# Emerging Market Currency Co-movement: an analysis of dynamic conditional correlations before and after the GFC and during periods of heightened economic uncertainty

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**Abstract**

This paper analyses emerging market currency co-movement, during different periods of global uncertainty. First we calculate dynamic conditional correlations before and after the global financial crisis between the Rand and several emerging market currencies. Then we stratify the CBOE Volatility Index (VIX) into quintiles for the two periods and compare the sample average conditional correlations to the average conditional correlations during periods of high and low VIX. The research is intended to be of relevance to investors managing portfolios with a high degree of exposure to EM countries. Using EM currency data from four groups of economies from 2002 to 2018, the paper finds that conditional correlations increase significantly following the financial crisis. However, we do not find significant differences in average conditional correlations during periods of high and low uncertainty, which suggests that emerging market currencies do not co-move more during periods of market stress. Our findings bear interesting insights for currency pairs traders and emerging market portfolio managers - idiosyncracies specific to emerging market countries may play a role in mitigating higher comovement during market turbulence. This has implications for currency hedging and asset allocation strategies.

*Keywords:* Currency co-movement, Global uncertainty, Emerging markets, DCC, GARCH

*JEL classification* L250, L100

## 1. Introduction

The purpose of this paper is to model the co-movement between emerging market (EM) currencies, during differing periods of uncertainty. We employ Engle (2002)'s Dynamic Conditional Correlation (DCC) methodology, to describe time-varying correlation and volatility. The main aim of the study to see whether currencies are more closely correlated during heightened global (economic) uncertainty gauged by the CBOE Volatility Index (VIX). However more generally, the paper discusses the relationships between the Rand (ZAR) and other groups of EM currencies. Our focus is on the *ZAR's* correlation with the rest of the currencies in our sample. Naturally, our question has important con-

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sequences for currency traders and emerging market portfolio managers, which motivates the purpose of this research.

The layout of the rest of this paper is as follows: section 2 discusses the data and sample used as well as the stratification method. Section 3 describes the methodology used to model currency co-movement. Section 4 reports the results and section 5 concludes and provides some recommendations to fund managers.[1]

## 2. Data

We study co-movement between the ZAR and four groups of currencies using data downloaded from Bloomberg. The currencies are grouped into four categories, namely BRICS, Asia, South America and Eastern Europe and are all measured relative to the Dollar (USD). The currencies are split into two sample periods; the first sample period starts in 2002 and ends in 2008 and the second sample period starts in 2010 and ends in November 2018. Weekly returns are calculated to ensure synchronicity in returns and to avoid the noise present in daily returns. Note that given the use of currency data, a positive return is synonymous with a "depreciation", whereas a negative return is synonymous with an "appreciation".

Table 6.1 in the appendix reports the summary statistics (mean and standard deviation) for all of the currencies in our sample[2]. It is interesting to note that most of the mean returns in the first period are positive whereas the majority are negative in the second period. In addition, it appears as though most of the currencies became more volatile in the second period when measured according the the standard deviation.

In this paper, we stratify the data according to differing periods of uncertainty. Figure 2.1 plots the VIX over the full sample period and shows the top and bottom quintiles for the first and second sample period. In order to ensure we have a sufficient amount of observations with which to calculate average conditional correlations with during times of high and low VIX we create a rule which specifies that the index must have breached the top or bottom quintile for at least 30 trading days. Such instances are shaded on figure 2.1. Further, to allow the conditional correlations to adjust to the change in sentiment we exclude the first 10 trading days in our mean calculations.

[1] The paper was written using the "Texevier" package developed by N.F. Katzke (2016).
[2] Refer to table 6.2 in the appendix for the full list of currencies considered.

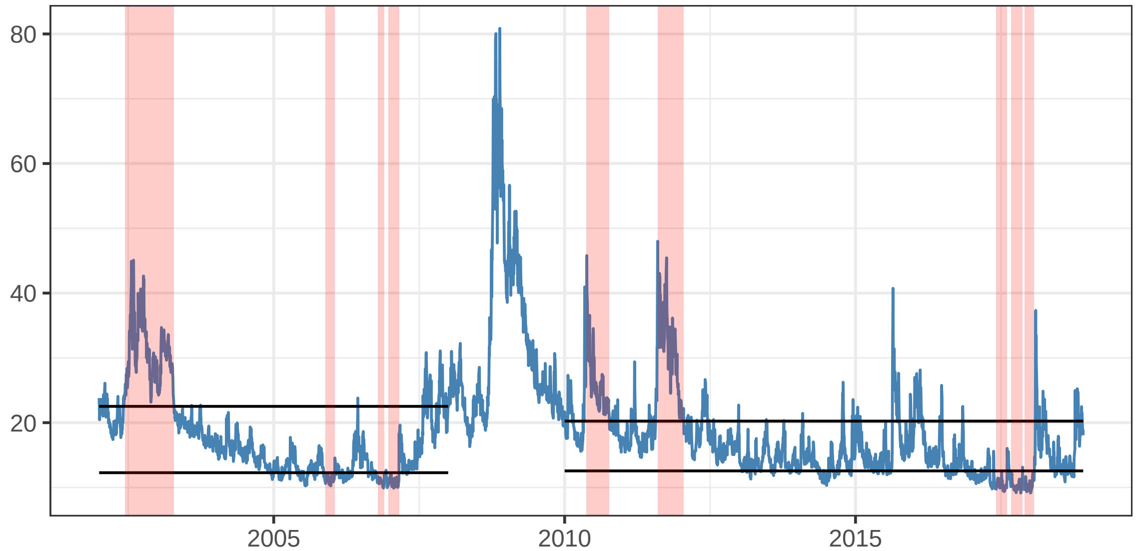


Figure 2.1: VIX

Figure 2.1 emphasises the spike in the VIX during the global financial crisis (GFC), which led to unprecedented effects on global capital markets. This motivates us to omit these dates from our analysis as we do not want this to bias our DCC estimates.

## 3. Methodology

This section discusses the theory behind the correlation estimates, namely DCC. We use the GARCH-DCC approach, first proposed by Engle (2002).[3] A major benefit of this method is that large correlation matrices can be estimated, given the flexibility of univariate GARCH processes. This is why Engle (2002)'s method is preferred for our correlation estimates. The GARCH-DCC approach is conducted by estimating univariate GARCH models after which the conditional correlations are computed. Hence, the process comprises of two steps which are discussed in this section. Section 3.1 defines GARCH models, whereas section 3.3 discusses the DCC estimation. Frequent reference is made to Engle (2002) throughout.

