazil, India, Mexico, or Thailand significantly decreased from the period spanning January 1976 – December 1993, which implies that markets were becoming more interconnected. De Roon, Nijman and Werker (2001) argue that imposing short-sale constraints wipes out diversification gains in emerging markets. Evidence from An and Brown (2010) suggests that investors from the US would have been better off investing in Brazil, Russia, and India. A study done by Bekiros (2014) supported these findings as co-movements between the US and China were relatively high, suggesting a lack of international diversification benefits. Contrasting these findings however was Lehkonen and Heimonen (2014), which found that out of all emerging markets, China offered the highest benefits for investors in terms of diversification as they are less susceptible to shocks in the US, which is not the case for Brazil, Russia, India, and South Africa.

One common theme that can be seen from most of these studies is that international diversification is measured from the US investors perspective. There is only a limited amount of literature that measures international diversification from the perspective of investors from other developed markets such as the UK. Neaime (2006) studies the relationship between emerging markets from the Middle East North Africa (MENA) region and two developed markets, the US and Europe. Saudi Arabia and the UK are seen to have correlation of 20%. The UK's returns and variance also seem to have an impact on Tunisian and Jordanian markets when it comes to market returns and return variances (Neaume, 2012). Countries that react more to commodity price changes have also been seen to have higher co-movements with the US in both bullish and bearish markets. Consequently, commodity exporting countries Brazil and Russia are the two emerging markets that are more susceptible to US shocks (Aloui, Ben Aissa & Nguyen, 2011). China is still found to be the most attractive destination among emerging markets for UK investors as correlation between the two markets are low (Yarovaya & Chi Keung Lau, 2016).

2.2 Interconnection and The Macroeconomy

According to Pretorius (2002), liberalization has made capital a lot more mobile and increased the likelihood of cross-border interconnections. The author further states that from a macroeconomic point of view, the degree to which equity markets are interconnected can be observed by looking at the bilateral trade agreements between countries, where stronger bilateral trade agreements between countries will likely result in strong co-movements between equity markets of those countries. Other macroeconomic variables such as interest rates and inflation could also be an indicator as they also affect equity market performance. For example, if interest rates of two countries share a similar trend over time, it is likely that they have similar monetary policies in place, and this would probably affect their local equity markets in a similar way thus causing co-movements between the two markets. Chi, Li and Young (2006) show financially integrated markets to be more efficient than segmented ones in terms of the allocation and flow of capital. Cai, Eidam, Saunders and Steffen (2018) also document interconnection through common exposures faced by financial institutions. They show that banks' degree of interconnection increases the more their syndicated loan portfolios resemble each other. A benefit identified from interconnection, however, is the increase transparency by emerging markets, which has in turn forced Multinational Corporations (MNCs) based in emerging markets to follow world standards in corporate governance. Another upside to integration is the efficiency in the allocation of capital and a market framework that is more robust (Umutlu, Akdeniz, & Altag-Salih, 2010). Market integration can also be of interest to some policy makers and regulators as they would try protecting the local market from any potential spill over effects. The shock transmitted from developed to emerging markets was a catalyst for discussions around the role that emerging markets can play to maintain macroeconomic stability and not be as susceptible to shocks in developed economies (Yarovaya & Chi Keung Lau, 2016). The Asian market for example had limited exposure to subprime instruments during the 2008 global financial crisis, however, due to the deleveraging from developed economies, there was a massive liquidation of Asian assets which then led to capital flowing out of Asia, resulting in the local equity market declining.

2.3 Interconnection in Developed Markets and Rest of Europe

In seminal work done by Kasa (1992) which focuses on developed markets across the world, the relationship between the US, Japan, United Kingdom (UK), Germany and Canada is estimated using a multivariate cointegration model developed by Johansen (1991) and results show a single common trend which acts as a driving force for all these countries' equity markets. A co-movement in equity market returns is observed by Cappiello, Kadareja, and Manganelli (2010) in European markets after 1998. Bartram and Wang (2015) attributed this finding to more European countries adopting the Euro as their currency; hence markets being interconnected through the use of a common currency. Scheicher (2001) tests for integration between European emerging markets, namely Hungary, Poland and Czech Republic and the global market between the period 1995 - 1997 and find limited integration among the markets. The study also finds these markets to have a weak relationship with developed markets, as was subsequently confirmed by a later study done by Li and Majerowska (2008). Kenourgios and Samitas (2011) study five Balkan markets, namely Romania, Turkey, Bulgaria, Croatia and Serbia and they find these equity markets to be interconnected with each other as well as developed markets such as UK, Germany, and Greece. The Athens Stock Exchange in Greece is seen to play a critical role amongst developed markets in leading these Balkan equity markets. This is due to extensive trade as well as the strong infiltration of Greek firms in these countries.

2.4 Interconnection in Asian Markets

In looking at markets in the Asian continent, Wong, Agarwald and Du (2003) study the Indian equity market and found it to be substantially integrated with the international financial market. These findings are contested by Mukherjee and Mishra (2005) who deny the existence of a link between India and world equity markets, however, a later study done by Srikanth and Aparna (2012) supports findings from the former authors. In a study done by Click and Plummer (2005), evidence points to a strong interconnection between markets in Indonesia, Malaysia, the Philippines, Singapore, and Thailand during the period spanning from July 1998 to December 2002. Jeon, Oh and Yang (2006) show East Asian markets to have become more integrated with the global market and not necessarily with each other. Lee (2008) observes financial market integration to lag real trade integration in the East Asian region. Shocks originating from the Indian market and spreading to the US are also shown to be an existing feature by Samarakoon (2011). Interconnection between India and Asia's three developed markets (Hong Kong, Japan, and Singapore) was explored by Gupta and Guidi (2012) from 1999 – 2009. They found that the 2008 crisis played a role in enhancing linkages between those markets, however, there was no evidence that this increased linkage was sustained into the long term as it was seen to be a short-term phenomenon. Loh (2013) reports the co-movement between the Asian and European equity markets to have increased during the 2008 global financial crisis and that it was only temporary due to spill over effects. Lee and Isa (2014) found Malaysian equity markets to be more integrated with European equity markets than with its Asian counterparts. Wang (2014) found that the integration between East Asian markets increased and was higher post crisis than they were pre crisis, suggesting that the spill over effect during the crisis was somewhat permanent.

2.5 Interconnection in MENA and Broader African Markets

Moving onto the MENA region, it was found that equity markets in Egypt, Morocco and Jordan are integrated within their region but are globally segmented (Darrat, Elkhal, & Hakim, 2000). Within the broader African context, Piesse and Hearn (2002) did work on Southern Africa and found evidence of causality running from Namibia, which is a relatively small market, to South Africa, which is a larger market. They admit to the result being unexpected but state that a possible reason could be that characteristics common to African emerging markets which are present in both markets, are stronger in Namibia. They claim that the fact South Africa is a more open market makes it easier for spill overs to flow in from Namibia. In a different study, in which the focus is extended to include a broader Sub-Saharan African market, Piesse and Hearn (2005) state that markets are more likely to be successful if they are integrated and that those that keep themselves segmented and isolated are doing themselves no good. Wang, Yang and Bessler (2003) found that the equity market long-run relationship between South Africa, Egypt, Morocco, Zimbabwe, and Nigeria was weakened due to the global financial crisis. The South African market was shown to have had significant influence on global markets pre-financial crisis while also being significantly responsive to innovations from the US, Nigeria, and Morocco. South Africa's influence on other markets increased substantially post-financial crisis, however, it's responsiveness to innovations in the remaining parts of Africa decreased. The Egyptian market's response to innovations in other African countries was inconsistent pre and post financial crisis. Morocco and Nigeria did, however, exert significant influence on the Egyptian market pre-financial crisis. The influence was less prevalent post-crisis. Ncube and Mingiri (2015) found South Africa, Nigeria, Botswana, Mauritius, and Namibia to be segmented from one another despite being among the fastest growing equity markets in the African continent. Some equity market integrations can be seen in the form of cross-border listings. Examples include cross listings between South Africa and Botswana in 1997 as well as South Africa and Ghana in 2004 (Adelegan, 2009).

