Sectoral dynamics of financial co-integration between BRICS and Developed stock markets

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LMXROL001

April 2019

Submitted to the Department of Finance and Tax at the University of Cape Town in fulfilment of the academic requirements for a Master of Commerce degree in Finance.

Abstract

This study examines the sectoral dynamics of co-integration between the BRICS (Brazil, Russia, India China and South Africa) and developed stock markets, represented by Germany, Japan, the UK and the US, during the four phases of the Global Financial Crisis (GFC), the three phases of the European Sovereign Debt Crisis (ESDC) and the UK Brexit crisis. The sample includes daily sectoral equity indices over the period January 2006 to December 2017. The study applies the ADCC GJRGARCH model to estimate the time-varying correlations across the nine countries within each sector and across sectors within each country, and assesses the conditional correlation dynamics during each of the phases of the three crisis periods. The results support the existence of financial co-integration across sectors and among all the nine countries during the GFC and ESDC. Only developed countries exhibit co-integration during the UK Brexit crisis. While some sectors were less affected during some of the crisis periods, on average, financials were the most affected during the GFC, ESDC and UK Brexit crisis. Further analysis on a crisis phase level reveals that most country pairs and sector pairs exhibit significant increases in conditional correlations in phase two of the GFC and ESDC, limiting the effectiveness of international diversification during this period. The results provide useful insights for policy makers and investors.

Declaration

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Roland Nubiga Lima

March 2019

Acknowledgements

I would like to give honour to my Lord Jesus Christ for giving me life and every day care.

I would like to express special appreciation and a heartfelt gratitude to my Supervisor, Associate Professor Francois Toerien for his insight and guidance. Without the sacrifice of your time, effort and consistent follow up, this thesis would not have been possible. My special thanks and heartfelt gratitude to Professor Francois for his efforts in securing financial support to enable me to carry on with my studies. His leadership spirit of self-sacrifice, ability to work all hours and pay no heed to his personal convenience in pursuit of service to all who come in contact with him are traits that I can only aspire to have.

I would also like to thank my co-supervisor, Associate Professor Co-Pierre Georg for imprinting in my mind that persistence is key to success. I would like to extend my sincere gratitude to Professor Co-Pierre for his effort to secure financial support through the ACQUFFR.

A special thanks to Allan Davids for his technical support and helping me understand the modelling part of my project. His encouragement and challenge to succeed will never go unnoticed.

I am grateful to my family for their continuous encouragement and prayers over the years.

Last but not the least; I will like to thank all my incredible friends both inside and outside the master labs on UCT campus for their endless support and encouragement.

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Abbreviations

AIC - Akaike information Criterion
ADCC - Asymetric Dynamic Conditional Correlaton
AR - Autoregressive Model
ARCH - Autoregressive Conditional Heteroskedasticity
ARMA - Autoregressive Moving Average Model
ARIMA - Autoregressive Integrated Moving Average Model
CCC - Constant Conditional Correlation
DCC - Dynamic Conditional Correlation
EGARCH - Exponential General Autoregressive Conditional Heteroscedasticity
IGARCH - Integrated General Autoregressive Conditional Heteroscedasticity
GARCH - General Autoregressive Conditional Heteroscedasticity
GJR - Glosten Jagannathan and Runkle
SIC - Schwarz-Bayesian Criterion
MA - Moving Average
MSCI - Morgan Standley Capital International
CS - Consumer staples Sector
FN - Financial Sector
MT - Material Sector
TC - Telecommunication Sector
UK - United Kingdom
USA - United States of America

Chapter 1

Introduction

1.1 Background of the study and motivation

The last two decades have seen a series of financial crises originating in one region and spreading over many parts of the world (Pappas, Ingham, Izzeldin and Steele, 2016). At the same time, the liberalisation of capital movements led to gradual and progressive systematic correlation of the leading financial markets (Prasad, Rogoff, Wei and Kose, 2005). The increasing integration of capital markets and globalization ease the operation of a "single market" [1]. Although the benefits of more integrated markets are known to help traders share their risk efficiently and make markets more efficient and more accessible to a wider range of investors, many researchers such as Alexakis and Pappas (2018), Bekaert, Ehrmann, Fratzscher and Mehl (2014) and Longstaff (2010), argue that financial integration may lead to the transmission of shocks across countries. Consequently, studying the relationships across financial markets is beneficial to policymakers, financial institutions, and investors.

The objective of this study is to examine the sectoral dynamics of financial co-integration between BRICS (Brazil, China, India, Russia, and South Africa) countries and selected developed markets (the US, Europe and Japan) during Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC) and the UK Brexit crisis. According to recent economic forecasts, the BRICS countries are expected to exhibit a very high economic growth rate over the next fifty years. This will result in BRICS economies growing at a rate greater than the G-6 (Group of six countries in the European Union) in U.S dollar terms (Shahrokhi, Cheng, Dandapani, Figueiredo, Parhizgari and Shachmurove, 2017; Wilson and Purushothaman,

[1] A single market is a type of trade bloc in which the movement of labour, capital, goods and services between the members states is as easy as within them. In other words, the fiscal (taxes), technical (standards) and physical (borders) trade barriers are removed to the maximum extent possible (Fontagné, Freudenberg, Péridy et al., 1998; Monti, 2010)

2003). Consequently, as international investors seek attractive investment opportunities and alternative investment style, BRICS capital markets continue to receive increasing inflows of funds from foreign economies (Havlik, Stollinger, Pindyuk, Hunya, Dachs, Lennon, Poplawski Ribeiro, Ghosh, Urban, Astrov et al., 2009; Syriopoulos, Makram and Boubaker, 2015). Understanding the interrelationships and potential spillover effects of BRICS markets among themselves and relative to leading developed markets therefore remains essential for policy makers, investors and portfolio managers.

1.2 Motivation for contagion analysis at the sector level

Previous studies have identified essential reasons for the analysis of sectoral contagion during crises period. According to the findings of Kaminsky and Reinhart (1999), some sectors like the financial sector may create major channels that facilitates the transmission of shocks across markets during crises period. Other studies demonstrate that linkages resulting from international trades may lead to the vulnerability of countries to international shocks (Forbes and Rigobon, 2002; Phylaktis and Xia, 2011). Following this line of reasoning, it implies that industries or sectors that are heavily involved in foreign trade are more exposed to foreign shocks compared to industries or sectors that have less involvement in foreign trade. Sectors like the banking sector might be a main channel for transmitting shocks across stock markets (Kaminsky and Reinhart, 1999). Consequently, sectors will respond differently to foreign shocks.This asymmetry in sector contagion may be profitable as diversification at the sector level might provide better returns than at market level.

1.3 Contributions of the study

The study contributes to the literature by modelling and estimating financial co-integration across sectors and within sectors of the BRICS and developed countries. The second contribution is applying the ADCC-GJRGARCH model to model sectoral asymmetric dynamic conditional correlations across nine countries. A third contribution is the inclusion of three crises (GFC, ESDC and Brexit) in the study. This was the first study to investigate co-integration across the three crises. The fourth contribution is the inclusion of the various phases of the GFC and ESDC in the study.

1.4 Data and Methodology

The data used in this study are daily prices of Morgan Stanley Capital Index (MSCI) aggregate equity indices and sector equity indices for five emerging countries (Brazil, Russia, India, China and South Africa) and four developed countries (the US, the UK, Germany and Japan). The data was collected for the period January 2006 to December 2017. The sample includes daily sectoral equity indices over the period January 2006 to December 2017. The study applies the ADCC-GJRGARCH model to estimate the time-varying correlations across the nine countries within each sector and across sectors within each country, and assesses the conditional correlation dynamics during each of the phases of the three crisis.

1.5 Thesis map

This thesis is structured as follows: Chapter two provides an overview of BRICS economies, an overview of the methodological literature related to contagion and literature on empirical results on contagion. Chapter three focuses on sources of data, the description and preliminary analysis of data, empirical analysis of descriptive statistics for aggregate data for each sector. This chapter also provides a further analysis of data characteristics. Chapter four discusses the methododology as well as the analysis of the results for this study. The final chapter (chapter 5) gives a summary of the main findings and conclusion.

Chapter 2

Literature Review

This chapter gives an overview of the BRICS economies, the methodological literature on contagion and discusses the empirical results on contagion. Section 2.1 provide an overview of the BRICS economies. Section 2.2 addresses the research methodologies used to test for contagion, and Section 2.3 discusses the literature on empirical results found with regards to contagion.

2.1 An overview of the BRICS economies

In the beginning of the 2000s, the global chief economist of Goldman Sachs, Jim O'Neill originated the acronym BRIC in order to emphasize the outstanding growth prospects of selected emerging economies (O'neill et al., 2001). These countries included China, Brazil, India and Russia. At the end of 2010, South Africa became a recognized member of BRIC and the acronym was expanded to BRICS (Carmody, 2019). According to O'Neill, Wilson, Purushothaman and Stupnytska (2005) in less than 50 years' time, the BRICS economies together are likely to outgrow the four biggest economies in Europe and the U.S in US dollar terms. Studies on BRICS economies acknowledge that BRICS countries are gradually changing their economic and political system to incorporate global capitalism (Robinson, 2015; Ye, van der Ploeg, Schneider and Shanin, 2019). According to studies carried out by Gusarova (2019), together, BRICS economies represent about forty two percent of the world's population, twenty six percent of the world's land area, twenty four percent of world GDP, seventeen percent of global trade, thirteen percent of world service market and forty five percent of global agriculture production. BRICS economies represent forty one percent of total global stock market capitalization, with China predicted to become the biggest equity stock market in the world by year 2030 (Hammoudeh, Santos and Al-Hassan, 2013).

In July 2016, the BRICS countries held a submit in Brazil, during which the five nations introduced two institutions: the Contingency Reserve Arrangement (CRA) and New Development bank (NDB) (Wang, 2019). These two instiutions (CRA and NDB) are intended to rival the European and the U.S - lead International Monetary Fund (IMF) and World Bank. Both institutions aim to compete globally on finance and development. The New Development Bank (NDB) had a total authorised capital of one hundred billion dollars. This capital is accessible to all the constituents of the United Nations. The Contingency Reserve Arrangement (CRA) had an initial capitalization of one hundred billion dollars. This amount is available to the members of BRICS countries (Shahrokhi et al., 2017). What follows is an analyses of economic characteristics and major determinants of economic development for each individual BRICS country.

2.1.1 Brazil

Brazil's current influence in global economy dates back to the historic role the country played as a major supplier of gold to the Portuguese empire (Shahrokhi et al., 2017). Being the fifth biggest country in terms of land area (8.5mil square km) and population (211mil people in 2018), the country is viewed as a key emerging economy in the world (Bacci, 2017; Hugo, 2017). The country has achieved energy independence and it is a commodity powerhouse with high growth potential (Brainard and Martinez-Diaz, 2009; Shahrokhi et al., 2017). Fleury, Fleury and Borini (2013) analyzed the international expansion and innovative approach of sixty one Brazilian firms and confirm the expansion of international multinational Brazilian companies with other emerging economies. Brazil has a unique competitive advantage in Latin America. While most Latin American countries are in search of products through which they can integrate with the global economy, Brazil is more innovative in a number of high-tech activities in automobiles and machinery, aircraft, energy and mining products among many others. With a stable political and economic alliance with Europe, both sides share numerous complimentaries which deliver several benefits to Brazil and Europe (Havlik et al., 2009). The next section gives an overview of Russia.

2.1.2 Russia

According to official statistics from The World Bank (2018), the population of Russia is about 142 million and the total number of working class population is about 75 million people. The average age of the country's population is 39 years. The country has a comparatively steady unemployment rate of 5.5 percent. Russia is blessed with a diverse range of natural deposits including oil, coal and natural gas and it is also a producer and exporter of aluminum and steel (Blasi, Kroumova and Kruse, 1997). Metals, natural gas, timber and oil account for more than 80 percent of Russia's exports. Many look to high oil prices and a relatively cheap ruble as the driving forces to Russia's economy growing progressively since the financial crisis of 1998. According to studies carried by Åslund (2005), Russia's extensive forests have disposed its economy with exceptional influence on the global lumber markets. According to studies carried out by Shahrokhi et al. (2017) on the evolution and future of Russia, the country is progressively revising the procedure for business start ups. It has shortened the length of time required to open a business bank account, simplified the process of obtaining electricity and facilitated the process of transferring property registration. Allocation of resources into scientific education and massive investment in infrastructure will aid Russia to exploit its comparative advantage.

2.1.3 India

According to official statistics from The World Bank (2018), India is the seventh biggest country in terms of territory. It has a population of about 1.1 billion people, making it the second largest country in the world in terms of population. The country has a highly diverse economy. Within the last decade, India has maintained a comparatively stable position in comparison with other BRICS members. According to studies carried out by Goldman Sachs, India was ranked fourth in PPP (purchasing power parity) and twelfth in nominal GDP at 3.6 trillion dollars. Their study projected that by 2050, India will be the third largest world economy in nominal terms, alongside the United States and China (Stuenkel, 2015). Other studies anticipate that India will mature into an international finance and trade power house by 2050 (Mostafa and Mahmood, 2015). India currently has two essential distinguishing factors: huge resource potential and demographics. It is one of the main producer of iron with vast deposits of resources such as bauxite, copper and iron ore that have not been greatly altered by a global deterioration of resources. The country's global economic advancement rests on its significant labour force. It has the most educated and best equipped workforce of all emerging markets. Consequently, it is one of the few countries to base its economic advancement on educated and young workforce (Shahrokhi et al., 2017). Its combined resources and demographics have placed India's GDP among the top ten in 2017 (Eren, Taspinar and Gokmenoglu, 2019). The country's present objective is geared towards maintaining high economic growth through strengthening of major institutions, efficient policy implementation in strategic sectors such as education, trade, investment and macroeconomic stability (Saini, Ansari and Kumawat, 2019). The next section gives an overview of China.

2.1.4 China

According to statistics from the The World Bank (2018), China is the 4th biggest country by territory. The country has a population of over 1.3 billion people making it the world's largest nation in terms of population. Being the world's most populous country, its major attraction is its large and fast growing market. The economy of China is characterized by three main factors: the country's domestic market, urban growth, technological advancement and innovation (Jin, Peng and Song, 2019; Kwak, Zhang and Yu, 2019). There is a presence of large domestic market in China, with more than half of the population who belong to the middle income class eager to have access to social amenities like clean water, housing, cars and good health. Given the large labour force of close to 950 million, economic activities are on the rise, leading to numerous real estate and infrastructure projects being initiated (Lacal-Arántegui, 2019). A significant proportion of the Chinese workforce would like to live and work in the cities and are recycling their liquidity to invest in houses and apartments, consequently, the real estate sector has been a major growth driver for many years (Wang, 2019). There is also high growth in high-tech companies in China. About 13000 new companies are started each day in China (about 4.5million in 2015) (He, Khan, Lew and Fallon, 2019). Startup companies in sectors like e-commerce, finance and technology experience growth within a few years of forty to sixty percent (Shahrokhi et al., 2017). With China making the largest contribution to the economic growth of BRICS combined, as well as to the world economy, researchers, investors and policy makers are anxious about the growth rate and economic development of China (Zheng and Walsh, 2019).

2.1.5 South Africa

South Africa joined the BRIC groupings on the 24th of December 2010 and the acronym BRIC changed to BRICS (Oliver, 2013). The country is a commited supporter of the BRICS financial architecture. For example, the African regional center headquarters of the New Development bank (NDB) is in South Africa (Shahrokhi et al., 2017). The country possesses mineral deposits of gold, vanadium, diamond and chrome ore worth over 2.5 trillion dollars (Nex and Kinnaird, 2019). Massive development in the transport sector such as increase in roads, railways, expansion in mining and other related projects in BRICS countries has unraveled these resources to BRICS members (Mostafa and Mahmood, 2015). The continuous realization of the economic goals of BRICS has been enhanced by the easy access of these mineral resources. The availability of mineral deposits in the country gives South Africa a unique comparative advantage among the BRICS countries. The next section discusses the methodology that will be used in this research.

2.2 An overview of the methodological literature related to contagion

The first attempt to specify a suitable model was made by Bollerslev, Engle and Wooldridge (1988), who proposed the VECH specification, which has a disadvantage of not providing the assurance of a positive definite variance-covariance matrix. Baba, Engle, Kraft and Kroner (BEKK) model takes care of this weakness in VECH, but does not overcome the dimensionality problem (Engle and Kroner, 1995). Effectively, BEKK and VECH models provide the framework for conditional covariances (Engle and Kroner, 1995), it follows that conditional correlations will be indirectly measured with BEKK and VECH models. On the other hand, the ADCC model provides the framework for the conditional correlations so that direct computations is possible.

The Constant Conditional Correlation (CCC) model was developed by Bollerslev (1990). However, the major drawback with this model is the assumption that correlation remains constant over time. Effectively, the CCC model is not practical or empirically sound. The Smooth Transition Conditional Correlation (STCC) model, which was developed from the CCC model, allows correlation to remain constant between two regimes, while allowing steady transition between those two regimes. However, the STCC has the same weakness as the CCC model, namely constant correlation. The ADCC model solves this problem by allowing correlations to vary over time.

The Dynamic Conditional Correlation (DCC) model proposed by Engle (2002) is the augmented version of the CCC model. The DCC model accommodates time varying correlation and captures the changes in correlation over time. Cappiello, Engle and Sheppard (2006) enhance the first model of Engle (2002) and propose an asymmetric specification, asymmetric dynamic conditional correlation (ADCC), to analyze asymmetries of the dynamics of conditional correlation and variances. What follows is a discussion on univariate volatility models:

2.2.1 Univariate Volatility Models

Univariate volatility models are a group of models that attempts to predict and model a single variable using only information that is contained in their historical values. Over the past decade, the theoretical and empirical studies on modelling and forecasting volatility across stock markets have been the focus among financial practitioners and researchers alike. The main reason or motivation for this line of studies is because volatility is the measure of risk and therefore considered one of the major concepts in the field of finance (Brooks, 2008). The volatility of an asset is the measure of risk associated with that asset and therefore volatility is the measure frequently used to model the risk of an asset. In practice, the volatility of an asset cannot be observed directly. Only the prices and associated derivatives of the price of the asset are observed. Therefore volatility is estimated from the observed asset prices. In addition to being measured indirectly, there are some characteristics of volatility that are associated with asset returns according to Tsay (2012):

- The first and probably the most significant characteristics is often referred to as volatility clusters. In other words, volatility tend to be low for a certain period and high for other periods.

- The second characteristics is commonly referred to as the leverage effect. Volatility tend to respond differently to major price hike and major drop in price. Large increase in volatility are associated with a large drop in price than equally large increase in price.

- A third characteristic is that, it is not common to observe volatility jumps. Instead, volatility often evolve in a continuous pattern over time.

- The fourth characteristics is that volatility normally varies within a fixed period of time and does not diverge into infinity.

These characteristics of volatility play an essential role in the development of appropriate models to measure volatility. There are many volatility models available in the literature. Volatility time series models are often referred to as a-theoretical models. In other words, the construction and application of these models does not depend on theoretical model characteristics of a variable. Instead, volatility time series models attempt to empirically capture important attributes of the data that may have arisen from a range of structural models (Brooks, 2008). AutoRegressive Integrated Moving Average (ARIMA) models is an essential group of time series models (Walter, 2015). Before discussing the properties and characteristics of ARIMA models, it is important to elaborate on the concept of stationarity and white noise. A time series is defined as a progression of observations obtained at successive intervals, for instance, monthly log returns on an equity stock (Ruppert, 2011). Stochastic processes are often applied to time series data. A stochastic process can also be interpreted as a random process. The assumption of stationarity is useful for obtaining parsimony in the modeling process of a time series data. A process is stationary if its covariance, mean and variance remains constant over the sample period of study. The simplest example of a stationary process is a white noise. Roughly speaking, a white noise involves a process with no apparent pattern. Therefore a white noise process is associated with zero autocovariances, constant variance and mean. An autoregressive and moving average (ARMA) processes offer more parsimony compared to an Authoregressive (AR) and moving average (MA) process when modeling a stationary time series that exhibit complex autocorrelation behaviour. An AR model is a model where the prevailing value of a variable, y_t, builds on past values that the variable took in preceding periods and an error term (Walter, 2015). An AR model of the order, p, denoted as AR(p), can be written as

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \mu_t \tag{2.1}$$

Where μ_t is an error term for white noise.

An MA model can be interpreted as a linear combination of white noise process, such that y_t builds on the present and preceding values of a white noise error term (Walter, 2015). An MA model is often referred to as simplest group of time series model in the literature. Let a white noise process be denoted by μ_t (t = 1,2,3,4.5..), where $E(\mu_t) = 0$ and $var(\mu_t) = \sigma^2$. Then considering the qth order MA model, the equation for MA(q) can be written as:

$$y_t = \mu + \sum_{i=1}^{q} \theta_i \mu_{t-i} + \mu_t \tag{2.2}$$

An ARMA(p,q) model is derived from a combination of AR(p) and MA(q) models. An ARMA(p,q) model involves a current value of a series y which builds linearly on its own preceding values plus an aggregate of current and previous values of a white noise error term. The model can be expressed as:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \mu_t - \sum_{i=1}^{q} \theta_i \mu_{t-i} \tag{2.3}$$

where μ_{t-i} is a white noise series and p and q are non negative integers. The convention of normalizing units is followed so that θ_0 is always unity. If the characteristics roots of equation 2.3 are all in the unit circle, y_t is called an ARMA model of y_t. However if one or more characteristic roots of equation 2.3 is greater than or equal to one (unity), the y_t sequence is said to be an integrated process and equation 2.3 is called an autoregressive integrated moving average (ARIMA) model. As stated in Walter (2015), "ARIMA models are used to model the conditional expectation of a process given the past, but in an ARIMA model, the conditional variance given the past is constant". However, when modelling stock returns and if the returns have a volatility that is much higher than normal, it can be expected that the next periods return is also more volatile than usual. On the other hand, an ARMA model cannot capture this type of behaviour because its conditional variance is constant. Hence better models are needed to model the non constant volatility (Walter, 2015). The ARCH and GARCH models are suitable for modelling the non-constant variance. The next section discusses the ARCH and GARCH model.

2.2.1.1 ARCH and GARCH

Financial decisions are often associated with the trade-off between risk and return. Volatility is therefore an integral part of finance as risk analysis is a central concept in portfolio optimization, risk management and asset pricing. In the seminal work of Engle (1982), the author presents evidence that many financial time-series data sets display periods of volatility clustering. In other words, the features of volatility process of asset prices is such that large changes tend to be followed by large changes and small changes tend to be followed by small changes, of either sign. In order to account for this, Engle (1982)'s approach controls for the long-run unconditional homoscedasticity of the residuals, as well as any short-run changes in the variance structure of the residuals which might show conditional heteroscedasticity. One of the shortcomings of the ARCH model is that it often requires a long lag.

In order to address this shortcoming, Bollerslev (1986) proposed the GARCH model where the conditional variance is allowed to display an autoregressive-moving–average (ARMA) process.

The next section gives further background on the ARCH model

2.2.1.2 ARCH Methodology

The autoregressive conditional heteroskedasticity (ARCH) model is an original model for capturing conditional heteroskedasticity. The ARCH model is the first model that provides an efficient framework for modelling volatility. The ARCH model was first proposed to take into account autocorrelation (or serially dependent) of the error variance displayed at certain periods. The ARCH process is similar to that of the ARIMA family, as it controls for periods of volatility persistence in the residual process specifically. Although we assume our time series (after stationarity transformations) is made time invariant, the earlier models only consider the unconditional (or long run) constant- means and - variance process overtime.

- Thus unconditional forecasts would imply forecasting using only the long run mean.

Following Engle's approach: although the residuals may be homoskedastic in the long run (unconditionally homoskedastic), the short run behaviour of the variance structure might be time-dependent - i.e. showing the presence of conditional heteroskedasticity which is persistence in the variance structure conditional upon a past period of higher than-normal variance. This gives by definition a better forecast. The key advantage of the ARCH model in analysing asset returns is that:

- The model can produce volatility clusters

As outlined in Xekalaki Evdokia (2010), the ARCH model also has some weaknesses that are worth mentioning:

- The ARCH model treats positive and negative shocks in the same way. This is because volatility depends on the square of the preceding shocks. However, in practice, financial asset returns tend to respond differently to positive and negative shocks.

- In terms of parameters, the model is very restrictive and has constraints which becomes sophisticated for higher order ARCH models. In other words, the ability of ARCH models to capture excess kurtosis is limited in practice.

- No insight is provided for verifying the cause of variation of the financial time series. The model merely provides a mechanical framework to interpret the behaviour of the conditional variance, and no indication about the causes of the occurrence of such behaviour is given.

- The model tend to be slow to respond to large isolated shocks and often over-predicts volatility associated with return series.

The ARCH framework implies the series can be serially uncorrelated and have stationary ordinary residuals that are unconditionally homoskedastic, but at times display heteroskedasticity conditional on past shocks. Thus the ordinary residuals, although uncorrelated, are dependent on past shocks. This implies that the ARCH model is able to capture calm periods and volatility in a series. As illustrated in the mathematics of the ARCH model below; after fitting the conditional variance equation, we should have:

- Stationary ordinary residuals (serially uncorrelated, but dependent)
- White Noise standardized residuals which implies after taking into account the conditional heteroskedascity, our standardized residuals are White Noise (Serially uncorrelated and independent).

The mathematics of the ARCH model is illustrated below: The return series used in this study is defined as

$$r_t = \log \frac{p_t}{p_{(t-1)}} \tag{2.4}$$

We will also assume y_t follows a stochastic process:

$$y_t = \alpha + \mu + \varepsilon \sim (0, \sigma^2) \tag{2.5}$$

where $\mu = E(r_t|I_{t-1})$ and $\sigma_t^2 = E(\epsilon_t^2|I_{t-1})$ and where I_{t-1} represents the information set available at time $t-1$.

Following Engle (1982), benchmark ARCH model can now be represented as :

$$\epsilon_t = \eta_t.h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 \tag{2.6}$$

where $\alpha_0 > 0$, $\alpha_i > 0$ & $0 < \sum_{i=1}^{q} \alpha_i < 1$.

ε_t is the ordinary residual which is serially uncorrelated but possibly time-dependent through its second moment. Therefore ε_t is a product of both the conditional variance, h_t and the standardized residual, n_t. Furthermore, since $n_t \sim N(0,1)$, this implies that the residuals should be white noise after the ARCH is fitted. The next section elaborate on the GARCH methodology.

2.2.1.3 GARCH Methodology

Despite the simplicity of the ARCH model, it often requires many parameters to adequately describe the volatility process of an asset return. Bollerslev (1986) then generalized the ARCH model (the approach proposed by Engle (1982)), by allowing the conditional variance term (h_t) to display an ARMA (p,q) process, by proposing the GARCH (p,q) model. This implies, that the GARCH (p,q) model will have the following form:

$$y_t = \alpha + \mu_t + \varepsilon_t$$

$$\varepsilon_t = h_t.n_t;$$

The benchmark GARCH (p,q) can be represented as :

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-1}^2 \tag{2.7}$$

Where $\alpha_0 > 0$, $\alpha_i > 0$, and $\beta_i > 0$. α_i represents the extent to which the impact of an unanticipated shock feeds into future volatility while β_i represents the momentum carried forward from part variance. Bollerslev (1986) shows that for a GARCH process of y_t, to be covariance stationary, $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i < 1$. Typically, we expect $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i$ to be close to 1, given the strong persistence normally found in the volatility process of financial time-series. When $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i = 1$, we have the IGARCH (p,q) model of Bollerslev (1986).

Following similar reasoning as for deriving the ARCH model, the unconditional mean of ε_t follows as:

$$E_t = E(h_t.n_t) = E(h_t)E(n_t) = 0$$

(using independence)

Unconditional variance:

$$E(\varepsilon_t^2) = E(h_t^2).1 = E(\alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-1}^2)$$

$$= \alpha_0 + (\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i)\varepsilon_{t-i}^2 \tag{2.8}$$

as $E(\varepsilon_{t-i}^2) = E(h_{t-1}^2)$

as:

$$E(\varepsilon_t^2) = E(\varepsilon_{t-i}^2) \rightarrow E(\varepsilon_t^2) = \frac{\alpha_0}{1 - (\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i)}$$

since it is a stationary process

With

$$0 < (\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i) < 1,$$

which is a constant and it is necessary condition for variance to be positive.

The Autocorrelation function:

$$E(\varepsilon_t^2, \varepsilon_{t-j}^2) = 0 \quad , \quad \forall j$$

Conditional Variance:

$$E_{t-1}(\varepsilon_t^2) = E_{t-1}(h_t^2 n^2) = E_{t-1}(h_t^2).1 = h_t^2$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-1}^2$$

which is a non-constant, conditional heteroskedasticity process with an ARMA form. As shown in the analysis of the ARCH/GARCH model, the GARCH model is identical to the ARCH model apart from the inclusion of the $\beta_i h_{t-1}^2$ in the conditional volatility equation, which accounts for the persistence in the conditional variance, dependent on its lags. As such, the GARCH (p,q) specification allows for an Autoregressive Moving Average (ARMA) variance process. It is important to note that the ARMA and GARCH orders need not equate. In most empirical studies setting $p = q = 1$ often suffices to reproduce the volatility dynamics of financial data. As such, The GARCH (1, 1) is the simplest and most robust of the family of volatility models. Furthermore, Hansen and Lunde (2006) surveyed many types of GARCH models and arrived at a conclusion that on aggregate, the model most commonly used in financial times series analysis is the GARCH (1,1).

Interpreting the coefficients of the GARCH model: Suppose we have the GARCH (1,1) process:

$$h_t^2 = \alpha_0 + \alpha \varepsilon_{t-i}^2 + \beta h_{t-1}^2$$

$\alpha \rightarrow$ extent to which a shock today feeds into tomorrow's volatility, or the response of h_t to new information on an unexpected shock. The top part can be written as: (adding and subtracting): $\alpha.h_{t-1}^2$

$$h_t^2 = \alpha_0 + \alpha(\varepsilon_{t-i}^2 - h_{t-1}^2) + (\alpha + \beta).h_{t-1}^2$$

So that from this form the two coefficients can be interpreted as:

- α is the impact of the unanticipated shock part.

- $(\alpha + \beta)$ is the degree of autoregressive decay, i.e the rate at which the effect of a previous shock dies down on the variance process. Typically, $(\alpha + \beta)$ tends to 1, implying that financial time-series show a slow decay/strong persistence in the volatility process.

Using the GARCH approach a modeller can fit a more parsimonious conditional variance equation if the ARCH fit requires a large order[i.e. a large p for ARCH(p)]. It is important to note that fitting a GARCH (p,q) process effectively implies fitting an ARMA process on the conditional variance (h_t^2) of the series y_t. This implies that the correlogram of the series y_t should display stationarity. While the squared residual correlogram (again, representing the volatility conditional on past shocks) would display an ARMA strucure.

To check if heteroskedascity is present in a series, we fit subsequent heteroskedasticity models and ARMA models simultaneously, using Max Likelihood techniques, and then testing which models fits the data closest using some identification criteria like AIC/SBIC. After fitting subsequent ARCH/GARCH models, we test its validy checking:

- The coefficients (both for statistical significance and whether they adhere to their constraints - collectively and individually),

- Equally important is graphing the squared standardized residuals, $[{n_t}^2]$and checking whether all conditional heteroskedasticity has been removed (as n_t is the true stochastic process of the system, it should represent a White Noise series). This requires testing for white noise on standardized residuals.

- The parameters should also adhere to its restrictions (here $\alpha + \beta < 1$ and each is > 0).

Comparing different ARCH/GARCH fittings to the model in an effort to control for conditional heteroskasdasticity, we can use the standard Akaike information Criteria (AIC) and Bayesian information Criteria (SBC) measures which we want ideally as small as possible ($-\infty$). Just like the ARCH model, the GARCH model also has its strengths and weaknesses. A major strength of the GARCH model is :

- It provides the means for controlling for conditional heteroskedasticity, which is particularly useful when studying financial data/data that exhibit periods of momentum/volatility clustering.

- Another advantage (although not particularly useful in the present study) is that it allows the modeller to forecast volatility into a future period, allowing the modeller to adjust the confidence interval band and be mindful of potential future volatility clustering.

A major weakness of using the GARCH model is that positive and negative shocks have the same effect on volatility. However, this is not necessarily the case in practice as negative and positive momentum in stock markets tend to behave differently. Furthermore, the GARCH model does not provide us with insight into the source of the conditional variance. Following the introduction of ARCH model, by Engle (1982) and their generalization by Bollerslev (1986), there have been numerous refinements of this approach to modelling conditional volatility. These modifications include the Exponential GARCH (EGARCH) and the Glosten-Jagannathan-Runkle GARCH (GJRGARCH) model, which address asymmetries between returns and volatility, and the AVGARCH which accounts for leptokurtic tails in the data (Glosten, Jagannathan and Runkle, 1993; Hentschel et al., 1995; Nelson, 1991). The next three subsections discusses the three modification of the GARCH model, which include the Integrated GARCH (IGARCH), GJRGARCH and EGARCH.

2.2.1.4 Integrated GARCH (GARCH)

In applications it often occurs that the estimated sum of the parameters α_1 and β_1 in the standard first-order GARCH model (equation 2.7) with p and $q = 1$ is close to unity. Engle and Bollerslev (1986), who first paid attention to this phenomenom, suggested imposing the restriction $\alpha_1 + \beta_1 = 1$, and called the ensuing model an integrated GARCH (IGARCH) model. The IGARCH is the modification of the GARCH model that deals with strong persistence in conditional volatility. Most volatility models show strong persistence (i.e. $\alpha + \beta \to 1$). As a result, the integrated GARCH (IGARCH) model has been proposed when the strength of persistence resembles a unit root process in the conditional variance equation (hence the "integrated" part). The IGARCH model restricts the parameters of the GARCH model to sum one, and it drops the coefficient:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t+1-i}^2 + \sum_{i=1}^{p} \beta_i h_{t+1-i}^2 \tag{2.9}$$

With :

$$\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i = 1$$

Note that this constraint implies the GARCH process acts like an autoregressive series with unit root. However, this is not the case, as it is a deterministic solution with no residuals. The IGARCH process then accounts for this unit root explicitly. Despite many series showing very strong volatility persistence, in practice the IGARCH form is regarded as a highly unlikely volatility process design and as such is not often used. Hence, the IGARCH will not be used in this study. The next section discusses the GJR-GARCH.

2.2.1.5 GJR-GARCH : Dealing with asymmetries

The conditional variance equation only considered the magnitudes of past residuals and ignored the signs. However, Glosten et al. (1993) showed that leverage effects matter for mean equations (where negative returns show greater persistence), Glosten et al. (1993) also showed that the volatility models show similar asymmetry. As such they proposed the Glosten, Jagannathan and Rungle - GARCH (GJR-GARCH) model (which is a special case of the threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model), which explicitly controls for *sign* in past residuals by introducing an indicator variable into the variance equation. The GJR- GARCH takes the following form:

$$h_t^2 = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2) + \phi.I_{t-1}(\varepsilon_{t-1}^2) + \beta h_{t-1}^2 \tag{2.10}$$

where $I = 1$ *if* $\varepsilon_{t-1} < 0$, and $I = 0$ *if* $\varepsilon_{t-1} \geq 0$ and where ε_{t-1}^2 represent previous period squared residual series and h_{t-1}^2 is the autoregressive term of the conditional variance. This implies that for a negative shock in h_{t-1}, the impact on the conditional variance in t is

$$h_t^2 = (\alpha_1 + \phi.I_{t-1})(\varepsilon_{t-1}^2) + \beta h_{t-1}^2 \tag{2.11}$$

Which is larger if ϕ is positive. When regressing the model, a significant t - statistic for ϕ implies the data contains a leverage effect. Typically it is found that ϕ is positive, indicating increased volatility persistence if the past shock was negative. The more general form of the GJR-GARCH model is the TGARCH. It basically suggest that there exists a threshold effect, T, where if residuals are larger than a certain threshold T, the conditional variance persistence increases. The GJR-GARCH is therefore a TGARCH with a threshold of zero (T= 0). The next section discusses the EGARCH.

2.2.1.6 EGARCH

Another popular and useful GARCH model in the literature is the Exponential GARCH (EGARCH) model. Nelson (1991), who developed the model, had two weaknesses of the standard GARCH model in mind.

- First, with the GARCH model, positive and negative shocks have equal effect on volatility. This implies that the model does not allow an asymmetric response to shocks.
- Secondly, the standard GARCH model is very restrictive in terms of parameters. In order to ensure conditional variance at every point in time, parameter restrictions are required.

Therefore the major advantage of the EGARCH is that it controls for asymmetry and does not need to impose non-negativity constraints in the variance equations. Nelson (1991)'s EGARCH model is as follows:

$$\ln h_t^2 = \beta_0 + \beta_1 \ln h_{t-1}^2 + \gamma_1 . \frac{\varepsilon_{t-1}}{h_t} + \gamma_2 (\left| \frac{\varepsilon_{t-1}}{h} \right| - \sqrt{\frac{2}{\pi}}) \tag{2.12}$$

With

$$E(\frac{\varepsilon_{t-1}}{h_t}) = \sqrt{\frac{2}{\pi}}$$

if normal distribution is assumed. Thus EGARCH always produces a positive conditional variance, requiring no restrictions on parameters, except that $|\beta_1| < 1$

As $\left| \frac{\varepsilon_{t-1}}{h_t} \right| and \varepsilon_{t-1} \frac{}{h_t}$ are included, h_t^2 will be asymmetrically distributed across positive/negative residuals, so that if $\gamma < 0$, there are leverage effects. The EGARCH thus accounts for both leverage and the level of impact of shocks to volatility persistence.

2.2.1.7 Comparing the GARCH, GJR-GARCH and EGARCH

Both the GJR-GARCH (p, q) and EGARCH (p,q) models account for asymmetry which is a major disadvantage of the standard GARCH (p,q) model. The most frequently applied parameterization of conditional hetersokedasticity is the standard GARCH model. Accordingly, it is common to assess an estimated EGARCH model by testing it against a comparable GARCH model. One major strength of the EGARCH model is that it controls for asymmetry of shocks. A GARCH model that has similar characteristic is the GJR-GARCH. Therefore, when comparing the EGARCH model with standard GARCH model, GJR-GARCH model will be a logical counterpart in such a comparison. Shephard (1996) developed appropriate model selection criterion that provide guidance for comparison and model selection.

2.2.2 Multivariate Models

Within the GARCH family, there is a differentiation between the univariate model and multivariate models. The simplest form of the GARCH model is classified under univariate models. In their simplest form, the variance only depends on one lag of past returns and past conditional variance. The univariate GARCH model can be extended into the multivariate GARCH model.

The multivariate model is an extension of the univariate model. The process for the extension into a multivariate framework requires allowing the conditional variance–covariance matrix of the N-dimensional zero mean random variables to depend on the constituents of the information set. The basic idea behind the extension from a univariate to multivariate GARCH model in financial applications is because financial volatilities tend to move together more or less across financial markets. Recognising this essential feature through multivariate framework should lead to more suitable empirical models compared to working with independent univariate models. The attempt at extending the univariate models into the multivariate framework involve the merging of all the univariate models for each series. The residual series can be written as:

$$\varepsilon_t = \sqrt{H_t}.\eta_t \tag{2.13}$$

with $\eta_t \sim N(0, I)$ where H_t is a covariance matrix. The literature on multivariate GARCH model is mainly focused on fitting the most suitable variance-covariance matrix H_t. Before proceeding to the various ways of the fitting the variance-covariance matrix, one important requirements worth mentioning is that multivariate models with a smaller number of coefficients or parameters are easier to interpret and explain. However, as the sample size increases, the number of parameters also tend to increase. Therefore the goal is to chose the appropriate model with the smallest number of parameters.

The two general approaches of fitting H_t are:

- First, by using VECH and BEKK models to model H_t directly. This amounts to direct extension of the univariate models.
- Second by independently applying the model to calculate the conditional variances and correlations. This amounts to combining univariate GARCH models using a non-linear approach. The CCC, DCC and ADCC are some of the examples of conditional correlation approaches.

The next section discusses the first multivariate GARCH model known as the VECH model.

2.2.2.1 VECH

VECH is not an abbreviation for anything. Though it is often mistaken in the literature to have a full meaning, VECH was the original name. Bollerslev et al. (1988) were the first to introduce the VECH-GARCH model. The conditional variance and covariance associated with the VECH-GARCH model is a function of lagged conditional variance and conditional covariance, including lagged cross-products of returns and lagged squared returns. The mathematical expression of the model may be written as:

$$VECH(H_t) = C + \sum A_j\, VECH(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + \sum B_j\, VECH(H_{t-1}) \tag{2.14}$$

Where H_{t-1} is a $2X2$ conditional variance-covariance matrix, VECH represents stack-operator that stacks the columns of the lower triangular part of the square matrix; C is a $3X1$ parameter VECH, and A and B are $3X3$ parameter matrices. The estimation of twenty one parameters are required by the model (C has 3 elements, A and B each have 9 elements). Estimation of the *VECH* model with more than 2 variables or assets has large demands on parameters. With the simplest case of two assets or variables, the conditional variance and conditional covariance equations for the unrestricted VECH model require 21 parameters. The VECH model does not allow the inclusion of too many assets as the estimation of the model becomes impractical with increase in number of assets. To solve this problem, Bollerslev et al. (1988) developed a restricted form of the VECH model where the model's conditional variance - covariance matrix are restricted and A and B are assumed to be diagonal. This decreases the number of parameters required for estimation to nine parameters (now A and B each have three elements). The restricted model is known as a diagonal VECH model.

The diagonal VECH model: The diagonal VECH (also known as D-VECH helps to counter the large number of parameters. A univariate GARCH process and a three dimentional D-VECH(1,1) model yields the same conditional variances for each series. The conditional variance can be written as :

$h_{11,t} = \omega_1 + \alpha_{11}\varepsilon_{1,t-1}^2 + b_{11}h_{11,t-1}$,

while the conditional covariance is $h_{12,t} = \omega_2 + \alpha_{22}\varepsilon_{1,t-1}^2 + b_{22}h_{12,t-1}$.

Although less parameters are required for modelling the D -VECH , it is still considered too restrictive because there is usually no interaction between conditional variances and covariances of the model. The lack of interaction between conditional variances and covariances of the model also imply that the dynamics of conditional correlations are not correctly accounted for. This is a major disadvantage of the diagonalised version of the VECH (D-VECH) model. Generally, a drawback of the VECH model is that there is no assurance that the model will give a positive semi-definite covariance matrix. It is generally appealing for a variance-covariance or correlation matrix to be 'positive semi-definite'. Taking into account other conditions, this implies that the variance-covariance matrix will be symmetrical about the leading diagonal and leading diagonal will all have positive numbers. From a mathematical standpoint, variances can never be negative and covariance between two variables is the same and positive definiteness guarantees this standard conditions. Hence, these characteristics are essential and as well as intuitively appealing. The next section discusses the BEKK model.

2.2.2.2 BEKK Model

The Baba, Engle, Kraft and Kroner (BEKK) MV-GARCH model addresses the weakness with VECH model of ensuring that the H matrix is always positive definite (Engle and Kroner, 1995). Essentially, the BEKK model is developed from the VECH model. The strength of the BEKK model is that it guarantee's the positive definiteness condition on an H_t matrix as follows (consider the bivariate case):

$$H_t = C^{'}C + A\varepsilon_{t-1}\varepsilon_{t-1}^{'}A^{'} + B^{'}H_{t-1}B \tag{2.15}$$

From equation 2.15, A and B are $2X2$ matrices of parameters, and C is an upper triangular matrix of parameters. The equation on the right hand side takes a quadratic nature and therefore ensures the positive definiteness of the covariance matrix. With reference to the BEKK model, from equation 2.15 A and B are matrices. A shows the interaction of conditional variances with past squred errors (ε_t^2. B illustrates volatility persistence. The scalar BEKK and Diagonal BEKK model are the two major restrictions on the full BEKK model.

The advantage of the diagonal BEKK model is that it restricts the matrices in equation 2.15 to be diagonal yielding fewer parameters for estimation. The scalar BEKK model is most parsimonious as it further reduces the parameter burden. The BEKK models and associated variants provide an efficient framework for using the multivariate models of the GARCH family. As shown in equation 2.15, the model enjoys a nice representation. In addition to this, it ensures positive-definite volatility matrices. On the other hand, the model has some drawbacks in real applications when utilizing moderate to a large number of variables or dimensions. For instance, for three variables, the volatility equation of a BEKK model of order (1,1) already has twenty four parameters. Therefore a BEKK model of order (1,10) is difficult to estimate when number of dimensions is greater than three. Given the large number of parameters needed for the BEKK model, it is considered to represent another extreme form of multivairate volatility modelling. A second major disadvantage of the model is that the estimates of the parameters associated with modelling BEKK (1,1) are typically statistically insignificant at the five percent level. So far in the academic literature, there is no indication of any link between the elements of the volatility matrix and the parameters of A and B in equation 2.15 since the matrix is a non linear function of the parameters in A and B. Moreover, there are currently no available techniques to simplify the embeded structrues in the BEKK model. Therefore, unrestricted BEKK can only be useful when the number of dimentions is small.

Despite the limitations of the BEKK models, they are very useful when analyzing volatility spill over effects. For instance, using daily data from January 1992 to June 2005, Hassan and Malik (2007) employed trivariate BEKK model to investigate the spillover effects of volatility and shocks between major US sector indices. The results suggest significant transmission of shocks and volatility across all US sectors. The next section discusses the CCC model.

2.2.2.3 Constant Conditional Correlation (CCC) model

The CCC model was first proposed by Bollerslev (1990). With the CCC model, the conditional correlations are kept constant over the entire modeling period. The major advantage of this approach is that the estimation process is simplified and there is parsimonious benefits as less parameters are used in the modelling process. As mentioned in the previous section, modelling conditional correlations using the BEKK model involves the independent calculations of the variance and covariance and the correlations inferred at the end of the modelling process. The disadvantage of this process is that it is time consuming. To address this drawback, Engle (2002) suggested modelling the correlations directly as a dynamic process that vary with time. Following this approach involves separately modelling the univariate volatility estimates and directly estimating the conditional correlations of the matrix. Compared to the VECH and BEKK models, this approach is a more direct method of fitting dynamic conditional correlations and also leads to benefit in parsimony as the process is less parameter hungry.

The CCC model looks as follows:

$$Dlog(Y_{i,t}) = r_{it} \tag{2.16}$$

$r_{it} = \mu_{it} + \varepsilon_{it}$

Where μ_{it} is the Conditional mean equation; ε_{it} is the conditionally heteroskedastic error series.

$$\varepsilon_{it} = \sqrt{H_{it}.\eta_i} \tag{2.17}$$

With $\varepsilon_{it} \sim N(0, H_t)$

Under the CCC-model, the H_t matrix is defined as

$$H_t = D_t R D_t \tag{2.18}$$

where the diagonal matrices D_t, can be defined as

$$diag(\sqrt{h_{11t}},..., \sqrt{h_{NNt}}) \tag{2.19}$$

where h_{11} then takes the functional form of the univariate GARCH model which describes the conditional variance process. Lastly, R_{ij} is a positive definite symmetric matrix that illustrate the conditional correlations among the series by the off-diagonal elements $\rho_{ij}(i \neq j)$.

$$H_t = D_t R D_t =$$

$$\begin{bmatrix} \sqrt{h_{11}} & 0 & 0 \\ 0 & \sqrt{h_{22}} & 0 \\ 0 & 0 & \sqrt{h_{33}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} & \rho_{12} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11}} & 0 & 0 \\ 0 & \sqrt{h_{22}} & 0 \\ 0 & 0 & \sqrt{h_{33}} \end{bmatrix} \tag{2.20}$$

or for a bivariate case written as :

$$h_{11t} = C_1 + \alpha_1 \varepsilon_{11.t-1} + \beta_1 h_{11,t-1}$$

,

$$h_{12t} = \rho_{12} \sqrt{h_{11,t}}.\sqrt{h_{22,t}}$$

$$h_{22t} = C_2 + \alpha_1 \varepsilon_{22.t-1} + \beta_1 h_{22,t-1}$$

In conclusion of the multivariate section, utilizing a multivariate modelling framework to underpin the co-movement of financial volatilities across assets in emerging markets provides immense benefits to investors. From a financial point of view, it provides portfolio managers the opportunity for better decision making in various areas such as hedging and risk management, option pricing, asset pricing and portfolio selection. This study focuses specifically on the dynamic nature of co-movement in the emerging markets between the main economic sectors.

2.3 Empirical results on Contagion

Financial contagion can be viewed as a major downside of financial integration (Alexakis and Pappas, 2018). Financial integration has been perceived by policy makers as fundamental to the efficient implementation of economic policies with beneficial effects upon economic well-being and prosperity (Alexakis and Pappas, 2018; Beine, Cosma and Vermeulen, 2010; Muñoz, Scuzzarella and Cihák, 2011). Conversely, financial contagion is characterised by unpredictability, market volatility and uncertainty in political and economic policies (Alexakis and Pappas, 2018; Peng and Ng, 2012).

Earlier research focus mainly on underpinning the various channels through which crises spread across countries and do not differentiate between the interpretation of interdependence and contagion (Pritsker, 2001). Accordingly, early studies view financial and market integration as the primary reason behind the spread of shocks across countries. On the other hand, later studies tend to focus on the theoretical and empirical interpretation of interdependence and contagion (Wiggins and Metrick, 2019). In order to implement effective and efficient policy responses to international shocks, it is imperative to fully understand the various contagion definitions, measurement of contagion, causes of contagion and channels through which shocks are propagated across countries. There is no clear consensus in past documented studies on the interpretation of financial contagion, hence, there is no universally approved interpretation of financial contagion in the literature

2.3.1 What is Financial contagion?

The seriousness of major financial crises within the last two decades have led to an increase in number of research studies focused on explaining the depth and impact of financial contagion. The term contagion derives from the field of epidemiology, is a scientific theory that means the direct or indirect spread of viral infection such as influenza (Cambridge, 1999). Therefore, the theory of financial contagion is a product of research on financial crises, investor herding behaviour and fundamentals of stock market linkages. Despite the lack of consensus on the definition of financial contagion, a useful framework guiding most researchers in the field of financial contagion studies, presupposes that financial contagion has three major components:

- A shock to a sector or market,
- that has a serious negative impact,
- that affects other markets or sectors

Any event within a financial system can be translated into a shock that may lead to a contagion flowing across different sectors, markets, countries or regions. Early studies concluded that a crisis in one bank can lead to crises in other banks, though the other banks are fundamentally sound (Gorton, 2010). Later studies identified crises that led to contagion from one country to other countries or regions (Kim, Song et al., 2017).

Examples of incidents or triggers that led to contagion are:

- The currency devaluation that led to the 1998 Russian crisis (Chiodo and Owyang, 2002).
- The dotcom bubble (the rising prices of technology stocks in the year 2000) that led to the technology crisis (DeLong and Magin, 2006)
- The bankruptcy of a bank, for example the fall of Lehman Brothers in 2008 (McKinley, 2018).
- A significant increase in a country's debt. For example, the high debt in Greece that exceeded GDP in 2009 led to the Eurozone sovereign debt crisis (Calice, Chen and Williams, 2013)

While there is no consensus on the definition of financial contagion, The World Bank (2018) outline three levels of definition on financial contagion. A broad view, a restrictive view, and a more restrictive definition of financial contagion.

The first definition of financial contagion gives a broad view, and it is a very general and vague one used in the earliest stages of the literature development on financial contagion. It is sometimes referred to as the early stage definition of financial contagion. Under the broad view or early stage approach, financial contagion is defined as the transmission of shocks across countries or regions or the general spillover effects across countries or regions during a crisis. Implied by this first definition is the notion that cross country spillovers or shocks can take place during both good and bad times and not necessarily during crises period. On the other hand, financial contagion has been perceived to occur during a crisis period. Therefore, there is no proper framework under the first definition to work with as there is no reference point linked to an event that trigger the crisis.

In the second more restrictive and focused definition, financial contagion is defined as the transmission of shocks from one country or region to other countries or the increase in cross country correlation above the amount of correlation related to common shocks or economic fundamentals. For instance, Masson (2004) defines financial contagion as "the transmission of shocks across countries that cannot be related to observed changes in macroeconomic fundamentals". Approaching the definition from a different angle, other authors have defined contagion as the increase in the likelihood of a crisis occurring in a particular country or region, conditional on the occurrence of a crisis in another country or region, after controlling for economic fundamentals (Bekaert et al., 2014; Eichengreen and Rose, 1999). This definition is often referred to as excess comovement - correlation that is observed after controlling for common shocks and economic fundamentals. The second definition is often interpreted in line with herding behaviour.

