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 quantiles 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 find that conditional correlations increase significantly following the financial crisis. However, we do not find significant differences during periods of high and low uncertainty, which suggests there may be other factors driving EM currency co-movement.

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) approach, 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. However more generally, the paper discusses the relationships between 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 consequences for currency traders, which provides good motivation to investigate the topic in more detail. For instance, if the ZAR is strongly positively (negatively) correlated with the Brazilian Real (BRL) when the CBOE Volatility Index (VIX) is higher than usual, then it would be sensible to sell (buy) BRL, as a diversification strategy.

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The layout of the rest of this paper is as follows: Section 2 discusses the data used, subset 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

The data includes EM currencies from 2002 to 2018. The currencies are grouped into four categories, namely BRICS, Asia, South America and Eastern Europe. Although the data is of daily frequency, we calculate the weekly returns to avoid the noise present in currency returns. Note that given the use of currency data, a positive return is synonymous with "depreciation", whereas a negative return is synonymous with a "depreciation". Furthermore, all currencies are measured relative to the United States dollar (USD).

Table **??** in the appendix reports the summary statistics (mean and standard deviation) for all of the currencies in our sample.[2] The summary statistics suggests that currency values (quotes) relative to the USD vary greatly, whereas the average weekly returns (and their corresponding standard deviations) are generally very low. This makes sense given that the weekly return calculation strips out the noise present in daily returns.

In this paper, we stratify the data according to differing periods of uncertainty. To gain an idea of how this looks in practice, see figure 2.1 which plots the VIX over the full sample period. The black lines distinguish the top and bottom quintiles from the rest, which is crucial for our calculations. Specifically, all observations above the black line are classified as "high uncertainty" and all observations below the black line are classified as "low uncertainty". We make this explicit by shading the dates which are pulled by stratification. We then compare correlations during these periods with average correlations during the full sample period.

[1] Paper written using the "Texevier" package developed by N.F. Katzke (2016).
[2] Refer to table 6.3 in the appendix for the full list of currencies considered.

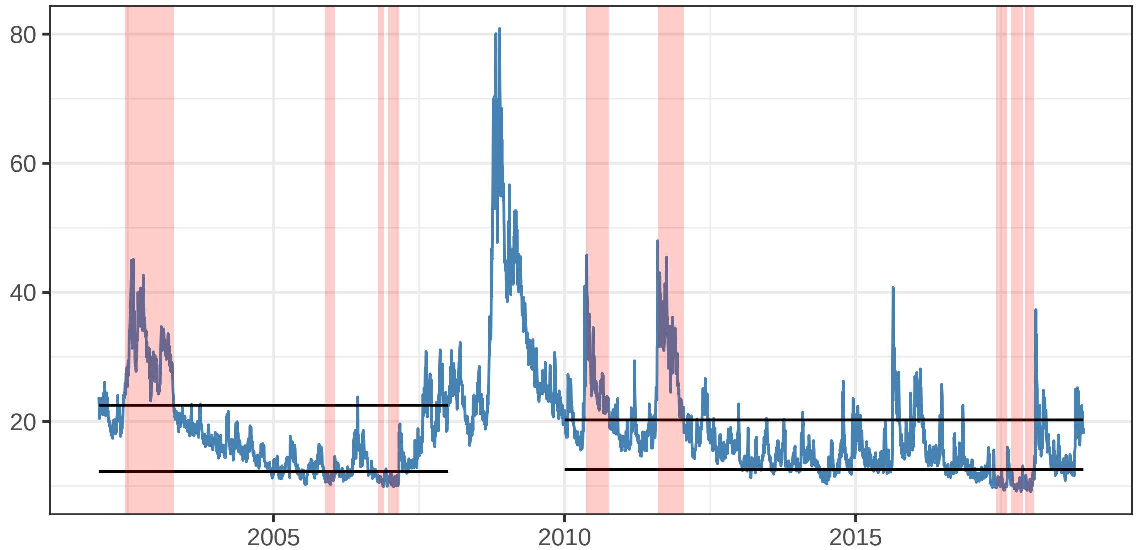

Figure 2.1: VIX

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 correlation estimate is computed. Hence, the process comprises two steps which are discussed in this section. Section 3.1 defines GARCH models, whereas section 3.3 discusses 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 μ_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:

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

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.