2.6 Interconnection Over Time

Another question that rises from interconnection studies is whether these relationships hold over time. In a study by Smith, Brocato and Rogers (1993), the sample period is not divided into pre- and post-crisis subsample periods as the decision on where to divide the two subsample periods might significantly influence the results obtained from empirical tests. To avoid this problem, the evolution of the problem is studied over time. The authors looked at how the relationship of equity markets between the US, UK, West Germany, and Japan evolved from 1979 and 1991. They found Granger causality during periods surrounding the crash but there was no such evidence during periods outside the crash. This led them to conclude that investors can still benefit from international diversification and that gains from such investments are still achievable. Arshanapalli, Doukas and Lang (1995) found the 1987 Black Monday crisis to be some sort of catalyst for integration as in their study, they define the period from January 1986 – September 1987 as the pre-crisis period and November 1987 – December 1992 as post-crisis period. They found no evidence of integration during the pre-crisis period but do find integration to be present during post-crisis period for Malaysia, Thailand, and the Philippines, which are developing markets and Singapore, Hong Kong, Japan, and the US, which are developed markets. These relationships are clearly largely influenced by a crisis, suggesting that they might not be constant over time. Liu, Pan and Shieh (1998) study the stability of relationships among Thailand, Taiwan, Japan, Hong Kong, Singapore, and the US for two subsample periods: 2 January 1985 – 16 October 1987 and 19 October 1987 – 31 December 1990. The results were indicative of a general increase in the interconnection of equity markets as well as an increase in the interconnection of equity markets with the Asia-Pacific region after the 1987 Black Monday crisis.

2.7 Methods Previously Used

Pagan and Soydemir (2000) use a vector autoregressive (VAR) model to capture the integration between Latin American equity markets as they argue that this method's usefulness is its ability to not set a priori restrictions in the system and allow for artificial shocks. A few other methods have been used throughout the years. One of the most well-known is the testing for unit root via the residual based augmented Dickey-Fuller test (ADF). More recent research, however, have opted to mix it with other methods due to its inability to consider the time varying nature of correlations. Kearney and Lucy (2004) take a somewhat different approach to measuring the extent of integration in the financial markets, which is to check for the equalization of rates of return. This would implicitly be alluding to the application of the law of one price, which in simple terms states that in a world of unrestricted capital flows, prices of similar assets should equate one another, regardless of the geographical location. They however go on to mention a limitation regarding this method, which was the difficulty in finding financial asset that are homogeneous enough in terms of their risk profiles to allow for fair comparisons. To this date, there are still ongoing debates about which methodology is best suited for measuring the level of interconnection between markets. Granger (1969) causality test is also a popular method among previous literature because of its simplicity but Mukherjee and Mishra (2010) study the integration and volatility spill overs among the Indian market and 12 Asian market using the famous GARCH (1,1) model, which essentially not only takes lagged values of the time series into account but also considers lagged volatilities. This model may have been favourable for reasons pointed out by Bekiros (2014), who stated that the Granger causality test does not accommodate causal impacts of both positive and negative shocks, therefore not allowing for asymmetry in the tests. Another reason which may have led to the popularity of the ARCH model and its several extensions is the existence of autoregressive conditional heteroskedasticity, which normally impacts statistics regarding linear tests.

3. DATA AND METHODOLOGY

The dataset used for this research is pulled from the Iress database as well as the Bloomberg terminal and is divided into two groups: the BRICS group and the African group. The data will comprise of weekly returns of the JSE All Share Index (JSE ALSI) as well indices representing other emerging markets (Brazil, Russia, India, and China) and other African markets (Botswana, Nigeria, and Namibia). The African sample was selected based on limited availability of data. The sample period pertaining to the BRICS markets is from January 2000 – December 2021 and that pertaining to the African markets is from February 2004 – December 2021. The periods were chosen to allow for the same number of years before and after the 2008 global financial crisis to be roughly the same without having to separate the two periods, which helps the study focus on the development of the relationship over time rather than at specific points in time. To investigate the interconnection of South Africa’s equity market to those of the remaining BRICS and selected African markets, the study will make use of a Vector Autoregressive (VAR) model using the following as a general representation:

$$\mathbf{JSE_k = \sum a_{k-z}JSE_{k-z} + \sum b_{k-z}IBOV_{k-z} + \sum c_{k-z}IMOEX_{k-z} + \sum d_{k-z}NIFTY_{k-z} + e_{k-z}SHCOMP_{k-z} + \varepsilon_t} \quad (1)$$

$$\mathbf{JSE_k = \alpha + \sum f_{k-z}JSE_{k-z} + \sum g_{k-z}BGSMDC_{k-z} + \sum h_{k-z}NGXINDX_{k-z} + \sum i_{k-z}FTN098_{k-z} + \varepsilon_t} \quad (2)$$

where JSE_k is the South African equity market index and $IBOV_{k-z}$, $IMOEV_{k-z}$, $NIFTY_{k-z}$, $SHCOMP_{k-z}$ represent the lagged values of the Brazilian, Russian, Indian, and Chinese equity market indices respectively while b_{k-z}, c_{k-z}, d_{k-z} and e_{k-z} represent the coefficients of the respective lags in Equation 1. Similarly in Equation 2, $BGSMDC_{k-z}$, $NGXINDX_{k-z}$, $FTN098_{k-z}$ represent the lagged values of Botswanan, Nigerian, and Namibian equity market indices respectively with g_{k-z}, h_{k-z}, i_{k-z} and being their respective coefficients. The coefficient for the South African index is denoted as a_{k-z} in Equation 1 and f_{k-z} in Equation 2. The model will be run for each country as a dependent variable within both groups. The VAR model helps identify a relationship between the dependent variable and the independent variables and proceeds to assign some predictive power to the independent variables. Before diving deep into the dynamics of the VAR model, the indices’ time series properties will be analyzed to test for stationarity using the Augmented Dickey Fuller (ADF) test. It is important to test for this as forecasting is dependent on the time series being stationary and abide to the mean and variance being constant over time. Results risk being spurious if the time series are non-stationary. In the past, integration has traditionally been measured by correlations; however, this has been shown to be an inappropriate measure as weak correlations can exist in perfectly integrated markets according to Pukthuanthong and Roll (2009).

If a relationship between stock markets exists, one would assume that the performance of one market affect the performance of the other. Or put differently, the past changes of price in one country's stock market should cause the change of price in another country's stock market. The Granger Causality model by Granger (1969) calculates the current value of a variable's correlation to the past values of other variables. One benefit of the Granger Causality is its ability to indicate the direction from which the causality flows (could be either or both).

4. EMPIRICAL RESULTS

4.1 VAR Estimation Results (BRICS Markets)

Table 1 reports the basic statistics relating to the five BRICS equity markets. All series except for the SHCOMP are shown to be leptokurtic while the IMOEX is the only series that is positively distributed. Both are characteristics of series that are not normally distributed. The IMOEX is seen to have a mean of 0.004, being the highest of the five during the sample period, which is not puzzling as it is also the most volatile with a standard deviation of 0.043, thus concurring with the notion that higher risk should yield higher returns.

Table 1: BRICS Markets' Descriptive Statistics

	JSE.ALSI	**IBOV.Index**	**IMOEX.Index**	**NIFTY.Index**	**SHCOMP. Index**
Nobs	1112.00	1112.00	1112.00	1112.00	1112.00
NAs	0.00	0.00	0.00	0.00	0.00
Minimum	-0.151	-0.200	-0.242	-0.159	-0.138
Maximum	0.174	0.183	0.493	0.154	0.150
1 . Quartile	-0.012	-0.020	-0.017	-0.014	-0.017
3 . Quartile	0.017	0.026	0.025	0.019	0.019
Mean	0.002	0.003	0.004	0.002	0.001
Median	0.003	0.004	0.004	0.004	0.002
Sum	2.454	2.788	4.038	2.722	1.458
SE Mean	0.001	0.001	0.001	0.001	0.001
LCL Mean	0.001	0.000	0.001	0.001	-0.001
UCL Mean	0.004	0.005	0.006	0.004	0.003
Variance	0.001	0.001	0.002	0.001	0.001
Stdev	0.026	0.038	0.043	0.030	0.032
Skewness	-0.104	-0.293	0.889	-0.307	-0.010
Kurtosis	4.462	3.328	17.426	3.104	2.353

Each time series is then tested for stationarity using the ADF test with the following hypothesis:

H_0: The time series is non-stationary

All five series produced similar results, yielding p-values that are less than 0.01 thus rejecting the null hypothesis and therefore confirming stationarity at the 95% confidence interval. It can therefore be said that the variables do not contain a unit root. The diagram below shows each individual time series separately while Figure 2 shows all the different time series on one plot. These diagrams can help visually deduce stationarity without running tests.