### *3.1. GARCH models*

To generalise univariate GARCH models to the multivariate sphere is a simple task. Given the stochastic process of financial returns, $x_t$ $(t = 1, 2, ...T)$, with dimension $N \times 1$ and mean vector $\mu_t$

[3]'GARCH' refers to generalized autoregressive conditional heteroskedasticity.

and given the information set $I_{t-1}$, we can write $x_t\,|I_{t-1}$ as follows:

$$x_t\,|I_{t-1} = \mu_t + \varepsilon_t, \tag{3.1}$$

where the residuals of the process are modelled as:

$$\varepsilon_t = H_t^{1/2} z_t. \tag{3.2}$$

$H_t^{1/2}$ above is an $N \times N$ positive definite matrix such that $H_t$ is the conditional covariance matrix of $x_t$. $z_t$ is an $N \times 1$ independent and identically distributed series, with a mean of zero and a variance of one.

*3.2. DCC Models*

As previously mentioned, DCC models offer a simple and more parsimonious means of doing multivariate volatility modelling. In particular, it relaxes the constraint of a fixed correlation structure, which is assumed by the constant conditional correlation (CCC) model, to allow for estimates of time-varying correlation.

The DCC model can be defined as:

$$H_t = D_t.R_t.D_t. \tag{3.3}$$

Equation 3.3 splits the variance-covariance matrix into identical diagonal matrices ($D_t$) and an estimate of the time-varying correlation ($R_t$). Estimating $R_t$ (which is the correlation matrix) requires it to be inverted at each estimated period, and thus a proxy equation is used:

$$\begin{aligned} Q_{ij,t} &= \bar{Q} + a\left(z_{t-1}z'_{t-1} - \bar{Q}\right) + b\left(Q_{ij,t-1} - \bar{Q}\right) \\ &= (1-a-b)\bar{Q} + a z_{t-1}z'_{t-1} + b.Q_{ij,t-1} \end{aligned} \tag{3.4}$$

Equation 3.4 has a similar structure to a GARCH(1,1) process, with non-negative scalars $a$ and $b$.

Furthermore, $Q_{ij,t}$ is the unconditional (sample) variance estimate between series $i$ and $j$ and $\bar{Q}$ is the unconditional matrix of standardized residuals from each univariate pair estimate.

Next, we use equation 3.4 to estimate $R_t$ (the conditional correlation matrix), which is expressed as:

$$R_t = diag(Q_t)^{-1/2} Q_t . diag(Q_t)^{-1/2}. \tag{3.5}$$

Equation 3.5 has bivariate elements:

$$R_t = \rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} . q_{jj,t}}} \tag{3.6}$$

The resulting DCC model is then formulated statistically as:

$$\begin{aligned}
\varepsilon_t &\sim N(0, D_t.R_t.D_t) \\
D_t^2 &\sim \text{Univariate GARCH(1,1) processes } \forall \text{ (i,j), i} \neq \text{j} \\
z_t &= D_t^{-1}.\varepsilon_t \\
Q_t &= \bar{Q}(1-a-b) + a(z_t' z_t) + b(Q_{t-1}) \\
R_t &= Diag(Q_t^{-1}).Q_t.Diag(Q_t{}^{-1})
\end{aligned} \tag{3.7}$$

## 4. Results

Next, we use the methodology discussed in section 3 to estimate the dynamic conditional correlations.[4] Our focus is on the bivariate correlation between ZAR and the rest of the currencies in the sample. However, in this section we only report the results for the BRICS economies. The full set of results is contained in the appendix.

Using the univariate GARCH methodology, figure 4.1 plots the conditional volatilities for all BRICS currencies for both periods.

[4] We omit China and Malaysia for Period 1 because their currencies were pegged to the USD until approximately 2005. Their inclusion induces zero returns for Period 1.

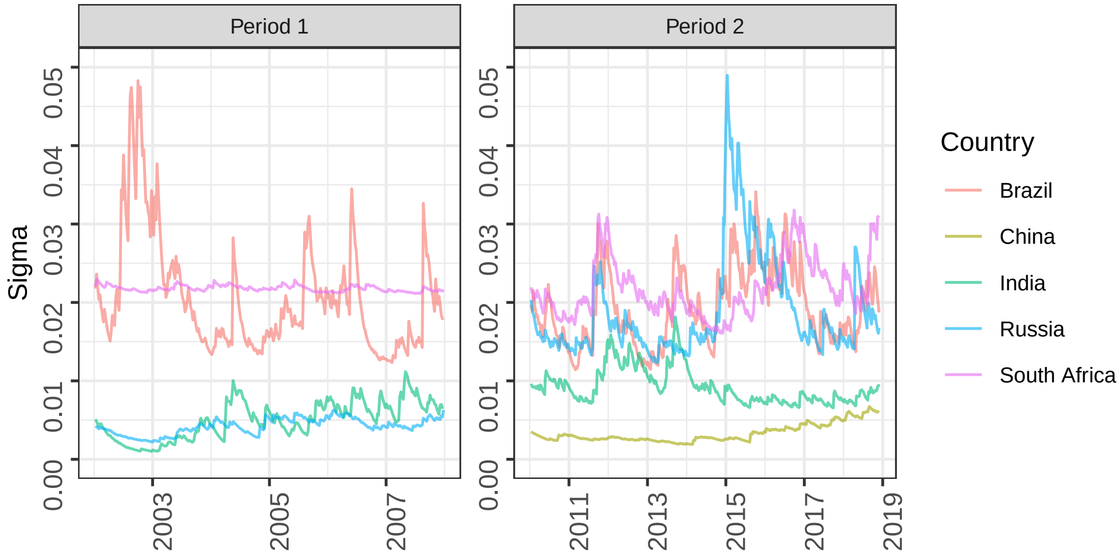


Figure 4.1: BRICS conditional volatility

Figure 4.1 suggests that prior to the financial crisis (Period 1), the BRL and the ZAR were the most volatile BRICS currencies whereas the Indian Rupee (INR) and the Russian Ruble (RUB) were the least. However, the story changed somewhat in the post-crisis era (Period 2): the Chinese Renminbi (CNY), as expected, remained the most stable currency of the group due to the currency being categorized as a managed float, whereas the RUB became markedy more volatile. Furthermore, the remaining BRICS currencies experienced large changes in their conditional volatilities. The results suggest, descriptively, that the most volatile currency groupings are BRICS and South America.

Turning to the DCC estimations, figure 4.2 plots the ZAR's dynamic conditional correlation with the other BRICS currencies.