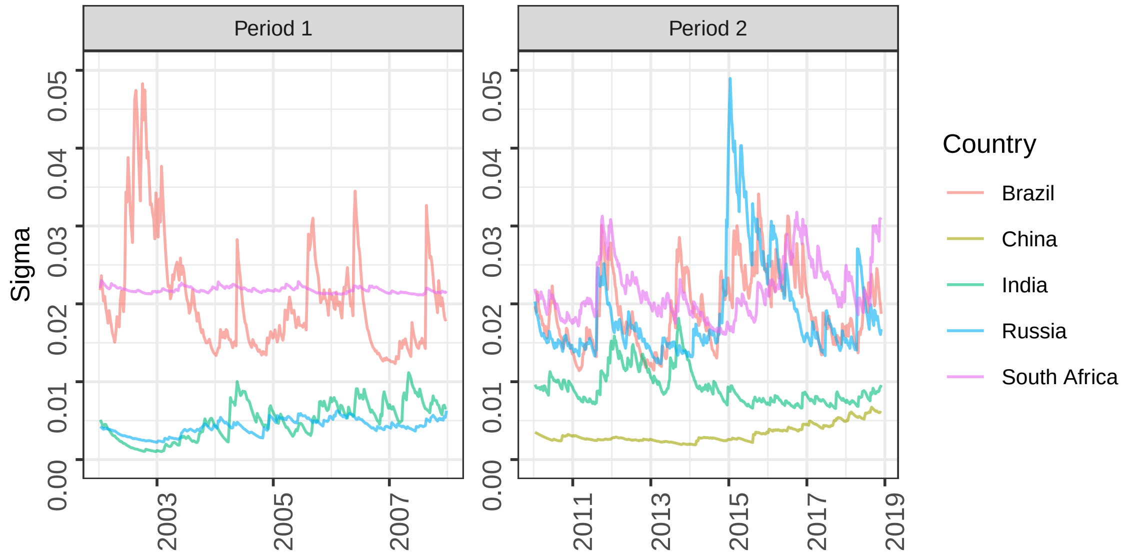

Figure 4.1: BRICS conditional volatility

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). However, the story changed somewhat in the post-crisis era (Period 2): the Chinese Renminbi (CNY), no longer pegged to the USD, remained the most stable currency of the group, whereas the RUB became markedy more volatile. Furthermore, the remaining BRICS currencies became more *unstable*, not necessarily more volatile. 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.

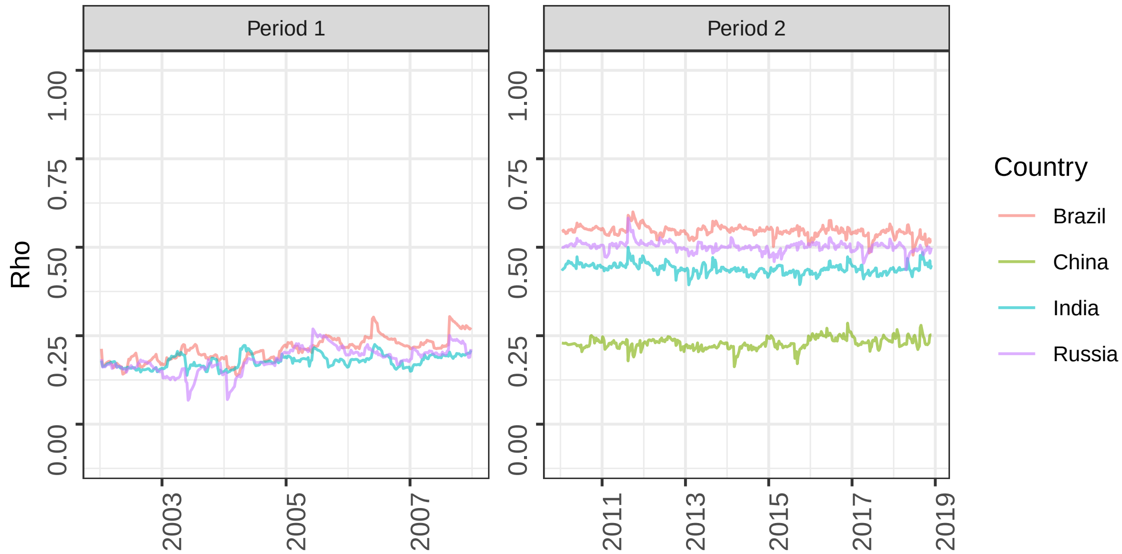

Figure 4.2: BRICS dynamic conditional correlation

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 flexible exchange rate regime. The plot clearly shows the ZAR being most highly 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 Period 2 conditional correlations 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 during more uncertain times (red overlay).

