Chapter

The Interdependence of Indexed Volatilities

Katlego Kola and Tumellano Sebehela

Abstract

Studies on indexed volatility spillovers are unique because indices encompass more information than other parameters used in illustrating volatility movements. Further, indices encompass most of the constituents listed on different stock exchanges around the globe. This chapter uses vector autoregression (VAR) for volatility spills and the Markov regime switching model to understand how different volatility regimes behave among bonds, commodities, equities and real estate indices of emerging markets. The results illustrate that volatility spillovers occur within (same) indices and across different indices. Moreover, those spillovers are within and across emerging countries. Interestingly, illiquid indices in certain situations move in between different volatility regimes more than liquid indices. Volatility strategies emanating from this study are equally applicable to both sell and buy sides in securities markets.

Keywords: BRICS, duration, Markov-regime switching, VAR(1), volatility spillovers

1. Introduction

Formation of organisation that represents countries with similar interests or likeminded goals can be traced many decades ago. Some of those organisations are continentally focused (i.e. African Union, former Organisation of African Unity in 1963 and European Union in 1958-its original roots) while other are global (i.e. United Nations in 1945). Recently, we have seen organisations that are Transatlantic-Brazil, Russia, India, China and South Africa (BRICS hereafter) countries. South Africa (SA) joined BRIC countries in 2009 through invitation by other member states while the four founding members originate from a term coined by Jim O'Neil (former Managing Partner of Goldman Sachs). While the origination of the BRIC term is influenced by the economic similarities, there are other interesting similarities about BRIC countries. The similarities of BRICS nation are (i) political structure-ruling parties stay in power for least 10 years without much challenge; although, we have recently seen the rising of opposition parties or citizens, (ii) country governance-ruling elites combine free market policies with socialism, and privatisation of government owned entities is extremely rare and (iii) economic policies-ruling parties champion economic direction and by extension economic of countries [1]. Some market commentators called that approach statism. However, statism is beyond the scope of this study. Those three traits have strong influence of the capital markets of those countries. The key question is what relationship exists between investments and associated risks. For this article, the special focus is on volatility spills.

That concept is commonly known as volatility transfer hypothesis (VTH). VTH is well documented across and within different traditional asset classes (i.e. stocks, bonds and money market instruments especially cash). Fundamentally, VTH argue that as one become familiar with a firm, the volatility of that firm decreases due to decrease in information asymmetry. However some scholars argue that VTH does not hold in every situation. On the practical side, specifically in among alternative asset classes, there are virtually no studies on VTH. This is the main gap that this article fills in. In analysis, the study draws data on bonds, commodities, equities and listed real estate from the BRICS countries. The analysis is essentially empirical. Both empirical and theoretical studies offer little, if any, insight on how volatility spillovers behave and their effects in the BRICS countries. The closest study that explores this theme is [2]. In [2], multivariate general autoregressive conditional heteroscedasticity (GARCH) and disaggregated value-at-Risk (VaR) are used to study traditional asset classes. This study goes beyond traditional asset classes and uses other models such as the regime-switching models. Similarly to [2], international diversification and risk management is central to volatility spillovers in BRICS countries.

A lot of policy documents show that jointly BRICS account for over billions of dollars investments including listed investments-in 2012 BRICS received over $1 billion in foreign aid. The population is highly consumptuous with a high percentage of population eligible to work for foreseeable future. In all those countries, ruling governments encourage their working force to save some of their earnings for later use in their life. Among the type of investments that potential future retiree can invest in include bonds, commodities, equities and listed real estate investments. Besides the type of investments that potential future retiree investments in, BRICS have their own special economic traits. South Africa offers one of the highly sophisticated capital markets in the world and China is the second biggest economy after the Unites States (U.S.). More, China has been moving at least 30 million people out of the poverty over the last 20 years. Given those massive investment opportunities in BRICS countries, how do investors maximise their returns and minimise their risks? One of the ways of minimising risks in the BRICS is by mitigating against volatility investment movements in the BRICS countries.

The consensus emerging from literature on asset co-movements is that asset markets are linked internationally, and volatility is transmitted from one market to another. Earlier studies of market linkages were habitually focused on developed countries however due to the financial liberalisation and trade openness of emerging economies, research has also focused on investigating cross-border links in emerging economies from developed countries. Emerging markets have increasingly played an important role in financial markets and were not spared from the impact of the global financial crisis. A better understanding of how emerging markets respond to exogenous shocks can assist investors and portfolio managers better understand if there are any diversification possibilities.

This article explores volatility spillovers in the BRICS countries based on alternative investment strategies. That is, alternative investment strategies involve investment in bonds, commodities, equities and real estate. For this study, seems real estate is listed because on one hand, the relationship between listed real estate and unlisted real estate is a mixed bag [3] and other the other hand, real estate is seen as a proxy for macroeconomic risks [4]. The macroeconomic risk proxy is also evident in other industries such as commodities. Moreover, diversification plays part in influencing commodity prices. Listed real estate is either real estate investment trusts (REITs) or real estate operating companies (REOCs). Further, those studies illustrate that those effects are trans-Atlantic. The reason why cash is not analysed in this article is because cash and money asset classes have been extensively researched. For example, over 60% of international trade is done on U.S. dollars and currency markets are the most liquid of all capital markets [5]. For this study, it is important to drive risk management strategies, especially when information is asymmetric.

The article similar to this study is one by Liow [6]. That study analysed spillovers of four major asset classes (public real estate, general equity, currency and bond) during 2007–2009 period. Given the longer period for this study, one foresees more interesting results than ones of Liow [6]. He used regime-switching, VAR and GARCH (1;1) models. This uses models used in [6] plus the regime-switching model. Liow [6] draws data from four continents; (i) Asia emerging countries, (ii) European emerging markets, (iii) Latin American emerging countries and (iv) South Africa. Other than being emerging countries, the BRICS are similar in the sense that ruling political elites stay in power for long periods (i.e. 15 years), more, those governments have come up with organisations that are most likely to compete with established institutions, i.e. the BRICS Bank is most likely to compete with the World Bank in future. Further, there is close political will among the BRICS which is not prevalent among all emerging countries. As volatility spills are driven by financial integration, liberalisation and crises contagion [6] among other factors, the former factors are likely to be key drivers for volatility spills among the BRICS countries. So far, it seems there are no major crises contagion reported in any of the BRICS countries.

To sum up, the results show that the indices (bonds, commodities, equities and real estate) illustrate that volatility spills are within and in between emerging countries. The volatility movements between countries are sporadic without any specific pattern(s)-most volatility spills are within countries. Those spills are evident in both out and in-sample data. Thus, lagged data of indices have evident volatility spillovers. Consistent with prior studies, the volatility spills move between different volatility regimes. Interestingly, liquid indices have less persistent regimes than illiquid indices. That would imply that illiquid indices are suitable for investments by intraday investors such as hedge funds while liquid indices are suitable for long-term investments-a rare finding. In [7], Markov-Switching-GARCH model is used, while this study uses general Markov regime switching model. The former model is univariate and discrete in nature while the latter is 'multivariate' and continuous in nature. Hedging was effectively reduced by 64% in [8] while in this study volatility risk is appropriately modelled.

The balance of this article is structured as follows: Section 2 is on literature review. Section 3 is on data and modelling, and Section 4 presents the analysis. Section 5 concludes the study.

2. Literature review

In criticising the prior studies this article divides literature review as per the four asset classes; (iii) bonds, (i) commodities, (ii) equities, and (iv) listed real estate. In this way, specific traits of each asset class are disentangled.

2.1 Bonds

In [9], it is explored volatility spills and return between equity and bond markets for Australia during the period of 1992–2006. They argue that volatility spills are important for diverse purposes; (i) asset allocation, (ii) portfolio management,

(iii) financial risk management, and (iv) capital market regulation. In this article, volatility spills are important largely for financial risk management. Among confirmed concepts on volatility spills (i) hedging demands increase with prices changes, (ii) positive news increases stock prices while prices fall when the discount rate rises. Normally, asymmetric price adjustment hypothesis (APAH) state that bad news affect bonds and stocks equally than good news. For modelling, they used joint process of conditional means, asymmetric Baba, Engle, Kraft and Kroner (BEKK) model, dynamic conditional correlation (DCC) model and bivariate GARCH model.

The data sample is on Australian equity and government bond markets, and the equity index was on 500 companies listed on Australian Stock Exchange. The preliminary results of [9] illustrate that equity volatility is lowest when returns of both markets are positive, and highest equity (bond) returns are negative (positive). More, when equity returns are negative, conditional correlation is stronger. As expected, distribution of returns are skewed and leptokurtic. Bond (equity) markets seem to react predominantly to negative (positive) news than positive (negative) ones. When the bond shock moves from negative angle to positive side, then equity variance surface tilts. Most volatility spills for equities are evident when returns are negative and visa verse for bonds. None of the used models were fully able to explain observed spills.

In [10], co-movements of volatilities in the international equity and bond markets were explored. They argue that genitive returns are more common and dependent than positive returns in international equity markets. In investigating volatility spills [10], the issue of fat tails was taken into account. The data presents the dependence between two leading markets in North-America (U.S. and Canada) and two major markets of the Euro zone (France and Germany). The U.S. equity index is based on the S&P500 index and Canadian equity index returns are based on DataStream index. The bond series are from 5-year government bond indices. The statistical tools used are exceedance correlation, extreme value theory (EVT) in order to capture fat tails and Gaussian bivariate GARCH or regime-switching models, specifically M-GARCH because of its ability to capture many variables. Copulas are used to increase the ability to capture asymmetric dependence.