The third definition is the most restrictive. This definition involves an increase in linkages across markets that emerge after a crisis period, following an increase in cross country correlation during crisis periods relative to correlation during tranquil periods. Since it is unlikely for fundamentals to change in a short period of time, it follows that the increase in cross market linkages can only be due to causes that are not related to fundamentals. Furthermore, Forbes and Rigobon (2002) argue that financial contagion is a significant increase in linkages across markets following a shock in a country or region. This is often referred to as "shift contagion". This definition implies that if two or more markets exhibit a high level of co-movement during tranquil (calm) periods and continue to maintain this level of market correlation after a crisis period, this does not necessarily imply that contagion is present. Contagion is only present if co-movement increases significantly across markets after the crisis period. If there is no significant increase in co-movement across markets, then any continued correlation across markets suggest linkages that exist during both calm and crisis times. The term that describe this situation is *interdependence.*

Although the third definition of contagion is the most restrictive, it has two major benefits for the study of contagion. The first benefit is that it provides a good framework that incorporates correlation coefficients that are easy to interpret and integrate within the framework (Bekaert, Hodrick and Zhang, 2009). Essentially, with this framework, the level of linkages across markets during a tranquil (calm) period is compared with the level of linkages after a crisis by observing the correlation coefficients across markets during each period. If there is a significant increase in linkages across markets after the crisis period, then contagion is said to be present. The second advantage of the third definition is that it matches with investor perceptions about risk. An increase in the appetite for risky assets leads to an increase in the demand for risky assets resulting in the simultaneous increase of these assets. On the other hand, investors tend to decrease their demand for risky assets when their appetite for risky assets falls, resulting in a simultaneous fall in the value of risky assets. This leads to an increase in comovement across markets, resulting in contagion. In the literature, this is often refered to as "pure contagion", since it is related to risk, and does not relate to fundamentals, exchange rates arrangements and international trade. (Kenourgios and Dimitriou, 2015).

2.3.2 Co-movement literature

A significant number of studies have been dedicated to the co-movement of stock markets. The research on co-movement can be classified into four main categories.

The first category examines the presence of financial contagion in global stock markets. Preceding research by Lee and Kim (1993), King and Wadhwani (1990) and Koch and Koch (1991) provide results which point towards an increase in unconditional correlations of equity stock returns across global stock markets. Contrarily, Forbes and Rigobon (2002) demonstrate that after taking into account the presence of heteroscedasticity, there is no significant increase in stock-return correlations. Their conclusion is that "there is no contagion, only interdependence". Further studies by Chiang, Jeon and Li (2007), Basu (2002) and Corsetti, Pericoli and Sbracia (2005) verify the presence of the contagion effect; therefore the confirmation of financial contagion, as noted by Corsetti et al. (2005), shows "some contagion and some interdependence".

The second category of studies highlight structural change. There is no agreement or consensus in the literature on the standard interpretation of contagion. Contagion is interpreted in this study as the magnitude of correlation, which is greater than the correlation, expected from economic fundamentals (Forbes and Rigobon, 2002). Using this definition, Corsetti et al. (2005) and Forbes and Rigobon (2002) study whether the correlations of stock market-returns shows significant disparity between calm and crisis period. The approach in the authors' study assumes that the date of structural break can be identified. This approach is therefore designed to uncover a structural change resulting from temporal exogenous shock. On the other hand, studies carried out by Chelley-Steeley (2005) and Lahrech and Sylwester (2011) conclude that a smooth transitional process is preceded by a correlation framework. Their model is designed to uncover structural change resulting from the liberalization of financial markets.

The third category of research concerns the industry/sector correlation changes, rather than equity stock aggregate changes in correlation (Chiang, Lao and Xue, 2016; Phylaktis and Xia, 2011). This category of research is inspired by the conclusion that international portfolio diversification benefits are decreasing accross countries as a result of increase in the correlation of the equity stock markets accross different regions and countries. Therefore researchers question if any diversification at the sectoral level can yield some benefits. The verification of difference in performance of the various sectors after an international shock provides evidence in support of the conclusion that international diversification benefits can be achieved at the sectoral level despite contagion at the aggregate or market level.

The fourth group of studies explored the methodologies utilized by researchers to identify structural changes in correlations. The majority of methodologies utilized are focused in identifying the change in correlation coefficient using data from the volatile period vs tranquil period see (Corsetti et al., 2005; Dungey*, Fry, González-Hermosillo and Martin, 2005; Forbes and Rigobon, 2002). Some of the models provide specific factors that provide clarity on the variation of returns. For example, Bekaert and Harvey (2003) introduces the Fama and French two factor and three factor asset pricing model to study contagion across various regions including Asia, Latin America and Europe during the Asian and Mexican crisis. The authors examine equity market contagion in the regions of Asia, Europe and Latin America during both the Asian and Mexican crises. Their results lead them to conclude that there was no contagion during the Mexican crisis after controlling for foreign and local shocks (two factors). The next section elaborate on other contagion studies.

2.3.3 Contagion studies in developed markets

In light of the U.S equity stock market crash of 1987, the 2008 financial crisis and the European sovereign debt crisis in developed economies and other financial crisis in emerging countries, a varied body of literature on contagion studies have been documented. Furthermore, a greater number of contagion studies suggest that the US equity market lead other developed equity stock markets (King and Wadhwani, 1990). For example, Susmel and Engle (1994) and Hamao, Masulis and Ng (1990) show that US equity returns tend to influence the returns of other countries equities. Previous research focused mainly on the advanced equity stock markets. For instance, according to King and Wadhwani (1990), there was evidence of international contagion in New York during the stock market crash in October 1987. Hamao et al. (1990) examined the interaction and linkage of equity stock markets of developed economies during the 1987 U.S. equity stock market crash by employing univariate GARCH models. By using Bayesian Model Selection analysing the pricing relationships between three developed markets, they verify spillovers from the U.S equity markets to Japan and the UK after the crash period, but no price volatility spillovers are found for the pre-October 1987 period.

By using Volatility Impulse Response Functions (VIRF) for GARCH models, Panopoulou and Pantelidis (2009) examine the volatility dynamics of transfer of information among the US stock market and the remaining six G7 countries. Their empirical results point towards more integration among the markets as evidenced from a substantial increase in amplitude and duration of volatility spillovers after 1995, as a result of more interdependence and persistence in the volatility across all stock markets. Using the most timely sample from January 2003 to April 2009, Cheung, Fung and Tsai (2010) examine the effect of the 2008 financial crisis on the interdependence among international equity stock markets. Their results confirm spillover effects from the US equity market suggesting increased leadership of the U.S market in relation to other stock markets.

2.3.4 Shifting focus to emerging markets

The emergence of the 1997 Asian financial crisis revived the interest in the effect of contagion and the impact of spillover financial crises on other equity stock markets, and turned the focus away from developed stock markets towards studies on the interrelationship between advanced and emerging equity stock markets. Applying VAR and EGARCH models on daily data, Lee, Rui and Wang (2004) investigate the interrelationships between the daily returns of Asian markets and NASDAQ during the 1997 Asian financial crises by employing EGARCH models, dynamic causality tests, and VAR - based forecast error decompositions using daily data of a sample period that includes the Asian financial crisis of 1997 and continues until April 20, 2001. Their findings reveal substantial evidence of spillovers and lagged returns from US market (NASDAQ) to Asian markets.

By applying a multivariate copula approach on a sample of daily data from March 2004 to March 2009 for emerging and US markets, Aloui, Aïssa and Nguyen (2011) investigate the intensity of the contagion effect induced. Their empirical findings points towards strong linkages between selected emerging markets and U.S markets. During bearish and bullish markets all pairs between emerging and US markets show high level of dependence persistence.

Applying the Dynamic Conditional Correlation (DCC) multivariate GARCH model of Engle (2002) to weekly return index of seven emerging equity stock markets of Central and Eastern Europe (CEE) for the period of 1997 to 2009, Syllignakis and Kouretas (2011) examine the presence of short-run interrelationships among the stock market returns of CEE, US, Germany, and Russia .Their findings point towards an increase in conditional correlations among the US, Germany and CEE equity stock returns during the 2008 global financial crises.

With a focus on emerging markets, two global indices and the US, Kenourgios and Padhi (2012) examine the financial contagion of three crises in emerging markets during the late 1990s, along with the subprime crises of 2007/2008. Applying VECH and integration analysis, their analysis show long and short run dynamics for the stocks during the Asian and Russian crises and the subprime crisis, whereas there was no effect on any of the examined equity markets during the Argentine crisis.

A few studies dwell on the interrelationships between Asian markets and their interdependencies with advanced economies. For example, Sheng and Tu (2000) investigate the interrelationships between the equity stock markets of twelve Asia-Pacific countries and the US before and during the Asian financial crisis for the period of 1997 to 1998. Using error correction test and co-integration models, their results point towards the presence of co-integration relationships between the national stock indices during the Asian financial crisis, but not before this financial crisis. Applying Multivariate Co-integration model on a monthly data from a period of 1980 to 1998, Phylaktis and Ravazzolo (2005) examine the interrelationship among the equity stock market of US and Japan with those of the Pacific Basin countries. Their results suggest that there were no interrelationships between the equity stock markets of US, Japan and several Asian Pacific Basin countries during this period.

Finally, applying an Exponential Generalized Auto-Regressive Conditional Heteroscedasticity (EGARCH) process to daily data from April 1999 to October 2006, Weber (2010) analyses the impact of volatility transmission among the equity stock market, money market and foreign exchange markets in the Asian Pacific region. Their findings confirm various volatility causality between the equity markets of the Asian Pacific region during this period.

Similar contagion dynamics as those for other emerging economies are registered in the MENA (Middle East and North Africa) region, contributing to plunging asset prices, decline in stock markets, increase in cost of capital, decrease in capital flows and a lower exports. For example, Neaime (2012) investigates the international and local financial interrelationships among equity stock markets in MENA countries and developed economies (US and EU), as well as intra regional financial interrelationships among oil and non-oil producing MENA countries' equity markets by applying variance GARCH models, the Threshold ARCH and ARCH-M models, and VAR analysis. The results show that the effect of the 2008 subprime crisis on the stock market of MENA countries vary to the degree that MENA countries are integrated with developed markets. By using a set of System Generalized Method of Moments (SGMM) and Panel Vector Autoregressive (PVAR) models to investigate the effect of international shocks on global cost of equity, Guyot, Lagoarde-Segot and Neaime (2014) examine whether global financial shocks can alter the cost of equity in emerging stock markets. Their findings suggest that foreign shocks can lead to high cost of equity in major emerging markets. Applying dynamic conditional correlations as per Engle (2002), Maghyereh, Awartani and Al Hilu (2015) investigate short term volatility spillovers and dynamic conditional correlations of stock market returns of the US and MENA countries before and after the fall of 2008 global financial meltdown. Their findings verify that the correlation of MENA stock markets with the US market was weak before the crisis, However, the correlation increased to a higher level after the crisis.

The next section focuses specifically on contagion at the aggregate stock market level.

2.3.5 Aggregate stock market contagion

Much of the early equity market contagion literature makes use of correlation analysis. Correlation analysis involves testing the changes in the correlation coefficients among two or more equity stock markets over a period which typically involves stable and unstable (volatile) periods. A significant increase in correlation coefficient between the two periods suggest that there is presence of contagion. Many studies applying this approach, investigate contagion immediately after the 1987 US market crash.

King and Wadhwani (1990) investigate the reason for the fall of almost all stock markets globally during the October 1987 crash despite their differences in economic circumstances. Using hourly data for London, New york and Tokyo for the period July 1987 to February 1988 to estimate cross market correlations between these markets, their findings suggest that there was an increase in contagion between United Kingdom, the United states and Japan during the crash. They conclude that economic fundamentals cannot explain the simultaneous fall in global stock markets during the 1987 crash. They put forward that the rise in correlation coefficients among the markets after the 1987 crash suggest that an increase in volatility leads to an increase in the size of contagion effects.

Longin and Solnik (1995) study the conditional correlation monthly excess returns among seven major countries over the period 1960 to 1990. Their findings suggest an increase in international correlation among the seven major markets (Canada, France, Germany, Japan, Switzerland, the UK and the US) over the past 30 years.

Notwithstanding, subsequent research observed that incorrect conclusions can result from focusing only on correlations. For example, Forbes and Rigobon (2002) challenge the above findings and show that the correlation coefficients were "biased due to heteroscedasticity in market returns". They demonstrate that tests on contagion based on unadjusted correlation coefficients are problematic because of heteroskedasticity (changing volatility in market returns). They point out that correlation coefficients are typically conditional on market volatility which lead to the upward bias of cross market correlation during a crisis. After adjusting for this upward bias, they find virtually no increase in uncondinational correlation coefficients (No evidence of contagion) during the 1997 Asian crisis, 1994 Mexican crisis and 1987 U.S crash. Instead, a high level of market co-movement is found during all states globally (during both stable and crisis periods), which reflects the linkages of markets globally. Their conclusion is that there is no contagion, but only interdependence.

An alternative argument is advanced in the study carried out by Corsetti et al. (2005) where, the authors investigate the global impact of 1997 Hong Kong stock market crisis. The results lead the authors to argue that the results of Forbes and Rigobon (2002) of "no Contagion, only interdependence" is inconsistent and places constraints on the volatility of country unique shocks that are not practical. Their analysis find the presence of contagion when idiosyncratic shocks are taken into account.

Bekaert and Harvey (2003) avoid using the correlation analysis approach, but instead utilise a two factor model that take in varying levels of stock market integration among different markets. This model is applied to three different regions: Europe, Latin America and Southeast Asia. After controlling for regional and international shocks, and interpreting contagion as correlation between model residuals, their results point towards no contagion as a result of the Mexican crisis. From the studies above and several other studies on contagion, it is clear that the literature on contagion is mostly concerned with the propagation of shocks across countries during financial crises. Karolyi (2003) refer to contagion as a downside phenomenon which involves the propagation of shocks from one country to another. However, as stated by Dungey, Fry and Martin (2003) in a comprehensive survey on this topic "Contagion is both difficult to define and difficult to measure". The next section deals with literature on industry/sector integration.

Other studies have incorporated the approaches mentioned in this section to study contagion:

Morales and Andreosso-O'Callaghan (2014) utilise three different econometric models to investigates the effects of contagion arising from the US subprime crisis within the worldwide framework. The results suggests that the 2008 US subprime crises had varying effects across the world. However, there is no evidence of contagion effects across world markets or regional markets. Their findings also suggest that global markets were impacted mostly by spillover effects, and not contagion effects. Spillover effects from the fall of Lehman Brothers were transmitted to some major countries across different regions such as the UK in Europe and Singapore in Asia.

Emin (2018) investigates the spillover effects of the US subprime crises to global markets by manipulating key components of financial contagion: timing, volatility and return denomination. Their results suggests that although the effect of contagion is considered the most important factor in the literature for the spread of shocks from one market to another during financial crises (for example the US subprime crises), statistical and empirical applications determine the final results. Using the statistical approach which involves comparing the results of unadjusted correlation coefficients with results where the heteroskedasticity effect on correlation coefficients are corrected, the results show that there was contagion across 28 countries during the US subprime crisis for unadjusted correlation coefficients. However, only 22 countries suffered from contagion during the US subprime crisis for the heteroskedasticity corrected correlation coefficients. The empirical approach involves comparing results of synchronized vs non-synchronized data and comparing results of local currency vs common currency data. The findings suggests that while a statistical approach which involves correcting for heteroskedasticity bias remarkably changes the final results regarding the presence of contagion, the empirical approach involving the use of local currency and or synchronized data does not have a major impacts on the final results, and only produce moderately different results compared to the common currency and or non-synchronized data.

The next section discusses sector level contagion.

2.3.6 Sector level contagion

While equity market contagion has been broadly studied, sector level integration only started to receive attention in recent times.

Individual sectors within a country tend to respond differently to international and local shocks, as well as during different economic cycles. Therefore, it is recommended to include a broad range of sectors in an investment portfolio.

Sectoral differences were revealed in a study carried out by Black, Buckland and Fraser (2002), who studied a range of UK sector indices for the period 1968 to 2000. Their findings provide evidence that the increase in both sector and subsector specific risk contributed to the volatility of the UK stock market during this period. Their findings illustrate the importance of taking into account movement of both sector and subsector specific risk when building an investment portfolio of stocks.

Using the Dynamic Conditional Correlation (DCC) GARCH model to analyze daily returns for the period of January 1987 to May 2003, Beine, Preumont and Szafarz (2006) studied the cross sector correlation among ten dow Jones European sector financial indices. By comparing the behaviour of sector correlation before and after the IT bubble periods the results provide evidence that sector indices are less affected by contagion (increase in correlation that reduces portfolio diversification) compared to country or aggregate market indices observed by other authors.

The present study is closely related to the above literature on sector diversification, and examines whether sectors are integrated at the global or regional level. However, our focus include the evidence in emerging economies like BRICS, while the above mentioned papers concentrate on Eurozone and developed countries like the United States.

2.4 Conclusion

In this chapter, the literature on financial contagion was reviewed. Given that there is a large body of literature on financial contagion, this chapter was divided into three sections. At first, an overview of the BRICS was provided. In the second section the methodological literature related to contagion was discussed, and the third section relates to relevant empirical results on contagion.

BRICS economies are among the fastest growing emerging markets in the world. Therefore the first section discussed the economic characteristics and major determinants of economic development for each of the BRICS countries.

In the section on methodological literature overview, two groups of models were discussed, namely univariate and multivariate models. The univariate models are normally used to analyze volatility spillovers. The univariate approach starts with the estimation of the AR, MA, ARMA and ARIMA. The ARMA models offers more parsimony compared to the AR and MA. The ARIMA models are used to model conditional variance given that the past is constant. However, stock returns are volatile. Hence the ARCH model of Engle (1982) and GARCH models of Bollerslev

(1986) are suitable for modelling non-constant variance. Other forms of GARCH models include the IGARCH applied in volatility modelling when the strength of the persistence resembles a unit root. Due to asymetric issues exhibited by some financial time series, the EGARCH and GJR GARCH models were developed. The multivariate model is an extension of the univarate model. The basic idea behind the extension of a univariate model to the multivariate GARCH model in financial applications is because financial volatilities tend to move together more or less across financial markets. Therefore the variants of multivariate models include the VEC, BEKK, CCC, DCC and ADCC models. The VEC and BEKK are only useful when the number of parameters involved is small. The CCC model addresses the shortcoming of the VEC and BEKK. The disadvantage of the CCC model is that conditonal correlations are kept constant over the entire modelling period. To address this drawback, Engle (2002) suggested the DCC model, where correlations are allowed to vary with time. The next chapter discusses the data used in this study.

Chapter 3

Data

This chapter presents the description and preliminary analysis of the data used and also provides a background on the challenges involved in getting the data. The empirical analysis of the descriptive statistics tables as well as further characteristics on the daily data used in the study is also presented in this chapter. Section 4.1 provide the description and preliminary analysis of data. Section 4.2 presents the empirical analysis of the descriptive statistics and Section 4.3 discusses the further characteristics of the daily data used in the study.

3.1 Description and preliminary analysis of data

The data used in this study are daily prices of Morgan Stanley Capital Index (MSCI) aggregate equity indices and sector equity indices for five emerging countries (Brazil, Russia, India, China and South Africa) and four developed countries (the US, the UK, Germany and Japan). The study started initially with nine sectors: financials, materials, industrials, consumer discretionary, consumer staples, health care, telecommunication services, utilities and technology. The data sourced from Bloomberg, covered the period from 3 January 1994 to 29 December 2017.

The challenge with the data availability was to find a subsample of the time period, where every country and every sector had complete data. In this respect, many countries and sectors had incomplete and missing data. To that degree, only the financials, materials, consumer staples and telecommunications were retained for completeness. Some sectors, for example, had missing data for the period 1994 to 2005. Furthermore, even within these categories, data quality was poor, with many sectors having missing values. Thus the period 2006 to 2017 represented the subsample of the data where all sectors across countries had complete data. This was therefore the sample that was used throughout the paper, leading to a final sample of 2972 observations. While ideally, a longer sample would have been preferred, given the sectoral focus of this study, completeness of data and sectors, rather than only focusing on sectors which had data available pre-2006 was considered more important. Inspired by existing research, for instance Wang (2014), this study exclude all holidays' data from the sample. All MSCI values are denominated in the US dollar. Following this procedure eliminates local currency inflation (Bekaert et al., 2014). In this study, daily return data was preferred to lower frequency data, such as weekly and monthly values, because transient responses to innovations which may last for a few days only, can be hidden or obscured by longer horizon prices or returns.

For each MSCI stock index, the continuously compounded return is estimated as

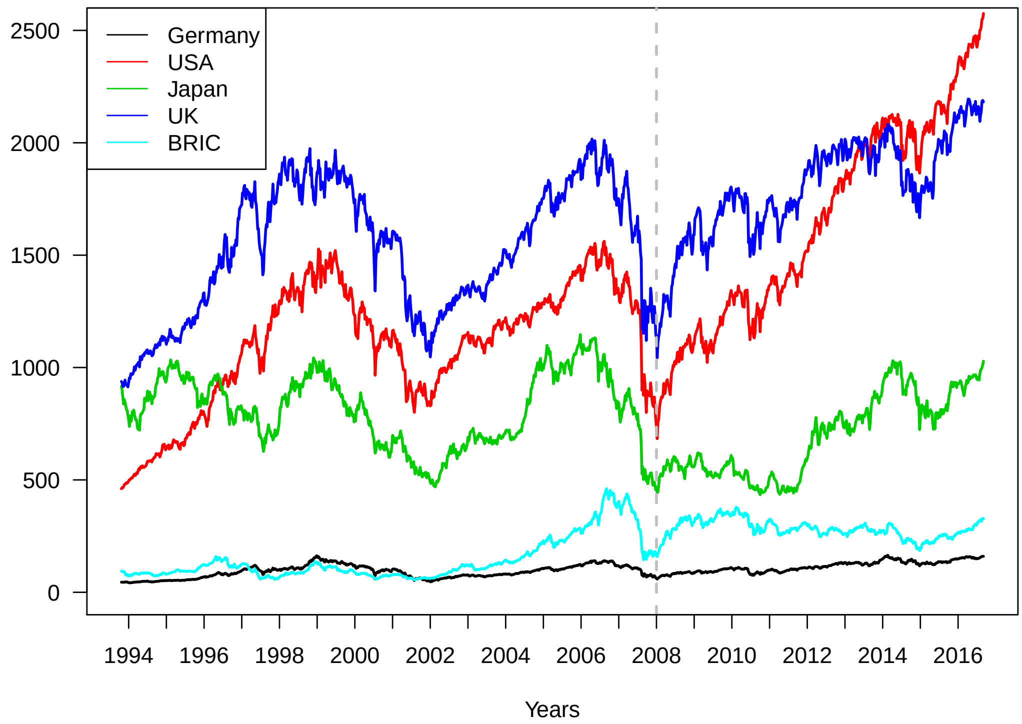
$$r_t = 100 * [\log \frac{p_t}{p_{t-1}}] \tag{3.1}$$

Where p_t is the price on day t.

The return series consists of 2971 observations as one observation is lost due to differencing the daily closing prices series.

Figure 3.1 presents the progression of the aggregate stock market indices during the period 1994 to 2017. The graph shows that the stock markets across these countries move in tandem during crisis period such as the US subprime crisis.

Figure 3.1: Aggregate stock market indices



3.2 Empirical analysis of descriptive Statistics

This section commences the empirical results with the analysis of descriptive statistics for aggregate data for the full sample period. This is followed by analysis of sample statistics for the full sample period for each sector (which include both stable and the three crisis periods) followed by the descriptive statistics for GFC, ESDC and Brexit sample period for each of the sectors under study. The objective of this section is to explore the characteristics in the behaviour of stylized facts of sample periods for all the sectors under study. The next section discusses the empirical analysis of descriptive statistics for aggregate data.

3.2.1 Empirical analysis of descriptive statistics for aggregate data

This subsection elaborates on the descriptive statistics of aggregate data. Table 3.1 reports the descriptive statistics of aggregate data for the full sample period. Scanning through the table, positive mean values are observed for all stock market returns across the nine countries. This is an indication that all the markets were profitable on average for the sample period under consideration. Among BRICS countries, the worst performance in terms of mean return is Russia, followed by Brazil. Among developed countries, the worst performance in terms of mean return is Japan and the UK.

Considering the volatility, among BRICS countries, the stock market with the highest volatilities is observed in the case of Russia (5.37), followed by Brazil (4.97). Among developed countries, the highest volatility is observed in Japan (1.97), followed by Germany (1.74). Suprisingly, the volatility of Germany is greater than that of the UK even though UK market exhibits lower returns.

The skewness measures indicate that the return series across all countries as negatively skewed. This is an indication that at least one of the crises had a severe impact on each country's stock markets. Kurtosis of the nine countries are leptokurtic indicating the occurence of several abnormal events.

Table 3.1: Descriptive Statistics for aggregate data

	USA	**UK**	**Germany**	**Japan**	**Brazil**	**Russia**	**India**	**China**	**RSA**
Minimum	-9.47	-9.16	-7.38	-10.44	-18.32	-25.59	-11.74	-12.84	-7.91
Maximum	10.96	9.27	11.13	13.06	16.62	23.98	16.42	14.06	5.96
Mean	0.02	0.01	0.02	0.01	0.02	0.01	0.04	0.04	0.04
Median	0.04	0.01	0.05	0.00	0.07	0.03	0.03	0.00	0.04
Variance	1.37	1.29	1.74	1.97	4.97	5.37	2.04	2.86	1.49
Stdev	1.17	1.13	1.32	1.40	2.23	2.32	1.43	1.69	1.22
Skewness	-0.36	-0.15	-0.04	-0.37	-0.35	-0.37	-0.01	-0.05	-0.21
Kurtosis	12.62	8.62	6.60	7.90	7.98	15.61	10.52	8.01	3.02

3.2.2 Empirical analysis of descriptive statistics for the financial sector

This subsection provides the descriptive statistics analysis of financial sector data. Table 3.2 reports the descriptive statistics for the full sample for the financial sector. Tables 3.3, 3.4 and 3.5 show the descriptive statistics of the financial sector during the GFC, ESDC and Brexit crisis periods respectively.

In Table 3.2, the mean for the financial sector across all countries was positive on average. This is an indication that the financial sector across the nine countries was profitable on average over the sample period. For BRICS countries, the highest mean daily return is observed for Russia (1.39), followed by Brazil (1.27), China (0.97), India (0.94) and South Africa (0.78). For developed countries, the highest daily return is observed for Japan (0.85), followed by Germany (0.82), the UK (0.75) and the USA (0.73). The country with the lowest daily return in the financial sector is the USA.

When compared to the GFC crisis period, the financial sectors across all nine countries exhibit negative average returns. This is an indication of a gloomy outlook in these sectors across all nine countries during the GFC. When the full sample period is compared to the ESDC, it is observed that only five out of the nine countries exhibit negative returns. Strikingly, the two major countries in the BRICS basket exhibit negative returns (Brazil (-0.03) and China (-0.06)) indicating the negative impact of a strong decline on the financial sectors of these two countries. When the full sample is compared to the Brexit crisis period, negative returns across all nine countries are not observed. This implies that the shock resulting from the UK/EU referendum results had little impact on the financial sectors of the nine countries during the entire Brexit sample period. These findings are confirmed by Aristeidis and Elias (2018) who did a study on the effect of the 23 June 2016 EU/UK referendum results on 43 major developed and emerging countries, and found that the impact and uncertainty of the referendum results were very limited because the stock markets quickly recovered their losses within a few days after the results of the referendum were released.

With regards to volatility, among BRICS markets, the highest volatility during the full sample period is observed in the case of Russia (9.40), and the lowest is South Africa (1.96). During the GFC period, the highest volatility is observed in the case of Russia (24.39), followed by Brazil (17.28), China (11.76), India (11.57) and South Africa (4.55). During the ESDC period, the highest volatility is observed in Russia (5.18), while the lowest is observed in South Africa (1.14). During Brexit, the highest volatility is observed for Brazil (4.19), followed by Russia (3.09), India (1.29), South Africa (1.80) and China (1.12). As far as volatility is concerned, Russia has the highest volatility across at least two crisis period and the full sample period. This finding is in line with previous research. For example, Kenourgios, Naifar and Dimitriou (2016) did a study on the effect of the global financial crisis and Eurozone sovereign debt crisis on Islamic equity stock markets. These authors provide evidence that the Russian Islamic stock index is the most volatile index during the full sample period, and for GFC and ESDC sample periods. Among developed countries, the highest volatility is observed in the case of the USA (4.26) for the full sample period. During the GFC, the USA financial sector also exhibits the highest volatility of 14.12. This is probably because the GFC started from the US financial sector. During the ESDC, the highest volatility is observed in the case of the UK (2.23). Suprisingly, during the Brexit crisis, the highest volatility is observed in Japan (3.01), followed by the UK (2.14). Again this result confirms that the effect of the referendum results only lasted for a few days, (Aristeidis and Elias, 2018). Therefore, the effect had little bearing on the volatility of the UK market.

With regards to skewness, most countries display negative skewness during the ESDC and Brexit crises period indicating the impact of each of these crisis during these periods. Kurtosis during the full sample period is leptokurtic across all nine countries and across most countries during the GFC. This is evidence of the occurence of several abnormal events during these sample periods.

Table 3.2: Descriptive Statistics of financial sector

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
Minimum	-20.03	-13.34	-12.50	-13.82	-12.40	-26.49	-10.53	-13.43	-17.80
Median	-1.22	-0.88	-0.82	-0.81	-0.94	-1.30	-0.69	-0.74	-0.67
Mean	1.27	0.97	0.82	0.94	0.85	1.39	0.78	0.75	0.73
Maximum	42.14	72.19	-15.05	131.35	-57.00	25.31	117.02	-44.63	7.12
Variance	6.53	3.80	3.39	3.75	3.52	9.40	1.96	3.31	4.26
Stdev	2.55	1.95	1.84	1.94	1.88	3.07	1.40	1.82	2.06
Skewness	0.02	0.14	0.17	0.09	-0.03	-0.01	-0.06	0.02	-0.16
Kurtosis	8.52	6.51	9.54	7.73	6.04	14.58	3.74	10.64	14.55

Table 3.3: Descriptive Statistics of financial sector during GFC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-20.03	-13.34	-12.50	-13.82	-12.40	-26.49	-8.14	-13.43	-17.80
Median	-0.09	0.00	-0.08	0.00	-0.06	-0.06	-0.08	-0.29	-0.26
Mean	-0.07	-0.07	-0.17	-0.08	-0.21	-0.34	-0.05	-0.21	-0.34
Maximum	23.12	13.65	16.08	10.30	14.49	32.85	6.48	17.61	16.04
Variance	17.28	11.76	10.07	11.57	9.99	24.39	4.55	11.35	14.12
Stdev	4.16	3.43	3.17	3.40	3.16	4.94	2.13	3.37	3.76
Skewness	0.22	0.18	0.37	-0.13	0.09	0.27	0.17	0.26	-0.20
Kurtosis	4.51	2.15	4.46	1.05	2.05	9.42	0.75	3.37	4.15

Table 3.4: Descriptive Statistics Financial sector during ESDC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-10.13	-6.23	-6.65	-4.82	-9.33	-9.53	-4.87	-5.44	-5.03
Maximum	7.51	4.39	8.35	4.55	5.87	8.81	4.46	8.62	5.31
Mean	-0.03	-0.06	-0.05	0.02	-0.06	0.06	0.03	-0.04	0.01
Median	0.00	-0.01	-0.02	0.00	0.00	0.05	0.00	0.00	0.00
variance	3.54	1.91	2.08	2.08	2.19	5.18	1.14	2.23	2.19
Stdev	1.88	1.38	1.44	1.44	1.48	2.28	1.07	1.49	1.48
Skewness	-0.43	-0.30	0.10	-0.02	-0.55	-0.11	-0.11	0.16	-0.20
Kurtosis	2.30	1.11	3.08	0.26	6.62	2.09	1.83	2.88	1.25

Table 3.5: Descriptive Statistics for financial sector during Brexit crisis

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-10.39	-4.59	-9.18	-4.16	-8.25	-5.55	-4.84	-11.32	-5.44
Maximum	5.25	2.68	4.19	3.35	8.60	5.09	3.12	4.11	3.93
Mean	0.17	0.08	0.10	0.09	0.11	0.12	0.01	0.09	0.12
Median	0.09	0.09	0.11	0.01	0.00	-0.02	0.02	0.07	0.11
Variance	4.19	1.12	1.66	1.29	3.01	3.09	1.80	2.14	0.98
Stdev	2.05	1.06	1.29	1.13	1.73	1.76	1.34	1.46	0.99
Skewness	-0.81	-0.50	-1.56	-0.21	0.24	0.01	-0.38	-2.68	-0.35
Kurtosis	3.91	1.34	11.80	1.32	4.85	0.34	0.76	19.45	5.11

3.2.3 Empirical analysis of descriptive statistics for Material sector

This subsection provides the descriptive statistics analysis of material sector data. Table 3.6 reports the descriptive statistics for the full sample period for the material sector. Tables 3.7, 3.8 and 3.9 show the descriptive statistics of material sector during GFC, ESDC and Brexit crisis period respectively. During the entire sample period, among BRICS countries, Brazil has the highest mean daily return of 1.35, followed by Russia (1.14), China (1.11), India (1.01) and South Africa (0.93). During the GFC, the mean daily return for all BRICS countries are negative, with Russia having the lowest mean daily return. During the ESDC, only three of the major BRICS countries (Brazil, China and India) exhibit negative mean returns indicating the strong impact of the downturn due to ESDC on the material sector of these countries. During Brexit, the only BRICS country with a negative mean daily return is South Africa. These results confirm the minimal impact that UK/EU referendum results had on BRICS countries. For developed countries, considering the entire sample period, the country with the highest mean daily return is the UK (1.23), while the lowest is the USA (0.78). During the GFC period, the USA has the lowest mean daily return of -0.17. This is probably expected as the GFC started in the US. During the ESDC, Germany and USA has the highest mean daily return of 0.06, while the lowest is Japan (-0.006). During Brexit, the USA has the lowest mean daily return. This implies that the UK/EU referendum results effect had a greater impact of the material sector of the USA compared to the other developed countries.

With regards to volatility, among the BRICS countries, for the entire sample period, Brazil is the country with the highest volatility (7.12), followed by Russia (6.13) while the lowest is South Africa (3.16). During both the GFC and ESDC periods, the highest volatility is still observed in the case of Brazil, followed by Russia, and the lowest is South Africa. During the Brexit crisis period, Brazil has the highest volatility. However, the lowest volatility is observed in the case of India. This implies that the material sector of Brazil is the most volatile. For developed countries, during the entire sample period, it is interesting that the highest volatility is observed in the case of the UK (5.90), while the lowest volatility is the USA (2.57). This pattern is maintained for the GFC, ESDC and Brexit crisis periods where the highest volatility is observed for Uk and lowest volatility for the USA. Therefore, the UK material sector is the most volatile compared to other developed countries, while the USA is the lowest across all three crises periods.

As far as skewness is concerned, during the entire sample period, the skewness across most countries is negative. During the GFC and ESDC, the skewness for most countries is negative indicating the severe impact of the GFC and ESDC. Among the three types of crisis (GFC, ESDC and Brexit), the occurence of negative skewness is lowest for Brexit, implying a lesser impact of Brexit.

Kurtosis is leptokurtic for all countries during the full sample period. The kurtosis is leptokurtic for most countries during the GFC. Two countries during ESDC sample period and four countries during Brexit crisis sample period have kurtosis which are leptokurtic.

Table 3.6: Descriptive Statistics Materials

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
Minimum	-22.08	-15.08	-10.46	-13.80	-12.56	-30.89	-10.09	-18.60	-13.10
Median	-1.34	-1.06	-0.72	-0.86	-0.82	-1.04	-0.98	-1.13	-0.62
Mean	1.35	1.11	0.84	1.01	0.90	1.14	0.93	1.23	0.78
Maximum	-0.58	31.57	77.51	77.84	-3.50	-13.21	-71.32	30.69	72.14
Variance	7.12	5.59	2.78	3.53	3.15	6.13	3.16	5.90	2.57
Stdev	2.67	2.36	1.67	1.88	1.77	2.48	1.78	2.43	1.60
Skewness	-0.22	0.27	-0.07	-0.19	-0.22	-1.13	-0.03	-0.11	-0.51
Kurtosis	5.94	7.86	7.02	5.92	7.53	17.08	3.07	6.40	8.48

Table 3.7: Descriptive Statistics Materials during GFC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-22.08	-15.08	-10.46	-13.80	-11.81	-30.89	-10.09	-18.60	-13.10
Maximum	17.19	22.43	13.87	9.93	15.97	20.22	9.24	18.44	12.77
Mean	-0.07	-0.14	-0.11	-0.11	-0.19	-0.19	-0.06	-0.08	-0.17
Median	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	0.00
Variance	18.97	17.17	7.33	9.43	8.07	18.92	7.09	17.37	7.52
Stdev	4.36	4.14	2.71	3.07	2.84	4.35	2.66	4.17	2.74
Skewness	-0.24	0.38	0.13	-0.40	0.05	-1.13	-0.28	-0.04	-0.31
Kurtosis	3.40	3.02	4.44	1.73	4.07	9.08	1.57	2.69	3.80

Table 3.8: Descriptive Statistics Materials during ESDC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-10.71	-6.33	-6.45	-5.31	-12.56	-8.56	-4.38	-7.09	-4.47
Maximum	7.73	5.50	5.69	5.93	8.71	9.74	4.69	7.33	4.63
Mean	-0.03	-0.03	0.06	-0.02	-0.03	0.10	0.01	0.03	0.06
Median	0.01	0.00	0.07	0.00	0.00	0.10	0.00	0.00	0.07
Variance	3.87	2.92	2.29	2.48	2.44	3.81	1.52	4.04	1.97
Stdev	1.97	1.71	1.51	1.57	1.56	1.95	1.23	2.01	1.40
Skewness	-0.44	-0.26	-0.26	-0.04	-0.87	0.01	0.08	-0.20	-0.25
Kurtosis	3.16	0.74	1.44	0.78	11.82	2.44	0.81	0.66	0.68

Table 3.9: Descriptive Statistics Materials during Brexit

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-7.45	-3.88	-6.34	-6.41	-8.00	-3.94	-4.13	-4.55	-4.50
Maximum	7.21	5.88	3.72	2.80	7.76	3.90	5.33	5.13	2.48
Mean	0.24	0.16	0.10	0.14	0.15	0.11	-0.05	0.19	0.06
Median	0.15	0.00	0.07	0.08	0.04	0.03	-0.12	0.16	0.07
Variance	6.56	1.79	1.18	1.54	2.22	1.71	2.81	3.05	0.74
Stdev	2.56	1.34	1.09	1.24	1.49	1.31	1.67	1.75	0.86
Skewness	-0.16	0.30	-0.74	-0.81	-0.09	-0.05	0.31	0.06	-0.94
Kurtosis	0.16	1.98	5.86	3.24	7.58	0.10	0.45	0.10	4.45

3.2.4 Empirical analysis of descriptive statistics for the Consumer staples

Table 3.10 reports the descriptive statistics for the full sample for the consumer staples sector. Tables 3.11, 3.12 and 3.13 show the descriptive statistics of the consumer staples sector during GFC, ESDC and Brexit crisis period respectively. Among BRICS countries, for the full sample period, the highest mean daily return is observed in the case of Russia (1.62), followed by Brazil (1.02), China (0.82), South Africa (0.75) and India (0.70). Three of the BRICS countries exhibit negative mean returns during the GFC (Brazil (-0.05), China (-0.06) and Russia (-0.14)). During the ESDC and Brexit crisis periods, none of the BRICS countries exhibit negative mean returns. This shows that the consumer staples sector for BRICS countries were more prone to shocks from the GFC than the ESDC and Brexit crises.

Among developed countries, for the full sample period, the highest mean daily return is observed in the case of Germany (0.69), and the lowest mean daily return is observed in the case of USA (0.45). During the GFC period, all four developed countries exhibit negative mean returns indicating a gloomy outlook for the stock markets of these countries during the GFC. During both the ESDC and Brexit, no negative mean return is observed across all developed countries. This implies that the consumer staples sector was more prone to shocks from the GFC compared to the ESDC and Brexit.

With regards to volatility, for the full sample period, among BRICS countries, the highest volatility is observed in the case of Russia (12.35), and the lowest volatility is observed in the case of South Africa (1.47). During the GFC, the highest volatility is observed in the case Russia (42.17) and the lowest in South Africa (2.54). During the ESDC, the highest volatility is again observed in the case of Russia (6.72) and lowest in South Africa. During Brexit, the highest volatility was observed in the case of Russia (4.17) and lowest in India (0.78). This indicates that the consumer staples sector of Russia was the most volatile among BRICS countries.

Among developed countries, for the full sample period, the highest volatility is observed in the case of Germany (1.59) and the lowest for the USA (0.75). During the GFC period, the highest volatility is observed in the case of Germany (3.51) and Japan (3.51), and the lowest in USA (2.02). During the ESDC the highest volatility is observed in the case of Japan (1.31) and the lowest volatility is observed in the case of the USA (0.45). During the Brexit period, the highest volatility is observed in the case of the Japan (1.0) and the lowest in the USA (0.45). Therefore, among developed countries, the USA has the least volatile consumer staples sector.

As far as skewness is concerned, most of the countries exhibit negative skewness during the full sample period and during all three crises (GFC, ESDC and Brexit). This implies that the three crises had an impact on the consumer staples sector of these countries. The Kurtosis of most countries during the full sample period and GFC sample period are leptokurtic indicative of the occurence of various uncommon events during these periods.

Table 3.10: Descriptive Statistics Consumer Staples

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
Minimum	-16.84	-19.14	-7.66	-8.95	-11.67	-31.98	-4.86	-8.33	-6.64
Median	-0.85	-0.71	-0.62	-0.58	-0.55	-1.54	-0.65	-0.48	-0.36
Mean	1.02	0.82	0.69	0.70	0.60	1.62	0.75	0.55	0.45
Maximum	91.01	94.96	75.00	148.73	54.75	87.95	146.65	90.18	82.26
Variance	3.57	2.17	1.59	1.71	1.56	12.35	1.47	1.03	0.75
Stdev	1.89	1.47	1.26	1.31	1.25	3.51	1.21	1.02	0.87
Skewness	-0.50	-1.00	0.13	-0.09	-0.35	0.86	0.11	-0.11	-0.02
Kurtosis	7.84	14.45	5.49	4.29	10.93	20.70	1.63	5.99	11.32

Table 3.11: Descriptive Statistics Consumer Staples during the GFC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-16.84	-19.14	-7.32	-8.95	-9.96	-31.98	-4.74	-8.33	-6.64
Maximum	13.00	9.02	10.90	6.13	11.48	47.14	7.15	8.01	8.80
Mean	-0.05	-0.06	-0.12	0.01	-0.12	-0.14	0.01	-0.04	-0.06
Median	0.00	0.00	-0.08	0.00	0.00	-0.05	0.00	0.00	0.00
Variance	9.79	5.14	3.51	3.99	3.51	42.17	2.54	2.65	2.02
Stdev	3.13	2.27	1.87	2.00	1.87	6.49	1.59	1.63	1.42
Skewness	-0.45	-1.48	0.59	-0.32	-0.00	0.98	0.39	-0.04	0.33
Kurtosis	4.28	12.17	4.72	1.97	6.99	9.44	1.22	3.81	7.70

Table 3.12: Descriptive Statistics Consumer Staples during the ESDC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-7.32	-4.92	-4.47	-3.48	-11.67	-11.84	-2.78	-2.94	-3.24
Maximum	6.13	5.44	4.43	4.25	7.73	10.75	2.99	3.62	2.72
Mean	0.05	0.04	0.03	0.05	-0.00	0.07	0.08	0.03	0.05
Median	0.09	0.01	0.01	0.00	0.00	0.00	0.10	0.06	0.05
Variance	2.26	1.60	1.22	1.27	1.31	6.72	0.88	0.76	0.45
Stdev	1.50	1.26	1.11	1.13	1.14	2.59	0.94	0.87	0.67
Skewness	-0.50	-0.18	-0.02	0.20	-1.71	-0.33	-0.03	-0.11	-0.42
Kurtosis	2.40	1.30	1.14	0.71	26.80	2.85	0.30	1.02	2.52

Table 3.13: Descriptive Statistics Consumer Staples during Brexit

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-6.85	-4.77	-2.67	-3.39	-6.17	-6.12	-4.81	-3.93	-2.81
Maximum	5.03	3.12	3.88	2.43	4.29	8.28	4.25	3.00	2.17
Mean	0.04	0.02	0.07	0.04	0.01	0.05	0.02	0.06	0.01
Median	0.05	0.00	0.07	0.00	0.00	0.00	0.00	0.02	0.04
Variance	2.40	1.08	0.71	0.78	1.00	4.71	1.56	0.74	0.45
Stdev	1.55	1.04	0.84	0.88	1.00	2.17	1.25	0.86	0.67
Skewness	-0.74	-0.27	0.39	-0.09	-0.84	0.18	0.09	-0.08	-0.73
Kurtosis	3.83	1.70	2.06	1.00	7.43	0.77	1.40	3.35	2.86

3.2.5 Empirical analysis of descriptive statistics for telecommunications

Table 3.14 reports the descriptive statistics for the full sample for Telecommunication sector. Tables 3.15, 3.16 and 3.17 show the descriptive statistics of the materials sector during the GFC, ESDC and Brexit crisis periods respectively.

Among the BRICS countries, for the full sample, the highest mean daily return is observed in the case of South Africa (0.03), followed by China (0.01). Negative mean daily returns are observed for the rest of the BRICS countries. During the GFC, four of the BRICS countries exhibit negative mean returns. During the ESDC two of the BRICS countries exhibit negative mean returns. This implies that the telecommunications sectors of these countries were unprofitable during the sample periods for GFC and ESDC. For developed countries, all four developed countries exhibit positive mean returns during the full sample period and ESDC period, and three of the developed countries exhibit positive mean returns during the Brexit crisis. This implies that on average the telecommunication sector of these countries were profitable during the respective sample periods. On the other hand, all the developed countries exhibit negative mean returns during the GFC period. This is an indication of the strong downturn on the telecommunication sector for the developed countries, implying that the telecommunication sector for these countries were unprofitable on average during the GFC period.

As far as volatility is concerned, among BRICS countries, for the full sample period, the highest volatility is observed in the case of Russia (6.98), and lowest in China (3.03). During the GFC period, the highest volatility is observed in Russia (21.81) and the lowest in South Africa (8.78). During the ESDC period, the highest volatility is observed in the case of India and the lowest in China (1.35). During Brexit, the highest volatility is observed in the case of Brazil (3.56) and the lowest in the case of China (1.21). Among developed markets, for the full sample period, the highest volatility is observed in the case of Germany (2.51) and the lowest in the USA (1.57). During the GFC period, the highest volatility is observed in the UK (5.90) and the lowest in Japan (4.33). During the ESDC period, the highest volatility is observed in Germany (1.85) and the lowest in USA (0.82). During Brexit crisis period, the highest volatility is registered in Japan (1.65) and the lowest in the USA (0.45). The volatilities for the telecommunications sectors for the BRICS and developed countries show the diversity in the responsiveness of the these countries telecommunication sectors to the various crises.

As far as skewness is concerned, most of the countries exhibit negative skewness during the full sample period. Only two BRICS and two developed countries exhibit negative skewness during the GFC. Most countries exhibit negative skewness during the ESDC and Brexit. This implies that the ESDC and Brexit had greater impact on the telecommunication sectors of these countries compared to the GFC. The Kurtosis of most countries are leptokurtic during the full sample and the GFC suggesting the occurence of several abnormal events.

Table 3.14: Descriptive Statistics Telecommunications

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
Minimum	-20.45	-9.64	-13.92	-21.08	-12.57	-28.25	-15.82	-12.15	-8.72
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	-0.01	0.01	0.01	-0.04	0.03	-0.03	0.03	0.02	0.01
Maximum	18.14	13.66	13.98	20.67	9.31	19.50	13.07	9.01	13.21
Variance	4.84	3.03	2.51	6.40	2.20	6.98	3.61	2.10	1.57
Stdev	2.20	1.74	1.58	2.53	1.48	2.64	1.90	1.45	1.25
Skewness	-0.17	0.38	-0.03	-0.23	-0.36	-0.57	-0.07	-0.26	0.25
Kurtosis	7.93	6.80	9.38	7.95	6.10	13.72	5.12	6.02	13.16

Table 3.15: Descriptive Statistics Telecommunications during GFC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-20.45	-9.64	-13.92	-21.08	-12.57	-28.25	-10.78	-12.15	-8.72
Maximum	18.14	13.66	13.98	15.33	8.11	19.50	13.07	9.01	13.21
Mean	-0.04	-0.05	-0.09	-0.17	-0.08	-0.13	0.01	-0.07	-0.14
Median	-0.04	0.00	0.00	0.00	0.00	-0.08	-0.06	-0.04	-0.02
Variance	11.65	9.83	5.54	16.22	4.33	21.81	8.78	5.90	5.17
Stdev	3.41	3.13	2.35	4.03	2.08	4.67	2.96	2.43	2.27
Skewness	0.02	0.45	0.18	-0.46	-0.45	-0.50	0.31	-0.11	0.45
Kurtosis	6.43	2.06	7.66	3.54	4.16	5.85	1.53	2.51	5.68

Table 3.16: Descriptive Statistics Telecommunications during ESDC

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-9.24	-5.13	-10.29	-15.45	-10.04	-9.00	-4.93	-4.86	-2.91
Maximum	6.27	4.11	10.68	14.07	9.31	10.19	6.74	4.69	2.55
Mean	0.02	0.01	0.01	-0.14	0.02	-0.05	0.04	0.04	0.05
Median	0.08	0.00	0.00	-0.11	0.00	-0.06	0.00	0.00	0.03
Variance	2.87	1.35	1.85	6.85	1.45	3.38	2.38	1.49	0.82
Stdev	1.69	1.16	1.36	2.62	1.20	1.84	1.54	1.22	0.91
Skewness	-0.34	-0.27	-0.24	0.19	-0.37	-0.09	0.08	-0.14	-0.27
Kurtosis	2.43	1.31	16.18	5.11	17.42	3.60	0.91	1.33	0.73

Table 3.17: Descriptive Statistics Telecommunications during Brexit

	Brazil	China	Germany	India	Japan	Russia	RSA	UK	USA
Minimum	-8.88	-3.74	-5.15	-5.88	-6.93	-5.77	-4.89	-9.08	-3.55
Maximum	5.74	3.72	4.13	5.06	4.88	4.61	6.06	4.07	2.45
Mean	0.12	-0.01	0.05	-0.01	0.05	0.04	-0.06	-0.07	0.02
Median	-0.04	-0.04	-0.05	0.00	0.00	0.04	-0.04	0.00	0.04
Variance	3.56	1.21	1.04	1.96	1.65	2.30	2.32	1.45	0.78
Stdev	1.89	1.10	1.02	1.40	1.28	1.52	1.52	1.20	0.88
Skewness	-1.06	-0.10	0.15	-0.16	-0.52	0.03	0.23	-2.06	-0.66
Kurtosis	5.21	1.41	4.07	1.66	4.48	0.99	1.19	14.72	1.64

3.3 Further Analysis of Data Characteristics

Figure 3.2 presents the time series plot of the MSCI USA daily closing prices.[1] It is evident from the figure that the time series of the USA daily closing prices is non-stationary due to the non-constant mean. For the purpose of getting stationary financial time series, the prices are transformed into natural logarithmic returns, which are displayed in Figure 3.3. The series of returns has a constant mean but a clearly non constant variance.

Figure 3.2: The daily closing price of the MSCI USA index

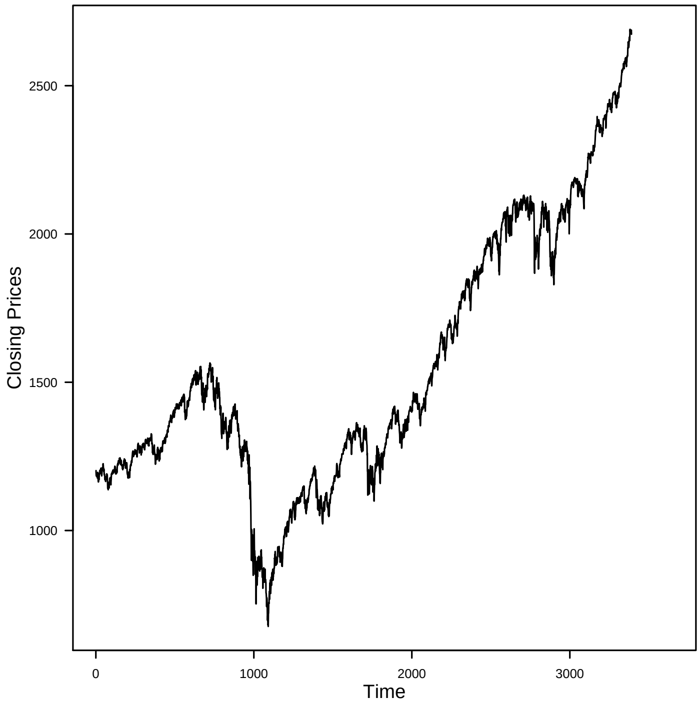


Figure 3.4 represents the Quantile-Quantile (QQ) plot of the data, with the straight line representing a normal distribution. The curvature implies that the data does not come from the normal distribution. From Table 3.1, the kurtosis for the MSCI USA index returns is 12.62 which is higher than the value of normal distribution, which is typically 3, The high value of the kurtosis confirms that the times series of returns possess the fat-tail characteristics. This characteristics is frequently known to exhibit itself in data from financial markets. The returns of the MSCI USA index are also left skewed, since the value of the skewness coefficient is -0.36. These results are consistent throughout the aggregate indices in Table 3.1, although South Africa's aggregate return index appears approximately normal, with a kurtosis value of 3.02. The next chapter discusses the methodology and results analysis.

