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SCHOOL OF ECONOMICS AND MANAGEMENT

# Risk Spillovers between BRICS Stock Markets, US Stock Market, Gold and Oil

A Portfolio Management Approach

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# Abstract

This study investigates the correlation between the US stock market, oil prices, gold prices and the stock markets of five emerging markets: Brazil, Russia, India, China and South Africa (BRICS), in order to explore the risk spillovers and the financial contagion between the markets. A DCC-GJR-GARCH model is applied to daily data of returns from January 2000 to April 2020 and considers both a full sample analysis along with a three-pronged subsample analysis. Additionally, with the aim to explore international diversification possibilities by investing in these emerging economies, the optimal portfolio choice is analysed. Due to the positive correlations identified between the US and BRICS, risk spillovers between these financial markets are confirmed. In addition, financial contagion effects are detected within the crisis periods. Oil is found to be interdependent with BRICS, with a persistent financial contagion effect appearing in the financial crisis. Further, the result suggests marginal financial contagion between the gold market and BRICS, indicating that gold may be used as a safe-haven asset. The minimum-variance portfolio consists on average mainly of gold (27.1%), the US (27.0%) and China (13.9%), whereas Brazil (2.2%) and oil (2.7%) have the lowest weights in the portfolio. Moreover, the portfolio's risk is compared to the risk of a portfolio excluding BRICS. The result implies an economically significant risk reduction, which particularly smoothens peaks and troughs of the portfolio's variance. On this ground, this study finds indications of diversification gains by including BRICS in a portfolio.

Keywords: BRICS, DCC-GJR-GARCH, risk spillovers, financial contagion, portfolio selection

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# 1. Introduction

Globalisation is the ongoing process of increased economic interdependence of the world. The increase of financial integration over markets enables investments across markets and borders, where emerging markets with high growth rates are naturally attractive to investors (Häusler, 2002). The financial integration causes correlation between markets, affecting the risk when assets are combined in a portfolio. The correlation can cause risk aggregation when changes in risk are spilling over from one market to other markets (Patra & Panda, 2019). Therefore, financial integration affects international investors' portfolio diversification strategies.

This study investigates the correlation between US stock market, gold prices, oil prices and the stock markets of the five most prominent emerging markets: Brazil, Russia, India, China and South Africa, commonly known as BRICS. The purpose is to offer insights regarding risk spillovers and financial contagion between the markets, and based on the markets' relations, investigate an optimal portfolio choice. When simultaneously investing in the eight assets, international diversification opportunities may be gained. Thus, this paper investigates:

- Correlations between BRICS stock markets, US stock market, gold market and oil market over the period 2000 to 2020.
- Correlations between BRICS stock markets, US stock market, gold market and oil market, over three subsamples in order to compare a period of high market turbulence to periods of calmer market conditions.
- Dynamic optimal portfolio choice with a portfolio containing all eight assets.

The analysis is conducted by applying the Dynamic Conditional Correlation (DCC)-GARCH model proposed by Engle (2002) to model the correlations between the markets. Further, the optimal portfolio weights are chosen upon Markowitz theory of minimising portfolio variance (see, e.g. Bodie, Kane & Marcus, 2018). The investigation is performed to create a more in-depth understanding of BRICS stock markets' relations to these global markets.

BRICS are interesting to investigate due to the high growth rate the countries experience in comparison to other large economies. The abbreviation BRIC became widely used after a report by The Goldman Sachs Group, which forecasted the BRIC countries to be larger in monetary terms than the US, Japan, UK, Germany, France and Italy altogether in less than 40 years (Wilson & Purushothaman, 2003). Later, South Africa was added to the group of the fastest-growing emerging economies in the world. The average annual GDP growth rate for BRICS over the period 1997 to 2018 was 2.3% for Brazil, 3.4% for Russia, 6.6% for India, 9.0% for China and 2.6% for South Africa. During the same period, the US had an annual GDP growth rate of 2.4% (The World Bank, 2019). The high growth rates within these emerging markets create a natural attraction for international investors.

Gold and oil prices are chosen to represent the commodity markets, and the US stock market index is chosen to represent financial markets. Both oil and gold are among the most traded, and therefore the most liquid, commodities in the world. Brazil, Russia, India and China together represent 25% of the world's total consumption of oil (US Energy Information Administration, 2020). Further, India, together with China, is the world's largest consumers of gold (World Gold Council, 2020). Gold is occasionally referred to as a safe-haven asset since research has shown that the gold price is relatively stable during turbulent stock market periods (e.g., Baur & Lucey, 2010). Additionally, gold can also be used as a hedge asset due to its periodically negative correlation with stock markets (e.g., Hood & Malik, 2013). Thus, the reasons for using gold and oil in this analysis is (i) these commodities are a frequent target for investors in existing diversification strategies and (ii) the BRICS economies are profoundly intertwined with the prices of these commodities.

Since high growth rates attract international investors, it is plausible that BRICS stock markets are correlated with other financial markets. The US stock market is commonly considered the biggest stock exchange in the world, and it is an important share of many investment portfolios. Therefore, the US stock market index is essential to take into account when analysing the diversification opportunities arising by including BRICS in the portfolio selection.

Several studies exploring portfolio diversification strategies with emerging economies use a broad set of model approaches, where different types of multivariate GARCH models are the most recognised and used. The primary motivation for the use of the DCC-GARCH model is its ability to account for more variables than similar models. The DCC model provides the possibility of investigating all markets simultaneously, instead of, e.g. first modelling the internal correlations between BRICS and then modelling BRICS as a group (using a constructed index) together with other financial and commodity markets as previous literature does (e.g., Patra & Panda, 2019). Possible diversification gains when investing in BRICS are explored by constructing optimal portfolio weights with a no short-selling constraint including all eight assets. Hence, this study adds to the field of portfolio diversification with emerging economies.

This study finds international diversification opportunities when studying the dynamic correlations between BRICS stock markets and the three global markets. Further, due to the positive correlation identified between the US and BRICS, interdependence among these financial markets is confirmed. In addition, financial contagion effects are observed during the global financial crisis of 2008. The BRICS countries' relations to the gold market are found to be country-specific. The results suggest weak correlations between BRICS and gold. However, investments in gold became riskier during the global financial crisis. On the other hand, the findings imply that oil is interdependent with BRICS, with a persistent financial contagion effect appearing during the global financial crisis. Comparing the portfolio including BRICS with a portfolio excluding BRICS confirms that economically meaningful diversification benefits can be achieved by investing in BRICS.

The paper is organised as follows. Section 2 presents a review of previous research concerning spillovers between BRICS and world-leading markets. The method is presented in section 3, and the data is described in section 4. Section 5 presents the results of the DCC-GJR-GARCH analysis, and section 6 provides the portfolio implications. The paper is concluded in section 7 where final remarks are made.

# 2. Literature Review

There is a large amount of research on correlations and spillovers between markets, and specifically between developed markets and emerging markets. A recurrent purpose within the field of finance is to use the estimated correlations to construct optimal portfolios. In this aspect, emerging markets are of interest both because of their high growth rate and their potential to be used for diversifying portfolio risk. The literature is mainly focused on volatility spillovers, and to a lesser extent return spillovers as well as the combination of return spillovers and volatility spillovers (e.g. Gilenko & Fedorova, 2014; Kenourgios, Samitas & Paltalidis, 2011). This line of research is divided into three fields: modelling correlations between the financial markets of emerging economies and other financial markets (Syriopoulo, Makram & Boubaker, 2015; Bhuyan, Robbani, Talukdar & Jain, 2016; Gilenko & Fedorova, 2014; Li & Giles, 2015; Kenourgios, Samitas & Paltalidis, 2011), modelling correlations between emerging financial markets and commodity markets (Adams & Glück, 2015; Basak & Pavlova, 2016; Roy & Roy, 2017; Pandey & Vipul, 2018; Jiang, Fu & Ruan, 2019), and modelling correlations between emerging financial markets and a mix of both financial and commodity markets (Patra & Panda, 2019).

Studies on spillover effects from different financial markets to the BRICS countries have previously been conducted. For instance, Bhuyan et al. (2016) examine the information transmission and the spillover effects between the US stock market and BRICS. They aim to investigate the investment opportunities by allocating funds in BRICS in order to gain international diversification benefits. The article studies both return and volatility spillovers from the US to BRICS as well as among BRICS, using a set of GARCH models. The authors argue that since the BRICS economies have been growing at a high rate, they have experienced a massive inflow of funds from the world, especially from the US, suggesting an increased interdependence. Bhuyan et al. (2016) find the US stock market's mean return and volatility to have a significant spillover effect on the BRICS stock markets.

Similar to Bhuyan et al. (2016), Syriopoulos, Makram and Boubaker (2015) investigate the dynamic risk-return profile of BRICS stock markets by assuming a US-market based portfolio manager. A VAR(1)-GARCH(1,1) model is used to analyse interactions between the US stock market and BRICS stock markets. They find the stocks' past volatility to be essential when determining future volatility. Furthermore, the results are in line with the findings by Bhuyan et al. (2016); there exist spillover effects from the US stock market to BRICS, and the most significant impact is on Brazil and India. Diversification gains can be made by allocating capital in both BRICS and the US, which would improve the overall risk-return performance of the portfolio.

Another article examining the relationship between BRICS stock markets and other financial markets is written by Kenourgios, Samitas and Paltalidis (2011). They study the financial contagion between BRIC, the US and UK equity markets over five financial crises. A multivariate approach is applied, using a regime-switching Gaussian copula model and checking robustness with an Asymmetric Generalised Dynamic Conditional Correlation (AG-DCC) model. Support is found for a financial contagion effect from the crisis country to all other countries in the study in the considered financial crises.

The financialisation of commodities has increased over the last decade, meaning that there has been a massive inflow of institutional funds into the commodity futures markets (Basak & Pavlova, 2016). Thus, analysing the spillovers between financial markets and commodity markets has become a popular topic in the literature. Basak and Pavlova (2016) discover the financialisation to be particularly relevant in high-risk markets. This finding supports the results by Adams and Glück (2015), who detect the transmission of shocks from the stock market to the commodity market to be absent prior to the financial crisis in 2008. In contrast, considerable volatility spillovers between the two markets were observed post-crisis. Thus, market conditions characterised by higher volatility cause larger risk spillovers. However, the co-movements of the stock markets and commodity markets after the financial crisis cannot be explained solely by the distress caused by the crisis. Instead, the new trend of investment in commodities made the bond between stock markets and commodity markets stronger. Thus, Adams and Glück (2015) predict investors to continue their inflow of institutional funds into commodities, increasing the economic interdependence. Therefore, the spillovers between the markets will remain high.

The spillover effects between financial markets and commodity futures markets are also investigated by Jiang, Fu and Ruan (2019). A DCC-GJR-GARCH framework is used to look at the risk spillovers between the BRICS's stock markets and precious metal (gold, silver, palladium and platinum) markets. The authors find the dynamic linkages between the markets to be long-persistent and the returns to have leverage effects. They also discover the optimal weights in the portfolio to be time-dependent and should, therefore, be changed by the portfolio manager over time. Besides, hedging possibilities are found for their diversified portfolio at some points in time, and gold appeared to be the most effective hedging asset towards the risk of BRICS stock markets.

Previous studies find spillovers both between financial markets and between financial markets and commodity markets. As an extension to these articles, Patra and Panda (2019) investigate the opportunity for investors to diversify portfolio risk, regarding BRICS stock markets, US stock market, gold and oil futures markets. A BEKK-GARCH model is used, accompanied by a spillover index for a deeper directional understanding of the return and volatility transmissions. The authors find higher return and volatility spillovers internally, among the BRICS countries, compared to externally, between BRICS (as a group), US stock market, oil and gold prices, suggesting investors being better off diversifying externally. In line with Jiang, Fu and Ruan (2019), gold arises as the preferred asset to include in the portfolio, along with South Africa when considering only the BRICS countries. The study conducted by Pandey and Vipul (2018) confirms Patra and Panda's (2019) findings of the existence of risk spillovers from oil and gold markets to BRICS stock markets. The study also detects leverage effects in the conditional volatilities.

The papers commonly model the correlations between markets. However, there are differences in when and where these correlations appear, considering different moments, markets and time periods. Differences are also found in which model best captures the correlations. Also, the results are heavily dependent on the specific context, i.e. the data of interest. With previous research in mind, this study investigates the contemporaneous conditional correlations between BRICS stock markets, US stock market, gold market and oil market.

# 3. Method

The efficient market hypothesis states that, if a market is efficient, there should not be autocorrelation in the returns of an asset since all historical information is reflected in today's price. However, autocorrelation can exist in volatility. Volatility modelling is, therefore, a key feature when managing financial data. The Autoregressive Conditional Heteroscedasticity (ARCH) model was introduced by Engle (1982), and an extension of this model was made by Bollerslev (1986) called the Generalized ARCH (GARCH) model. The purpose of these models is to estimate the conditional variance. The ARCH and GARCH models are often applied to financial time series due to the models' ability to capture the main characteristics of this type of data. Some of these characteristics are non-stationarity of price series, volatility clustering, fat-tailed distribution, leverage effects and seasonality (Francq & Zakoian, 2019). When the series show temporal or contemporaneous dependencies, a joint analysis of the variables is useful. Therefore, a natural extension to the GARCH model is a Multivariate GARCH (MGARCH) model. The MGARCH specifies both conditional variance and conditional covariance of the series in the estimated covariance matrix (Martin, Hurn & Harris, 2019). Previous literature uses different types of MGARCH models to estimate volatility spillovers, such as versions of the BEKK model developed by Engle and Kroner (1995) or versions of the Dynamic Conditional Correlation (DCC) model proposed by Engle and Sheppard (2001) and Engle (2002). Following Jiang, Fu and Ruan (2019), a DCC-GARCH model is applied, contributing to existing literature regarding dynamic correlations analysed with a DCC-GARCH framework. The method and its application are presented below.