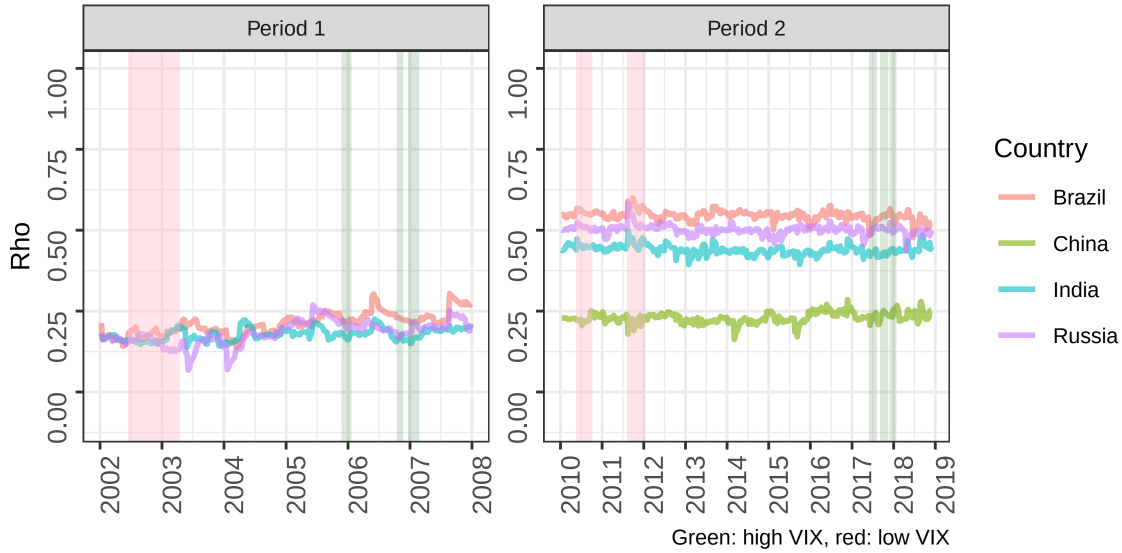

Figure 4.3: BRICS dynamic conditional correlation

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 closely correlated with other EM currencies when the VIX is in its top quintile (or in the bottom quintile, for that matter). 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 could be induced by large-scale asset purchases (quantitative easing) in the United States or other factors, such as high yield differentials and resulting carry trade. Thereafter, we stratify the VIX into quantiles and

[6] Table 6.4 in the appendix contains the average pairwise correlations, for the full sample and during times of high and low VIX.

consider the top quantile 'high VIX' (uncertainty) and the bottom quantile 'low VIX' (uncertainty). After calculating the average correlations for these periods and comparing it to the average for the full sample period, we find very few changes. Therefore, our study suggests that higher-than-usual (or lower-than-usual) economic uncertainty does not result in higher EM currency co-movement. Investors should therefore rely on factors other than economic uncertainty when making strategic investment decisions.

6. Appendix

6.1. Summary statistics

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

Table 6.1: Period 1 returns

	Ticker	Mean	StandardDeviation
1	ARS Curncy	0.01	0.02
2	BGN Curncy	0.00	0.01
3	BRL Curncy	0.00	0.02
4	CLP Curncy	0.00	0.01
5	CNY Curncy	0.00	0.00
6	COP Curncy	0.00	0.02
7	CZK Curncy	0.00	0.02
8	HUF Curncy	0.00	0.02
9	INR Curncy	0.00	0.01
10	KRW Curncy	0.00	0.01

11	MXN Curncy	0.00	0.02
12	MYR Curncy	0.00	0.01
13	PEN Curncy	0.00	0.01
14	PHP Curncy	0.00	0.01
15	RON Curncy	0.00	0.01
16	RUB Curncy	0.00	0.02
17	SGD Curncy	-0.00	0.01
18	THB Curncy	0.00	0.01
19	TWD Curncy	-0.00	0.01
20	ZAR Curncy	0.00	0.02

Table 6.2: Period 2 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 6.3: Currencies considered