The preliminary results of [10] show that there is a large, extreme dependence in international equity and bond markets while bond-equity dependence has a negative effect. The latter statement encourages international diversification and switching form equities into the domestic bonds. Historically, correlation between Canadian equity and bond markets has been relatively high. Further, results show that asymmetric regime of dependence and negative shocks are more likely to be transmitted to other markets than positive shocks. After the introduction of the Euro, France and Germany became more dependent. Broadly, high volatilities are associated with asymmetric dependence.

Ehrmann et al. [11] disentangled complexity of financial transmission process across different assets-domestically and internationally. They focus spillovers on two largest economies in the world-the U.S. and Euro area. The period covered is from 1998 to 2008 for two-daily returns over a 20-year period for seven asset prices: short-term interest rates, bond yields and equity market returns. For the U.S., data includes the 3-month Treasury bill rate for the short rate, the 10-year Treasury bond rate for the long rate and the S&P500 index for the stocks. For the Euro area, data is 3-month interbank rate-the FIBOR rate before 1999, the EURIBOR after 1999-for short rate, the German 10-year government bond for the long rate, and the S&P Euro index for the equity market and the U.S. dollar-euro since 1999. Every data is expressed as a percentage.

To model those spills [11], it was used a behavioural model that incorporated seven variables which had a 7×7 matrix. For reduced estimators, they used ordinary least squares (OLSs) model. Other methods used for Cholesky decomposition, alternative methodology for identification known as identification through heteroscedasticity (IH). They assume that structural shocks are uncorrelated and the matrix is stable for the entire. The latter principles are consistent with prior literature especially for ARCH and GARCH models. In presenting results [11], international transmission (i.e. direct effects and overall effects), response of the exchange rate and variance decomposition are shown. On international transmission, the direct effects show that spillovers are positive, both domestically and internationally. In those spills, the rise in foreign equity markets leads the spills. For overall effects, the key finding is that international transmissions are large for most assets but there are also international cross-market linkages. Moreover, the U.S. shocks led Euro shocks. Most of the co-movements were among the bond markets. Overall, the U.S. equity markets played a central role of influencing world stock markets. In relation to response of the exchange rate, the overall changes in relation to exchange rate reaction to bond yield changes are fairly small than direct effects. On the variance decomposition, during the 1989–2008 financial period, major spills were driven by the U.S. markets across every asset class in the study. The robustness tests support the earlier findings of the study. Thus, in global asset allocation one should mitigate against spills across most asset classes.

2.2 Commodities

In [12], volatility spills were investigated in commodity markets since 1700. They argue that some authors raised questions regarding the volatility of commodity prices been more than manufacturing ones, the secular trend since 1700 and relationship between globalisation and commodity volatilities. However, none of the scholars have addressed those questions using a long term series indeed.
For poor countries [12], it was argue that volatilities for those countries should be high because those countries specialise in agriculture and mineral production. The data used in [12] is for the world and various trends are outlined during specific periods. This is to consolidate reasons that drove commodity prices during those periods. They calculated log prices for their study, and used Dickey-Fuller and Phillips-Perron tests to validate their illustrate volatilities. Prebisch-Singer hypothesis was central to their analysis. Preliminary results of [12] show that volatilities among different commodities are different. In poor countries, volatilities tend to be higher because those countries are dependent on agriculture and mineral production. Sauerbeck-Statist shows no evidence of secular patterns from 1800 onwards. Further analysis illustrates that French and American Revolutionary Wars, the Napoleonic Wars and the War of 1812 contributed to increase in volatilities. In order to test the robustness of their results [12], GARCH (1;1) model and GARCH (1;1) was used and it was confirmed that results are robust. Seasonality also played a role in driving higher volatilities.

Antonakakis and Kizys [13] investigated dynamic spills between commodity and currency markets. In [13], it is argued that precious metals (gold, silver, platinum and palladium) have been seen as safe havens during final crisis. Further, they state that inclusion of precious metals in equity portfolios decreases systematic risk of investments; therefore, diversification accrues in those investments. They research is centred on these questions; (i) how time-varying spills differ among commodity and currency markets, and (ii) what is the relationship between returns and volatilities during financial transmission. In answering those questions, Antonakakis and Kizys [13] used the spillover index which is performed by using rolling-window forecast error variance decomposition (FEVD) by transmitters and receivers of shocks.

The weekly data in [13] is made up of the spot prices of the four precious metals, crude oil spot prices, euro (EUR/USD), Japanese yen (JPY/USD), British pound (GBP/USD) and the Swiss franc (CHF/USD) spot exchange rate, each versus U.S. dollar. They use weekly daily in order to synchronise data and error elimination [13]. The period of the data is from January the 6th, 1987 to July the 22nd, 2014, totalling 1438 observations. The usage of the four precious metals is well documented by numerous studies. The preliminary analysis of data illustrate that volatilities increased dramatically especially from 2000/2001 period for the precious metals and oil, while currencies volatility decreased from 2000/2001 onwards. Moreover, preliminary analysis shows that spot prices are positively skewed with exception of GBP/USD and CHF/USD. The absolute returns (volatility) for all parameters are positively skewed. And the Jarque-Berra tests confirm non-normality of distributions. Further analysis includes using vector autoregressive (VAR) model to illustrate return transmission across all the parameters. One of the advantages of VAR model is that it can cater for many variables.

The results of the VAR model illustrate volatility spills across all variables. Total spillovers index indicates 42.41% average contribution. Most transmission was from gold, followed by silver and then platinum. Crude oil had lowest transmissions. On the other hand, crude oil's demand is linked to four commodities as for production of those metals, crude oil is used. One of notable thing about [13] is that negative skewness has higher probabilities. Normally, the opposite should be true because positive skewness constituent more risk than a negative one. For all variables, the curves are positively skewed and leptokurtic. The latter statement would imply that prices spreads are significantly probably due to high volatilities. According [13], volatilities in commodity and currency markets are likely to occur during less volatile episodes. For robustness test, they used h-step-ahead forecast error variance decompositions and alternative rolling windows, and robustness tests confirmed that results main qualitatively similar.

Basak and Pavlova [14] modelled financialization for commodities markets. Prior studies have documented index and non-index commodities; however, the theory of financialization which is far-reaching implications had limited synthetisation [14]. The latter point is central to study of [14]. The main variables that were analysed in the study are (i) commodity supply shocks, (ii) commodity demand shocks, and (iii) (endogenous) changes in wealth shares of the two investor classes. The theoretical model that they built is a closed form. Fundamentally, in [14], it was argued that value assets pay off more in high-index states. In building the model, they assumed that the model follow Brownian motion (BM). The model included a parameter that signal arrival of news, supply news of uncorrelated commodities, model distinguish between index and non-index commodities, and the inventors were accounted for; (i) normal investors and (ii) institutional investors. Moreover, equilibrium effects of financialization of commodities were accounted for. Centrally to the last statement, instead of the model behaving like a trading model, it behaved like one for normal investor. Other equilibrium issues included (i) equilibrium commodity futures prices shaped on corollary, (ii) futures volatilities and correlations, and (iii) economy with demand shocks. Further, the illustrated commodity prices and inventories. For the commodity prices and inventories, they (i) incorporating storage where additional economic agents (i.e. consumers and firms) were added, (ii) equilibrium commodity prices and inventories. The second proposition is on how the discount factor is affected by institutional inventors. And finally, (iii) cross-commodity spillovers and the import of income shocks. The latter proposition is about how institutional demand increases for all assets are positively correlated with index, especially demand for commodity storage.

The results for [14] illustrated those volatilities in futures markets do spillover into other commodities. Further, there is a trade-off between investors due to relative performance fluctuates. The latter phenomenon is consistent with what is illustrated by VIX volatility index [14]. In addition, the model information is 'asymmetric and investors have the same beliefs'.

In [15], excess co-movements of commodity prices in developed (118 variables from Australia, Canada, France, Germany, Japan, the UK and the U.S.) and emerging markets (six variables from China, Brazil, Brazil, Taiwan, Mexico, etc.) were investigated. They argue that prior studies illustrate that financialization in the commodities markets lead to excess price volatility. One possible reason for that is that commodities especially of currency nature such as gold are characterised by spikes in prices. Central to their investigation is that (i) co-movements imply that 'demands and supplies are affected by unobserved forecast of the economic variable' and (ii) portfolio management strategies are affected by co-movements. The latter phenomenon resonates with this study. The variables that [15] are (i) the U.S. index of industrial production, (ii) consumer price index (CPI), (iii) effective $US exchange rate, (iv) three-month Treasury bill interest rate, (v) M1 monetary measure and (vi) S&P500 stock index.

One thing which is evident in [15] is that they are dealing with a large database which has numerous variables. And in order to probably account for those variables, you need a model that accounted for such variables. For the commodity prices, they used wheat, copper, silver, soybeans, raw sugar, cotton, crude oil and live cattle. Further, arbitrariness and computational difficulties should be minimised. One of the ways of how to avoid arbitrariness and computational difficulties is to use principal component analysis (PCA) and stepwise regression, although stepwise is time consuming when one uses many variables. In their analysis [15] focused on filtering commodity returns using large approximate factors models. And for that [15] used (i) static factor model and (ii) ARCH-LM for illustrating spillovers and (iii) SUR model to test whether residuals are unrelated.

