Dynamic conditional correlations and connectedness in emerging market exchange rates

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Abstract

The financialization of international markets driven by widespread financial innovations resulted in growing paths of volatility for various assets, including exchange rates. This paper investigates the dynamic effects of shocks on exchange rates conditional correlations and analyzes the connectedness between pairs of exchange rates for developed and emerging countries, represented by the BRICS countries plus Turkey (BRICS+T). The sample covers the period from January 2000 to March 2022 in a daily basis. We apply the DCC-GARCH model to obtain conditional correlations of pairwise exchange rates and estimate a SVAR to identify exogenous shocks. The results indicate that shocks to conditional correlation of developed countries exchange rates decrease the conditional correlation in emerging markets. A connectedness index illustrates the dependence among exchange rates and support the presence of time-varying co-movement and volatility connectedness. The findings suggest that concentration of volatility in core countries increases instabilities in emerging economies.

Keywords: Exchange rates; Volatility; Conditional correlation; Connectedness.

JEL Codes: F31; C58.

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1. Introduction

The increase in financial integration between countries and the recurrence of financial innovations have consolidated the financialization of foreign exchange markets. This process significantly increased price volatility, thus causing direct effects on emerging economies that were already vulnerable to external shocks. As a result, volatility modeling has become an essential component of modern finance to obtain better portfolio allocation and served as a parameter for evaluating financial effects in the economy and forecasting yields and volatility. Bernard et al (2008), Wang and Hsu (2010), for instance, estimated stochastic models for commodity prices and Pilbeam and Legeland (2014) found significant outperform of volatility forecasts by using GARCH models in periods of low and high volatility of foreign exchange rates.

Financial markets began recording daily exchange rates from 2000 onwards. Since then, the global financial system has faced several crises, which have given an adverse course to exchange rate volatility. The BRICS countries (Brazil, Russia, India, China, and South Africa) also went through some of these crises with similar economic performance, as well as other emerging countries. Although the BRICS are usually referred to as emerging countries, they have provided financial support to low-income countries and are engaged in a South-South cooperation mainly through a new Development Bank, which substantially increased their financial integration.

The objective of this paper is to investigate the dynamic effects of shocks on exchange rates conditional correlations and evaluate the connectedness between pairs of developed and emerging countries exchange rates. By emerging markets, we consider the BRICS countries plus Turkey (BRICS+T), which share important economic, social, and political similarities among themselves. The developed countries exchange rates are represented by the UK pound and EZ Euro due to their geographical and economical relevance for the BRICS+T countries. We apply the DCC-GARCH model to obtain the dynamics of the conditional correlations for exchange rates pairwise and estimate a Structural Autoregressive Vector model (SVAR) to account for exogenous shocks. Then, we compute a connectedness index to express the dependence among the selected currencies.

Dummy variables are included in the estimations to account for the effects of exogenous economic crises.

The BRICS+T countries have showed correlated dynamics of financial development, economic growth, and external vulnerabilities since the 2000s. This evidence is relevant for the pairwise estimation to obtain the dynamic conditional correlation of exchange rates and the effects of exogenous shocks on this correlation. The literature that evaluates conditional correlation shocks is still focused on macroeconomic variables and commodity prices. This practice differs from our approach that uses pairwise exchange rates from emerging and developed countries with daily quotations to evaluate the effects of dynamic shocks on conditional correlations. The results indicate that the growth of the dynamic correlation of the Euro and Pound ratio generates decreases in the conditional volatility of the BRICS+T countries. The DCC-GARCH allowed to assess the dynamic effects on the exchange rates volatility. Although the SVAR model manages to capture the dynamic characteristics of multivariate time series, we transformed the residuals variance-covariance matrix to have orthogonal shocks, analyze the impulse-response functions and decompose the forecast error.

Some authors stress that emerging countries have a sensitive exchange rate dynamics because it is the main determinant of international trade, such as Cashin, Cespedes and Sahay (2003) and Chen, Rogoff and Rossi (2010). Lizardo and Mollick (2010) analyzed dollar fluctuations in the face of oil shocks and found that oil exporting countries are more sensitive to oil shocks in their exchange rates. Hegerty (2014; 2016) modeled macroeconomic spillovers and used a VAR-GARCH methodology to identify commodity shocks in economic variables in emerging countries and Latin America. Studies addressing exchange rates and financial risks of the BRICS countries are also quite extensive and report results that consider geopolitical risks, as Salisu, Cuñado, Gupta (2022), external vulnerabilities, as Hall et al (2010), and relationship between exchange rates and stock market returns, as Chkili and Nguyen (2014).

Furthermore, there is a large literature that implement VAR models to analyze the role of monetary policy shocks, such as Faust and Rogers (2003), for exchange rates and other assets in the financial markets. Raza et al. (2016) found a positive impact on stock market prices of gold prices in the BRICS economies. Christiano et al. (1996) and Sari et al. (2010) used oil prices, metal prices and exchange rates data to investigate co-movements between these variables.

The literature that employs the SVAR and SVAR-GARCH methodology using financial variables and commodity prices is also extensive. Akkoc and Civcir (2019) investigate volatility spillover from oil and gold to the Borsa Istanbul Stock Exchange Index through distinct SVAR-DCC-GARCH models. Lütkepohl and Milunovich (2016) show that changes in residual volatility in VAR models can be used for identifying structural shocks in a structural VAR analysis. Thus, testable conditions to identify the changes of volatility can be modelled by a multivariate GARCH.

Identifying the conditional correlation of volatility is the starting point for investigating the dynamics of connectedness between exchange rates. The framework was formalized by Diebold and Yilmaz (2014) and the application for exchange rate data follows Gabauer (2019) for developed countries.

The paper is organized as follows. The next section describes the empirical strategy, represented by the DCC-GARCH model, SVAR and connectedness index. Section three reports and analyzes the major results. Finally, section four is dedicated to the concluding remarks.