6.3. Volatility plots

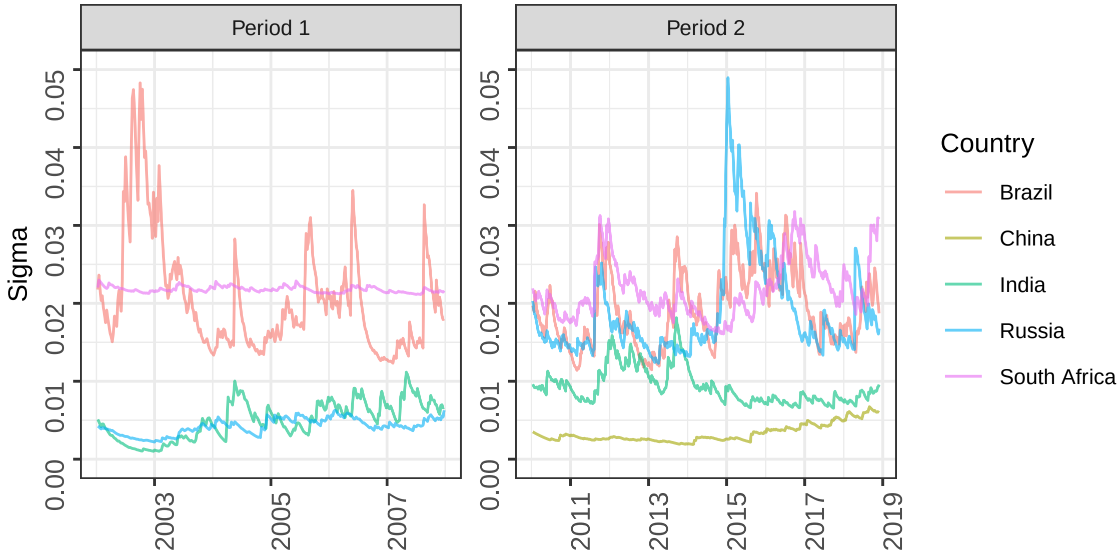

Figure 6.1: BRICS Conditional Volatility

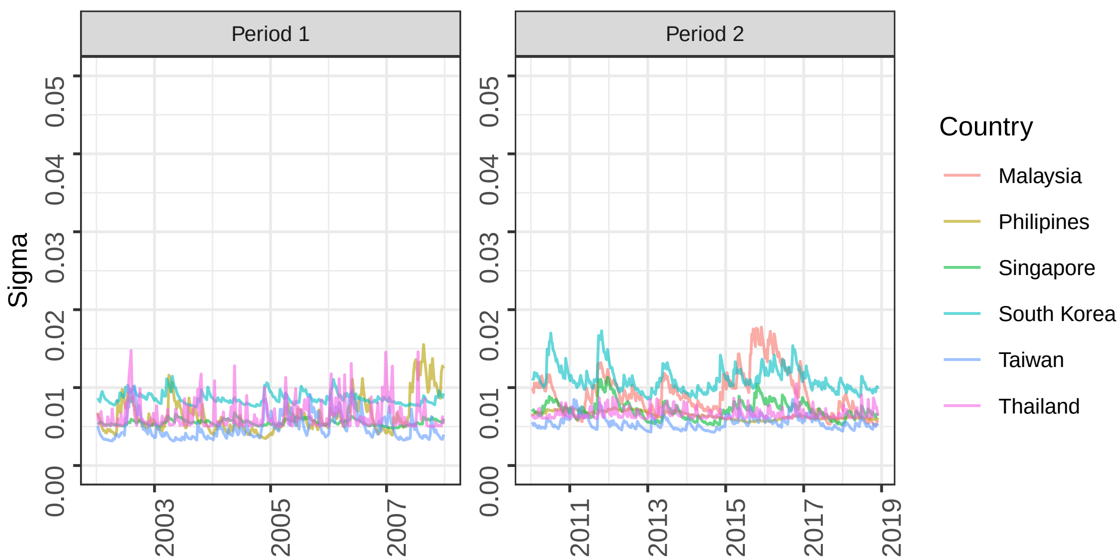

Figure 6.2: Asia Conditional Volatility

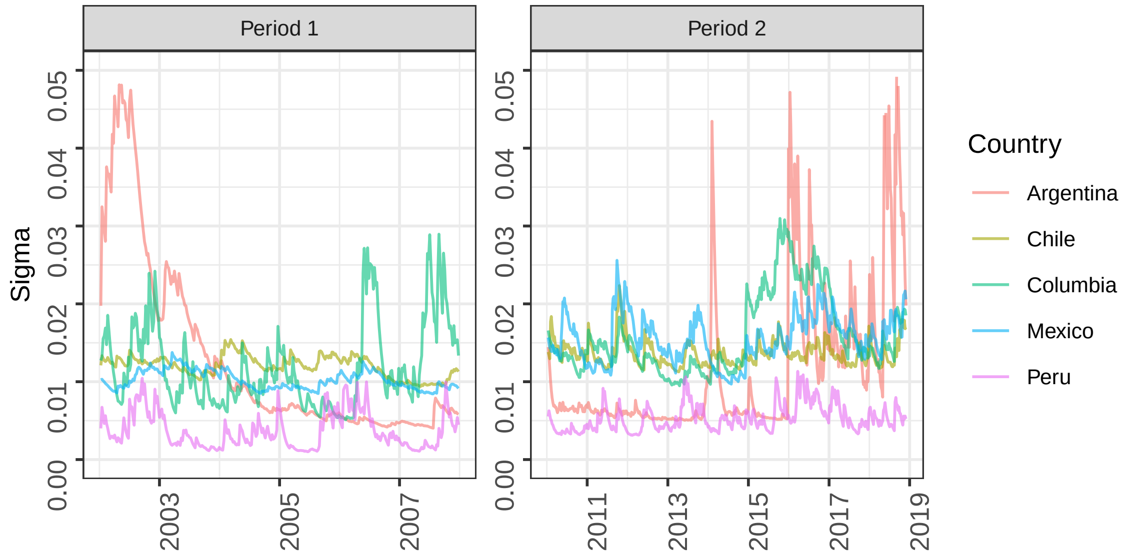