The preliminary analysis of [15] the skewness of all commodities except of wheat is negatively skewed. Thus, wheat should have high volatilities than the rest of the commodities. And the Jarque-Berra test confirms non-normality for all commodities. The latter illustration is consistent with other studies on commodities. The correlation matrix shows that all commodities are correlated with one another except with live cattle. That is, live cattle in when compared with the seven commodities might offer diversification benefits. The results of returns show that crude oil and copper are costly correlated with variables of emerging markets. Monetary measures have more influence in emerging markets than developed countries. When they test for excess co-movement of commodity returns, results exemplify that commodity co-movements are common and influencing across all markets. Moreover, those co-movements are sampling dependent. In [15], it stated that given that the speculation is rife in commodity markets, some co-movements might be driven by speculation. The OLS model confirms the presence of endogeneity.

2.3 Equities

The Black Monday of October 1987, the U.S. born global financial crisis of 2008 and 2009, as well as the European debt crisis that occurred in late 2009 are known as the some of the few financial crisis in the past three decades that have resulted in the volatility of financial markets and further resulted in wide spread international crisis. These are known as co-movements of financial markets defined as volatility spillovers from one market to another. Volatility spillover studies have come to the vanguard as they are largely associated with risks that have implications on (i) optimal portfolio construction, (ii) financial stability and (iii) implementation of policies that may render harmful shock transmissions in financial markets. Recent studies that address the issue of volatility dynamics indicate that volatility spillover effects among countries or financial markets are time varying, most importantly during times of crisis. This has particularly significant consequences for investors and policy makers. Consequently, understanding the changing aspects of volatility spillovers is imperative.

In [16], both implied and realised volatility linkages were analysed through a rolling correlation analysis across global equity markets. This covers the U.S., European, German, Japanese, and Swiss markets during the sample period of 1999 to 2009. Implied volatility indices provide information regarding future uncertain expectations of stock price movements. Using the VAR method, the study indicates that both unconditional and conditional correlations for implied and realised volatility exhibit large fluctuations during that sample period. These results coincide with market fluctuations that occurred during the period of the global financial crises.

The consensus emerging from literature on asset co-movements is that asset markets are linked internationally, and volatility is transmitted from one market to another. Earlier studies of market linkages were habitually focused on developed countries however due to the financial liberalisation and trade openness of emerging economies, research has also focused on investigating cross-border links in emerging economies from developed countries. Emerging markets have increasingly played an important role in financial markets and were not spared from the impact of the global financial crisis. A better understanding of how emerging markets respond to exogenous shocks can assist investors and portfolio managers better understand if there are any diversification possibilities.

On another standpoint [2], volatility spillover effects were identified on a sectorial basis (industrial and financial sectors) from the U.S. as a developed country to BRICS nations as emerging markets using a VAR(1)-GARCH (1,1) framework. In the industrial sector, overall results indicate that the volatility transmission from the U.S. predominantly affects Brazil, Russia and India, while in the financial sector; it predominantly affects Brazil and Russia. In [17], the volatility impact is also indicated from developed markets by looking at regional spillovers across transitioning emerging markets and frontier equity markets, particularly in the Middle East and Africa together with the U.S. as the developed market. The study examines the stock markets of Saudi Arabia, UAE, South Africa and Israel from the period of 1994 to 2010 using a multi-timescale analysis using a wavelet-based time and frequency distributions compositions. The study finds that the Middle Eastern countries were more susceptible to the U.S. subprime crisis as compared to South Africa, however indication of short-term shocks that produced additional vulnerability in the South African equity market prior to the global financial crisis are noted, which could have potentially been due to investor sentiment.

Despite the increased studies of volatility spillover analyses from developed to emerging markets, there continues to be limited cross-market studies that are undertaken in equity markets of emerging nations. The possible integration of emerging markets continues to be of great concern as theory suggests that expected returns might be expected to reduce, following a greater integration of emerging markets in the world economy. Ref. [8] contributes to the empirical literature of volatility spillover dynamics between equity markets by examining the returns and volatility dynamics of Ghana, Kenya, Nigeria and South Africa for the period

2005–2010. The study employs a multivariate VAR-EGARCH framework and finds that Nigeria is the dominant in volatility transmission to Ghana, Kenya and South Africa and while it is not a receiver of volatility from these markets. The study however finds that the domestic volatility indices of these markets are the highest coefficients for all these markets, which implies that domestic shocks may impact these markets more than external shocks.

In [2], it was positioned that a more effective way of better understanding efficient asset pricing, volatility forecasting, efficient cross-market allocation and hedging decisions along with optimal international portfolio strategies is through understanding the stock market dynamics and volatility spillover effects of listed asset sectors individually in particular markets. Several literatures have focused on volatility spillovers in financial markets on a global, regional and country level. This section particularly focuses on volatility spillovers among equity stocks in financial markets. Cross-market volatility linkages in global developed equity markets attracted much attention in research. An earlier study of [18] studied the return volatility dynamics and transmission among the G-7 countries' equity markets using both the GARCH and VAR models. They find that while in these markets, domestic market shocks are the largest single source of domestic volatility variation for other markets, (apart from the U.K. and U.S.) shocks to foreign markets account for a significant portion of domestic market volatility. The study provides empirical evidence of volatility spillover effects in the equity markets of these industrialised countries. The results also indicate that volatility spillovers in these equity markets for this period had significant changes due to the global financial crises.

Studies such as [19] find that during tranquil times there are particular countries that are net transmitters of risk and others are net receivers of risk in global financial markets. The study particularly analyses the global financial shifts of volatility spillovers by employing the [20] forecast-error variance decomposition and incorporating a Markov switching framework which considers economic regime changes, into the generalised vector autoregressive (VAR) model. The study uses the following daily stock market volatility indices as proxies of market risk; the VIX (S&P 500 volatility, U.S.), VFTSE (FTSE 100 volatility, U.K). VCAC (CAC 40 volatility, France), VDAX (DAX 30 volatility, Germany). VAEX (AEX 25 volatility Netherlands), VSMI (SMI 20 volatility, Switzerland), VHSI (HIS 50 volatility, Hong Kong) and JNIV (Nikkei 225 volatility, Japan) for the period 2001 to 2017. The results of the study support the theory of shock transmissions and volatility spillovers by finding that all markets are more intense and are at the frequent risk of shock transmission and reception during turbulent times.

2.4 Listed real estate

The co-movement of real estate stocks and financial markets has been studied extensively. Previous literature has documented the theory that low correlation of an asset with other capital markets, international and domestic portfolios provides the opportunity for risk reduction and diversification in an investment [21]. In [22], the local, regional and global linkage of securitized real estate and stock markets and possible integration in nine developed markets from the three regions of North America (the U.S.), Europe (Germany, France, Netherlands and the U.K.) and Asia-Pacific (Japan, Hong Kong, Singapore and Australia) in the period 1990–2011 were investigated.

The study employs the spillover index of [20] that produces variance decompositions that are insensitive to variable ordering by allowing correlated shocks and historically observed distribution of the errors to account for the shocks. The spillover index is further based on a multivariate VAR that can capture market fluctuation of more than two countries concurrently rather than bivariate models. Liow [22] finds evidence of the following: (i) time-varying return co-movement and volatility spillovers in all markets and positive association with the global financial crisis (ii) a bi-directional and regime-dependant relationship of cross-volatility spillover effects, (iii) synchronisation between co-movements of volatility spillovers and correlation spillover cycles. Liow [23] studied time-varying co-movements of Asian real estate and the linkages of local, regional and global stock markets over the period of 1995 to 2009. Correlations of assets are interpreted to indicate co-movement and integration across financial markets. The integration of markets is also interpreted to indicate interdependence of markets which can lead to transmission crises.

Liow [23] demonstrates through an Asymmetric Dynamic Conditional Correlation (ADCC) model, also a specific class of multivariate GARCH models. Liow [23] finds time-varying conditional real estate-stock correlations at local, regional and global stock markets and some asymmetry and furthermore real estate-global stock correlation is impacted significantly by volatilities at local, regional and global levels. In this period, Liow [23] also finds that real estate and stock volatilities are more substantial in influencing co-variances more than correlations during and post the global financial crises. Hoesli and Reka [24] provided evidence on a national and international basis by investigating volatility spillovers between the U.S. and the U.K. real estate market, The U.S. and Australian real estate market as a national analysis and the U.S equity and real estate markets as an international analysis. The period of the study extends from 1990 to 2010 and the volatility spillovers are studied using the covariance matrix of the asymmetric t-BEKK (Baba-Engle-Kraft-Kroner) specification. On a national basis, the U.S is the net transmitter of volatility spillovers; this can be expected as the subprime crisis originated in the U.S. On an international basis, the three markets have more influence of volatility of the global market than the reverse, indicating quite the importance of these developed markets.

Liow and Ye [25] employed both univariate and multivariate switching regime beta models in the period of 2000–2015 to illustrate regime-dependant excess return distribution and volatility spillovers pre and post the global financial crises. The study examines the developed markets of the U.S., the U.K., France, Germany, Australia, Japan, Hong Kong and Singapore and their linkages with the world stock market and world real estate markets. The study uses switching regime models to allow for different economic conditions as well to capture the changes in the stochastic volatility process driving the real estate markets. The study reports a higher volatility parameter in response to the global financial crises compared to the 'normal' period. The real estate market linkages with the world market were affected differently by the global financial crises however they are amplified post-crises particularly for the European region, while the Asian real estate markets displayed reduced volatility spillovers with world markets in low volatility state post-crises.