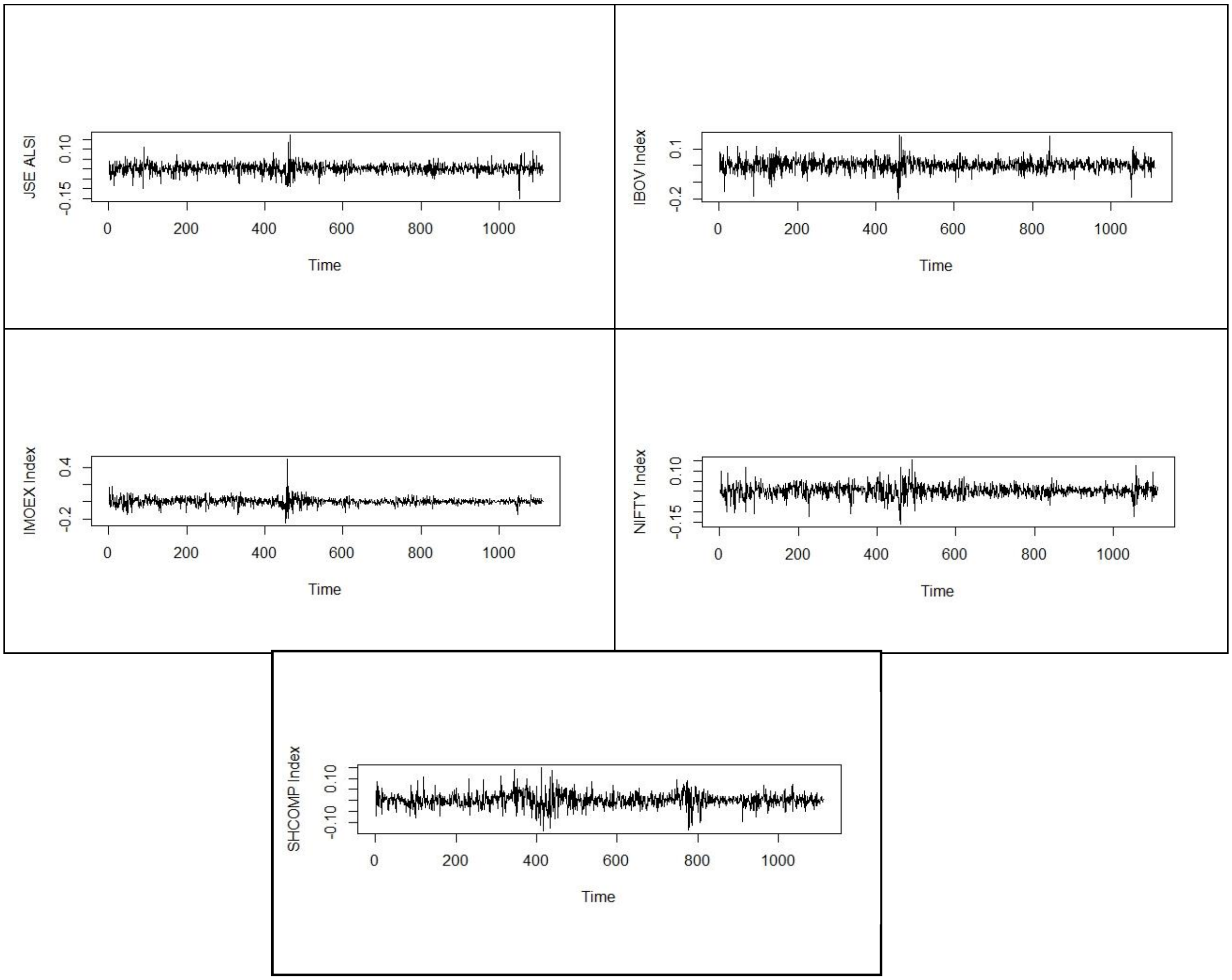

Figure 1: Individual Plots (BRICS Markets)

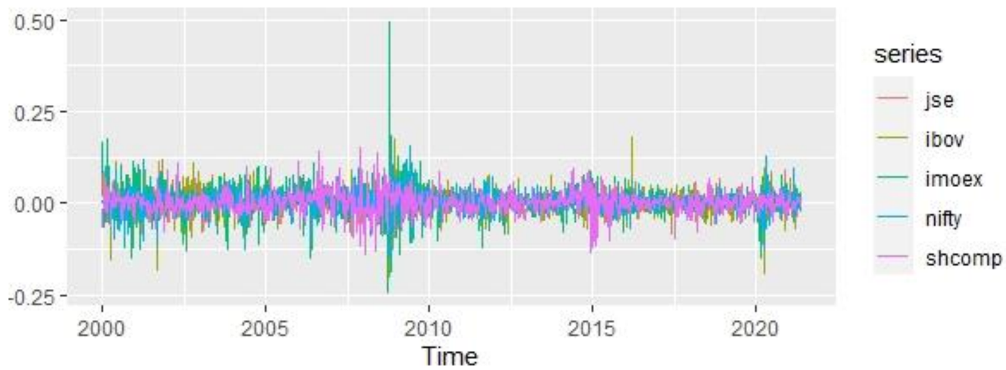

Figure 2: Grouped Plots (BRICS Markets)

Before going on to run the VAR model, it is imperative that an optimal lag is selected for use in the model. There are numerous ways of doing this, however, this study will employ the Akaike Information Criteria (AIC) as it is generally the most used. After running lag selection tests, it is determined that three lags is optimal as shown below.

AIC (n)	HQ (n)	SC (n)	FPE (n)
3	1	1	3

BRICS Markets Optimal Lag Selection

The VAR model is then applied conditional to the lag order.

Table 2: JSE Estimation Results

jse = jse.l1 + ibov.l1 + imoex.l1 + nifty.l1 + shcomp.l1 + jse.l2 + ibov.l2 + imoex.l2 + nifty.l2 + shcomp.l2 + jse.l3 + ibov.l3 + imoex.l3 + nifty.l3 + shcomp.l3 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.l1	-0.113	0.038	-2.978	0.003 **
Ibov.l1	0.070	0.026	2.710	0.007 **
Imoex.l1	0.052	0.018	2.808	0.005 **
Nifty.l1	-0.001	0.031	-0.023	0.982
Shcomp.l1	-0.012	0.024	-0.490	0.624
Jse.l2	-0.071	0.038	-1.839	0.066 .
Ibov.l2	0.040	0.027	1.498	0.135
Imoex.l2	0.001	0.018	0.070	0.944
Nifty.l2	0.027	0.031	0.871	0.384
Shcomp.l2	-0.019	0.024	-0.790	0.430
Jse.l3	-0.045	0.038	-1.185	0.236
Ibov.l3	-0.049	0.026	-1.886	0.060 .
Imoex.l3	0.111	0.018	6.126	0.000***
Nifty.l3	0.006	0.031	0.206	0.837
Shcomp.l3	-0.025	0.024	-1.059	0.290
Const	0.002	0.001	2.517	0.012 *
Signif codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Residual Standard Error: 0.02575 on 1093 degrees of freedom				
Multiple R-Squared: 0.05922, Adjusted R-Squared: 0.04631				
F-statistic: 4.586 on 15 and 1093 DF, p-value: 0.00000001452				

.