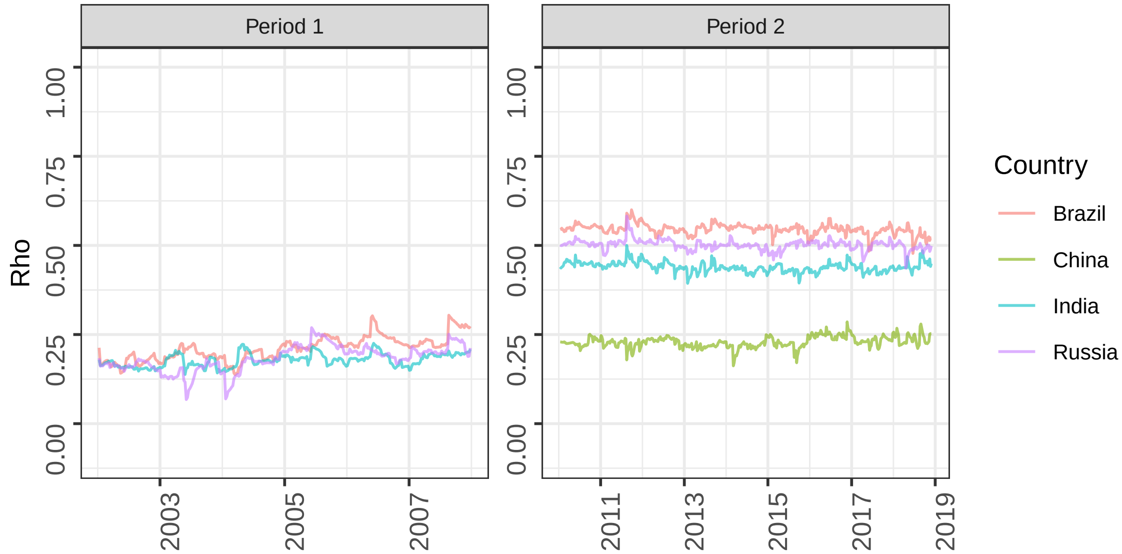


Figure 4.2: BRICS dynamic conditional correlation

The pre-crisis estimations suggest seemingly constant correlation over the period at approximately 0.25 (one might argue in favour of a slight increase in correlation in Period 1). Following the crisis, correlations doubled all except for the CNY which had recently switched to a managed floating exchange rate regime. The plot clearly shows the ZAR being the most correlated with the BRL, Russian Ruble (RUB) and Indian Rupee (INR), respectively. These three bivariate correlations hover around the 0.50 mark, which implies that a two per cent appreciation in the ZAR results in a one per cent appreciation in the BRL, RUB and INR, on average. This is indeed a high correlation.

An interesting note on the DCC results[5] is that conditional correlations in period 2 are significantly higher than period 1. This result is also found by NF Katzke and Polakow (2017). This could suggest a structural change in EM currency correlations following the GFC. NF Katzke and Polakow (2017) note the significance of quantitative easing between 2013 and 2016, which drove asset prices and currencies closer to one another. Carry trade, which refers to a trading strategy that exploits cross-country interest rate differentials, may also explain a great deal of the increased EM currency co-movement. Given lower interest rates in the US (as well as Japan, UK and EU), investors borrowed in these countries to invest in high-yielding EMs, such as South Africa and Brazil, which fuelled the observed co-movement.

To see whether the correlations increase during times of heightened economic uncertainty, we plot the DCC estimations and overlay the dates which we consider as 'high VIX' and 'low VIX'. Figure 4.3 suggests that we should not downplay an increase in correlation during 'high VIX' periods. This

[5] See the appendix (section 6).

follows as eyeballing the figure could suggest that correlations creep up initially in some cases (red overlay).

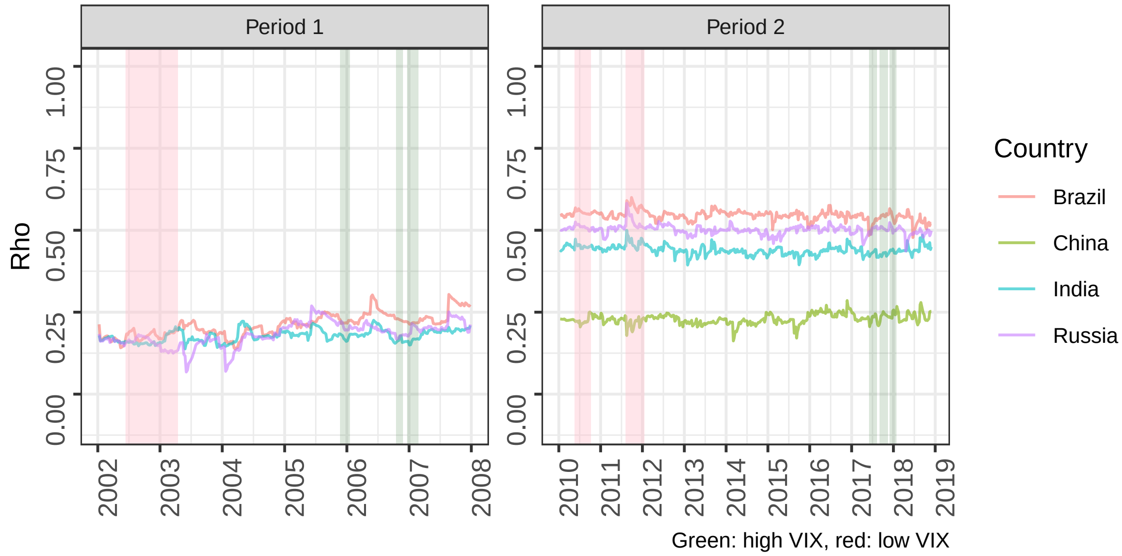


Figure 4.3: BRICS dynamic conditional correlation

However, when calculating average sample correlations and comparing them to correlations for high and low VIX periods, we do not find significant differences.[6] Hence, we must conclude that the ZAR is *not* more (less) closely correlated with other EM currencies when the VIX is in its top (bottom) quintile. Of course, this conclusion is only reached by using our method of calculating average correlations (full sample and stratified dates). What we do find, however, is that following the GFC, EM currencies became much more correlated than before. This fact emerges strongly from the DCC plots in section 6.4.

## 5. Conclusion

This paper studies EM currency co-movement, using Engle (2002)'s dynamic conditional correlation approach. After subsetting the sample into two periods (before and after the financial crisis), we model the co-movement (bivariate correlation) between the Rand and 19 other EM currencies using the DCC-GARCH framework. Our findings suggest higher post-crisis correlation, which were likely induced by large-scale asset purchases (quantitative easing) in the United States. High yield differentials and resulting carry trade were the prominent drivers behind higher co-movement in period 2. After

[6] Table 6.3 in the appendix contains the average pairwise correlations, for the full sample and during times of high and low VIX.

calculating the conditional correlations, we stratified the VIX into quintiles and considered the top quintile ’high VIX’ (high uncertainty) and the bottom quantile ‘low VIX’ (low uncertainty). After calculating the average correlations for these periods and comparing it to the average for the full sample periods, we do not find evidence of salient increases (decreases) in conditional correlations during times of high (low) economic uncertainty. Therefore, our study suggests that higher-than-usual economic uncertainty does not result in higher EM currency co-movement.