Regime changes are associated with significant shifts in the fundamental relation between the risks and return trade-off and the probability that a switch can be initiated from one regime to another [26]. In [26], it was incorporated multiple regimes changes by modelling the return-volatility transmissions of real estate through the multivariate regime-dependent asymmetric dynamic covariance (MRDADC) model. They study the real estate markets of the U.S., the U.K, Japan, Hong Kong and Singapore for the period of 1990 to 2009. Firstly, the study finds that asymmetry, variance and covariance, associated with multiple regime changes, jointly influence return-volatility transmission in real estate markets and secondly the study finds that the five markets generally interact well with one another by finding significant mean-volatility linkages under different volatility regimes. Consequently, this has implications on diversification benefits that these markets can offer.

3. Data and modelling

3.1 Data

The weekly data is for the five BRICS countries (general equities, real estate, commodities and bonds) for the period 1 January 2007–31 December 2017 obtained from Bloomberg. The out-sample is from 2007 to 2017 and in-sample from 2012 to 2017. The in-sample is for parameters estimation and out-sample for evaluating forecasting performance. The use of weekly data ameliorates concerns over non-synchronicities and bid-ask effects in daily data [13]. The phenomenon of using returns to illustrate the descriptive nature of volatility spillovers is synonymous with [6, 27]. The returns are logarithm returns and they are consistent with VAR model. All returns are calculated based on the indices of those countries. The indices are as follows; (i) general equities, Brazil IBRX 50 for Brazil, Moex Russian index for Russia, Nifty 50 for India, SSE50 for China and JSE top 40 index for South Africa, (ii) listed real estate, IMOB for Brazil, for Russia the index is created based on PIKK Group, PJSC LSR Group, World Trade Centre 'ordinary shares' and World Trade Centre 'preferred shares' because Russia does not have a listed real estate index-the market capitalisations of those firms where aggregated over time, Nifty Realty for India, SHROP for China and all Property index (J803) for South Africa, (iii) commodities, BM&F BOVESPA for Brazil, MICEX Oil and Gas Index-from the Moscow exchange for Russia, Nifty Commodities for India, CCI for China and JCGMSAG (gold mining index) for South Africa and (iv) bonds, for Brazil-Brazil 8 7/8 04/15/24 bond, Russia-RFLB 08/29/18 bond, India-Nifty 10 yr. benchmark, China-GT USDCN 15yr bond and South Africa-SAGB 10 ½ 12/26 bond. Skintzi and Refenes [28] used indices to investigate regional and country shocks. This article is the first one that uses indices to illustrate shocks in the BRICS countries. According to [28], one of the advantages of modelling volatility shocks using indices is that

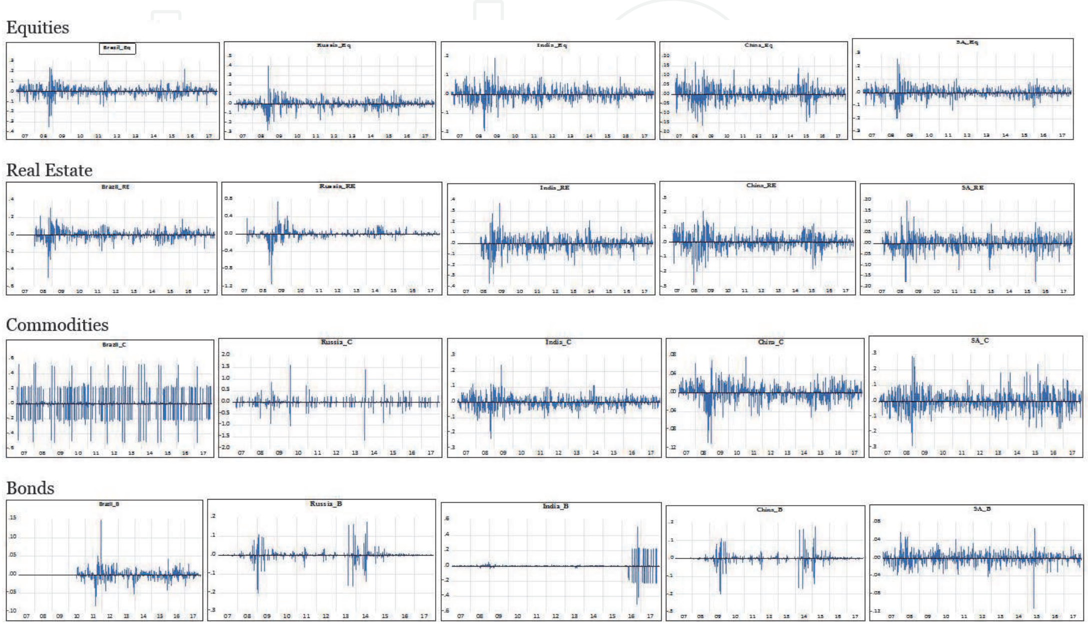

Figure 1.
BRICS log returns.

shocks are captured both as endogenous and exogenous variables. Just like [6, 27], this article presents diagnostic analysis based on graphs as part of volatilities transmission investigation.

For every index per a row, the first country is Brazil, followed by Russia, then India; thereafter, China and finally South Africa. A close inspection of **Figure 1** illustrate that the log returns of BRICS countries as shown by different graphs, BRICS returns were characterised by spikes during 2007–2017 period. The latter statement might be interpreted as the presence of changing volatility patterns and probably spillovers. Similar arguments were put forward by [6, 27] on return patterns. The years are on the x-axis and the log-returns on the y-axis. During 2008/2009, there was a global financial crisis that mainly affected western countries-western Europe and U.S. were the hardest hit by that subprime crisis. According to the Bank of International Settlements (BIS) Brazil only reacted to the global subprime crisis after Lehman Brothers collapsed. Due to that reaction, there was panic in Brazil lead to property market falling but IBOVESPA rose by 20%-in local currency; local capital issuance stood around $165 billion around 5.6% of Brazilian GDP. And bank credit increased to 36% from 32% during that period. Although, there still spikes after 2009, but they hoovered around same levels until 2017. For Russia, one sees similar pattern to Brazil. For both countries-Brazil and Russia, during subprime crisis, real estate reacts more than other indices. Does that imply that during subprime crisis volatilities are much higher in real estate?

Volatility modelling will provide answer(s) to that. Similar patterns are observable about Indian and Chinese indices. However, India and China have very strong capital markets and those countries are self-reliant on financing countries infrastructure. It seems that India and China tend to be insulated from external capital shocks [29]. South Africa is a unique member of the BRICS which joined through invitation. During year 2008, South African indices reacted to global capital markets movement; however, there was no subprime crisis effects felt in South Africa [30]. A study by PWC South Africa in 2016 illustrate that there was (i) a decline in new equity capital raised in South Africa, (ii) active and growing bond market in South Africa and (iii) number of corporate transactions decreased in South Africa. The decline in commodities index during 2014–2016 can be attributed to decline in commodities price and demand in commodities by South Africa trading partners. All those graphs illustrated diagnostic analysis on volatility spills. Now, the article takes the analysis further and it explores formative assessment of global transmission in the BRICS countries. The next section presents descriptive statistics of indices of the BRICS countries.

3.2 Data description and preliminary statistics

Table 1 provides the descriptive statistics of the returns of general equities, real estate, commodities and bonds.

Panel 1 indicates the equity information across all countries. Russia leads with the highest return at 28.41% while China has the lowest maximum return of 16.80%. Over the full period, Russian equities are also the most volatile with a standard deviation of 5.20% and the lowest volatile equities being that of China at 3.72%. The distribution of returns over time is negatively skewed with the exception of India and China. In addition, for all countries, the excess kurtosis exceeds 3, indicating that the return series is leptokurtic which is inconsistent with a normal distribution. The real estate data in panel 2 for the five countries indicate Russia with the highest return of 52.82% while the South Africa closed off with a lowest maximum return of 17.81% return. Russia is the most volatile with a weekly standard deviation of 7.65% while South Africa reports the lowest standard deviation of

Descriptions	Mean	Minimum	Maximum	SD	Kurtosis	Skewness	JB
Panel 1: general equity							
Brazil	0.0007	−0.3547	0.2385	0.051	7.0571	−0.6941	1235.05
Russia	0.0009	−0.4031	0.2841	0.052	9.1638	−0.0484	1987.64
India	−0.001	−0.1906	0.1956	0.037	3.2816	0.2699	264.06
China	−0.001	−0.1704	0.168	0.04	2.1323	0.0068	106.28
South Africa	−6E − 04	−0.2606	0.1984	0.043	5.1509	−0.0227	633.49
Panel 2: real estate							
Brazil	−0.002	−0.5044	0.3097	0.066	8.8189	−1.0306	1780.53
Russia	−0.001	−0.7145	0.5282	0.077	22.483	−1.3087	11613.2
India	0.003	−0.3752	0.3719	0.072	4.0292	0.2754	384.67
China	−0.002	−0.2161	0.2894	0.054	2.6673	0.3788	179.68
South Africa	−0.001	−0.1961	0.1781	0.037	4.2404	0.4225	428.42
Panel 3: commodities							
Brazil	0.0002	−0.529	0.5435	0.177	2.0477	0.0046	100.11
Russia	−8E − 04	−1.6035	1.6337	0.199	22.8521	−0.2209	12.385
India	0.0009	−0.2369	0.2432	0.042	3.8767	−0.0754	359.35
China	0.0005	−0.1096	0.0768	0.02	4.0293	−0.7607	442.87
South Africa	−0.002	−0.2866	0.286	0.065	2.0176	0.3055	106.1
Panel 4: bonds							
Brazil	0.0001	−0.0845	0.1474	0.016	21.5203	1.6562	7763.32
Russia	−2E − 04	−0.2019	0.1777	0.029	20.4736	−0.7622	9466
India	−3E − 04	−0.5151	0.5113	0.065	26.9833	−1.1651	17455.1
China	−3E − 04	−0.1126	0.0661	0.015	7.2105	−0.5118	1266.32
South Africa	−1E − 04	−0.2019	0.1777	0.029	20.4549	−0.7619	9431.2

Note: SD stands for standard deviation and JB for Jarque-Bera test for the return normality.