Two technical problems are occurring when estimating an MGARCH model. First, the covariance matrix, as such, needs to be positive definite. Second, when adding more variables to the MGARCH model, the number of unknown parameters grows exponentially (Martin, Hurn & Harris, 2019). Both the BEKK and the DCC framework are designed to address these two issues. This paper uses the DCC framework as it reduces the number of unknown parameters to a greater extent than the BEKK model, thereby allowing for a larger amount of variables. In addition, when variables are added to the model, the volatility forecasts of the assets remain unchanged (Engle, 2002). The DCC framework addresses the time-varying conditional correlation in the time series directly, whereas the BEKK model estimates the time-varying conditional covariances.

The DCC-GARCH procedure is divided into two steps. First, univariate GARCH models are estimated for all variables in order to calculate the standardised residuals. Second, the dynamic conditional correlation coefficients of the model are calculated based on the standardised residuals. With the purpose of computing the input residuals for the univariate GARCH models, mean equations are constructed and determined based on the autocorrelation function (ACF) and partial autocorrelation function (PACF). If no autocorrelation is found, a simple constant-mean-return model of the log returns is used. Further, a GARCH model is applied to capture volatility clustering. The number of lags of the univariate model for each of the residual return series is chosen based upon the Bayesian Information Criterion (BIC). The DCC model assures that the univariate and multivariate volatility forecasts are consistent, hence, defining the appropriate univariate models using BIC is sufficient (Engle, 2002). Since financial data often exhibit leverage effects the Glosten-Jagannathan-Runkle (GJR)-GARCH model is considered as an additional specification to incorporate asymmetric effects[1]. Hence, this model is chosen if the asymmetric parameter is significant. The conditional variance of the GJR-GARCH model with lag order (1,1) is specified as:

$$\sigma_t^2 = \psi + \varphi\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \eta\sigma_{t-1}^2 \tag{1}$$

where, $\varepsilon_{t-1}$ is the residual term in the previous time period, and $\sigma_{t-1}$ is the conditional volatility in the previous time period. $d_{t-1}$ is a dummy that captures the leverage effects; if $\varepsilon_{t-1}$ is less than zero, $d_{t-1}$ is equal to 1. More lags may be included in Equation (1) in case it is proposed by BIC. Further, if $\gamma$ is equal to zero, no leverage effect exists, and the return series is estimated using a standard GARCH model. All estimated parameters of the eight univariate GARCH models are tested for significance using a Wald test. Further, the DCC framework is presented. The conditional covariance matrix, $H_t$, is modelled as:

$$H_t = D_t R_t D_t \tag{2}$$

[1] Additionally, a Threshold ARCH (TARCH) model was considered but proved to produce inferior fits compared to the GJR-GARCH model for all series.

$R_t$ is a $(N \times N)$ matrix of conditional correlations and $D_t$ is a diagonal matrix of conditional standard deviations:

$$D_t = \begin{bmatrix} \sigma_{1,t} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_{N,t} \end{bmatrix} \tag{3}$$

Each element of $D_t$ are estimations from the univariate GARCH-processes specified in Equation (1). The product of these two matrices equals $H_t$, which is the conditional covariance matrix in period t. Further, the conditional correlation matrix, $R_t$, is specified as:

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{4}$$

where $Q_t$ has the GARCH (1,1) specification:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1} \tag{5}$$

$Q_t$ is a function of two scalar parameters $\alpha$ and $\beta$, the lag of $Q_t$, the lag of the standardized residuals, $z_{t-1}$, and the unconditional covariance matrix of the standardized residuals, $\bar{Q}$. The standardized residuals are given by:

$$z_{i,t} = \frac{\varepsilon_{i,t}}{\sigma_{i,t}} \tag{6}$$

and the unconditional covariance matrix of these residuals is defined as:

$$\bar{Q} = \frac{1}{T} \sum_{t=1}^{T} \begin{bmatrix} z_{1,t}^2 & \cdots & z_{1,t} z_{N,t} \\ \vdots & \ddots & \vdots \\ z_{N,t} z_{1,t} & \cdots & z_{N,t}^2 \end{bmatrix} \tag{7}$$

In Equation (5), the parameter $\alpha$ reflects the influence of the lagged standardised residual on the dynamic correlation coefficient, and the parameter $\beta$ represents the dependence on its previous lag. The lag order in the DCC estimation is determined by the BIC. Further, the DCC parameters, $\alpha$ and $\beta$, are tested for significance using a Likelihood Ratio (LR) test, suggested by Martin, Hurn and Harris (2019). In the LR test, the DCC model is the unrestricted model allowing for the influence of the lagged standardised residual and dependence on previous lag. Further, the Constant Conditional Correlation (CCC)-GARCH model (Bollerslev, 1990) is a confined version of the DCC-GARCH model, and in the test, this serves as the restricted model. The difference between the models is that the correlation is allowed to vary over time in the DCC framework. Hence, the CCC model does not allow for the influence of the lagged standardised residual and dependence on previous lag, by setting $\alpha$ and $\beta$ equal to zero. Therefore, the LR test also indicates whether the DCC-GARCH model is appropriate or if a CCC-GARCH model is preferred.

The estimated correlation is used to measure the spillovers and financial contagion between the markets. There is a distinction between the two effects and no consensus in the research of these definitions. In general, financial contagion is mainly present in periods with high financial distress, whereas spillovers are present in both calm and turbulent market conditions (Rigobon, 2019). The DCC-GJR-GARCH model estimates the time-varying conditional correlations, and in this paper, these correlations are used to describe the spillovers between the markets. Hence, spillover effects are defined as movements in markets, both positive and negative, that are transmitted between markets. The financial contagion is measured as the difference between the unconditional correlations of the subsamples, in line with Kolb (ed. 2011), and it is defined as the increase in the unconditional correlation during distressed market conditions.

In line with previous research (e.g. Jiang, Fu & Ruan, 2019; Patra & Panda, 2019; Yaya, Tumala & Udomboso, 2016), the analysis is extended by calculating optimal portfolio weights based on Markowitz portfolio selection theory (Bodie, Kane & Marcus, 2018). Kroner and Ng (1998) use this method and conclude that in order to compute the optimal portfolio weights, the accuracy of the covariance matrix is of great importance. Imperfect correlation between assets allows diversifying risk, implying that the volatility of a portfolio is lower than the volatility of the underlying asset. A negative correlation between assets allows hedging the risk of the underlying asset with the hedge asset. A minimum-variance portfolio subject to a no short-selling constraint is constructed to explore the possible diversification opportunities of investing in BRICS. The optimization problem is the following (see Bodie, Kane & Marcus, 2018, for further information):

$$\min_{\boldsymbol{w}} \sigma_{p,m}^2 = \boldsymbol{w}'\boldsymbol{\Sigma}\boldsymbol{w} \qquad s.t. \tag{8}$$

$$\boldsymbol{w}'\mathbf{1} = 1$$

$$w_i \geq 0$$

where, $\boldsymbol{w} = (w_{US}, w_{Gold}, w_{Oil}, w_B, w_R, w_I, w_C, w_S)'$ which is the weight of each asset. $\boldsymbol{\Sigma}$ is the covariance matrix, and in this case, the matrix obtained from the DCC estimation is used. $\sigma_{p,m}^2$ is the variance of the portfolio. Further, the optimization problem has two constraints. The first constraint ensures the sum of the weights to be equal to one and the second constraint restricts the weights to be less than zero, hence a no short-selling constraint. When imposing an inequality constraint, this problem does not have an analytical solution. Therefore, this optimization problem is solved numerically for each point in time using the respective estimate of conditional correlations among all assets.

A minimum-variance portfolio is also calculated for a portfolio consisting of the US stock market, gold and oil, in order to evaluate if the emerging markets offer diversification gains. The variances of the two portfolios are compared, and the Relative Risk Reduction (RRR) is calculated using the following equation (following Jiang, Fu & Ruan, 2019):

$$RRR_t = \frac{h_t^{P_E} - h_t^{P_I}}{h_t^{P_E}} \tag{9}$$

$h_t^{P_I}$ is the variance of the portfolio including BRICS and $h_t^{P_E}$ is the variance of the portfolio excluding BRICS. Hence, the RRR calculates the percentage of risk reduced by including BRICS in the portfolio in relation to excluding them.

# 4. Data

The data used in this paper is daily observations of gold and crude oil future prices (GC1:com and CL1:com), US stock market index (S&P 500) and the stock markets indices of BRICS (IBOV:IND Ibovespa São Paulo Stock Exchange Index, IMOEX:IND MOEX Russia Index, SENSEX:IND BSE SENSEX Index, SHCOMP:IND Shanghai Stock Exchange Composite Index and JALSH:IND FTSE/JSE South Africa Index). All series are collected from Bloomberg. One may consider using high-frequency data instead of daily data of the return series. In theory, an estimation which uses high-frequency data in a correctly specified model increases its accuracy in terms of forecast errors. However, standard models tend to have poor performance when they are applied to high-frequency data (Andersen, Bollerslev & Lange, 1999). For this type of data, Bollerslev & Wright (2001) show that standard autoregressive models tend to perform better than GARCH models. Additionally, when applying high-frequency data to the model, the portfolio manager is required to change the portfolio weights more often in comparison to when using daily data. Therefore, with the aim to apply a DCC-GJR-GARCH model to the data set and to evaluate the results from a portfolio manager's point of view, daily frequency in the data is used (following e.g., Jiang, Fu & Ruan, 2019; Bhuyan et al., 2016).

The data include eight series of daily closing prices over the period from January 2000 to April 2020. The indices are countrywide and are chosen in accordance with previous literature (Patra & Panda, 2019; Jiang, Fu & Ruan, 2019), which also applies to the gold and crude oil future prices. The chosen period leaves out the Asian financial crisis in 1997, and the Russian financial crisis in 1998, whereas the period includes the global financial crisis. By excluding observations before 2000, the period before the global financial crisis can be used as a benchmark since it isolates an initial period without financial distress. This benchmark allows comparing the spillovers before the crisis to the spillovers during and after the crisis. Therefore, this time period allows capturing dynamic correlations between the markets during both turbulent and calm periods. Furthermore, the length of the series also allows for division into subsamples, enabling a deeper understanding of portfolio selection in different market conditions.

The analysis is conducted for the full sample length, but also for three subsamples (in line with Patra & Panda, 2019). By construction, the parameters estimated in the DCC model are constant. However, when the sample is divided, the parameters can differ between the subsamples. Calculating the dynamic conditional correlations between the markets and the optimal portfolio weights over a shorter period creates a more in-depth understanding of how the correlation and the diversification opportunities change in distressed market periods. Therefore, the sample is divided into three subsamples: (i) January 2000 to December 2007 covering the pre-crisis period, (ii) December 2007 to June 2009 covering the global financial crisis (The National Bureau of Economic Research, 2012) and (iii) July 2009 to April 2020 covering the post-crisis period. Due to financial contagion, the correlation between financial markets is expected to be higher during the crisis period compared to the periods before and after.

Using the US stock market timetable, the series are scanned to find missing values and are completed using piecewise constant interpolation[2]. Further, daily log returns are employed and calculated as $r_t = \ln\left({p_t}/{p_{t-1}}\right)$, resulting in the total number of observations to be 5096 for each series. The return series show typical financial data characteristics, displaying mean reversion and volatility clustering (see Appendix A Figure 1). In Appendix Table 1, the descriptive statistics of the return series are presented. The average daily return is positive for all return series, where the Russian stock market has the highest mean and oil the lowest. Meanwhile, the return of the oil future market has the highest unconditional volatility, measured as standard deviation, and the return of the gold future market has the lowest volatility among the eight variables. Within BRICS, the Russian stock market is the most volatile and the South African market is the least volatile. Low negative skewness can be observed for all return series. Additionally, excess kurtosis is found for all series but is exceptionally large for the US stock market, oil futures market, the Russian stock market and the Indian stock market, indicating non-normality in the return series. This indication is confirmed using the Jarque-Bera test, where the null hypothesis of a normal distribution is rejected for all return series (see Appendix A Table 2). Even though the Jarque-Bera test signifies deviations from normality, estimating a DCC model under different distributional assumptions is outside the scope of this thesis.

[2] The number of missing values in relation to the available data is negligible. Therefore, the results should not be affected by the interpolation.

The augmented Dickey-Fuller test shows that all return series are stationary at a 5% significance level (see Appendix A Table 2). In both the residual return series and the squared residual return series autocorrelation is found for some of the variables using the Ljung-Box test. The gold return series is the only series where the Ljung-Box test statistic cannot reject the null hypothesis of independent distribution for all tested lags at a 5% significance level. However, when looking at the ACF and the PACF, no significant lag is visible for any of the return series (see Appendix A Figure 2 and 3). This result motivates the use of a constant-mean-return model as a mean equation. Further, the null hypothesis of the Ljung-Box test is rejected for the squared residual return series of all variables at all lags, revealing strong dependency in the distribution of the squared returns. Engle's test for ARCH effect, with the null hypothesis of no ARCH effects, is rejected for all series at a 5% significance level, indicating that GARCH specifications are appropriate.