2. Empirical Strategy

2.1 DCC-GARCH model

Financial time series such as commodity prices and exchange rates, as noted in the literature previously referred, present the phenomenon of heteroscedasticity. That is, there are periods in which the prices/values of these series show significant fluctuation. Heteroscedasticity issues are essentially dealt with by Engle (1982), who presented the Auto-Regressive Conditional Heteroscedasticity (ARCH) models in a study of inflation rates. These models seek to estimate time-dependent volatility as a function of previously observed volatility. Henceforth, the model originally proposed by Engle (ibid.) was premised on modeling the variance of errors in a regression model as a linear function of lagged values of squared regression errors. Using Tsay's (2005) mathematical notation, we can write an ARCH(p) model as follows:

$$R_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 R_{t-1}^2 + \cdots + \alpha_q \alpha_1 R_{t-q}^2 \qquad (2)$$

Where the dependent variable R_t is the returns of the prices of a financial series in a given frequency of logarithmic changes, as it can be the returns of an exchange rate analyzed here. The conditional volatility is represented by σ_t^2 at time t, while α_q are the parameters of the ARCH model. The ARCH model often demands many parameters/lags return a good explanation of the volatility process of a financial series. To solve this problem, Bollerslev (1986) extended Engle's original work by developing a technique allowing the conditional variance to be an ARMA process. Formally, we can define a GARCH (p,q) model as follows:

$$R_t = \sigma_t \epsilon_t \quad (conditional\ average) \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \Sigma_{i=1}^{q} \alpha_i R_{t-i}^2 + \Sigma_{j=1}^{p} \beta_j \sigma_{t-j}^2 \ (conditional\ variance) \quad (4)$$

Where ϵ_t is a sequence of independent and identically distributed random variables with mean zero, variance equal to one, and $\alpha_0 > 0$ for $i > 0$. With such properties, the coefficients α_i satisfy conditions to ensure that the unconditional variance is finite and positive.

The multivariate GARCH models grant the conditional covariance matrix of the dependent variables to follow a flexible dynamic structure and allow the conditional mean to follow a vector autoregressive (VAR) structure and then turn possible to estimate a SVAR model. The general MGARCH model can be written as:

$$y_t = C x_t + r_t \qquad (5)$$

$$r_t = H_t^{1/2} \nu_t \quad (6)$$

Where y_t represents a m-vector of dependent variables, C is a $m \times k$ parameter matrix, x_t is a k-vector of explanatory variables, possibly including lags of y_t, $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t , and ν_t is a m-vector of zero-mean. By the way, in this general framework, H_t is a matrix generalization of univariate GARCH models. For example, a general MGARCH (1,1) model must be written as:

$$vech(\boldsymbol{H_t}) = \boldsymbol{s} + \boldsymbol{A} vech(r_{t-1} r_{t-1}') + \boldsymbol{B} vech(H_{t-1}) \qquad (7)$$

The variables inserted above are r_{t-1}, the $N\ x\ 1$ vector of returns observed at a time t, s is an $N(N+1)/2$ vector of constants; A and B are square $N(N+1)/2$ parameter matrices. The $vech(\cdot)$ function returns a vector containing the unique elements of its matrix argument. In addition, there are a commonly models supported considering MGARCH model, specially the DVECH that assumes that the matrices **A** and **B** in equation (6) are diagonal.

However, a DCC-GARCH model (Dynamic Conditional Correlation-GARCH) is a member of the multivariate GARCH family, and it is used to estimate the dynamic conditional correlations. The DCC-GARCH goes back to Engle et al. (1990) and Bollerslev (1990) that introduces a constant conditional correlation GARCH model (CCC-GARCH). The CCC-GARCH model assumes that all conditional correlation among various assets is constant. The work of Engle (2002) developed the dynamic conditional correlation GARCH (DCC-GARCH) model that eases the constant conditional correlation assumption and allows for time-varying correlations that are measurable with respect to the past values of the variables. In the DCC-GARCH model, the number of parameters does not increase exponentially but linearly, thereby solving a dimensionality problem.

Because of its popularity, we focus on the following DCC model due to Engle (2002) that determination of the variance-covariance matrix of the residuals, H_t, can be written as:

$$H_t = D_t R_t D_t \quad (8)$$

Where D_t is the diagonal matrix of the time-varying standard deviations from univariate GARCH estimations and R_t is the time-varying correlation matrix of variables. Based on Boudt, Galanos, Payseur and Zivot (2019), R_t contains conditional correlation coefficients that should be equal to or less than one. R_t can be defined as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (9)$$

$$Q_t = (1-a-b)Q^* + a\varphi_{t-1} + bQ_{t-1} \quad (10)$$

Q is the unconditional variance between the series, Q^* is the unconditional covariance between the series estimated in the first step, and φ_{t-1} is the empirical matrix of standardized residuals. Thus, a and b are implying the persistence of shocks. The sum of them which measure volatility persistence, is restricted to be less than one.

The DCC GARCH model has its parameters estimated from the Maximum Likelihood Method. The Log-Likelihood function is composed as follows:

$$LL = \frac{1}{2}\Sigma_{i=1}^{T}\left(nlog\frac{2}{\pi} + 2log|D_t| + \log|R_t| + v_t' R_t^{-1} v_t\right) \quad (11)$$

$$= \frac{1}{2}\Sigma_{i=1}^{T}\left(n\log\frac{2}{\pi} + 2\log|D_t| + \varepsilon_t' D_t^{-1} D_t^{-1} \varepsilon_t\right)$$
$$- \frac{1}{2}\Sigma_{i=1}^{T}(v_t' v_t + \log|R_t| + v_t' R_t^{-1} v_t) \quad (12)$$

$$= LL_V(\eta_1) + LL_R(\eta_1, \eta_2) \quad (13)$$

Where $LL_v(\theta_1)$ is the volatility component with θ_1 parameters and $LL_R(\theta_1, \theta_2)$ is the correlation component with θ_1 and θ_2 parameters.

The DCC-GARCH parameters will be estimated in different pairs of exchange rates to obtain the conditional correlation between the series in a complete way to serve as an input to the SVAR estimation, as detailed in *section 3.2.* Conditional correlation estimation must cover all combinations of currency pairs.