## 6. Appendix

### *6.1. Summary Statistics*

| | Ticker | Mean Period 1 | SD Period 1 | Mean Period 2 | SD Period 2 |
|---|---|---|---|---|---|
| 1 | ARS Curncy | 0.00 | 0.04 | 0.01 | 0.02 |
| 2 | BGN Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 3 | BRL Curncy | -0.00 | 0.02 | 0.00 | 0.02 |
| 4 | CLP Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 5 | CNY Curncy | -0.00 | 0.00 | 0.00 | 0.00 |
| 6 | COP Curncy | -0.00 | 0.01 | 0.00 | 0.02 |
| 7 | CZK Curncy | -0.00 | 0.01 | 0.00 | 0.02 |
| 8 | HUF Curncy | -0.00 | 0.02 | 0.00 | 0.02 |
| 9 | INR Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 10 | KRW Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 11 | MXN Curncy | 0.00 | 0.01 | 0.00 | 0.02 |
| 12 | MYR Curncy | -0.00 | 0.00 | 0.00 | 0.01 |
| 13 | PEN Curncy | -0.00 | 0.00 | 0.00 | 0.01 |
| 14 | PHP Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 15 | RON Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 16 | RUB Curncy | -0.00 | 0.00 | 0.00 | 0.02 |
| 17 | SGD Curncy | -0.00 | 0.01 | -0.00 | 0.01 |
| 18 | THB Curncy | -0.00 | 0.01 | 0.00 | 0.01 |
| 19 | TWD Curncy | -0.00 | 0.01 | -0.00 | 0.01 |
| 20 | ZAR Curncy | -0.00 | 0.02 | 0.00 | 0.02 |

Table 6.1: Period 1 Returns

### *6.2. List of currencies considered*

| | Country | Name | Ticker | Group |
|---|---|---|---|---|
| 1 | Brazil | Real | BRL Curncy | BRICS |
| 2 | Russia | Ruble | RUB Curncy | BRICS |
| 3 | India | Rupee | INR Curncy | BRICS |
| 4 | China | Renminbi | CNY Curncy | BRICS |
| 5 | South Africa | Rand | ZAR Curncy | BRICS |
| 6 | Taiwan | Dollar | TWD Curncy | Asia |
| 7 | Thailand | Baht | THB Curncy | Asia |
| 8 | Philipines | Peso | PHP Curncy | Asia |

| | | | | |
|---|---|---|---|---|
| 9 | Singapore | Dollar | SGD Curncy | Asia |
| 10 | Malaysia | Ringgit | MYR Curncy | Asia |
| 11 | South Korea | Won | KRW Curncy | Asia |
| 12 | Mexico | Peso | MXN Curncy | South America |
| 13 | Peru | Sol | PEN Curncy | South America |
| 14 | Columbia | Peso | COP Curncy | South America |
| 15 | Chile | Peso | CLP Curncy | South America |
| 16 | Argentina | Peso | ARS Curncy | South America |
| 17 | Romania | Leu | RON Curncy | Eastern Europe |
| 18 | Bulgaria | Lev | BGN Curncy | Eastern Europe |
| 19 | Czech | Koruna | CZK Curncy | Eastern Europe |
| 20 | Hungary | Forint | HUF Curncy | Eastern Europe |