In Appendix Table 3, the correlations of the variables are presented. The correlation between the US stock market and gold is negative but close to zero, which reinforces the theory of gold being a safe-haven asset and a hedge asset for the US stock market in the unconditional case. The US stock market has the highest correlation with the Brazilian stock market of 0.62. Further, gold and oil have a relatively low correlation with the BRICS countries, with values ranging from 0.03 to 0.14 for gold and from 0.09 to 0.25 for oil. Correlations within BRICS vary, where the highest correlation (0.49) is found between Russia and South Africa, and the lowest (0.10) is found between Russia and China. Based on the relatively low correlation between the series, possible diversification opportunities are expected in line with the theory of portfolio selection.

# 5. Results and Analysis

## 5.1 Full sample results

A constant-mean-return model is chosen based on the non-significance of lags in the ACF and the PACF of the return series. After demeaning the return series, univariate GJR-GARCH models are estimated for each return series since the leverage effect is shown to be significant. As mentioned in section 3, the lag order is chosen to minimise the BIC.

In Appendix B Table 1, the results of the univariate GJR-GARCH models are presented. The Indian stock returns and the Chinese stock returns are estimated using a lag order of (1,1). The US stock returns, the returns of the oil prices and the Brazilian stock returns are estimated with two ARCH lags and one GARCH lag, (2,1). In contrast, the returns of the gold prices, the Russian stock returns and the South African stock returns are estimated with two lags on both the ARCH and GARCH effects, (2,2). All parameters, except two, are significant at a 5% significance level according to the Wald test. The coefficients for the leverage effect are positive and significant for all return series, except for gold where the coefficient is significant but negative. The coefficient's significance indicates that the market reacts differently depending on if the shock is positive or negative. Further, a positive coefficient implies that if the shock is negative, the conditional volatility increases, and vice versa, a negative coefficient implies that a negative shock decreases the conditional volatility. When looking at the joint value of the parameters, the values of oil and China are close to one, indicating non-stationarity in the volatilities. These high values may suggest the series to have unit roots or to experience structural breaks. This result further motivates dividing the sample into subsamples to allow the parameters to change between periods.

The DCC for the full sample is estimated with a lag order of (1,1) as suggested by the BIC, and the result is presented in Appendix Table 1. The coefficients, $\alpha$ and $\beta$, are 0.006 and 0.990, respectively. The values of coefficients imply a low dependence on the lagged standardised residual and a high dependence on the conditional correlation of the previous period. Further, the high value of the parameter $\beta$ indicates strong persistence in the conditional correlations.

Similar to two of the univariate GARCH models, the joint value of the parameters is close to one, indicating non-stationarity in the correlation. Again, this motivates the division into subsamples. A joint test of constant correlation using the LR test is performed, which produces a test statistic of 806.5 with a p-value of 0. Thus, the null hypothesis, the restricted model being in favour of the unrestricted model, is rejected. The result indicates the unconstrained model to fit the data more accurately, and constant correlation is rejected. Therefore, the parameters in the DCC model are concluded to be significantly different from zero.

The time-varying conditional correlations of the market pairs are presented in Appendix B Figure 1. In general, the correlations of all pairs display considerable fluctuations over the full sample period. These fluctuations give implications for a dynamic portfolio choice. Overall, the correlations between the US, gold and oil, and each of the BRICS countries vary in level and display country-specific ranges. However, the patterns of the series exhibit the influence of shocks in the US stock market, gold and oil. For instance, all correlation pairs of BRICS and gold exhibit a sharp decrease at the end of 2011, and all pairs of BRICS and oil show a decline in the correlations at the end of 2014 followed by a peak in 2016. Several of the pairs show an increase in the correlation connected to the global financial crisis. Consequently, increases in the correlations make diversification among the assets more difficult. Diversification opportunities for different periods are further explored in the subsample analysis.

The correlation between Brazil and the US is ranging between 0.3 and 0.7, remaining positive over the whole period. This is not the case for the correlation between Brazil and gold, as well as Brazil and oil. The correlation between Brazil and gold ranges between -0.1 and 0.4, and the correlation between Brazil and oil fluctuates around zero until 2005. The correlation is thereafter positive, with a peak of almost 0.5. A similar pattern is found for Russia, where the dynamic correlation with the US is positive over the whole period. However, Russia's relationship to gold fluctuates around zero, and the correlation between Russia and oil displays some mean reversion to zero until the second half of 2005 and thereafter becomes positive. India has a positive correlation with the US throughout the period. However, India's correlation with both gold and oil fluctuates around zero, where the correlation with gold is more negative than positive and vice versa for oil. At the beginning of the sample period, the correlation between China and the US is positive, and in 2001 it moves closer to zero. After 2001 the correlation fluctuates around zero throughout the period with a slightly positive trend. This mean-reverting pattern to zero is repeated in the correlation between China and gold as well as China and oil. However, there is a sharp decrease in the correlations between China and the two commodities in late 2014. Furthermore, the correlation between South Africa and the US is positive throughout the period, whereas its correlation with gold fluctuates around zero. The same is observed for the correlation between South Africa and oil. However, the average is larger than zero.

The dynamic conditional correlations between the US and the two commodities are presented in Appendix B Figure 2. The relationship between the US and gold is predominantly negative, contrasting the unconditional correlation between these variables. Hence, economically meaningful deviations from zero are observed in different parts of the sample. The relationship between the US and oil is fluctuating around zero until June 2008 and is thereafter positive. Lastly, the relation between gold and oil is mainly positive. In addition, higher variability in the conditional correlation can be observed for all pairs from the beginning of the global financial crisis in December 2007 until late 2013.

To summarise, the correlation for the majority of the pairs are positive in most of the sample period, which supports previous literature regarding the existence of risk spillovers between these markets. Further, some of the pairs have a close to zero correlation, implying that one of the assets could be used as a safe-haven asset towards the other market. Gold is the asset with the strongest negative correlation with the stock markets. Therefore, gold may be used as a hedge in the portfolio selection, implying diversification gains. The relations between BRICS and the financial and commodity markets prove to be country-specific. In general, positive correlations between BRICS and the US are observed, close to zero relations are found between BRICS and gold, and weakly positive correlations are observed between BRICS and oil. The dynamic conditional correlation between the assets will be used to analyse the portfolio selection in section 6.

## 5.2 Subsample results

The subsample analysis is conducted in line with the procedure for the full sample, and the results are presented in Appendix B Table 2-4. The parameters of all the univariate GARCH models and the DCC models are significant. The majority of the joint univariate GARCH parameter values, as well as the sum of the DCC parameters, have decreased in the subsamples in comparison to the full sample. The reductions indicate structural breaks in the data, which justify the subsample analysis. Further, the $\beta$ parameters of the DCC models in the subsamples exhibit high values in comparison to the $\alpha$ values, implying a high dependence on previous conditional correlation.

The first period, ranging from 2000 to 2007, reflects a calmer period before the global financial crisis, and the dynamic correlations are presented in Appendix B Figure 3. A remarking high correlation in the first period is found between Brazil and the US. It fluctuates around 0.4 and rapidly increases in the middle of 2006 to around 0.6. Further, the relations between BRICS and the US are positive for all countries except for China, where its correlation with the US varies around zero. The BRICS economies' correlations to gold are mainly alternating around zero until late 2003, with a substantial decrease for all countries in late 2001. After 2003, the correlations exhibit a slightly increasing trend throughout the sample. Similar to the relation to gold, the conditional correlations between BRICS and oil are fluctuating around zero with country-specific deviations throughout the period. Over the period 2000 to 2007, the US has a negative correlation with both gold and oil. Further, gold and oil have a positive time-varying correlation (see Appendix B Figure 4).

The dynamic conditional correlations for the period isolating the global financial crisis, December 2007 to June 2009, are presented in Appendix B Figure 5. The highest correlation can again be found between Brazil and the US. Similar to the results in the previous period, the correlations between BRICS and US are positive for all countries except for China, where the correlation fluctuates around zero. Brazil, Russia and South Africa display clear positive relationships with gold, whereas India and China on average display mean-reverting relations to gold, fluctuating around zero throughout the sample. In contrast to the calmer period, BRICS and oil have positive correlations over the global financial crisis. During this period, the US has a negative correlation with gold and a positive correlation with oil. Gold and oil have a positive correlation throughout the period (see Appendix B Figure 6). In Appendix B Table 5, the difference between the unconditional correlations of subsample one and two are presented. As described in section 3, these differences measure the financial contagion in markets with distress. The highest financial contagion is observed between oil and Brazil, with an increase in unconditional correlation of 0.37. The financial contagion is high between all BRICS and oil, with the lowest increase of 0.11. Further, the differences in unconditional correlations between the US and BRICS is country-specific, with a relatively low contagion effect for China and South Africa and a relatively high contagion effect for Brazil, Russia and India. The financial contagion between gold and BRICS is generally low, and negative for China and India.

Additionally, the contagion between the US and oil is strongly positive, and the contagion between the US and gold is negative. This result supports the theory of gold being a hedge asset. The financial contagion between oil and gold is relatively high.

Lastly, the period 2009 to 2020 is investigated, and the time-varying conditional correlations are presented in Appendix B Figure 7. The correlations between BRICS and the US are positive, and the values are on average higher than during the global financial crisis. In the cases of Brazil, Russia and South Africa, patterns of persistent financial contagion are observed, showing high correlations after the crisis which decline over time. The relation between BRICS and gold is mainly positive, with a higher correlation at the beginning of the sample, which is gradually decreasing towards zero. Similar to the period of the global financial crisis, the correlations between BRICS and oil are positive. Also, high correlations between BRICS and oil are observed at the beginning of the period and are gradually decreasing over the period. These high correlations indicate that there is persistent financial contagion between the markets. Further, the US and gold are fluctuating around zero, whereas the US and oil have a positive dependency (see Appendix Figure 8). The latter is also the case for the two commodities. Further, positive spikes towards the end of the sample are observed for all series (see Appendix B Figure 7-8), which coincide with the beginning of the corona pandemic. Further, the persistence in the financial contagion during the global financial crisis can be measured by comparing the unconditional correlation of subsample one, acting as a benchmark, with the unconditional correlation of subsample three (see Appendix B Table 6). The co-movements of the US stock market and BRICS have increased for all countries after the global financial crisis, except for Brazil. Further, there are only marginal differences in the correlation between gold and BRICS. Lastly, the co-movements between oil and BRICS have increased after the crisis, where the correlation to Brazil has the largest increase of 0.32. Thus, the persistence in the risk spillovers is found to be highest between the financial markets, as well as between BRICS and oil.

The results of the DCC-GJR-GARCH model based on the subsamples imply changes in the pattern of the conditional correlations during and after the global financial crisis. These changes are confirmed when calculating the differences in the unconditional correlations between the subsamples, indicating financial contagion. Since the unconditional correlation between BRICS and the US as well as oil remained high after the crisis, the contagion is persistent.

## 5.3 Comparison of results

In Figure 5.3.1, the conditional correlations obtained from the three subsamples are plotted together with the full sample estimation as well as with vertical lines separating the different periods. The grey line in Figure 5.3.1 represents the stacked subsamples and the black line represents the full sample. In the stacked sample the correlation between Brazil and the US displays a peak, building up before the crisis and falling afterwards, ending up reverting to a lower level from 2015 and onward compared to the beginning of the stacked sample period. The stacked samples of the correlations between the US and Russia, India and South Africa display relatively low correlations in the first period. These correlations increase during and after the global financial crisis, alternating around higher levels of correlation than before the crisis. However, the level of correlations differs across countries, where India has the lowest level of correlation with the US among these three countries and South Africa the highest. The correlation between China and the US of the stacked subsample is seemingly low, with an increased fluctuation during the crisis. Besides, China displays an increased correlation with the US after the global financial crisis. Before the global financial crisis, the full sample correlations and the stacked subsample correlations are almost identical in the relation between BRICS and the US. During the global financial crisis, the stacked sample exhibits larger fluctuations for all countries. In the third period, the level of the stacked sample is higher in comparison to the full sample for the correlation between the US and Russia, China, India and South Africa, whereas it is lower for the correlation between the US and Brazil.

For the stacked sample, the correlations between gold and Brazil, Russia and South Africa have a positive mean which is close to zero throughout the sample. In contrast, India and China display negative but close to zero correlation with gold. The correlations between gold and BRICS display variable and mean-reverting patterns during the global financial crisis and a more stable period before and after the crisis. The correlations between gold and Brazil, Russia, India and South Africa display downward trends for the full sample during the global financial crisis, whereas for the stacked subsamples there is no clear trend, only large fluctuations around zero. China's correlation with gold displays reversion to zero for both series, where greater variability is observed for the stacked sample.