Figure 6.3: South America Conditional Volatility

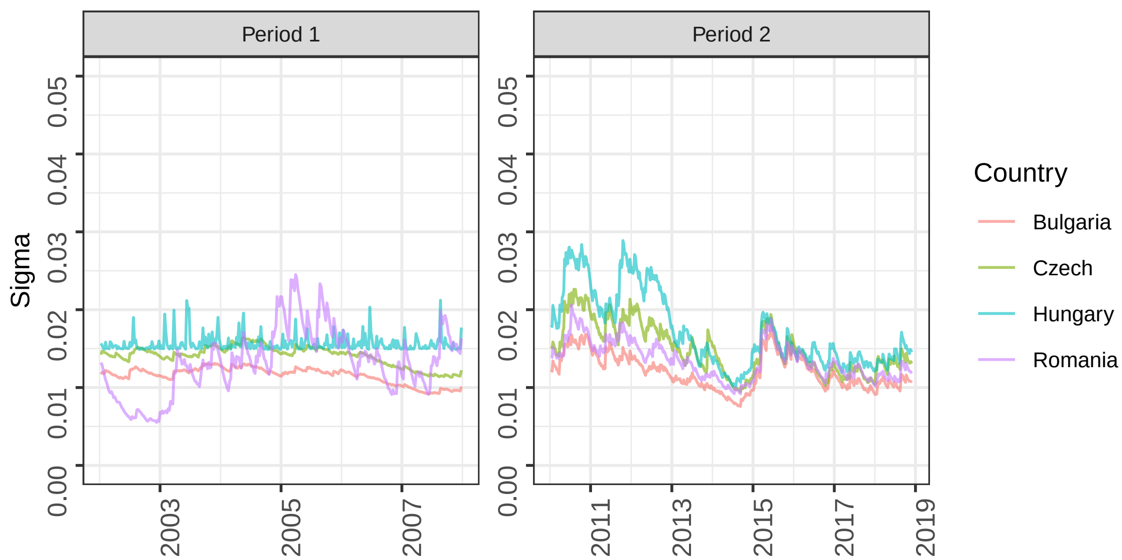

Figure 6.4: Eastern Europe Conditional Volatility

6.4. Dynamic Conditional Correlations

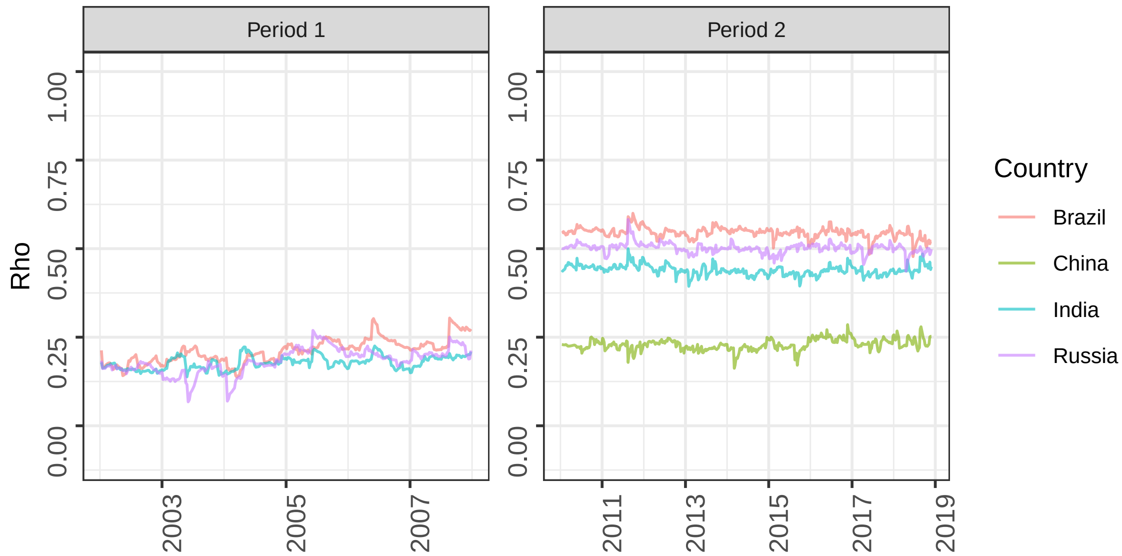

Figure 6.5: ZAR-BRICS DCC