[1]This subsection only reports results for the MSCI USA daily closing prices for brevity. I however implement the same procedures using all the aggregate and sectoral data

Figure 3.3: The daily returns for the MSCI USA index

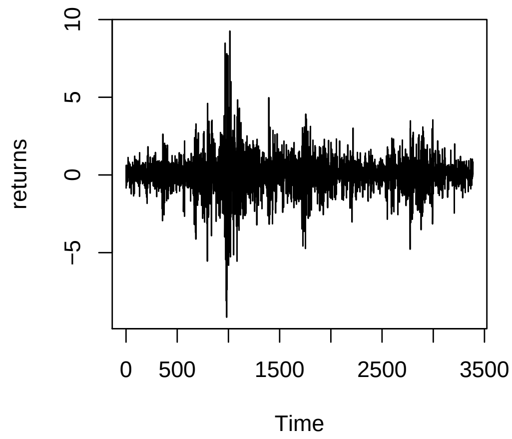
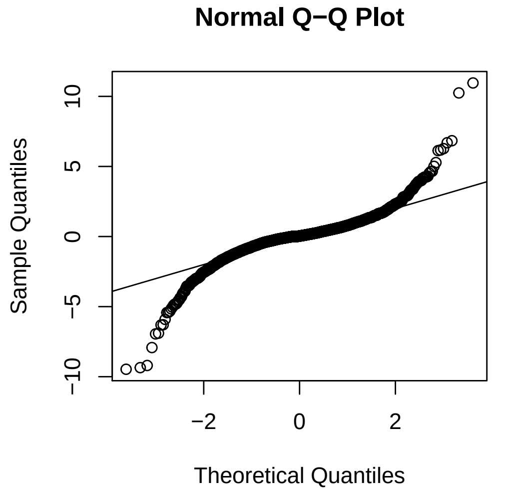


Figure 3.4: QQ Plot for the MSCI index returns data



Chapter 4

Methodology, Results and Analysis

This section presents the methodology and results. Section 4.1 discusses the mathematical derivation of the DCC and ADCC that was used in the study, as well as the crises identification periods. Section 4.2 discusses the three GARCH models considered in the study and the comparison tests of the best performing GARCH models used in the rest of the study. Section 4.3 utilises the best performing GARCH model (GJR-GARCH) selected in section 4.2 to generate plots for the time varying dynamic conditional correlation for cross country, within sector and cross sector within country. Section 4.4 utilises the standardized residuals calculated from GJR-GARCH model to generate plots for the time varying asymetric conditional correlations for cross country, within sector and cross sector within country. A diagnostic test is also carried out to compare the DCC-GJR-GARCH and ADCC-GJR-GARCH models. The best performing model is ADCC-GJR-GARCH, which was used to model the asymmetric dynamic conditional correlations. Section 4.5 reports the asymmetric dynamic conditional correlations for cross country, within sector correlation and cross sector within country corelatons.

4.1 Brief background and mathematical aspects of the methodology

From a methodological perspective, several studies have utilised a range of models appropriate for studying volatility, correlation dynamics and transmission mechanism among financial markets. For example, Albulescu, Goyeau and Tiwari (2015), Aloui, Hammoudeh and Hamida (2015) and Burzala (2016) use a wavelet coherency technique and spectral and cospectral analysis. Boubaker, Jouini and Lahiani (2016) and Werkmann (2019) utilize co-integration relationships. Zorgati, Lakhal and Zaabi (2019), Mohti, Dionísio, Ferreira and Vieira (2019), Cubillos-Rocha, Gomez-Gonzalez and Melo-Velandia (2019), Couto, Duczmal, Burgarelli, Álvares and Moreira (2019) and BenMim and BenSaïda (2019) use the copulas approach. Guidolin and Pedio (2017), among others, adopt Markov-Switching models. The multivariate Dynamic Conditional Correlations Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) framework has been found to be quite useful in contagion/linkages studies. The major advantage of applying the wavelet techniques is that it allows for complex modelling. However, the DCC technique is easier to interpret in comparison to the wavelet approach.

Previous studies in the area of financial contagion present evidence that DCC-GARCH model and Copula approaches arrive at similar conclusions in most contagion studies (Kenourgios, 2014). Therefore, the DCC-GARCH and ADCC-GARCH approach are used in this study so as to make the findings comparable to a broad part of the literature. This study find the Asymmetric Dynamic Conditional Correlation (ADCC) model to be a suitable model in evaluating interdependence between sectors and aggregate equity stock markets.

4.1.1 DCC-GARCH

The two multivariate GARCH models used in this study are the DCC model proposed by Engle (2002), which is used to estimate dynamic conditional correlation (DCC), and the ADCC model similar to Gjika and Horvath (2013), which is used to estimate asymmetric dynamic conditional correlation (ADCC). In addition to modelling the time varying nature of volatilities co-movement across markets, the ADCC model also accounts for asymmetry. The DCC models were introduced independently by Tse and Tsui (2002) and Engle (2002). Subsequent extensions of the DCC-GARCH models are of two kinds:

The first extension occurs in the univariate volatility modelling phase where the univariate GARCH models has been made outdated by other models that account for asymmetries.[1] The second extension relates to the estimation of the DCC model. Aielli (2013) proposed a corrected DCC-GARCH model that provide an alternative, unbiased asymptotic estimator. Additional extensions make room for the ADCC-GARCH model. The ADCC model has an added benefit as it accounts for asymmetric effects to impact the conditional correlations (Cappiello et al., 2006).

[1]These include: EGARCH, GJRGARCH, long memory models like the FIGARCH and regime changing models like the Markov Switching (MS-GARCH) model, to name a few

Both the DCC and ADCC are used as the baseline model in this study for several reasons:

The first motivation for applying the DCC model in this study is modeling parsimony (the model is not parameter hungry). As mentioned in the literature review section, multivariate GARCH models like VECH and BEKK models that are used in the analysis of conditional volatility and conditional correlation are constrained by a possible curse of dimensionality. The DCC model is more flexible. Instead of calculating conditional volatilities and conditional correlations seperately as it is done with the BEKK and VECH model, the DCC model utilizes standardized residuals to estimate the conditional correlation matrix directly. This leads to greater flexibility by decreasing the number of parameters to estimate.

A second reason is inferred from the forecasting performance evaluation and model selection guidlines suggested by Laurent, Rombouts and Violante (2012). Applying the model confidence set approach (MCS) and the superior predictive ability (SPA) tests, which allow isolation of superior models in terms of predictive ability, these authors find that the best models do not provide significant better forecast than the DCC model of Engle (2002) with a leverage effect in the conditional variances of the returns.

A third reason relates to the computational advantages that is associated with applying the DCC-GARCH model. There is a clear computational advantage in that the number of series to be correlated is not dependent on the number of parameters estimated in the corerlation process (Hotta and Tsay, 2012).

4.1.2 Estimation of the DCC GARCH Model

Consider a 1x9 vector stochastic process, r_t, of continuously compounded daily returns of the major sectors examined in this study. Under the assumption that the returns are demeaned and follow a conditionally heteroskedastic normal distribution, the series' can be described by the notation below:

$$r_{it} = \mu_i + \varepsilon_{it} \tag{4.1}$$

$$\varepsilon_{it} = \sqrt{H_{it}.\eta_{it}}, \quad \varepsilon_{it} \sim N(0, H_t) \quad \text{and} \quad \eta_{it} \sim N(0, I) \tag{4.2}$$

Where μ_i is the intercept and ε_{it} is the error term, H_t is NxN conditional covariance matrix and the η_{it} the standardized residuals. A range of multivariate GARCH modelling techniques have been proposed to model the covariance process, H_t, depicted in equation 4.2.

This study makes use of the parsimonious DCC and ADCC modelling techniques formulated by Engle (2002). In order to simplify the equations showing the steps of the estimation, the methodology assumes a bivariate stochastic process. The DCC estimation has two stages.

- First stage entails fitting univariate volatility equations to each series to obtain GARCH conditional volatility estimates
- The second step involves applying the log-likelihood approach to estimate time varying dynamic conditional correlation using the standardised residuals extracted in stage one.

In this study, the first step made use of the GJR-GARCH (1,1) univariate specification in order to account for leverage effects and volatility feedback.

The GJR-GARCH takes the following form:

$$h_t^2 = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2) + \phi.I_{t-1}(\varepsilon_{t-1}^2) + \beta h_{t-1}^2 \tag{4.3}$$

where $I = 1$ *if* $\varepsilon_{t-1} < 0$, and $I = 0$ *if* $\varepsilon_{t-1} \geq 0$ and where ε_{t-1}^2 represent previous period squared residual series and h_{t-1}^2 is the autoregressive term of the conditional variance.

Therefore, in step one the univariate GJR-GARCH process for each sector was fitted to output the conditional variance used to standardize the residuals as illustrated mathematically below:

$$\eta_{i,t} = \varepsilon_{i,t}/\sqrt{h_{ii,t,}} \tag{4.4}$$

In the second step, the standardized residuals were used to estimate time varying correlations. The DCC (1,1) model as formulated by Engle (2002) is defined as:

$$H_t = D_t R_t D_t \tag{4.5}$$

With R_t = time varying conditional correlations now.

Equation 4.5 splits the variance covariance matrix into identical diagonal matrices and an estimate of the time-varying correlations. The diagonal matrices are defined as:

$$D_t = diag(\sqrt{h_{ii,t}}, .\sqrt{h_{jj,t}}) \tag{4.6}$$

The dynamic conditional correlation structure is derived as follows:

$$Q_{ij,t} = (1 - a - b)\bar{Q_{ij}} + a\eta_{i,t-1}\eta_{j,t-1}^{'} + b.Q_{ij,t-1} \tag{4.7}$$

where $Q_{ij,t}$ is the unconditional variance between series i and j, $\bar{Q_{ij}}$ is the unconditional covariance between the univariate series estimated in step 1 and a and b are non-negative scalar parameters satisfying $a + b < 1$. In order to make sure the $R_{ij,t}$ has a unique solution, the determinant was tested for positive definiteness. The mathematical derivation of the time varying conditional correlation is represented below as:

$$R_t = (Q_{ij,t}^{*})^{-1}.Q_{ij,t}.(Q_{ij,t})^{-1} \tag{4.8}$$

with $Q_{ij,t}$ being a diagonal matrix with the square root of the diagonal elements of $Q_{ij,t}$ as its entries. The validity of this process can be thought of intuitively as taking the multiplication of both sides of equation 4.5 by the inverse of Diagonal matrix D_t. The dynamic conditional correlation matrix, R_t therefore had entries in the bivariate framework as follows:

$$R_t = \rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t}.q_{jj,t}}} \tag{4.9}$$

where

$$\frac{q_{i,j,t}}{\sqrt{q_{ii,t}.q_{jj,t}}} = \frac{(1 - a - b)\bar{q}_{ij} + a\eta_{i,t}\eta_{j,t-1} + bq_{ij,t-1}}{\sqrt{((1 - a - b)\bar{q}_{ii} + a\eta_{i,t-1}^2 + bq_{ii,t-1})((1 - a - b)\bar{q}_{jj} + a\eta_{j,t-1}^2 + bq_{jj,t-1}}} \tag{4.10}$$

The DCC model was estimated by maximising the log-likelihood function for equation 4.7. The joint log-likelihood function takes the following form:

$$L(\gamma, \varphi) = -\frac{1}{2}\sum_{t=1}^{T} \log(2\pi) + log(|D_t R_t D_t|) + \varepsilon_t{}'(D_t R_t D_t)^{-1}\varepsilon_t)) \tag{4.11}$$

$$-\frac{1}{2}\sum_{t=1}^{T}(\log(2\pi) + log(|D_t|) + \log(|R_t|) + \log \varepsilon_t^{'} R_t{}^{-1}\varepsilon_t) \tag{4.12}$$

Where γ and φ are the parameters in D_t and R_t respectively. Despite the attractive benefits of using the DCC model, there are a few disadvantages with DCC approach as outlined in Bauwens, Laurent and Rombouts (2006). One disadvantage of using the DCC model is that it assumes that the dynamic conditional correlation process perform the same over time in reaction to past shocks. In other words, the DCC approach assumes a and b in Equation 4.10 remain the same although a and b are likely to change over time and hence can be considered a major drawback. Another drawback with the model is that there is no built in leverage function. Consequently the DCC model does not distinguish between negative and positive shocks. Cappiello et al. (2006) therefore propose the introduction of the leverage effects into the DCC model resulting in the Asymmetric DCC (ADCC) model. The next section discusses the ADCC as well is the steps in the modelling process that were followed in this study.

4.1.3 ADCC

The ADCC model addresses the drawback in DCC model of no built-in leverage function. As mentioned in the DCC section, this is a major drawback as it means the DCC model does not distinguish between negative and positive shocks. The introduction of the leverage effects by Cappiello et al. (2006) takes care of the drawback in DCC model. In this study this was done by extending the Q - equation as follows:

$$Q_{ij,t} = (1-a-b).\bar{Q} - g(\bar{W}_t) + \alpha(\eta_{i,t} - 1\eta'_{j,t-1}) + \beta(Q_{ij,t-1}) + g(\xi_{i,t-1}\xi'_{j,t-1}) \quad (4.13)$$

where:

$$\xi_{i,t-1} = 1.\eta^2_{i,t} \ \mathit{if} \ \eta_{i,t} < 0, \ \mathit{zero\ otherwise}$$

$$W_t = \mathit{covariance\ of}\ (\xi_{i,t-1}\xi'_{j,t-1}) \ \mathit{using\ sample\ analogue,\ thus:}$$

$$E(\xi_{i,t-1}\xi'_{j,t-1}) \approx \frac{1}{n}\sum(\xi_{i,t-1}\xi'_{j,t-1})$$

4.1.4 Identification of crisis

The identification of turmoil (or crisis) periods and their duration potentially heighten the difficulty associated with the empirical study of contagion. This difficulty arises due to the sensitivity of the contagion tests to the crisis period chosen. In the literature on contagion, the identification of crises period normally follow one of two approaches: an economic or a statistical approach. The economic approach uses an informal definition of the crisis period. The economic approach is guided by major financial and economic crises (Forbes and Rigobon, 2002). The statistical approach gives evidence of the crises period based on the excess volatility of the tranquil or turmoil period (Boyer, Kumagai and Yuan, 2006; Rodriguez, 2007; Tamakoshi and Hamori, 2014). Both approaches come with benefits and drawbacks. For instance, the economic approach provides flexibility in the modelling process but it may be impractical to assume that a crisis in one country or region is equally applicable to all countries under study, as it is sometimes the case with this approach. On the other hand, the statistical approach may increase the accuracy of the crisis identification period, but lacks flexibility in the modelling process, since it avoids relating the crisis period identification to financial and economic shocks. There are a considerable number of statistical approaches that facilitates the identification of crisis periods in a financial time series. Some of these approaches include; structural break analysis models (Bai and Perron, 2003), Markov-Switching models (Hamilton, 1995) and smooth transition autoregressive models (SETAR) (Teräsvirta, 1994). Recent studies combine both the economic and the statistical approach in contagion studies (Kenourgios, 2014). However, it is worth mentioning that both the statistical and the economic methods are arbitrary at least to some degree. As stated in Kenourgios (2014), some studies that may avoid discretion in the choice of either econometric model to estimate location of crisis, use discretion in the definition of crisis period. The economic identification approach was used in this study.

The length of the Global Financial Crisis (GFC), European Sovereign Debt Crisis (ESDC) and Brexit crisis were defined using the economic approach, which depends on major financial and economic shocks or events (Forbes and Rigobon, 2002). Applying this approach, the crises were defined based on major economic and financial news events published by official accredited sources. According to the Bank for International Settlements (Filardo, George, Loretan, Ma, Munro, Shim, Wooldridge, Yetman, Zhu et al., 2010), the time line of GFC is split into four phases. Phase 1 begins on the 1 August 2007 and ends on the 15 September 2008, and is described as the "initial financial turmoil". Phase 2 is a period of "sharp financial market deterioration", spanning from 16 September 2008 until 31 December 2008. Phase 3 is described as market "macroeconomic deterioration", and spans from 1 January 2009 to 31 March 2009, and Phase 4 described as "stabilization and tentative signs of recovery" including a financial market "rally", and begins from 1st April 2009 onwards. Therefore the first three phases of the crisis begins from August 2007 until March 2009.

The European sovereign debt crisis (ESDC) is determined based on time lines from Reuters and the European Central Bank (ECB) as outlined by Kenourgios (2014). The time line of the crisis was constructed by combining the dates and events from the two sources mentioned as follows: Phase 1 begins from 5 November 2009 until 22 April 2010, and includes the announcement of the Greek budget deficit (greater than twice the amount previously disclosed) and the sharp increase of European sovereign risk. Phase 2 starts not long before the Greek bailout in May 2010, when the Greek Prime Minister makes an announcement regarding the shortage of the austerity packages and requested for a bailout plan from the Eurozone and the IMF, effectively spanning a period of 23 April 2010 to 14 July 2017. Phase 3 (15 July 2011 onwards) began when the European government published the stress tests for financial institutions and austerity measures announced by other European countries (i.e., Italy).

The time line of the Brexit crisis are inferred from Aristeidis and Elias (2018) and Davies and Studnicka (2018). The UK European membership referendum results were announced on the 23 June 2016 and the subsequent trigger of the British government Article 50 for withdrawal from the European union occured on 29 March 2017. Therefore, the time line for the Brexit crisis for this study starts from 23 June 2016 to 29 April 2017. The Brexit crisis time line ends one month after the date of Article 50 trigger in order to incorporate the effect of the trigger on the stock markets that would have lingered around for a few months.

Section 5.1 of the results presents the univariate GARCH (1,1) model, Section 5.2 discusses the results of the DCC model and section 5.3 evaluates the effect of the GFC and ESDC on sector conditional correlations between the countries in this study.

4.2 Univariate GARCH (1,1) models

This section presents the autocorrelation, heteroscedasticity, estimation of parameters of the GARCH model and model selection. All of the output displayed in earlier figures, tables, as well as the parameter estimations of model discussed in this section are processed using the R Programming language and a range of software packages. The R software packages include: rmgarch package for modelling the univariate GARCH models, rugarch package for modelling the dynamic conditional correlations (DCC) and asymmetric dynamic conditional correlation (ADCC), xtable and fbasics packages for modelling the descriptive statistics sector returns and ggplot package used to enhance all the DCC and ADCC plots. The analysis for autocorrelation, heteroscedasticity and model selection have been done with aggregate and sectoral data. For simplicity of presentation, only the analysis of the MSCI USA daily returns is presented. The next subsection discusses the analysis of autocorrelation for the MSCI USA index daily returns.

4.2.1 Autocorrelation

As evident in Figure 4.1, the autocorrelation function (ACF) for the MSCI USA index daily returns shows sizeable autocorrelation at the first lag[2]. Thus the correlation among the MSCI index returns is significant. To test joint significance of the ACF lags, a Box-Ljung test is employed. The value of the Box-Ljung test statistic is 132.98 and its corresponding p-value is less than 0.001. Hence, the null hypothesis (that there is no autocorrelation) is rejected at the significance level 0.001. We therefore accept an alternative hypothesis that there is autocorrelation.

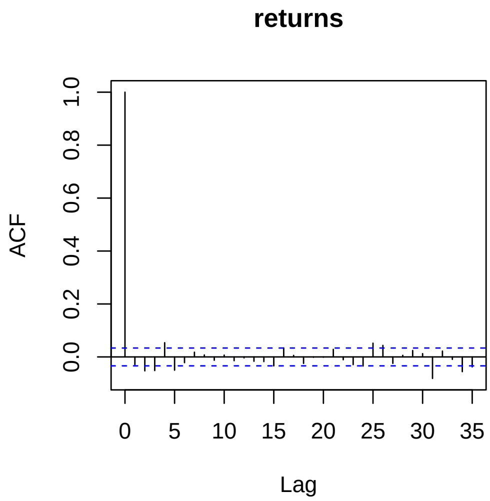


Figure 4.1: The ACF for MSCI index returns data

4.2.2 Heteroscedasticity

In order to detect the presence of heteroscedasticity, the ACF square returns is plotted. The ACF of the squared returns in Figure 4.2 exhibits a higher length of serial autocorrelation through to the 38th lag. Hence heteroscedasticity is also present in the returns.

[2]This analysis has been done with all the aggregate and sectoral data. For simplicity of presentation, only the analysis of the ACF for MSCI USA daily returns is presented here

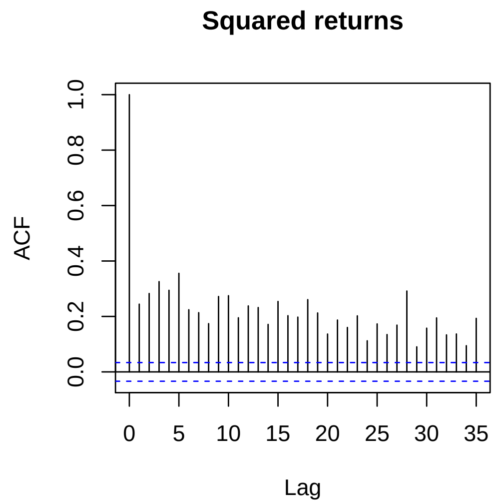


Figure 4.2: The ACF for MSCI index square returns data

4.2.3 Model Selection

In time series modelling it is often essential to identify the model that best fits the data from a set of candidate models. In this section, we now consider some of the selection criteria or procedures that have been proposed in the financial times series literature for selecting among various possible choices for GARCH models.

An essential task in modelling volatity using GARCH models is the determination of the ARCH order p and GARCH order (p, q) for a particular series. The GARCH order commonly used in most time series research and analysis is the GARCH (1,1) (Engle, 2002; Forbes and Rigobon, 2002; Pappas et al., 2016). Therefore GARCH (1,1) was used in this analysis. A range of univariate GARCH models exist. In this study three GARCH models were considered: standard GARCH (Bollerslev, 1986), the EGARCH (Nelson, 1991) and the GJR-GARCH (Glosten et al., 1993). The Akaike Information Criterion (AIC) and the Schwartz Bayesian Information Criterion (BIC) were used to select the model with the best goodness of fit. Furthermore, while the earlier QQ plot suggested that returns were non-normal, each of the GARCH models under both a normal distribution and a student-t distribution were estimated, where the latter is particularly suited to capture return non-normality.

Table 4.1 below shows the goodness of fit measures for the three GARCH (1,1) models for both normal and student-t distributions, modelled on MSCI USA index daily returns[3]. According to the AIC and BIC, the GJR-GARCH (1,1) model with student t distribution has the best goodness of fit. Therefore, the GJR-GARCH

[3]This analysis has been done with all the aggregate and sectoral data. For simplicity of presentation, only the analysis of the MSCI USA daily returns is presented here

was selected as the model to be used for this analysis. The distribution that shows the lowest AIC and BIC with the GJR-GARCH was the student-t distribution; unsurprisingly given the earlier evidence of return non-normality. The GJR-GARCH was therefore used in conjunction with the student-t distribution in this study.

Table 4.1: Model Selection for the estimated GARCH (p, q) model assuming normal and student t distribution

Distribution	**Information criteria**	**Model**		
		SGARCH	**EGARCH**	**GJRGARCH**
Normal	AIC	$3,3652$	$3,3502$	$3,3428$
	BIC	$3,3753$	$3,3623$	$3,3549$
Student t distribution	AIC	$3,3036$	$3,2880$	$3,2864$
	BIC	$3,3158$	$3,3028$	$3,3006$

4.2.4 Diagnostic Checking of the GJR-GARCH (1,1) Model

After the specification of the GARCH model, it is imperative to investigate its adequacy. In order to explore the relationship between the residuals obtained from the fitted model, the corresponding conditional standard deviations were therefore studied. Also, the QQ plot helps to assess normality of the residuals. If the standardized residuals come from the gaussian distribution, the plot should be a straight line. Figures 4.3, 4.4 and 4.5 show the plot of the residuals, estimated conditional standard deviation and QQ-plot respectively. The QQ-plot in Figure 4.5 substantiates the findings that normal standardized residuals are rejected.

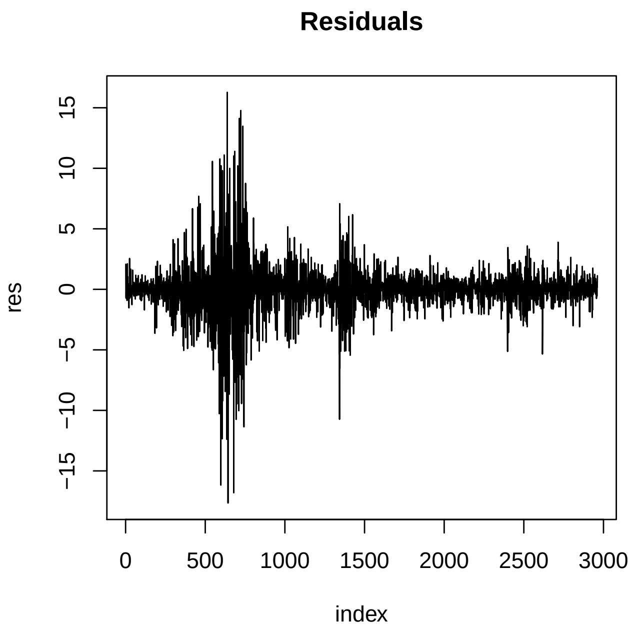


Figure 4.3: A plot of residuals

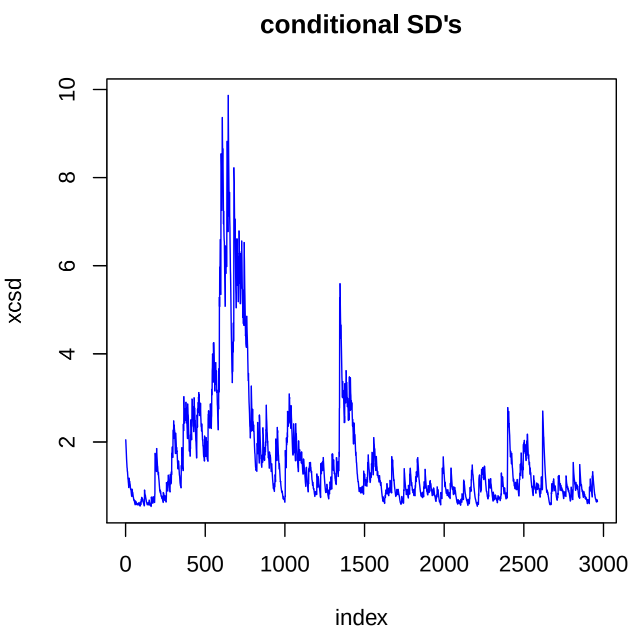


Figure 4.4: The plot of estimated conditional standard deviations

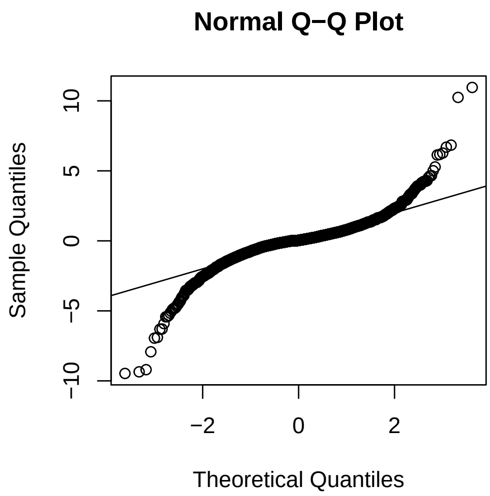


Figure 4.5: QQ-plot of standardized residuals

4.2.5 Univariate GARCH results

Tables 4.2 to 4.4 show the coefficient estimates, the standard errors, and goodness of fit statistics for the GJRGARCH model for the Financials, Materials, Consumer Staples and Telecommunications sectoral indices respectively. The volatility of most of the indices display a high persistence, since the sum of the estimated ARCH and GARCH ($\alpha_1 + \beta_1$) coefficients in each variance equation is close to 1. This is indicative of the persistence of volatility clustering, or market momentum, which is a common feature of financial returns series. The leverage effect γ_1, is positive and statistically significant, suggesting that the volatility of all equity indices exhibits asymmetric responses to good and bad news.

Table 4.2: GJR-GARCH (1,1) estimates: Financial Sector

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
μ	0.024	0.022	0.023	0.059	-0.024	0.013	0.032	-0.006	0.053
	(0.512)	(0.428)	(0.278)	(0.024)	(0.366)	(0.717)	(0.089)	(0.757)	(0.000)
ar_1	0.084	0.057	0.011	0.008	0.085	-0.865	-0.939	-0.902	0.658
	(0.611)	(0.915)	(0.966)	(0.986)	(0.662)	(0.007)	(0.000)	(0.000)	(0.000)
ω	0.096	0.047	0.037	0.041	0.069	0.066	0.029	0.025	0.020
	(0.003)	(0.001)	(0.009)	(0.011)	(0.002)	(0.021)	(0.006)	(0.001)	(0.002)
α_1	0.024	0.036	0.000	0.017	0.025	0.036	0.022	0.020	0.038
	(0.043)	(0.001)	(1.000)	(0.034)	(0.012)	(0.008)	(0.172)	(0.066)	(0.006)
β_1	0.916	0.908	0.909	0.919	0.886	0.919	0.910	0.899	0.891
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_1	0.090	0.089	0.154	0.104	0.145	0.079	0.107	0.151	0.136
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.000)
AIC	4.383	3.761	3.529	3.764	3.735	4.547	3.255	3.401	3.285
BIC	4.399	3.777	3.545	3.780	3.751	4.563	3.271	3.417	3.302
N	2970	2970	2970	2970	2970	2970	2970	2970	2970

Table 4.3: GJR-GARCH (1,1) estimates: Materials Sector

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
μ	-0.003	0.004	0.059	0.052	0.030	0.028	-0.042	0.003	0.062
	(0.947)	(0.916)	(0.003)	(0.089)	(0.257)	(0.364)	(0.125)	(0.907)	(0.000)
ar_1	-0.093	-0.015	-0.321	0.401	0.492	0.070	-0.766	0.843	0.774
	(0.599)	(0.922)	(0.032)	(0.146)	(0.550)	(0.713)	(0.266)	(0.000)	(0.000)
ω	0.056	0.049	0.033	0.054	0.064	0.046	0.021	0.026	0.015
	(0.011)	(0.002)	(0.004)	(0.001)	(0.002)	(0.012)	(0.032)	(0.005)	(0.027)
α_1	0.023	0.037	0.014	0.034	0.010	0.028	0.033	0.015	0.012
	(0.024)	(0.000)	(0.158)	(0.000)	(0.417)	(0.008)	(0.009)	(0.029)	(0.366)
β_1	0.941	0.919	0.910	0.904	0.890	0.930	0.942	0.947	0.922
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_1	0.055	0.072	0.124	0.091	0.150	0.063	0.036	0.064	0.109
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)	(0.000)	(0.000)
AIC	4.520	4.109	3.456	3.810	3.644	4.156	3.772	4.230	3.226
BIC	4.536	4.125	3.472	3.826	3.660	4.172	3.7887	4.246	3.242
N	2970	2970	2970	2970	2970	2970	2970	2970	2970

Table 4.4: GJR-GARCH (1,1) estimates: Consumer Staples Sector

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
μ	0.064	0.005	0.041	0.048	0.032	0.040	0.035	0.043	0.041
	(0.019)	(0.808)	(0.017)	(0.002)	(0.044)	(0.345)	(0.070)	(0.000)	(0.000)
ar_1	-0.163	-0.453	0.736	0.932	0.083	-0.715	-0.946	0.962	0.563
	(0.357)	(0.262)	(0.000)	(0.000)	(0.785)	(0.000)	(0.000)	(0.000)	(0.000)
ω	0.069	0.061	0.024	0.076	0.051	0.077	0.041	0.030	0.018
	(0.001)	(0.005)	(0.024)	(0.001)	(0.002)	(0.030)	(0.001)	(0.000)	(0.000)
α_1	0.025	0.049	0.011	0.057	0.034	0.032	0.029	0.000	0.016
	(0.018)	(0.000)	(0.134)	(0.000)	(0.007)	(0.020)	(0.021)	(0.964)	(0.288)
β_1	0.908	0.880	0.935	0.857	0.860	0.940	0.898	0.892	0.874
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
γ_1	0.088	0.082	0.074	0.094	0.137	00.044	0.094	0.147	0.155
	(0.000)	(0.002)	(0.003)	(0.002)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)
AIC	3.814	3.060	3.010	3.170	2.901	4.896	3.111	2.581	2.106
BIC	3.830	3.076	3.112	3.186	2.917	4.866	3.128	2.597	2.122
N	2970	2970	2970	2970	2970	2970	2970	2970	2970

Table 4.5: GJR-GARCH (1,1) estimates: Telecommunication Sector

	Brazil	**China**	**Germany**	**India**	**Japan**	**Russia**	**RSA**	**UK**	**USA**
μ	0.064	0.005	0.041	0.048	0.032	0.040	0.035	0.043	0.041
	(0.019)	(0.808)	(0.017)	(0.002)	(0.044)	(0.345)	(0.070)	(0.000)	(0.000)
ar_1	-0.163	-0.453	0.736	0.932	0.083	-0.715	-0.946	0.962	0.563
	(0.357)	(0.262)	(0.000)	(0.000)	(0.785)	(0.000)	(0.000)	(0.000)	(0.000)
ω	0.069	0.061	0.024	0.076	0.051	0.077	0.041	0.030	0.018
	(0.001)	(0.005)	(0.030)	(0.001)	(0.002)	(0.030)	(0.001)	(0.000)	(0.000)
α_1	0.025	0.049	0.011	0.057	0.034	0.032	0.029	0.000	0.016
	(0.018)	(0.000)	(0.134)	(0.000)	(0.007)	(0.020)	(0.021)	(0.964)	(0.288)
β_1	0.908	0.880	0.935	0.857	0.860	0.940	0.898	0.892	0.874
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0209)	(0.000)	(0.000)	(0.000)	(0.000)
γ_1	0.088	0.082	0.074	0.094	0.137	0.044	0.094	0.147	0.155
	(0.000)	(0.002)	(0.003)	(0.002)	(0.000)	(0.012)	(0.019)	(0.000)	(0.000)
AIC	3.814	3.327	3.4168	3.170	2.901	4.1955	3.111	2.581	2.106
BIC	3.830	3.344	3.4310	3.186	2.917	4.2097	3.128	2.597	2.122
N	2962	2962	2962	2962	2962	2962	2962	2962	2962

4.3 DCC GJR-GARCH Results

The second stage of the estimation made use of the standardized residuals obtained from the abovementioned estimated GJR-GARCH (1,1) univariate model, in order to estimate the time-varying DCC correlations.

Table 4.6 indicates that the time-varying correlations are mean reverting since $a+b < 1$, for all four sectors. The coefficient a measures the effect of past standardised innovations on dynamic conditional correlations, while b reports the impact of lagged dynamic conditional correlations on the current dynamic conditional correlations (Katzke et al., 2013). Furthermore, the parameters in Table 4.6 are all statistically significant, indicating significant variation over the specified period. The statistical significance of a and b led to the conclusion that a DCC model was more suitable than a CCC model for this study.

Table 4.6: DCC GARCH parameter estimates

	a	**b**
Financials	0.007***	0.982***
	(0.001)	(0.005)
Materials	0.004***	0.994***
	(0.001)	(0.001)
Consumer goods	0.004***	0.981***
	(0.001)	(0.004)
Telecommunications	0.004***	0.985***
	(0.001)	(0.004)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.3.1 Within Country Cross sector Correlation

Figures 4.6 to 4.14 show the time-varying correlations across sectors in each of the BRICS countries and developed countries. For each of the DCC plots, FN stands for financial sector, MT for material sector, CS for consumer staples and TC for telecommunications. The DCC plots for sector pairs in these countries exhibit fluctuations over the entire sample period, suggesting that the assumption of constant correlations is not appropriate. The next section discusses the results for the DCC plots for the sector pairs in BRICS countries.

4.3.1.1 BRICS

Brazil

Figure 4.6 show the time-varying correlations across sector indices in Brazil. For the pairs FN-MT and MT-CS, the correlations between 0.6 and 0.8 are observed until 2012, followed by a sharp drop in 2013 to a correlation of 0.4, and by fluctuations in correlation between 0.4 and 0.8. For the pairs FN-CS and FN-TC the correlations between 0.5 and 0.9 are observed, as well as a sharp decrease in 2013 and 2015, after which the fluctuation in correlations stabilizes between 0.6 and 0.9. For the pair MT-TC and CS-TC the correlations between 0.4 and 0.9 are observed, with a sharp drop in 2015 and 2017 and a spike in 2016, after which the correlation fluctuates between 0.5 and 0.9.

Among all the downward spikes of the sector pairs during the entire sample period, the most significant downward spikes occur in 2013. This can be attributed to myriad of protest and mass demonstrations that erupted in the major cities of Brazil in 2013 (Holston, 2014; Saad-Filho, 2013). Studies have shown that mass protests affect the various sectors and corresponding stock market returns in a particular country because of its social and economic implications (Chau, Deesomsak and Wang, 2014). Researchers have found that protests with high media coverage that are related to consumer or labour issues can incite a significant pessimistic reaction by investors, which can lead to a fall in sector stock market returns (King and Soule, 2007). Another posible reason for the downward spike is that, leading to the year 2013, the economy of Brazil was experiencing an unfavourable exchange rate. The economic policy adopted by the Brazilian government prior to 2013 was aimed at obtaining low inflation and fiscal suplus through the retention of a floating exchange rate (Marques and Nakatani, 2015). This led to the attraction of foreign funds from investors seeking high returns. Moreover, quantitative easing coupled with low interest rates in some advanced economies (e.g the USA and Europe) triggered capital flows to Brazil. The flow of funds from abroad led to the appreciation of the real (the Brazilian currency) and consequently, a prolonged high interest rate. The result was a continual worsening of the current account of Brazil's balance of payment and unfavorable trade balance which affected the international position of Brazil. Consequently, there was a shift away from the export of goods from several sectors which had very little foreign demand towards the exports of goods where demand was most inelastic. This led to a fall in revenue across several sectors leading to a fall in stock market returns. Moreover, the subsequent unraveling of quantitative easing in advanced economies led to the outflow of funds from Brazil which negatively affected the Brazilian stock exchange. For instance, "the Sao Paolo stock exchange fell from 62000 points in January 2013 to 46000 in July 2013 and triggered a rapid devaluation of the real between May and June" (Saad-Filho and Morais, 2014).

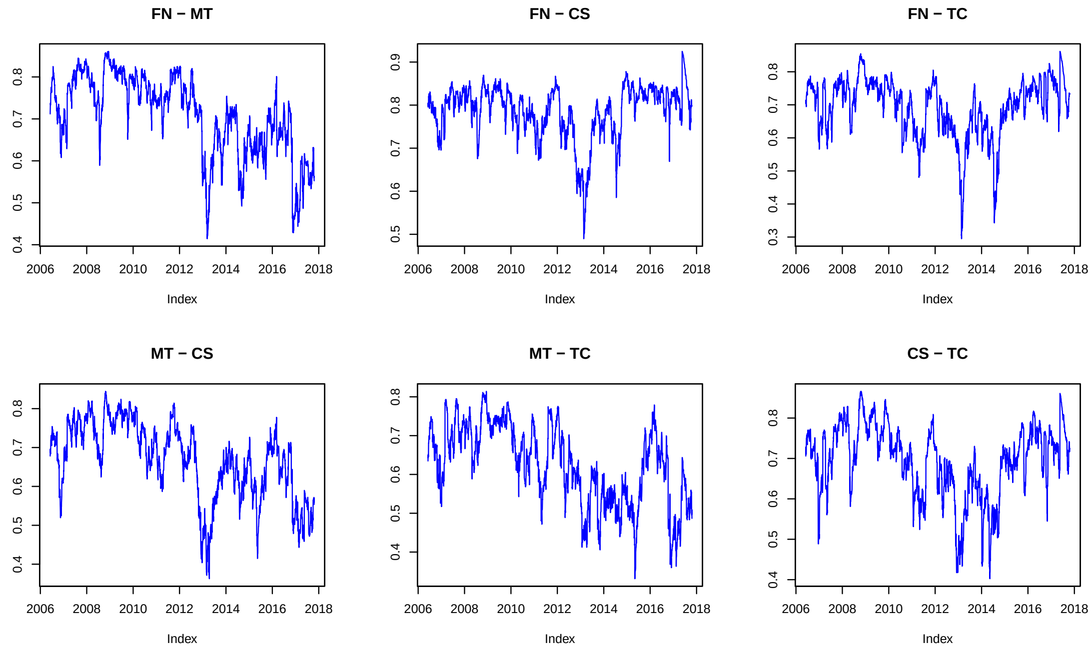


Figure 4.6: DCC across sectors within Brazil

Russia

Figure 4.7 shows the time-varying correlations across sectors in Russia. For all the sector pairs, downward spikes between the end of 2007 and 2008 are observed. This was likely due to the sharp decline in the growth rate of Russia's Gross Domestic Product (GDP) during this period. Any change in Gross Domestic Product (GDP) has a corresponding effect on the health of the financial market (Jareño and Negrut, 2016). An increase in GDP of a particular country reflects a positive movement in the earnings and production of the various business sectors in that country. In effect, investor confidence in the companies in these sectors increases, which increases their confidence in the stock market. Prior to 2007, Russia's GDP growth was fueled by trade gains achieved primarily through the soaring oil prices and demand for oil and gas in the world market (Kuboniwa, 2007). The decrease in GDP growth between the end of 2007 and 2008, which caused the downward spikes evident in all the sector pairs, were caused mainly by the fall in oil prices and the decline in export volume of oil and gas. The decline in oil prices during this period, which led to a decrease in trade gain, was among the factors underlying the general decline of Russia's output. Secondly, not only did export prices fall in relative dollar terms, but the volume of export goods declined in physical terms considerably, mainly due to an unexpected decline in demand of natural gas and oil in world markets resulting from low demand in China and Europe, during this period. For the pairs FN-CS, FN-TC, MT-TC and CS-TC, downward correlation spikes in 2011 are observed. This finding is in line with the results of Ahmad, Sehgal and Bhanumurthy (2013) who found that in 2011, the Russian stock market fell by 43 percent on the fear of collapse of the European banking system. For all the sector pairs, downward spikes is observed in 2014. This can be attributed to economic sanctions levied by the US and Europe on the Russian economy. The sanctions were imposed following Russian military intervention in the Ukraine. The economic sanctions affected the Russian economy through a number of channels:

- First, most international financial markets were closed to Russian companies and banks. Consequently, Russia's access to western financial markets were greatly reduced.
- Second, the multilateral economic sanctions of Russia increased the unpredictability of Russia's economic performance, resulting in the impairment of consumer and business confidence in Russia.
- Third, the Ukraine-Russia geopolitical tensions led to huge capital outflows and a decline in Russia's capital and financial account balance. Furthermore, a decrease in demand for oil in the world market led to a decrease in the price of oil resulting in a considerable decrease in the ruble against the US dollar. The depreciation of the Russian ruble led to an increase in inflation, resulting in the tightening of the monetary policy through increased interest rates. The high cost of borrowing restricted the access to domestic loans for both consumers and investors.
- Lastly, there was a drastic fall of foreign investment into Russia.

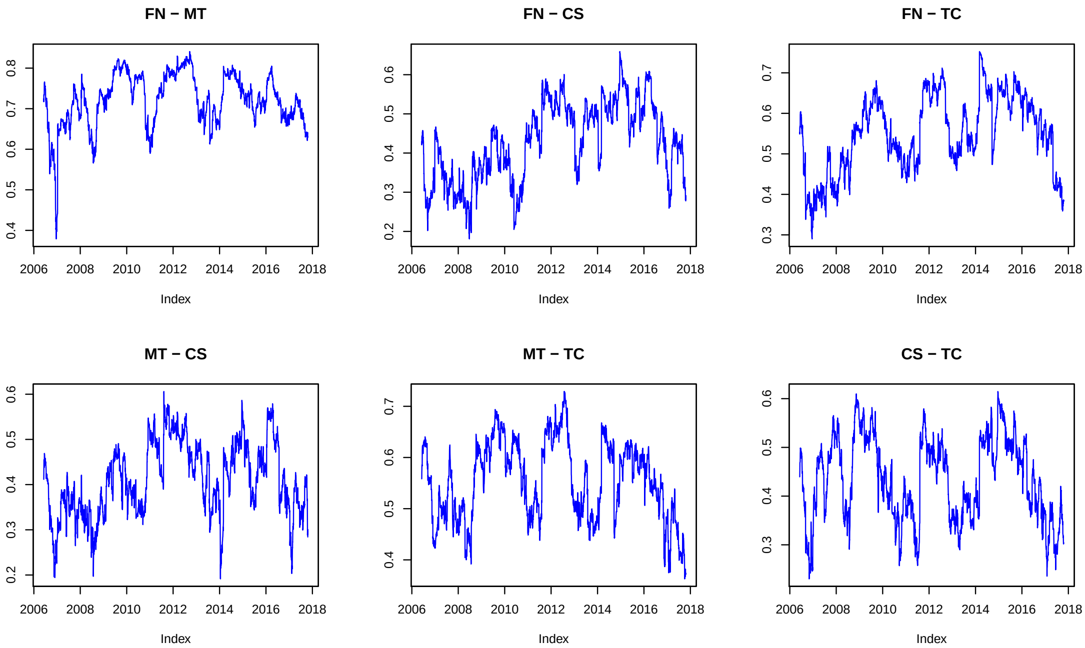


Figure 4.7: DCC across sectors within Russia

India

Figure 4.8 shows the time-varying correlations across equity market sectors in India. A visual inspection of the plot of the sector pairs reveals that the sector pairs display downward spikes between 2007 and 2008, 2013 and 2015. This is likely attributable to the decline in oil prices during these periods. In 2011, crude oil accounted for about 29 percent of India's total energy consumption (Jain and Biswal, 2016). As the fourth largest importer of crude oil in the world, international oil price fluctuations have a significant impact on sector returns and stock market performance in India (Arouri and Rault, 2012). The theoretical ground for this relationship dynamics is that the effect of the change in the price of oil leads to changes in macroeconomic fundamentals, which in turn leads to changes in liquidity of the stock market. Shocks from changes in the oil price affect sector returns or stock market prices through their effect on expected earnings. The effect on sector returns or stock market prices can be through the supply side or demand side. From the demand side, increase in oil prices may lead to high inflation, which can cause the central bank to tighten monetary policy to raise interest rates. Consequently, investment in the stock market is discouraged by the increase in interest rates. From the supply side, many sectors require oil or natural gas in production or operations. Therefore, an increase in the international price of oil may increase the cost of production for sectors that utilises oil, leading to a fall in profits.

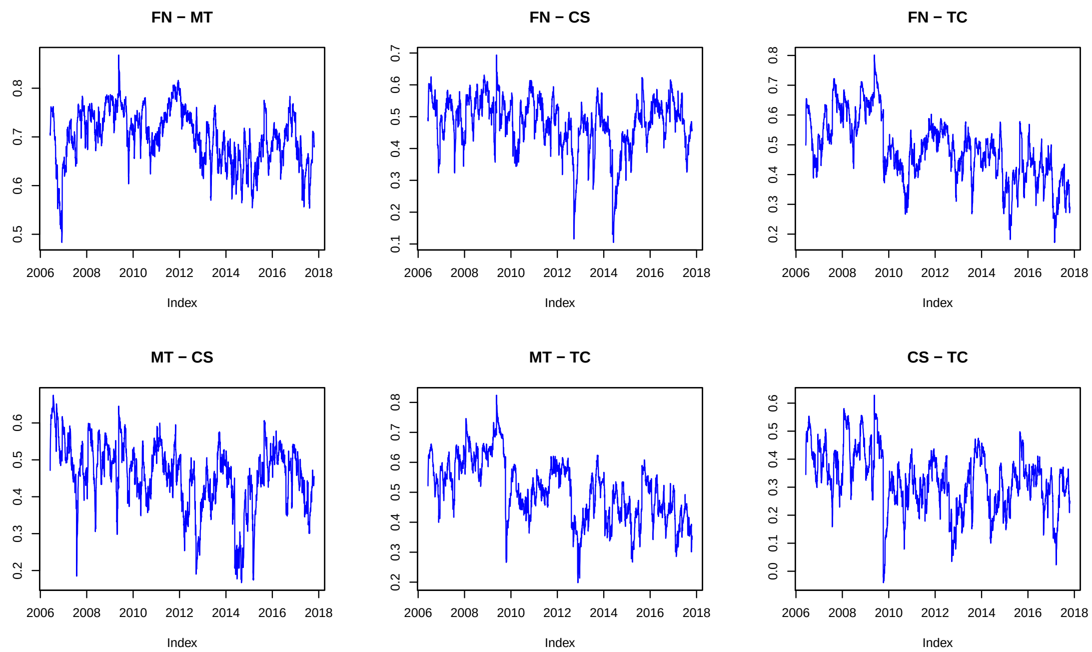


Figure 4.8: DCC across sectors within India

China

Figure 4.9 shows the time-varying correlations across equity market sectors in China. An inspection of the plot of the sector pairs reveals highly volatile conditional correlations through out the sample period for some sector pairs like FN-CS, MT-CS and CS-TC, while moderate volatility is observed for the sector pairs FN-MT, MT-TC and FN-TC throughout the sample period. For the period 2008 to 2009, multiple downward spikes for some sector pairs and fewer downward spikes were observed for other sector pairs. These differences can be attributed to the opposing effects of both the 2008 financial crisis and the four trillion Chinese yuan economic stimulus package program across the various sectors (Ouyang and Peng, 2015). The economic stimulus package announced by China's State Council in 2008 was an attempt to reduce the negative effects of the 2008 financial crisis. Therefore, the stimulus package was meant to generate what can be described as good volatility, which is the opposite of the bad volatility generated by the 2008 global financial crisis. In addition, distinct downward spikes for all sector pairs were observed between 2011 and 2012. This can be attributed to the effect of European debt crisis across these sectors.

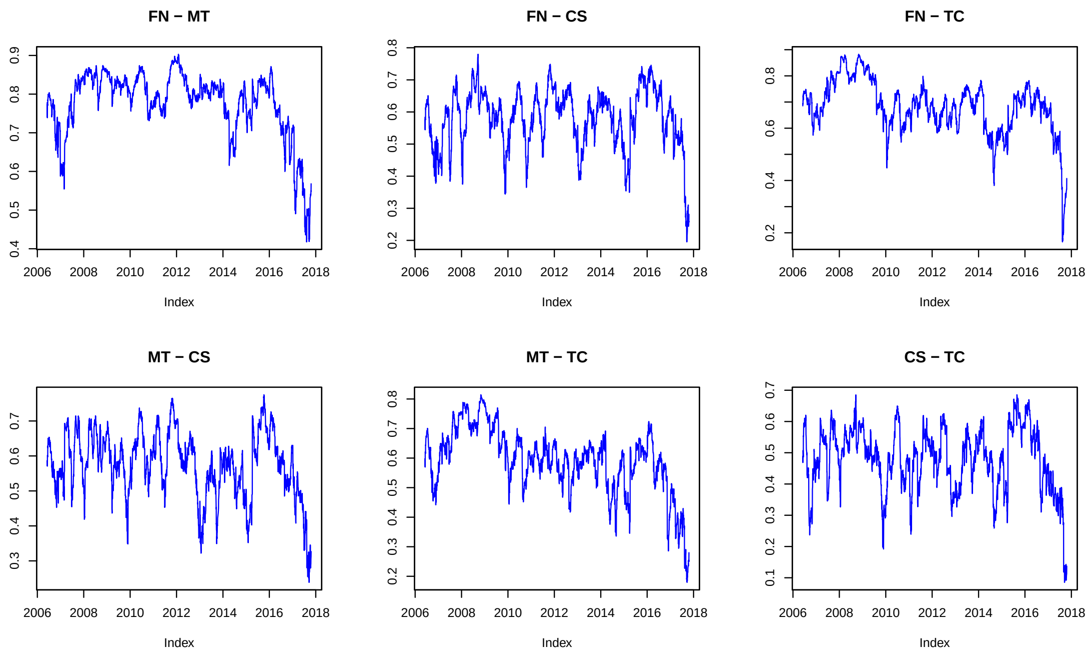


Figure 4.9: DCC across sectors within China

South Africa

Figure 4.10 shows the time-varying correlations across equity market sectors in South Africa. Heterogeneity of dynamic correlations across the sector pairs is evident. The results of this study are in line with that of Katzke et al. (2013), who found that there is no consistent and clear decrease or increase in correlation in the sector pairs during the global financial crisis of 2008. This might be an indication that the 2008 financial crisis had a very limited effect on the South African economy. For all the sector pairs, significant downward spikes are observed in 2016. This can be attributed to a number of related factors. The primary reason behind the factors that contributed to the downward spikes in 2016 was the fact that South African finance minister Nhlanhla Nene got fired (Roberts, 2018). The decision to fire the finance minister Nene led to a loss in investor confidence in the South African economy. Consequently, foreign investors pulled more than 12 billion rands out of the country within just one week of this event. The total withdrawal of capital from the South African economy (and specifically from the Johannesburg Stock Exchange) by investors exceeded the outflow of capital in 2008, and was considered the fourth largest withdrawal of capital by foreign investors in South African history (Asmal, Soni and David, 2016).