2.2 SVAR Model

The SVAR model can be used alternatively to the VAR and will be estimated using the results of DCC-GARCH as inputs for our estimation. The SVAR estimation is equivalent to the problem of estimating a simultaneous equation model with covariance restrictions. Breitung, Brüggeman and Lütkepohl (2004) consider that SVAR is a model without restrictions on the long-run effects of the shocks and is usually instrumentalized for macroeconomic models. It is valid to denote the SVAR model highlighting that ε_t is a white noise with $\varepsilon_t \sim N(0, I_K)$. First, the basic form of a VAR(p) is printed below following Enders (2004):

$$y_t = \Pi_0 + \Pi_1 y_{t-1} + \cdots + \Pi_p y_{t-p} + u_t \quad (14)$$

Where Π_0 is a K-dimensional constant term, the expression $\Pi_j (j = 1, \ldots, p)$ are $(K\ x\ K)$ coeffincient matrices and u_t is the serially uncorrelated error term with mean zero and unconditional covariance matrix Σ_u. The literature often assumes that u_t follows a Multivariate Normal distribution and the matrix Σ_u is positive definite.

Using a lag operator B, we can rewrite the model as:

$$\left(\boldsymbol{I} - \Pi_1\boldsymbol{B} - \cdots - \Pi_\mathrm{p}B^p\right)y_t = \Pi_0 + u_t \quad (15)$$

Where $\boldsymbol{I}$ is a identity matrix $k\ x\ k$. This representation can be written as:

$$\boldsymbol{\Pi}(B)\boldsymbol{y_t} = \Pi_0 + u_t \quad (16)$$

Where $\boldsymbol{\Pi}(B) = \boldsymbol{I} - \Pi_1\boldsymbol{B} - \cdots - \Pi_\mathrm{p}B^p$ is a polynomial matrix. If y_t is weakly is weakly stationary, so we have:

$$\mu = \left(I - \Pi_1 - \cdots - \Pi_p\right)^{-1}\Pi_0 \quad (17)$$

The expression $\left(I - \Pi_1 - \cdots - \Pi_p\right)^{-1}$must be non-singular (non-zero determinant) for the vector of means to exist. Doing $\overline{y_t} = y_t - \mu$ the VAR(p) estimation becomes:

$$\overline{y_t} = \Pi_1\overline{y_{t-1}} + \cdots + \Pi_p\overline{y_{t-p}} + u_t \quad (18)$$

From now on, after estimating the volatility models via MGARCH it will be estimated a Structural Autoregressive Vector (SVAR) model, as in Cavalcanti and Jalles (2013):

$$y_t\ =\ c\ +\sum_{t=1}^{p}\varphi_i\, y_{t-i} + \varepsilon_t \qquad (19)$$

Where y_t corresponds to a vector of endogenous variables $(n\,x\,1)$, $c = (c_1, \dots, c_n)'$ is the intercept vector (n), φ_i is the i-th matrix $(n\ x\ n)$ of autoregressive coefficients for $i\ =\ 1, 2, \dots, p$, and $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{nt})$ is the generalization (n) of a white noise process. In this study, the vector of endogenous variables includes the DCC-GARCH combined pairs of conditional correlation estimated. Economic criteria about developed and developing economies will support this choice to run this model and the impulse-response function of most exogenous pair of conditional correlation on the other conditional correlations estimated pairs.

The identification of the structural residuals is required before estimating the Structural VAR. Estimation of the reduced form VAR produces the variance-covariance matrix, as in Gottschalk (2001) and Bueno (2011):

$$\sum = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} \\ \sigma_{21} & \sigma_2^2 & \sigma_{23} & \sigma_{24} & \sigma_{25} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \sigma_{34} & \sigma_{35} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_4^2 & \sigma_{45} \\ \sigma_{51} & \sigma_{52} & \sigma_{53} & \sigma_{54} & \sigma_5^2 \end{bmatrix}$$

Where each element is estimated by:

$$\widehat{\sigma_{\iota,\jmath}} = \frac{1}{T}\sum_{t=1}^{T} \widehat{e_{\iota t}}\,\widehat{e_{\jmath t}} \quad (20)$$

Thus, $\widehat{e_t}$ are the estimated residuals. It is interesting to stress that the approach to identify a SVAR model is firstly to understand that the model follows a dynamic of simultaneous equation, as supported by Sims (1980).

The variance-covariance matrix contains the variances of the endogenous variables on its diagonal elements and covariances of the errors on the off-diagonal elements. The covariances contain information about contemporaneous effects each variable has on the others. The covariance matrices of standard VAR models is symmetric. This reflects the idea that the relations between the endogenous variables only reflect correlations and do not allow to make statements about causal relationships.

Contemporaneous causality or, more precisely, the structural relationships between the variables is analyzed in the context of SVAR models, which impose special restrictions on the covariance matrix and – depending on the model – on other coefficient matrices as well. The drawback of this approach is that it depends on the subjective assumptions made by the estimation. This type of model is too much subjective information, even if sound economic theory is used to justify them.

It is also intended to explore, from the system of equation highlighted above, the impulse-response functions for a shock of one standard deviation in the variables. Amisano and Giannini (1997) and Bagliano and Favero (1998) stress that the technique of impulse response analysis, firstly introduced in VAR modelling, is a descriptive device representing the immediate reaction of each variable to shocks in the different equations of the system simultaneously. With this, the accuracy of the impulse response estimation can be evaluated with the confidence interval bands. Henceforth, according to Zivot and

Wang (2005), the impulse response calculation requires the introduction of a one-period residual shock in an endogenous variable.

The Cholesky decomposition includes an ordering for the identification of the structural model categorizing the less endogenous pair (Euro-Pound) estimated to the more endogenous one. The SVAR model unifies economic theory with VAR analysis. The SVAR approach applies economic theory (rather an ordering of variables as the Cholesky decomposition) to recover structural innovations from the residuals. The constraints imposed on the model are determined by the researcher. With the SVAR, it is possible to verify the response of a variable to a structural shock in the other variables.