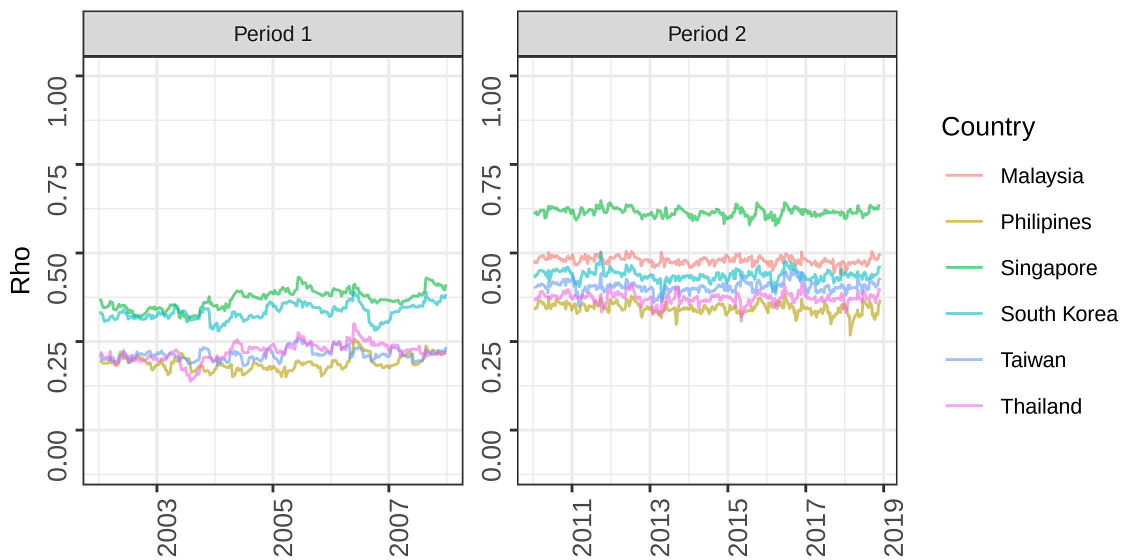

Figure 6.6: ZAR-Asia DCC

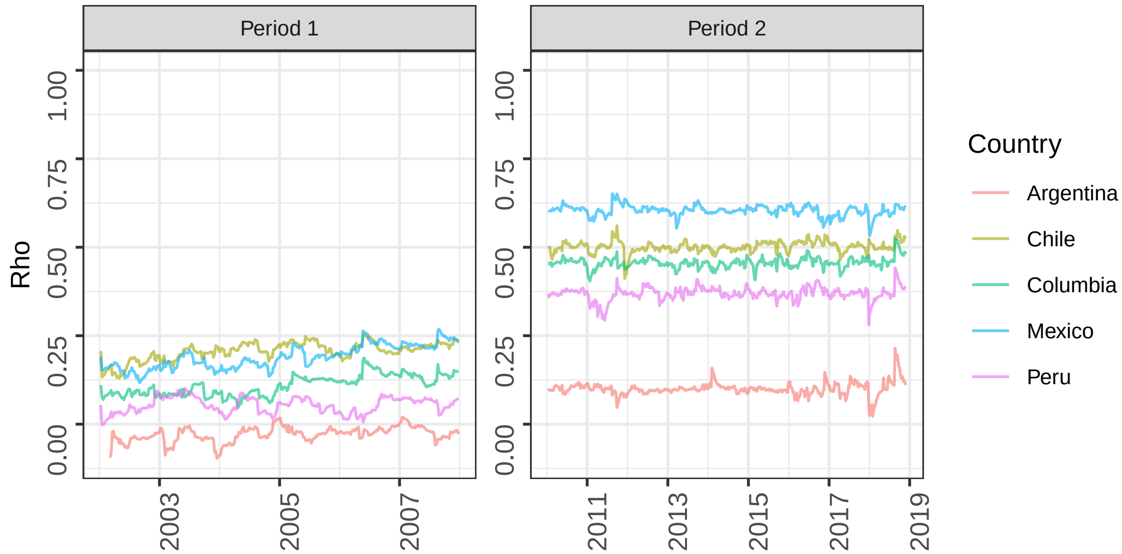

Figure 6.7: ZAR-South America DCC

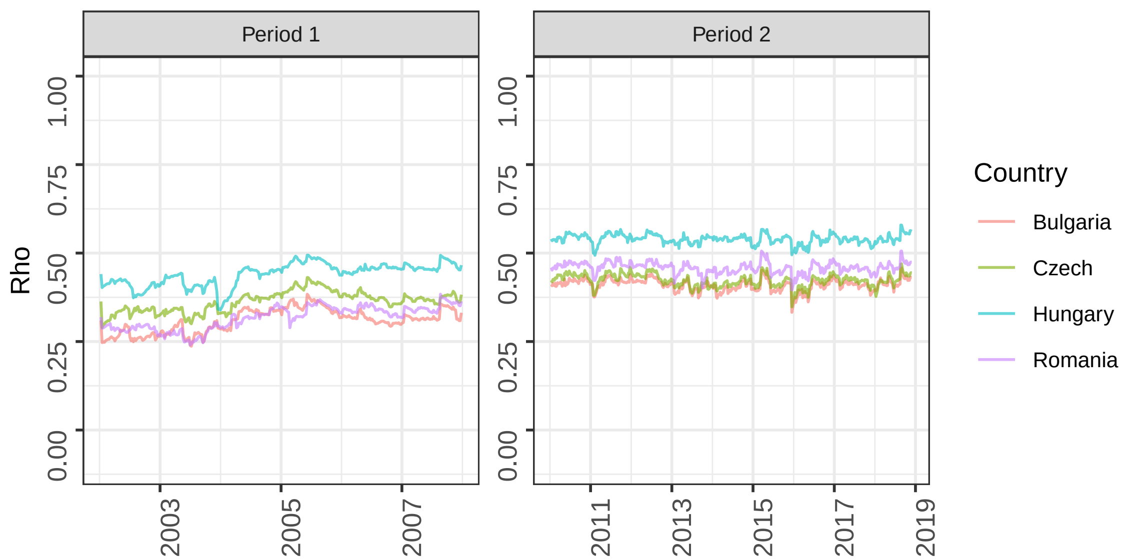

Figure 6.8: ZAR-Eastern Europe DCC