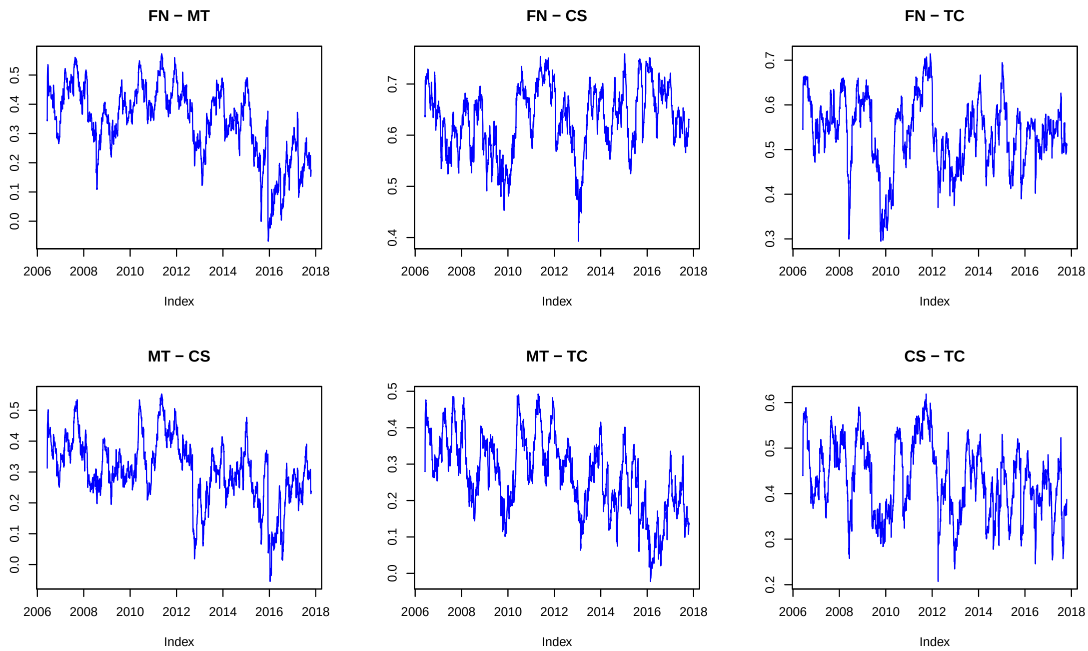


Figure 4.10: DCC across sectors within South Africa

4.3.1.2 Developed Countries

Figure 4.11 to 4.14 shows the time-varying correlations across sectors in four developed countries namely the UK, Germany, Japan and the USA. A visual inspection of the sector pairs reveals a significant downward spike in 2017 across all sector pairs in these four countries. This can be attributed to Brexit. Brexit is an abbreviation for the term "British Exit" that is comparable to the term "Grexit" which was used some time in 2012 to refer to the possibility of Greece withdrawing from the

Eurozone. Brexit therefore refers to the possibility of Britain departing from the European Union (EU) (Clarke, Goodwin, Goodwin and Whiteley, 2017). Researchers refer to British citizens decision on the 23 June 2016 to exit the European Union as major international event since the 2008 financial crisis (Ramiah, Pham and Moosa, 2017; Tielmann and Schiereck, 2017). While the issue is of greater relevance within the United Kingdom, the effect is also substantial in other developed countries. This explains why the most downward spikes are observed in 2017 across most sector pairs within the four developed countries. Researchers assert that the economic cost of Brexit will exceed the benefit for Europe, the UK and other developed countries like the US and Japan (Kierzenkowski, Pain, Rusticelli and Zwart, 2016). The uncertainties that lie ahead post-Brexit will threaten the economic growth prospects of the EU and the UK.

Figure 4.11 shows the time-varying correlations across sectors in the UK. Compared to sector pairs within other developed countries, the sector pairs within the UK show greater significant downward spikes across sectors pairs in 2017. This is likely due to the greater potential post effect of Brexit on all the sector pairs within the UK. The German Bertelesmann foundation estimates that a loss of about seventy eighth billion euros a year (for ten years) will be incurred by the UK on leaving the EU (Wilfried, 2019). This cost to the UK is very likely, since leaving the EU will lead to

- customs barriers implying a decline in foreign trade due to tariffs on export to European countries.
- The partial loss of the extensive EU market
- Post Brexit, uncertainty is inevitable. Therefore the stock market perception of investment and economic risk of the UK will increase leading to the depreciation of the pound. The depreciation of the pound increases cost of borrowing for businesses, which in turn lead to a fall in stock market prices and sectoral returns.

Analysis across sector pairs in all four developed countries reveal significant downward spikes in 2008. This can be attributed to the 2008 global financial crisis, which spread to all four advanced economies and had an effect on most of the sectors.

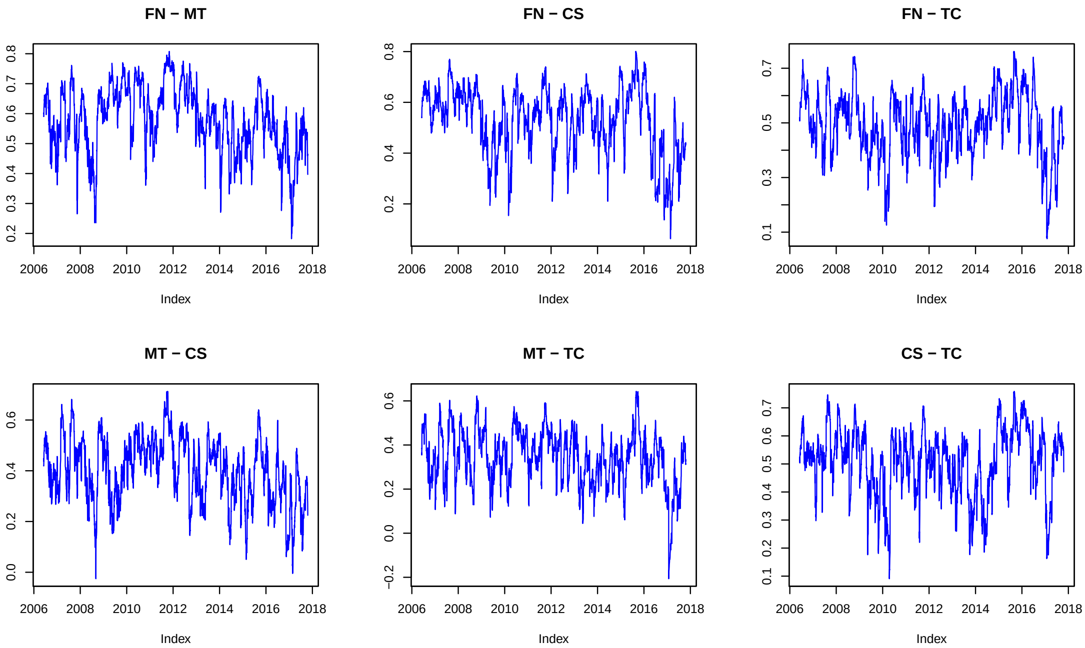


Figure 4.11: DCC across sectors within the UK

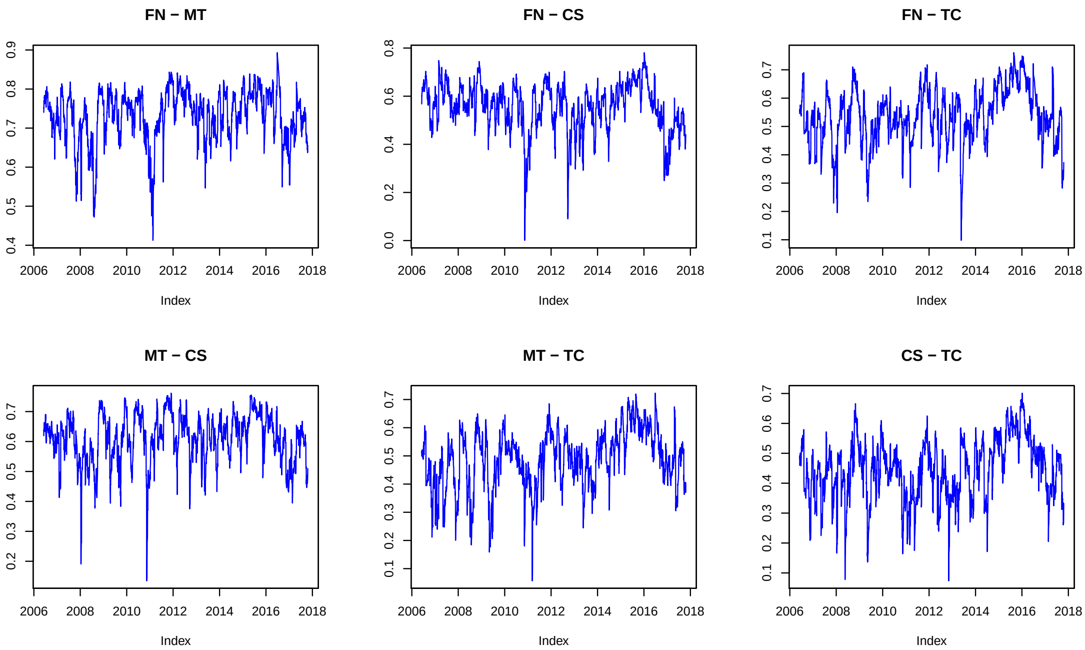


Figure 4.12: DCC across sectors within Germany

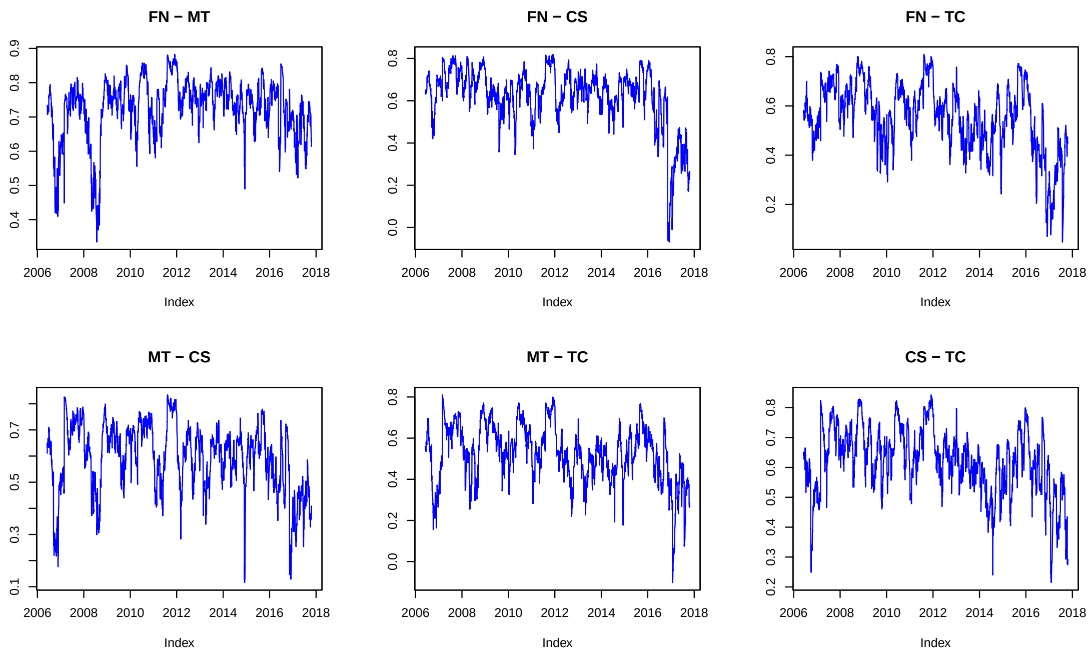


Figure 4.13: DCC across sectors within the USA

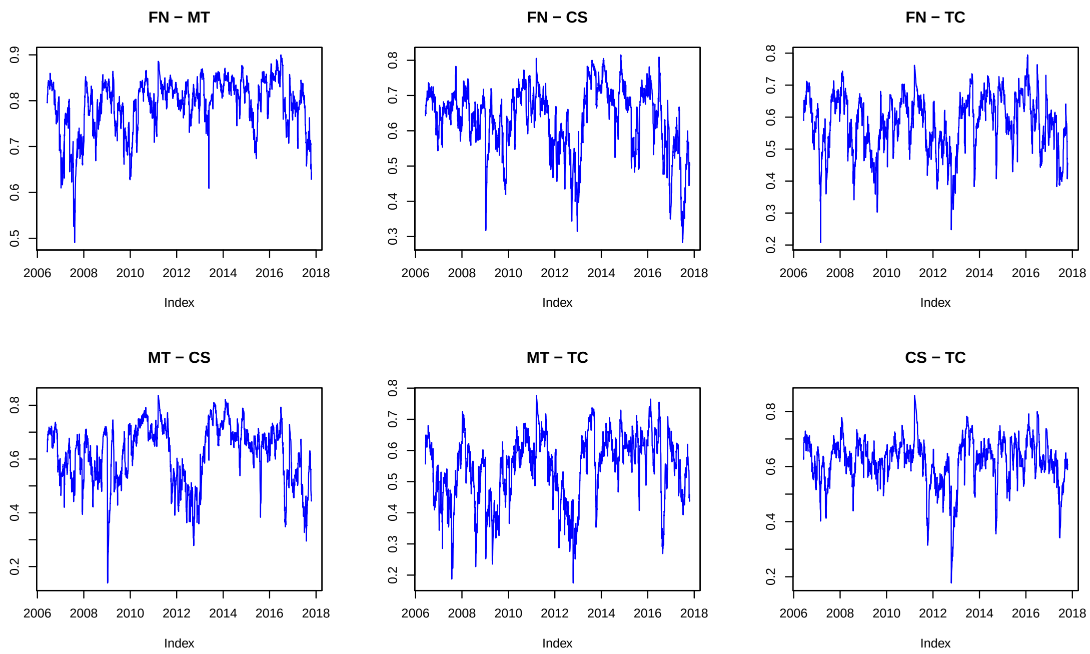


Figure 4.14: DCC across sectors within Japan

4.3.2 Cross Country within sector correlation

For ease of presentation, only the results for South Africa and USA are presented in this section. The results of the other countries are presented in the appendix. USA was chosen due to the greater influence of the USA on the rest of the eight countries. The second country was chosen to capture any other patterns that might not be captured by the correlation of USA with other countries. Figures 4.15 to 4.22 show the time-varying dynamic conditional correlations of the respective sectors, between each of the BRICS countries and four developed countries respectively. The figures point towards heterogeneity in the correlations between the sector pairs over time, and reveals that static estimates of co-movement (in modelling terms), the constant conditional correlations (or CCC), might be misleading.

4.3.2.1 Financials

Figure 4.15 shows the time varying cross country correlations between South Africa and the rest of the eight countries for the financial sector equity indices. We observe downward spikes for all eight country pairs in 2008. This can be attributed to the 2008 financial crisis. This implies that the 2008 financial crisis decreased the correlation between the financial sector of South Africa with the rest of the eight countries at the beginning of the 2008 global financial crisis. Of all the BRICS countries, South Africa has the highest correlation with Russia. The correlation level for the pair South Africa - Russia is around 50 percent. For developed countries, South Africa has the highest correlation with Germany and the UK. Correlation levels for the pairs South Africa -Germany and South Africa - UK are above 50 percent, whereas the lowest correlation appears to be with Japan, with correlation levels around 0.3.

Figure 4.16 shows the time varying cross country correlation between the United States and the rest of the eight countries within the financial sector equity indices. For the BRICS countries, the highest correlation is observed between the USA and Brazil with correlation level of up to 60 percent. The lowest correlation appears to be with China, with a correlation level at around 25 percent. For developed countries, the highest correlation is observed with the pair USA-Germany and USA-UK where the correlation level goes beyond 65 percent. The lowest correlation is with Japan at about 35 percent.

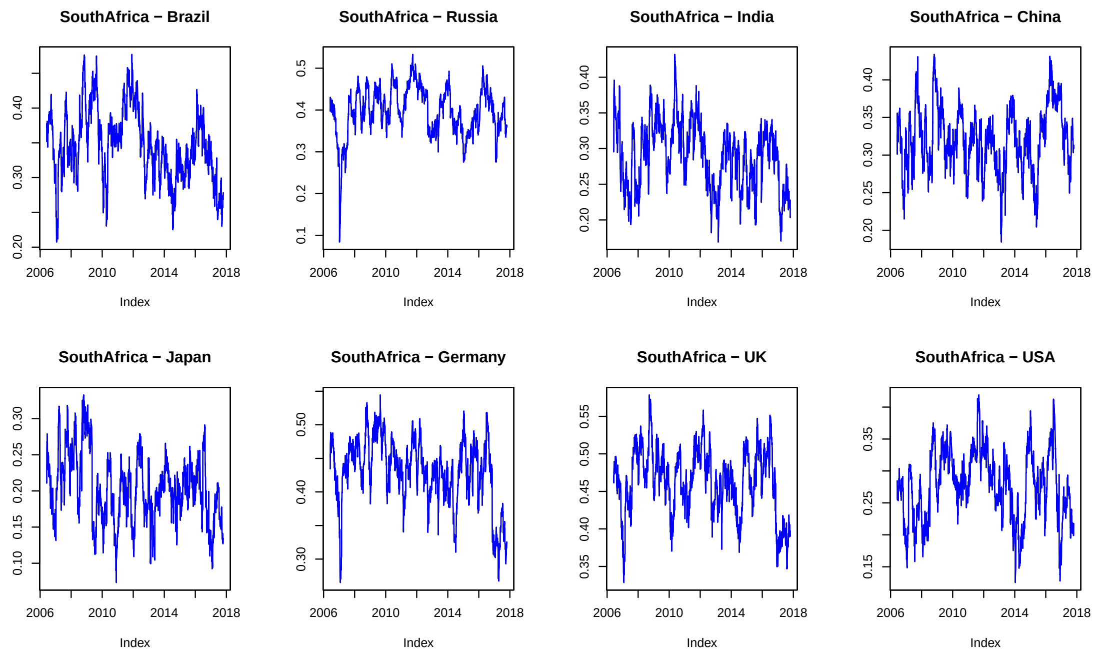


Figure 4.15: DCC within financial sector between South Africa and other countries

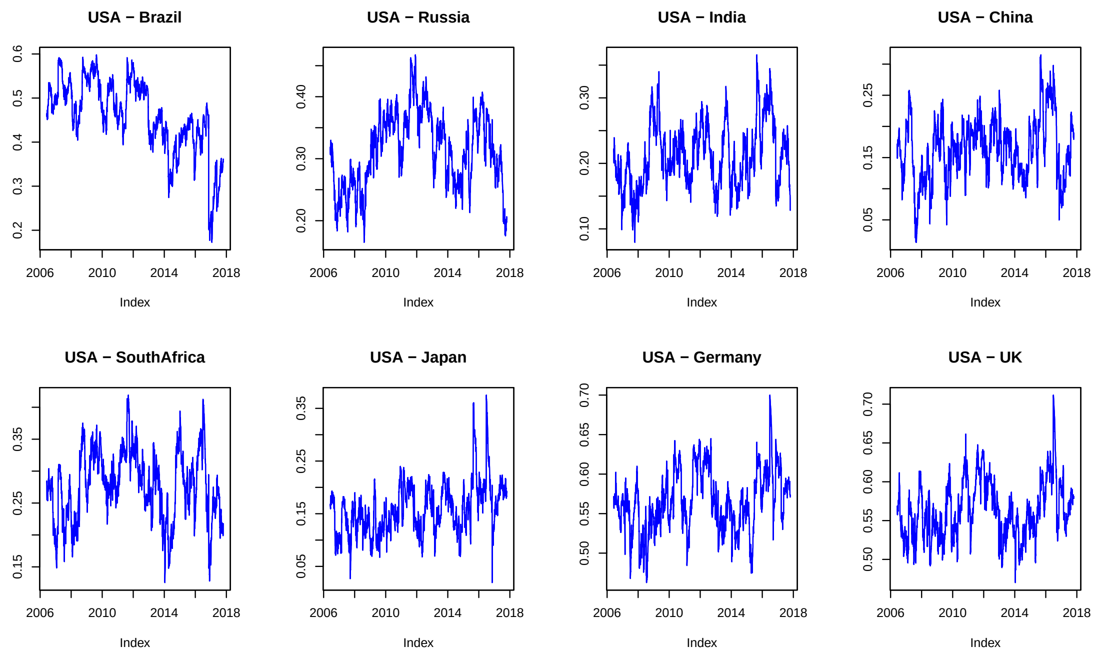


Figure 4.16: DCC within financial sector between USA and other countries

4.3.2.2 Materials

Figure 4.17 shows the time varying cross country correlations between South Africa and the rest of the eight countries within the materials sector equity indices. For BRICS countries, the highest correlation is observed between South Africa and Russia. The correlation level for the pair South Africa - Russia is about 50 percent. Compared to the financial sector, it is interesting to note that the correlation between South Africa and Brazil is lower for the material sector suggesting an opportunity for diversification. For the developed countries, South Africa has the highest correlation with the UK with a correlation level of about 55 percent, while the correlation level with Germany is second highest with a correlation level of about 40 percent.

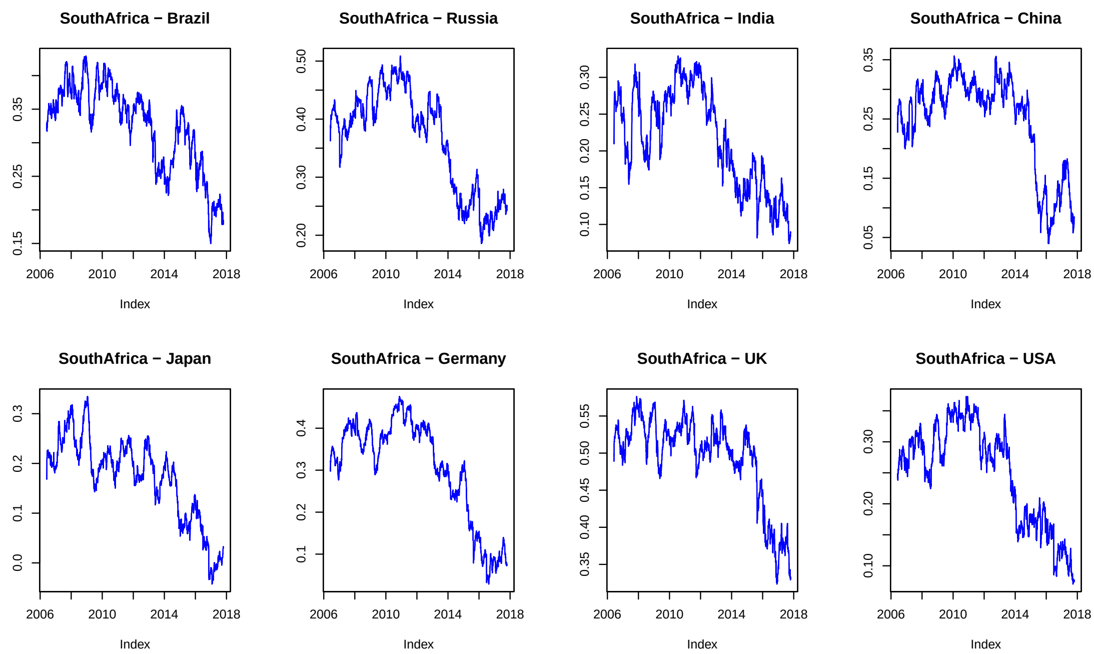


Figure 4.17: DCC within Materials sector across South Africa and other countries

Figure 4.18 shows the time varying cross country correlations between the USA and the rest of the eight countries within the materials sector indices. For the BRICS countries, the highest correlation is with Brazil. The correlation level for the pair, USA-Brazil is 70 percent. The lowest correlation level is seen with China, with a correlation level of 25 percent. With regards to the correlation level between the USA and developed countries, highest correlation are with pairs USA - UK with a correlation level of about 65 percent. The correlation level with Germany is second highest at 60 percent. The lowest correlation is with Japan at a level of 25 percent.

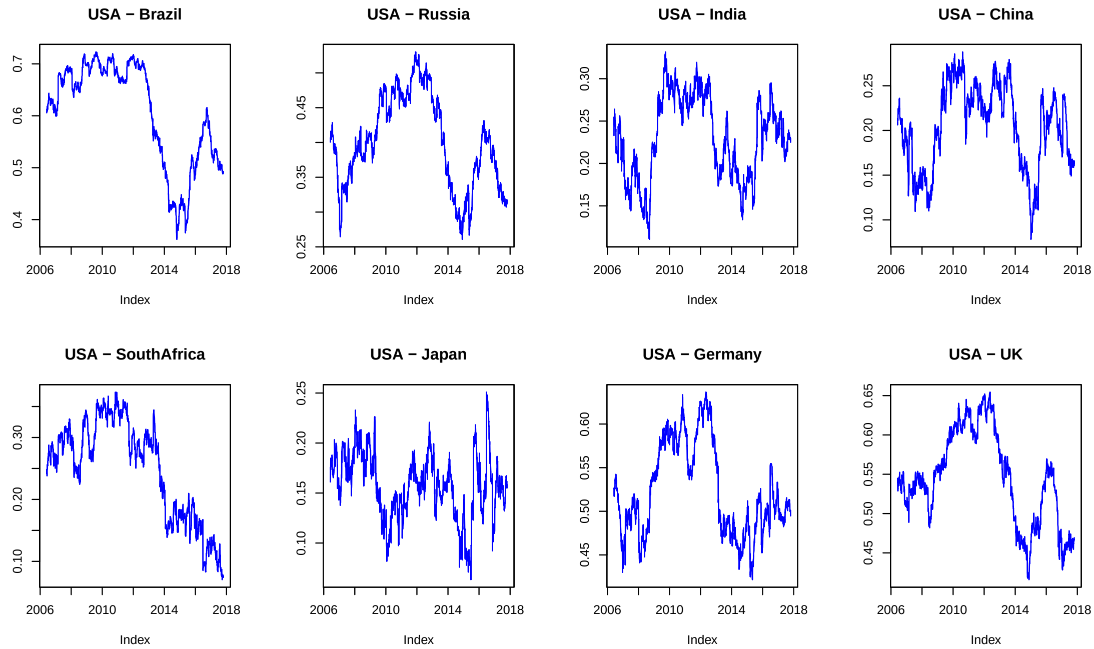


Figure 4.18: DCC within Materials sector across USA and other countries

4.3.2.3 Consumer Staples

Figure 4.19 shows the time varying cross country correlations between South Africa and the rest of the eight countries within the consumer staples sector equity indices. With regards to the correlation between South Africa and BRICS countries, the highest correlation is for the pair South Africa - Brazil, at a level of 36 percent. For developed countries, the highest correlation is seen for the pairs South Africa - Germany and South Africa - UK at a level of 35 percent. Correlation is lowest for Japan, at a level of 20 percent.

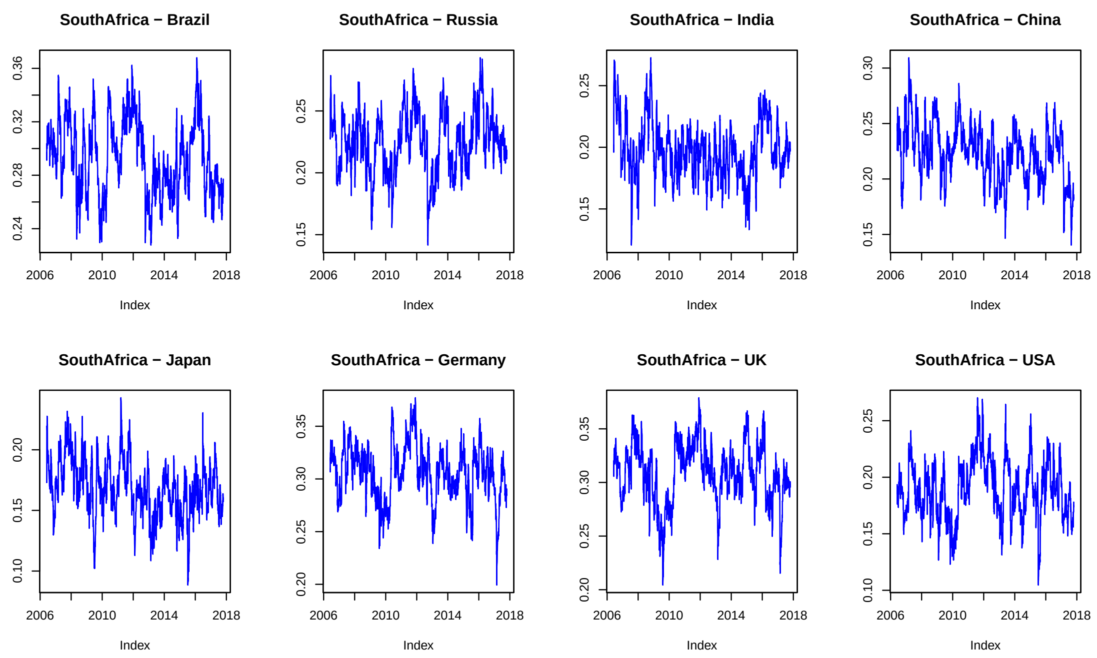


Figure 4.19: DCC within Consumer staples sector across South Africa and other countries

Figure 4.20 shows the time varying cross country correlations between the USA and the rest of the eight countries within the consumer staples sector equity indices. For the correlation pairs with BRICS countries, the highest correlation is observed for the pair USA-Brazil, and the lowest correlation with the pair USA-China. With regards to correlation with developed countries, the highest correlation is observed for the pair USA - UK, the second highest correlation with Germany at a level of 48 percent, and lowest correlation with Japan at a level of 20 percent.

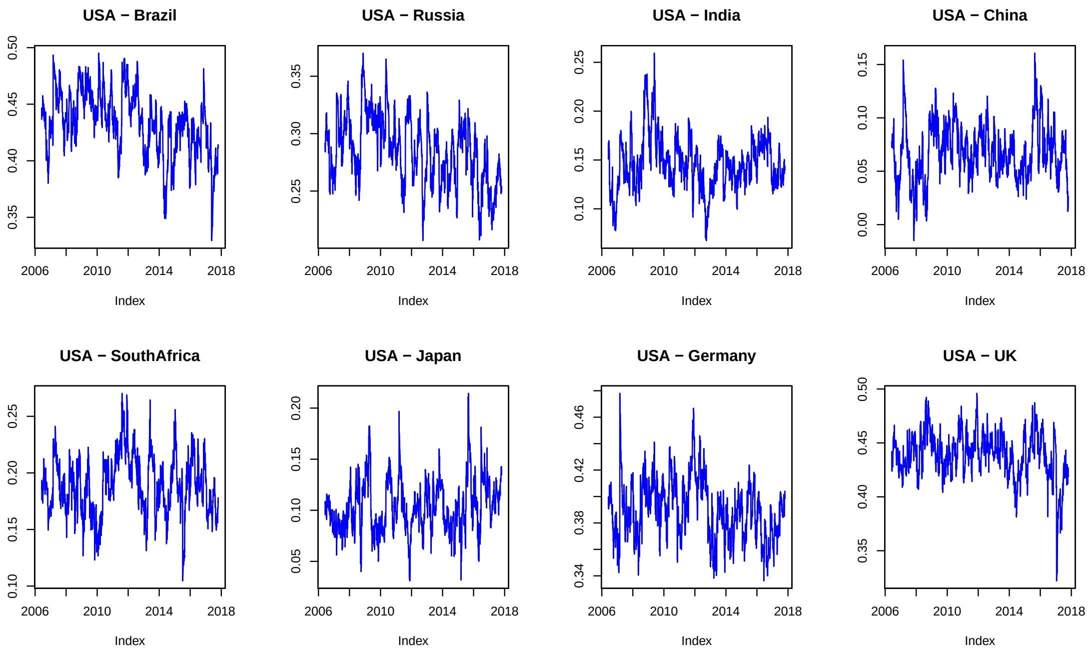


Figure 4.20: DCC within Consumer staples sector across USA and other countries

4.3.2.4 Telecommunications

Figure 4.21 shows the time varying cross country correlations between South Africa and the rest of the eight countries within the telecommunication sector equity indices. For the correlation pairs with BRICS countries, the highest correlation is observed with the pair South Africa - Russia, the second highest correlation with the pair South Africa - Brazil at a level of 35 percent, the third highest correlation with South Africa - Brazil at a level of 30 percent and the lowest correlation with India at a level of 25 percent. For the correlation pairs with developed countries, the pair with the highest correlation is South Africa - UK with a correlation level of 30 percent.

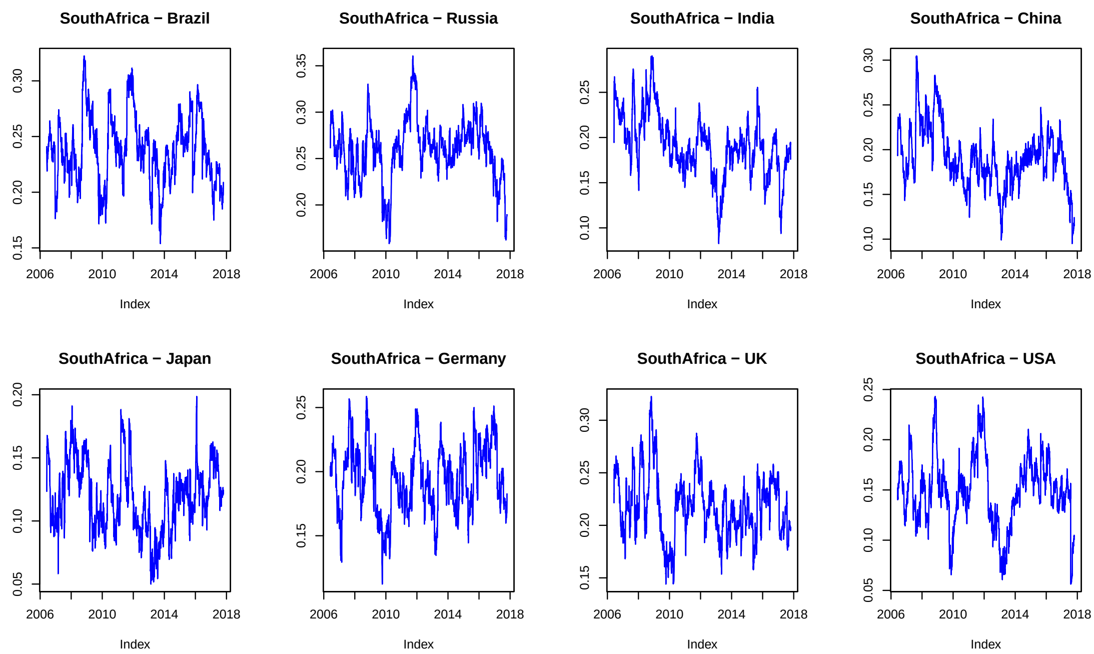


Figure 4.21: DCC within Telecommunications sector across South Africa and other countries

Figure 4.22 shows the time varying cross country correlations between USA and the rest of the eight countries within the telecommunication sector equity indices. For the correlation pairs with BRICS countries, the highest correlation is observed for the pair USA-Brazil at a level of 50 percent, and the lowest correlation is observed with the pair USA - China, at a level of 15 percent. With regards to the correlation pairs with developed countries, the highest correlation is observed with the pair USA-UK at a level of 50 percent, and the second highest is observed with the pair USA - Germany at a level of 48 percent.

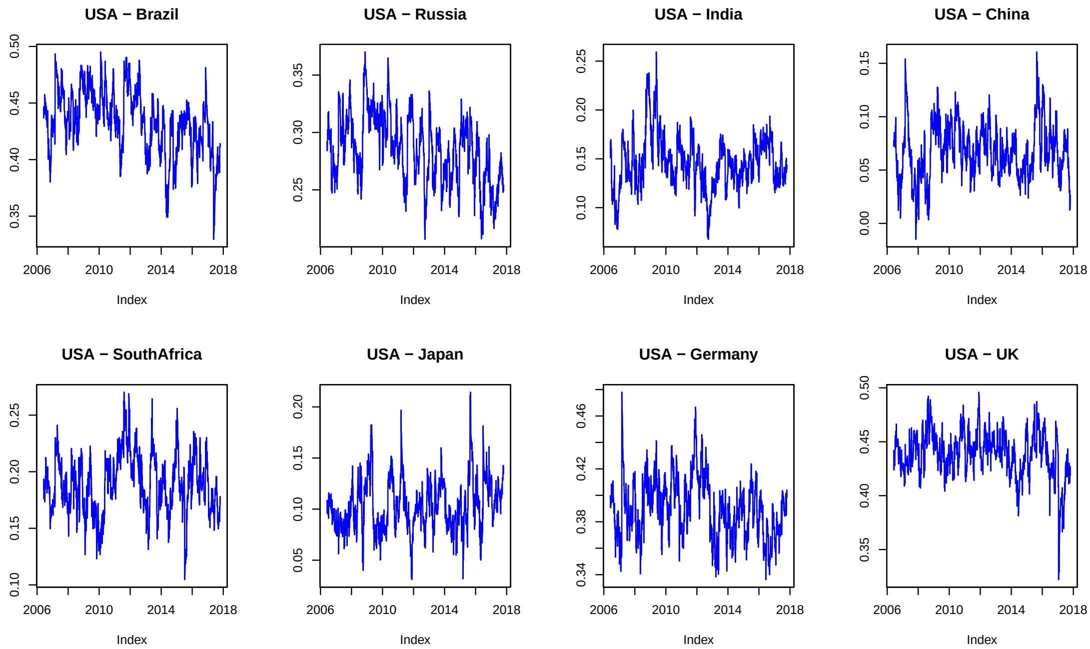


Figure 4.22: DCC within Telecommunications sector across USA and other countries

4.4 ADCC-GJRGARCH Results

4.4.1 Within Country Cross sector Correlation

Figures 4.23 to 4.31 show the asymmetric time-varying correlations across sectors in each of the BRICS countries and developed countries. The ADCC plots for sector pairs in these countries exhibit fluctuations over the entire sample period, suggesting that the assumption of constant correlations is not appropriate. The next section discusses the results for the ADCC plots for the sector pairs in BRICS countries.

4.4.1.1 BRICS

Brazil

Figure 4.23 shows the asymmetric time-varying correlations across sectors in Brazil. For the pairs FN-MT and MT-CS, the correlations between 0.6 and 0.8 are observed until 2012, thereafter a sharp drop in 2013 to a correlation of 0.4, followed by fluctuations in correlation between 0.4 and 0.8. For the pairs FN-CS and FN-TC the correlations are between 0.5 and 0.9 and a sharp decrease in 2013 and 2015, after which the fluctuation in correlations stabilizes between 0.6 and 0.9. For the pair MT-TC and CS-TC the correlations vary between 0.4 and 0.9, and include sharp drops in 2013 and 2017 and a spike in 2016, after which the correlation fluctuates between 0.5 and 0.9. The results of the cross sector ADCC plot for Brazil confirm the results of the DCC plots for Brazil.

Russia

Figure 4.24 shows the asymmetric time-varying correlations across sectors in Russia. For all sector pairs, the correlation begins at a level of 75 percent and makes a sharp downward spike in 2007. This is in line with the DCC plot. The downward spike can be attributed to the 2007 financial crisis. Between 2008 and 2018, the correlation for all sector pairs varies between 50 percent and 80 percent. The results of the cross sector ADCC plot for Russia support the results of the DCC plots for Russia.

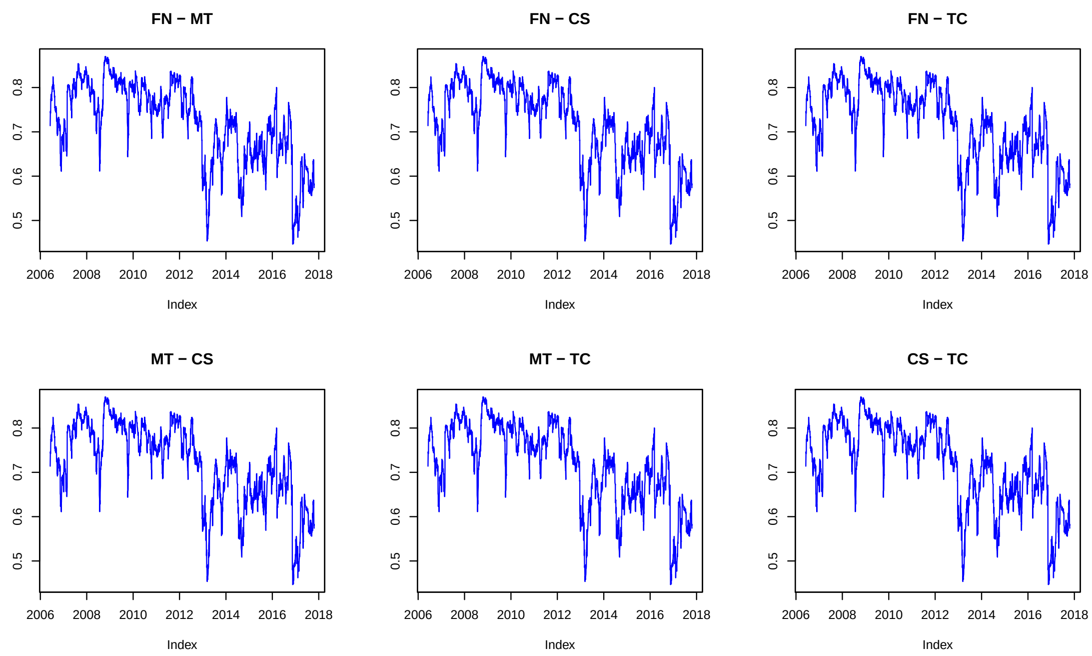


Figure 4.23: ADCC across sectors within Brazil

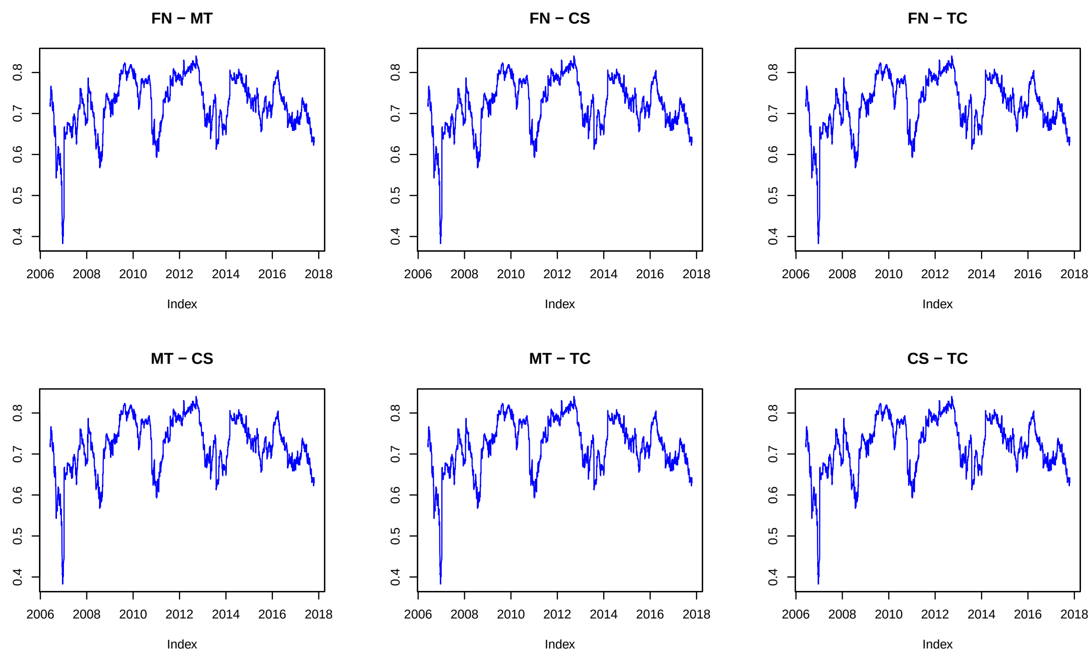


Figure 4.24: ADCC across sectors within Russia

India

Figure 4.25 shows the asymmetric time-varying correlations across sectors in India. There are downward spikes for all sector pairs in 2007. The downward spikes can be attributed to the 2007-2008 global financial crisis. Beyond 2008, the correlations fluctuate between a correlation level of 0.6 and 0.8. The results of the cross sector

ADCC plots reinforces the results of the DCC plots for India.

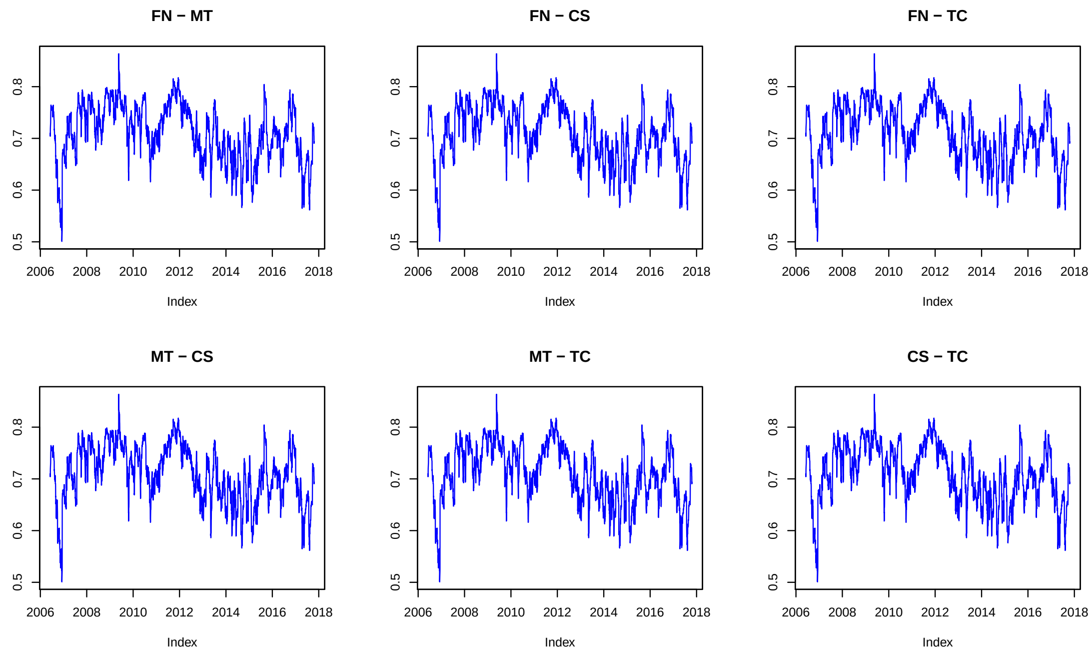


Figure 4.25: ADCC across sectors within India

China

Figure 4.26 shows the asymmetric time-varying correlations across sectors in China. For all the sector pairs, correlation plots of between 0.6 and 0.9 are observed up till 2016. Between 2016 and 2018, correlation are between 0.4 and 0.75 with a sharp drop for all the sectors in 2018. The results of the ADCC plot substantiate the results of the DCC plots for china.

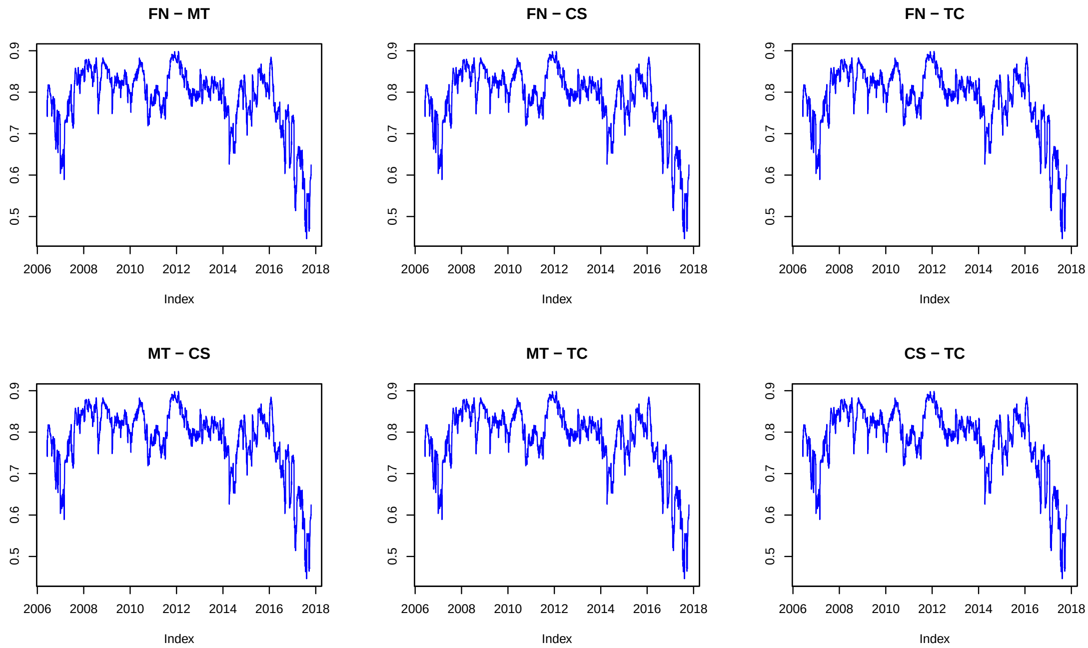


Figure 4.26: ADCC across sectors within China

South Africa

Figure 4.27 shows the asymmetric time-varying correlations across sectors in South Africa. For all sector pairs, a correlation of between 0.1 and 0.6 are observed from 2006 to 2014, after which there is a sharp drop in correlation in 2016. Beyond 2016, correlation are between 0.0 and 0.4 for all the sector pairs. The results of the ADCC plot validate the results of the DCC plots South Africa.

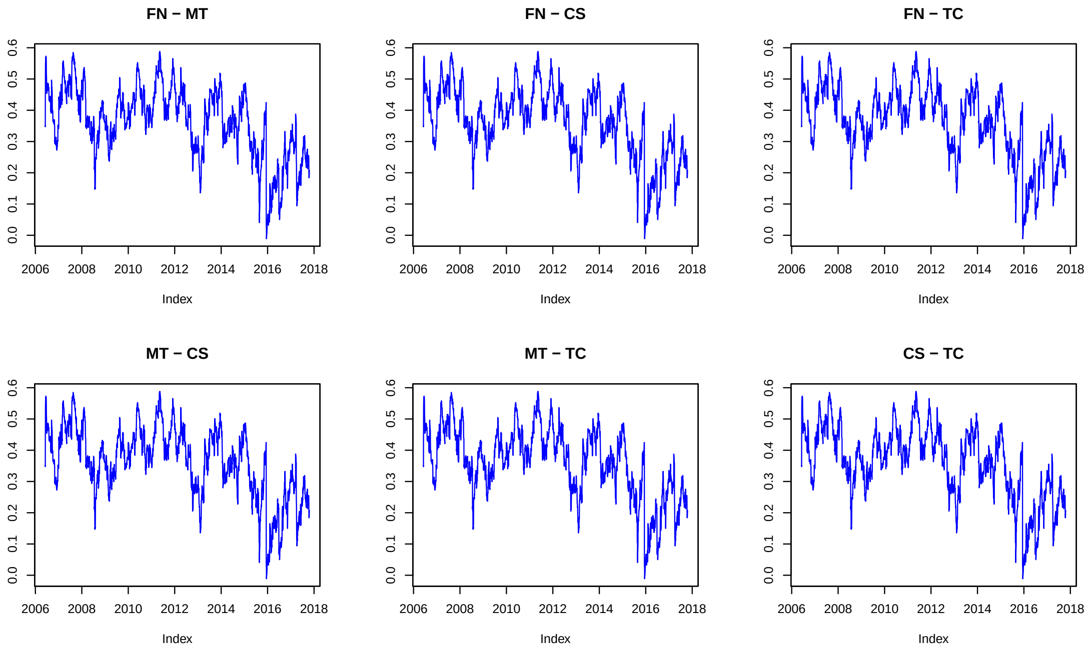


Figure 4.27: ADCC across sectors within RSA

The ADCC plots across sectors within each BRICS country closely follow a similar pattern observed with DCC plots. The reasons for the patterns mentioned under the DCC plots also apply to the ADCC plots.