Table 3: IBOV Estimation Results

ibov = jse.l1 + ibov.l1 + imoex.l1 + nifty.l1 + shcomp.l1 + jse.l2 + ibov.l2 + imoex.l2 + nifty.l2 + shcomp.l2 + jse.l3 + ibov.l3 + imoex.l3 + nifty.l3 + shcomp.l3 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.l1	0.067	0.055	1.215	0.224
Ibov.l1	-0.119	0.037	-3.191	0.001 **
Imoex.l1	0.044	0.026	1.654	0.098 .
Nifty.l1	0.043	0.045	0.948	0.343
Shcomp.l1	0.019	0.035	0.546	0.585
Jse.l2	-0.014	0.055	-0.255	0.799
Ibov.l2	0.061	0.038	1.596	0.111
Imoex.l2	0.017	0.026	0.640	0.522
Nifty.l2	0.012	0.045	0.278	0.781
Shcomp.l2	0.011	0.035	0.309	0.758
Jse.l3	0.015	0.055	0.269	0.788
Ibov.l3	-0.002	0.038	-0.047	0.962
Imoex.l3	0.150	0.026	5.740	0.000 ***
Nifty.l3	-0.018	0.045	-0.407	0.684
Shcomp.l3	-0.010	0.035	-0.280	0.779
Const	0.002	0.001	1.425	0.154
Signif codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1				
Residual Standard Error: 0.03709 on 1093 degrees of freedom				
Multiple R-Squared: 0.04674, Adjusted R-squared: 0.03366				
F-statistic: 3.573 on 15 and 1093 DF, p-value: 0.00000444				

The JSE appears to be significantly affected by JSE_{k-1}, $IBOV_{k-1}$, $IMOEX_{k-1}$, and $IMOEX_{k-3}$, the JSE_{k-1} being the only one having a negative effective with a coefficient of -0.113. The effects are all significant at the 99% confidence interval. With regards to IBOV, it is only significantly affected by $IBOV_{k-1}$, $IMOEX_{k-1}$, and $IMOEX_{k-3}$, with $IBOV_{k-1}$ having a coefficient of -0.119, the only one with a negative relationship. It is also worth noting that results relating to $IMOEX_{k-1}$ are only significant at the 90%

confidence interval while the others are significant at the 99% confidence interval, as is the overall model, which produces a p-value of 0.000. When analysing IMOEX, it is seen that $NIFTY_{k-2}$ and $IMOEX_{k-3}$ have a negative effect with coefficients of -0.200 and -0.091 respectively, which are significant at the 99% confidence interval. $IBOV_{k-2}$ has a positive relationship with IMOEX, however, results are only conclusive at the 95% confidence interval while results relating to JSE_{k-2} and $SHCOMP_{k-2}$ are only statistically significant at 90% confidence interval. Moving on to NIFTY, it is seen that $IBOV_{k-1,}$ $IBOV_{k-2,}$ and $IMOEX_{k-3}$ all have a positive effect with coefficients of 0.083, 0.084 and 0.142 respectively. Another commonality between the three variables is that they are all significant at the 99% confidence interval, while the positive relationship shared with JSE_{k-1} and $IMOEX_{k-1}$ is only significant at the 90% confidence interval. The SHCOMP only shares a statistically significant relationship with $SHCOMP_{k-2,}$ however, the model is statistically insignificant and therefore inconclusive.

Table 4: IMOEX Estimation Results

imoex = jse.l1 + ibov.l1 + imoex.l1 + nifty.l1 + shcomp.l1 + jse.l2 + ibov.l2 + imoex.l2 + nifty.l2 + shcomp.l2 + jse.l3 + ibov.l3 + imoex.l3 + nifty.l3 + shcomp.l3 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.l1	-0.014	0.062	-0.223	0.824
Ibov.l1	0.070	0.043	1.642	0.101
Imoex.l1	-0.003	0.030	-0.112	0.911
Nifty.l1	-0.022	0.051	-0.435	0.664
Shcomp.l1	0.019	0.039	0.480	0.631
Jse.l2	0.105	0.063	1.662	0.097 .
Ibov.l2	0.104	0.043	2.386	0.017 *
Imoex.l2	-0.040	0.030	-1.329	0.184
Nifty.l2	-0.200	0.051	-3.915	0.000 ***
Shcomp.l2	-0.068	0.039	-1.729	0.084 .
Jse.l3	0.060	0.062	0.972	0.331
Ibov.l3	0.061	0.043	1.429	0.153
Imoex.l3	-0.091	0.030	-3.075	0.002 **
Nifty.l3	-0.009	0.051	-0.176	0.860
Shcomp.l3	-0.012	0.039	-0.313	0.754
Const	0.004	0.001	2.908	0.004 **
Signif codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1				
Residual standard error: 0.04219 on 1093 degrees of freedom				
Multiple R-Squared: 0.03356, Adjusted R-squared: 0.0203				
F-statistic: 2.53 on 15 and 1093 DF, p-value: 0.001058				

Table 5: NIFTY Estimation Results

nifty = jse.l1 + ibov.l1 + imoex.l1 + nifty.l1 + shcomp.l1 + jse.l2 + ibov.l2 + imoex.l2 + nifty.l2 + shcomp.l2 + jse.l3 + ibov.l3 + imoex.l3 + nifty.l3 + shcomp.l3 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> $\lvert t \rvert$)
Jse.l1	0.079	0.043	1.827	0.068 .
Ibov.l1	0.083	0.030	2.813	0.005 **
Imoex.l1	0.040	0.020	1.921	0.055 .
Nifty.l1	-0.050	0.036	-1.410	0.159
Shcomp.l1	0.002	0.027	0.064	0.949
Jse.l2	-0.033	0.044	-0.756	0.450
Ibov.l2	0.084	0.030	2.763	0.006 **
Imoex.l2	0.003	0.021	0.125	0.900
Nifty.l2	0.039	0.036	1.109	0.268
Shcomp.l2	-0.004	0.027	-0.150	0.881
Jse.l3	0.059	0.043	1.363	0.173
Ibov.l3	-0.018	0.030	-0.611	0.541
Imoex.l3	0.142	0.021	6.839	0.000***
Nifty.l3	-0.031	0.035	-0.887	0.376
Shcomp.l3	0.015	0.027	0.538	0.591
Const	0.001	0.001	1.431	0.153
Signif codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1				
Residual standard error: 0.0294 on 1093 degrees of freedom				
Multiple R-Squared: 0.07713, Adjusted R-squared: 0.06446				
F-statistic: 6.09 on 15 and 1093 DF, p-value: 0.000000000002105				

Table 6: SHCOMP Estimation Results

shcomp = jse.l1 + ibov.l1 + imoex.l1 + nifty.l1 + shcomp.l1 + jse.l2 + ibov.l2 + imoex.l2 + nifty.l2 + shcomp.l2 + jse.l3 + ibov.l3 + imoex.l3 + nifty.l3 + shcomp.l3 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.l1	0.022	0.048	0.454	0.650
Ibov.l1	-0.020	0.033	-0.601	0.548
Imoex.l1	0.011	0.023	0.487	0.626
Nifty.l1	-0.004	0.039	-0.106	0.916
Shcomp.l1	0.049	0.030	1.634	0.103
Jse.l2	-0.022	0.048	-0.457	0.648
Ibov.l2	0.031	0.033	0.934	0.351
Imoex.l2	-0.028	0.023	-1.242	0.215
Nifty.l2	0.002	0.039	0.043	0.966
Shcomp.l2	0.062	0.030	2.056	0.040 *
Jse.l3	0.027	0.048	0.574	0.566
Ibov.l3	-0.017	0.033	-0.513	0.608
Imoex.l3	-0.005	0.023	-0.236	0.813
Nifty.l3	-0.006	0.039	-0.145	0.885
Shcomp.l3	0.042	0.030	1.389	0.165
Const	0.001	0.001	1.156	0.248
Signif codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1				
Residual standard error: 0.0323 on 1093 degrees of freedom				
Multiple R-Squared: 0.0125, Adjusted R-squared: -0.001056				
F-statistic: 0.9221 on 15 and 1093 DF, p-value: 0.5388				

4.2 Granger Causality Test Results (BRICS Markets)

The study then proceeds to test whether there is granger causality flowing in either direction for the relationships previously observed. The null hypothesis for this test will have the following general form:

H_0: Variable X does not granger cause variable Y

It was observed in Table 2 that the JSE shared a significant relationship with its own lag, IBOV lag and IMOEX lag. This notion is further cemented as in Table 7 as the null hypothesis is rejected when IBOV and IMOEX lags are used as independent variables respectively, both producing results that are statistically significant at the 99% confidence interval, thus indicating that South Africa's market is granger caused by the Brazilian and Russian markets. We fail to reject the null hypothesis in the case of NIFTY and SHCOMP lags being independent variables respectively.