Table 6.2: Currencies considered

*6.3. Volatility plots*

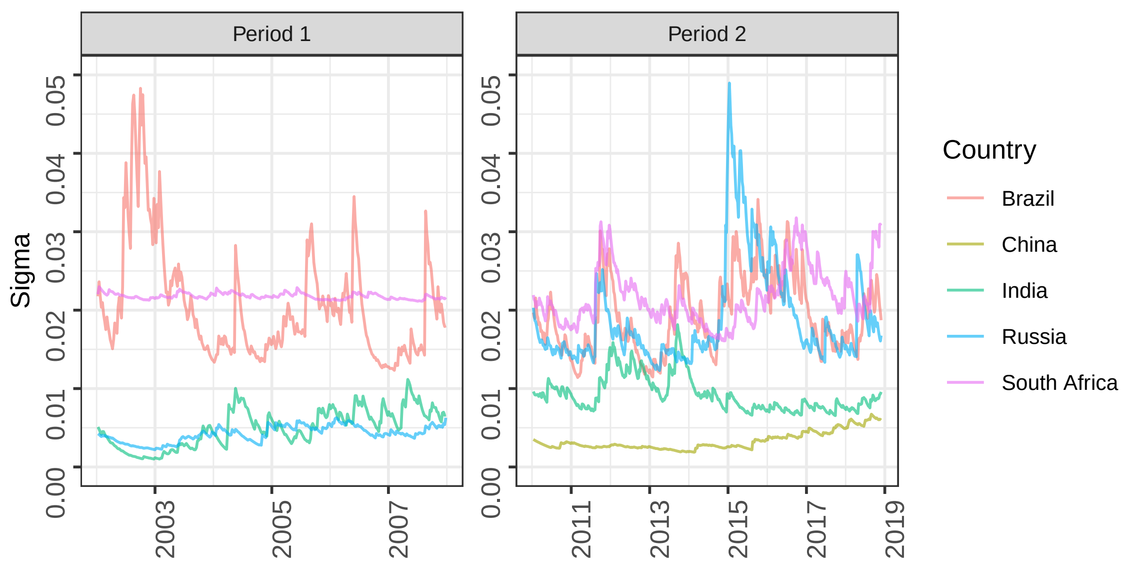


Figure 6.1: BRICS Conditional Volatility

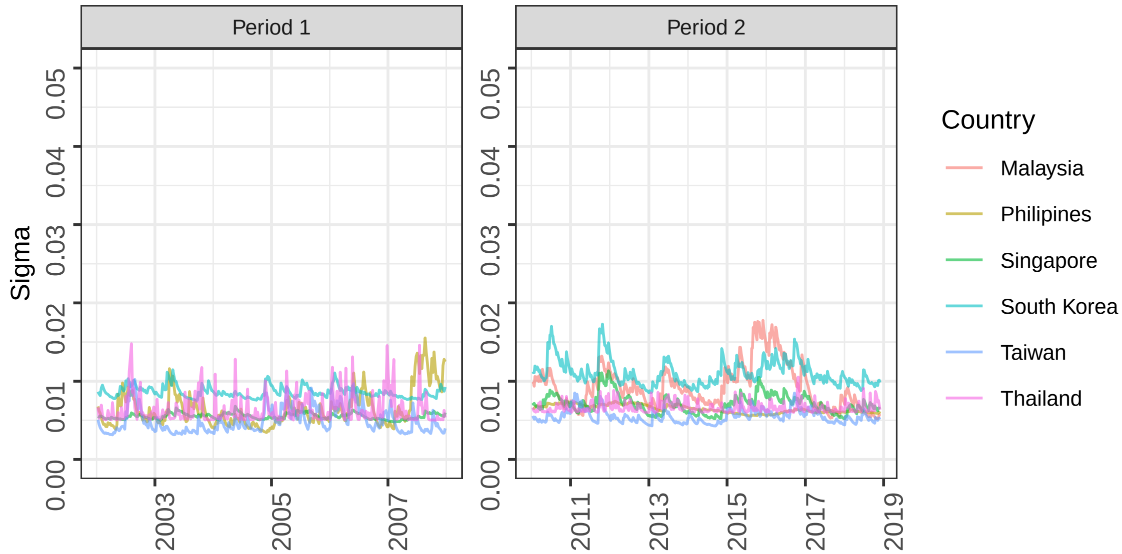


Figure 6.2: Asia Conditional Volatility

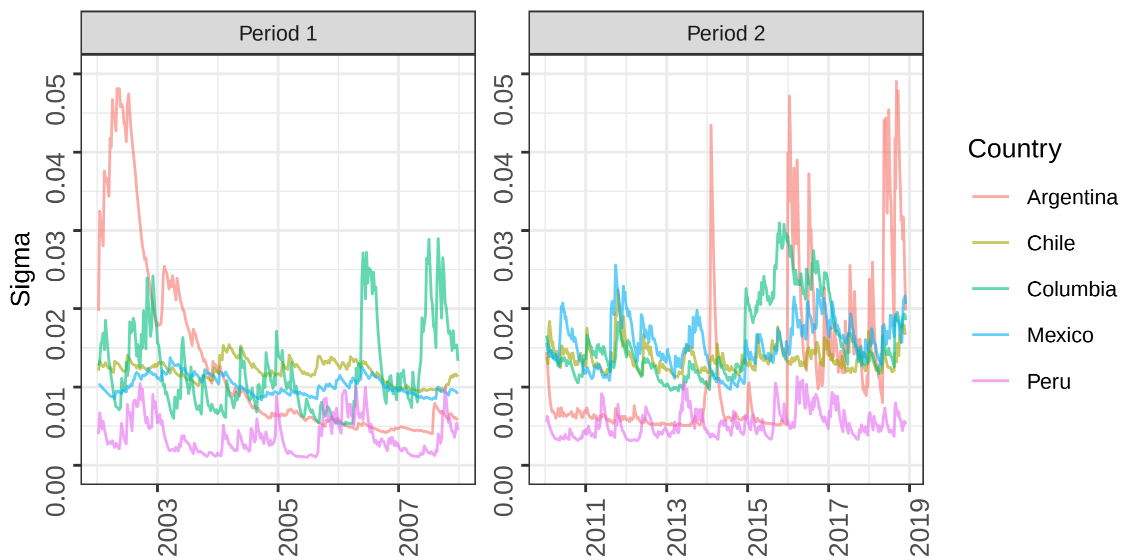


Figure 6.3: South America Conditional Volatility

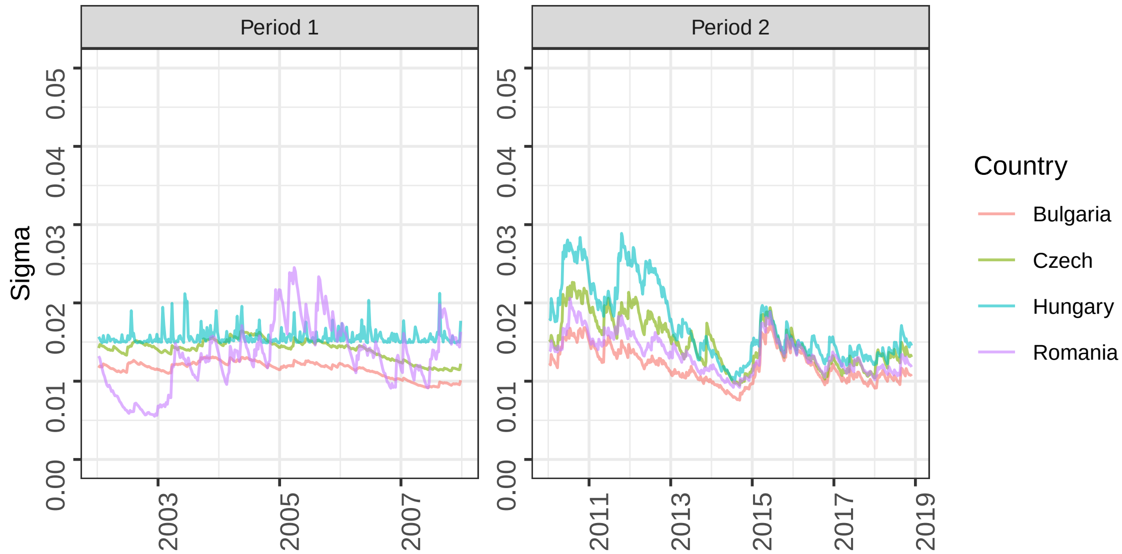


Figure 6.4: Eastern Europe Conditional Volatility

### *6.4. Dynamic Conditional Correlations*

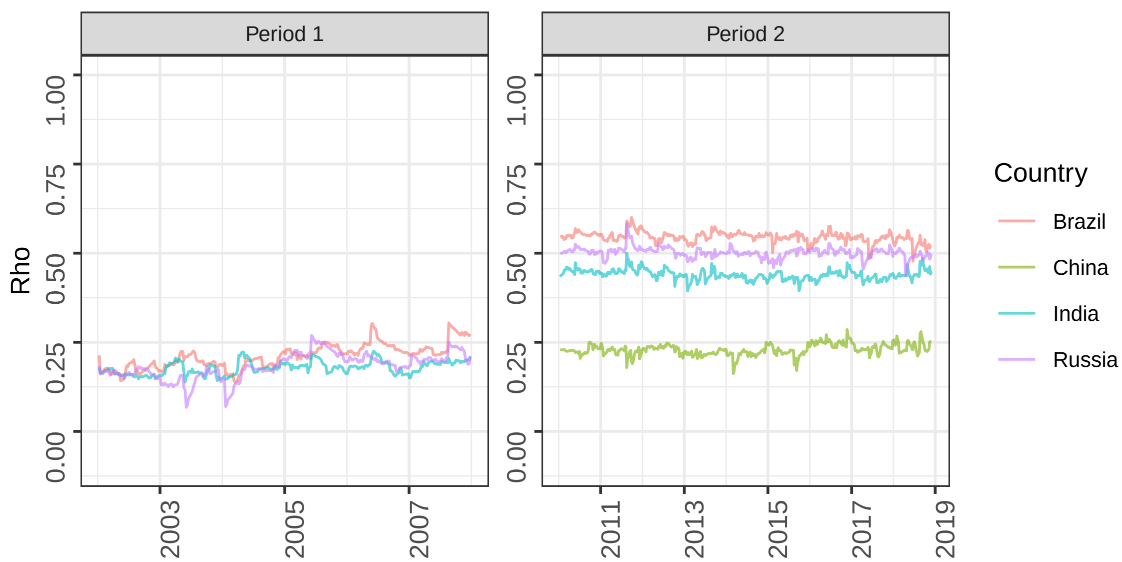


Figure 6.5: ZAR-BRICS DCC

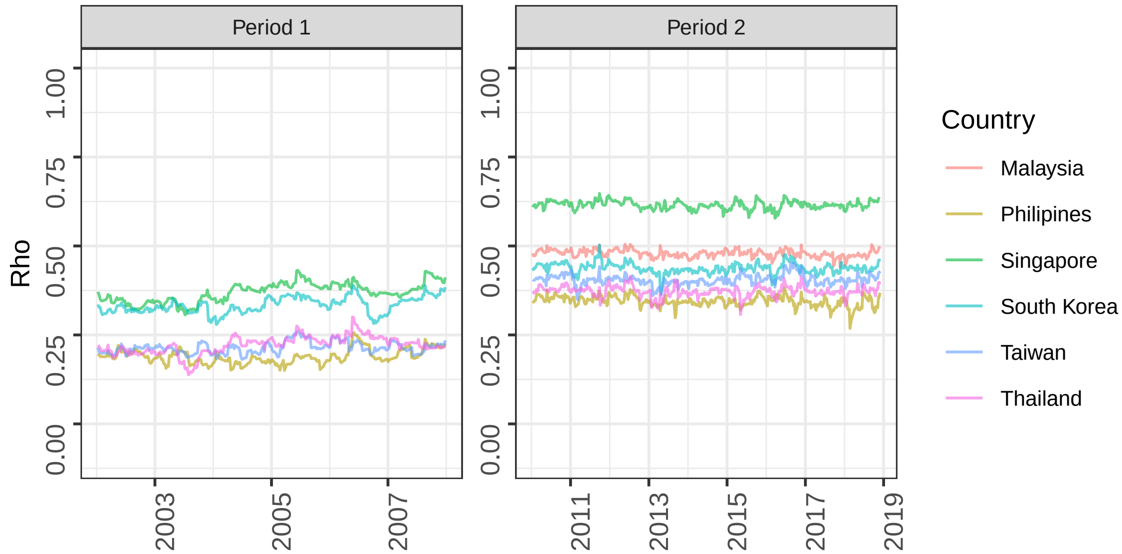


Figure 6.6: ZAR-Asia DCC

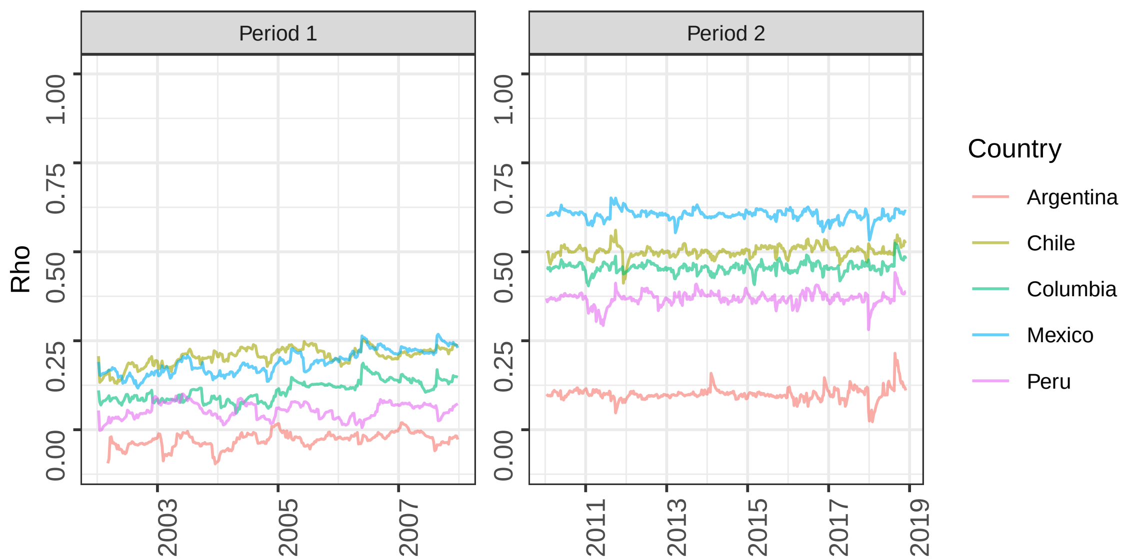


Figure 6.7: ZAR-South America DCC

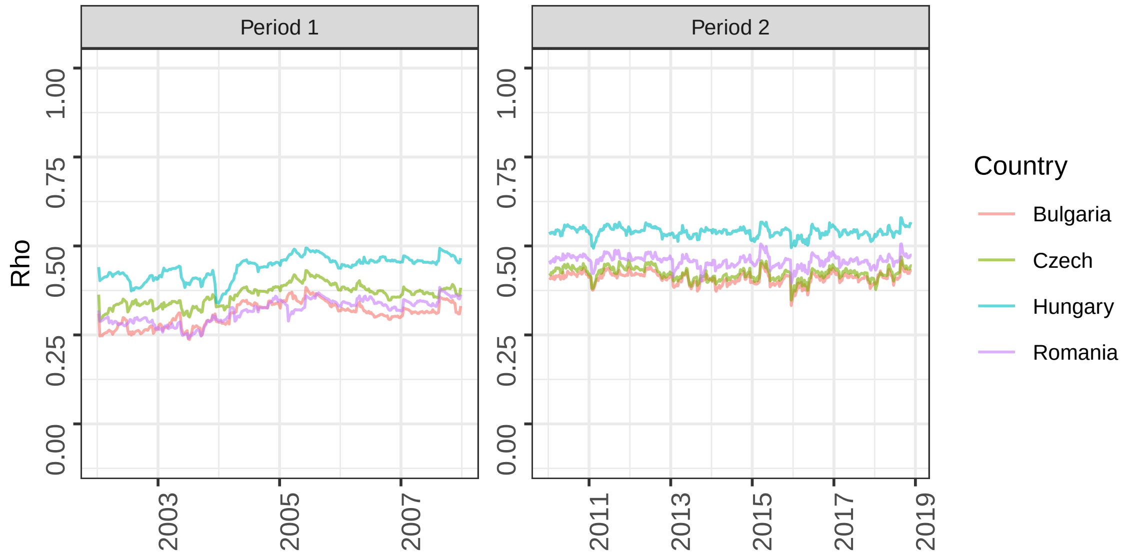


Figure 6.8: ZAR-Eastern Europe DCC

*6.5. Dynamic Conditional Correlations (uncertainty overlayed)*

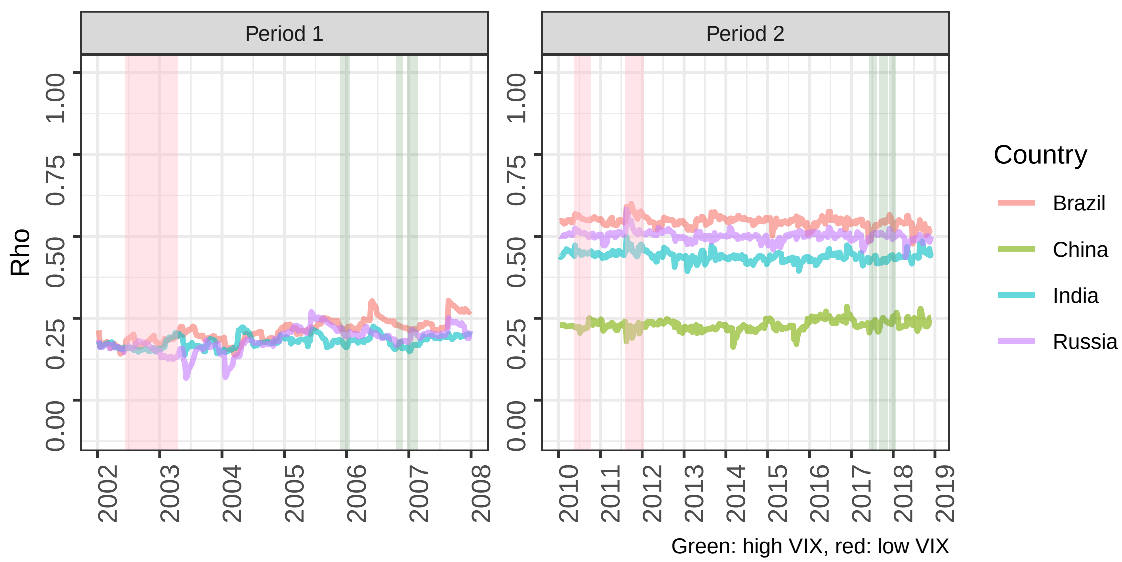


Figure 6.9: ZAR-BRICS DCC

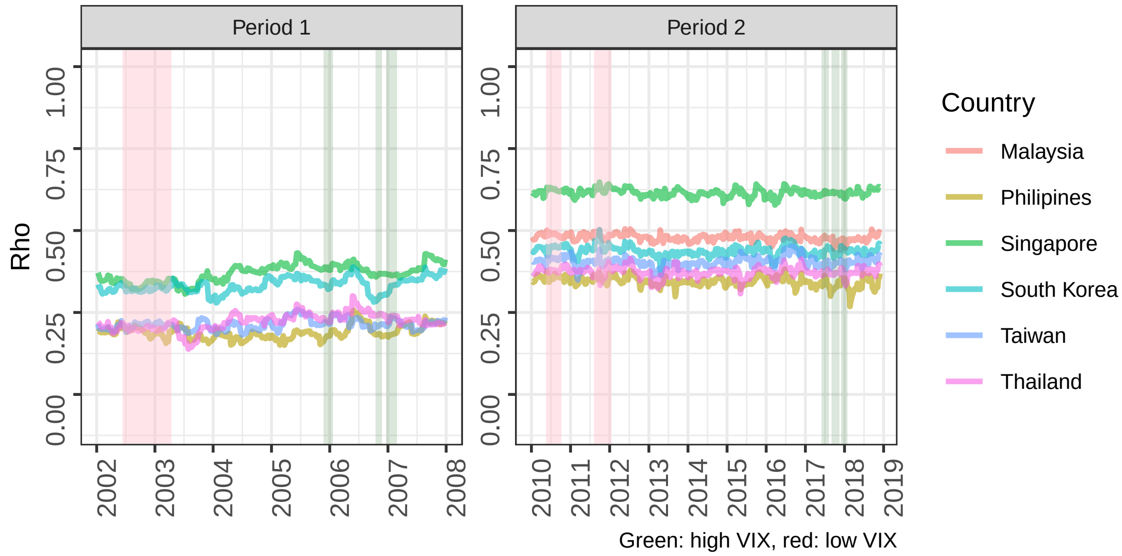


Figure 6.10: ZAR-Asia DCC

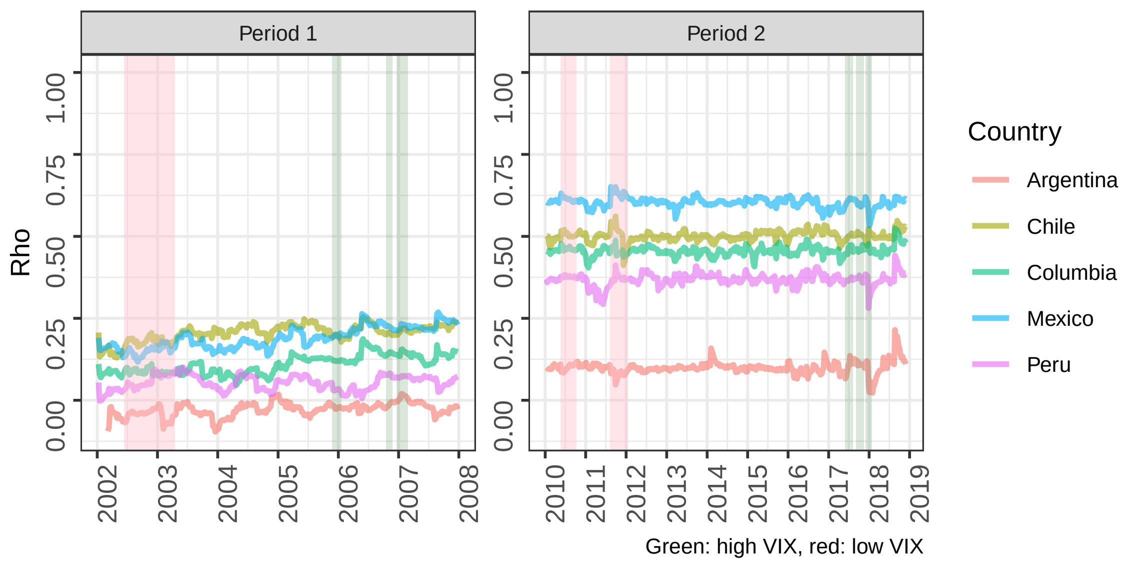