6.5. Dynamic Conditional Correlations (uncertainty overlayed)

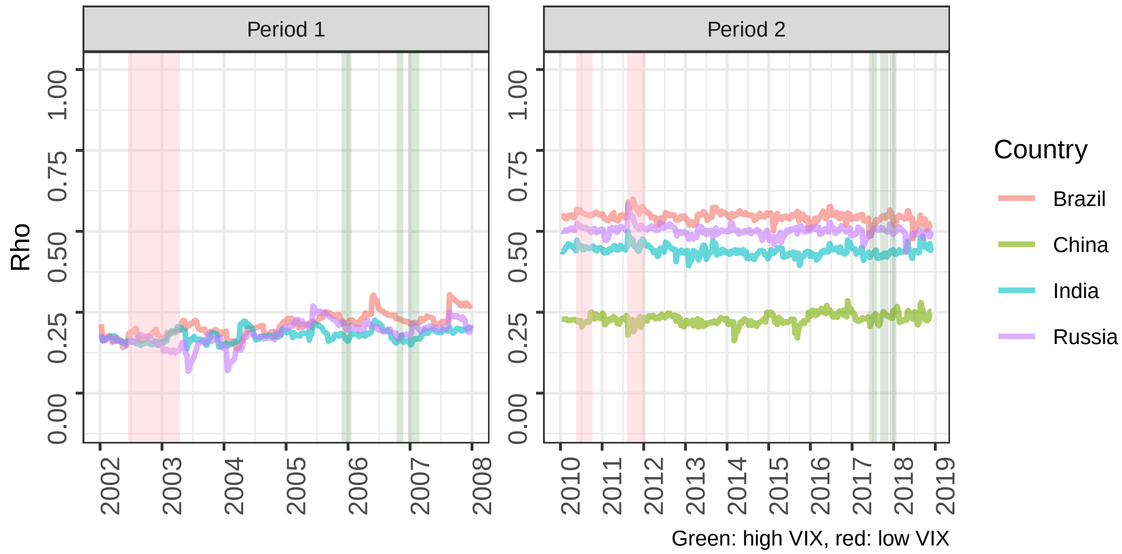

Figure 6.9: ZAR-BRICS DCC

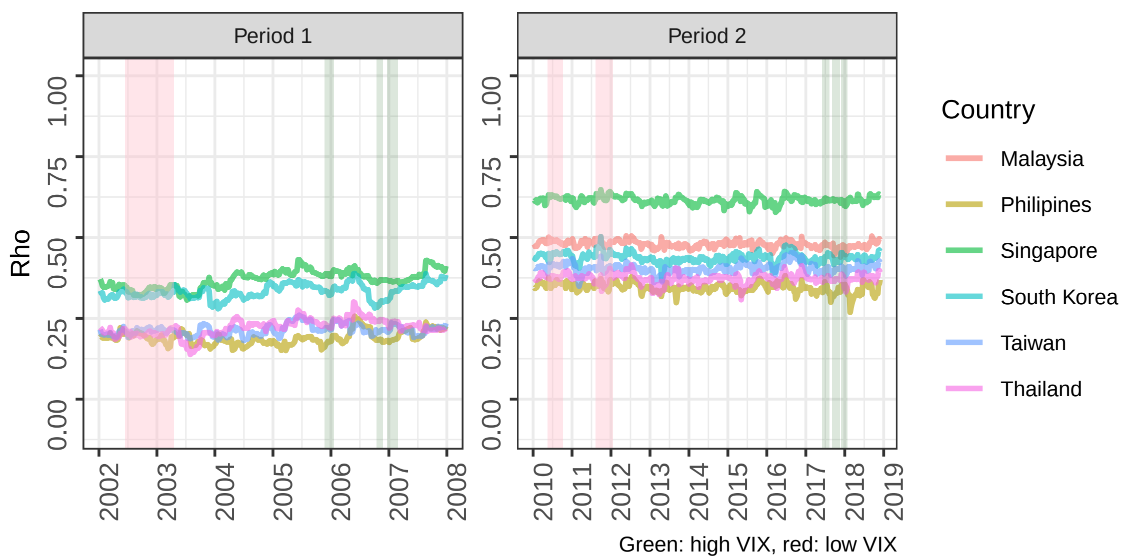

Figure 6.10: ZAR-Asia DCC

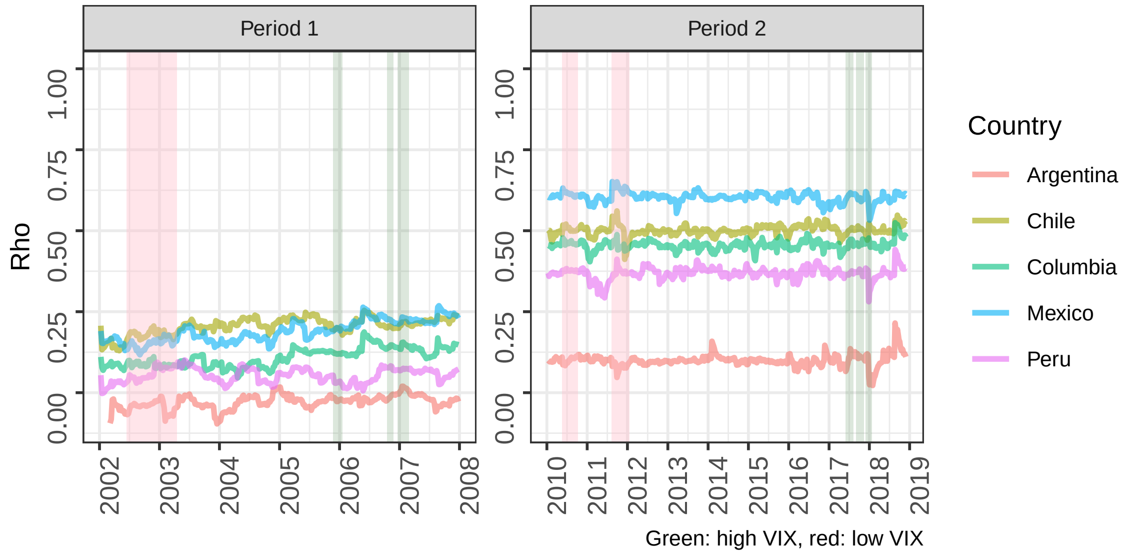