Table 8 proceeds to show results with IBOV as the dependent variable. Evidence points to IBOV being granger caused by the IMOEX lags, as supplemented by Table 3 where it was seen that $IMOEX_{k-1}$ had a significant impact at the 90% confidence interval. The model produces a p-value of 0.000, thereby rejecting the null hypothesis that IMOEX lags do not granger cause IBOV. This is completely different from findings in Dasgupta (2014), which shows China to be the main driving force behind the Brazilian market. We fail to reject the null hypothesis when tests are run for the remaining variables, inferring that they do not granger cause IBOV.

Table 7: JSE Granger Causality Test Results

Granger causality test
Model 1: jse ~ Lags(jse, 1:3) + Lags(ibov, 1:3)
Model 2: jse ~ Lags(jse, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 4.7385 0.002732 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Granger causality test
Model 1: jse ~ Lags(jse, 1:3) + Lags(imoex, 1:3)
Model 2: jse ~ Lags(jse, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 15.079 0.000000001271 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Granger causality test
Model 1: jse ~ Lags(jse, 1:3) + Lags(nifty, 1:3)
Model 2: jse ~ Lags(jse, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.8377 0.4732
Granger causality test
Model 1: jse ~ Lags(jse, 1:3) + Lags(shcomp, 1:3)
Model 2: jse ~ Lags(jse, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.775 0.508

Table 8: IBOV Granger Causality Test Results

Granger causality test
Model 1: ibov ~ Lags(ibov, 1:3) + Lags(jse, 1:3)
Model 2: ibov ~ Lags(ibov, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.8389 0.4726
Granger causality test
Model 1: ibov ~ Lags(ibov, 1:3) + Lags(imoex, 1:3)
Model 2: ibov ~ Lags(ibov, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 11.853 0.0000001211 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Granger causality test
Model 1: ibov ~ Lags(ibov, 1:3) + Lags(nifty, 1:3)
Model 2: ibov ~ Lags(ibov, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.7348 0.5313
Granger causality test
Model 1: ibov ~ Lags(ibov, 1:3) + Lags(shcomp, 1:3)
Model 2: ibov ~ Lags(ibov, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.1557 0.9261

Tests on IMOEX as the dependent variable produce puzzling results as in Table 4, it was seen that the index has a statistically significant relationship with a few of the indices' lags. However, there only seems to be causality running from IBOV lags. The null hypothesis for IBOV lags as the independent variables is rejected at the 95% confidence interval. These results are in line with findings from Dasgupta (2014), who showed the Brazilian market to be a driving force for the Russian market. Dasgupta (2014) also goes on to state that there is bidirectional granger causality for the BRIC markets (excluding South Africa) and concludes that the dominant market within this group is India as it fastest growing market. This is perhaps eyebrow raising as results in this study on NIFTY as the dependant variable are much different. The null hypothesis is rejected when test is done JSE, IBOV and IMOEX lags respectively. They all produce results that are statistically significant at the 99% confidence interval. It can therefore be inferred that the Indian market is somewhat of a follower within the BRICS group as it is granger caused by three of the five markets. This is somewhat in line with Srikanth and Aparna (2012), who found the Indian markets to be interconnected to global markets. This study took it a step further clarity on which direction granger causality runs.

The test is lastly done with the SHCOMP as the dependent variable. We fail to reject the null hypothesis for each BRICS equity market and thus is enough evidence to deduce that the SHCOMP is not granger caused by any of its BRICS counterparts. The SHCOMP index is not influenced by what happens to external markets and can somewhat block outside noise. This implies that China is an attractive market for investors that are looking for diversification benefits as the market is not too closely linked to any other international market, corroborating what was found by Lehkonen and Heimonen (2014).

Table 9: IMOEX Granger Causality Test Results

Granger causality test
Model 1: imoex ~ Lags(imoex, 1:3) + Lags(jse, 1:3)
Model 2: imoex ~ Lags(imoex, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 1.7758 0.15
Granger causality test
Model 1: imoex ~ Lags(imoex, 1:3) + Lags(ibov, 1:3)
Model 2: imoex ~ Lags(imoex, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 2.9825 0.03044 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Granger causality test
Model 1: imoex ~ Lags(imoex, 1:3) + Lags(nifty, 1:3)
Model 2: imoex ~ Lags(imoex, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 1.9554 0.119
Granger causality test
Model 1: imoex ~ Lags(imoex, 1:3) + Lags(shcomp, 1:3)
Model 2: imoex ~ Lags(imoex, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 1.1069 0.3452

Table 10: NIFTY Granger Causality Test Results

Granger causality test
Model 1: nifty ~ Lags(nifty, 1:3) + Lags(jse, 1:3)
Model 2: nifty ~ Lags(nifty, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 4.6695 0.003007 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Granger causality test
Model 1: nifty ~ Lags(nifty, 1:3) + Lags(ibov, 1:3)
Model 2: nifty ~ Lags(nifty, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 7.6841 0.00004392 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Granger causality test
Model 1: nifty ~ Lags(nifty, 1:3) + Lags(imoex, 1:3)
Model 2: nifty ~ Lags(nifty, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 17.136 0.00000000007005 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Granger causality test
Model 1: nifty ~ Lags(nifty, 1:3) + Lags(shcomp, 1:3)
Model 2: nifty ~ Lags(nifty, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.0945 0.9631

Table 11: SHCOMP Granger Causality Test Results

Granger causality test
Model 1: shcomp ~ Lags(shcomp, 1:3) + Lags(jse, 1:3)
Model 2: shcomp ~ Lags(shcomp, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.0279 0.9937
Granger causality test
Model 1: shcomp ~ Lags(shcomp, 1:3) + Lags(ibov, 1:3)
Model 2: shcomp ~ Lags(shcomp, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.4719 0.702
Granger causality test
Model 1: shcomp ~ Lags(shcomp, 1:3) + Lags(imoex, 1:3)
Model 2: shcomp ~ Lags(shcomp, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.6163 0.6045
Granger causality test
Model 1: shcomp ~ Lags(shcomp, 1:3) + Lags(nifty, 1:3)
Model 2: shcomp ~ Lags(shcomp, 1:3)
Res.Df Df F Pr(>F)
1 1102
2 1105 -3 0.0417 0.9887

4.3 VAR Estimation Results (African Markets)

The exact same tests are now done for the African markets to see how they interact with each other. Table 12 starts off by showing basic statistics pertaining to each market. Each series shows evidence of leptokurtosis. The JSE ALSH and FTN098 are negatively skewed while BGSMDC and NGSINDX are positively skewed. The JSE produced the highest average return of 0.23%, with BGSMDC having the lowest at 0.11%. FTN098 was the most volatile with a standard deviation of 0.033. All these characteristics again showing that none of the series are normally distributed.

Table 12: African Markets' Descriptive Statistics

	JSE.ALSH	BGSMDC.Index	NGXINDX.Index	FTN098.Index
Nobs	932.00	932.00	932.00	932.00
NAs	0.00	0.00	0.00	0.00
Minimum	-0.151	-0.065	-0.135	-0.182
Maximum	0.174	0.149	0.169	0.176
1 . Quartile	-0.012	-0.003	-0.013	-0.017
3 . Quartile	0.016	0.004	0.015	0.020
Mean	0.002	0.001	0.001	0.002
Median	0.003	0.000	0.000	0.002
Sum	2.160	1.085	1.089	1.942
SE Mean	0.001	0.000	0.001	0.001
LCL Mean	0.001	0.000	-0.001	-0.000
UCL Mean	0.004	0.002	0.003	0.004
Variance	0.001	0.000	0.001	0.001
Stdev	0.025	0.011	0.032	0.033
Skewness	-0.061	2.493	0.119	-0.316
Kurtosis	5.589	37.783	4.268	3.535

Each series is tested for stationarity using the ADF test and all produce p-values less than 0.01, thus confirming the series do not have unit roots, rejecting the null hypothesis and confirming stationarity. AIC is also used to determine the optimal lag selection, and, in this case, two lags is determined as optimal. Conditional to this optimal lag, the VAR model is the applied for the African markets.