4.4.1.2 Developed Countries

Figures 4.28 to 4.31 show the asymmetric time-varying correlations across sectors in four developed countries namely the UK, Germany, Japan and the USA. A visual inspection of the sector pairs reveal a significant downward spike in 2017 across all sector pairs in each of the four countries. As mentioned under the DCC section, this can be attributed to Brexit (Britain's exit from the European Union). Also evident are significant downward spikes across all sector pairs in each of the developed countries. This can be attributed to the 2008 global financial crisis which seems to have affected most sectors in developed countries. The results of the ADCC plots confirm the results of the DCC plots for all developed countries considered.

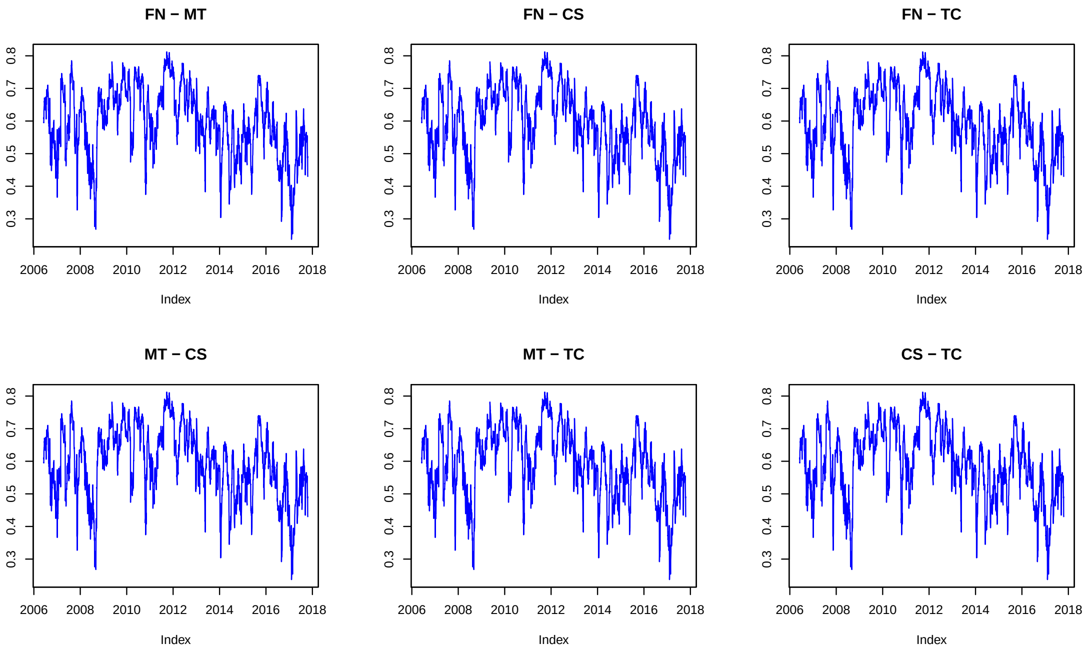


Figure 4.28: ADCC across sectors within UK

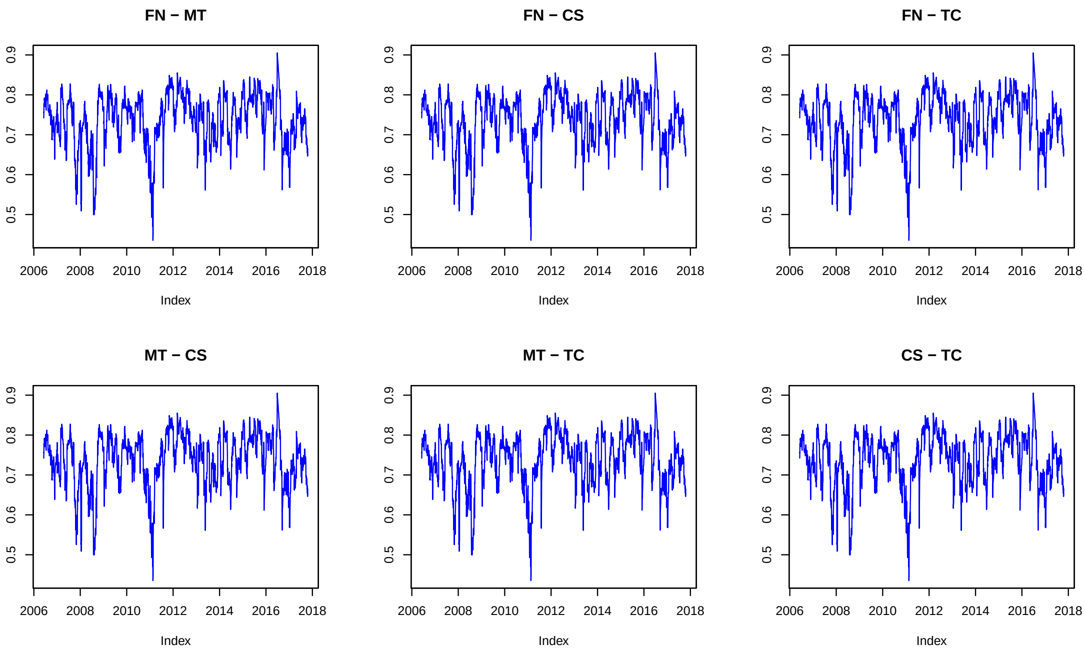


Figure 4.29: ADCC across sectors within Germany

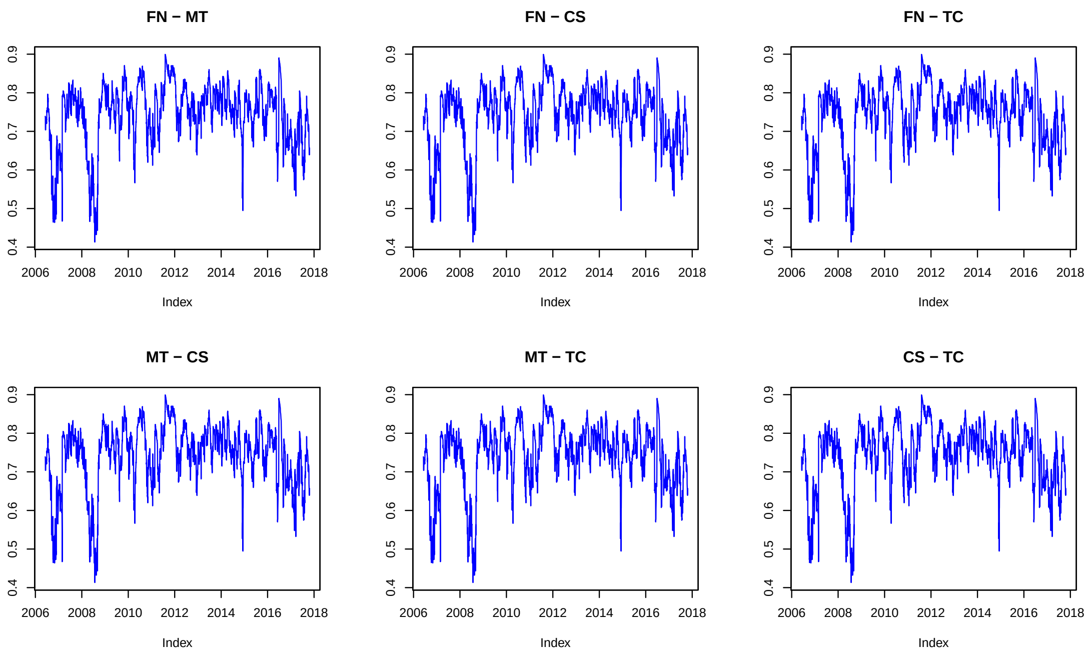


Figure 4.30: ADCC across sectors within USA

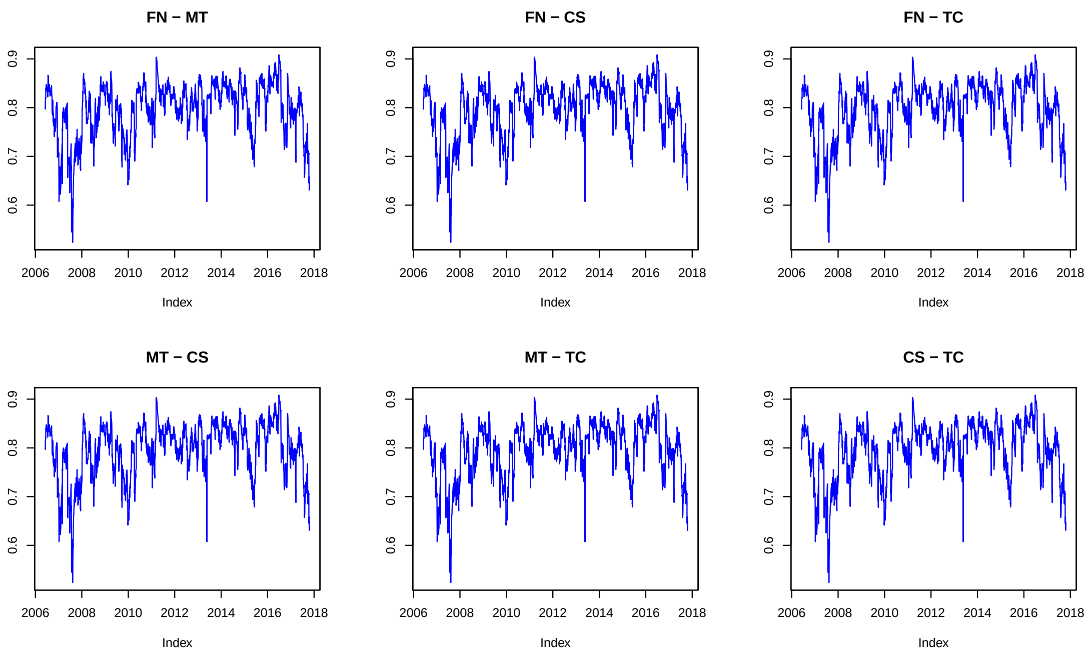


Figure 4.31: ADCC across sectors within Japan

4.4.2 Cross Country within sector correlation

For ease of presentation, only the results for South Africa and USA are presented in this section. The results of the other countries are presented in the appendix. USA was chosen due to the greater influence of the USA on the rest of the eight countries. The second country was chosen to capture any other patterns that might not be captured by the correlation of USA with other countries. Figures 4.32 to 4.39 show the asymmetric time-varying dynamic conditional correlations of the respective sectors, between each of the BRICS countries and four developed countries, respectively. The figures point towards heterogeneity in the correlations between the sector pairs over time and reveal that static estimates of co-movement (in modelling terms), the constant conditional correlations (or CCC), might be misleading.

4.4.2.1 Financials

Figure 4.32 shows the asymmetric time varying cross country correlations between South Africa and the rest of the eight countries for the financial sector. Significant downward spikes are observed for all country pairs in 2008. As noted in DCC section, this can be attributed to the 2008 financial crisis. For correlation with BRICS countries, similar results are reported as with the DCC plot with the highest correlation being with Russia at a level of 50 percent. For developed countries, the highest correlation is observed with the UK, at a level of 55 percent.

Figure 4.33 shows the asymmetric time varying cross country correlations between the United States and the rest of the eight countries for the financial sector equity indices. For BRICS countries, the highest correlation is observed between the USA and Brazil, with a correlation level up to 60 percent. For developed countries, the highest correlation is observed for the pair USA-Germany and USA-UK where the correlation level goes beyond 65 percent. For the correlation with developed countries, the results of the ADCC plots further substantiate the results of DCC plots .

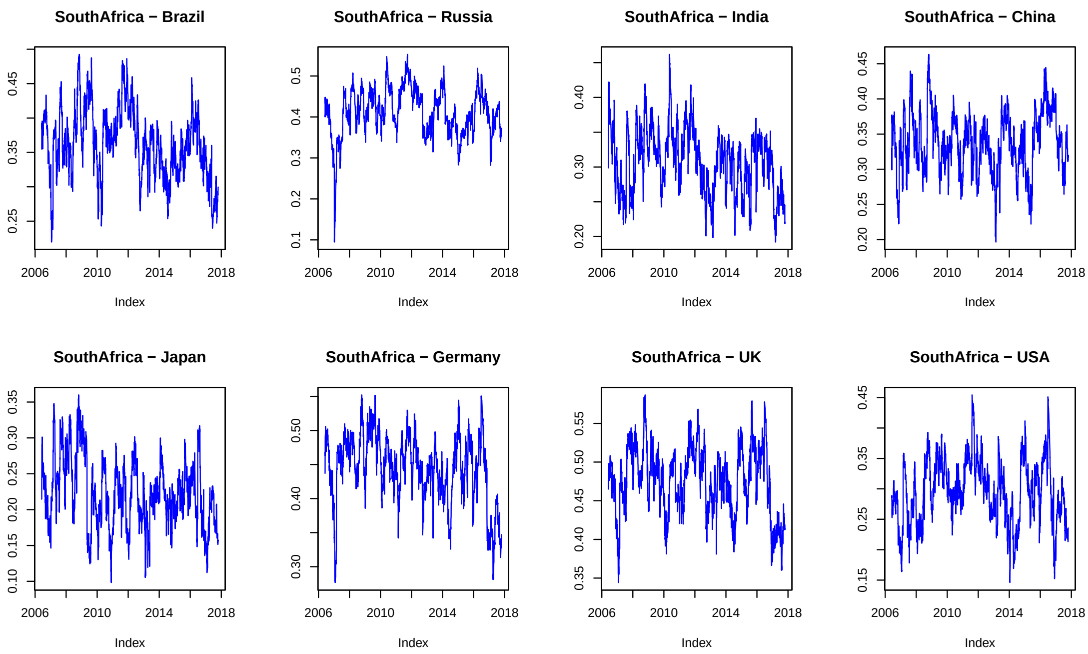


Figure 4.32: ADCC within Financial sector across South Africa and other countries

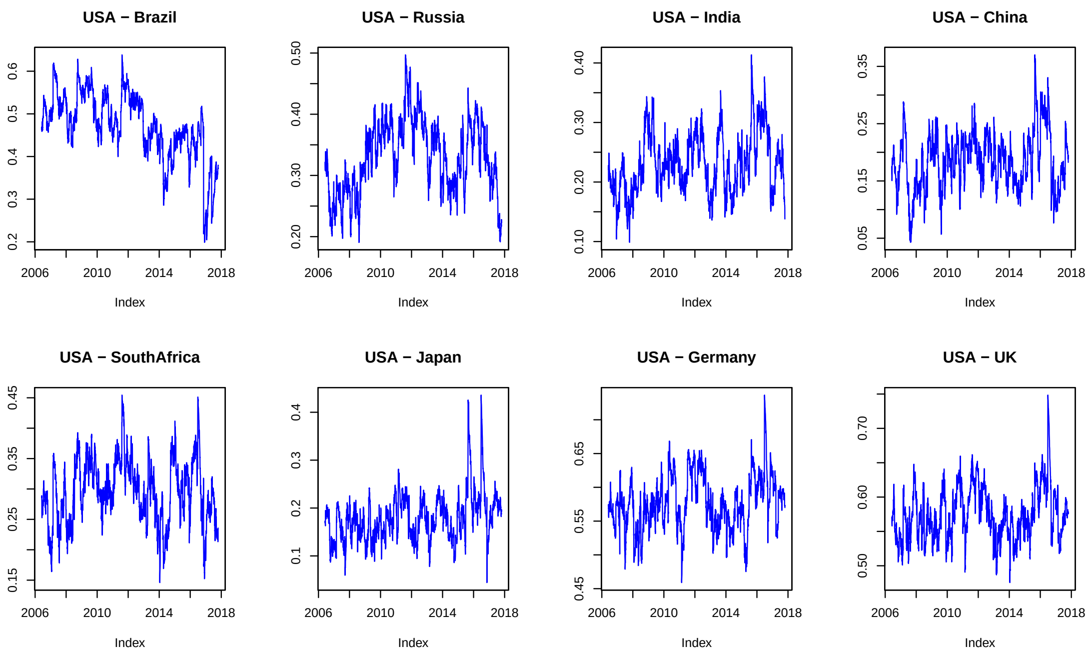


Figure 4.33: ADCC within Financial sector across USA and other countries

4.4.2.2 Materials

Figure 4.34 shows the asymmetric time varying cross country correlations between South Africa and the rest of the eight countries for the materials sector equity indices. For BRICS countries, the highest correlation is observed between South Africa and Russia. The correlation level for the pair South Africa - Russia is about 35 percent. For the developed countries, South Africa has the highest correlation with the UK, with a correlation level of about 55 percent, while the correlation level with Germany is second highest at about 30 percent. The correlation between South Africa and other BRICS countries tend to be more volatile for ADCC plots compared to DCC plots.

Figure 4.35 shows the asymmetric time varying cross country correlations between USA and the rest of the eight countries for the materials sector equity indices. For the BRICS countries, the highest correlation is with Brazil, at 70 percent. The lowest correlation level is seen for China with a correlation level of 25 percent. With regards to correlation levels between the USA and developed countries, the highest correlation is for the USA - UK pair with a correlation level of about 65 percent. The correlation level with Germany is second highest at 60 percent. The lowest correlation is with Japan at a level of 25 percent. The results reported for the ADCC plots between the USA and the rest of the eight countries confirm the results reported for the DCC plots.

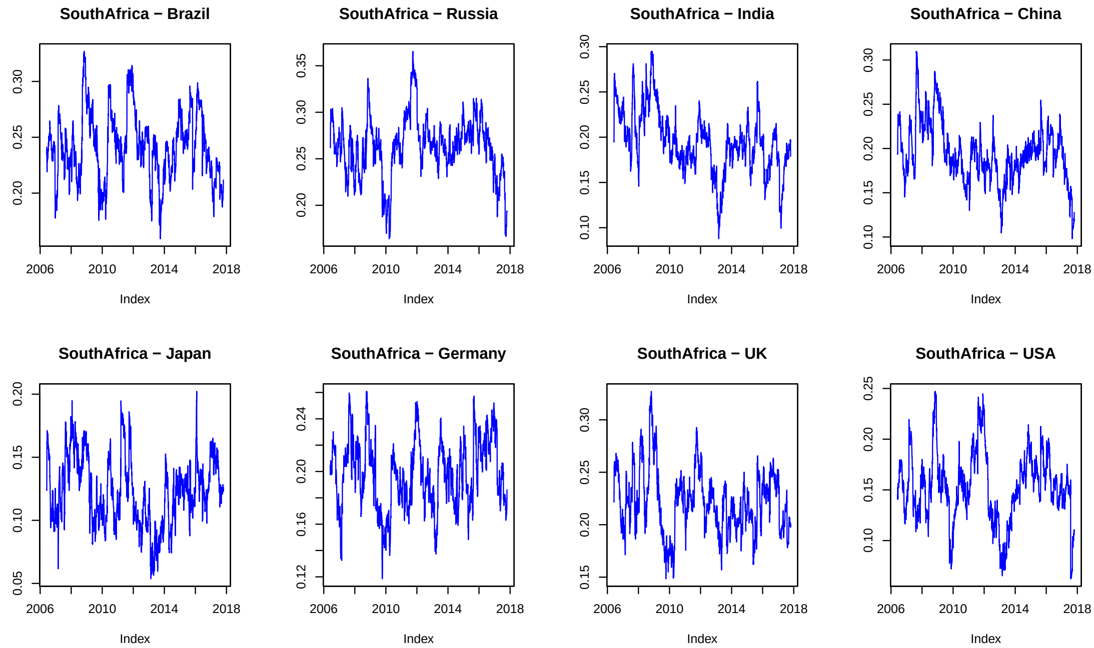


Figure 4.34: ADCC for the materials sector across South Africa and other countries

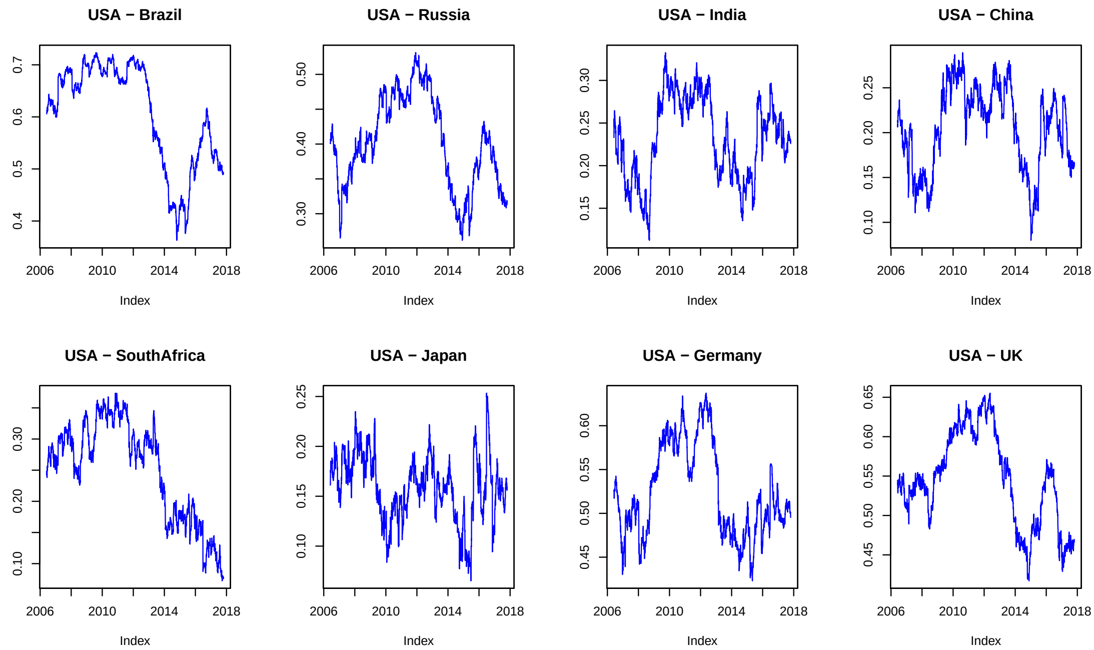


Figure 4.35: ADCC for the materials sector across USA and other countries

4.4.2.3 Consumer Staples

Figure 4.36 shows the asymmetric time varying cross country correlations between South Africa and the rest of the eight countries for the consumer staples sector equity indices. With regards to the correlation between South Africa and BRICS countries, we observe the highest correlation with the pairs South Africa - Brazil and South Africa - China at levels of 35 percent. For developed countries, the highest correlation is seen for the pairs South Africa - Germany and South Africa - UK, at a level of 40 percent. The correlation is lowest for Japan at a level of 25 percent.

Figure 4.37 shows the asymetric time varying cross country correlations between USA and the rest of the eight countries for the consumer staples sector. For the correlation pairs with BRICS countries, the highest correlation is the pair USA-Brazil and the lowest correlation the pair USA-China. With regards to correlations with developed countries, the highest correlation is for the pair USA - Germany, the second highest correlation with the UK at a level of 50 percent, and the lowest correlation with Japan at a level of 20 percent. The results reported for the ADCC plots between the USA and the rest of the eight countries Support the results reported for the DCC plots.

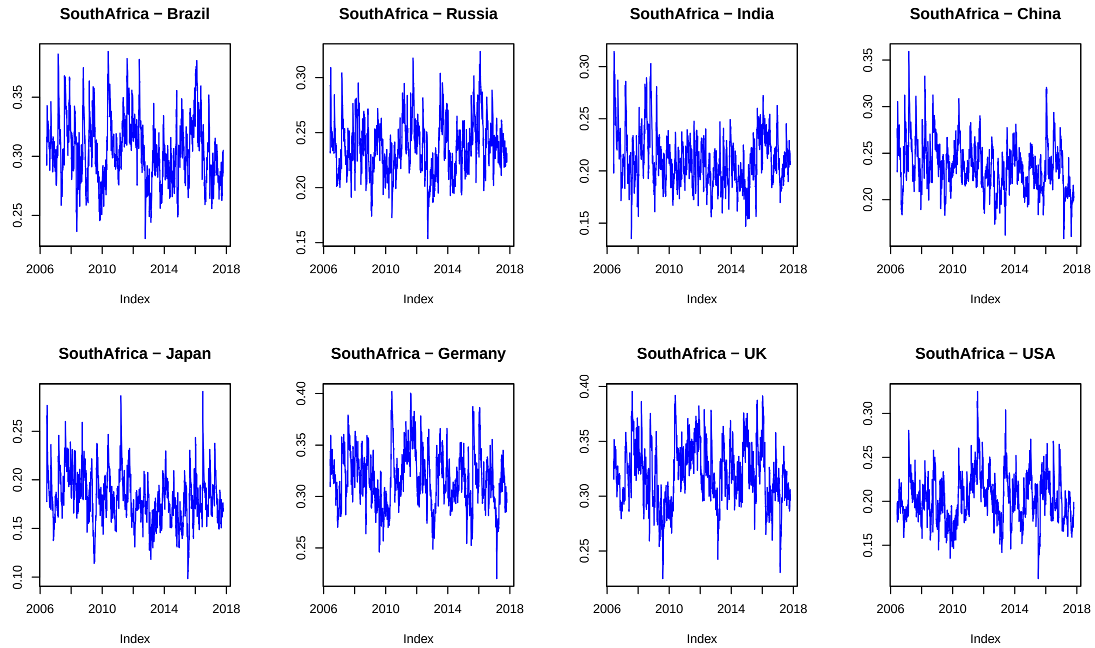


Figure 4.36: ADCC within Consumer staples sector across South Africa and other countries

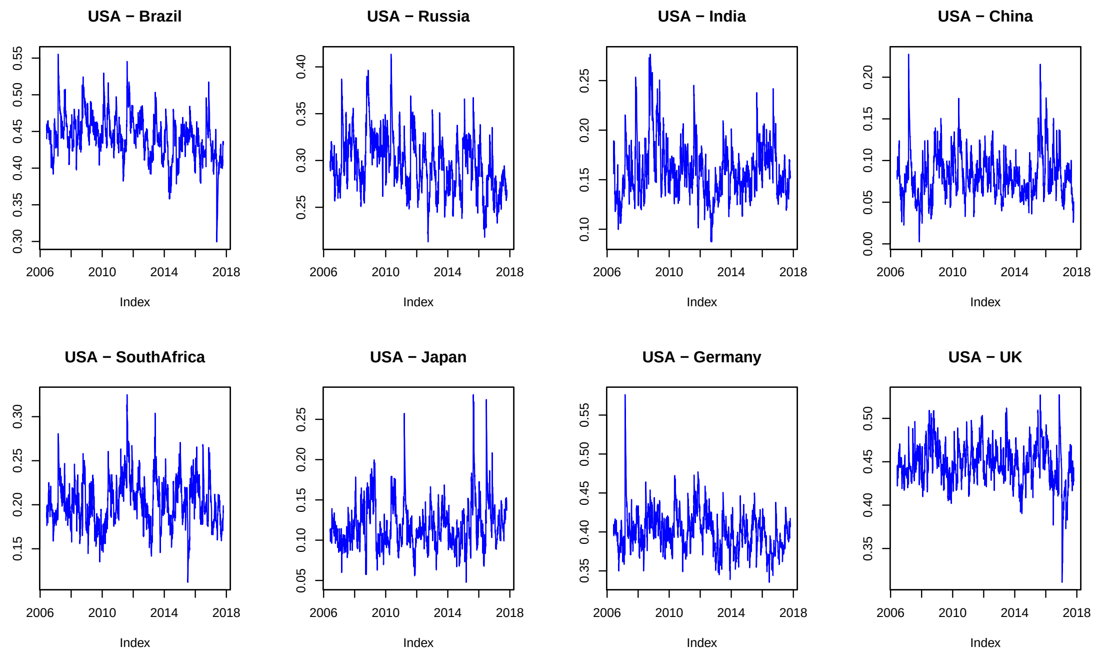


Figure 4.37: DCC within Consumer staples sector across USA and other countries

4.4.2.4 Telecommunications

Figure 4.38 shows the time varying cross country correlations between South Africa and the rest of the eight countries within the telecommunication sector equity indices. For the correlation pairs with BRICS countries, the highest correlation is for the pair South Africa - Russia and the second highest correlation the pair South Africa - Brazil at a level of 35 percent and lowest correlation for South Africa - Brazil at a level of 30 percent. For the correlation pairs with developed countries, the pair with the highest correlation is South Africa - UK with a correlation level of 30 percent.

Figure 4.39 shows the time varying cross country correlations between USA and the rest of the eight countries within the telecommunication sector. For the correlation pairs for BRICS countries, the highest correlation is observed with USA-Brazil at a level of 50 percent and the lowest correlation with the pair USA - China at a level of 15 percent. With regards to the correlation pairs with developed countries, the highest correlation is observed with the pairs USA-UK and USA - Germany at a level of 40 percent. The results reported for the ADCC plots between USA and the rest of the eight countries reinforces the results reported for the DCC plots.

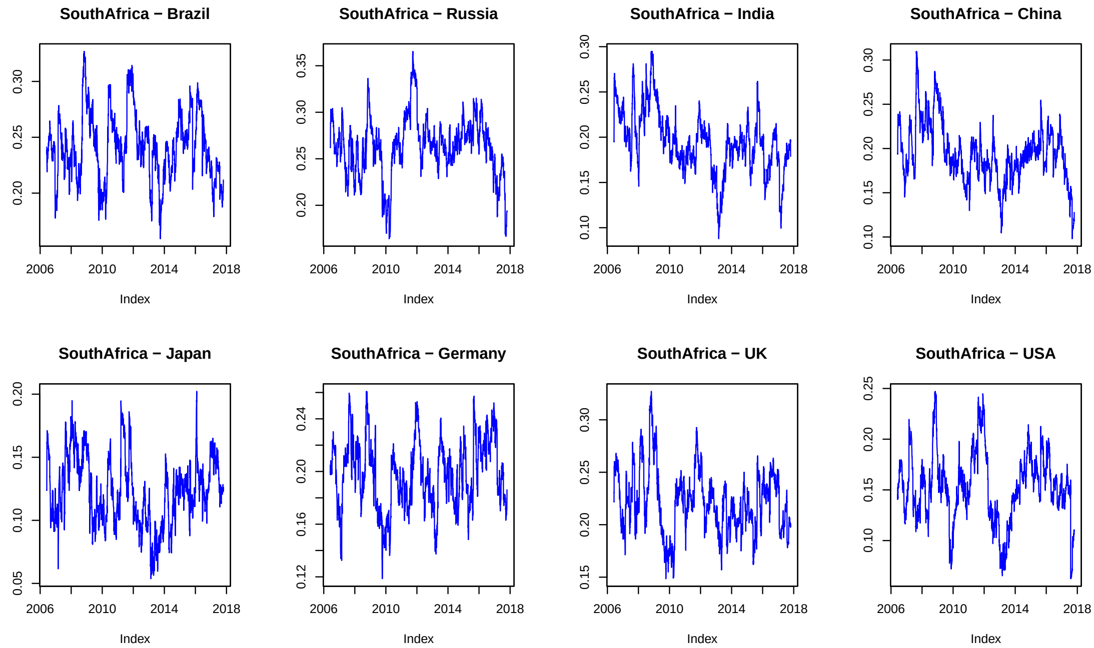


Figure 4.38: ADCC for the telecommunications sector across South Africa and other countries

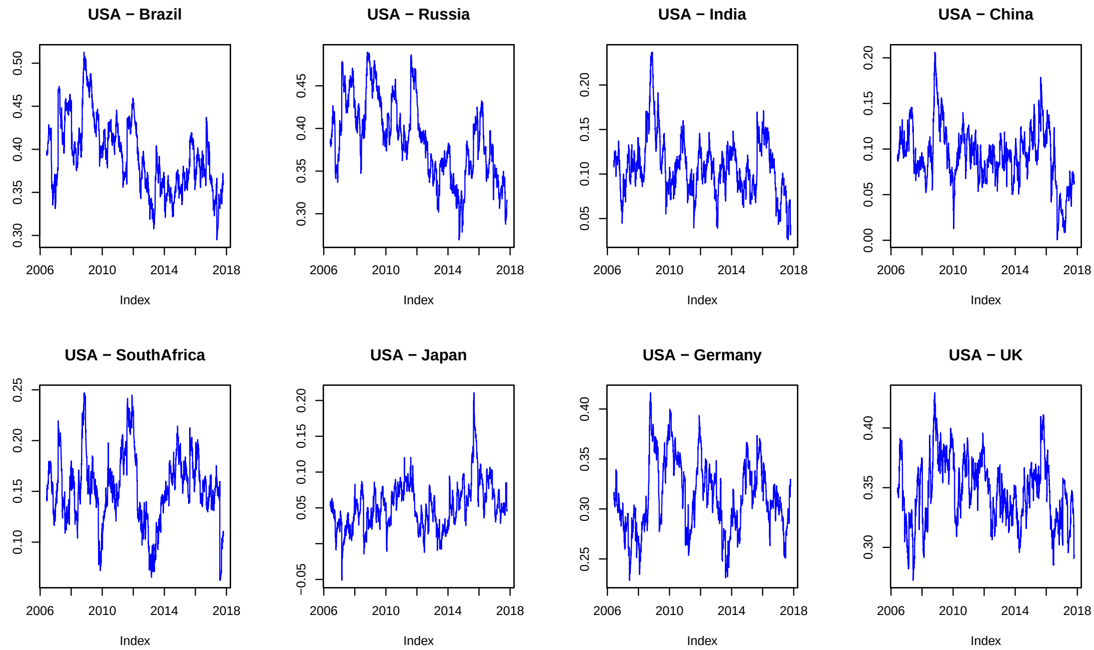


Figure 4.39: ADCC for the telecommunications sector across USA and other countries

4.4.3 Comparing the performance of the DCC-GARCH relative to the ADCC-GARCH

In order to assess how well the DCC-GJRGARCH and ADCC-GJRGARCH performed, the Akaike Information Criterion (AIC) and the Schwartz Bayesian Information Criterion (BIC) were used to select the model with the best goodness of fit. The decision on the best model is based on the model that has the lowest AIC and BIC. Table 4.7 below shows the goodness of fit measures for the DCC-GJRGARCH and ADCC-GJRGARCH [4]. According to the AIC and BIC, the ADCC-GJRGARCH (1,1) model outperform the DCC-GJRGARCH model, in terms of lower AIC and BIC values for all within country cross sectors and within sectors cross countries analysis. Therefore, ADCC-GJRGARCH was selected as the model to be used for the regression analysis dynamic conditional correlation.

Table 4.7: Model performance for the estimated DCC GJRGARCH/ADCC GJR-GARCH model

Country or Sector	**Information criteria**	**Model**	
		DCC gjrGARCH	**ADCC gjrGARCH**
South Africa (across sector)	AIC	13.051	13.050
	BIC	13.132	13.132
USA (across sector)	AIC	9.5227	.5034
	BIC	9.6034	9.5861
Financial Sector (across country)	AIC	30.968	30.964
	BIC	31.190	31.188

4.5 Analysis of ADCC correlation dynamics across the GFC, ESDC and Brexit crisis periods

Given the results presented in the previous section, the next step was to establish the co-integration dynamics effects of inter-sector and cross-sector asymetric conditional correlations across both developed and BRICS countries. Specifically, it was investigated whether the conditional correlation between a pair of countries or sectors increased during the four phases of the GFC, three phases of the ESDC, and the Brexit crisis. This section presents the results from GJR-GARCH (1,1,1)-ADCC model for the sectors under examination. The results presented are divided into two main sections. The first section deals with cross-country within sector asymmetric conditional correlation and the second section deals with within country cross sector asymetric conditional correlation. Each section reports the average correlation

[4]This analysis has been done for all nine countries accross sectors and within all sectors accross countries. For simplicity of presentation, only the analysis of within country cross sector for Brazil and USA and within financial sector across country results are presented here

during each crisis period, and the estimated results of correlation across the phases of the GFC and the ESDC. The following OLS regressions were used:

$$\rho_{i,j,s,t} = c + D_{GFC} + D_{ESDC} + D_{Brexit} + \varepsilon_{i,j,t} \tag{4.14}$$

$$\rho_{i,j,s,t} = c + \sum_{k=1}^{7} \beta_k dum_{k,t} + \eta_{i,j,t} \tag{4.15}$$

In Equation 4.14 $\rho_{i,j,t}$ represents the pairwise dynamic conditional correlation between returns of sector s in country i and country j, c represents a constant, D_{GFC}, D_{ESDC} and D_{Brexit} are dummy variables for GFC, ESDC and Brexit crises period respectively. Each dummy variable takes a value of 1 during the crisis period and zero otherwise. Thus, the D_{GFC} dummy variable takes a value of 1 from 1st of August 2007 to 31 October 2009 and 0 elsewhere. The D_{ESDC} dummy variable takes a value of 1 from 5 November 2009 to 30 August 2011, and 0 elsewhere, and D_{Brexit} dummy variable takes a value of 1 from June 24 2016 (news of UK referendum results) to 29 April 2017 [5]. In terms of crisis dates, the fall of Lehman Brothers is chosen as the proxy date for the commencement of the GFC, the announcement of the Greek budget deficit is chosen as proxy date for the commencement of the ESDC and news of the UK referendum results is chosen as proxy date for the commencement of the Brexit crisis.

In Equation 4.15, $\rho_{i,j,t}$ represents the pairwise dynamic conditional correlation between returns of sector s in country i and country j, c represents a constant, $dum_{k,t}$ (k = 1,2,3,4,5,6,7) corresponds to the phases of the GFC and ESDC. The first four phases are for the GFC and the remaining three phases are for the ESDC. In the analysis of the correlation dynamics across the phases of the crisis period, seven dummy variables which were set equal to one for each phase of the crisis and zero otherwise. Essentially, for the GFC, the period 1st of August 2007 to 31 October 2009 was subdivided into four phases and for the ESDC the period from 5 November 2009 to 30 August 2011 was divided into three phases according to the economic approach presented in Section 4.1.4. The next section discusses the results for cross-country within sector correlations.

[5] a month after the trigger of Article 50

4.5.1 Cross-country within sector correlation

This section presents the tables and discussion on estimated coefficients for Equation 4.14 and 4.15 associated with cross country within sector financial contagion during the GFC, ESDC and Brexit. The tables also show the statistical significance of the coefficients of the dummy variables for each of the pairwise conditional correlations.[6]. This section is organised into three subsections: The first subsection presents the analysis of ADCC results across developed countries within sector. The second subsection presents the analysis of ADCC results across BRICS countries within sectors and the third subsection presents the analysis of ADCC results across BRICS and the developed countries within sector.

Analysis of ADCC results across developed countries within sectors

This subsection seeks to answer the question: did correlations increase between developed country pairs within each of the sectors under study during the mentioned crises ?

Table 4.8 presents average conditional correlation coefficients of developed country pairs during the GFC, ESDC and Brexit crisis periods across developed countries within sectors. Table 4.9 provides results for the correlation coefficients across the four phases of the GFC and three phases of the ESDC. From Table 4.8 the majority of the dummy variable with positive coefficients associated with GFC, ESDC and Brexit crises are positive and statistically significant at a 1 percent level, indicating that inter-sector conditional correlations were higher during the GFC, ESDC and Brexit crisis periods for developed countries. The results verify that positive correlation coefficients for the country pairs as evidenced at varying magnitudes across the four sectors under study.

In Table 4.8, the conditional correlations for the pairs Germany-Japan, Japan-UK show positive correlation coeffients across all sectors for the GFC, while the pair Japan-USA shows a negative correlation for the financial sector and almost zero correlation for the other sectors during the GFC. According to studies carried out by Kaltenhaeuser (2003) on country and sector specific spillover effects in the Japanese, US and European markets, the impact of European sectors on their Japanese equivalents increased considerably during the late 1990. However, despite shocks or fluctuations in the US sectors, US sector innovations have very little influence on Japanese industry. These findings offer some insight for the reason behind the negative correlation between Japan and the USA.

With regards to the Brexit crisis, the most affected sector is the financial sector

[6]For brevity, standard errors are not reported, but only the significance levels

which shows positive correlation for all country pairs. This is likely due to the inter connectivity of the financial sector of the these developed countries that provided the channel for the spread of the effect of UK referendum results announcement and subsequent Article 50 trigger. The other sectors, namely materials, the consumer sector and telecommunications show negative correlations for most of the country pairs. These sectors are less connected across the developed countries under study, and thus appear to not have transmitted the effect at the Brexit referendum. Additionally, these sectors may also be less impacted by it than the financial sector.

Table 4.9, indicates that all correlation country pairs show positive correlation during at least one phase of the GFC. Generally, the correlation analysis on the GFC crisis phase across developed countries indicate that the highest number of country pairs that showed an increase in correlation (positive correlation coefficients) occured in the second phase (" the sharp financial market deterioration) and the fourth phase ("stabilization and signs of recovery"). These results suggest that broadcasting of foreign news from foreign stock markets have uniformly extensive effects. The lowest number of positive correlation coefficients for the country pairs is registered in the first phase of the GFC (13 out of 65 cases, or 20 percent). This finding suggests that most sectors were more insulated during phase one of the GFC. However, in the second phase of the crisis, the number of linkages reemerged at the beginning of the second phase of the GFC up to the end of the third phase. Under the definition of "Pure Contagion", this may be as a result of " shifts in investor's common but changing appetite for or aversion to risk"(Kumar and Persaud, 2002). As investors became aware of the spread of the GFC, their appetite for risk decreased and they reduced their exposure to financial assets considered as risky. In other words, investors sold their financial assets and moved into cash or bought safer assets such as government bonds, leading to high correlations and consequently contagion aftermath. It appears that after the collapse of Lehmann Brothers, investors responded by reducing their exposure to sectors which they believed to be risky markets. The number of country pairs with positive correlation coefficients in the fourth phase of GFC (18) is greater than the third phase of the GFC (16). This implies that linkages in global equity markets increased during the last phase of the GFC compared to the third phase. This finding suggests a lower probability of simultaneous crashes.

With regards to the ESDC, the first phase exhibits the most cases of significant negative correlation of the country pairs across all the sectors. The first phase (5 November 2009 to April 2010) is characterised by a sharp depreciation of the Euro due to the Greek debt crisis, resulting in unpredictability in the future of the Euro retaining the status of a single Eurozone currency. According to the findings of Dimitriou and Kenourgios (2013), the negative correlation between the Euro and the currencies of developed countries was likely the reason for the significant negative correlation coefficients for the country pairs. In the second and third phase of the ESDC, there is a significant increase in the number of country pairs with significant positive correlation coefficients across all sectors. This finding confirms that as investors became more aware of the ESDC, the fears and uncertainty among investors increased. This is an indication of the global impact of potential Grexit (the possibility of Greece leaving the Eurozone) and foreign shock resulting from Greek sovereign insolvency.

Table 4.8: Asymmetric dynamic conditional correlation coefficients of GFC/ESDC/Brexit across developed countries within sectors

	Germany Japan	**Germany UK**	**Germany USA**	**Japan UK**	**Japan USA**	**UK USA**
			Financials			
GFC	0.059^{***}	0.035^{***}	-0.026^{***}	0.042^{***}	-0.024^{***}	-0.010^{***}
ESDC	-0.006^{*}	-0.008^{***}	0.0059^{*}	-0.032^{***}	0.008^{***}	0.007^{***}
Brexit	0.0341^{***}	0.000	0.035^{***}	0.030^{***}	0.036^{***}	0.021^{***}
			Materials			
GFC	0.056^{***}	0.012^{**}	-0.024^{***}	0.098^{***}	0.039^{***}	-0.008^{**}
ESDC	-0.028^{***}	0.124^{***}	0.066^{***}	-0.013^{***}	-0.0307^{***}	0.080^{***}
Brexit	0.010^{***}	-0.115^{***}	-0.012^{***}	-0.084^{***}	0.013^{***}	-0.072^{***}
			Consumer Goods			
GFC	0.017^{***}	0.007^{***}	0.007^{***}	0.017^{***}	0.013^{***}	0.012^{***}
ESDC	0.009^{***}	-0.003^{**}	0.006^{***}	-0.000	0.003^{***}	0.000
Brexit	-0.010^{***}	-0.006^{***}	-0.020^{***}	-0.001	0.021^{***}	-0.024^{***}
			Telecommunications			
GFC	0.021^{***}	0.046^{***}	0.002^{***}	0.023^{***}	-0.016^{***}	0.014^{***}
ESDC	-0.026^{***}	-0.020^{***}	0.020^{***}	-0.021^{***}	0.014^{***}	0.011^{***}
Brexit	0.048^{***}	0.023^{***}	-0.008^{***}	0.010^{***}	0.023^{***}	-0.019^{***}

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.9: Asymmetric dynamic conditional correlation coefficients of GFC and ESDC phases across developed countries within sectors

	Germany Japan	Germany UK	Germany USA	Japan UK	Japan USA	UK USA
			Financials			
GFC						
Phase 1	0.040***	0.039***	−0.032***	0.032***	−0.023***	−0.006**
Phase 2	0.134***	0.051***	−0.011*	0.107***	−0.024***	−0.007
Phase 3	0.040***	0.003	−0.023***	0.001	−0.053***	−0.028***
Phase 4	0.102***	0.026***	−0.006	0.067***	0.038***	−0.020**
ESDC						
Phase 1	−0.058***	−0.011***	−0.000	−0.078***	−0.022***	−0.025***
Phase 2	0.011***	−0.009***	0.002	−0.017***	0.017***	0.016***
Phase 3	0.026***	0.015*	0.072***	0.011	0.044***	0.069***
			Materials			
GFC						
Phase 1	0.036***	−0.017***	−0.044***	0.082***	0.038***	−0.018***
Phase 2	0.109***	0.053***	0.003	0.139***	0.046***	0.003
Phase 3	0.078***	0.074***	0.015*	0.119***	0.026***	0.010
Phase 4	0.085***	0.087***	0.031**	0.109***	0.056***	0.018
ESDC						
Phase 1	−0.064***	0.127***	0.072***	−0.046***	−0.053***	0.074***
Phase 2	−0.018***	0.124***	0.064***	−0.003	−0.024***	0.083***
Phase 3	0.034***	0.075***	0.047***	0.023	0.010	0.071***
			Consumer Goods			
GFC						
Phase 1	0.011***	0.008***	0.002	0.013***	0.002	0.009***
Phase 2	0.034***	0.013***	0.020***	0.029***	0.014***	0.027***
Phase 3	0.023***	−0.000	0.015***	0.026***	0.044***	0.014***
Phase 4	0.013*	−0.009*	0.014**	0.002	0.063***	−0.007
ESDC						
Phase 1	−0.016***	−0.006**	−0.002	−0.023***	−0.018***	−0.011***
Phase 2	0.018***	−0.002*	0.007***	0.006***	0.012***	0.005***
Phase 3	0.027***	0.003	0.023***	0.021***	−0.014*	−0.001
			Telecommunications			
GFC						
Phase 1	0.009***	0.035***	−0.028***	0.007***	−0.016***	−0.002
Phase 2	0.055***	0.075***	0.074***	0.067***	−0.026***	0.061***
Phase 3	0.036***	0.061***	0.049***	0.046***	−0.013***	0.033***
Phase 4	0.019*	0.051***	0.016*	0.022***	0.020**	0.021***
ESDC						
Phase 1	−0.046***	0.020***	0.063***	−0.063***	−0.015***	0.008***
Phase 2	−0.022***	−0.035***	0.005**	−0.006***	0.023***	0.013***
Phase 3	0.025***	−0.022***	−0.006	−0.006	0.042***	0.009

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Analysis of ADCC results accross BRICS country within sector

This subsection, seeks to answer the question: did correlation increase between BRICS country pairs within each of the sectors under study over the mentioned crises period?

Table 4.10 presents average conditional correlation coefficients of developed country pairs during the GFC, ESDC and Brexit crisis periods across BRICS countries within sectors. Tables 4.11 and 4.12 provide results for the correlation coefficients across the four phases of the GFC and three phases of the ESDC for BRICS countries. Positive correlation coefficients for the country pairs are found at varying magnitudes across the BRICS countries for the four sectors under study. From Table 4.10 the majority of dummy variables associated with the GFC and ESDC are positive and statistically significant at the 1 percent level, indicating that inter-sector conditional correlations were higher during the GFC and ESDC crisis period for BRICS countries.

On the other hand, the majority of the dummy variables associated with the Brexit crisis across the table are negative and statistically significant at a 1 percent level, indicating that inter-sector conditional correlations were lower during the Brexit crisis period for BRICS countries. This result is in line with the findings of Burdekin, Hughson and Gu (2018), who did a study on the effect of Brexit on global markets, and found that BRICS markets were among the least affected markets.

The correlation results within BRICS sectors during the phases of the GFC presented in Table 4.11 are related to their trade and financial characteristics. Russia, Brazil and South Africa are commodity price dependent markets. Hence, their revenue are sensitive to the export of commodity products. On the other hand, the trade characteristics of India and China are such that their economic performance depends on the export of finished products or manufactured goods. Hence the two countries are final products export oriented markets, as their economic performance depends on export of manufactured products (Raghuramapatruni, 2015). For all the phases of the GFC, the Brazil-Russia country pair exhibit positive correlation across all four sectors. This can be explained by the common trade characteristics that exist between these two countries. Both countries are commodity price dependent and therefore responded in a similar way to the GFC across all phases. Though there is a considerable number of positive correlation among the India, China and South Africa country pairs across all sectors, Brazil and Russia has the highest number of positive correlation across all sectors, indicating that Brazil and Russia have a greater correlation than do the other markets (China, India and South Africa).