Table 1.
Descriptive statistics.

3.68%. All five countries exceed the kurtosis of 3 and with the exception of Brazil and Russia, the data is positively skewed.

For commodities indicated in panel 3, Russia reports the highest maximum of 163.37% in returns, while India reports the lowest at 7.68%. Russia commodity stocks are more volatile with a standard deviation of 19.87% and the Chinese stocks are the least volatile at the standard deviation of 2.02% All countries exceed the kurtosis of 3 and the data is negatively skewed with the exception of Brazil and South Africa. In the bonds market indicated in panel 4, India has the highest return at 51.13% while China has the lowest maximum return at 6.61%. India is also the most volatile with a standard deviation of 6.50% and China. The data is also leptokurtic and is negatively skewed with the exception of Brazil. JB values in all panels (i.e. 1–4) illustrate that the four indices are abnormal and that can be interpreted as the presence of shocks. In [6], the same view on JB values was stated. The skewness values show that some countries have negative skews while others have positive skews for different capital markets. That mixture of different skewness assist in hedging volatility while positive skewness assist in generating high alpha and/or arbitrage opportunities. The former phenomenon is ideal for risk managers while the latter phenomenon is suitable for intraday investors-traders.

3.3 Volatility spillover modelling

Volatility and volatility transmission can be illustrated using most econometric models including VAR model. The formula for VAR model is:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t \tag{1}$$

Where the l-periods back observation y_{t-1} is called the l-th lag of l-th lag of y, c is a $k * 1$ vector of constants (intercepts), A_j is the time-invariant $k * k$ matrix and e_t is a $k * 1$ vector of error terms satisfying $\mathrm{E}(e_t) = 0$, every error term has mean zero. $\mathrm{E}\left(e_t e_t'\right) = \Omega$, the contemporaneous covariance matrix of error terms is Ω (a $k * k$ positive-semidefinite matrix. $\mathrm{E}\left(e_t e_{t-k}'\right) = 0$, for any non-zero k, there is no correlation across time; in particular, no serial correlation in individual error terms.
In order to have a deeper insight in volatility spills, this article proposes using regime-switching model in order to capture different spills regimes. The common model used for regime-switching variables is Markov switching model. The simple Markov model of conditional mean presented when s_t denotes an unobservable state variable assuming the value one or zero. A simple switching model for the variable z_t involves two AR specifications:

$$z_t = \begin{cases} \alpha_0 + \beta z_t + \varepsilon_t, s_t = 0, \\ \alpha_0 + \alpha_1 + \beta z_t + \varepsilon_t, s_t = 1, \end{cases} \tag{2}$$

where $|\beta| < 1$ and ε_t are i.i.d. random variables with mean zero and variance σ_ε^2. This is a statitionay AR (1) process with the mean $\frac{\alpha_0}{1-\beta}$ when $s_t = 0$, and it switches to another stationary AR (1) process with mean $\frac{\alpha_{0+\alpha_1}}{1-\beta}$ when $s_t = 1$. If $\alpha_1 \neq 0$ then the model admits two dynamic structures at different levels, depending on the value of the state variable s_t. In this case, z_t are governed by two regimes with distinct means, and s_t determines switching between two different regimes. The transition matrix for the Markov is:

$$\mathcal{P} = \begin{bmatrix} IP(s_t = 0|s_{t-1} = 0) IP(s_t = 1|s_{t-1} = 0) \\ IP(s_t = 0|s_{t-1} = 1) IP(s_t = 1|s_{t-1} = 1) \end{bmatrix} \tag{3}$$

and

$$= \begin{bmatrix} p_{00} \; p_{01} \\ p_{10} \; p_{11} \end{bmatrix}, \tag{4}$$

where p_{ij} $(i, j = 0, 1)$ denote the transition probabilities of $s_t = j$ given that $s_t = i$. The transition probabilities satisfy $p_{i0} + p_{i1} = 1$. The matrix governs the random behavior of the state variable, and it contains two parameters $\left(p_{00} \text{ and } p_{11}\right)$.
One can extend model (5) such that a more general dynamic structure is captured. Then model (2) is extended into:

$$z_t = \alpha_0 + \alpha_1 s_t + \beta_1 z_{t-1} + \dots + \beta_k z_{t-k} + \varepsilon_t \tag{5}$$

where $s_t = 0, 1$ are still the Markovian state variables with the transition matrix (3a) and ε_t are i.i.d. random variables with zero and variance σ_ε^2. This is a model with a general $AR(k)$ dynamic structure and switching intercepts. For the d-dimensional time series $\{z_t\}$, Eq. (4) can be re-written as:

$$z_t = \alpha_0 + \alpha_1 s_t + B_1 z_{t-1} + \dots + B_k z_{t-k} + \varepsilon_t \tag{6}$$

while $s_t = 0, 1$ are still the Markovian state variables with the transition matrix (3a), $B_i(i = 1, \dots, k)$ are matrices of parameters, and ε_t are i.i.d. random vectors with zero and variance–covariance matrix $\sum_0$. Eq. (5) is a VAR model with switch intercepts. Although generalisation is easy but some parameters such as d variables might be difficult to estimate.

4. Analysis

In presenting the empirical results, the article starts with VAR calculations. Thereafter, Markov regime-switching results are presented in order to explore if one can infer interdependence of volatilities regimes. In order to verify which VAR is suitable, the first and second order tests (i.e. residual serial correlation) testing validity are used. Thereafter, a lag-length criterion is used. All those tests confirmed the appropriateness of VAR (1) model. Further, in order to interpret the results Cholesky decomposition is used. Generally, when using Cholesky decomposition the order of VAR parameters order matters. The BRICS countries are inputted in alphabetical order because that order is consisted with normal writing order. Although, VAR results might be different when one inputs them in a different format, one views normal order as an appropriate one. It can be inferred from [31] alphabetical order modelling leads to better estimates. In **Tables 2** and **3** all variables highlighted in grey are statistically significant for VAR values as they are at least 2 irrespective of being negative or positive. The F-statistic is basically Anova values and one reads the in the following manner. Assume the following inequality $F(2, 12) = 22.59, p < 0.05)$, the 2 is the degrees of freedom numerator, 12 is total observations of freedom denominator, 22.59 is the calculated Anova value and 0.05 is alpha (i.e. significance level). This article assumes that both the degrees of freedom numerator and total observations of freedom denominator are infinities in order to illustrate the best case scenario. In the latter situation, the critical value is 1.22. Thus, F-statistic values highlighted in grey fall within the non-rejection (i.e. acceptable) regions while values which are not highlighted fall within rejection regions. That is, latter values exemplify autocorrelation for those VAR(1) model.

The results panel 5 of **Table 2** illustrates that one-lag in Brazilian indexed volatility of bonds cause one-lag in Brazilian indexed volatility of bonds by 0.18 units. The letter statement is sensible given that what happens in one market should have similar effect in the short run-regimes show that regimes time is just over 2 weeks. Similarly, a one-lag in Brazilian indexed volatility of bond cause one-lag in South African indexed volatility of bonds-this probably that of similarities between the two countries, i.e. ruling political parties stay in power much longer; historically, Brazil and South Africa have good trade relations and further, the BRICS formation is strengthening that relationship even more. The one-lag in Indian volatility of bonds cause one-lag in Indian volatility of bonds. The phenomenon is similar with the one of Brazil lags; however, Indian one is negative while Brazil one is positive. One possible explanation for India negative lag is that in India the government is highly involved in driving economic growth than in Brazil.