2.3 Dynamic connectedness

The dynamic connectedness will serve to obtain a measure of the interconnectivity of the evaluated series, since our data converge to a relatively homogeneous sample of emerging and developed countries. Furthermore, this analysis is often used as a proxy for market uncertainty and investors' feelings showing the influence of risk distribution of multiple assets and liquidity management. Using the generalized forecast error variance decomposition (GFEVD) through the exchange rates logarithmic variation it is possible to calculate total connectedness index (TCI). The time-varying coefficients of the vector moving average (VMA) is the main point of a connectedness index using the generalized impulse response function (GIRF) and the GFEVD firstly designed by Pesaran and Shin (1998). The GFVED is usually interpreted as the variance share of one variable explains others. The GFEVD is characterized as Gabauer (2019):

$$\tilde{\Phi}_{i,j,t}^{g}(J) = \frac{\Sigma_{t=1}^{J-1}\Psi_{i,j,t}^{2,g}}{\Sigma_{\mathrm{j}=1}^{\mathrm{N}}\Sigma_{t=1}^{J-1}\Psi_{i,j,t}^{2,g}} \quad (21)$$

Where the expression $\Sigma_{j=1}^{\mathrm{N}}\tilde{\Phi}_{i,j,t}^{g}(J) = 1$ and $\Sigma_{i,j=1}^{\mathrm{N}}\tilde{\Phi}_{i,j,t}^{g}(J) = N$. The superior part of the fraction represented above, $\Sigma_{t=1}^{J-1}\Psi_{i,j,t}^{2,g}$, means the cumulative effect of the *i*th shock on j variable, while the denominator, $\Sigma_{\mathrm{j}=1}^{\mathrm{N}}\Sigma_{t=1}^{J-1}\Psi_{i,j,t}^{2,g}$, means register the aggregate cumulative effect of all the shocks. Its defined, using this expression, we can define the TCI as:

$$C_t^g(J) = \frac{\Sigma_{i,j=1,i\neq j}^{N} \widetilde{\Phi}_{i,j,t}^{g}(J)}{N} \quad (22)$$

This index will be used to compare the DCC-GARCH conditional correlation. For this comparison to be fair analytically better to visualize, we will compare the currency separating the variables in blocs: Emerging *versus* Euro and Pound, and then do the same analyze considering all series. This model corroborates mainly to find out which block concentrates greater connectivity and pair set has greater conditional correlation.

2.4 Unit root tests

The previous analysis assumes stationarity of the time series. To check for the presence of unit root, we will apply the new generation of tests, represented by the modified Dickey-Fuller tests ($MADF^{GLS}$) and modified Phillips-Perron (MPP^{GLS}), as proposed by Elliot, Rottemberg and Stock (1996) and Ng and Perron (2001). These tests combine the application of GLS (Generalized Least Square) to extract the deterministic trend and the modified Akaike information criterion (MAIC) for lag selection. The results are unit root tests with greater power, but smaller statistical size distortions when compared to the traditional ADF and PP tests.

The conventional ADF test can be represented by the formula below:

$$\Delta \mathrm{y}_t = \mu + \rho \mathrm{y}_{\mathrm{t}-1} + \sum_{j=1}^{p} \gamma_{\mathrm{j}} \Delta \mathrm{y}_{t-j} + \mathrm{u}_{\mathrm{t}} \quad (23)$$

Where μ is the intercept, ρ is the regression parameter $\mathrm{y}_{\mathrm{t}-1}$ and u_{t} is the error to be considered by Dickey e Fuller (1979) as a white noise. It should be noted that the standard stationarity tests went through proposals for changes in the standard unit root test by Dickey and Fuller (1979), which were based on two central aspects: (i) the extraction of trends in time series using ordinary least squares (OLS) is inefficient; and, (ii) the importance of an appropriate selection for the lag order of the augmented term, in order to obtain a better approximation to the true data generating process. In the first case, (ii), Elliot, Rottemberg and Stock (1996) proposed to use generalized least squares (GLS) to extract the stochastic trend of the series. The standard procedure is used to estimate the ADF^{GLS} statistic as the t statistic to test the null hypothesis $H_0: \beta_0 = 0$, indicating the presence of a unit root, of the following regression.

$$\Delta \tilde{y}_t = \beta_0 \tilde{y}_{t-1} + \sum_{j=1}^{k} \Delta \tilde{y}_{t-j} + e_{tk} \quad (24)$$

In the regression represented above $\tilde{y}_t$ is the series with trend removed by generalized least squares, Δ is the first difference operator and e_{tk} is the non-autocorrelated and homoscedastic residual. Regarding the second aspect, (ii), listed above, Ng and Perron (2001) demonstrate that the Akaike (AIC) and Schwarz (SIC) information criteria tend to select low values for the k lag, when there is a large negative root (close to -1) in the series moving average polynomial, leading the unit root tests to serious distortions. This motivated the development of the MAIC for autoregressive lag selection, to minimize distortions caused by inadequate lag selection in the equation. The MAIC is designed to select a relatively long lag length in the presence of a moving-average root close to unity, to avoid distortions, and a smaller lag length in the absence of such a root, so that the power of the test does not gets compromised.

The Phillips-Perron test consist of the following regression model:

$$y_t = \alpha_0 + \alpha y_{t-1} + u_t \quad (25)$$

According to Rapach and Weber (2004), the Z_α test uses a statistic that combines $T(\hat{\alpha} - 1)$ with a semi-parametric adjustment to correct the serial correlation, so that:

$$Z_\alpha = T(\hat{\alpha} - 1) - 0{,}5 \left(\frac{T^2 \widehat{\sigma_\alpha}}{s^2} \right) \left(\hat{\lambda} - \widehat{\gamma_0} \right) \quad (26)$$

Where $\hat{\alpha}$ is the estimation of α of the equation drawn above by Ordinary Least Squares (OLS) and $\widehat{\sigma_\alpha}$ it's standard error; $s^2 = (T-2)^{-1} \sum_{t=1}^{T} \widehat{u_t}$ e $\widehat{u_t}$ is the residue of the equation; $\hat{\lambda}$ is the estimate of the spectral density with zero frequency of u_t, based on the covariance estimator $\widehat{\gamma_v} = T^{-1} \sum_{T=v+1}^{T} \hat{u}_t \hat{u}_{t-v}$.