Table 4.10: Asymmetric dynamic conditional correlation coefficients for GFC/ESDC/Brexit across BRICS countries

	Brazil China	**Brazil India**	**Brazil Russia**	**Brazil RSA**	**India China**	**India Russia**	**India RSA**	**China Russia**	**China RSA**	**Russia RSA**
					Financials					
GFC	0.041***	0.040***	0.017***	0.026***	0.062***	0.050***	0.025***	0.028***	0.026***	0.019***
ESDC	0.009***	0.021***	0.071***	0.006**	0.021***	0.022***	0.029***	0.017***	−0.002***	0.031***
Brexit	−0.043***	−0.042***	−0.030***	−0.024***	−0.001***	−0.037***	−0.022***	−0.021***	0.033***	−0.005
					Materials					
GFC	−0.012***	−0.004***	0.017***	0.069***	−0.009***	0.010***	0.035***	0.028***	0.047***	0.064***
ESDC	0.031**	0.087***	0.071***	0.058***	0.088***	0.073***	0.091***	0.046***	0.080***	0.121***
Brexit	−0.019***	−0.010*	−0.030***	−0.127***	0.001	−0.055***	−0.104***	−0.020***	−0.122***	−0.142***
					Consumer Goods					
GFC	0.002	0.010***	0.013***	0.004***	0.007***	0.012***	0.014***	−0.012***	0.014***	−0.002*
ESDC	0.003**	−0.002	−0.000	0.003***	−0.007***	−0.009***	−0.005***	−0.007***	0.007***	−0.007***
Brexit	−0.011***	−0.001	−0.006***	−0.013***	0.001	−0.004**	−0.002	0.014***	0.002	0.006***
					Telecommunications					
GFC	0.020***	0.038***	0.054***	0.009***	0.079***	0.022***	0.050***	0.008*	0.059***	−0.004
ESDC	0.000	−0.011***	0.011***	−0.005***	−0.029**	−0.012***	−0.012***	0.019***	−0.015***	−0.013***
Brexit	−0.021***	−0.025***	−0.034***	−0.017***	0.005*	−0.013***	−0.026***	−0.002	0.000	−0.021***

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.11: Asymmetric dynamic conditional correlation coefficients for 4 phases of GFC across the BRICS countries

	Brazil China	**Brazil India**	**Brazil Russia**	**Brazil RSA**	**India China**	**India Russia**	**India RSA**	**China Russia**	**China RSA**	**Russia RSA**
					Financials					
GFC										
Phase 1	0.014***	0.015***	0.013***	0.008***	0.047***	0.062***	0.008**	0.018***	0.008***	0.019***
Phase 2	0.088***	0.089***	0.035***	0.084***	0.093***	0.047***	0.063***	0.09***	0.088***	.033***
Phase 3	0.084***	0.072***	0.040***	0.030***	0.078***	0.007	0.043***	−0.005	0.035***	−0.006
Phase 4	0.104***	0.104***	0.070***	0.057***	0.108***	0.042***	0.057***	0.019	0.038***	0.056***
					Materials					
GFC										
Phase 1	−0.044***	−0.028***	0.011**	0.068***	−0.037***	−0.008**	0.032***	0.005	0.038***	0.055***
Phase 2	0.033***	0.020**	0.032***	0.101***	0.028***	0.051***	0.038***	0.085***	0.070***	0.094***
Phase 3	0.043***	0.047***	0.017*	0.058***	0.038***	0.036***	0.045***	0.056***	0.065***	0.081***
Phase 4	0.077***	0.076***	0.039**	0.008	0.081***	0.042***	0.032*	0.064***	0.037*	0.045**
					Consumer Goods					
GFC										
Phase 1	−0.005***	−0.004**	0.000	0.004**	0.007***	0.002*	0.013***	−0.014***	0.011***	0.005***
Phase 2	0.018***	0.055***	0.044***	0.008**	0.041*** 0.016***	0.037***	0.034***	−0.010***	0.041***	−0.010***
Phase 3	0.011***	0.023***	0.028***	0.000	0.001	0.021***	0.002	−0.005	0.004	−0.028***
Phase 4	0.015**	0.019***	0.036***	0.004	−0.001	0.025***	0.007	−0.003	−0.003	−0.004
					Telecommunications					
GFC										
Phase 1	−0.007***	0.023***	0.038***	−0.011***	0.079***	0.001	0.038***	−0.012***	0.053***	−0.017***
Phase 2	0.077***	0.073***	0.096***	0.064***	0.083***	0.057***	0.084***	0.054***	0.078***	0.036***
Phase 3	0.065***	0.057***	0.072***	0.034***	0.073***	0.064***	0.061***	0.044***	0.066***	0.010**
Phase 4	0.052***	0.052***	0.081***	0.029***	0.083***	0.063***	0.044***	0.024***	0.044***	−0.008

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.12: Asymmetric dynamic conditional correlation coefficients for 3 Phases of ESDC across the BRICS countries

	Brazil China	**Brazil India**	**Brazil Russia**	**Brazil RSA**	**India China**	**India Russia**	**India RSA**	**China Russia**	**China RSA**	**Russia RSA**
					Financials					
ESDC										
Phase 1	−0.006	0.021***	−0.002***	−0.038***	0.023***	−0.006	0.002	0.008	−0.016***	0.000
Phase 2	0.016***	0.022***	0.010***	0.020***	0.019***	0.032***	0.040***	0.021***	0.004*	0.039***
Phase 3	0.005***	0.015***	0.031***	0.052***	0.046***	0.028**	0.022***	0.005	−0.024**	0.085***
					Materials					
ESDC										
Phase 1	0.040***	0.079***	0.067***	0.077***	0.063***	0.062***	0.071***	0.048***	0.094***	0.104***
Phase 2	0.030***	0.090***	0.071***	0.053***	0.096***	0.078***	0.097***	0.047***	0.076***	0.128***
Phase 3	−0.009	0.071***	0.067***	0.026*	0.106***	0.052***	0.093***	0.018	0.048**	0.103***
					Consumer Goods					
ESDC										
Phase 1	0.009***	−0.003	0.014***	−0.027***	−0.009***	−0.022***	−0.006***	−0.005*	0.003	−0.021***
Phase 2	0.004**	−0.002	−0.005***	0.012***	0.014***	−0.005***	−0.004**	−0.008***	0.009***	−0.002*
Phase 3	−0.035***	−0.000	−0.019***	0.033***	−0.006	0.003	−0.010	−0.001	−0.007	−0.001
					Telecommunications					
ESDC										
Phase 1	−0.005	−0.040***	0.045***	−0.044***	−0.036***	−0.007**	−0.002	0.001	−0.014***	−0.073***
Phase 2	0.004*	−0.001	−0.000	0.007***	−0.026***	−0.014***	−0.016***	0.026***	−0.015***	0.005***
Phase 3	−0.012	−0.003	−0.007	0.019***	−0.037***	−0.024***	−0.016*	0.007	−0.017*	0.035***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Analysis of ADCC results across BRICS and developed countries within sector

This subsection seeks to answer the question: did correlations between developed and BRICS country pairs within each of the sectors under study increase during the crisis periods?

Table 4.13 presents the average conditional correlation coefficients of developed country pairs during the GFC, ESDC and Brexit crisis periods across developed-BRICS country pairs within sectors. Tables 4.14 and 4.15 provide results for the correlation coefficients across the four phases of the GFC and three phases of the ESDC for developed-BRICS country pairs. Positive correlation coefficients for the country pairs are found at varying magnitudes across the four sectors under study. The majority of the dummy variables with coefficients associated with the GFC are positive and significant at a 1 percent level (table 4.13), indicating that inter-sector conditional correlations were higher during the GFC period for developed-BRICS country pairs.

On the other hand, the majority of the dummy variables with coefficients associated with the ESDC and Brexit are *negative* and statistically significant at the 1 percent level, indicating that inter-sector conditional correlations were lower during the ESDC and Brexit crisis period for developed-BRICS countries. The negative correlation coefficients reported for the BRICS and developed country pairs for UK Brexit referendum and subsequent trigger of Article 50 is in line with the findings of Aristeidis and Elias (2018), who carried out a study on the market reactions to the EU/UK referendum results. These authors found that the UK referendum results was mostly confined to the Eurozone and had very minimal prolonged effect on stock markets in other countries.

Correlation coefficients are also higher for some country pairs involving developed and developing markets. Brazil and Russia, for example, have higher correlations (in magnitude) with developed markets, as can be seen in the results presented in Table 4.13. This is consistent with the results of Aloui et al. (2015). Brazil and Russia are dependent on revenues from exports of commodity products. Therefore, both countries can be viewed as commodity price dependent countries.

From Table 4.13 it is worth noting that, although the correlation between China and developed markets increased during the GFC, its level of correlation with developed markets (and especially the US) is still the lowest compared to other BRICS countries. The reason may lie in the difference in macroeconomic trends between China and developed countries, leading to a lack of long term synchronicity between the US and China (Cao, He and Cao, 2018). Moreover, price changes in the Chinese stock market are mainly affected by government interventions and domestic policies.

Therefore, it is expected that the stock market of China, whose currency cannot be exchanged freely, will not be in step with the stock markets of Europe and the US, whose currency can be exchanged freely. Consequently, there is an isolation layer between the stock market of China and any turmoil that might be present in the global market. Hence, any decline in the US and European markets has limited impact on the Chinese stock market. The consistency in significant positive correlation coefficients between South Africa and Germany and between South Africa and the UK for the financial sector, as well as across all three other sectors, is possibly due to the strong bilateral relationship between the European Union (EU) and South Africa. The EU is South Africa's largest investor and South Africa is also the EU's biggest trading partner in Africa (Sehgal, Jain and Deisting, 2018). The significant positive correlation for the pair Brazil-USA across all sectors during the GFC might be as a result of investment and trade links that exist between Brazil and USA by virtue of the North American Free Trade Agreement (NAFTA), coupled with geographic proximity.

From Table 4.14 the asymmetric conditional correlation coefficient estimates following the economic crisis identification approach, show a general pattern of decoupling for most of the US-BRICS pairs during the early phases of the GFC crisis and an increase in correlation for these pairs after the failure of Lehman Brothers. For example, the pairs China-USA, India-USA, Russia-USA and RSA-USA exhibit a negative correlation during the first phase of the GFC for at least two of the sectors. Most of these pairs exhibit a positive correlation in the third and fourth phase of the GFC across all four sectors. The reason for the negative correlations of the BRICS-US pairs in the first phase of the GFC can be explained as follows: after BRICS formal recognition as an economic bloc, BRICS countries as a group have built up strong industry supply chains, strengthened their consumer demand, increased the countries levels of foreign exchange reserves and accumulated a considerable amount of budget surplus (Shahrokhi et al., 2017). These benefits could be the reason behind the delayed shock of the GFC for most of the BRICS-US country pairs. Another possible reason for the negative correlation for most of the BRICS countries with the USA during the first phase of the crisis is that investors might have considered the news of the US financial crisis as a unique country crisis (affecting only the US) and hence ignored the crisis signal (assuming that the crisis was not relevant to global investors). However, the gravity of the crisis gradually led to greater awareness among global investors causing them to respond accordingly, leading to increase in positive correlation of the USA with BRICS countries in the third and fourth phase of the GFC across most sectors. In other words, there was a reduction in global investors appetite for risk. As the GFC became more severe, investors rush to dispose of their financial assets and move into cash and safer assets like bonds. This scramble to dispose of their financial assets led to higher correlations between BRICS and US sector indices, leading to contagion. It appears that after the collapse of Lehman brothers, investors appetite for risky assets fell and they quickly reduced their exposure to markets and sectors that were considered risky. This collective simultaneous reaction among global investors led to the US and BRICS sectors falling in value together, leading to the high correlation among the BRICS-US country pairs across the sectors.

Table 4.13: Conditional Correlation coefficients for GFC/ESDC/Brexit across BRICS and developed countries

	Brazil Germany	**Brazil Japan**	**Brazil UK**	**Brazil USA**	**China Germany**	**China Japan**	**China UK**	**China USA**	**India Germany**	**India Japan**	**India UK**	**India USA**	**Russia Germany**	**Russia Japan**	**Russia UK**	**Russia USA**	**RSA Germany**	**RSA Japan**	**RSA UK**	**RSA USA**
										Financials										
GFC	0.078***	0.035***	0.064***	0.058***	0.025***	0.079***	−0.021***	−0.030***	0.065***	0.062***	0.021***	−0.004***	0.036***	0.058***	0.031***	−0.047***	0.037***	0.068***		−0.009***
ESDC	0.012**	−0.019***	0.017***	0.022***	0.007***	−0.006*	−0.006*	0.012***	−0.007**	−0.037***	0.002***	−0.007**	0.025***	−0.013***	0.035***	0.043	0.004	−0.016***	−0.012***	0.020***
Brexit	−0.122***	−0.029***	−0.096***	−0.111***	−0.006*	−0.012**	0.016***	−0.023***	−0.014***	0.007*	−0.023***	0.009**	−0.060***	−0.036***	−0.044***	−0.001	−0.045***	−0.025***	−0.032***	−0.017***
										Materials										
GFC	0.065***	0.076***	0.020***	0.086***	0.011***	0.060***	0.009***	−0.052***	−0.001***	0.028***	−0.011***	−0.053***	−0.013***	0.063***	0.004	−0.015***	0.094***	0.115***	0.055***	0.046***
ESDC	0.097***	−0.017***	0.027***	0.094***	0.036***	0.053***	0.029***	0.054***	0.074***	0.023***	0.086***	−0.053	0.091	−0.013***	0.086***	0.078***	0.144***	0.046***	0.044***	0.112***
Brexit	−0.075***	−0.003***	0.007**	−0.045***	−0.001	−0.076***	−0.003***	0.011***	0.013***	0.020***	−0.018***	0.059***	−0.072***	−0.031***	−0.039***	−0.024***	−0.250***	−0.177***	−0.133***	−0.141***
										Consumer Goods										
GFC	0.023***	0.019***	0.028***	0.017***	0.004***	0.019***	0.004**	−0.006***	0.031***	0.021***	0.029***	0.022***	0.012***	−0.000	0.016***	0.021***	0.010***	0.022***	0.008***	−0.004**
ESDC	0.008***	−0.007***	0.005***	0.007***	0.007***	0.006***	0.004**	0.006***	−0.012***	−0.008***	−0.006***	0.000***	0.002	−0.004***	0.007***	0.008***	0.004***	0.006***	0.007***	0.002*
Brexit	−0.009***	−0.003***	−0.010***	−0.008***	−0.008***	−0.005*	0.002	0.001	−0.011***	0.006***	−0.004***	0.003***	−0.020***	0.004**	−0.020***	−0.023***	−0.017***	0.010***	−0.021***	−0.000
										Telecommunications										
GFC	0.022***	0.013***	0.051***	0.059***	0.006***	0.031***	0.026***	0.017***	0.045***	0.047***	0.043***	0.040***	0.014***	−0.011***	0.033***	0.057***	0.019***	0.033***	0.036***	0.008***
ESDC	0.016***	−0.016***	0.006***	0.013***	−0.010***	0.005**	−0.019***	0.000	−0.017***	−0.020***	−0.036***	−0.008***	0.018***	0.000	0.021***	0.017***	−0.020***	0.003*	−0.013***	−0.000
Brexit	0.007***	0.007***	−0.001	−0.022***	0.023***	0.019***	−0.007***	−0.056***	0.013***	−0.006*	0.006*	−0.023***	0.017***	0.047***	−0.001***	−0.038***	0.027***	0.014***	0.008***	−0.005***

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.14: conditional correlation coefficients for four phases of the GFC across BRICS and developed countries

	Brazil Germany	**Brazil Japan**	**Brazil UK**	**Brazil USA**	**China Germany**	**China Japan**	**China UK**	**China USA**	**India Germany**	**India Japan**	**India UK**	**India USA**	**Russia Germany**	**Russia Japan**	**Russia UK**	**Russia USA**	**RSA Germany**	**RSA Japan**	**RSA UK**	**RSA USA**
										Financials										
GFC																				
Phase 1	0.073***	0.034***	0.058***	0.032***	−0.002***	0.071***	−0.050***	−0.061***	0.052***	0.059***	0.003	−0.044***	0.030***	0.044***	0.022***	−0.069***	0.031***	0.054***	0.035***	−0.028***
Phase 2	0.098***	0.049***	0.076***	0.114***	0.106***	0.121***	0.074***	0.022***	0.118***	0.079***	0.100***	0.071***	0.056***	0.148***	0.054***	−0.032***	0.054***	0.106***	0.060***	0.039***
Phase 3	0.071***	−0.001	0.068***	0.085***	0.041***	0.059***	−0.028***	0.016**	0.049***	0.030***	0.000	0.048***	0.028***	0.011*	0.036***	0.008	0.033***	0.082***	0.018***	−0.000
Phase 4	0.097***	0.093***	0.083***	0.111***	0.076***	0.094***	0.042***	0.043***	0.109***	0.130***	0.056	0.090***	0.073***	0.067***	0.060***	0.026*	0.065***	0.080***	0.041***	0.050***
										Materials										
GFC																				
Phase 1	0.038***	0.069***	0.009***	0.076***	−0.023***	0.042***	−0.026***	−0.073***	−0.032***	0.008***	−0.029***	−0.072***	−0.031***	0.039***	−0.000	−0.022***	0.098***	0.107***	0.058***	0.035***
Phase 2	0.095***	0.090***	0.028***	0.112***	0.075***	0.093***	0.072***	−0.022***	0.048***	0.064***	0.003	−0.042***	0.012	0.132***	0.014	0.004	0.111***	0.148***	0.066***	0.084***
Phase 3	0.118***	0.079***	0.042***	0.099***	0.064***	0.092***	0.066***	−0.016***	0.059***	0.055***	0.028***	−0.013*	0.019*	0.095***	0.007	−0.009	0.086***	0.135***	0.049***	0.057***
Phase 4	0.148***	0.101***	0.061***	0.101***	0.096***	0.087***	0.105***	0.024***	0.061***	0.083***	0.057***	0.032***	0.025	0.049***	0.018	0.000	0.009	0.043**	−0.005	0.025
										Consumer Goods										
GFC																				
Phase 1	0.017***	0.015***	0.028***	0.007***	−0.005***	0.022***	−0.002	−0.021***	0.023***	0.013***	0.015***	0.005***	0.000	−0.004***	0.013***	0.007***	0.015***	0.025***	0.014***	−0.006***
Phase 2	0.045***	0.022***	0.050***	0.047***	0.042***	0.029***	0.022***	0.017***	0.057***	0.044***	0.076***	0.080***	0.047***	0.008**	0.033***	0.066***	0.010***	0.028***	0.005	0.010***
Phase 3	0.026***	0.022***	0.022***	0.018***	0.010**	−0.003	0.007*	0.023***	0.037***	0.029***	0.035***	0.027***	0.025***	−0.008**	0.014***	0.027***	0.002	−0.002	−0.005	−0.015***
Phase 4	0.022***	0.055***	−0.016**	0.033***	0.000	0.009	0.022***	0.019***	0.034***	0.028***	0.029***	0.048***	0.015**	0.036***	0.003	0.028***	−0.014**	0.029***	−0.021***	0.004
										Telecommunications										
GFC																				
Phase 1	−0.001	0.014***	0.030***	0.036***	−0.010***	0.040***	0.005**	−0.007***	0.034***	0.038***	0.033***	0.017***	0.001	−0.020***	0.031***	0.041***	0.016***	0.035***	0.022***	−0.007***
Phase 2	0.068***	0.018***	0.089***	0.107***	0.032***	0.024***	0.074***	0.079***	0.090***	0.055***	0.070***	0.110***	0.041***	−0.022***	0.048***	0.095***	0.040***	0.042***	0.082***	0.069***
Phase 3	0.067***	0.007*	0.089***	0.092***	0.036***	0.019***	0.064***	0.045***	0.050***	0.078***	0.061***	0.050***	0.038***	0.017***	0.031***	0.076***	0.010***	0.019***	0.052***	0.006
Phase 4	0.042***	0.009	0.077***	0.093***	0.042***	−0.029***	0.027***	0.054***	0.023***	0.051***	0.037***	0.069***	0.027***	0.052***	0.019***	0.089***	0.016***	0.009	0.021***	0.007

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.15: Asymetric dynamic conditional correlation coefficients for the three phases of the ESDC across BRICS and developed countries

	Brazil Germany	**Brazil Japan**	**Brazil UK**	**Brazil USA**	**China Germany**	**China Japan**	**China UK**	**China USA**	**India Germany**	**India Japan**	**India UK**	**India USA**	**Russia Germany**	**Russia Japan**	**Russia UK**	**Russia USA**	**RSA Germany**	**RSA Japan**	**RSA UK**	**RSA USA**
										Financials										
ESDC																				
Phase 1	0.034***	−0.046***	0.033***	0.003	−0.005	−0.014**	−0.014**	0.007	0.001	−0.057***	0.021***	−0.008	0.030***	−0.029***	0.013*	0.048***	0.006	−0.034***	−0.037***	0.014**
Phase 2	−0.000	−0.013***	0.008*	0.024***	0.013***	−0.008*	−0.004	0.012***	−0.008**	−0.033***	−0.002	−0.008**	0.020***	−0.008**	0.039***	0.037***	0.002	−0.008**	−0.006*	0.018***
Phase 3	0.072***	0.040***	0.053***	0.088***	0.004	0.072***	0.009	0.038***	−0.035**	0.007	−0.026**	0.011	0.054***	0.010	0.089***	0.105***	0.008	−0.023*	0.036***	0.076***
										Materials										
ESDC																				
Phase 1	0.133***	−0.016***	0.036***	0.094***	0.034***	0.068***	0.033***	0.067***	0.065***	0.019***	0.066***	0.068***	0.087***	−0.045***	0.086***	0.065***	0.099***	0.041***	0.031***	0.112***
Phase 2	0.086***	−0.017***	0.025	0.094***	0.038***	0.049***	0.028***	0.049***	0.079***	0.026***	0.093***	0.055***	0.095***	−0.002	0.086***	0.082***	0.159***	0.046***	0.049***	0.110***
Phase 3	0.040*	−0.025**	0.000	0.083***	0.021*	0.019	0.010	0.044***	0.043***	−0.001	0.084***	0.058***	0.045***	−0.003	0.069***	0.080***	0.153***	0.065***	0.045***	0.105***
										Consumer Goods										
ESDC																				
Phase 1	0.008***	−0.001	−0.005	0.014***	−0.015***	0.001	−0.012*	0.007**	−0.031***	−0.008***	−0.016***	0.001	0.015***	−0.021***	0.010***	0.017***	−0.029***	−0.003	−0.026***	−0.032***
Phase 2	0.008***	−0.008***	0.010***	0.003*	0.014***	0.005***	0.009***	0.006***	−0.005***	−0.007***	−0.002	−0.001	−0.004**	0.000	0.005***	0.005**	0.015***	0.010***	0.019***	0.012***
Phase 3	0.006	−0.026***	−0.014*	0.026***	0.034***	0.039***	0.017**	−0.000	−0.012*	−0.018**	−0.019***	0.026***	0.018***	0.027***	0.014*	−0.002	0.037***	0.000	0.016**	0.052***
										Telecommunications										
ESDC																				
Phase 1	0.023***	−0.033***	−0.007*	0.011**	−0.033***	0.006*	−0.080***	−0.024***	−0.029***	0.005	−0.041***	−0.021***	0.037***	−0.016***	−0.006*	0.008*	−0.046***	−0.019***	−0.053***	−0.037***
Phase 2	0.016***	−0.010***	0.013***	0.014***	−0.004**	0.003	0.001	0.010***	−0.011***	−0.028***	−0.032***	−0.001	0.010***	0.006***	0.031***	0.018***	−0.011***	0.011***	0.000	0.011***
Phase 3	−0.017**	−0.011*	−0.037***	−0.003	0.040***	0.026***	0.019***	−0.005	−0.035***	−0.048***	−0.072***	−0.042***	0.019**	0.016*	0.027***	0.037***	−0.014**	0.005	0.005	0.045***

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

On average across all tables reported in this section, changes in correlation during the GFC is more evident in financials, followed by consumer goods, telecommunications and materials . During the ESDC, the change in correlation was strong in magnitude and had varying impacts across the sectors. Specifically, telecommunications was the most affected, followed by financials, materials and consumer goods. Financials were the most affected when considering the GFC, ESDC and Brexit. This result is not unanticipated. The GFC crisis originated in the financial sector and therefore the financial sector is highly exposed (Baur, 2012). Also the GFC gave birth to the ESDC which therefore also has its roots in the the financial sector. Brexit is about the UK leaving the Eurozone, London is the financial hub of Europe, and therefore linked to the financial sectors of other countries. This provides a channel for spreading the effect of the EU/UK referendum and subsequent Article 50 trigger. The next section is the discussion on within country cross sector correlation.

4.5.2 Within country cross sector correlation

This section presents tables and the discussion on the estimated coefficients for Equations 4.14 and 4.15 associated with within country cross sector financial contagion during the GFC, ESDC and Brexit. The tables also show the statistical significance of the coefficients of the dummy variables for each pairwise conditional correlations.[7]. This section is organised into three subsections: The first subsection presents the analysis of ADCC results across sectors during the GFC within each country. The second subsection presents the analysis of ADCC results across sectors during ESDC within each country and the third subsection presents the analysis of ADCC results within each country across sectors during the period of the EU/UK referendum results release and subsequent trigger of Article 50 for withdrawal from the Eurozone. The next section discusses the analysis of ADCC results across sectors during the GFC within each country.

4.5.2.1 Analysis of ADCC results across sectors during the GFC within each country.

This subsection seeks to answer the question: did correlation increase for the sector pairs within each of the nine countries during the GFC?

Table 4.16 presents the estimated coefficients associated with within-country cross-sector financial contagion during the GFC. Table 4.17 presents the estimated co-

[7]For brevity, standard errors are not report.

efficients associated with within-country cross-sector financial contagion across the phases of the GFC.

From the correlation coefficients across the nine countries shown in table 4.16, it is evident that domestic market shocks no longer affect sectors in a specific country or currency area in a similar manner. Thus sectors in each of the nine countries become more heterogeneous over the sample period. The increased heterogeneity of sector returns is a global phenomenum (Alexakis and Pappas, 2018; Baur, 2012). Japanese, European and emerging country industries (sectors) showed this trend only after 1999, while, this trend started in the early 1990s in the United States (Kaltenhaeuser, 2003).

In Table 4.16 the majority of the conditional correlation coefficients are positive and statistically significant at the 1 percent level, indicating that the cross sector conditional correlation of those sector pairs were higher during the GFC period. There is more evidence for sectoral heterogeneity across the different countries during the GFC. For instance, for BRICS countries, the magnitude of pairwise conditional correlation for the pair financials-materials, financials-consumers, financials-telecommunications and materials-telecommunication for China is greater than the same sector pairs in rest of the BRICS countries during the GFC.

Similarly, for developed countries, the magnitude of the pairwise conditional correlation for all the sector pairs for the US are greater than those of the other sample developed countries (Germany, Japan and the UK) during the GFC. A possible reason for this greater magnitude in sector pair conditional correlation for China and the US is because the industry returns of the sector pairs in these two countries are more dependent on domestic market shocks, and therefore the returns of these sectors are more integrated domestically (Kaltenhaeuser, 2003).

In Table 4.17 the presence of positive correlation coefficients for sector pairs in each country is evident for at least one of the phases of the GFC.

Within the BRICS countries, the sector pairs for Brazil exhibit positive correlation coefficients significant at the 1 percent level across all the four phases. This is an indication that the sectors in Brazil are susceptible to foreign shocks originating from the US. Other sector pairs within BRICS that exhibit positive correlation across most phases are India and China. Most of the sector pairs within Russia and South Africa exhibit negative correlation across a number of phases. This implies that Russia and South Africa were the least affected by the global financial crisis.

For developed countries, the sector pairs within the US exhibit positive correlation across all four phases of the GFC. The US is the only developed country whose sector pairs exhibit this pattern. This is expected, as the crisis originated in the US. The country with the least number of the sector pairs with positive correlation coefficients across all phases is Japan. This shows that the sectors within Japan were the least affected among all developed countries by the GFC.

Table 4.16: Asymmetric dynamic conditional correlation coefficients during the GFC across sectors within each country

	Fin - Mat	**Fin - Cons**	**Fin - Tele**	**Cons - Mat**	**Mat - Tele**	**Cons - Tele**
			BRICS countries			
Brazil	0.099***	0.029***	0.072***	0.098***	0.109***	0.085***
Russia	-0.026***	-0.128***	-0.060***	-0.081***	-0.028***	0.061***
India	0.053***	0.053***	0.154***	0.042***	0.138***	0.105***
China	0.068***	0.053***	0.151***	0.052***	0.157***	0.065***
RSA	0.024***	-0.025***	0.043***	0.032***	0.055***	0.051***
			Developed countries			
Germany	-0.041***	0.040***	-0.015***	-0.036***	-0.021***	0.003***
Japan	-0.021***	0.014**	0.016***	-0.033***	-0.046***	0.031***
UK	-0.014**	0.072***	0.045***	0.034***	0.065***	0.069***
USA	0.051***	0.086***	0.128***	0.047***	0.080***	0.092***

Table 4.17: Asymmetric dynamic conditional correlation coefficients during the four phases of the GFC across sectors within each country

	Fin - Mat	Fin - Cons	Fin - Tele	Cons - Mat	Mat - Tele	Cons - Tele
			BRICS countries			
Brazil						
Phase 1	0.080***	0.021***	0.054***	0.084***	0.091***	0.066***
Phase 2	0.148***	0.055***	0.137***	0.145***	0.172***	0.144***
Phase 3	0.122***	0.026***	0.074***	0.093***	0.109***	0.088***
Phase 4	0.104***	0.057***	0.074***	0.125***	0.124***	0.124***
Russia						
Phase 1	-0.042***	-0.149***	-0.103***	-0.097***	-0.070***	0.026***
Phase 2	0.000	-0.103***	-0.001	-0.081***	0.049***	0.140***
Phase 3	-0.002	-0.077***	0.024*	-0.045***	0.032***	0.117***
Phase 4	0.014	-0.078***	0.054**	0.010	0.066***	0.091***
India						
Phase 1	0.045***	0.045***	0.142***	0.044***	0.131***	0.105***
Phase 2	0.070***	0.104***	0.182***	0.073***	0.131***	0.159***
Phase 3	0.067***	0.059***	0.164***	0.038***	0.152***	0.076***
Phase 4	0.073***	-0.031***	0.186***	-0.060***	0.202***	0.007***
China						
Phase 1	0.069***	0.060***	0.144***	0.065***	0.153***	0.070***
Phase 2	0.087***	0.058***	0.187***	0.044***	0.205***	0.075***
Phase 3	0.058***	0.039***	0.149***	0.028*	0.142***	0.044***
Phase 4	0.035*	-0.008	0.129***	-0.015	0.094***	0.019***
RSA						
Phase 1	0.046***	-0.016***	0.024***	0.039***	0.0505***	0.038***
Phase 2	0.020	-0.001	0.074***	0.055***	0.083***	0.112***
Phase 3	-0.040**	-0.071***	0.089***	-0.011	0.041***	0.045***
Phase 4	-0.052*	-0.094***	0.057***	-0.013	0.068***	0.029*
			Developed countries			
Germany						
Phase 1	-0.078***	0.038***	-0.032***	-0.069***	-0.050***	-0.024***
Phase 2	0.039***	0.088***	0.095***	0.050***	0.081***	0.099***
Phase 3	-0.007	0.029*	-0.028*	0.028**	0.028*	0.026*
Phase 4	0.055***	-0.052**	-0.119***	-0.086***	-0.114***	-0.023
Japan						
Phase 1	-0.048***	0.029***	0.027***	-0.030***	-0.026***	0.028***
Phase 2	0.030***	0.035***	0.062***	0.03**	0.002	0.053***
Phase 3	0.026***	-0.083***	-0.051***	-0.136***	-0.139***	0.035***
Phase 4	0.017	0.022	-0.085***	-0.025	-0.197***	-0.016
UK						
Phase 1	-0.051***	0.109***	0.044***	0.020**	0.043***	0.063***
Phase 2	0.043***	0.098***	0.142***	0.119***	0.157***	0.117***
Phase 3	0.030*	-0.035*	-0.023	0.049**	0.097***	0.055***
Phase 4	0.120***	-0.175***	-0.057*	-0.101***	-0.040	0.038
USA						
Phase 1	-0.086***	0.090***	0.112***	0.019**	0.037***	0.081***
Phase 2	0.037***	0.150***	0.212***	0.112***	0.176***	0.177***
Phase 3	0.024*	0.010	0.106***	0.076***	0.124***	0.038**
Phase 4	0.033*	0.045	0.130***	0.102***	0.173***	0.110***

4.5.2.2 Analysis of ADCC results across sectors during the ESDC within each country

This section seeks to answer the question: did correlations increase for the sector pairs within each of the nine countries during the ESDC?

Table 4.18 presents the estimated coefficients associated with within-country cross-sector financial contagion during the ESDC. Table 4.19 presents the estimated coefficients associated with within-country cross-sector financial contagion across the three phases of the ESDC. There is more evidence of sectoral heterogeneity across the BRICS and the developed countries under study during the ESDC. Cross sector differences reveal that financials, materials and consumer sectors are the most affected sectors across all BRICS countries, as evident from the consistent positive correlation coefficients for the sector pairs financials - materials and consumer - materials. The least affected sector across BRICS countries is telecommunication which displays correlation with other sectors across BRICS countries. The correlation coefficient of most sectors pairs for South Africa is about three times more than those of at least three of the other BRICS Countries. This shows that diversification benefits among BRICS would have been achieved during the ESDC.

For developed countries, the USA is the most affected, as indicated by the positive correlation coefficients of most sectors which are significant at the 1 percent level. This is probably due to the fact that the ESDC was also linked to the aftermath of the GFC, and hence domestic sectors in the US were more exposed to the ESDC.

Germany is the least affected among the developed countries. This might be due to good economic fundamentals with the German economy.

Table 4.18: Asymmetric dynamic conditional correlation coefficients across sectors across sectors within each country during the ESDC

	Fin - Mat	**Fin - Cons**	**Fin - Tele**	**Cons - Mat**	**Mat - Tele**	**Cons - Tele**
			BRICS countries			
Brazil	0.065***	-0.015***	-0.018***	0.050***	0.035***	-0.007
Russia	0.014***	-0.054***	-0.037***	0.012***	0.009*	-0.068***
India	0.021***	0.015***	-0.0457***	0.017***	-0.016***	-0.048***
China	0.022***	-0.016***	-0.015***	0.022***	0.008***	-0.025***
RSA	0.090***	0.013***	-0.014***	0.065***	0.052***	0.022***
			Developed countries			
Germany	-0.024***	-0.046***	-0.017***	0.003	-0.032***	-0.044***
Japan	0.000	0.038***	0.034***	0.097***	0.061***	0.043***
UK	0.060***	0.001***	-0.039***	0.082***	0.035***	-0.042***
USA	0.024***	0.003	0.021***	0.048***	0.048***	0.043***

Table 4.19: Asymmetric dynamic conditional correlation coefficients during the three phases of the ESDC

	Fin - MAT	**Fin - Cons**	**Fin - Tele**	**Cons - Mat**	**MAT - Tele**	**Cons - Tele**
			BRICS countries			
Brazil						
Phase 1	0.083***	0.006	0.056***	0.098***	0.081***	0.061***
Phase 2	0.056***	-0.024***	-0.045***	0.029***	0.015***	-0.030***
Phase 3	0.074***	0.002	-0.031	0.073***	0.063***	-0.064***
Russia						
Phase 1	0.059***	-0.055***	0.022**	-0.007	0.060***	-0.016*
Phase 2	-0.003	-0.058***	-0.059***	0.017***	-0.007	-0.086***
Phase 3	0.026	0.019***	-0.04*	0.050**	-0.039*	-0.092***
India						
Phase 1	0.028***	-0.021***	-0.022*	0.005***	-0.002	-0.065***
Phase 2	0.015***	0.030***	-0.057***	0.023***	-0.020***	-0.039***
Phase 3	0.060***	-0.004	0.007	-0.009***	-0.027	-0.066**
China					-	
Phase 1	0.034***	-0.049***	-0.059***	-0.009	-0.007	-0.081***
Phase 2	0.018***	-0.002	-0.004	0.034***	0.010	-0.009
Phase 3	0.022	-0.025	0.073***	0.014	0.064**	0.056**
RSA						
Phase 1	0.046***	-0.084***	-0.155***	0.000	-0.065***	-0.069***
Phase 2	0.109***	0.045***	0.031***	0.088***	0.098***	0.050***
Phase 3	0.048*	0.082***	0.085***	0.084***	0.016	0.107***
			Developed countries			
Germany						
Phase 1	0.020***	-0.029***	0.017*	-0.000	0.043***	0.020*
Phase 2	-0.039***	-0.054***	-0.038***	0.002	-0.062***	-0.070***
Phase 3	-0.039**	-0.018	0.090***	0.028	-0.015	-0.020
Japan						
Phase 1	-0.062***	-0.028***	0.001	0.045***	-0.010	0.004
Phase 2	0.022***	0.062***	0.046***	0.116***	0.084***	0.061***
Phase 3	0.015	0.046*	0.03*	0.094***	0.108***	-0.003
UK						
Phase 1	0.070***	-0.070***	-0.159***	0.043***	-0.038***	-0.154***
Phase 2	0.052***	0.024**	0.002	0.091***	0.062***	0.001
Phase 3	0.112***	0.064*	0.009	0.127***	0.054*	-0.065**
USA						
Phase 1	0.013	-0.016	-0.057***	0.063***	0.007	0.004
Phase 2	0.022***	0.002	0.042***	0.035***	0.058***	0.053***
Phase 3	0.104***	0.106***	0.138***	0.139***	0.129***	0.101***

4.5.2.3 Analysis of ADCC results across sectors during the Brexit crisis within each country.

This subsection seeks to answer the question: did correlations increase for the sector pairs within each of the nine countries during the EU/UK referendum results and subsequent trigger of Article 50?

Table 4.20 presents the estimated coefficients associated with within-country cross-sector financial contagion during the Brexit crisis period. The period between the date of the Brexit referendum announcement on 24 June 2016 and the few weeks after the date (29 March 2017) on which Article 50 for withdrawal from the European union was triggered. The table shows mostly negative correlation coefficients for the sector pairs across all nine countries. Within BRICS countries, the country with the most sector pairs with positive correlation coefficients is Brazil, with positive correlation coefficients for financials-Consumer, financials - telecommunications and consumers - telecommunications. This implies that among BRICS countries, Brazil was the most affected by the results of the UK's Brexit referendum and the subsequent trigger of Article 50 for withdrawal from the European Union. This finding is in line with the findings of Aristeidis and Elias (2018), who did a study on the effects of Brexit on forty three major developed and emerging stock markets. The authors empirical results showed instant financial contagion to a very few emerging markets. Among these emerging markets, Brazil's stock markets were the most affected. As shown in Table 4.20, other BRICS countries (South Africa, India and Russia) have only one sector pair with positive correlation coefficients. China was the least affected by the results of the UK EU referendum as all the sector pairs for china shows negative correlation coefficients.

Of the developed countries, Germany and Japan are the only countries with at least one sector pair with positive correlation coefficients. As far as the sector pairs are concerned, the UK and USA show negative correlation coefficients for the sector pairs. The results for the sector pairs in the UK are in line with the findings of Raddant (2016) who carried out a study on the response of European stock markets to Brexit. From the author's, findings, there were a pronounced differences in the price impact for all the sectors within UK. This implies that the sectors were affected differently, leading to a decrease in correlation of the various sector pairs in the UK. The UK results could also be used as a guide to explain the negative correlation across all sectors pairs in the US. The reason for the minimal effect of the Brexit in most of the nine countries sector pairs can be infered from the results of Aristeidis and Elias (2018). The empirical results of these authors shows the contagion to countries studied (both developed and emerging) was not significant and lacked significant duration. In other words, overall, the negative reactions of the market was small and lasted for a short period of time.

Table 4.20: Asymmetric dynamic conditional correlation coefficients across sectors within each country due to Brexit crisis

	Fin - Mat	**Fin - Cons**	**Fin - Tele**	**Cons - Mat**	**Mat - Tele**	**Cons - Tele**
			BRICS countries			
Brazil	-0.124***	0.024***	0.059***	-0.089***	-0.116***	0.030***
Russia	-0.030***	-0.021**	0.011***	-0.043***	-0.072***	-0.073***
India	-0.002***	0.036***	-0.108***	0.001	-0.092***	-0.066***
China	-0.116***	-0.007***	-0.020***	-0.045***	-0.110***	-0.043***
RSA	-0.146***	0.032***	-0.006	-0.079***	-0.091***	-0.033***
			Developed countries			
Germany	-0.027***	-0.118***	0.0035***	-0.072***	0.017***	0.001
Japan	0.000	-0.061***	-0.001	-0.052***	0.009	0.026***
UK	-0.157***	-0.236***	-0.113***	-0.137***	-0.128***	-0.072***
USA	-0.040***	-0.225***	-0.232***	-0.119***	-0.151***	-0.089***

Chapter 5

Conclusion

Financial co-integration is a key aspect in the literature on financial crisis and linkages across stock markets. This study investigates the effect of the Global Financial Crisis (GFC), European Sovereign Debt Crisis (ESDC) and UK Brexit crisis on the stock markets of the BRICS (Brazil, Russia, India, China and South Africa) and developed stock markets (Germany, Japan, Uk and USA). The study utilised sectoral equity indices over the period January 2006 to December 2017 that represents financials, materials, consumer staples and telecommunication sectors. The methodology utilised was the multivariate asymmetric conditional correlation GJR generalized autoregressive conditional heteroskedasticity (ADCC-GJRGARCH) model. The ADCC-GJRGARCH model was used to estimate asymmetric dynamic conditional correlations. The study utilised the economic approach to identify the crisis length. The economic approach is guided by major financial and economic events published in official news sources. This approach is used to identify the crises dates for all three crises considered. With regards to financial co-integration, the study adjusted the framework used by Forbes and Rigobon (2002), Phylaktis and Xia (2011) and Baur (2012) to allow for sectoral data. Specifically, the study allowed for two variants of financial co-integration. First, the study focused on sectoral equity indices, but across the nine countries. Secondly, the study looked at each country in isolation, but across sectors.

The analysis of asymmetric dynamic conditional correlations for cross country, within sector conditional correlations provide substantial evidence on the existence of co-integration effects due to herding behaviour across developed stock markets as well as between developed and the BRICS equity stock markets. Summary result for cross country within sector asymetric dynamic conditional correlations coefficients during the different phases of the GFC and ESDC crises are presented in Table 4.9, 4.11, 4.12. The results show that most sectors and countries considered were insulated to shocks during the first phase of both the GFC and ESDC, whereas phase two and three for both crises exhibited the most incidences of the significant positive conditional correlation of the country pairs within each sector considered. Under the definition of "pure contagion", this may be as a result of shifts in investor's common but changing appetite for risk (Kumar and Persaud, 2002). The appetite for risk among international investors decreased in the second and third phase of the crisis periods when they became aware of the spread of the crisis. It appears that some developed and BRICS countries like Japan, India and China with moderate exposure via trade were not greatly affected by the crisis suggesting the benefits for diversification that might still exists during crises periods in those markets.

With regards to the Brexit crises, developed countries were hardest hit by impact of UK Brexit referendum results compared to the BRICS countries which appear to have been insulated from the crises.

On average, financials were the most affected during the GFC, ESDC and UK Brexit crisis. This results is not unanticipated. The financial sector was affected the most because the GFC crisis originated in the financial sector and therefore highly exposed (Baur, 2012). Also the GFC gave birth to the ESDC which therefore also has its roots in the financial sector. Brexit is about the UK leaving the Eurozone, London is the financial hub of Europe and therefore connected to the financial sectors of other countries.

The results for within country cross sector conditional correlation show that the asymetric dynamic conditional correlations vary across sectors and across the three crises considered. The study relied on the model used by Papanikolaou (2011) to provide an interpretation of the asymetric dynamic conditional correlation across sectors. According to the author, sector heterogeneity of conditional correlations can be associated with sensitivity differences to shocks or crisis.

To explain the possible reasons for the transmission of shocks across sectors, the study relied on the findings of Kenourgios and Dimitriou (2015). First, the rapid increase in derivative trading as well as the constituents of derivatives traders, such as credit default swap dealers, commodity and hedge funds has increased the exposure of many non financial sectors to financial shocks making them more vulnerable to fluctuations in international equity markets. Secondly, multinational cooperation contribute to cross sector correlation since shock on a country with one of its subsidiaries can easily spread to the country where the multinational company is located.

The findings of the study may be of certain interest to policy makers and investors. Sector heterogeneity of conditional correlation imply there are certain sectors that can still provide the benefit of international diversification despite contagion existing at the market level. In terms of policy considerations, this study adopts the view that policy makers in BRICS countries should implement policies that ensure a stable financial system of BRICS that protects each economy from international shocks. This can be achieved by monitoring the amount of capital flows into the country as this usually provides a channel for transmission of financial shocks or crises.

This study contributes to the literature by modelling and estimating financial co-integration across sectors and within sectors of the nine countries. The second contribution is applying the ADCC GJRGARCH model to model sectoral asymmetric dynamic conditional correlations across nine countries. A third contribution is the inclusion of three crises (GFC, ESDC and Brexit) in the study. This was the first study to investigate co-integration across the three crises. The fourth contribution is the inclusion of the various phases of the GFC and ESDC in the study.

Future research on this same topic can extend this research by incorporating countries like Indonesia and South Korea. Therefore, future research can look at co-integration between BRIICKS and developed markets. Future studies can also use intra daily data to better capture the effect of UK Brexit crisis.