Panel 5: bonds					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	0.1833 (4.4095)	−0.0202 (−0.2429)	0.2881 (1.5718)	−0.0201 (−0.24301)	0.0332 (0.7153)
China	0.0077 (0.0038)	1.7959 (−0.4477)	−0.8782 (−0.0993)	−1.4175 (−0.3533)	0.2652 (0.1185)
India	−0.0004 (−0.0440)	0.0050 (0.2812)	−0.4140 (−10.5584)	0.0049 (0.2801)	0.0114 (1.1494)
Russia	−0.0226 (−0.0113)	1.4237 (0.3549)	0.8546 (0.0966)	1.0447 (0.2605)	−0.2573 (−0.1150)
South Africa	0.1055 (2.7839)	−0.0280 (−0.3701)	0.0383 (0.2292)	−0.0280 (−0.3697)	−0.0003 (−1.9232)
F-statistic	5.2479	17.9005	23.0227	17.9331	1.1701
Akaike AIC	−5.8292	−4.4438	−2.8618	−4.4433	−5.6106
Schwarz SC	−5.7830	−4.3973	−2.8157	−4.3907	−5.5643

Panel 6: commodities					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	−0.4092 (−10.5168)	−0.0125 (−2.6652)	−0.0063 (−0.6138)	0.0339 (0.7887)	−0.0089 (−0.5621)
China	0.3609 (0.9718)	0.2844 (6.3448)	0.0436 (0.4442)	−0.5516 (−1.3461)	−0.2129 (−1.4044)
India	0.0028 (0.0162)	0.0159 (0.7539)	0.0670 (1.4443)	0.1208 (0.6232)	−0.0092 (−0.1288)
Russia	−0.0701 (−1.9894)	0.0059 (1.3848)	0.0048 (0.5099)	−0.2919 (−7.5058)	0.0033 (0.2270)
South Africa	−0.0943 (−0.8626)	−0.0078 (−0.5876)	0.0627 (2.1706)	0.1935 (1.6049)	−0.0114 (−0.2545)
F-statistic	22.7883	11.7035	2.3085	12.2434	0.7016
Akaike AIC	−0.8059	−5.0351	−3.4670	−0.6091	−2.5984
Schwarz SC	−0.7597	−4.9888	−3.4208	−0.5629	−2.5522

Panel 7: equities					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	−0.1469 (−2.0726)	−7.4597 (−1.3644)	1.2495 (0.2433)	2.5543 (0.3575)	7.1695 (1.2132)
China	0.0000 (−0.0920)	0.0178 (0.4235)	0.1028 (2.5982)	−0.0552 (−1.0039)	−0.0616 (−1.3525)
India	−0.0002 (−0.3129)	−0.0531 (−0.8988)	−0.0257 (−0.4625)	0.1499 (1.9421)	0.0724 (1.1336)
Russia	−0.0008 (−2.0001)	−0.0213 (−0.6589)	−0.0082 (−0.2684)	−0.0094 (−0.2233)	0.0520 (1.4883)
South Africa	−0.0004 (−0.4955)	0.0826 (1.2342)	0.1263 (2.0106)	0.0982 (1.1239)	−0.0959 (−1.3261)

Panel 7: equities					
	Brazil	**China**	**India**	**Russia**	**South Africa**
F-statistic	1.9912	2.5000	2.7793	2.7791	2.7064
Akaike AIC	−12.2983	−3.6080	−3.7334	−3.0728	−3.4525
Schwarz SC	−12.2520	−3.5618	−3.6871	−3.0266	−3.4062
Panel 8: real estate					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	−0.0197 (−0.3642)	−0.1362 (−2.9988)	−0.0720 (−1.2489)	0.0276 (0.4412)	0.0031 (0.1009)
China	0.0236 (0.4708)	−0.0399 (−0.9456)	0.1344 (2.5099)	−0.0325 (−0.5584)	−0.0011 (−0.0391)
India	−0.0259 (−0.5738)	−0.0286 (−0.7487)	0.0162 (0.3345)	−0.1256 (−2.3889)	0.0097 (0.3717)
Russia	−0.0229 (−0.6359)	−0.0504 (−1.6582)	0.0466 (1.2075)	0.1679 (4.0062)	0.0332 (1.6033)
South Africa	0.0107 (0.1145)	−0.0780 (−0.9927)	0.1783 (1.7871)	0.0010 (0.0093)	−0.0233 (−0.0449)
F-statistic	0.2134	2.6753	3.8118	5.8949	0.6335
Akaike AIC	−2.6706	−3.0149	−2.5382	−2.3731	−3.7809
Schwarz SC	−2.6244	−2.9687	−2.4919	−2.3269	−3.7347

Note: in each cell, the first number is the coefficient and the number in brackets is the t-test. All variables highlighted in grey are statistically significant for VAR values as they are at least 2 irrespective of being negative or positive. The interpretation of results is based on Cholesky decomposition.

Table 2.
VAR (1): out-sample period (2007–2017).

All other indexed volatilities of bonds in other BRICS countries are statistically insignificant. However, those latter results should be read with caution as using Cholesky decomposition for curves for those countries to start at zero. Panel 6 of **Table 2** illustrates results for commodities indexed volatilities.

The statistically significant results are for Brazil and Brazil-this is for the same reasons as in panel 5, Brazil and China-Brazil is the producer of commodities while China is a consumer. This implies that the one-lag in producer of commodities indexed volatilities causes one-lag in consumer indexed volatilities but not visa verse. More, the coefficient is negative because the effects spillover to the consumer from the producer. The results for China lags can be explained by same reasons as the Brazil lags. Similarly, the one-lag in Indian index volatility cause a one-lag in South African indexed commodities volatility-the same as the Brazil and China one lags. The Russian lags are the same as China lags. Note that China lag with itself is positive while Russia lag with itself is negative. The positive lag for China lag with itself is probably due the economic influence that China has on the major world issues. The influence of Russian on major economic issues is limited. Thus, it might imply that South Africa needs to establish itself globally before the South African government can play a major on South African economic issues.

Panel 7 shows that spillovers which are statistically significant are for Brazil lags with itself-this pattern has been explained before, Brazil lag with Russian lag-in

Panel 9: bonds					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	0.1876 (3.8632)	−0.0120 (−0.1567)	0.2688 (1.1956)	−0.0121 (−0.1578)	0.0278 (0.6435)
China	−0.0817 (−0.0304)	−2.0308 (0.4779)	−1.6449 (−0.1322)	−1.5335 (−0.3608)	−0.7866 (−0.3289)
India	0.0001 (0.0114)	0.0056 (0.3399)	−0.4205 (−8.7141)	0.0056 (0.3386)	0.0099 (1.0653)
Russia	0.0553 (0.0259)	1.6457 (0.3874)	1.6068 (0.1292)	1.1477 (0.2701)	0.7689 (0.3216)
South Africa	0.1664 (3.0025)	0.08445 (0.9643)	−0.1679 (−0.6544)	0.0837 (0.9552)	−0.1354 (−2.7462)
F-statistic	4.5645	14.0761	15.7002	14.1098	2.0675
Akaike AIC	−5.5172	−4.6011	−2.4522	−4.6006	5.7506
Schwarz SC	−5.4585	−4.5423	−2.3935	−4.5419	−5.6919

Panel 10: commodities					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	−0.3855 (−7.4290)	−0.0166 (3.4736)	−0.0097 (−0.9339)	0.0746 (1.2989)	(−1.0249)
China	0.8517 (1.3579)	0.1761 (3.0423)	0.0542 (0.4329)	−1.2171 (−1.7521)	(−1.6324)
India	−0.3983 (−1.3512)	0.0242 (0.8910)	0.0728 (1.2363)	−0.1864 (−0.5711)	(1.2772)
Russia	−0.1453 (−3.0541)	0.0010 (0.2295)	0.0015 (0.1561)	−0.3677 (−6.9804)	(1.1867)
South Africa	0.0280 (0.1981)	0.0177 (1.3538)	0.0216 (0.7648)	0.1967 (1.2551)	(1.2906)
F-statistic	12.6282	5.3503	0.7579	11.8936	0.0651
Akaike AIC	−0.8229	−5.5888	−4.0445	−0.6187	−2.6074
Schwarz SC	−0.7506	−5.5165	−3.9722	−0.5464	−2.5350

Panel 11: equites					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	0.0795 (1.0222)	−6.1630 (−0.9579)	−3.1423 (−0.6267)	−15.9395 (−2.1685)	−4.7373 (−0.8339)
China	0.0011 (1.6271)	0.0537 (0.9391)	0.0342 (0.7611)	−0.1100 (−1.6849)	−0.1395 (−2.7636)
India	0.0009 (0.8208)	−0.0566 (−0.6371)	0.1208 (1.7324)	−0.0125 (−0.1229)	−0.0386 (−0.4921)
Russia	−0.0002 (−0.2543)	−0.1442 (−2.3803)	0.0363 (0.7626)	−0.1418 (−2.0488)	0.0223 (0.4165)
South Africa	0.0009 (0.7747)	0.0287 (0.3102)	−0.0790 (−1.0876)	0.1526 (1.4447)	−0.0512 (−0.6272)
F-statistic	0.8648	1.5195	1.2508	3.1221	1.6589
Akaike AIC	−12.7912	−3.9589	−4.4415	−3.6926	−4.2078

Panel 11: equites					
Schwarz SC	−12.7188	−3.8867	−4.3692	−3.6203	−4.1355
Panel 12: real estate					
	Brazil	**China**	**India**	**Russia**	**South Africa**
Brazil	0.0041 (0.0635)	0.0284 (0.4825)	−0.0729 (−0.9954)	−0.1126 (−2.1609)	−0.0207 (−0.4699)
China	0.1213 (1.8983)	−0.0306 (−0.5308)	0.1037 (1.4455)	0.0393 (0.7707)	−0.0794 (−1.8378)
India	−0.0482 (−0.8873)	−0.0046 (−0.0943)	0.0426 (0.6990)	−0.0174 (−0.4013)	−0.0282 (−0.7678)
Russia	−0.0309 (−0.4209)	−0.0771 (−1.1644)	−0.0512 (−0.6213)	−0.0362 (−0.6179)	−0.0266 (−0.5363)
South Africa	−0.0128 (−0.1304)	0.0293 (0.3308)	0.1061 (0.9652)	−0.1355 (−1.7336)	−0.0415 (−0.6271)
F-statistic	1.0215	0.3552	0.0529	1.5103	0.8958
Akaike AIC	−3.2510	−3.4551	−3.0200	−3.7027	−4.0345
Schwarz SC	−3.1787	−3.3828	−2.9477	−3.6305	−3.9622

Note: in each cell, the first number is the coefficient and the number in brackets is the t-test. All variables highlighted in grey are statistically significant for VAR values as they are at least 2 irrespective of being negative or positive. The interpretation of results is based on Cholesky decomposition.