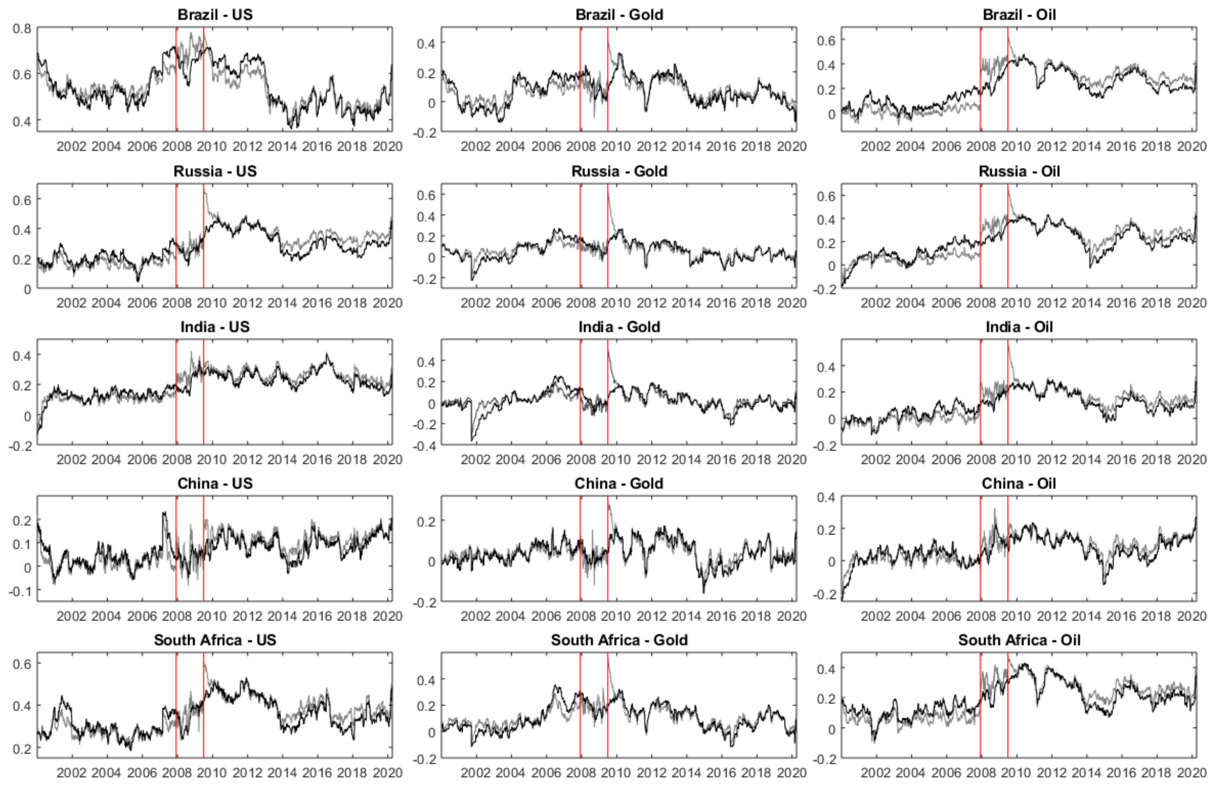


*Figure 5.3.1. Comparison between the full sample estimation and the subsample estimation. Note: The black line represents the series of the full sample estimation, and the grey line represents the series of the stacked subsample estimations.*

The correlations between BRICS and oil in the stacked sample exhibit structural breaks in the cut-off between period one and two. After the global financial crisis, BRICS correlations with oil display patterns of peaks and troughs and are fluctuating around a higher level than before the crisis. The correlations between BRICS and oil also show greater variability during the global financial crisis for the stacked sample than for the full sample. Additionally, the correlations of the stacked sample are on a lower level in the first period and on a higher level during and after the global financial crisis in comparison to the full sample series.

The observations suggest the correlations being smoothened in the full sample analysis, whereas the correlations in the subsample analysis may fit the data better in the specified period. The reason may be due to the fact that the DCC parameters are constant in the full sample. In the subsample analysis, the DCC parameters are allowed to differ between the periods. Hence, the results suggest an increase in the fluctuations of the correlations for the three subsamples, particularly during the global financial crisis. Therefore, indicating the parameters to be time-varying over periods ranging from calmer market conditions to markets with high distress (see Appendix B Table 2-4).

# 6. Portfolio Implications

## 6.1 Optimal portfolio weights of the full sample

Due to the result of less than perfectly correlated assets over the full sample period, a portfolio containing the eight assets may offer some degree of diversification gain. Using the Markowitz theory of portfolio selection and imposing a no short-selling constraint, the optimal risk minimising portfolio weights are obtained. The result is presented for each of the assets in Figure 6.1.1.

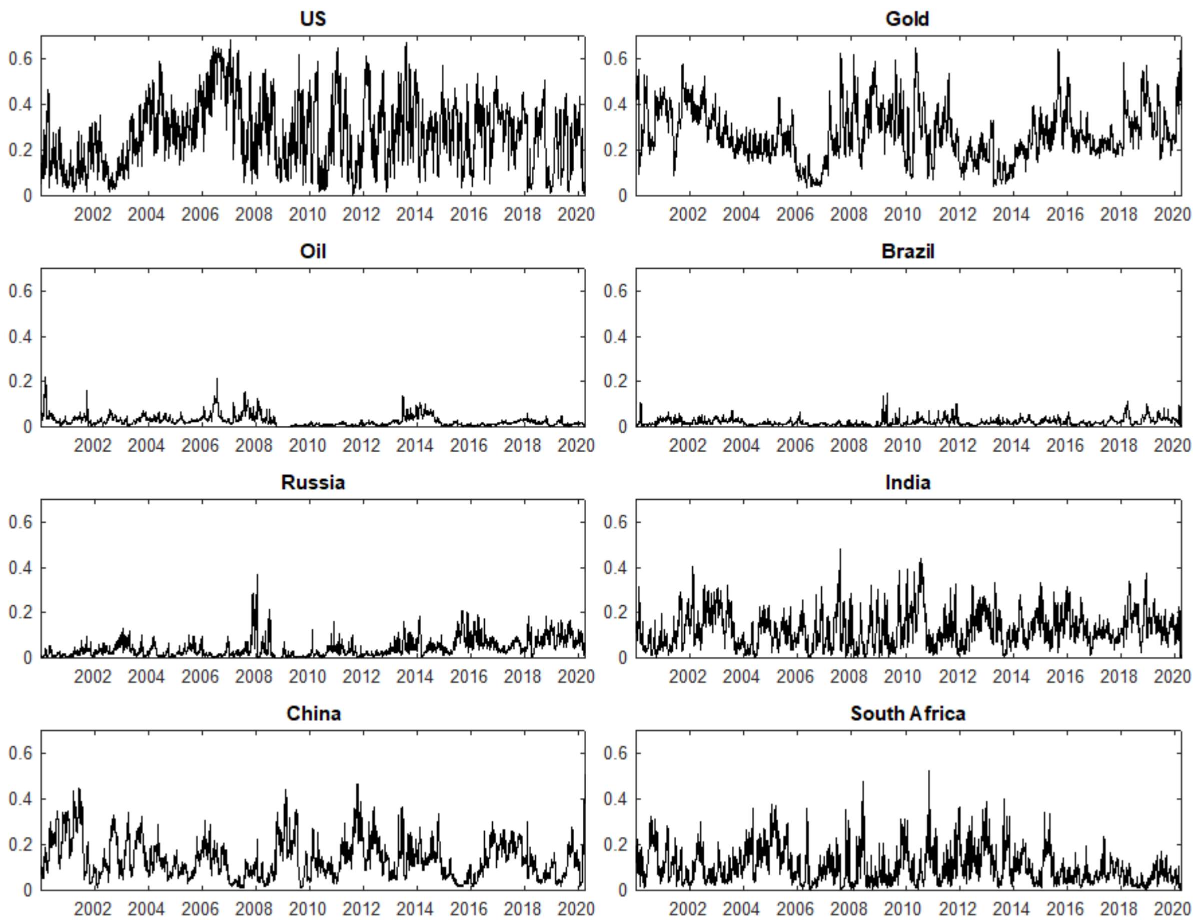


*Figure 6.1.1. Optimal weights for the full sample*

Figure 6.1.1 illustrates the US stock market and gold being the assets with the highest weight in the portfolio. The average weight of the entire period for the US stock market and gold is

27.0% and 27.1% respectively (see Appendix C Table 1). Hence, on average, the highest portfolio weight over the full sample period is suggested to be invested in the gold market. The weight of the US stock market fluctuates to a greater extent than the portfolio weight of gold. This result is confirmed when calculating the variance of the weights over the full sample period (see Appendix C Table 2), where the weight of the US stock market has a substantially higher variance than gold and the other assets. The weight of oil is relatively low over the full period, with an average weight of 2.7%. Also, the variance of the weight of oil is low with the highest fluctuations around 2000 and in the middle of 2006.

When looking at the weights of the BRICS countries' stock markets, the weight of both Brazil and Russia are relatively low with average weights of 2.2% and 4.3%, respectively. Peaks above 10% are found for Brazil at the beginning of the sample and the end of the global financial crisis. A peak of almost 40% is found during the global financial crisis for the weights of the Russian stock market. Low variance is also characteristics of these two weights. The weights of India, China and South Africa fluctuate to a greater extent than the weights of the two previous countries. Nevertheless, the weights are higher on average, 12.4%, 13.9% and 10.4%, respectively. Since the conditional correlation is time-varying and volatile, this creates an incentive for the portfolio manager to change its portfolio weights with the market conditions, which is confirmed by the results from the full sample portfolio selection analysis.

## 6.2 Optimal portfolio weights of the subsamples

The optimal portfolio weights are obtained in the same way as for the full sample, and the results for all subsamples are presented in Appendix C Figure 1-3. In addition, the mean weights for the subsamples are presented in Table 6.2.1.

Table 6.2.1. Mean weights for the subsamples

| | US | Gold | Oil | Brazil | Russia | China | India | South Africa |
|---|---|---|---|---|---|---|---|---|
| Subsample 1 | 28.57% | 26.43% | 4.55% | 1.62% | 2.61% | 15.19% | 9.99% | 11.06% |
| Subsample 2 | 28.02% | 38.27% | 0.83% | 0.61% | 3.21% | 16.77% | 5.63% | 6.66% |
| Subsample 3 | 26.12% | 25.57% | 1.64% | 2.88% | 5.36% | 12.42% | 16.22% | 9.79% |

Consistent with the full sample results, the subsample results suggest investing the highest weights in the US and gold. Specifically, investing in the US stock market during the first and second period is particularly beneficial. Additionally, a high weight on gold is beneficial in the second period, over the global financial crisis. Since the result suggests investing in gold in order to minimise portfolio risk in turbulent periods, it is in line with the theory of gold being a safe-haven asset. The weight in oil is relatively low for all periods, being the highest (approximately 4.5%) in the first period. When looking at the plot of the returns of oil (see Appendix A Figure 1), the first period is relatively stable with only small volatility clusters, and for the two most recent periods the return series has higher volatility and several high volatility clusters. This pattern of the residual returns may be one reason for investing in oil in the first period rather than in the two most recent periods.

When considering investing in BRICS, the average weights change profoundly over the three periods. Brazil is weighted the lowest during all three periods and is particularly low during the global financial crisis. The reason for the low weights may be explained by its high correlation with the US. For diversification purposes, it would not be optimal to invest a large amount in both the US and Brazil due to the assets' correlation. When looking at the return plots (see Appendix A Figure 1), Brazil is experiencing higher volatility than the US, which may be a reason why a higher weight is chosen for the US. The average optimal weight of Russia is increasing during all three periods, and in the last period, the optimal weight is over 5%. The results of the optimal portfolio weights suggest that India should be weighted higher in the non-crisis periods, with an average weight of 10.0% and 16.2% respectively. In the period after the global financial crisis, the results imply that India is the preferred investment destination among BRICS. On the contrary, China generates high weights over all three periods which peak during the crisis periods. Presented in Table 6.2.1, China appeared to be the preferred investment destination among BRICS in the first two periods. However, after the global financial crisis, China emerged as the second most preferred investment alternative with an average weight of 12.4%. Lastly, the average weights of South Africa over the three time periods are ranging from 6.7% to 11.1%. The highest weight is obtained in the first period and the lowest during the global financial crisis. Due to the relatively high weight in the non-crisis periods, this suggests that South Africa may be a good investment alternative during more calm periods.

When considering BRICS, China was the preferred destination for investments over the calm period ranging from 2000 to 2007 and during the global financial crisis, whereas India emerged as the hotspot after the financial crisis. However, both the US and gold have an average weight higher than BRICS for all three periods, suggesting that these are the most preferred investment destinations. The sum of the average weights of BRICS is 40.5% in the pre-crisis period, 32.9% during the global financial crisis and 46.7% in the post-crisis period. Thus, by investing the above weight in BRICS, some diversification gains in terms of lower portfolio risk can be obtained.

## 6.3 Diversification gains

The diversification benefits of including BRICS in the portfolio are further explored by constructing a second portfolio, which includes the US stock market, gold and oil. The optimal risk minimising portfolio weights of the second portfolio is calculated, and the two portfolios' variances are compared. The comparison enables to draw conclusions regarding diversification opportunities in the emerging markets. In Appendix C Figure 4, the variances of the two portfolios are presented. The patterns of the variances follow each other closely. However, the variance of the portfolio including BRICS is lower throughout the entire period. In particular, the peaks of the variances are remarkably lower for the portfolio including BRICS. This implies that the portfolio excluding the emerging markets has a higher risk in comparison to the portfolio including these markets.