Chapter 6

Appendix

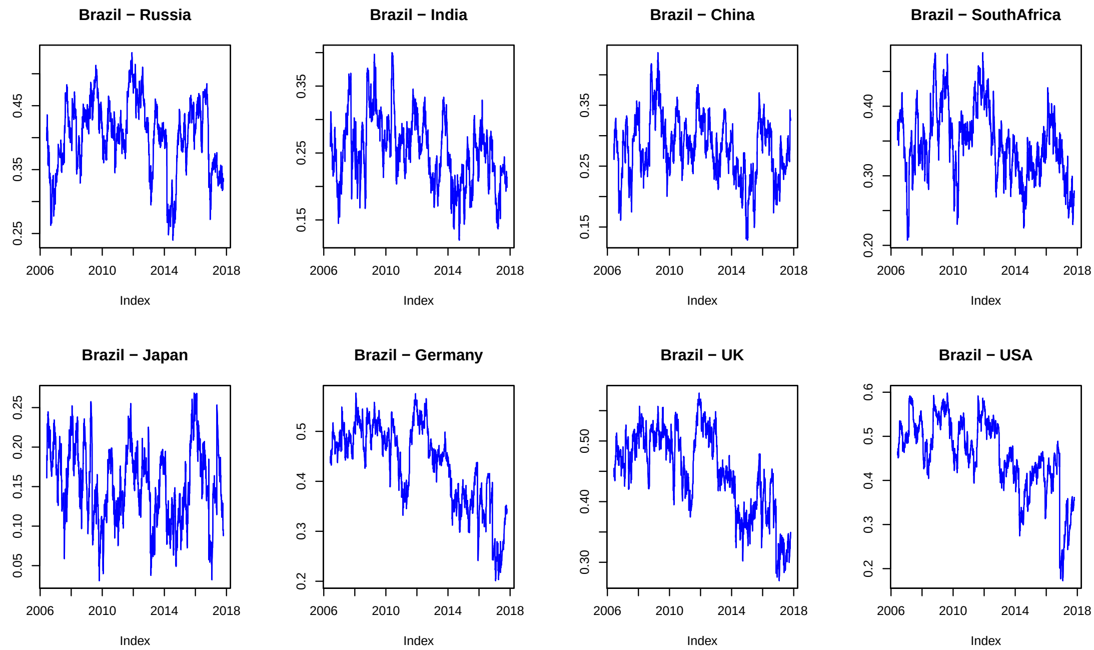


Figure 6.1: DCC within financial sector between Brazil and other countries

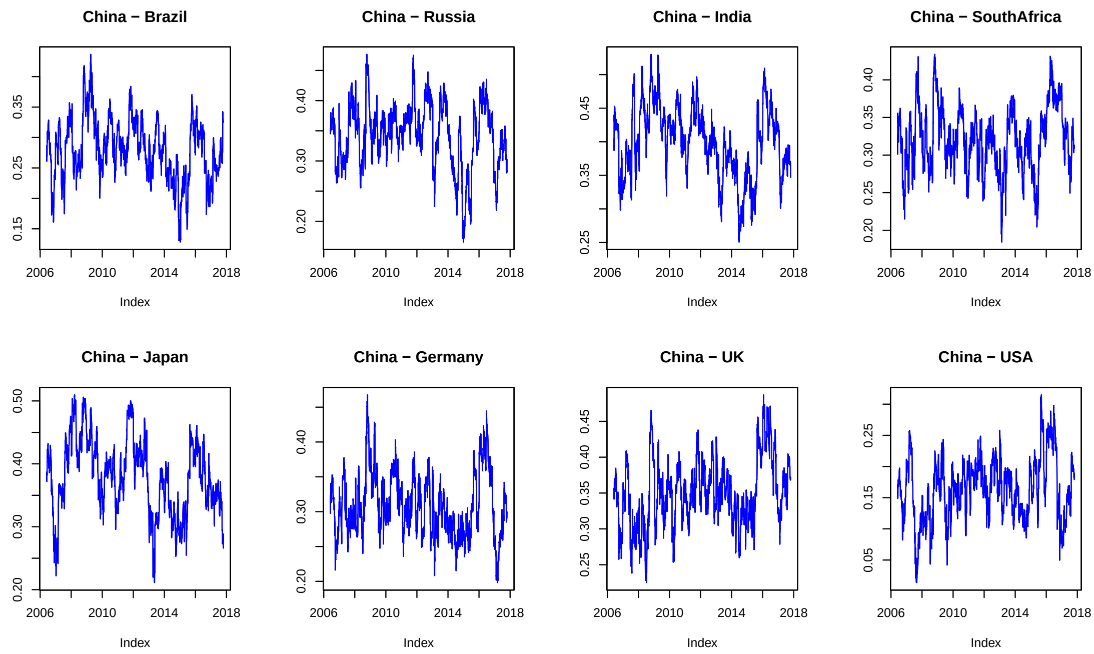


Figure 6.2: DCC within financial sector between China and other countries

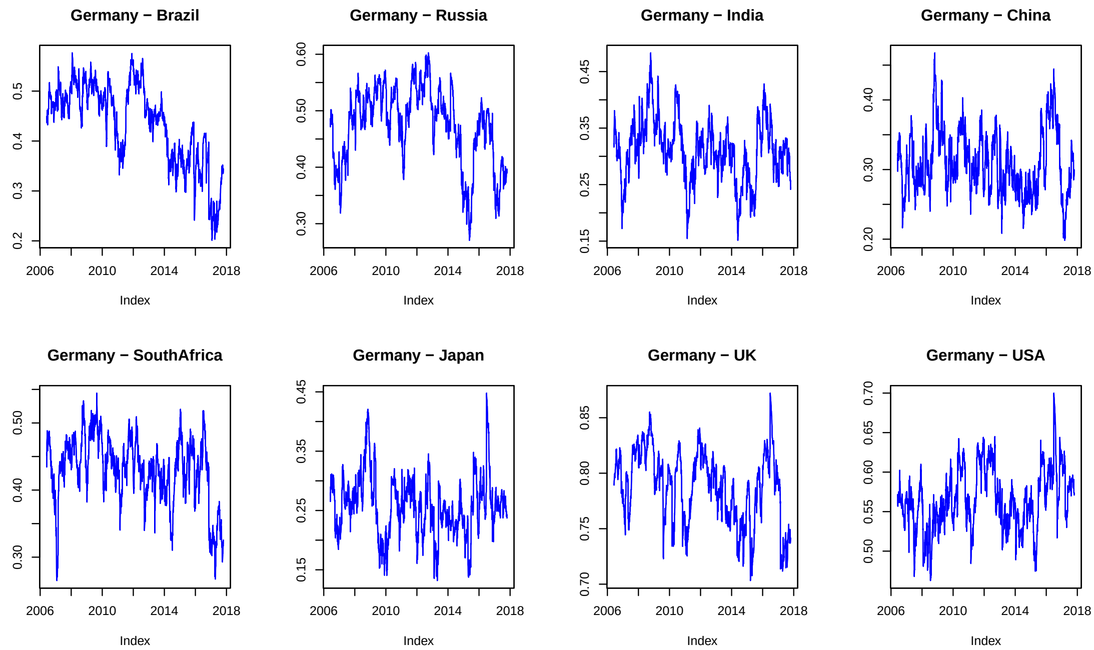


Figure 6.3: DCC within financial sector between Germany and other countries

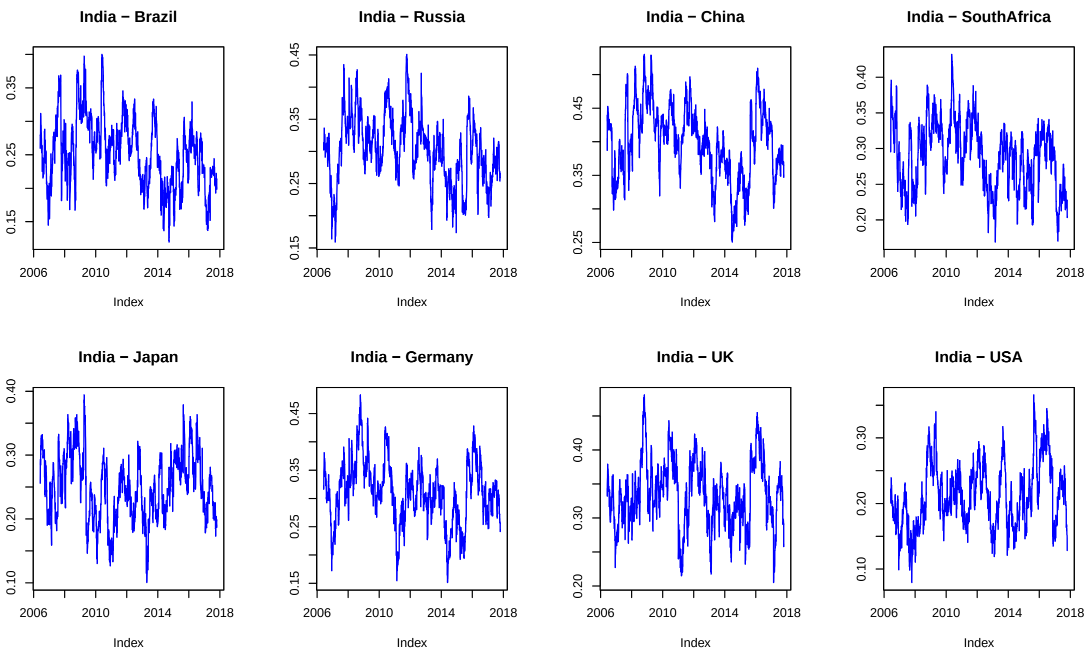


Figure 6.4: DCC within financial sector between India and other countries

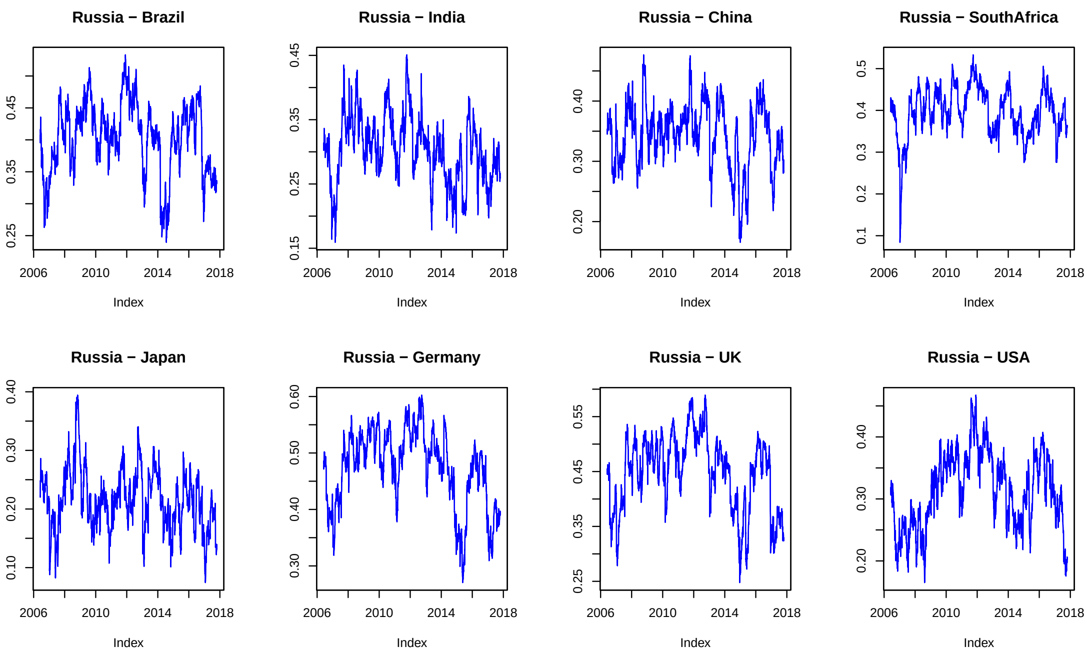


Figure 6.5: DCC within financial sector between Russia and other countries

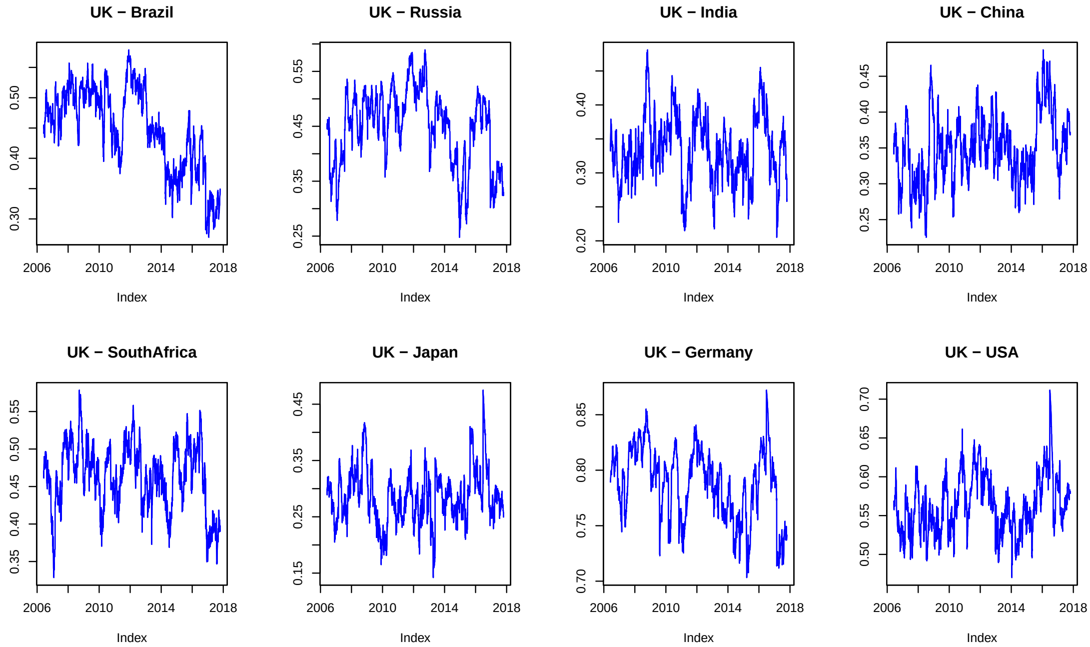


Figure 6.6: DCC within financial sector between UK and other countries

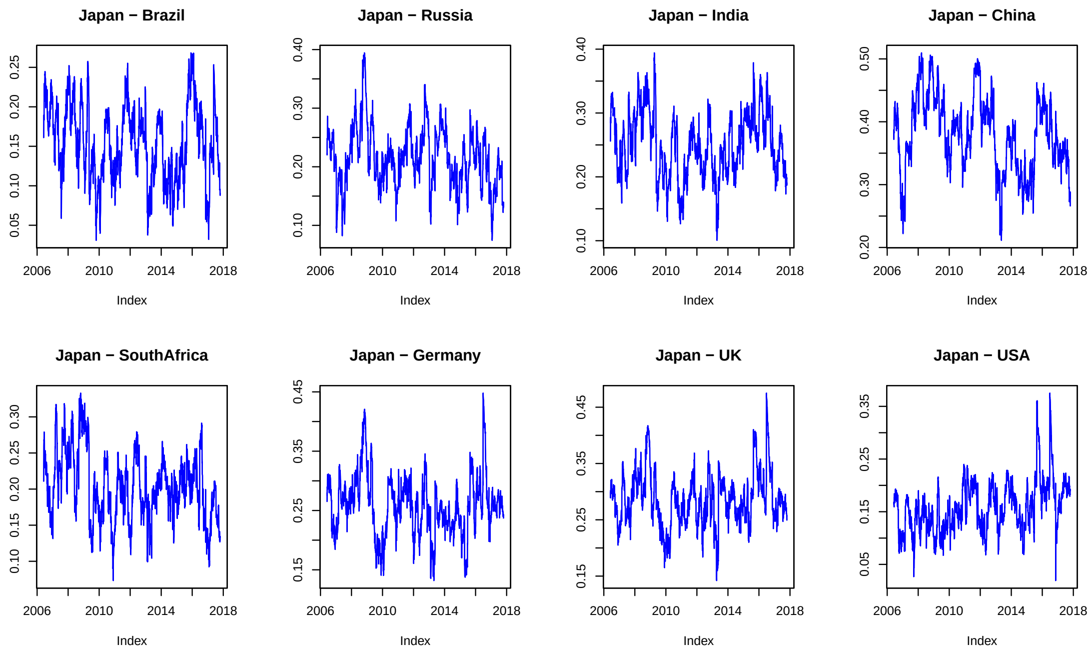


Figure 6.7: DCC within financial sector between Japan and other countries

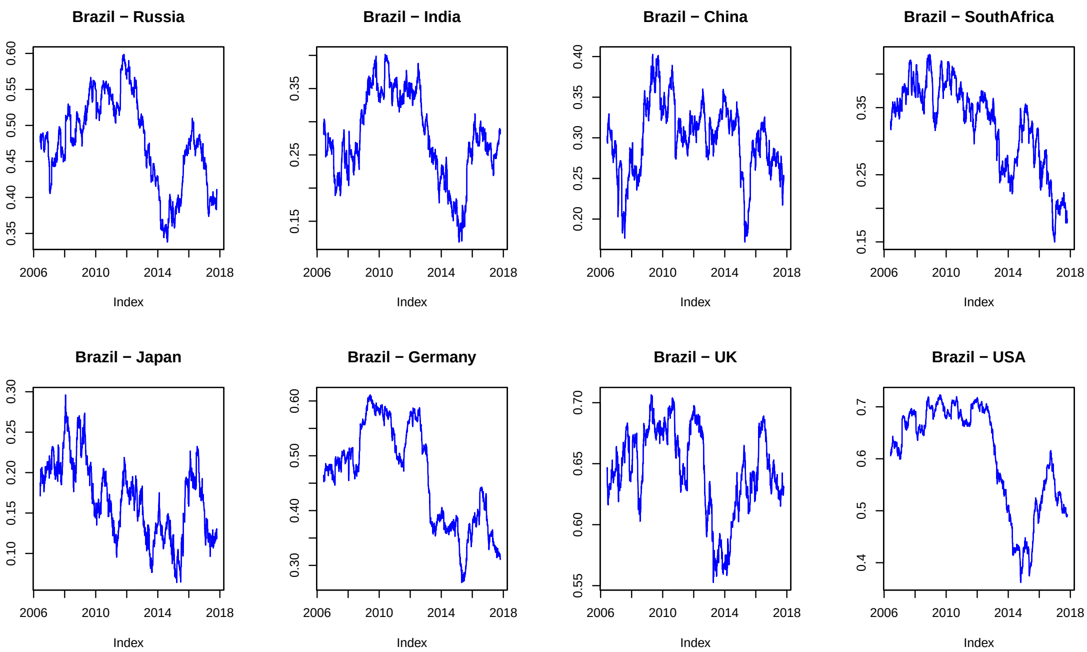


Figure 6.8: DCC within Material sector between Brazil and other countries

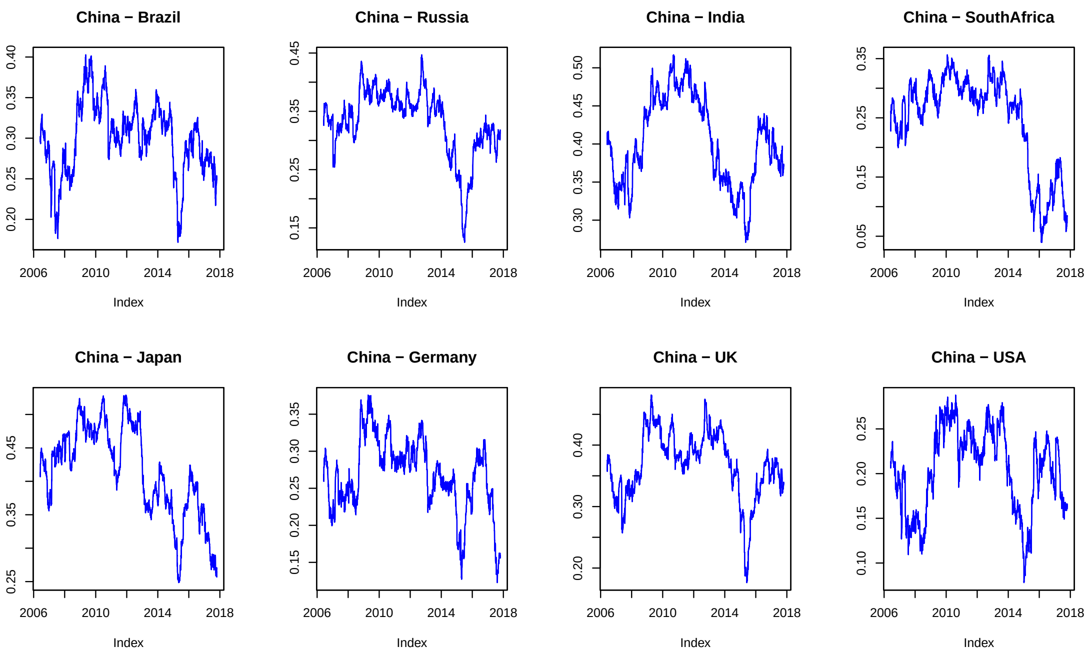


Figure 6.9: DCC within Material sector between China and other countries

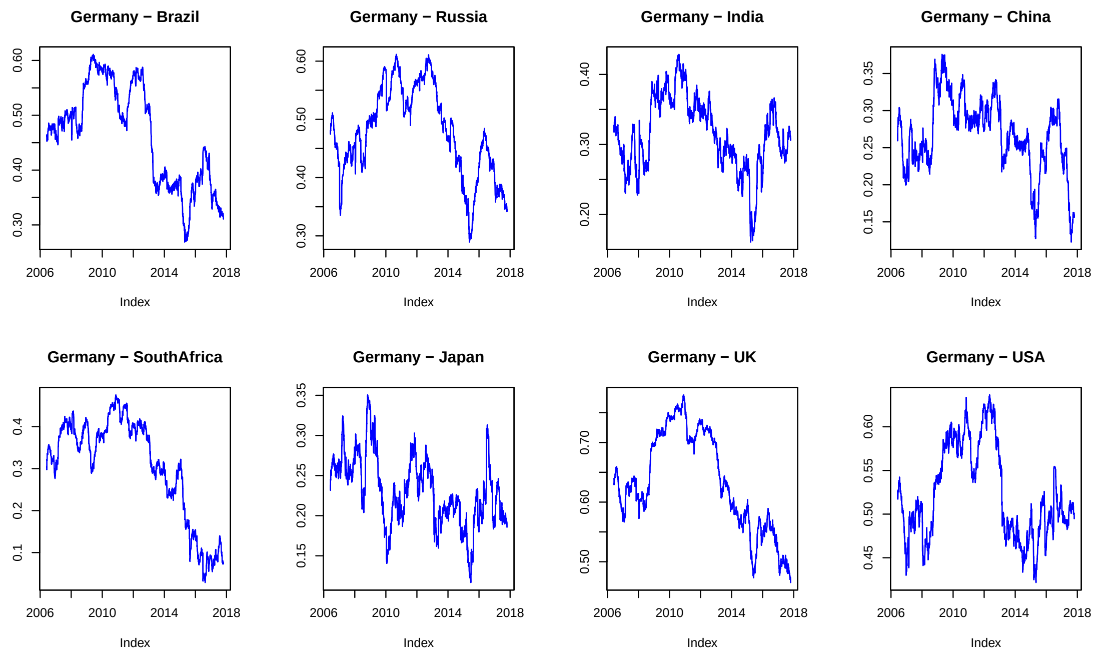


Figure 6.10: DCC within Material sector between Germany and other countries

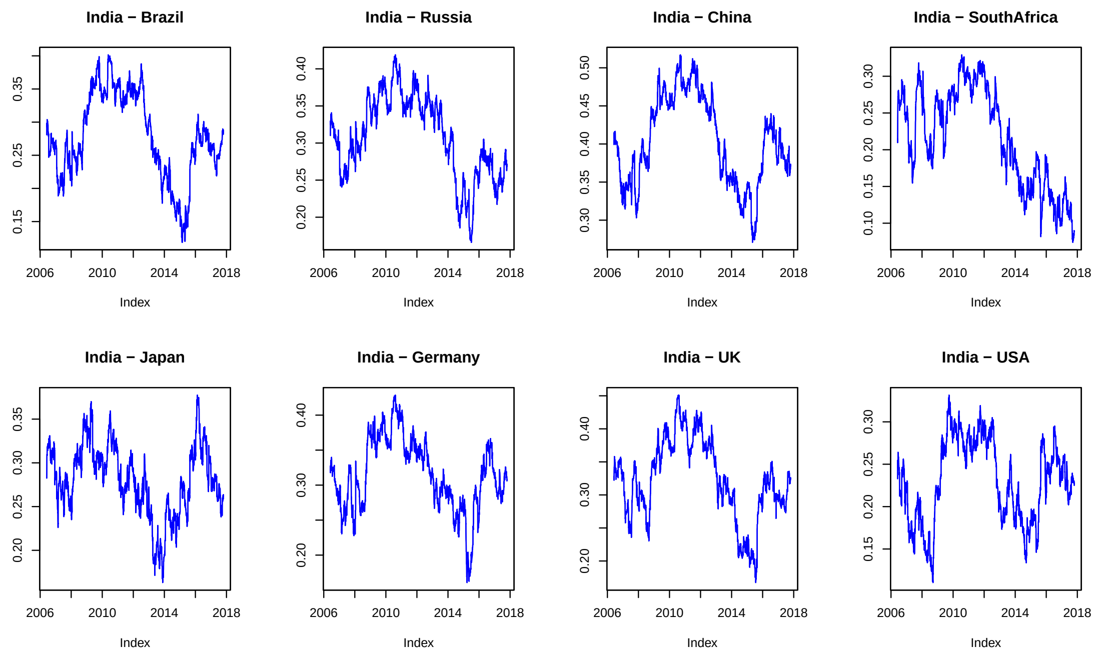


Figure 6.11: DCC within Material sector between India and other countries

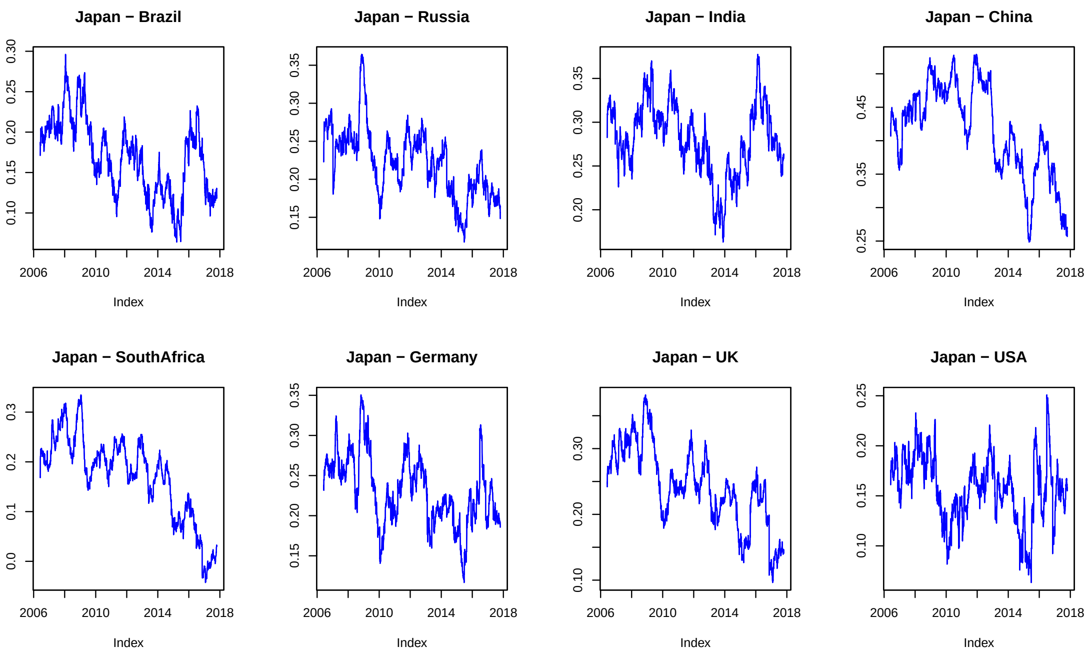


Figure 6.12: DCC within Material sector between Japan and other countries

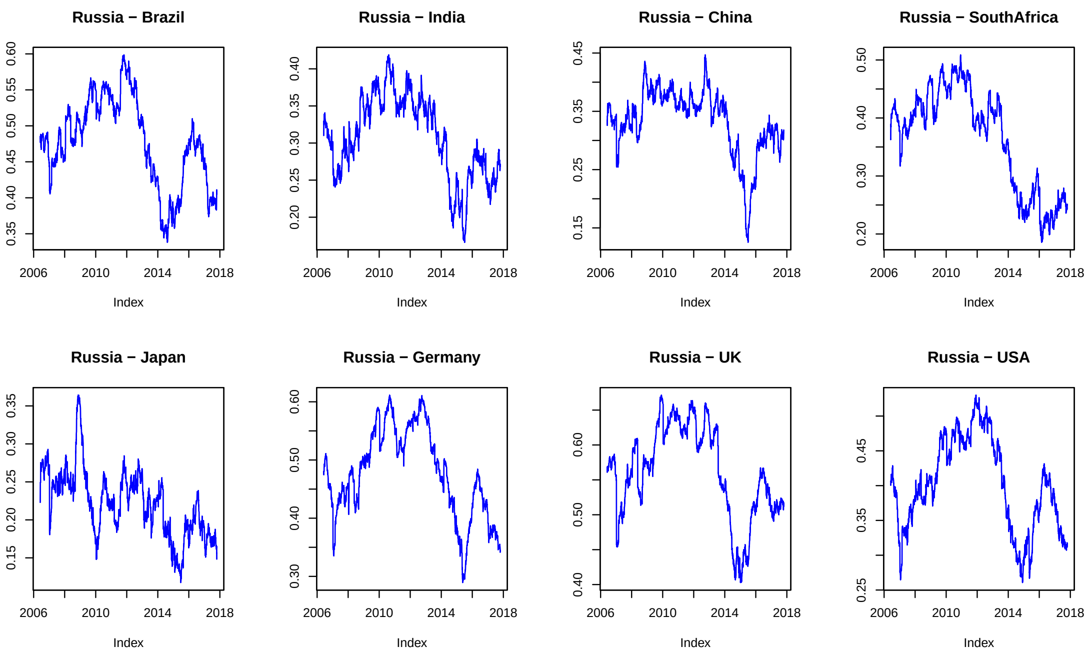


Figure 6.13: DCC within Material sector between Russia and other countries

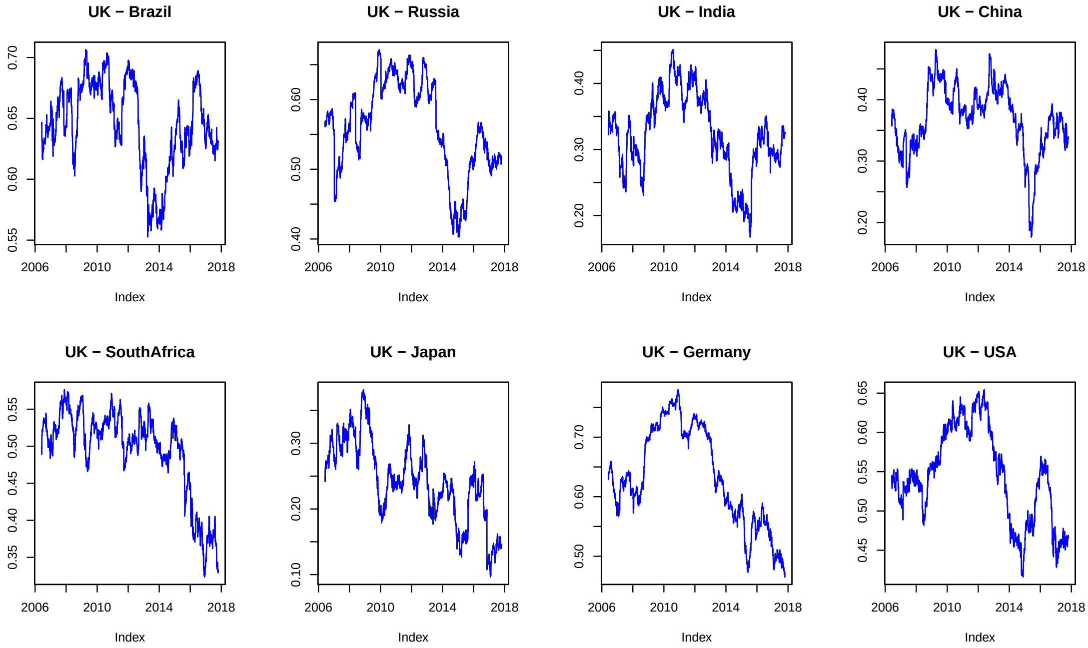


Figure 6.14: DCC within Material sector between UK and other countries

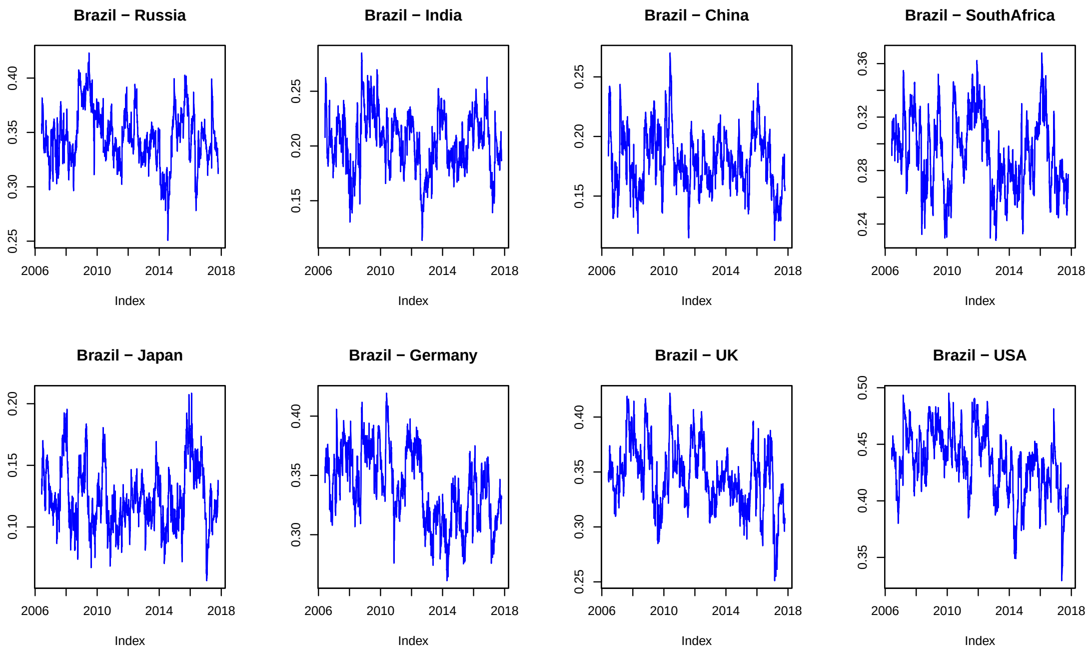


Figure 6.15: DCC within Consumer-staples sector between Brazil and other countries

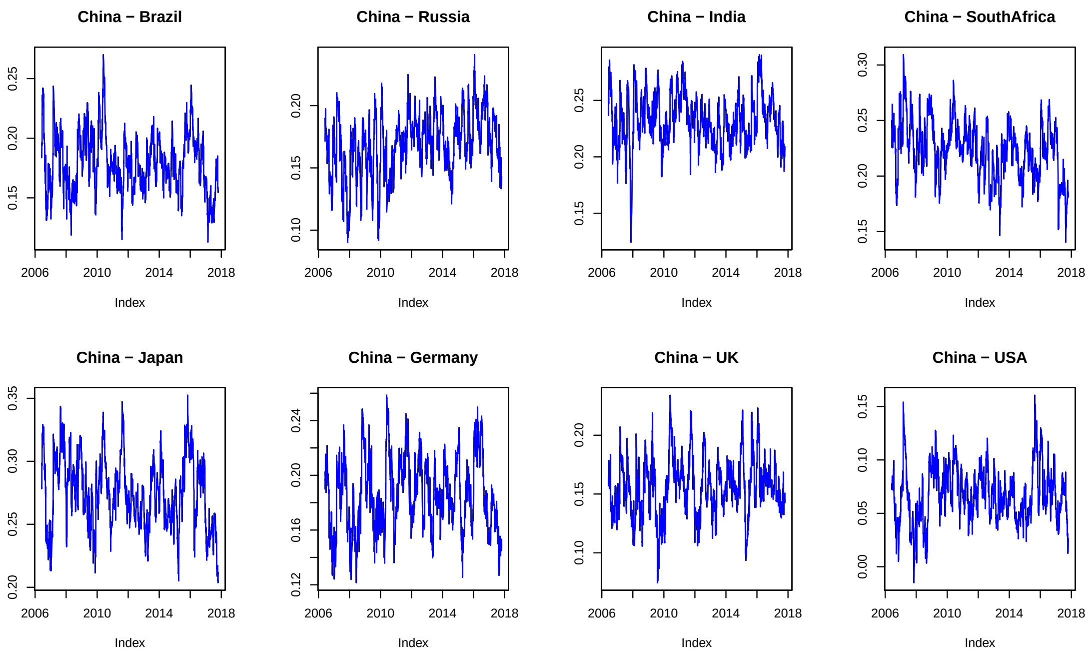


Figure 6.16: DCC within Consumer-staples sector between China and other countries

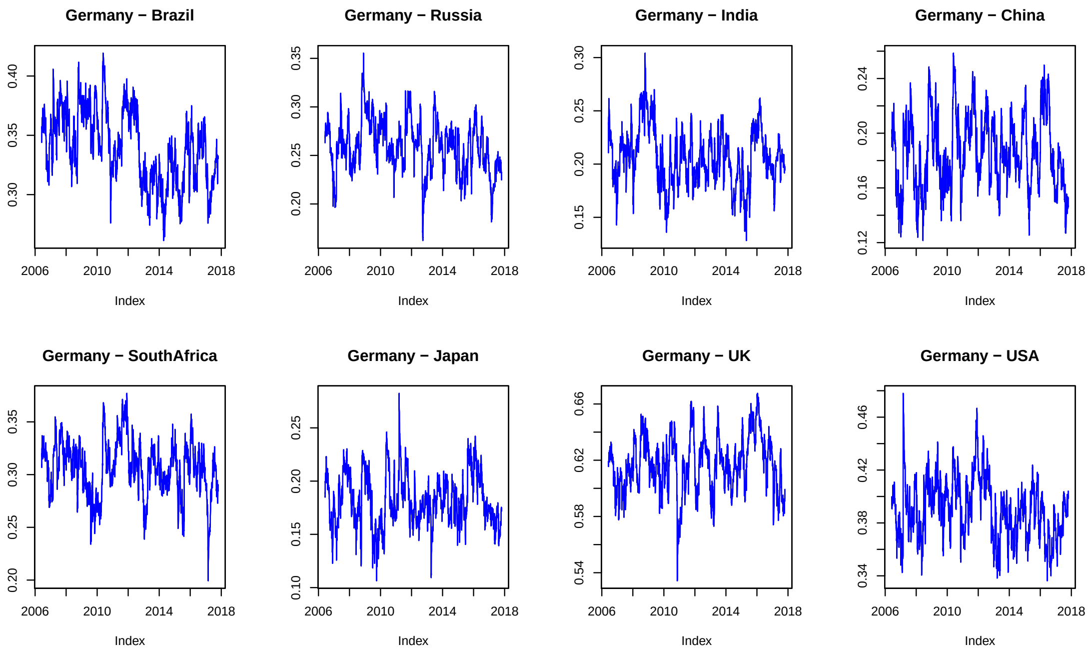


Figure 6.17: DCC within Consumer-staples sector between Germany and other countries

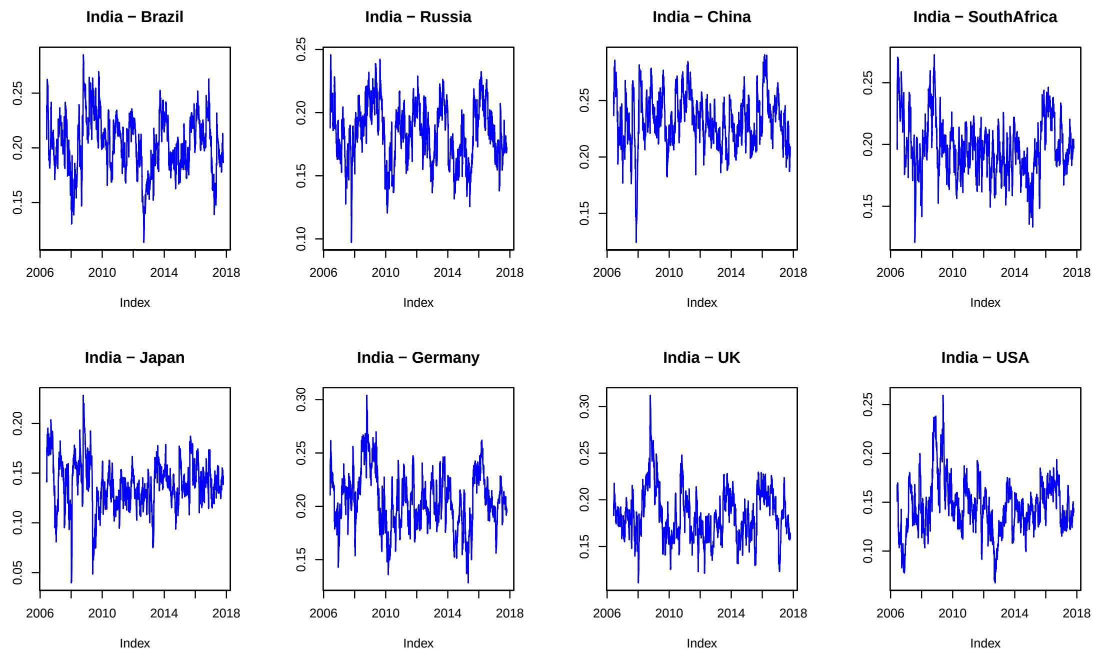


Figure 6.18: DCC within Consumer-staples sector between India and other countries

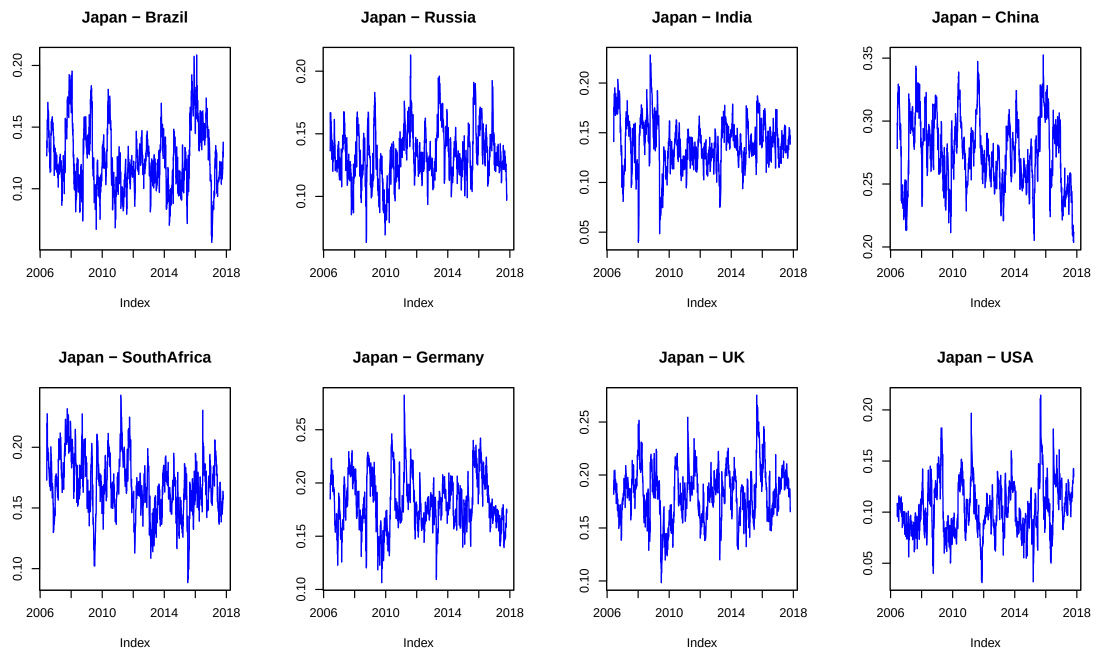


Figure 6.19: DCC within Consumer-staples sector between Japan and other countries

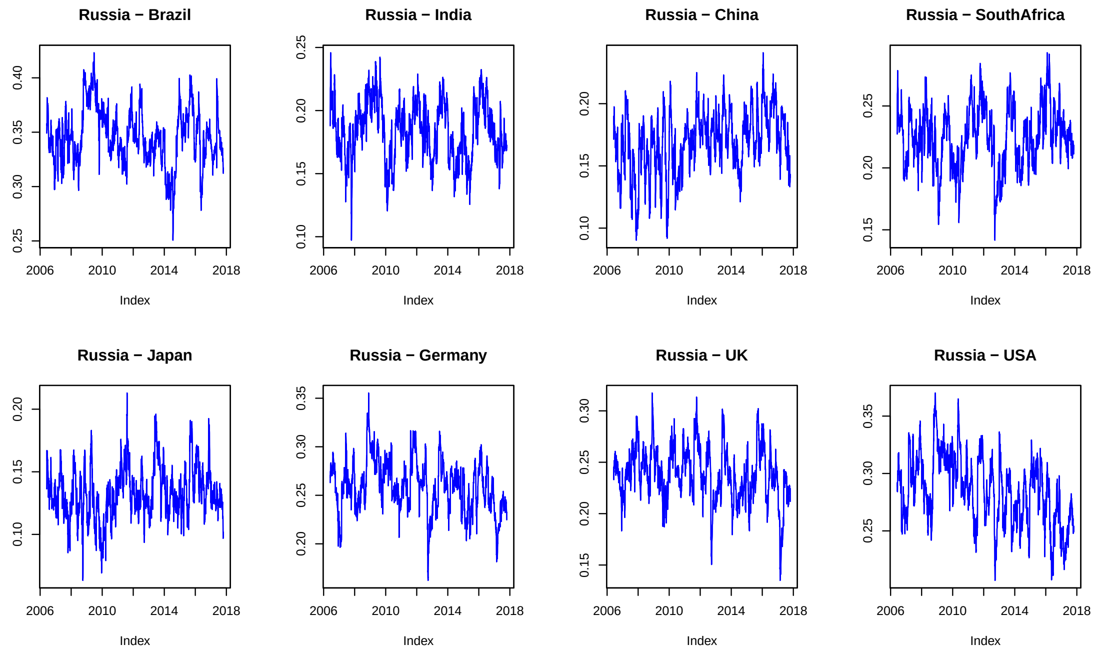


Figure 6.20: DCC within Consumer-staples sector between Russia and other countries

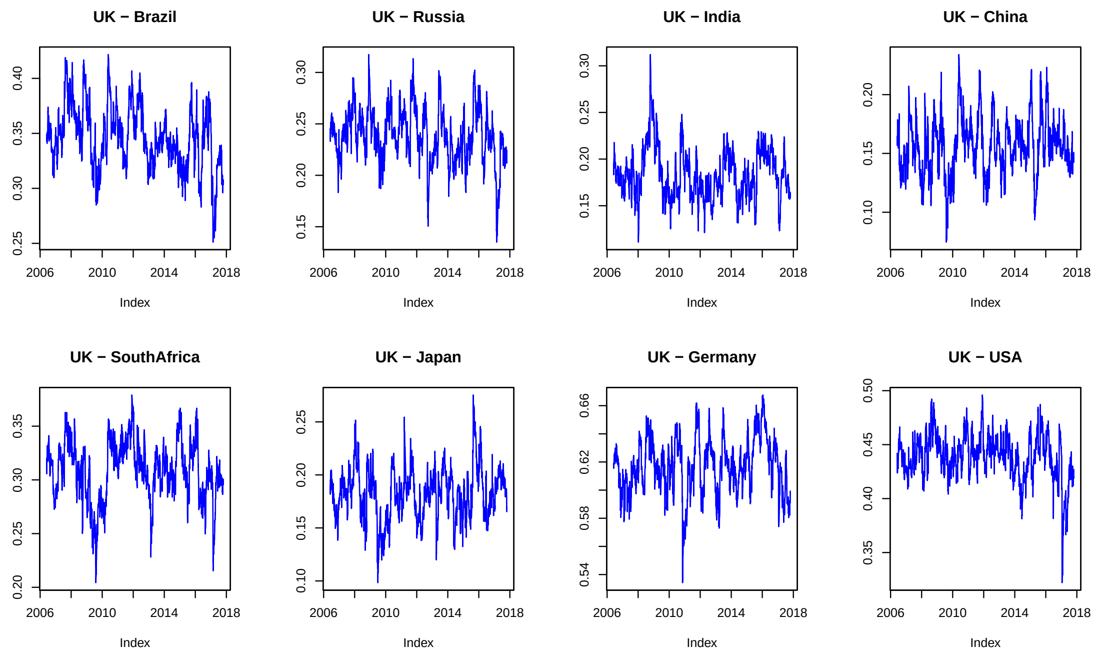


Figure 6.21: DCC within Consumer-staples sector between UK and other countries

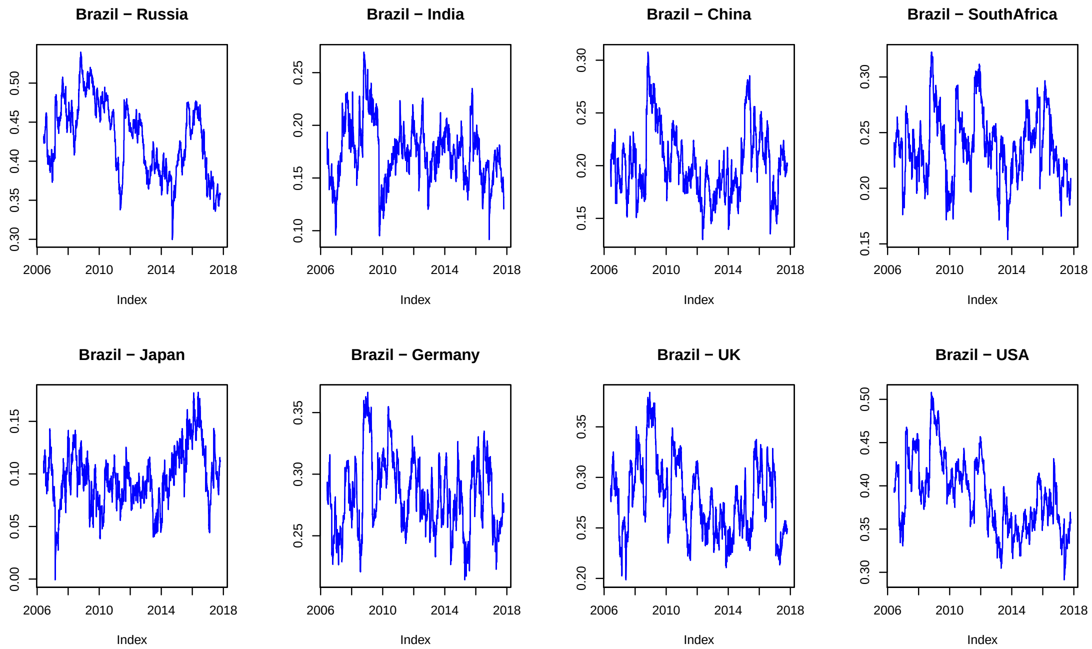


Figure 6.22: DCC within Telecommunication sector between Brazil and other countries

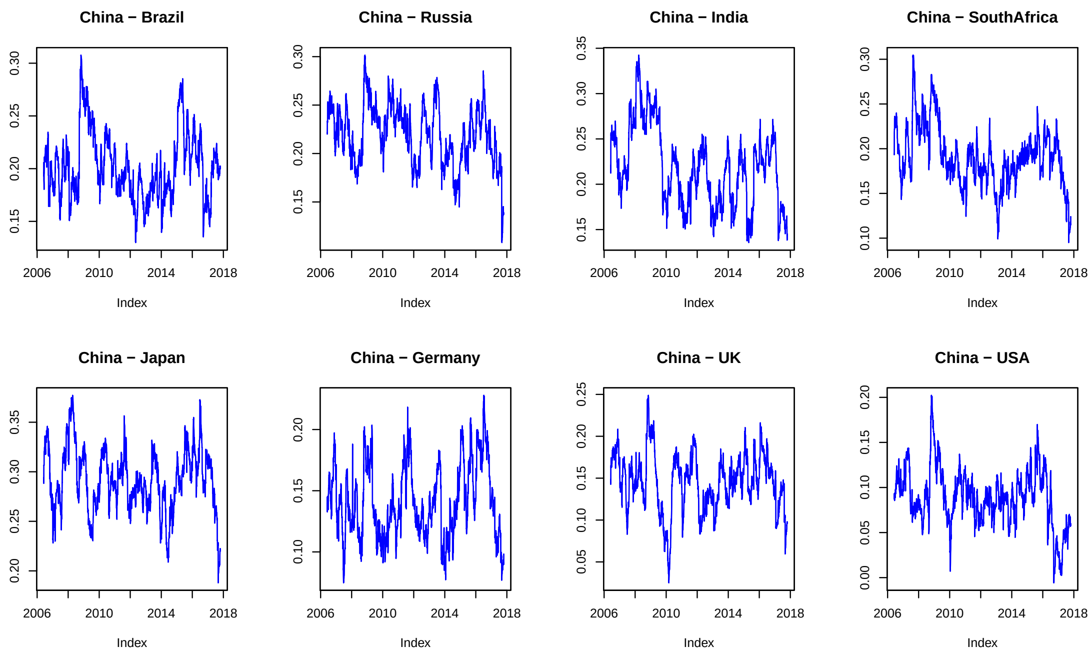


Figure 6.23: DCC within Telecommunication sector between China and other countries

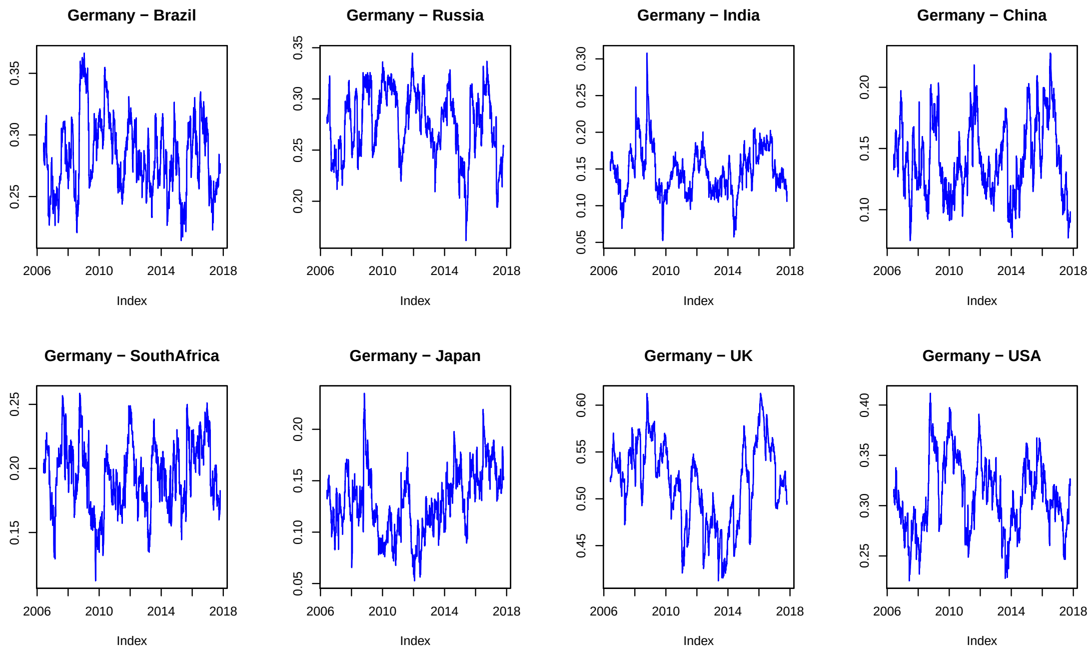


Figure 6.24: DCC within Telecommunication sector between Germany and other countries

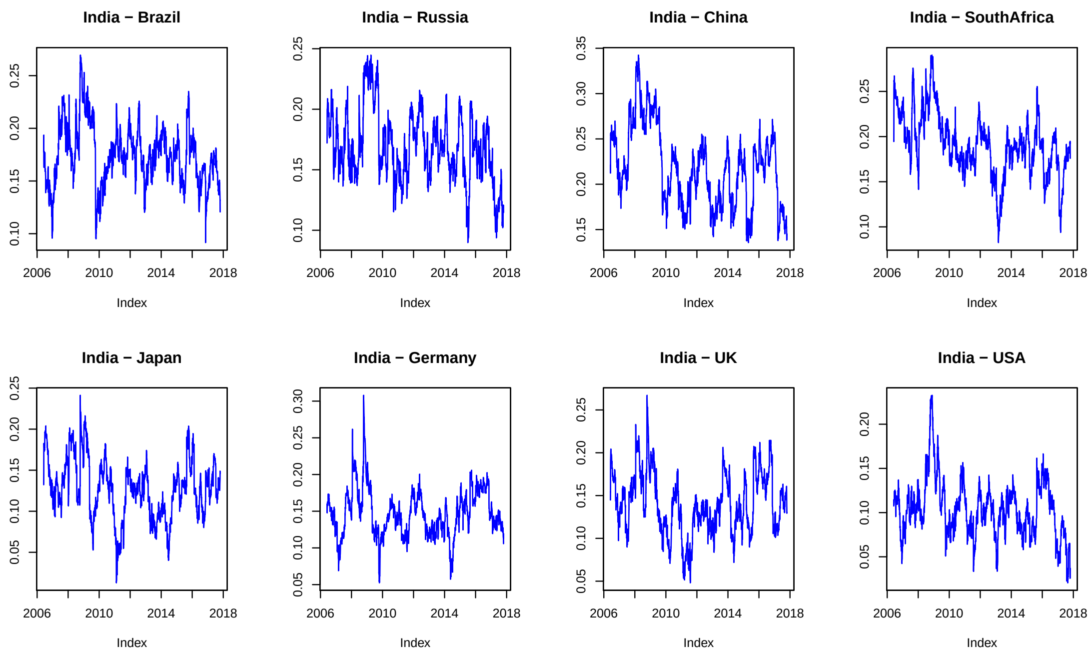


Figure 6.25: DCC within Telecommunication sector between India and other countries

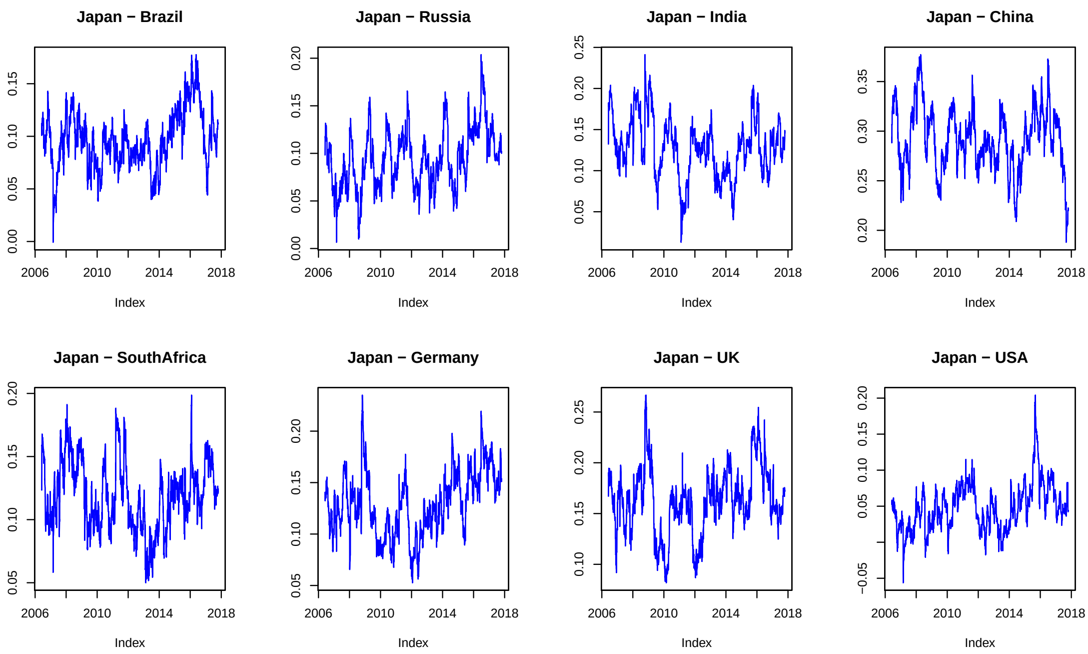


Figure 6.26: DCC within Telecommunication sector between Japan and other countries