Figure 6.11: ZAR-South America DCC

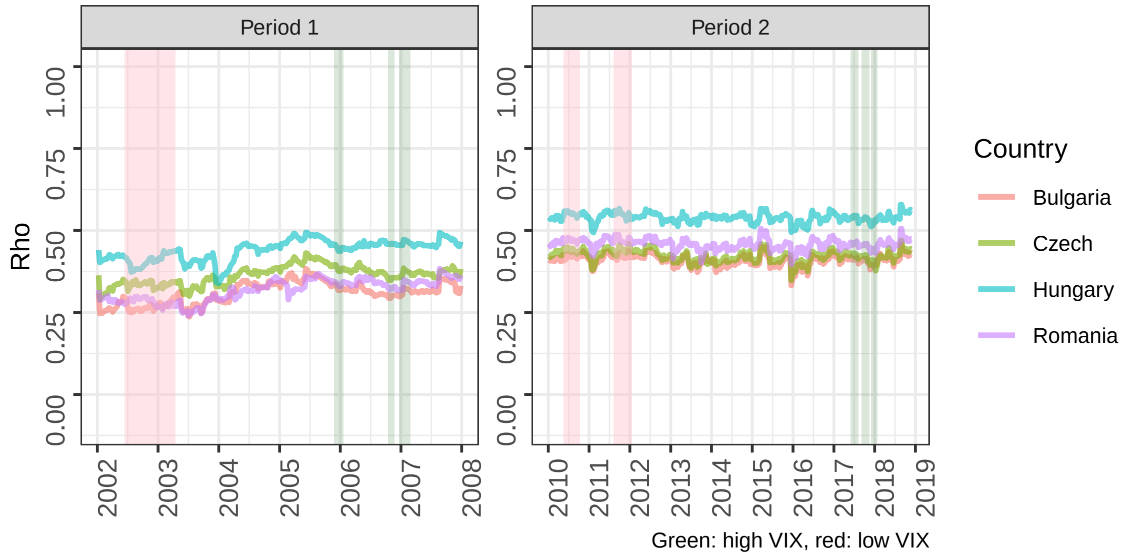


Figure 6.12: ZAR-Eastern Europe DCC

*6.6. Average pairwise correlations*

| | Pairs | Period | Group | Country | SampleAverage | HighVIX | LowVIX |
|---|---|---|---|---|---|---|---|
| 1 | ZAR_MYR | Period 2 | Asia | Malaysia | 0.48 | 0.49 | 0.47 |
| 2 | ZAR_PHP | Period 1 | Asia | Philipines | 0.19 | 0.19 | 0.18 |
| 3 | ZAR_PHP | Period 2 | Asia | Philipines | 0.34 | 0.36 | 0.34 |
| 4 | ZAR_SGD | Period 1 | Asia | Singapore | 0.37 | 0.34 | 0.37 |
| 5 | ZAR_SGD | Period 2 | Asia | Singapore | 0.62 | 0.63 | 0.61 |
| 6 | ZAR_KRW | Period 1 | Asia | South Korea | 0.33 | 0.32 | 0.32 |
| 7 | ZAR_KRW | Period 2 | Asia | South Korea | 0.44 | 0.45 | 0.44 |
| 8 | ZAR_TWD | Period 1 | Asia | Taiwan | 0.21 | 0.21 | 0.22 |
| 9 | ZAR_TWD | Period 2 | Asia | Taiwan | 0.40 | 0.41 | 0.40 |
| 10 | ZAR_THB | Period 1 | Asia | Thailand | 0.22 | 0.20 | 0.23 |
| 11 | ZAR_THB | Period 2 | Asia | Thailand | 0.37 | 0.37 | 0.37 |