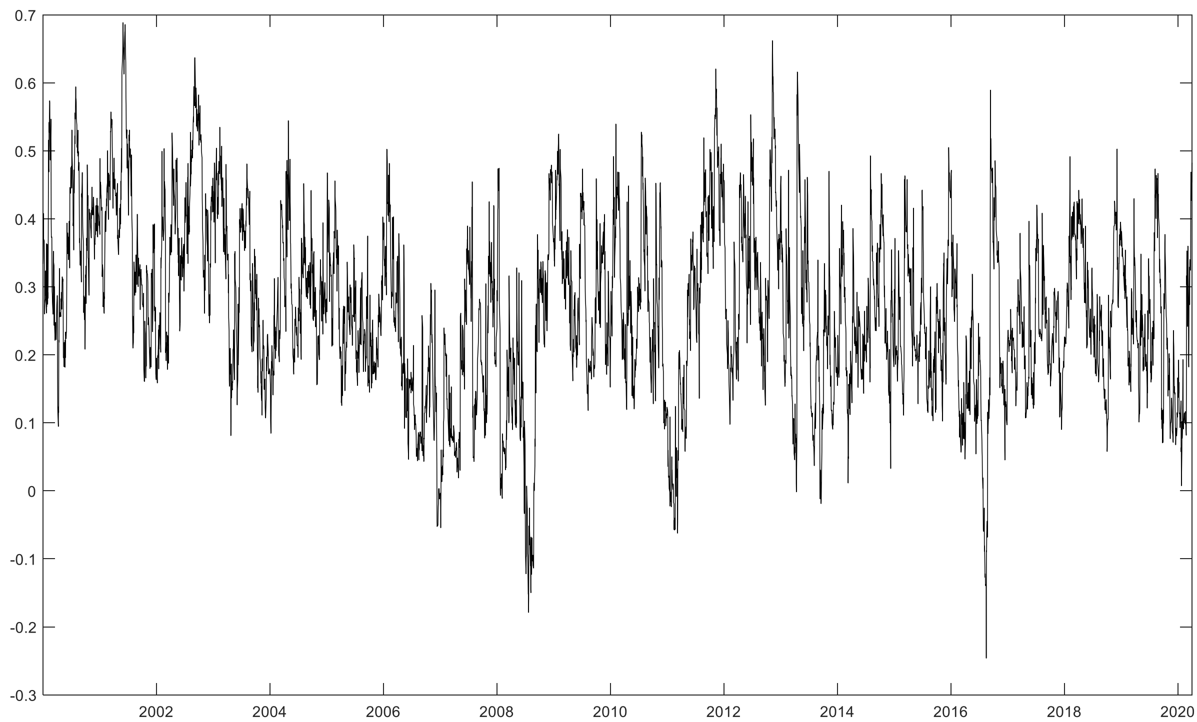


*Figure 6.3.1. Relative Risk Reduction*

Further, the Relative Risk Reduction (RRR) is calculated using the portfolios, and the result is presented in Figure 6.3.1. The risk reduction of including BRICS in the portfolio varies over the period and is mainly positive, with a few drops below zero. The average reduction of the full period is 26.7%. Hence, by including BRICS in the portfolio, the risk is reduced by 26.7% on average in comparison to the portfolio including the US, gold and oil solely. Therefore, the result suggests that diversification benefits can be extracted by investing in BRICS regarding this portfolio context.

# 7. Conclusion

This paper studies risk spillovers between BRICS stock markets and the US stock market, gold and oil by estimating the correlations between the markets using a DCC-GJR-GARCH model. By studying the interdependence of the markets, meaningful implications about portfolio management are obtained. Hence, using the results from the DCC estimation, a variance-minimizing portfolio is constructed. In addition, the analysis is conducted for the full sample, as well as for three subsamples, which provide valuable insights regarding the risk spillovers and financial contagion in different states of the markets.

Positive correlations are found throughout the period between BRICS and the US stock market, except for China. The correlation between China and the US is alternating around zero with a slightly increasing trend. The positive correlation implies interdependence of these financial markets. In addition, financial contagion is found between the markets, which is particularly high for Brazil, Russia and India.

A similar conclusion cannot be made for the BRICS economies' relations to gold. The emerging markets' relations to gold mainly fluctuate around zero, implying ambiguous and at some observations weak dependency between the markets. The correlations display amplified fluctuations during the global financial crisis and higher levels shortly after the crisis. The unusual decrease in the gold price during this turbulent period may explain the increased correlation between the BRICS and the gold futures market. The decrease in the gold price followed the stock markets' movements downward, amplifying the correlation between the markets. However, the generally low correlations, in addition to the low financial contagion between BRICS and gold, strengthens the proposition of gold being a safe-haven asset not only for the US stock market but also for BRICS. When a negative correlation is observed, gold can be used as a hedge towards the financial market. However, the correlations between gold and BRICS are most volatile during the global financial crisis, implying that investments in gold are riskier over the period when a safe-haven asset is most desired.

Further, the relations between BRICS and oil are found to be alternating from zero to positive. The correlations are particularly low prior to the global financial crisis and increase substantially during the crisis. These high levels are maintained in the post-crisis period, indicating risk spillovers between the markets. Financial contagion is discovered between the markets during the global financial crisis, which is persistent after the crisis.

The US and gold have the largest weights in the portfolio. Among BRICS, China is suggested to have the largest weight in the portfolio for the periods prior to, and during the crisis. India surpassed China with the largest weight after the global financial crisis. On the other hand, the South African stock market has relatively high and stable weights throughout the period. The two least preferred assets are the Brazilian stock market and oil. Brazil has a high positive correlation with the US and a higher standard deviation than the US. Oil has a high level of correlation with gold and is more volatile compared to gold. Hence, investing in any of these when having large weights in gold and the US stock market does not improve the portfolio further since it does not reduce the risk. Further, the total weight of BRICS in the portfolio is lower during the financial crisis than in the pre- and post-crisis period. All weights are time-varying and volatile, suggesting the portfolio manager to change the portfolio weights with a daily frequency. Besides, the weights display variations depending on the market conditions. Thus, the portfolio manager is also suggested to adjust investments conditioning on the state of the economy.

When comparing the variance of the portfolio including BRICS to a portfolio excluding BRICS, diversification opportunities are attained. The variance is lower for the portfolio including BRICS, in particular over peaks and troughs. Adding assets to a portfolio generally lowers the risk, since it provides more diversification opportunities. However, in the case of including BRICS in the portfolio, the RRR is economically significant with high values throughout the period. Thus, it should not be regarded as a marginal improvement of the variance.

Risk spillovers are found between emerging financial markets and other financial markets as well as between emerging financial markets and commodity markets. The relations between the markets are confirmed to be both dynamic and dependent on the state of the economy. This study provides knowledge of spillover effects and enables international investors to manage the risk of their portfolio. An interesting extension of this study would be to include expected returns when constructing the optimal portfolio in order to add to the research on portfolio selection. The standard approach in this field is to assume normality and disregard other distributions of the return series. Since financial return series often are subject to non-normality, considering other distributions for the DCC estimation may be beneficial.

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# Appendix A

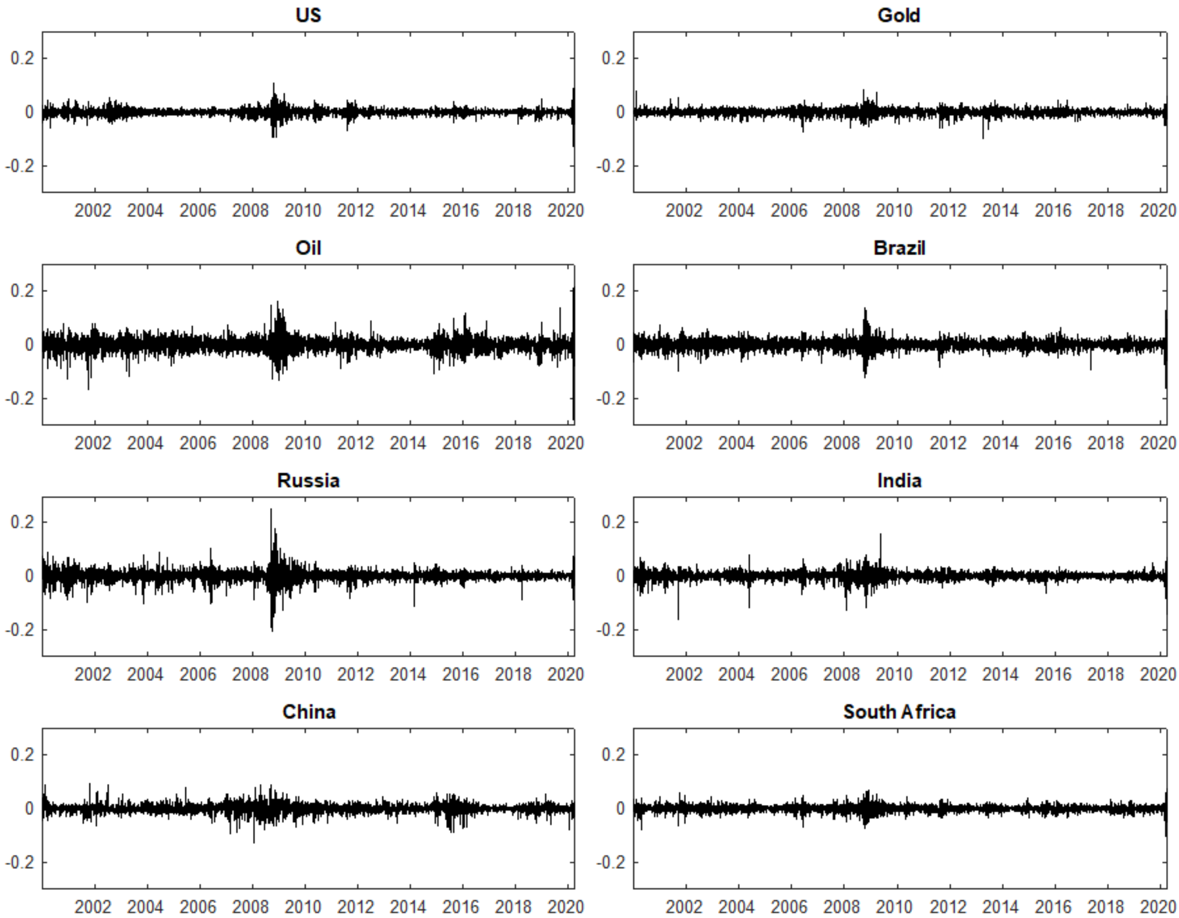

Figure 1. Return series

Table 1. Descriptive statistics

| | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| Variance | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| SD | 0.012 | 0.011 | 0.025 | 0.018 | 0.020 | 0.015 | 0.015 | 0.012 |
| Skewness | -0.405 | -0.205 | -0.437 | -0.363 | -0.307 | -0.718 | -0.421 | -0.402 |
| Kurtosis | 14.31 | 8.876 | 14.74 | 9.935 | 19.24 | 15.73 | 9.056 | 8.486 |
| Minimum | -0.128 | -0.098 | -0.282 | -0.160 | -0.207 | -0.161 | -0.128 | -0.102 |
| Maximum | 0.110 | 0.086 | 0.220 | 0.137 | 0.252 | 0.160 | 0.094 | 0.073 |
| Median | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Table 2. Test statistics

| | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Jarque Bera | 27307* | 7368* | 29414* | 10325* | 56077* | 34865* | 7939* | 6529* |
| LBQ (1) | 63.67* | 0.154 | 15.99* | 2.249 | 4.139* | 4.842* | 0.016 | 2.871 |
| LBQ (5) | 69.70* | 0.742 | 22.19* | 7.634 | 14.64* | 10.10 | 23.54* | 8.698 |
| LBQ (10) | 85.96* | 12.63 | 32.09* | 22.04* | 26.25* | 39.65* | 32.67* | 22.83* |
| LBQ squared residuals (1) | 560* | 110* | 429* | 544* | 83* | 124* | 110* | 193* |
| LBQ squared residuals (5) | 3040* | 307* | 701* | 2903* | 958* | 611* | 458* | 2070* |
| LBQ squared residuals (10) | 5183* | 507* | 1821* | 4081* | 1442* | 915* | 727* | 3440* |
| ARCH effects | 1260* | 133* | 489* | 1231* | 568* | 218* | 158* | 802* |
| ADF | -80* | -72* | -75* | -73* | -69* | -69* | -71* | -70* |