3 Results

3.1 Data

The sample of countries is represented by the BRICS+T, as previously mentioned. These emerging countries went through a process of economic growth in the mid-2000s, where part of them took advantage of the commodities boom having impact on GDP and balance of payments. The currencies of developed countries were included in the estimation for being the strongest currencies against the dollar in the international monetary system and to obtain comparative effects of the conditional correlation and will also serve as an exogenous variable to the SVAR model. The selected currency quotes were Brazilian Real (BRL/USD), Russian Ruble (RUB/USD), Indian Rupee (INR/USD), Chinese Yuan (CHN/USD), South African Rand (ZAR/USD), Turkish Lira (TRY/USD), Pound Sterling (GBP/USD) and Euro (EUR/USD), all quoted against the US Dollar. The data set starts on January 4, 2000 and ends in March 31, 2022 in a daily basis. The chosen period is due to the initial of daily exchange rate quotes, and it ends with the interruption of Ruble quotations on international exchanges with the insurgency of the Ukraine's War. To better characterize the financial series, below is a table characterizing the quotes.

Table 1 – Settlement prices and quotes

Series	Real name	Quote
BRL/USD	Brazilian Real	Real to US Dollar
RUB/USD	Russian Ruble	Ruble to US Dollar
INR/USD	Indian Rupee	Rupee to US Dollar
CNY/USD	Chinese Yuan	Yuan to US Dollar
ZAR/USD	South African Rand	Rand to US Dollar
EUR/USD	Euro	Euro to US Dollar
GBP/USD	Pound Sterling	Pound to US Dollar
TRY/USD	Turkish Lira	Lira to US Dollar

The Table 2 reports the descriptive statistics. It is noted that the foreign exchange rates of developed countries have quotation averages below 1, meaning that these currencies are overvalued relatively to the dollar, both the pound sterling (GBP/USD) and the euro (EUR/USD), the currency of transactions in the Euro Zone.

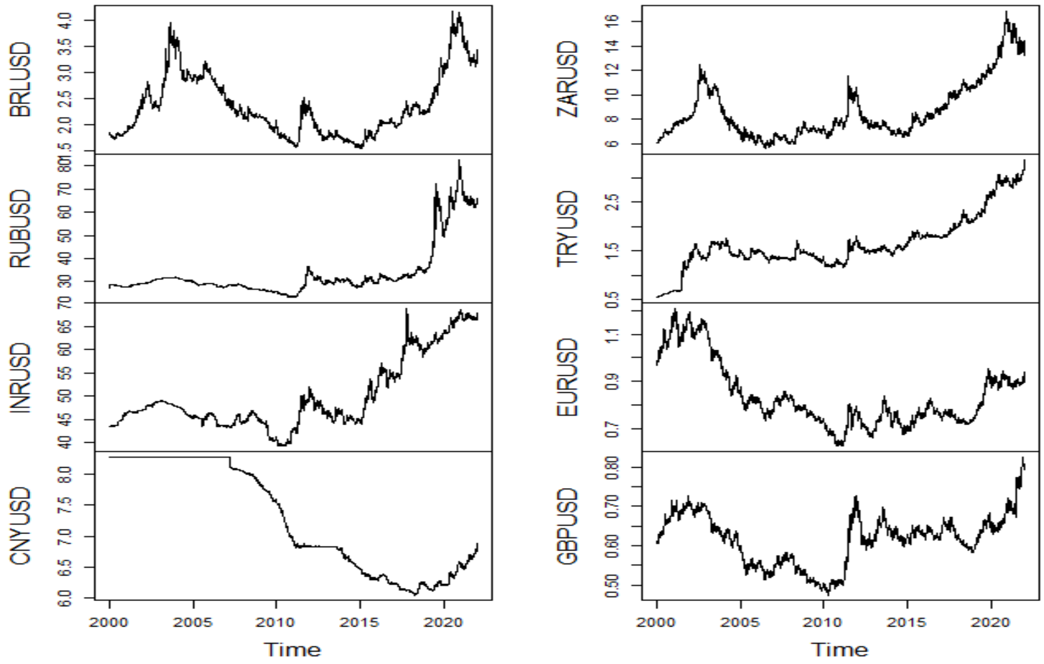
It is possible to notice that all emerging currencies underwent a devaluation process at two specific moments, starting in 2008 and after 2015. Next, quotations were transformed into logarithmic differences for estimation of stationarity tests and econometric estimation, as we can see in Figure 2.

Table 2 – Descriptive statistics of exchange rates (Jan 2000 to March 2022)

	BRL/USD	*RUB/USD*	*INR/USD*	*CNY/USD*	*ZAR/USD*	*EUR/USD*	*GBPUSD*	*TRY/USD*
Average	2.8208	41.6063	54.9062	7.1451	10.0447	0.8458	0.6516	2.7411
Std. Error	0.0141	0.2340	0.1469	0.0105	0.0432	0.0016	0.0013	0.0308
Median	2.4220	31.2137	48.9050	6.8382	8.7472	0.8285	0.6434	1.6601
Std. Deviation	1.0729	17.8074	11.17939	0.7993	3.2865	0.1206	0.0858	2.3503
Variance	1.1513	317.1047	124.9788	0.638998	10.80158	0.014559	0.007367	5.5242
Kurtosis	0.45806	-0.72434	-1.29847	-1.45339	-0.99449	0.43269	-0.79095	5.4654
Assimetry	1.1040	0.8813	0.4805	0.3954	0.5830	0.89166	0.03412	2.2099
Minimun	1.5391	23.1577	39.265	6.0409	5.6175	0.6253	0.4745	0.5405
Maximum	5.887	120.4025	76.9662	8.2799	19.0815	1.2089	0.8706	16.41
Observations	5787	5787	5787	5787	5787	5787	5787	5787