AIC (n)	HQ (n)	SC (n)	FPE (n)
5	1	1	5

African Markets Optimal Lag Selection

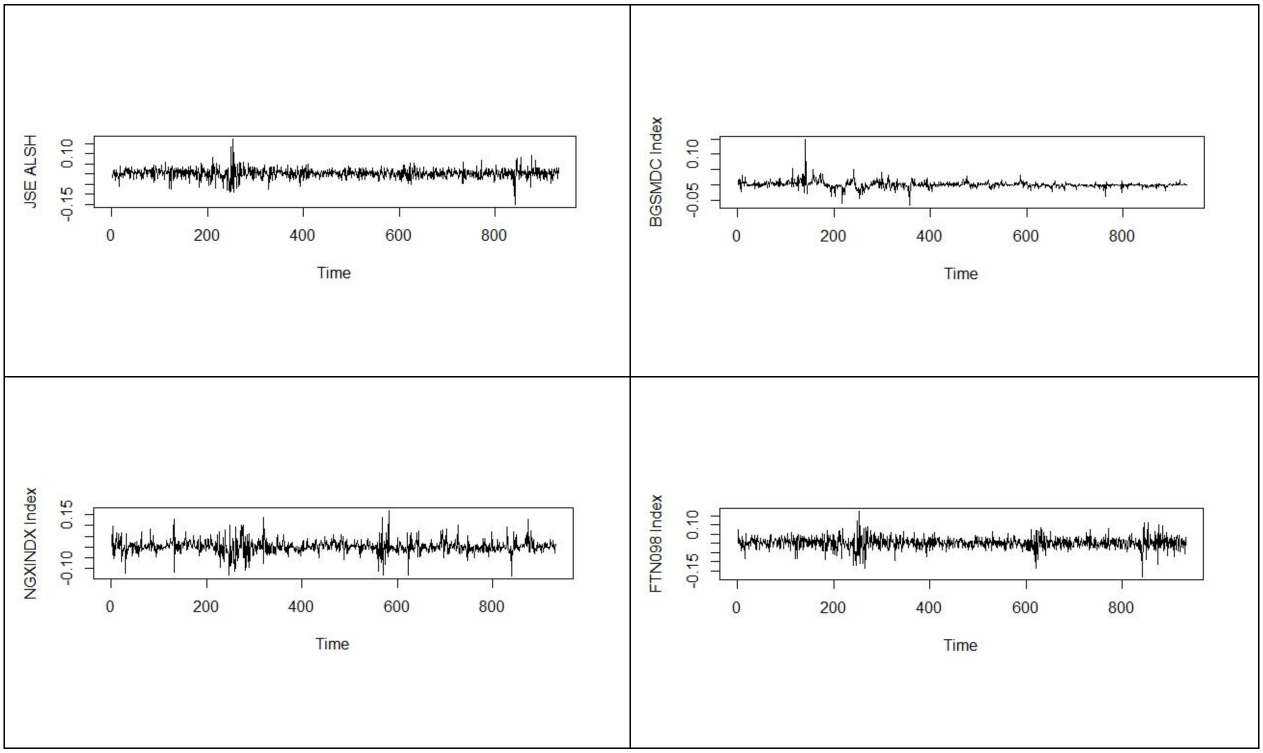

Figure 5: Individual Plots (African Markets)

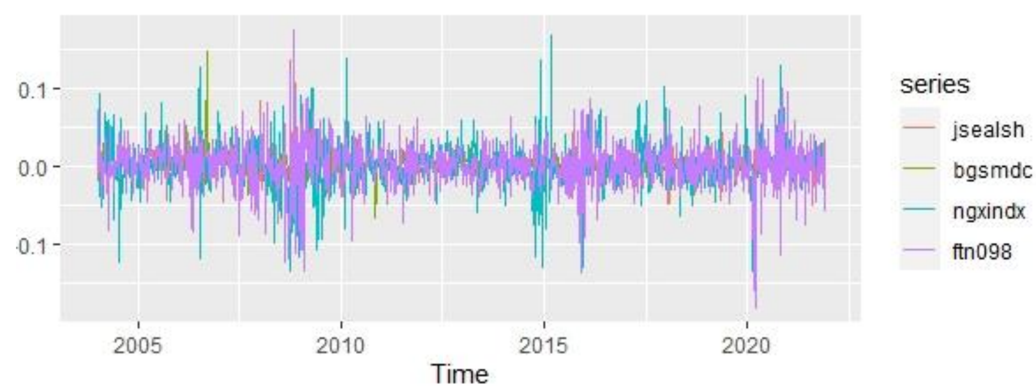

Figure 6: Grouped Plots (African Plots)

Table 13: JSE ALSH Estimation Results

<table>
<tr><td colspan="5">jse.alsh = jse.alsh.l1 + bgsmdc.l1 + ngxindx.l1 + ftn098.l1 + jse.alsh.l2 + bgsmdc.l2 + ngxindx.l2 + ftn098.l2 + jse.alsh.l3 + bgsmdc.l3 + ngxindx.l3 + ftn098.l3 + jse.alsh.l4 + bgsmdc.l4 + ngxindx.l4 + ftn098.l4 + jse.alsh.l5 + bgsmdc.l5 + ngxindx.l5 + ftn098.l5 + const
(VAR estimates predictive power that lags have on dependent variable)</td></tr>
<tr><td></td><td>Estimate</td><td>Std.Error</td><td>t value</td><td>Pr (> | t |)</td></tr>
<tr><td>Jse.alsh.l1</td><td>-0.065</td><td>0.072</td><td>-0.906</td><td>0.365</td></tr>
<tr><td>Bgsmdc.l1</td><td>-0.064</td><td>0.082</td><td>-0.778</td><td>0.437</td></tr>
<tr><td>Ngxindx.l1</td><td>0.108</td><td>0.027</td><td>4.054</td><td>0.000 ***</td></tr>
<tr><td>Ftn098.l1</td><td>-0.022</td><td>0.055</td><td>-0.402</td><td>0.688</td></tr>
<tr><td>Jse.alsh.l2</td><td>0.083</td><td>0.072</td><td>1.156</td><td>0.248</td></tr>
<tr><td>Bgsmdc.l2</td><td>0.064</td><td>0.083</td><td>0.771</td><td>0.441</td></tr>
<tr><td>Ngxindx.l2</td><td>0.051</td><td>0.027</td><td>1.897</td><td>0.058 .</td></tr>
<tr><td>Ftn098.l2</td><td>-0.098</td><td>0.056</td><td>-1.763</td><td>0.078 .</td></tr>
<tr><td>Jse.alsh.l3</td><td>0.045</td><td>0.072</td><td>0.623</td><td>0.533</td></tr>
<tr><td>Bgsmdc.l3</td><td>-0.072</td><td>0.083</td><td>-0.863</td><td>0.388</td></tr>
<tr><td>Ngxindx.l3</td><td>0.008</td><td>0.027</td><td>-0.288</td><td>0.774</td></tr>
<tr><td>Ftn098.l3</td><td>-0.095</td><td>0.056</td><td>-1.714</td><td>0.087 .</td></tr>
<tr><td>Jse.alsh.l4</td><td>-0.003</td><td>0.072</td><td>-0.039</td><td>0.969</td></tr>
<tr><td>Bgsmdc.l4</td><td>0.004</td><td>0.082</td><td>0.043</td><td>0.966</td></tr>
<tr><td>Ngxindx.l4</td><td>0.067</td><td>0.027</td><td>2.488</td><td>0.013 *</td></tr>
<tr><td>Ftn098.l4</td><td>-0.008</td><td>0.056</td><td>-0.141</td><td>0.888</td></tr>
<tr><td>Jse.alsh.l5</td><td>-0.155</td><td>0.070</td><td>-2.204</td><td>0.028 *</td></tr>
<tr><td>Bgsmdc.l5</td><td>-0.084</td><td>0.081</td><td>-1.037</td><td>0.300</td></tr>
<tr><td>Ngxindx.l5</td><td>-0.049</td><td>0.027</td><td>-1.839</td><td>0.066 .</td></tr>
<tr><td>Ftn098.l5</td><td>0.083</td><td>0.055</td><td>1.525</td><td>0.128</td></tr>
<tr><td>Const</td><td>0.003</td><td>0.001</td><td>3.294</td><td>0.001 **</td></tr>
<tr><td colspan="5">Signif codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1</td></tr>
<tr><td colspan="5">Residual standard error: 0.02508 on 906 degrees of freedom</td></tr>
<tr><td colspan="5">Multiple R-Squared: 0.05583, Adjusted R-squared: 0.03498</td></tr>
<tr><td colspan="5">F-statistic: 2.678 on 20 and 906 DF, p-value: 0.00009437</td></tr>
</table>