*Indicates significance on a 5%-level

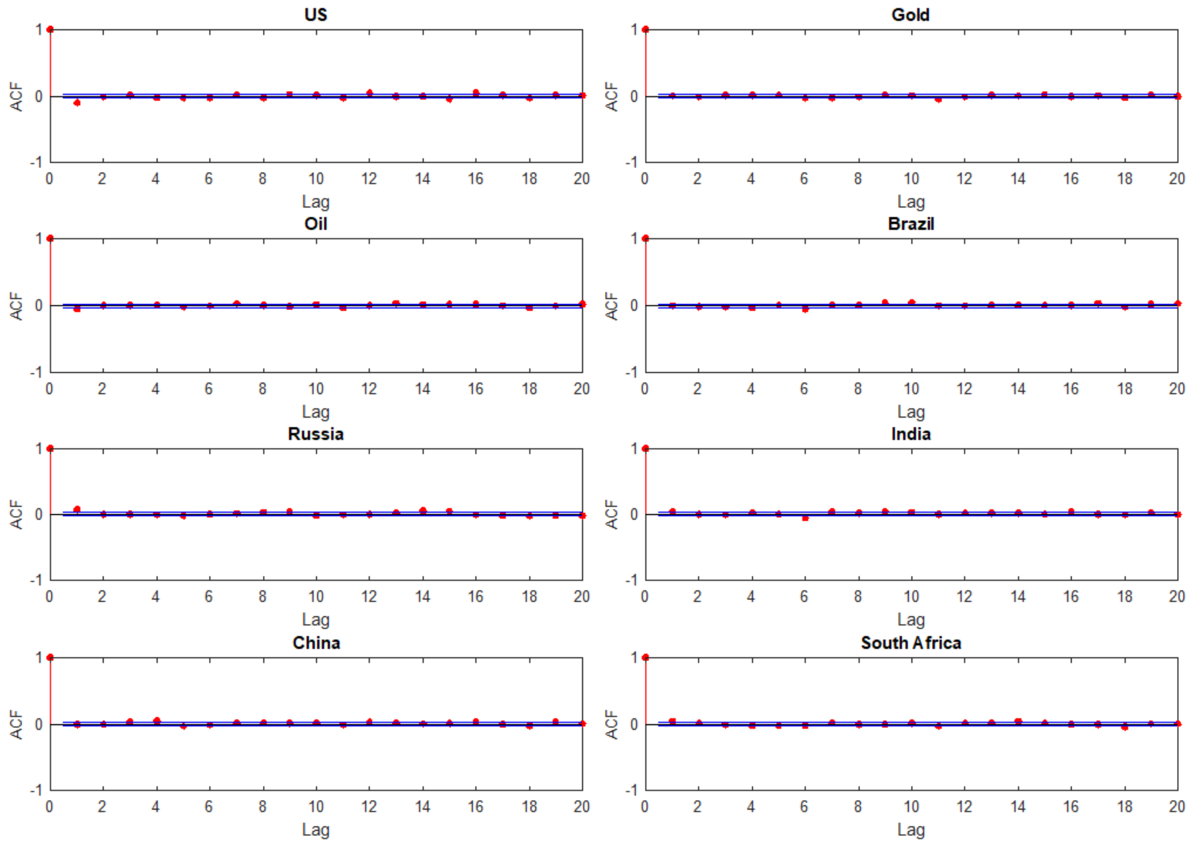


Figure 2. Autocorrelation functions of the return series

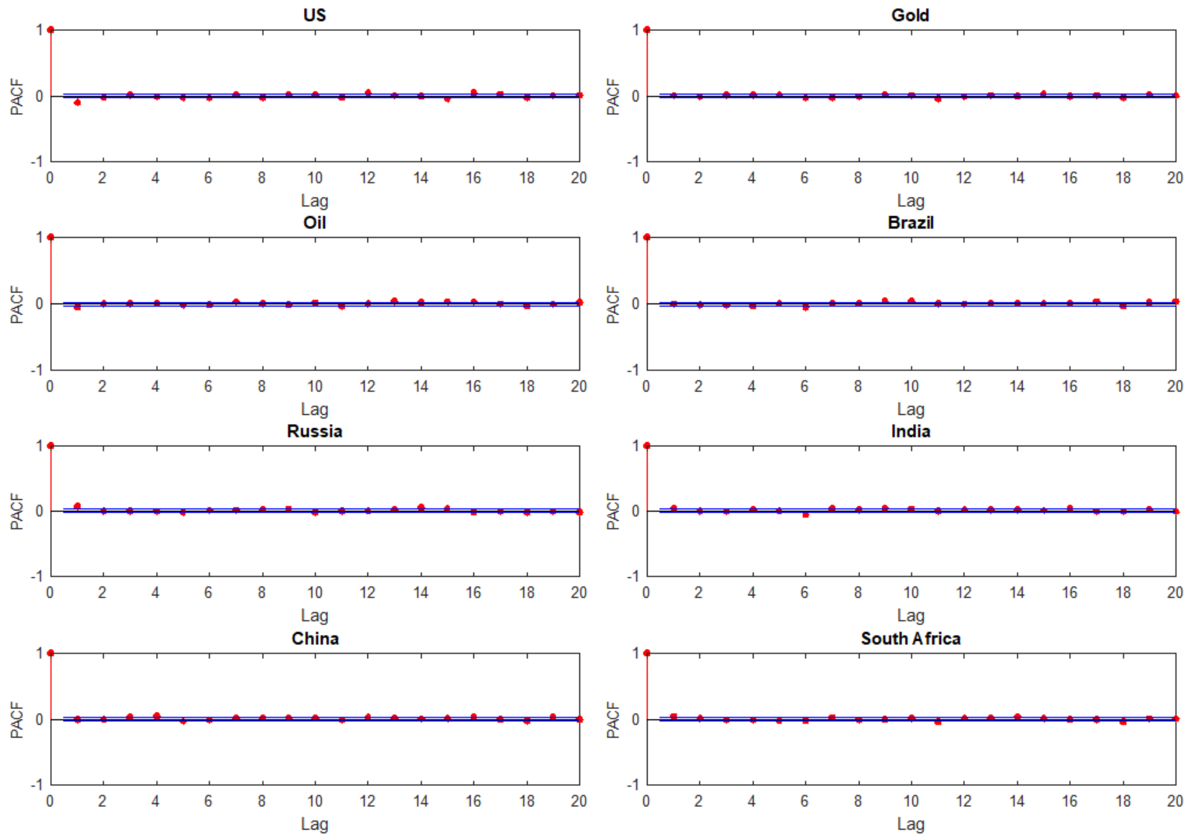


Figure 3. Partial autocorrelation functions of the return series

Table 3. Correlation matrix

| | S&P500 | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| S&P500 | | | | | | | | |
| Gold | -0.020 | | | | | | | |
| Oil | 0.231 | 0.207 | | | | | | |
| Brazil | 0.621 | 0.073 | 0.249 | | | | | |
| Russia | 0.281 | 0.088 | 0.220 | 0.327 | | | | |
| India | 0.242 | 0.040 | 0.117 | 0.271 | 0.314 | | | |
| China | 0.076 | 0.031 | 0.089 | 0.134 | 0.097 | 0.190 | | |
| South Africa | 0.397 | 0.143 | 0.225 | 0.390 | 0.489 | 0.387 | 0.170 | |

# Appendix B

Table 1. Full Sample: DCC and univariate GARCH parameters

| Univariate GARCH | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Arch effect | 0.000 | 0.062 | 0.025 | 0.000 | 0.000 | 0.035 | 0.055 | 0.000 |
| Arch effect 2 | 0.000 | 0.000 | 0.000 | 0.027 | 0.104 | | | 0.042 |
| Leverage | 0.208 | -0.015 | 0.070 | 0.094 | 0.102 | 0.170 | 0.022 | 0.165 |
| Garch effect | 0.875 | 0.436 | 0.935 | 0.899 | 0.196 | 0.866 | 0.931 | 0.420 |
| Garch effect 2 | | 0.497 | | | 0.633 | | | 0.433 |
| DCC Parameters | $\alpha$ | $\beta$ | | LR-Test | T stat | P-value | Critical value | |
| | 0.006 | 0.990 | | | 806.5 | 0 | 5.996 | |

All parameters are significant at a 5% level(except the GARCH parameters for gold)

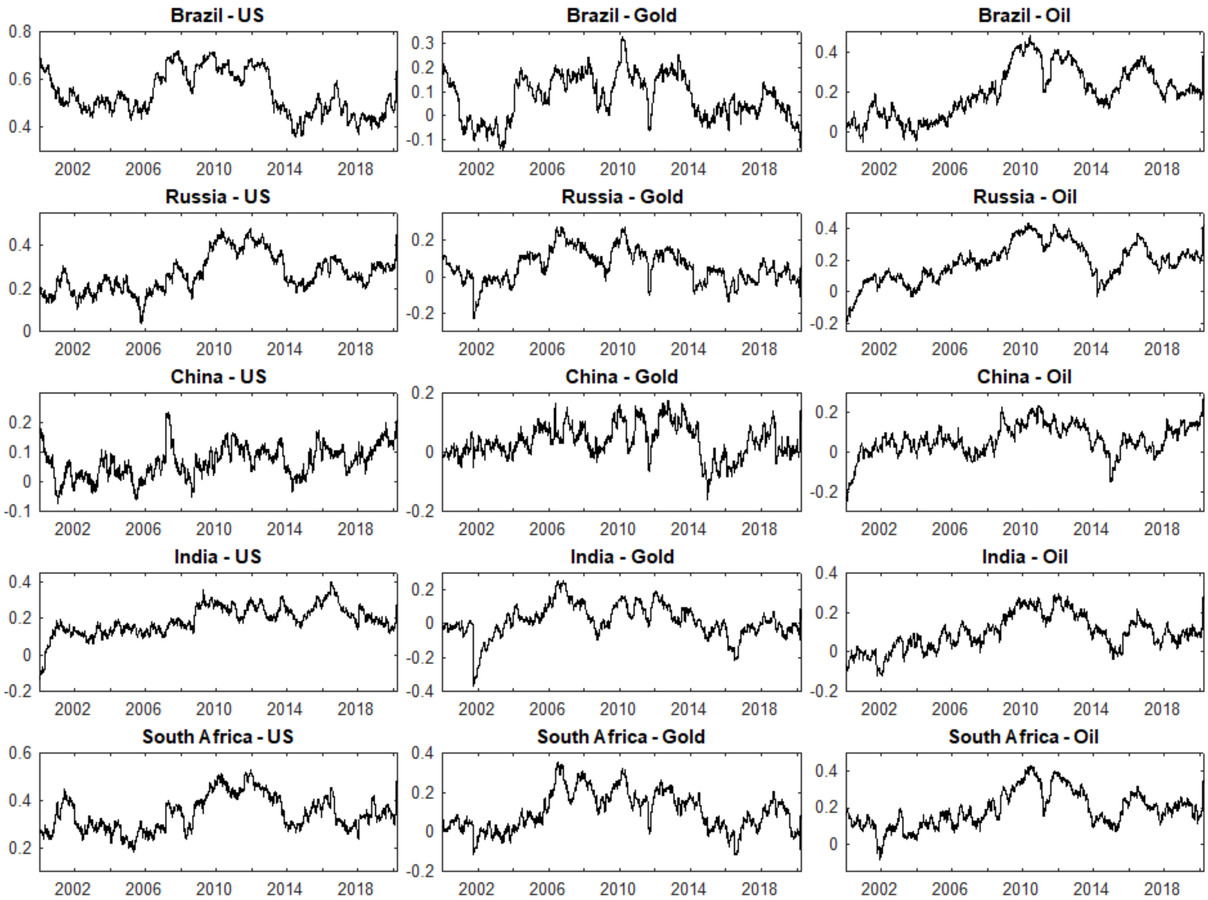


Figure 1. Correlation between BRICS and the US, gold and oil in the full sample

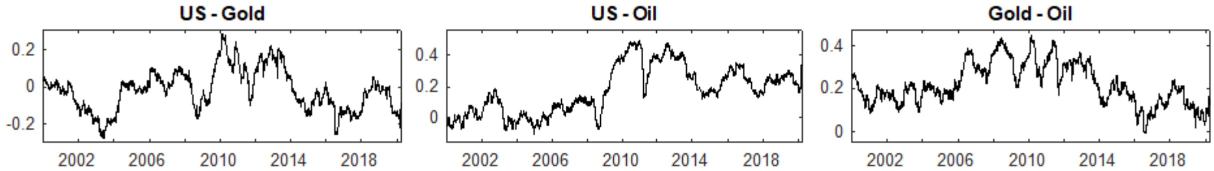

Figure 2. Correlation between the global markets in the full sample

Table 2. Subsample 1: DCC and univariate GARCH parameters

| Univariate GARCH | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Arch effect | 0.000 | 0.044 | 0.019 | 0.000 | 0.057 | 0.000 | 0.059 | 0.037 |
| Leverage | 0.124 | -0.033 | 0.028 | 0.084 | 0.068 | 0.324 | 0.049 | 0.128 |
| Garch effect | 0.925 | 0.961 | 0.945 | 0.922 | 0.857 | 0.742 | 0.907 | 0.867 |
| Garch effect 2 | | 0.000 | | | | | | |
| DCC Parameters | $\alpha$ | $\beta$ | | LR-Test | T stat | P-value | Critical value | |
| | 0.007 | 0.976 | | | 99.16 | 0 | 5.996 | |

All parameters are significant at a 5% level

Table 3. Subsample 2: DCC and univariate GARCH parameters

| Univariate GARCH | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Arch effect | 0.000 | 0.047 | 0.106 | 0.000 | 0.146 | 0.000 | 0.000 | 0.000 |
| Arch effect 2 | 0.009 | | | | | | | |
| Leverage | 0.125 | | | 0.139 | | 0.138 | 0.145 | 0.121 |
| Garch effect | 0.914 | 0.933 | 0.886 | 0.908 | 0.854 | 0.839 | 0.878 | 0.932 |
| Garch effect 2 | 0.000 | | | | | | | |
| DCC Parameters | $\alpha$ | $\beta$ | | LR-Test | T stat | P-value | Critical value | |
| | 0.018 | 0.905 | | | 36.07 | 0 | 5.996 | |

All parameters are significant at a 5% level

Table 4. Subsample 3: DCC and univariate GARCH parameters

| Univariate GARCH | US | Gold | Oil | Brazil | Russia | China | India | South Africa |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Arch effect | 0.000 | 0.047 | 0.011 | 0.018 | 0.021 | 0.055 | 0.000 | 0.000 |
| Arch effect 2 | | | 0.000 | | | | | 0.000 |
| Leverage | 0.305 | -0.004 | 0.129 | 0.123 | 0.097 | | 0.142 | 0.196 |
| Garch effect | 0.813 | 0.945 | 0.541 | 0.870 | 0.908 | 0.943 | 0.905 | 0.385 |
| Garch effect 2 | | | 0.376 | | | | | 0.485 |
| DCC Parameters | $\alpha$ | $\beta$ | | LR-Test | T stat | P-value | Critical value | |
| | 0.007 | 0.983 | | | 272.2 | 0 | 5.996 | |