| 12 | ZAR_BRL | Period 1 | BRICS | Brazil | 0.21 | 0.18 | 0.22 |
| 13 | ZAR_BRL | Period 2 | BRICS | Brazil | 0.54 | 0.56 | 0.53 |
| 14 | ZAR_CNY | Period 2 | BRICS | China | 0.23 | 0.22 | 0.24 |
| 15 | ZAR_INR | Period 1 | BRICS | India | 0.18 | 0.16 | 0.17 |
| 16 | ZAR_INR | Period 2 | BRICS | India | 0.44 | 0.46 | 0.43 |
| 17 | ZAR_RUB | Period 1 | BRICS | Russia | 0.18 | 0.15 | 0.20 |
| 18 | ZAR_RUB | Period 2 | BRICS | Russia | 0.50 | 0.52 | 0.50 |
| 19 | ZAR_BGN | Period 1 | Eastern Europe | Bulgaria | 0.31 | 0.27 | 0.31 |
| 20 | ZAR_BGN | Period 2 | Eastern Europe | Bulgaria | 0.41 | 0.42 | 0.41 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 21 | ZAR_CZK | Period 1 | Eastern Europe | Czech | 0.36 | 0.34 | 0.37 |
| 22 | ZAR_CZK | Period 2 | Eastern Europe | Czech | 0.42 | 0.44 | 0.41 |
| 23 | ZAR_HUF | Period 1 | Eastern Europe | Hungary | 0.44 | 0.41 | 0.46 |
| 24 | ZAR_HUF | Period 2 | Eastern Europe | Hungary | 0.54 | 0.55 | 0.53 |