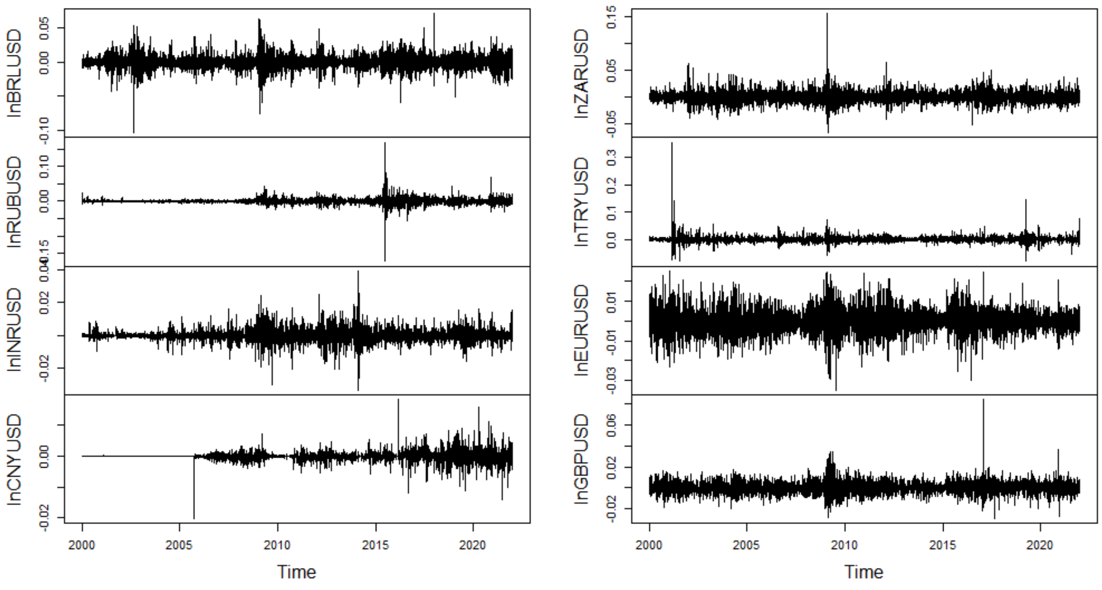
Source: Bloomberg. Authors calculation

Figure 1 - Evolution of exchange rates – 2000 to 2022



Source: Bloomberg. Authors Calculation

Figure 2 – Log returns of exchange rates



Source: Bloomberg. Authors Calculation

To evaluate the stationarity and try to verify if there is a unit root or not. The series were analyzed both in level and in first difference and considering a constant variance and deterministic trend. Unit root tests were all stationary, therefore the series don't have unit root, as shown in Table 3. The results found for the first difference of the price series are stationary, as indicated by the statistical significance at the 5% level of the test statistics of the MDF^{GLS} and MPP^{GLS}. As the series have the same size, start and end in the same period, it was decided to establish the same number of lags for all quotes when running the unit root tests. Thus, the null hypothesis of unit root is rejected for all series.

Table 3- Unit root tests

Variables	Model	$MPP\ GLS$		$MDF\ GLS$	
		Test statistic	Lags	Test statistic	Lags
BRL/USD	C/T	-3.30**	10	-41.51***	10
RUB/USD	C/T	-3.33**	10	-28.83***	10
INR/USD	C/T	-2.78**	10	-36.77***	10
CNY/USD	C/T	-3.47***	10	-34.94***	10
ZAR/USD	C/T	-3.36**	10	-38.40***	10
TRY/USD	C/T	-4.44***	10	-40.35***	10
EUR/USD	C/T	-4.60***	10	-39.85***	10
GBP/USD	C/T	-5.32***	10	-35.91***	10

Notes: 1 – "C" means constant and "T" means deterministic trend. (***) significance at 1%; (**) significance at 5%; (*) significance at 10%. Maximum initial count of 10 lags. 2 - Critical values of MPP^{GLS} (Trend) are = -3.42 for 99%; -2.91 for 95% and -2.62 for 90% of confidence. 3 - Critical values of MDF^{GLS} test = -3.48 for 99% of confidence, -2.89 for 95% of confidence and -2.57 for 90% of confidence.

3.2 DCC-GARCH estimates for BRICS+T

Moving to the econometric model, specifically in its first part that concerns the conditional correlations of the DCC-GARCH, it is emphasized that a and b parameters are associated with the short run and long run persistence of shocks on the dynamic conditional correlations. This indicates that the conditional correlations are time varying. High values of b for all equations indicate the long run persistence of volatility spillover between the foreign exchange returns. Information criteria of the equations helped to choose the best specification. According to the estimation of the models, there is a greater long-term persistence in the conditional correlation in all estimations (coefficient b). In most cases, the greater the persistence of the shock in the short term (coefficient a), smaller will be the long-term parameter (coefficient b), see Table 6. These parameters proved to be mostly significant for all sets of estimated pairs. Individually, it should be noted that the coefficients α and β of the univariate GARCH are mostly significant with 1% significance, as shown in Table 5.

The α term indicates how much influence the last observed return has on the conditional variance, while the β term indicates how much the volatility of the previous period should influence the volatility today. The higher the α, the greater the immediate impact of shocks on the time series data, and the higher the β, the longer the duration of the impact. To estimate the parameters, the maximum likelihood method is used. A property of this model is that all parameters are not negative, $\omega, \alpha, \beta \geq 0$. The ω parameter can be understood as the variance that would look like if the information about past variances were not being passed to the model.

From our results, it is possible to identify that the Brazilian Real (BRL/USD) is the currency that has the greatest influence of the last return on the conditional variance. While the series that shows the greatest influence of the volatility of the previous period on the current volatility is the Euro (EUR/USD).

Table 5 -GARCH estimation

	Real	Ruble	Rupee	Yuan	Rand	Lira	Euro	Pound
μ	0.0000	0.0000	0.0000	0.0000	-0.0003	-0.0004***	0.0000	0.0000
ω	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
α	0.1279***	0.0619	0.0892***	0.0524***	0.0718***	0.1133***	0.0331***	0.055***
β	0.8696***	0.937***	0.9081***	0.8997***	0.9217***	0.8797***	0.9643***	0.9348***

Note: ***, ** and * denote the significance at the 1%, 5% and 10% levels, respectively

The Figure 3 shows that most of conditional correlations amongst the variables are relatively more unstable between 2005 and 2010. The vast differences between the maximum and minimum values of correlation in this period indicate the higher risks in the financial markets and foreign exchange rates markets. Practically all the pairs estimated with the Yuan denote correlation peaks (expressive or not) with the Yuan in mid-2005, exactly in the period that the fixed exchange rate regime is abdicated. We highlight the strong positive correlation of 0.5 points or more of Rupee-Yuan (2005), Real-Rand (2008 to 2012), Real-Euro (2009 to 2011), Ruble-Euro (2006 to 2008), Ruble-Pound (2007 to 2008), Ruble-Rand (2010 to 2011), Rand-Euro (2006), Rand-Pound (2007) and Euro-Pound (almost every period, with some drops throughout the series). Except for the Rupee-Yuan pair, estimates against the Chinese currency did not show significant correlations throughout the estimated series. Most conditional correlations hit an uptrend from 2007 and 2008. It was applied a sensibility analysis with Yuan pairs reducing the estimation from 2000 to 2005 and the results don’t indicate any change in the estimations results and the conditional correlation trend. Therefore, we maintained our estimates considering the complete period of our sample, from 2000 to 2022.