Table 3.
VAR(1;1): In-sample period (2012–2017).

both countries, commodities firms are the main constituents of equities indices. And the causal relationship is slightly negative. Thus, 1 unit lag in Brazilian indexed volatilities emanating from equities cause −0.0008 lag in Russian indexed volatility of the same index. The latter strategy is synonymous with hedging and speculation in equity markets. More, straddles work in a similar manner. Panel 8 shows the results of lags in real estate indices. The statistically significant lags are for Russia with itself-that pattern has been explained before, China and Brazil-Brazil is probably the most powerful economy in South American while China is the second biggest economy after the United States. China has been on major infrastructure projects including real estate and many academics and practitioners have questioned whether the bubble is in the horizon in China. The negative coefficient is probably due to ‘overbuilding’ in China. Indian lagged volatility cause a positive lag in China. The latter finding is probably due to ruling parties’ influences in managing their economies. Interestingly, one-lag in Russian volatility causes one-lag in India. Normally, collapse of currencies and commodities markets precede other capital markets products. Overall, one can see that volatility spillovers in the BRICS countries based on four indices during 2007–2017 period, exemplify opportunities to diversification opportunities-when indexed volatilities move in different directions and risk management opportunities-when indexed volatilities move the same direction.

The influence of Brazil lag to South Africa lag during period of 2012–2017 is the same as during the 2007–2017 period as illustrated in panel 9. The period of 2012–2017 was largely a bull market while 2007–2017 had some bearish years, i.e. 2008/2009 period. This implies that indexed volatilities of bonds during out-sample

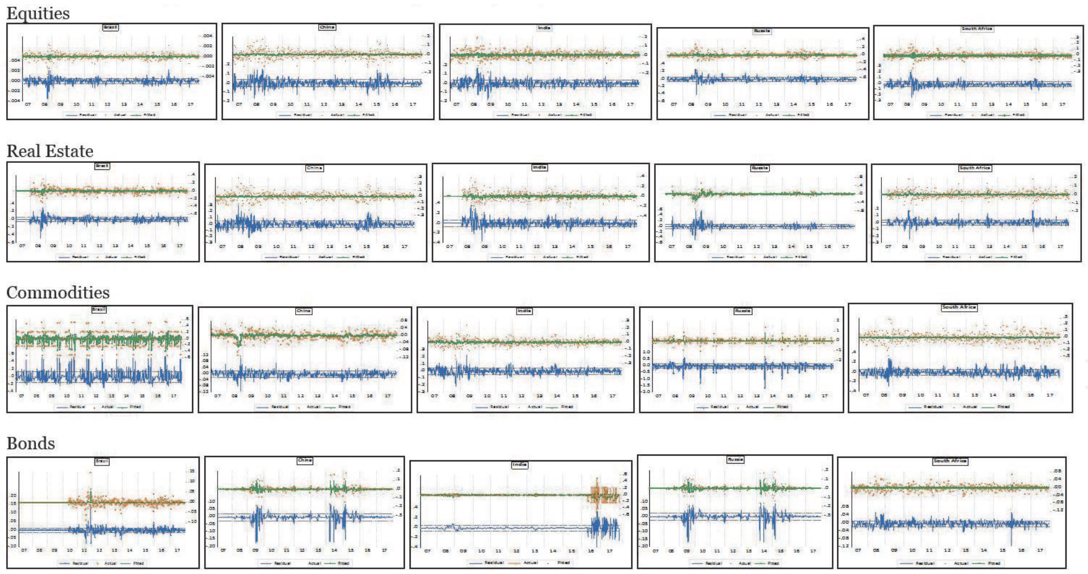

Figure 2.
Filtered regime probabilities-out sample: 2007–2017.

reflect similar patterns as in-sample period. The sample phenomenon can be advocated on the influence the one-lag of Indian volatility on the lag of India. The interesting result in panel 9 is the one-lag of South Africa with itself-during the in sample period the lag is influential. During 2012–2017, the South African long-and short-term yields were on an upward trajectory. This is probably why one-lag for South Africa in during the in-sample period had a casual effect. For commodities indices-panel 10, the rests are the same as in **Table 2** except the one-lag of Brazilian volatility on one-lag of Russia. During 2012–2017, commodities prices were stable. In panel 11, one-lag of China has influence on one-lag of Russia and one-lag of South Africa had one-lag on China-all the lags are negative. This is probably to declining consumption on commodity products by China. The rest of results are in panel 11 are the same as in panel 7. For panel 12, only one-lag of has a negative influence one-lag of Brazil. In short-run volatilities tend to be spiky than in the long run. That is, the volatility spillovers might be temporary.

For every index type in **Figure 2** in every row, the first country is Brazil followed by China and then India; thereafter Russia. The last country is always South Africa. For equities indices, all the five countries have main shocks in 2007–2008 period as illustrated by residuals. This is the period of the last subprime crisis. However, the actual date reveals a similar picture. The upward regimes in all countries were during 2007–2009 period. It can be inferred from [6, 27] that when indices move in the same direction, the volatilities should follow a similar pattern. But, those graphs do not tell one from and to which are the volatilities. The equities volatilities in Brazil and South Africa seem to hover around the same level during the entire out sample. In [30], it was illustrated the subprime effects of 2007–2009 in South Africa were minimal. From what was reported in media, Brazil never suffered much from the subprime effects of 2007–2009. Real estate indices show the similar patterns as equities indices except for China and India. Sometimes during subprime crises, equities movements preceded real estate movements. The real estate indices of China and India show similar and strong patterns. One of the reasons for that is the BRIC relation between those two countries precedes the establishment of the BRIC countries. More, they have large populations and their respective governments are at the heart of driving those economies.

For the commodities indices, Brazil and South Africa have the most and similar volatile indices patterns. One of the reasons of that is that Brazil and South Africa

Panel 13: equities										
	Brazil		China		India		Russia		South Africa	
CTP	1	2	1	2	1	2	1	2	1	2
1	0.5703	0.4297	0.5009	0.4991	0.4943	0.5057	0.5058	0.4942	0.5661	0.4339
2	0.4993	0.5107	0.5126	0.4874	0.5034	0.4967	0.5216	0.4784	0.6033	0.3967
CED	1	2	1	2	1	2	1	2	1	2
	2.3274	2.0436	2.0034	1.9507	1.9775	1.9864	2.0233	1.9171	2.3047	1.6577
Panel 14: real estate										
CTP	1	2	1	2	1	2	1	2	1	2
1	0.4983	0.5017	0.0000	1.0000	0.9827	0.0173	0.4689	0.5311	0.3442	0.6558
2	0.4893	0.5107	0.0244	0.9756	0.8896	0.1004	0.0210	0.9789	0.0074	0.9926
CED	1	2	1	2	1	2	1	2	1	2
	1.9932	2.0439	1.0000	40.9669	57.7020	1.1116	1.8827	47.5343	1.5248	134.6585
Panel 15: commodities										
CTP	1	2	1	2	1	2	1	2	1	2
1	0.5206	0.4795	0.9093	0.0907	0.4737	0.5263	0.4965	0.5035	0.0000	1.0000
2	0.5024	0.4976	0.0021	0.9979	0.4544	0.5456	0.4998	0.5002	0.0141	0.9859
CED	1	2	1	2	1	2	1	2	1	2
	2.0857	1.9903	11.0248	485.6439	1.8999	2.2007	1.9859	2.0007	1.0000	70.8325
Panel 16: bonds										
CTP	1	2	1	2	1	2	1	2	1	2
1	0.4959	0.5040	0.2862	0.7138	0.9919	0.0081	0.4817	0.5185	0.5067	0.4933
2	0.0018	0.9985	0.4598	0.5402	0.7747	0.2253	0.3799	0.6201	0.4853	0.5147
CED	1	2	1	2	1	2	1	2	1	2
	1.9841	556.1991	1.4009	2.1748	123.8068	1.2908	1.9285	2.6323	2.0270	2.0605

Note: CTP and CED stand for constant transition probabilities and expected duration, respectively.

Table 4.
Markov transition-out sample: 2007–2017.

are rich in mineral resources. On the other hand, China and India consume most of commodities products. Surprisingly, Russia had the most stable commodity index during 2007–2017 period. Unlike Brazil and South Africa, Russia is mainly rich in oil while the other two countries are rich in minerals. The bonds indices show similar patterns to real estate indices. Numerous studies illustrate that listed real estate exhibit traits of other capital markets, especially bonds. The patterns of bonds indices are dissimilar except for China and Russia. It can be inferred that bonds volatilities of those two countries follow in the same direction. The graphs show diagnostic patterns and in order to have more depth, this article illustrates Markov transitions as shown in **Table 4**. In most studies, transition probabilities and expected durations, are used to illustrate Markov transitions.

Panel 13 (14) illustrates Markov transitions for equities (real estate) while panel 15 (16) shows Markov transitions for commodities (bonds). For equities indices, for the four countries; Brazil, China, India and Russia, there is considerable transition dependence between the two regimes as the original regimes start from as low 0.50 and increase to as high as 0.57. The non-original regimes are as low as 0.50.