The VAR model is applied with the JSE.ALSH as the dependent variable and results point to the existence of several significant relationships. For starters, $NGXINDX_{k-1}$ is seen to have a positive effect that is statistically significant at the 99% confidence interval, with a coefficient of 0.108. Results relating to $NGXINDX_{k-4}$ and $JSE.ALSH_{k-5}$ are significant at the 95% confidence interval while $NGXINDX_{k-2}$, $FTN098_{k-2,}$ $FTN098_{k-3,}$ and $NGXINDX_{k-5}$ are significant at the 90% confidence interval respectively.

In Table 14, it is noted that BGSMDC is most significantly affected by $BGSMDC_{k-1}$, $BGSMDC_{k-2}$ and $BGSMDC_{k-4,}$ with all three variables having a positive effect. $NGXINDX_{k-1}$ and $NGXINDX_{k-3}$ also have a positive effect on BGSMDC with coefficients of 0.024 and 0.026 respectively, which are significant at the 95% confidence interval.

NGXINDX, for which results are tabulated in Table 15, shares a significant relationship with $JSE.ALSH_{k-3,}$ $FTN098_{k-3,}$ $JSE.ALSH_{k-4}$, $FTN098_{k-4,}$ and $NGXINDX_{k-5}$. $FTN098_{k-5}$ has an effect of -0.119 on NGXINDX, however, the results are only significant at the 90% confidence interval. The model also produces a p-value of 0.010, thereby solidifying findings.

Lastly, the VAR model is tested for FTN098 as the dependent variable and results show that its relationship with $NGXINDX_{k-1}$ and $FTN098_{k-1}$ respectively is statistically significant while the relationship with $NGXINDX_{k-4}$ and $FTN098_{k-4}$ is only statistically significant at the 90% confidence interval.

Table 14: BGSMDC Estimation Results

bgsmdc = jse.alsh.l1 + bgsmdc.l1 + ngxindx.l1 + ftn098.l1 + jse.alsh.l2 + bgsmdc.l2 + ngxindx.l2 + ftn098.l2 + jse.alsh.l3 + bgsmdc.l3 + ngxindx.l3 + ftn098.l3 + jse.alsh.l4 + bgsmdc.l4 + ngxindx.l4 + ftn098.l4 + jse.alsh.l5 + bgsmdc.l5 + ngxindx.l5 + ftn098.l5 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.alsh.l1	0.014	0.029	0.476	0.634
Bgsmdc.l1	0.214	0.033	6.499	0.000***
Ngxindx.l1	0.024	0.011	2.260	0.024 *
Ftn098.l1	-0.001	0.022	-0.061	0.952
Jse.alsh.l2	0.041	0.029	1.402	0.161
Bgsmdc.l2	0.131	0.033	3.925	0.000***
Ngxindx.l2	0.008	0.011	0.772	0.440
Ftn098.l2	-0.009	0.022	-0.404	0.687
Jse.alsh.l3	-0.021	0.029	-0.708	0.479
Bgsmdc.l3	0.055	0.034	1.629	0.104
Ngxindx.l3	0.026	0.011	2.386	0.017 *
Ftn098.l3	0.013	0.022	0.573	0.567
Jse.alsh.l4	-0.017	0.029	-0.586	0.558
Bgsmdc.l4	0.099	0.033	2.983	0.002 **
Ngxindx.l4	0.001	0.011	0.110	0.913
Ftn098.l4	0.001	0.023	0.032	0.975
Jse.alsh.l5	0.018	0.028	0.634	0.526
Bgsmdc.l5	0.053	0.033	1.640	0.101
Ngxindx.l5	-0.001	0.011	-0.069	0.945
Ftn098.l5	0.020	0.022	0.911	0.363
Const	0.000	0.000	0.892	0.373
Signif codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1				
Residual standard error: 0.01012 on 906 degrees of freedom				
Multiple R-Squared: 0.1783, Adjusted R-squared: 0.1602				
F-statistic: 9.83 on 20 and 906 DF, p-value: < 0.00000000000000022				

Table 15: NGXINDX Estimation Results

ngxindx = jse.alsh.l1 + bgsmdc.l1 + ngxindx.l1 + ftn098.l1 + jse.alsh.l2 + bgsmdc.l2 + ngxindx.l2 + ftn098.l2 + jse.alsh.l3 + bgsmdc.l3 + ngxindx.l3 + ftn098.l3 + jse.alsh.l4 + bgsmdc.l4 + ngxindx.l4 + ftn098.l4 + jse.alsh.l5 + bgsmdc.l5 + ngxindx.l5 + ftn098.l5 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.alsh.l1	0.015	0.089	0.163	0.870
Bgsmdc.l1	0.041	0.102	0.407	0.684
Ngxindx.l1	0.053	0.033	1.602	0.109
Ftn098.l1	0.051	0.069	0.735	0.463
Jse.alsh.l2	-0.119	0.089	-1.330	0.184
Bgsmdc.l2	0.073	0.103	0.709	0.478
Ngxindx.l2	0.007	0.033	0.205	0.838
Ftn098.l2	0.076	0.069	1.103	0.271
Jse.alsh.l3	-0.184	0.089	-2.056	0.040 *
Bgsmdc.l3	-0.072	0.104	-0.692	0.489
Ngxindx.l3	0.045	0.033	1.350	0.177
Ftn098.l3	0.162	0.069	2.340	0.020 *
Jse.alsh.l4	-0.207	0.089	-2.310	0.021 *
Bgsmdc.l4	-0.110	0.102	-1.076	0.282
Ngxindx.l4	0.039	0.033	1.161	0.246
Ftn098.l4	0.160	0.069	2.304	0.021 *
Jse.alsh.l5	0.127	0.087	1.461	0.144
Bgsmdc.l5	0.001	0.100	0.008	0.994
Ngxindx.l5	0.099	0.033	2.969	0.003 **
Ftn098.l5	-0.119	0.068	-1.749	0.081 .
Const	0.001	0.001	1.010	0.313
Signif codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1				
Residual standard error: 0.0312 on 906 degrees of freedom				
Multiple R-Squared: 0.04018, Adjusted R-squared: 0.019				
F-statistic: 1.897 on 20 and 906 DF, p-value: 0.01011				

Table 16: FTN098 Estimation Results

ftn098 = jse.alsh.l1 + bgsmdc.l1 + ngxindx.l1 + ftn098.l1 + jse.alsh.l2 + bgsmdc.l2 + ngxindx.l2 + ftn098.l2 + jse.alsh.l3 + bgsmdc.l3 + ngxindx.l3 + ftn098.l3 + jse.alsh.l4 + bgsmdc.l4 + ngxindx.l4 + ftn098.l4 + jse.alsh.l5 + bgsmdc.l5 + ngxindx.l5 + ftn098.l5 + const **(VAR estimates predictive power that lags have on dependent variable)**				
	Estimate	Std.Error	t value	Pr (> | t |)
Jse.alsh.l1	0.122	0.093	1.313	0.190
Bgsmdc.l1	-0.100	0.106	-0.941	0.347
Ngxindx.l1	0.108	0.034	3.144	0.002 **
Ftn098.l1	-0.175	0.072	-2.441	0.015 *
Jse.alsh.l2	0.064	0.093	0.688	0.492
Bgsmdc.l2	0.130	0.107	1.214	0.225
Ngxindx.l2	0.059	0.035	1.698	0.090 .
Ftn098.l2	-0.110	0.072	-1.523	0.128
Jse.alsh.l3	0.009	0.093	0.101	0.919
Bgsmdc.l3	-0.072	0.108	-0.666	0.506
Ngxindx.l3	0.007	0.035	0.198	0.843
Ftn098.l3	-0.077	0.072	-1.076	0.282
Jse.alsh.l4	-0.143	0.093	-1.537	0.125
Bgsmdc.l4	-0.039	0.107	-0.370	0.712
Ngxindx.l4	0.068	0.035	1.954	0.051 .
Ftn098.l4	0.127	0.072	1.754	0.080 .
Jse.alsh.l5	-0.130	0.091	-1.433	0.152
Bgsmdc.l5	-0.120	0.105	-1.151	0.250
Ngxindx.l5	-0.023	0.035	-0.669	0.503
Ftn098.l5	0.097	0.071	1.370	0.171
Const	0.002	0.001	2.179	0.030 *
Signif codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1				
Residual standard error: 0.03247 on 906 degrees of freedom				
Multiple R-Squared: 0.04461, Adjusted R-squared: 0.02352				
F-statistic: 2.115 on 20 and 906 DF, p-value: 0.002973				