All parameters are significant at a 5% level

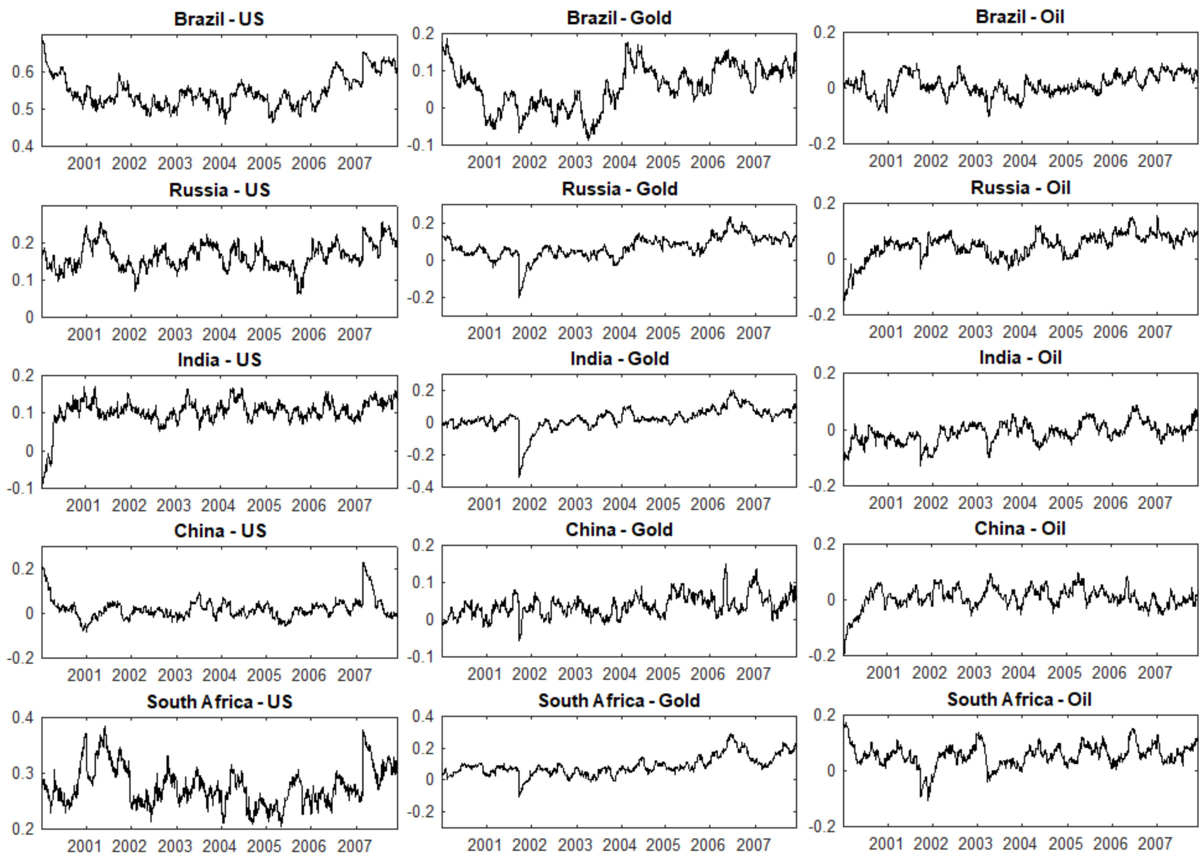


Figure 3. Correlation between BRICS and the US, gold and oil in the first subsample

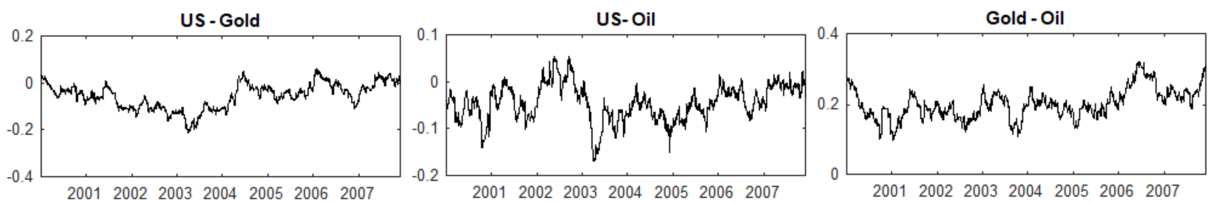


Figure 4. Correlation between the global markets in the first subsample

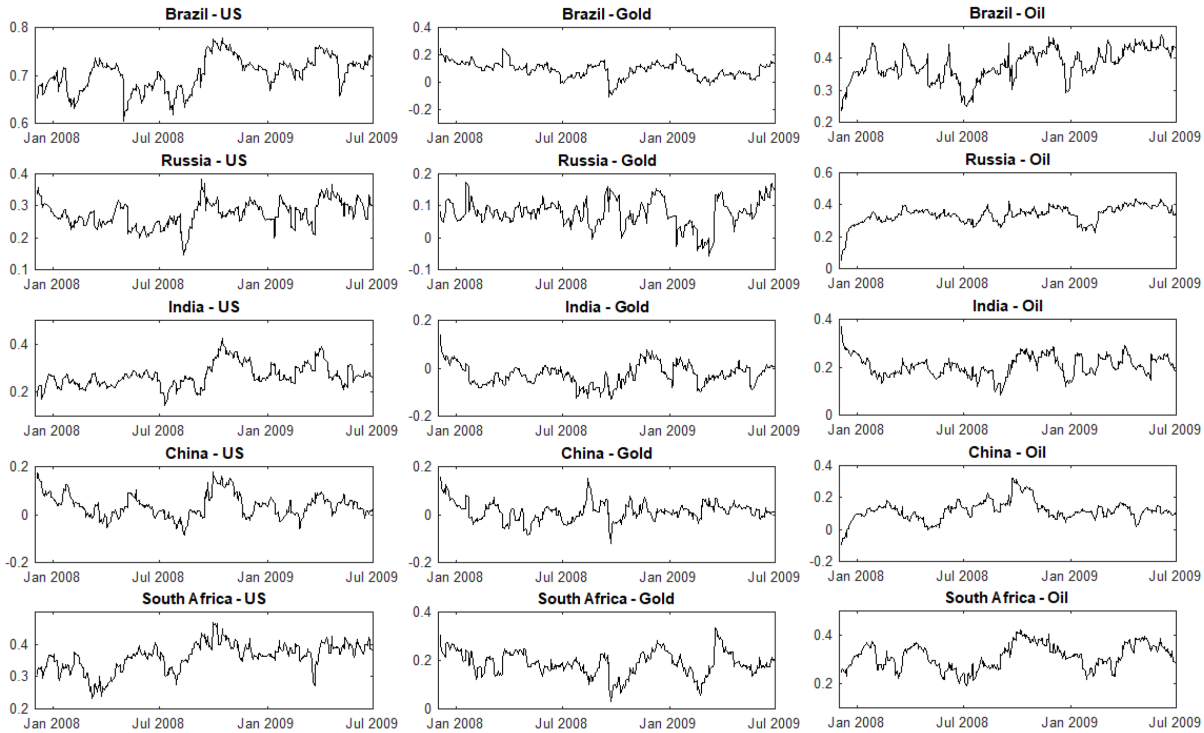

Figure 5. Correlation between BRICS and the US, gold and oil in the second subsample

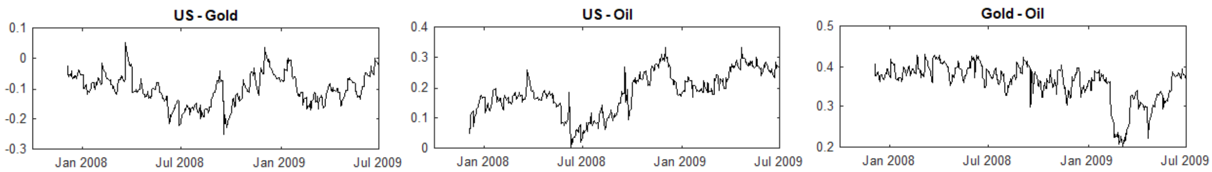

Figure 6. Correlation between the global markets in the second subsample

Table 5. The difference in unconditional correlation between subsample one and two

| | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| US | | | | | | | | |
| Gold | -0.048 | | | | | | | |
| Oil | 0.236 | 0.159 | | | | | | |
| Brazil | 0.161 | 0.032 | 0.374 | | | | | |
| Russia | 0.109 | 0.008 | 0.292 | 0.157 | | | | |
| India | 0.163 | -0.056 | 0.212 | 0.160 | 0.109 | | | |
| China | 0.019 | -0.029 | 0.114 | 0.152 | 0.084 | 0.244 | | |
| South Africa | 0.086 | 0.091 | 0.261 | 0.262 | 0.181 | 0.113 | 0.175 | |

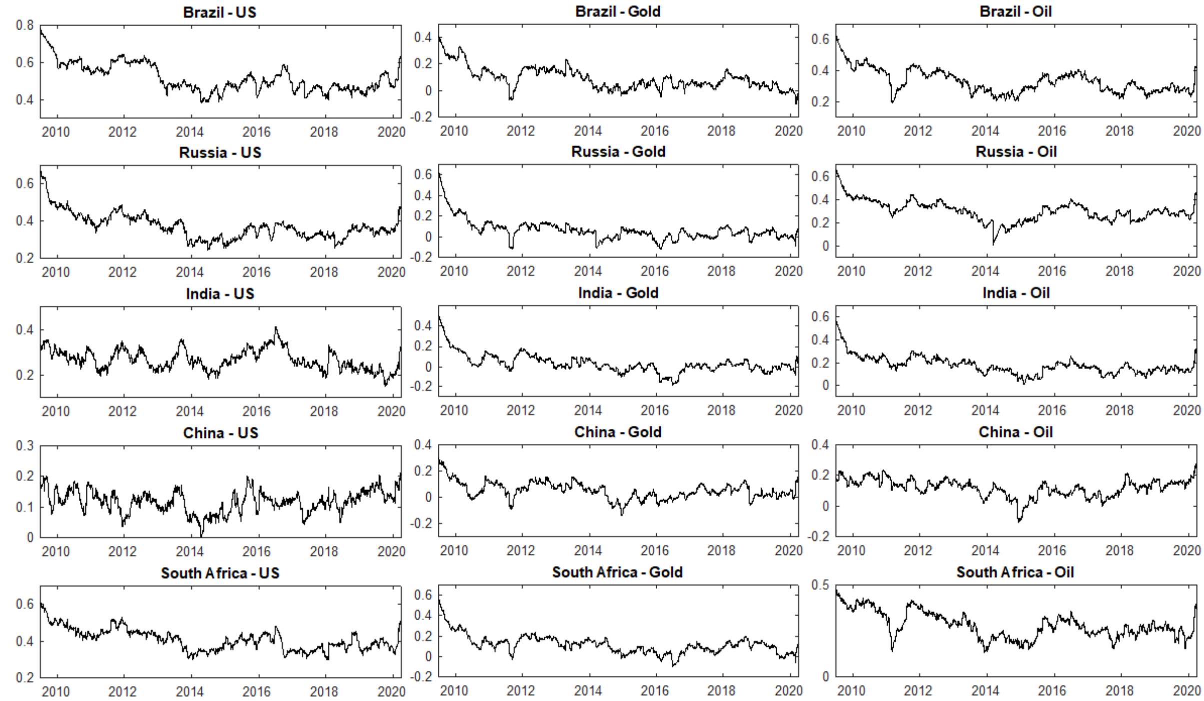

Figure 7. Correlation between BRICS and the US, gold and oil in the third subsample

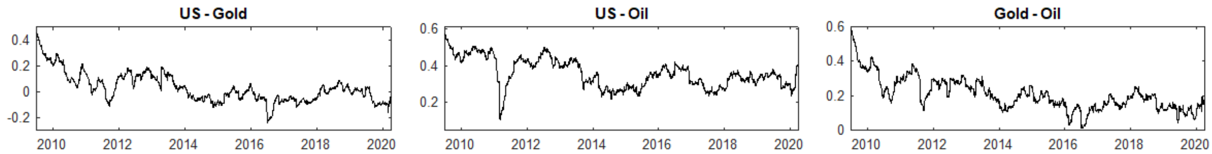

Figure 8. Correlation between the global markets in the third subsample

Table 6. The difference in unconditional correlation between subsample one and three

| | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| US | | | | | | | | |
| Gold | 0.072 | | | | | | | |
| Oil | 0.400 | -0.003 | | | | | | |
| Brazil | -0.031 | 0.024 | 0.316 | | | | | |
| Russia | 0.203 | -0.021 | 0.242 | 0.140 | | | | |
| India | 0.160 | -0.003 | 0.183 | 0.077 | 0.068 | | | |
| China | 0.103 | 0.008 | 0.111 | 0.065 | 0.130 | 0.160 | | |
| South Africa | 0.130 | 0.012 | 0.226 | 0.091 | 0.134 | 0.120 | 0.215 | |

# Appendix C

Table 1. Average weights for the full period

| | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Full sample | 27.04% | 27.09% | 2.67% | 2.19% | 4.33% | 12.40% | 13.86% | 10.42% |

Table 2. Variance of the weights for the full period

| | US | Gold | Oil | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|---|
| Full sample | 0.022 | 0.013 | 0.001 | 0.000 | 0.001 | 0.006 | 0.007 | 0.005 |