Table 6 -DCC-GARCH parameters

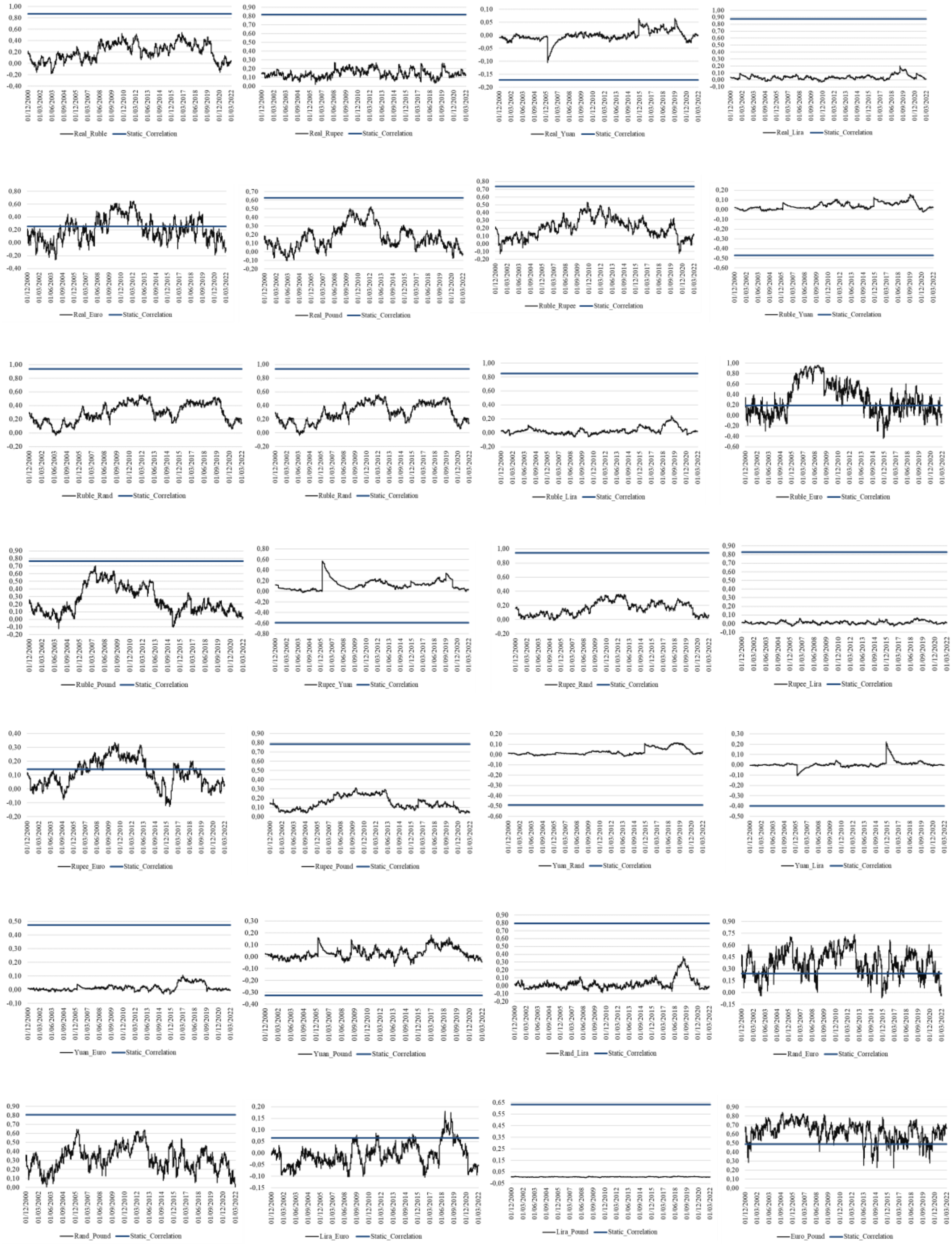
	Real_Ruble	Real_Rupee	Real_Yuan	Real_Rand	Real_Lira	Real_Euro	Real_Pound
a	0.0129***	0.006900	0.008***	0.0129***	0.0037***	0.0205***	0.0094***
b	0.9831***	0.9808***	0.9897***	0.9852***	0.9911***	0.9755***	0.9889***
	Ruble_Rupee	**Ruble_Yuan**	**Ruble_Rand**	**Ruble_Lira**	**Ruble_Euro**	**Ruble_Pound**	**Rupee_Yuan**
a	0.0104***	0.0071***	0.0095***	0.0044***	0.0416***	0.0114***	0.0067***
b	0.986***	0.9925***	0.9881***	0.9923***	0.9561***	0.9871***	0.9933***
	Rupee_Rand	**Rupee_Lira**	**Rupee_Euro**	**Rupee_Pound**	**Yuan_Rand**	**Yuan_Lira**	**Yuan_Euro**
a	0.0059***	0.002900	0.007***	0.0034***	0.0051***	0.0081***	0.0109***
b	0.9919***	0.9874***	0.9901***	0.9951***	0.9945***	0.9903***	0.9861***
	Yuan_Pound	**Rand_Lira**	**Rand_Euro**	**Rand_Pound**	**Lira_Euro**	**Lira_Pound**	**Euro_Pound**
a	0.0145***	0.0071***	0.0257***	0.0143***	0.0067***	0.000500	0.0269***
b	0.9847***	0.9902***	0.9661***	0.9821***	0.9881***	0.9838***	0.9648***

Note: ***, ** and * denote the significance at the 1%, 5% and 10% levels, respectively.