4.4 Granger Causality Test Results (African Markets)

As was done for the BRICS markets, granger causality tests are done for the African markets to identify in which direction causality flows, with the same null hypothesis as previously mentioned. Table 17 shows that there is granger causality running from the Nigerian market to the South African market, with results being statistically significant at the 99% confidence interval. There is clearly no granger causality running from the Namibian market to the South African, which surprisingly was the case in a study done by Piesse and Hearn (2002), who argue that it is maybe due to the fact that South Africa is a much more open market, thus making it much more susceptible to unwanted spill over effects.

Table 17: JSE.ALSH Granger Causality Test Results

Granger causality test
Model 1: JSE ALSH ~ Lags(JSE ALSH, 1:5) + Lags(bgsmdc, 1:5)
Model 2: JSE ALSH ~ Lags(JSE ALSH, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 0.6389 0.6701
Granger causality test
Model 1: JSE ALSH ~ Lags(JSE ALSH, 1:5) + Lags(ngxindx, 1:5)
Model 2: JSE ALSH ~ Lags(JSE ALSH, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 6.2086 0.00001135 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Granger causality test
Model 1: JSE ALSH ~ Lags(JSE ALSH, 1:5) + Lags(ftn098, 1:5)
Model 2: JSE ALSH ~ Lags(JSE ALSH, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 1.8001 0.1102

Table 18 tabulates results of the same tests, with BGSMDC being the dependant and it is evident that the Botswana market seems to be the most influenced as there is granger causality running from the South African, Nigerian, and Namibian markets respectively with all results being significant at the 99% confidence interval. Thus, Botswana seems to be a follower within this pack. A possible reason for this could be the substantial number of foreign firms, particularly from South Africa being listed on the market in Botswana, thus making it susceptible to events happening in the mother country of these firms.

Table 18: BGSMDC Granger Causality Test Results

Granger causality test
Model 1: bgsmdc ~ Lags(bgsmdc, 1:5) + Lags(JSE ALSH, 1:5)
Model 2: bgsmdc ~ Lags(bgsmdc, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 3.9162 0.001614 **
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Granger causality test
Model 1: bgsmdc ~ Lags(bgsmdc, 1:5) + Lags(ngxindx, 1:5)
Model 2: bgsmdc ~ Lags(bgsmdc, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 3.1668 0.007676 **
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Granger causality test
Model 1: bgsmdc ~ Lags(bgsmdc, 1:5) + Lags(ftn098, 1:5)
Model 2: bgsmdc ~ Lags(bgsmdc, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 3.5057 0.003815 **
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

When analysing Table 19, which has NGXINDX, we fail to reject the null hypothesis on all three tests, meaning that there is no granger causality running from neither the JSE.ALSH, BGSMDC nor FTN098. Thus, the Nigerian market can be seen as one of the leaders within the pack. This is not surprising as Nigeria is considered to be the largest economy in the African continent, hence its ability to lead other African equity markets.

Lastly, Table 20 shows that the Namibian market is granger caused by the Nigerian market, as the model produces a p-value of 0.001, rejecting the null hypothesis and confirming statistical significance at the 99% confidence interval, which is again testament to Nigeria's ability to lead other African equity markets due to its economic position within the continent.

Table 19: NGXINDX Granger Causality Test Results

Granger causality test
Model 1: ngxindx ~ Lags(ngxindx, 1:5) + Lags(JSE ALSH, 1:5)
Model 2: ngxindx ~ Lags(ngxindx, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 0.7625 0.577
Granger causality test
Model 1: ngxindx ~ Lags(ngxindx, 1:5) + Lags(bgsmdc, 1:5)
Model 2: ngxindx ~ Lags(ngxindx, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 0.443 0.8185
Granger causality test
Model 1: ngxindx ~ Lags(ngxindx, 1:5) + Lags(ftn098, 1:5)
Model 2: ngxindx ~ Lags(ngxindx, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 1.1719 0.321

Table 20: FTN098 Granger Causality Test Results

Granger causality test
Model 1: ftn098 ~ Lags(ftn098, 1:5) + Lags(JSE ALSH, 1:5)
Model 2: ftn098 ~ Lags(ftn098, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 1.5772 0.1638
Granger causality test
Model 1: ftn098 ~ Lags(ftn098, 1:5) + Lags(bgsmdc, 1:5)
Model 2: ftn098 ~ Lags(ftn098, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 0.8501 0.5143
Granger causality test
Model 1: ftn098 ~ Lags(ftn098, 1:5) + Lags(ngxindx, 1:5)
Model 2: ftn098 ~ Lags(ftn098, 1:5)
Res.Df Df F Pr(>F)
1 916
2 921 -5 3.9876 0.001388 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

5. CONCLUSION

The study's aim was to investigate the degree to which South African, selected African and BRICS equity markets are interconnected and to assess the direction of granger causality amongst them, if any. With regards to the BRICS markets, the results show that interconnection exists as most lags from alternative markets within the group provide statistically and economically significant results. When it comes to granger causality within the group, the Russian and Chinese appear to be the somewhat stronger markets for different reasons. The Russian market can be seen as the leader as there is evidence of it granger causing all the remaining markets with the exception of the Chinese market, while only being granger caused by the Brazilian market. China on the other hand does not granger cause any market and is not granger caused by any of the markets. One can argue that it is positive because it shows that it is able to block out external influence and is able to provide diversification benefits for international investors. This is somewhat in line with findings from Lehkonen and Heimonen (2014) which showed that China was the most attractive BRICS market for US investors looking for diversification benefits. Others can argue that it is negative because it lacks the ability to influence other markets. The Indian market is the follower in the pack as it is granger caused by South Africa, Brazil and Russia while lacking the power to granger cause any market.

The same can be said for the African markets in terms of the interconnection between them. There is sufficient statistically and economically significant results within the group, which points to the existence of some sort of predictive power among some markets. This infers that there is interconnection between the African markets. With granger causality however, Nigeria, which is the biggest economy in Africa, emulates Russia in being the leader within the African group as it granger causes all the markets within the sample and is not granger caused by any of the markets. Botswana, like India, is the follower within the pack as it is granger caused by all the other markets within the group. There is no evidence of Namibia granger causing South Africa as was the case in a study by Piesse and Hearn (2002), which focused on Southern African markets.

The evidence points to the oil exporting markets, which are the relatively bigger economies to be the leaders as Russia is known to be one of the world's biggest oil exporters, mainly supplying the EU. Nigeria is also the biggest exporter in Africa, predominantly supplying to countries such as India, Netherlands, Spain, Brazil and South Africa. This does not necessarily mean that the smaller economies are to be the followers, as within the BRICS group, South Africa has the smallest economy, however, India is seen to be the follower of the pack. Same goes for the African markets, where Namibia has the smallest economy, but Botswana is seen to be the follower.

As globalization continues to rise and liberalization of financial markets continue, interconnection is becoming a more prominent characteristic of the global financial market. To expand on this study, further studies should look at how different macroeconomic factors affect the level of interconnection and explore the implications that interconnected markets have on international investors looking to diversify their portfolio.

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