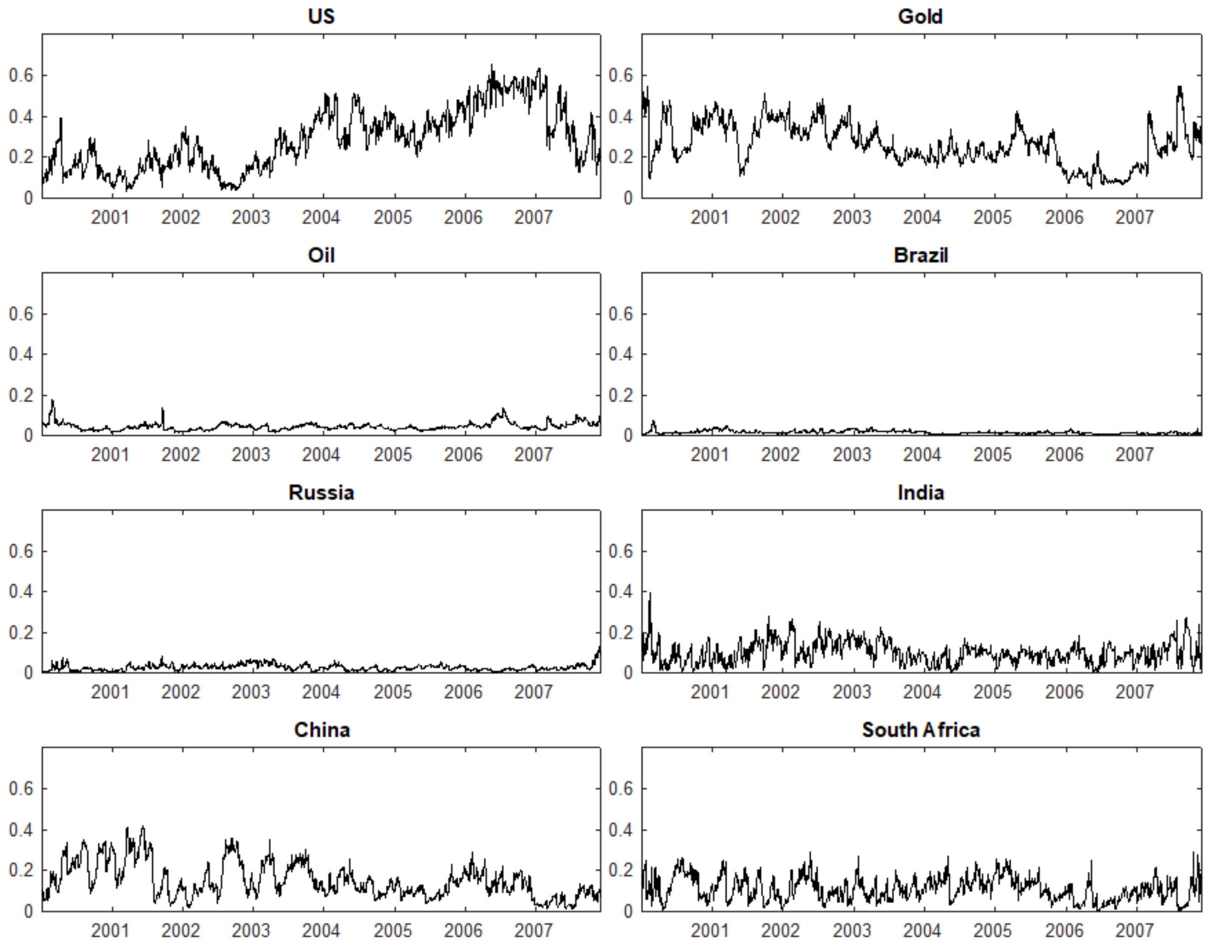


Figure 1. Optimal weights of subsample one

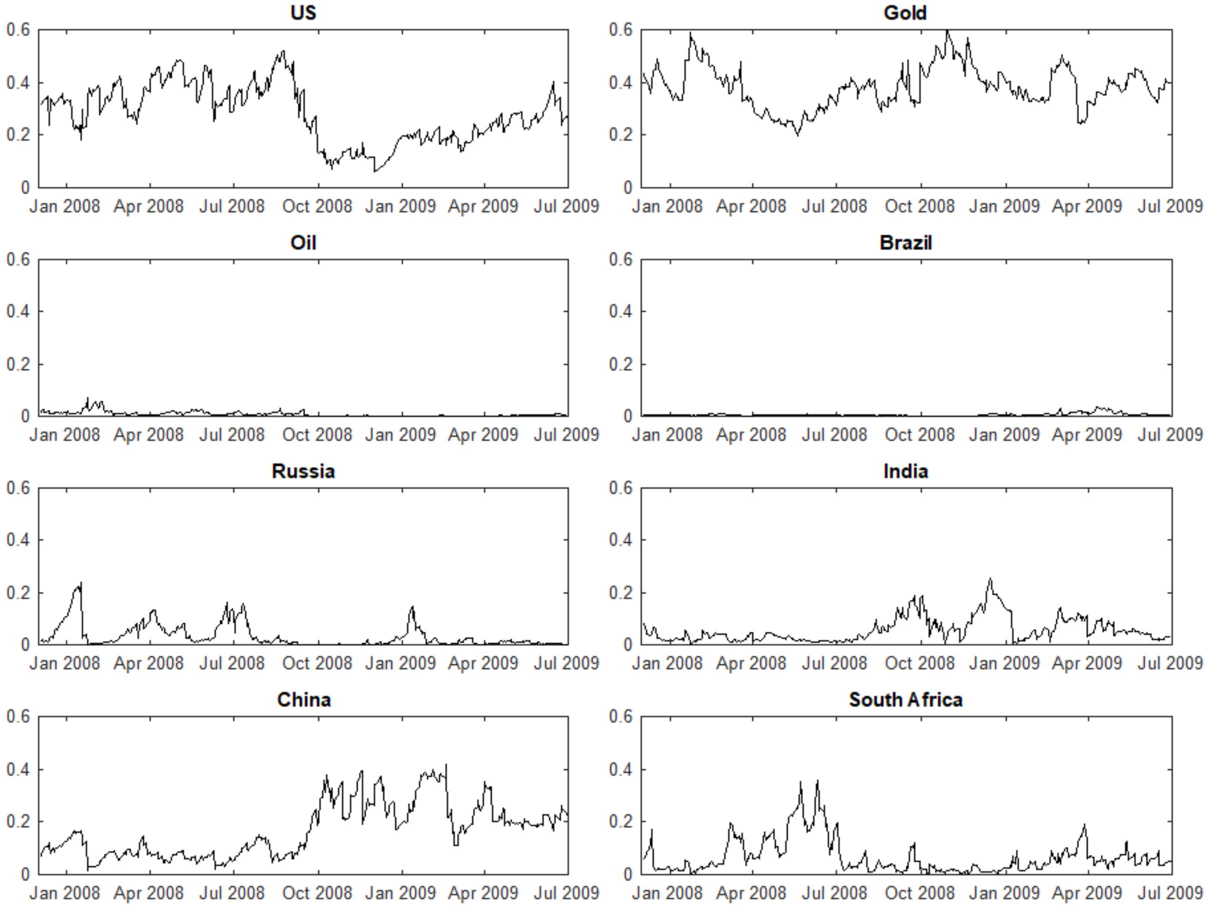

Figure 2. Optimal weights of subsample two

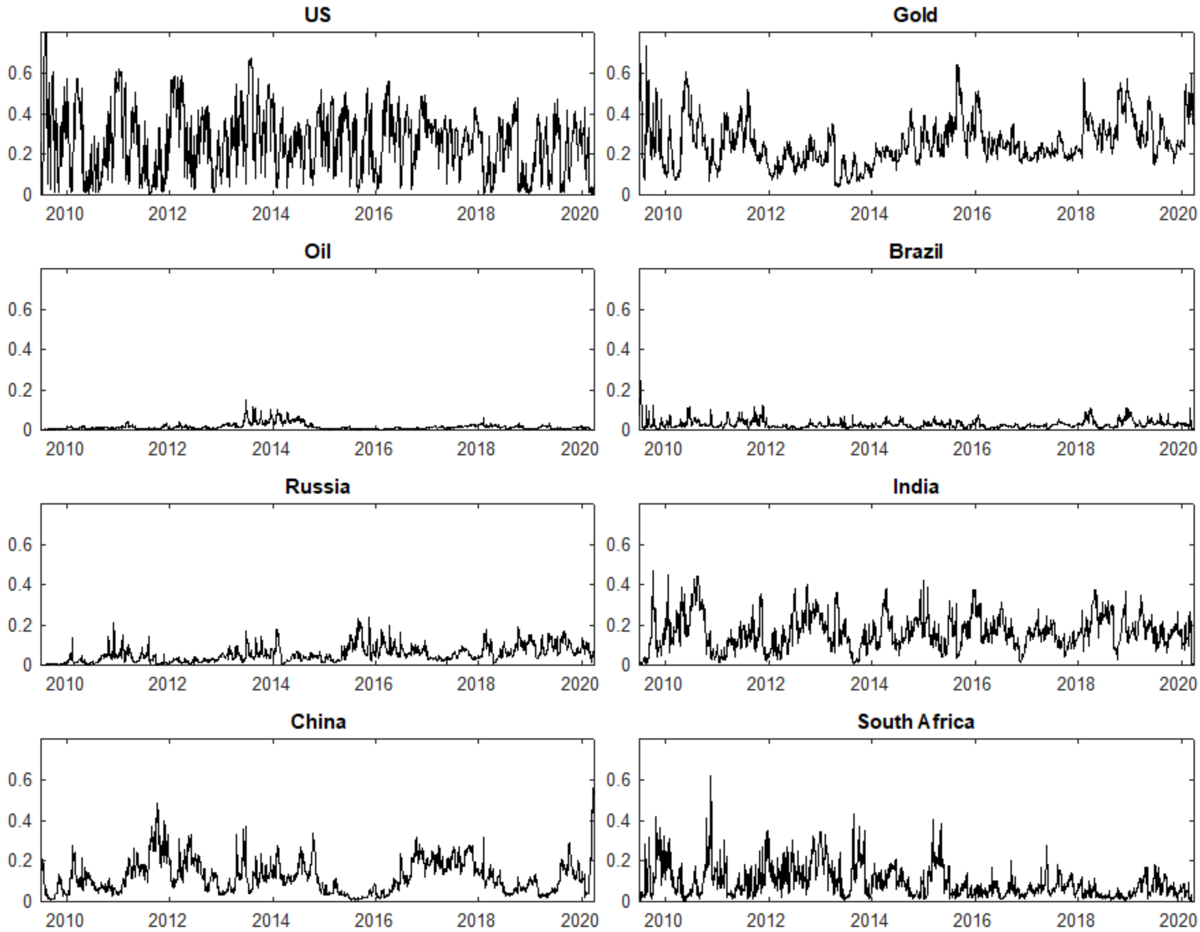

Figure 3. Optimal weights of subsample three

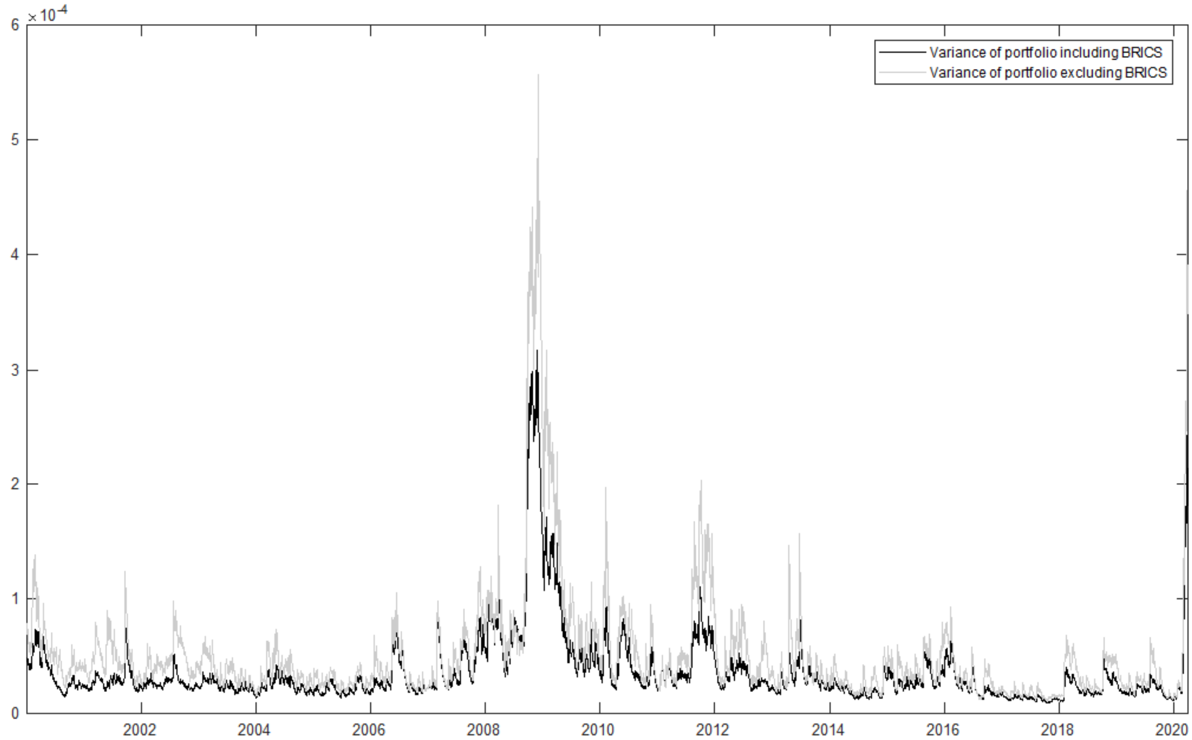


Figure 4. Variance of the portfolio including BRICS and portfolio excluding BRICS