Figure 6.11: ZAR-South America DCC

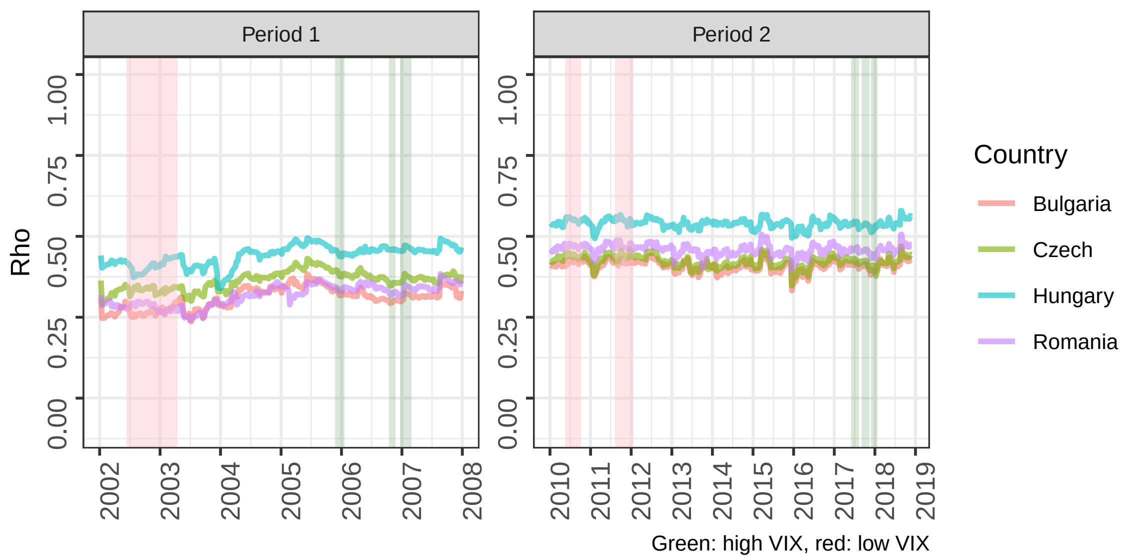

Figure 6.12: ZAR-Eastern Europe DCC

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 6.4: Average pairwise correlations

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