Although the original regime for South Africa 0.56 (relative high) but the non-original regime seems less dependent on the original regime. The expected durations of all countries are approximately 2 weeks. The quickly changing patterns in equities would be excepted given that equities markets are quite volatile that other capital markets. For real estate indices, China and South Africa show an interesting pattern-the original regimes are very low but the non-original regimes are highly dependent of the original regimes. That rare scenario is hardly observable in most countries in the world. That could be possibly due to the influence of governments which translate into financial markets in those countries. For Brazil, India and Russia, the two regimes seem to be dependent on each other. The excepted durations for real estate indices show interesting results-the expected durations are shorter their equities counter-parts mostly for first regimes. That is high unexpected. One possible explanation is that real estate indices in those countries are quite thin and represent a few constituencies. For commodities indices, the original regimes and non-original regimes are dependent. South Africa is the only country that illustrate a unique regime-non original regime is not some much dependent on original regime. All the regimes with exception of China and South Africa last for a few weeks. The reason why China and South Africa have longer accepted durations is because China consumes most commodities in the world while South Africa is a country rich in minerals. The regimes of bonds indices of all countries seem to be dependent. One possible explanation for that is that bonds are the oldest market in the capital markets. More, bonds are used mostly in those countries to finance private and public infrastructure. The expected durations of Brazil and China are entirely longer. Probably those two countries use their bond markets frequently for their capital markets offerings.

For every index type in **Figure 3** in every row, the first country is Brazil followed by China and then India; thereafter Russia. The last country is always South Africa. For equities indices, the later periods of China, Russia and South Africa show similar regimes patterns. Thus, there is a possibility that equities indexed volatilities of those move from and to with each other. For all the five countries, in year 2014, equities indexed volatilities show similar movements. Most of the 2014 year was characterised by bull markets most countries throughout the world. At that time, probably volatilities are spillover each other. The real estate indices for of all for

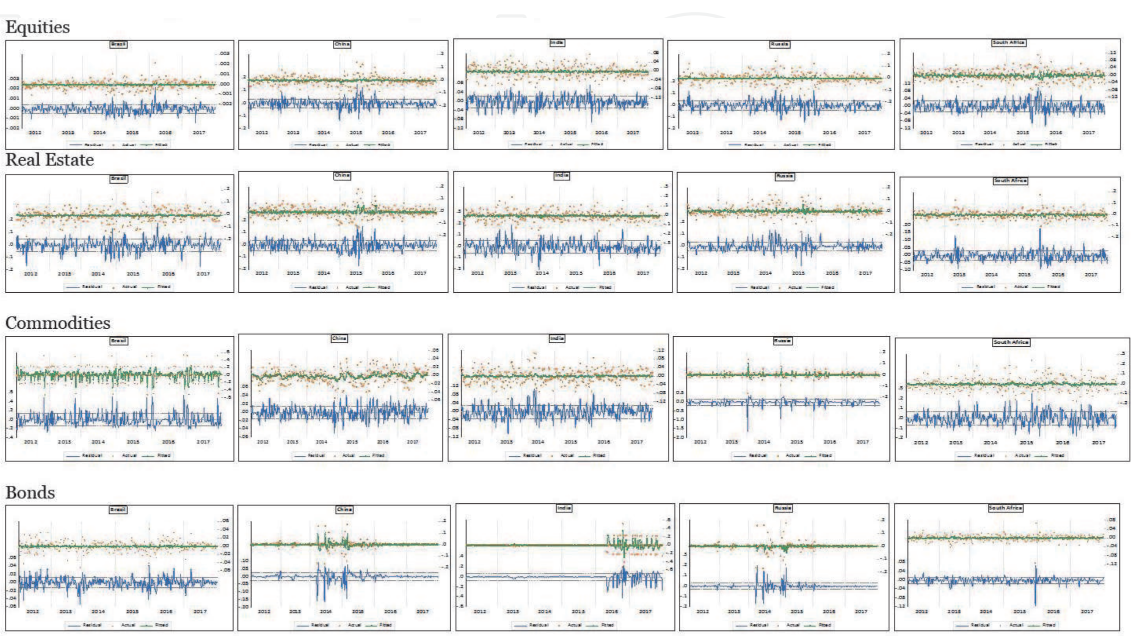

Figure 3.
Filtered regime probabilities-in sample: 2012–2017.

Panel 17: equities										
	Brazil		**China**		**India**		**Russia**		**South Africa**	
CTP	1	2	1	2	1	2	1	2	1	2
1	0.5147	0.4853	0.4494	0.5506	0.9731	0.0269	0.9756	0.0244	0.0000	1.0000
2	0.5159	0.4841	0.5897	0.4102	0.9977	0.0023	0.6888	0.3112	0.3045	0.6955
CED	1	2	1	2	1	2	1	2	1	2
	2.0605	1.9382	1.8161	1.6955	37.1527	1.0023	40.9446	1.4518	1.0000	3.2839
Panel 18: real estate										
CTP	1	2	1	2	1	2	1	2	1	2
1	0.0000	1.0000	0.9847	0.0153	0.0000	1.0000	0.1127	0.8873	0.9934	0.0066
2	0.0544	0.9456	0.5366	0.4634	0.0343	0.9657	0.0744	0.9256	1.0000	0.0000
CED	1	2	1	2	1	2	1	2	1	2
	1.0000	18.3795	65.2176	1.8635	1.0000	29.1281	1.1271	13.4442	153.0187	1.0000
Panel 19: commodities										
CTP	1	2	1	2	1	2	1	2	1	2
1	0.0000	1.0000	0.3956	0.6044	0.1097	0.8903	0.0189	0.9811	0.4853	0.5147
2	1.0000	0.0000	0.0466	0.9534	0.9999	0.0000	0.0000	0.9997	0.3379	0.6621
CED	1	2	1	2	1	2	1	2	1	2
	1.0000	1.0000	1.6545	21.4513	1.1232	1.0000	1.0193	3059.4310	1.9430	2.9595
Panel 20: bonds										
CTP	1	2	1	2	1	2	1	2	1	2
1	0.9738	0.0262	0.0000	0.9999	0.5174	0.4826	0.0000	1.0000	0.0000	1.0000
2	1.0000	0.0000	1.0000	0.0000	0.5776	0.4224	0.0197	0.9802	0.0033	0.9967

Panel 17: equities										
	Brazil		**China**		**India**		**Russia**		**South Africa**	
CED	1	2	1	2	1	2	1	2	1	2
	38.2366	1.0000	1.0000	1.0000	2.0720	1.7314	1.0000	50.6053	1.0000	303.1733

Note: CTP and CED stand for constant transition probabilities and expected duration, respectively.

Table 5.
Markov transition-in sample: 2012–2017.

countries with exception of Brazil exemplify the same pattern. One possible reason is that listed real estate mimics similar movements. So far, the diagnostic assessments illustrate that there is some relationship between indexed volatilities of equities (real estate). This might imply that volatilities of indices move together during bullish periods than bearish periods.

The indexed commodities volatilities of Brazil, China, India and South Africa exemplify similar movements. Brazil and South Africa are some of the main producers of minerals while China and India are some of the main consumers of mineral products. The bonds volatilities show different all countries show different movements. The indexed volatilities for in-sample period seem to be spiky than ones of out-sample period. It can be inferred from [32] that volatilities flatten out in the long-run because of diversification benefits which are more prevalent in the long-run. Broadly, the graphs of in-sample regimes are similar to ones of out-sample. Just like in the out-sample analysis for indexed volatilities, Markov transitions are calculated in order to deepen the insights on how indexed volatilities during in-sample period behave.

Panel 17 of **Table 5** illustrates that non-original regimes are dependent for indexed volatilities; however, the original regimes are not necessarily trend setters. One of the reasons that might explain that pattern is that during 2012–2017 period most equities market experience bull phase. The expected durations for all equities volatilities are fairly short with exception of the Russian market. Panel 18 illustrates the same pattern as panel 17 except in the case of South Africa. Surprisingly, excepted durations of real estate are far shorter than ones of equities. The patterns of regimes in panels 19 and 20 show similar patterns as in **Table 5**. The interesting part is that excepted durations for Russia-excepted durations of Russia are fairly long. Normally, currencies markets lead movements in stock markets, followed by equities, then bonds and final the real estate. Based on the latter principle, Russian commodities Markov transitions are longer because of long excepted duration of Russian bond index which was preceded by equities volatilities. Similar, real estate volatilities follow the same pattern. The Russian commodities volatilities are higher because Russian is major player in the commodities market in the world.

5. Conclusion

To sum up, this study illustrates that; firstly, there are spillovers that happen across, in-between and within bonds, commodities, equities and real estate indices. Secondly, sometimes the illiquid indices contribute more to volatility spillovers than liquid indices. Thirdly, expected durations of illiquid indices have shorter time spans than liquid indices. Fourth, in most cases, the volatility spillovers patterns during the out-sample period are similar to ones emanating during the in-sample period. Finally, periodical movement patterns vary across, in-between and within bonds, commodities, equities and real estate indices.

The implications from this study as follows. Firstly, similar governmental formations should be encouraged throughout the world provided that there economic benefits associated with those formations. Secondly, investing in different indices should be encouraged-diversification pays. Thirdly, there are risk management strategies that one can design based on volatility spillovers across, in-between and within bonds, commodities, equities and real estate indices. Fourth, the BRICS formation has indirectly influenced how capital markets (i.e. bonds, commodities, equities and real estate indices) behave. Finally, there are numerous investment strategies that investment managers can build based on volatility spills.

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Conflict of interest

The authors declare no conflict of interest.

Additional classification

JEL: C32, C33.

Author details

Katlego Kola* and Tumellano Sebehela*
School of Construction Economics and Management, WITS University, Johannesburg, South Africa

*Address all correspondence to: 461696@students.wits.ac.za and tumellano.sebehela@wits.ac.za

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