| 25 | ZAR_RON | Period 1 | Eastern Europe | Romania | 0.32 | 0.28 | 0.33 |
| 26 | ZAR_RON | Period 2 | Eastern Europe | Romania | 0.46 | 0.47 | 0.45 |
| 27 | ZAR_ARS | Period 1 | South America | Argentina | -0.03 | -0.04 | -0.01 |
| 28 | ZAR_ARS | Period 2 | South America | Argentina | 0.10 | 0.09 | 0.10 |
| 29 | ZAR_CLP | Period 1 | South America | Chile | 0.21 | 0.18 | 0.20 |
| 30 | ZAR_CLP | Period 2 | South America | Chile | 0.50 | 0.50 | 0.50 |
| 31 | ZAR_COP | Period 1 | South America | Columbia | 0.11 | 0.09 | 0.14 |
| 32 | ZAR_COP | Period 2 | South America | Columbia | 0.46 | 0.46 | 0.46 |
| 33 | ZAR_MXN | Period 1 | South America | Mexico | 0.19 | 0.15 | 0.21 |
| 34 | ZAR_MXN | Period 2 | South America | Mexico | 0.60 | 0.62 | 0.60 |
| 35 | ZAR_PEN | Period 1 | South America | Peru | 0.05 | 0.06 | 0.06 |
| 36 | ZAR_PEN | Period 2 | South America | Peru | 0.37 | 0.37 | 0.36 |

Table 6.3: Average pairwise correlations

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