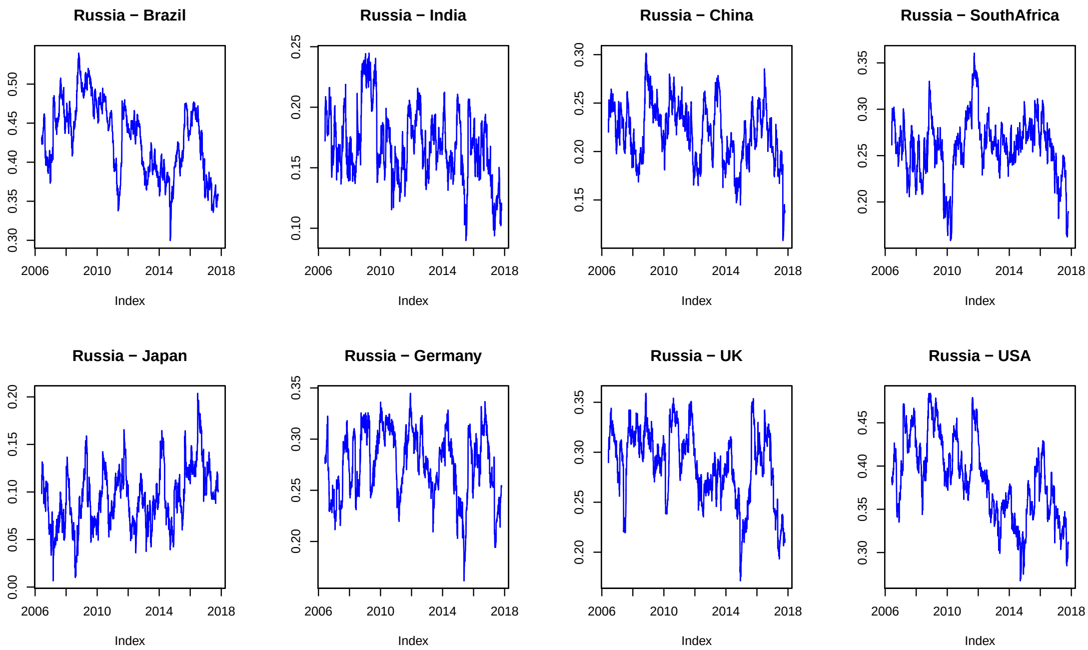


Figure 6.27: DCC within Telecommunication sector between Russia and other countries

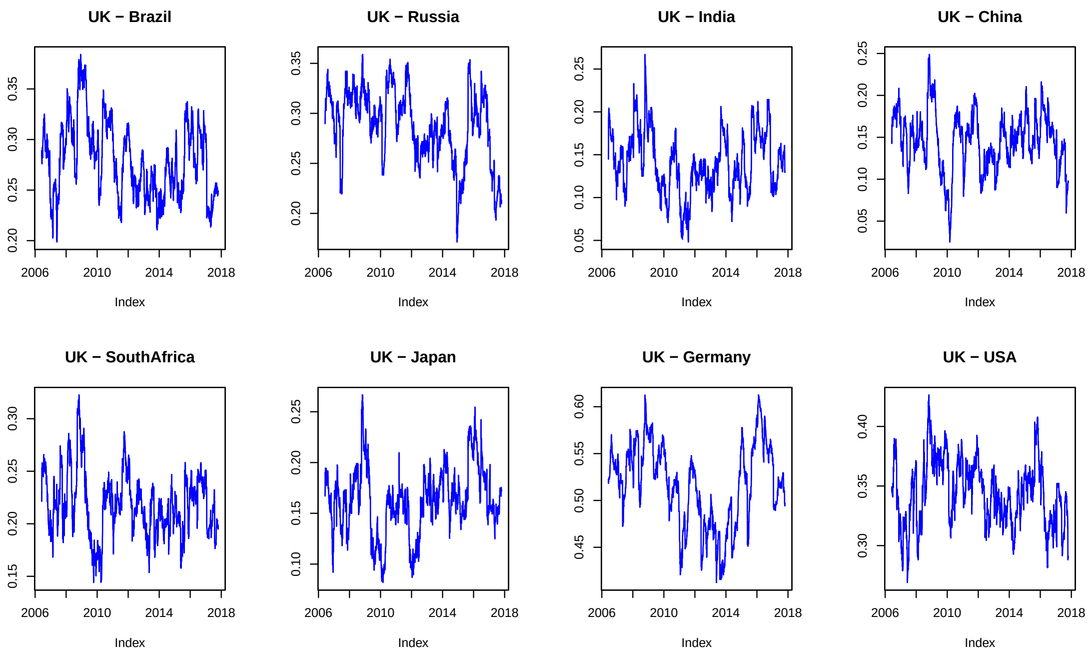


Figure 6.28: DCC within Telecommunication sector between UK and other countries

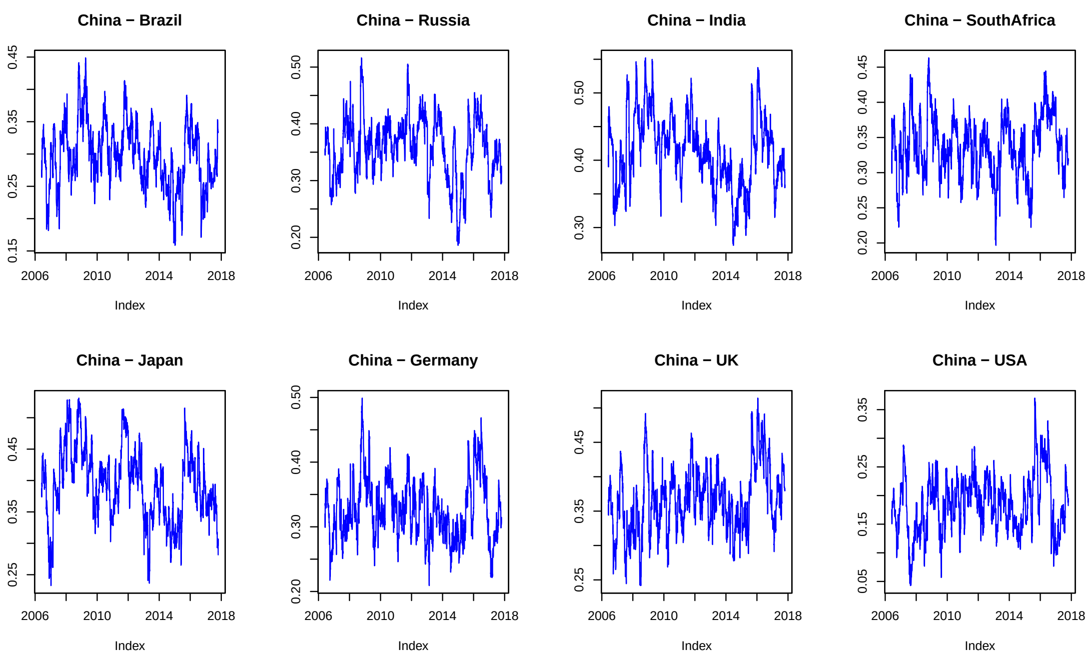


Figure 6.29: ADCC within Financial sector across China and other countries

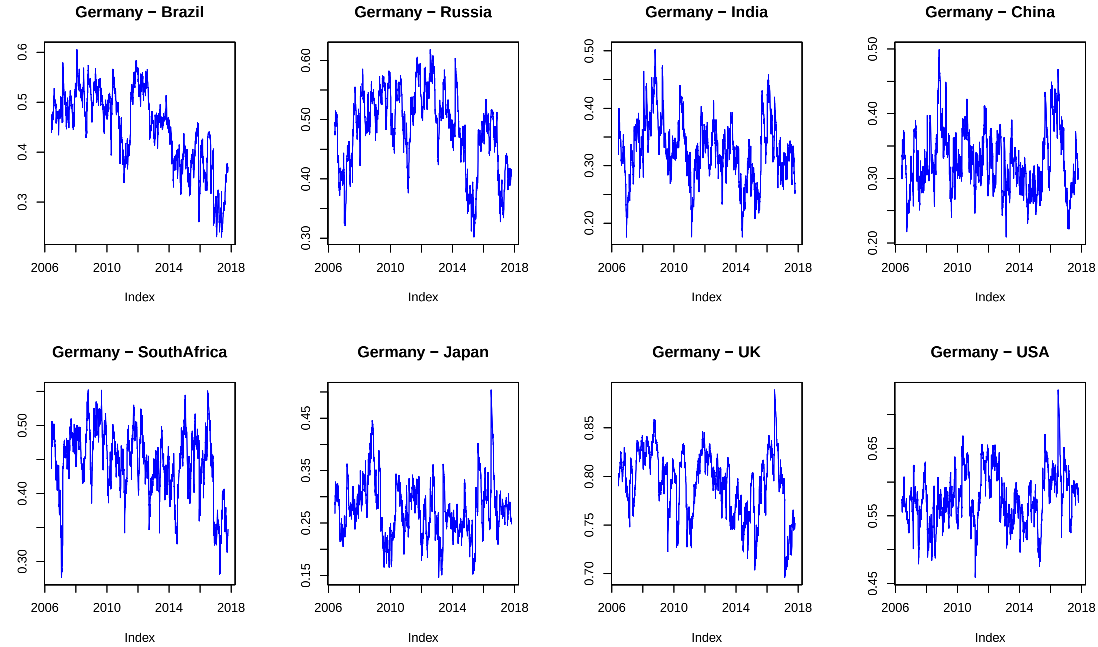


Figure 6.30: ADCC within Financial sector across Germany and other countries

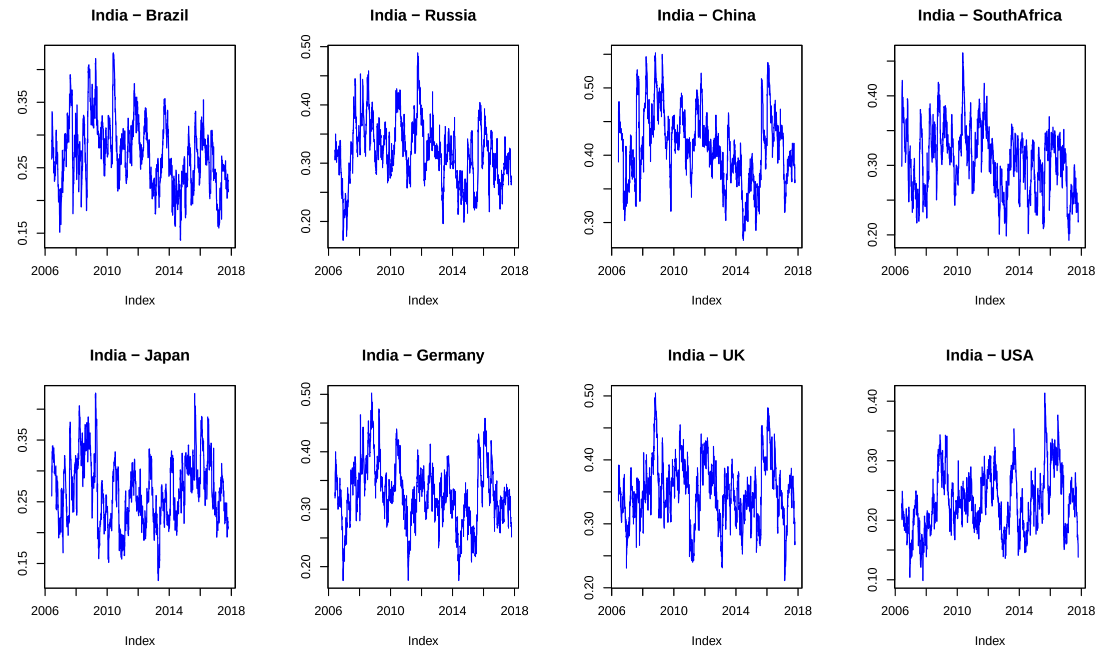


Figure 6.31: ADCC within Financial sector across India and other countries

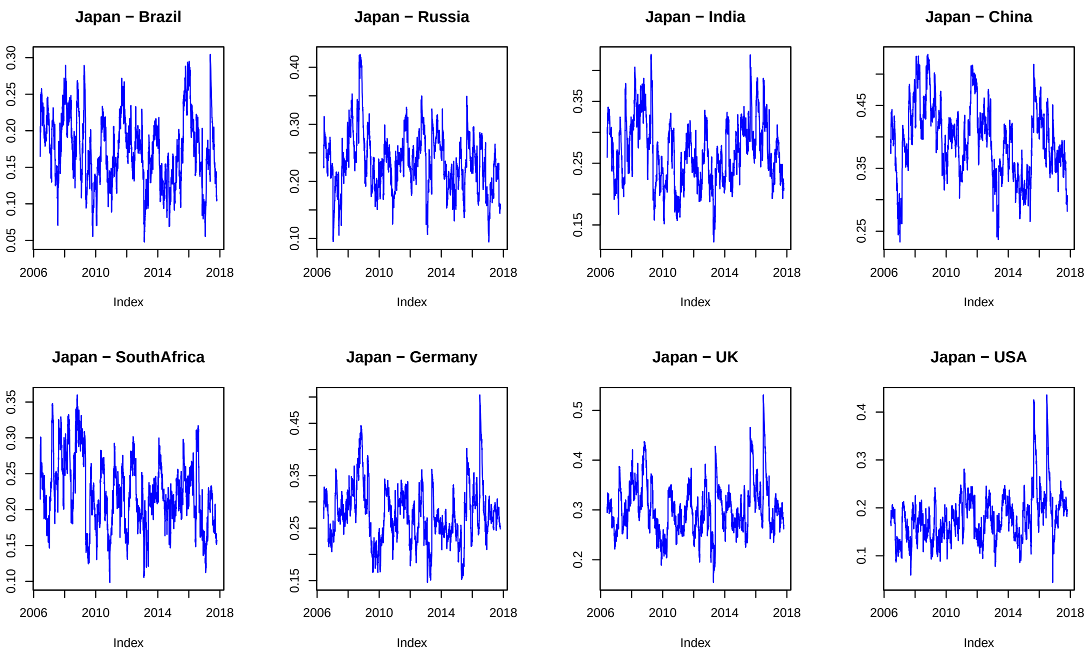


Figure 6.32: ADCC within Financial sector across Japan and other countries

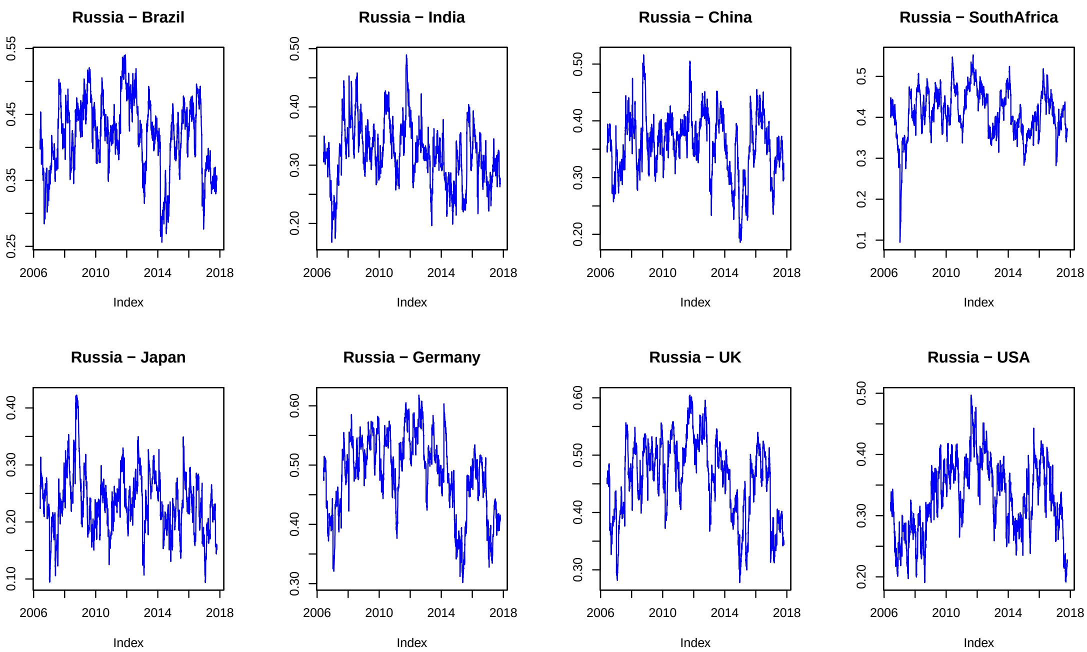


Figure 6.33: ADCC within Financial sector across Russia and other countries

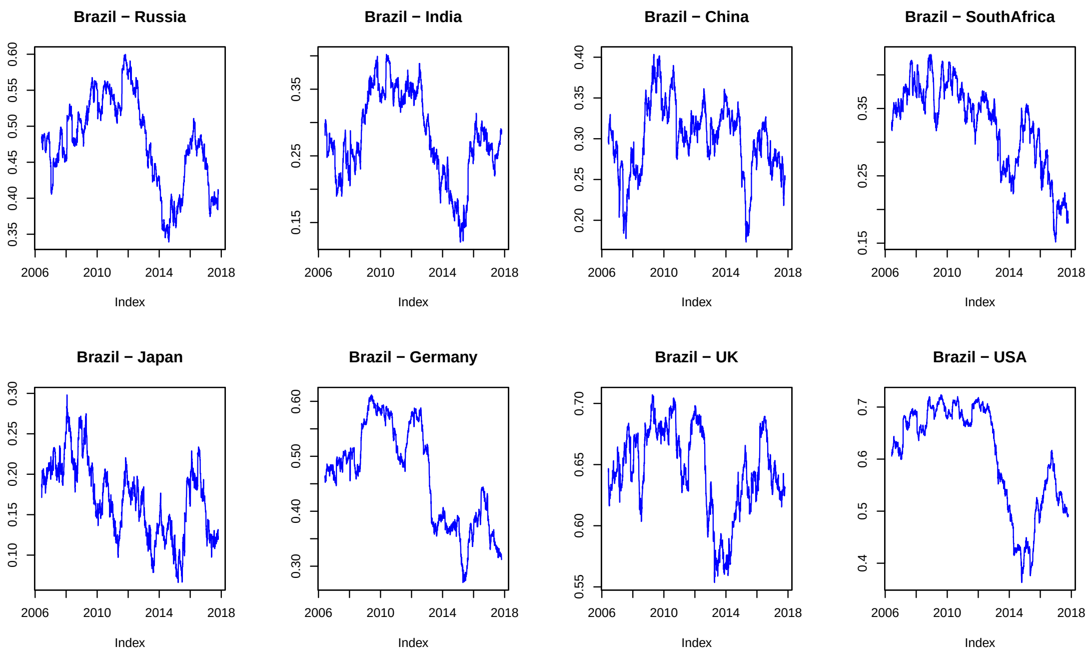


Figure 6.34: ADCC within Materials sector across Brazil and other countries

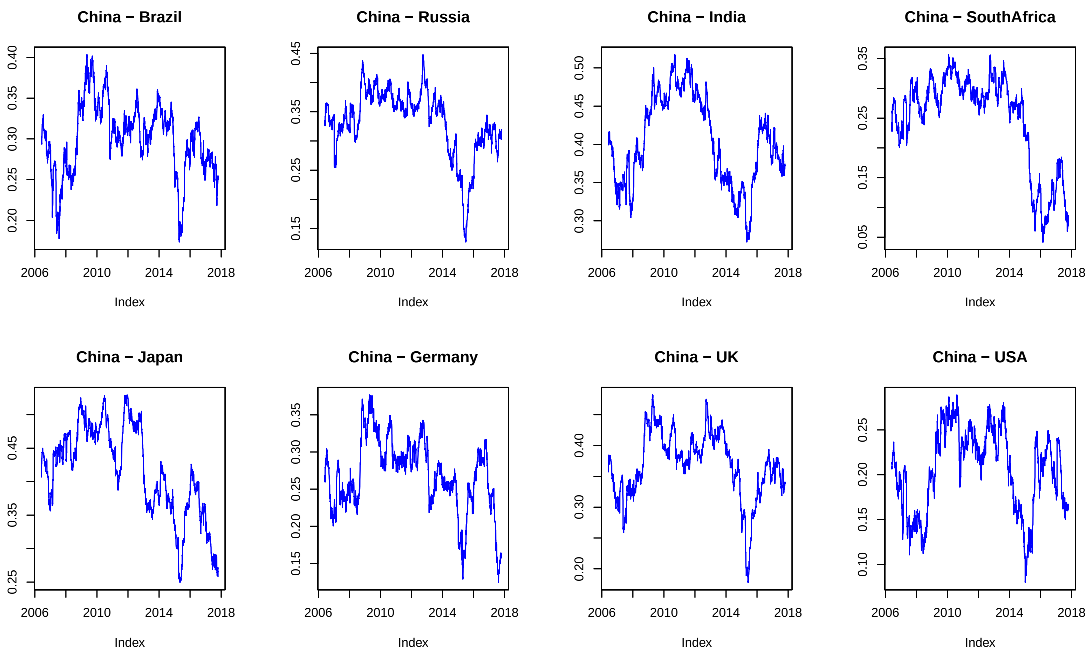


Figure 6.35: ADCC within Materials sector across China and other countries

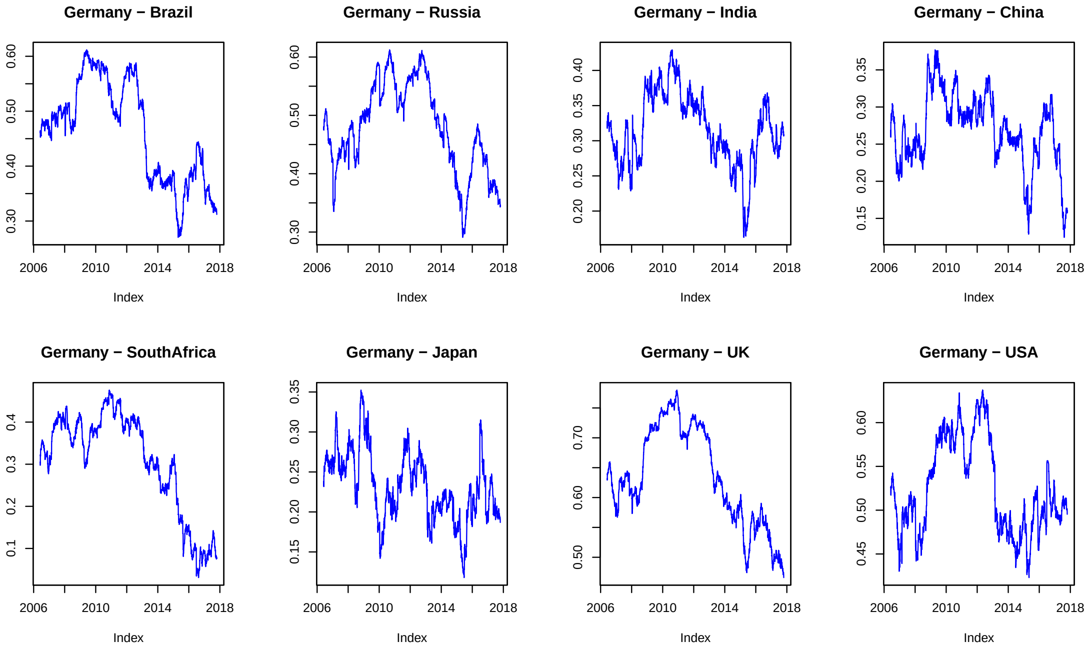


Figure 6.36: ADCC within Materials sector across Germany and other countries

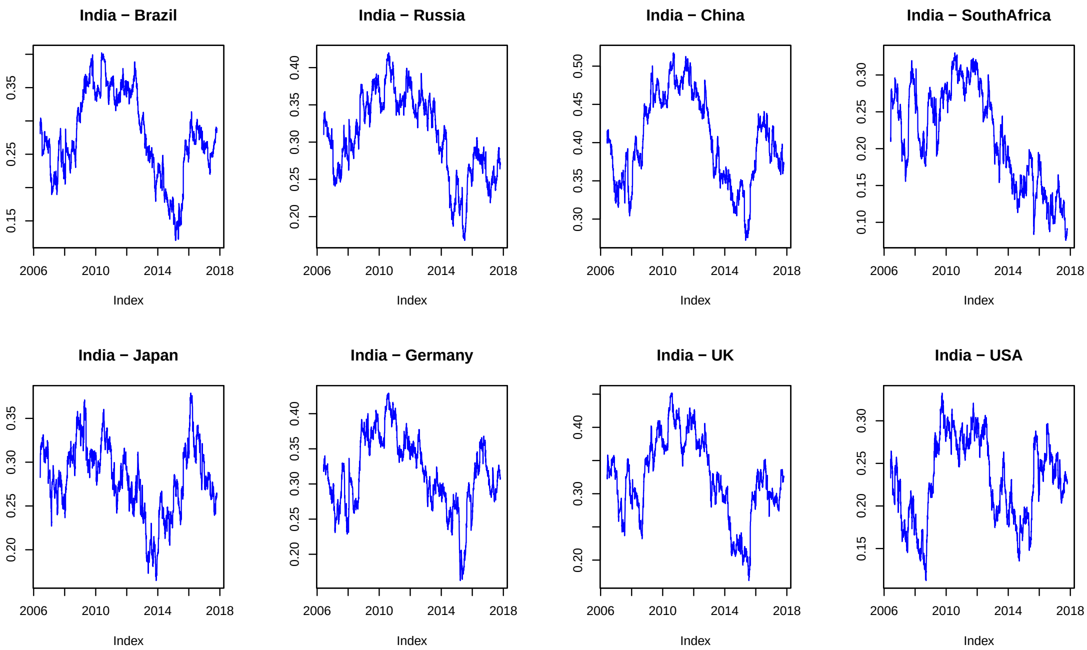


Figure 6.37: ADCC within Materials sector across India and other countries

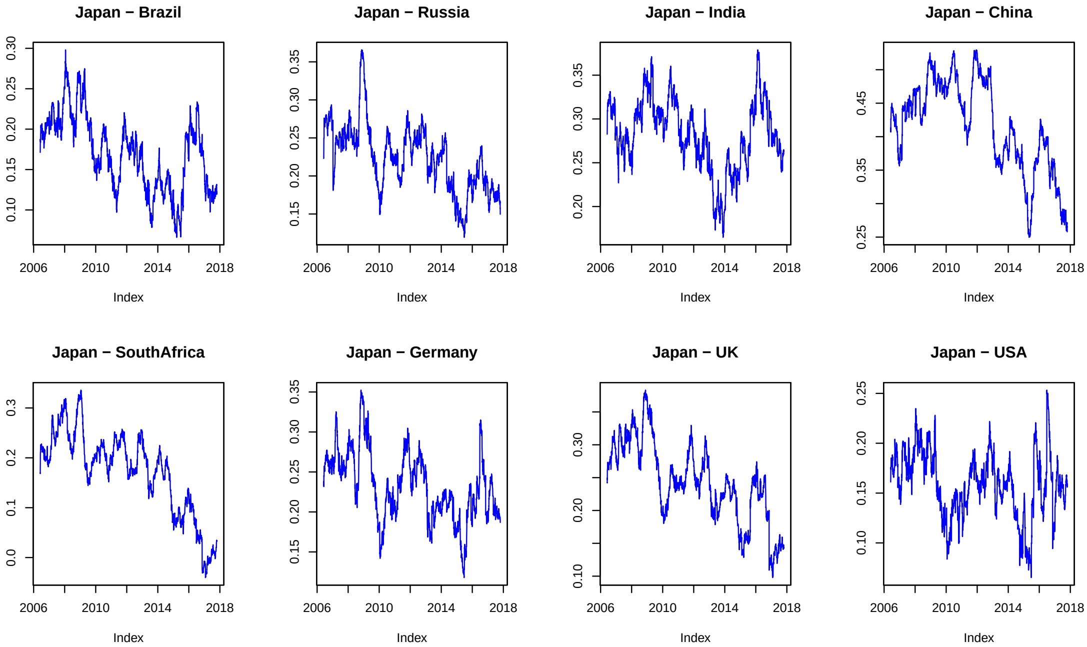


Figure 6.38: ADCC within Materials sector across Japan and other countries

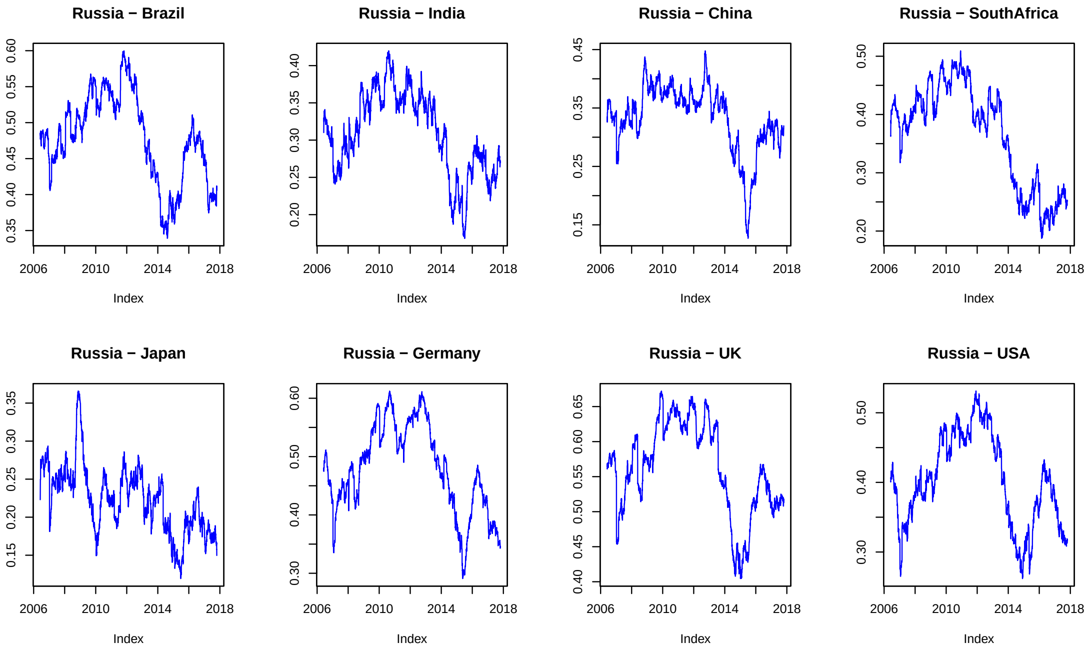


Figure 6.39: ADCC within Materials sector across Russia and other countries

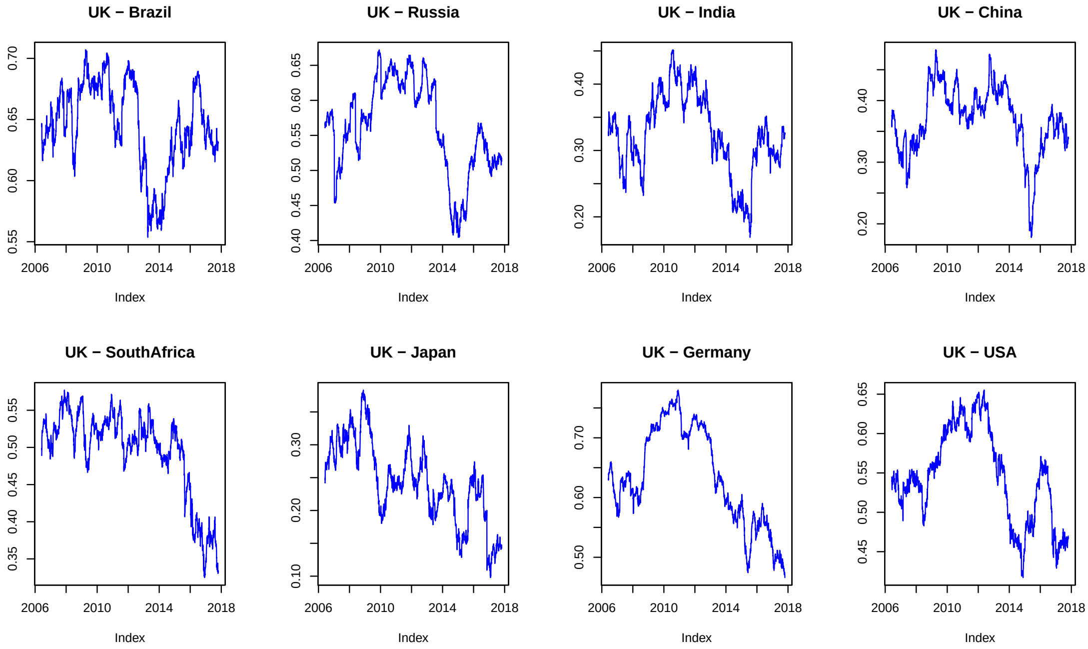


Figure 6.40: ADCC within Materials sector across UK and other countries

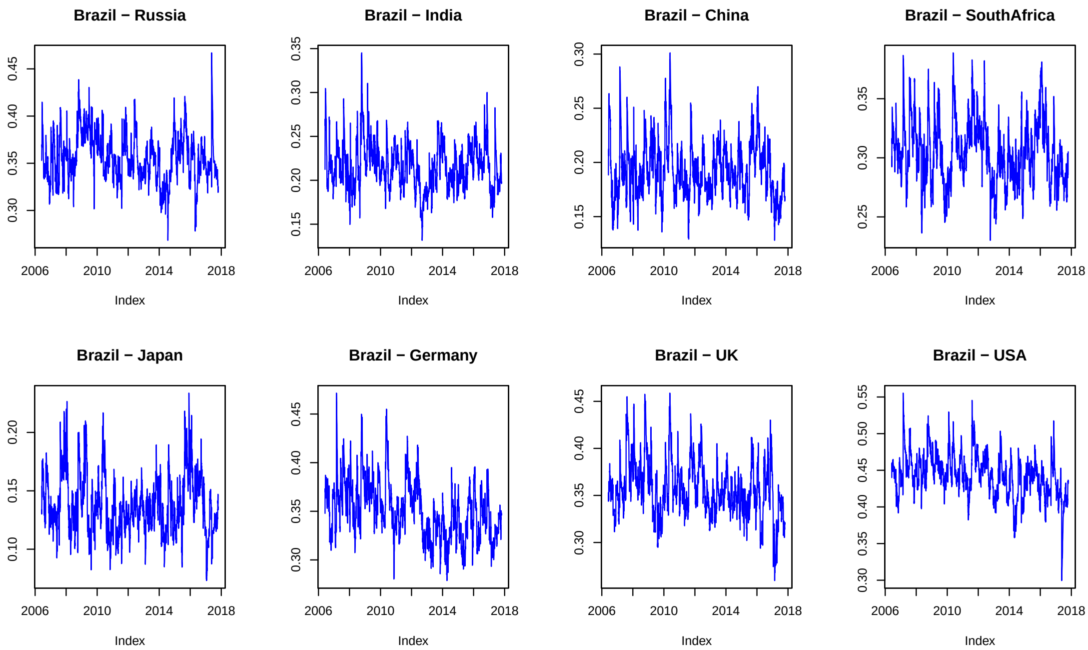


Figure 6.41: ADCC within Consumer-staples sector across Brazil and other countries

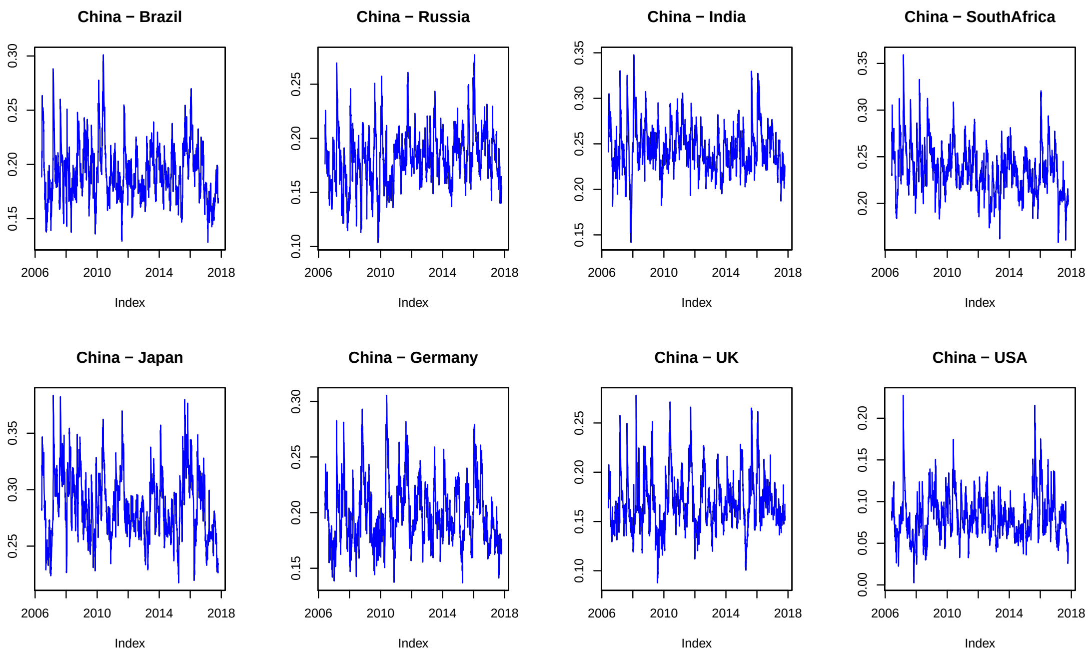


Figure 6.42: ADCC within Consumer-staples sector across China and other countries

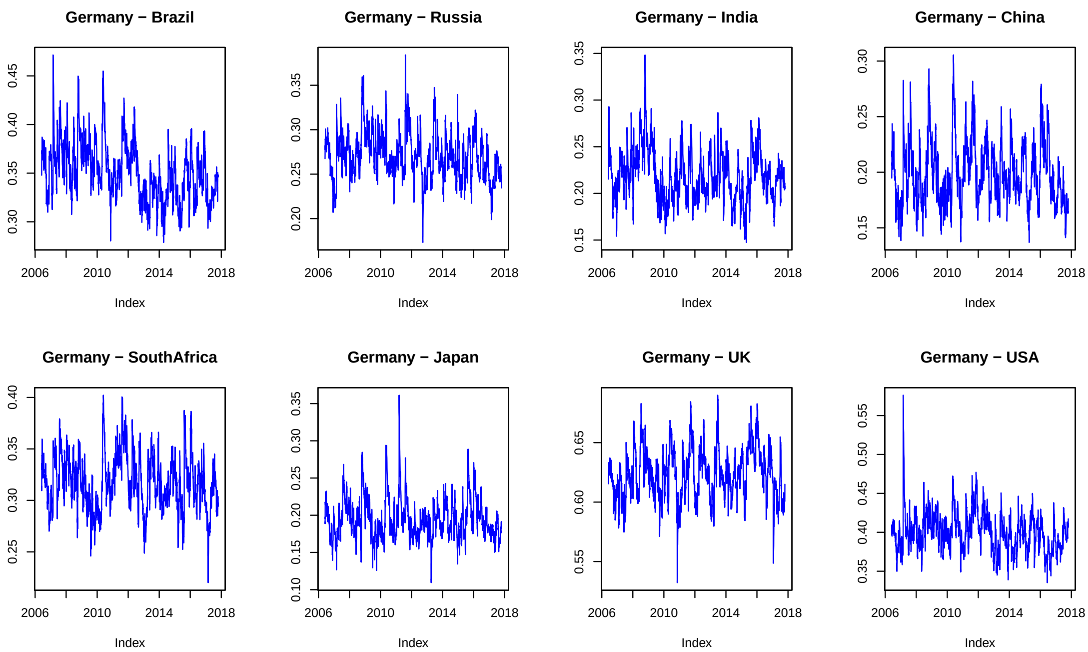


Figure 6.43: ADCC within Consumer-staples sector across Germany and other countries

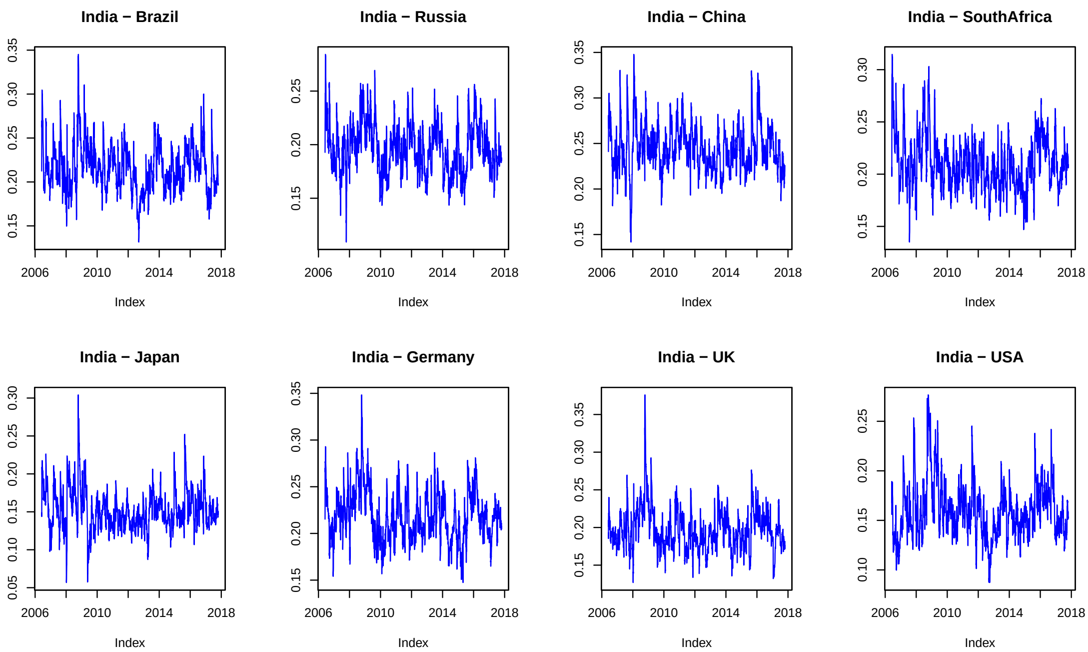


Figure 6.44: ADCC within Consumer-staples sector across India and other countries

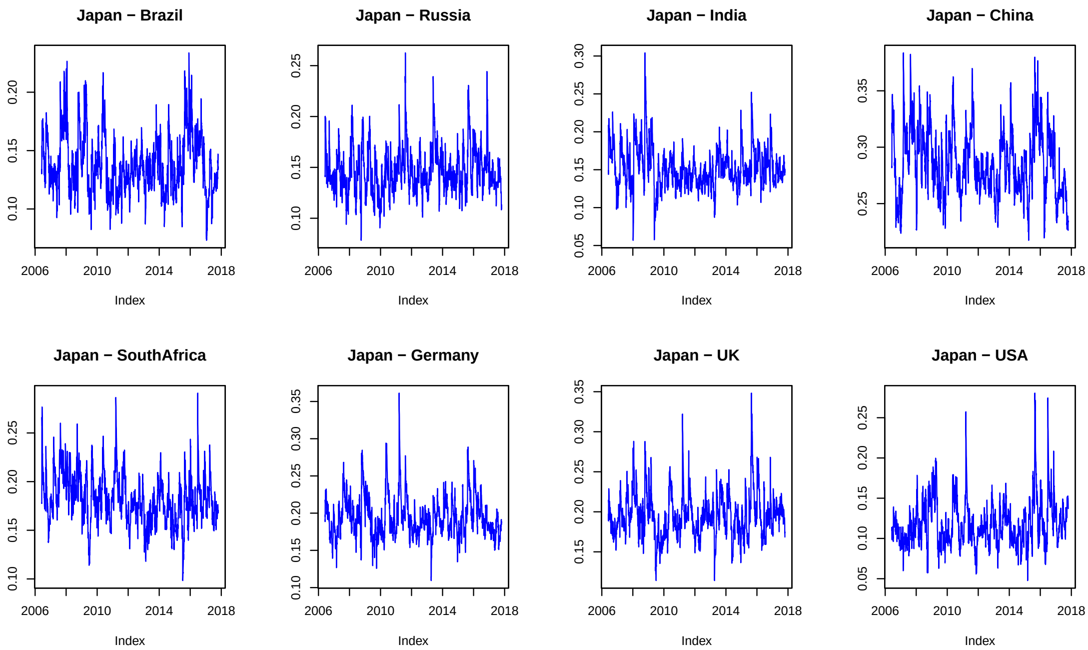


Figure 6.45: ADCC within Consumer-staples sector across Japan and other countries

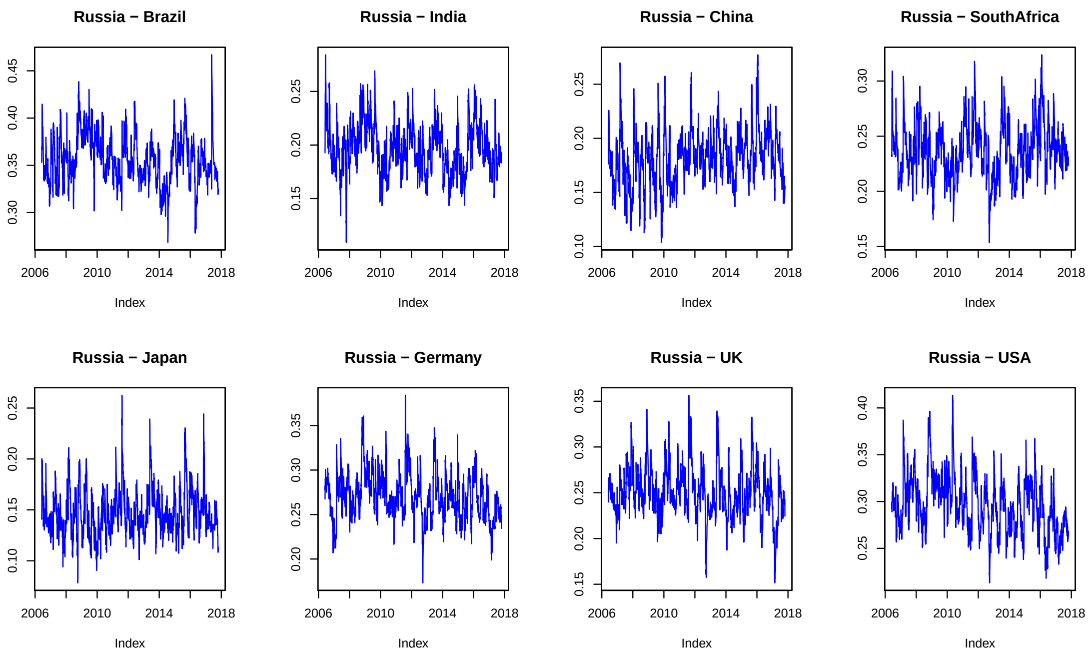


Figure 6.46: ADCC within Consumer-staples sector across Russia and other countries

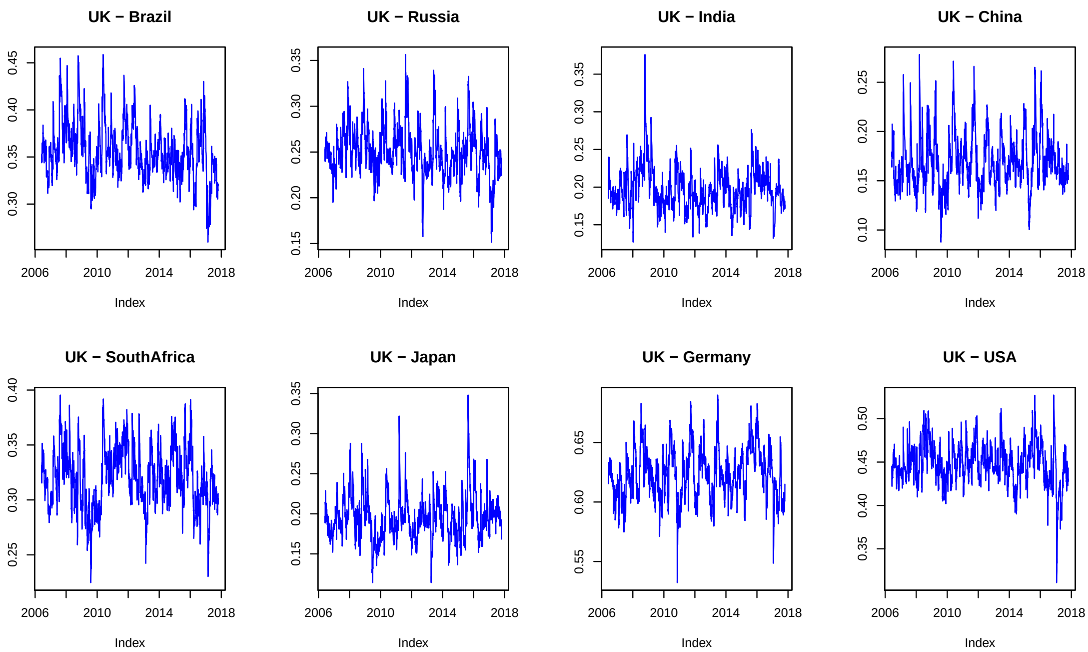


Figure 6.47: ADCC within Consumer-staples sector across UK and other countries

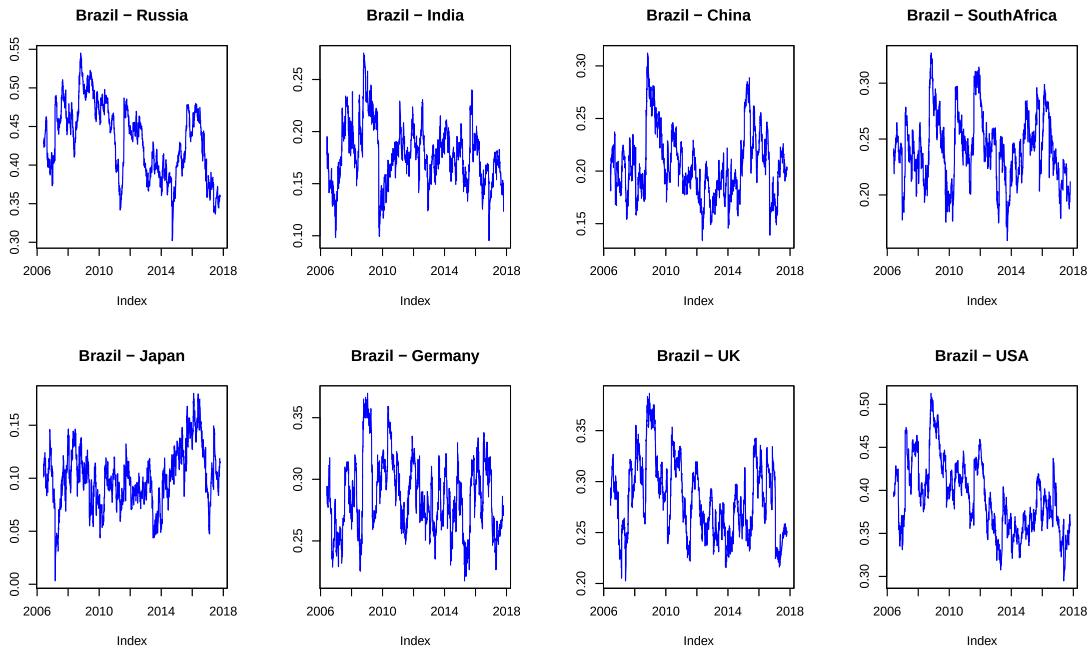


Figure 6.48: ADCC within Telecommunications sector across Brazil and other countries

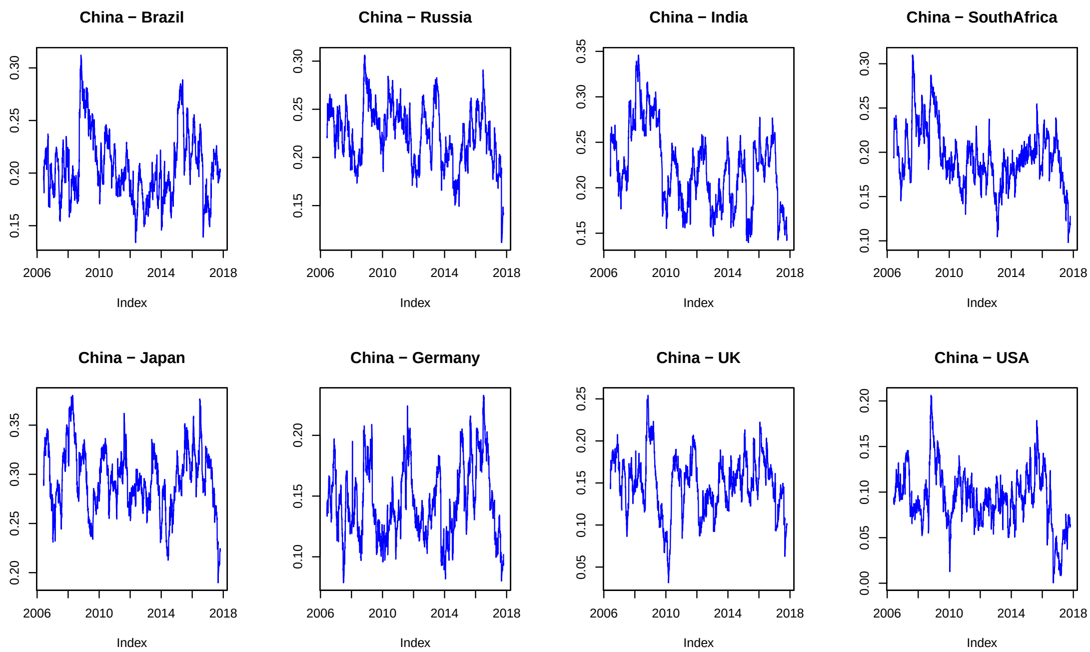


Figure 6.49: ADCC within Telecommunications sector across China and other countries

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