The black line represents the conditional correlation estimated by the DCC-GARCH and the blue line is the Pearson correlation, kept static. It is possible to see that fifteen estimations presented conditional correlation lower than the standard correlation. All pairs estimated with Euro shows a conditional correlation crossing the standard correlation. Nonetheless, the pairs estimated with Yuan show a lower and negative correlation than the estimated by the DCC-GARCH model.

There is an inversely proportional distribution between the short- and long-term persistence of volatility and most of the estimated pairs concentrate values of *b* at 0.98, as we can see in Table 6. The long-term coefficients here are mostly very close to 1, implying persistence to the stronger long-term shock. Once the series of the conditional correlation pairs were estimated, the same unit root tests in Table 3 were estimated for these results and the stationarity remained the same.

Figure 3 – Conditional Correlation – DCC GARCH results



3.3 SVAR and impulse response functions

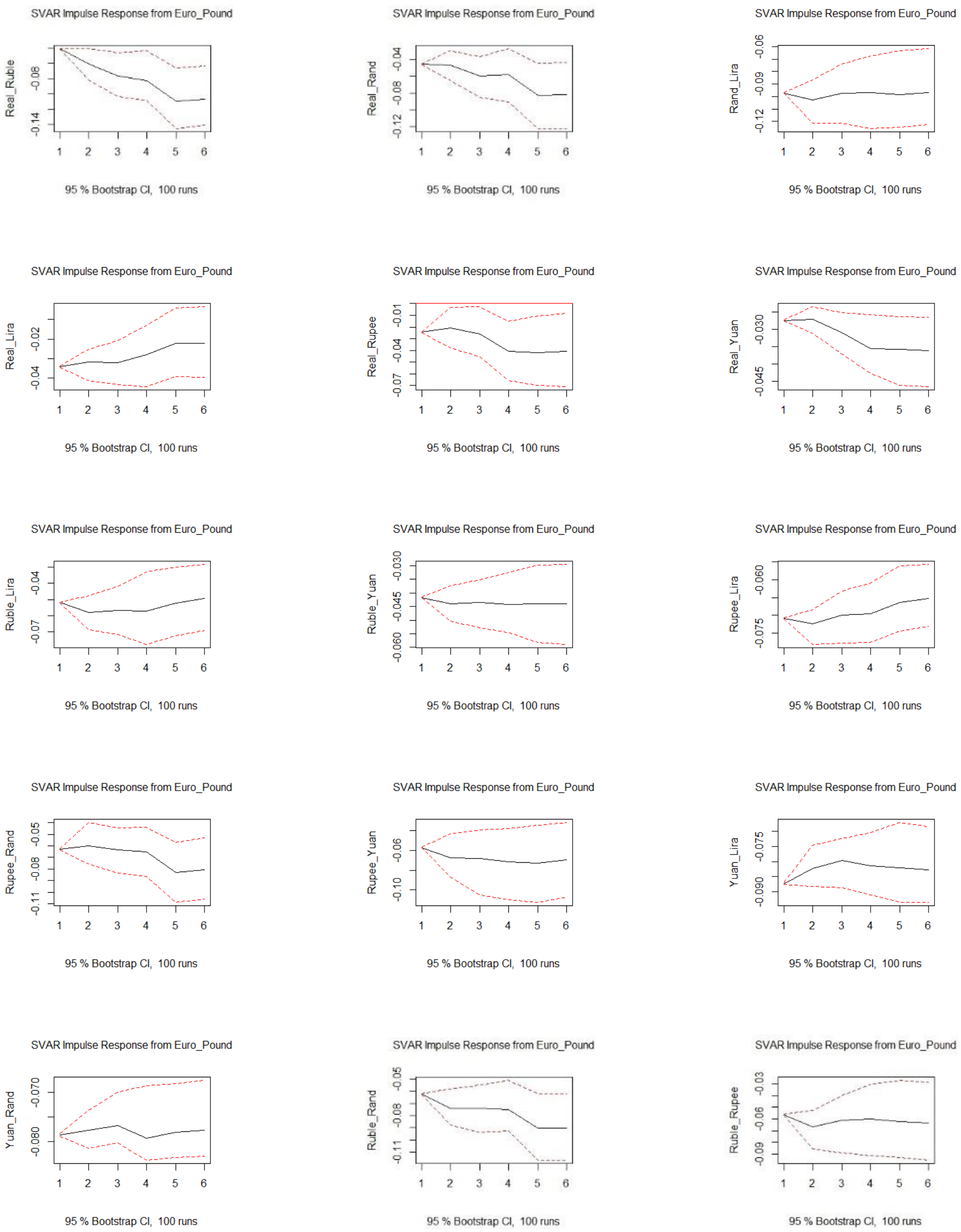
The SVAR model requires a vector of dummies to account for economic crises during the sample period. Thus, following the literature and some current recession cycles, we introduced some dummies to control for adverse effects that would compromise the significance of the tests and are turning points in the prediction of exchange rate volatility and conditional correlation. To mitigate instabilities that could generate effects on exchange rates, it is necessary to point and introduce some events as: Dot-com bubble crisis (from March 2000[1] to April 2001[2]), the US-China Technological Trade War in 2015, as highlighted by Congressional Research Service Report (2019), COVID-19 insurgency (from November 2019[3] to April 2020[4]) - the COVID-19 outbreak is often referred to as a unique crisis that profoundly impacts many countries (Kulic et al. 2021), and Ukraine's War (Februrary 2022).

Thus, Figure 4 show the estimated Impulse-Response Function for Euro-Pound shocks on exchange rate conditional correlation though the SVAR estimation. The pair Euro-Pound is the most exogenous financial series followed not only because involves the two currencies of developed countries used in this study, but also because they had an average conditional correlation above 0.60. Objectively, it was decided to evaluate the dynamics of a Euro-Pound shock in pairs that of conditional correlation excluding the those who contains "Euro" or "Pound" of DCC-GARCH results - evaluates the shock in conditional correlation matched pairs without crossing the estimated results of the more exogenous pair. We added temporal dummies highlighted that reflect moments of crisis in the international financial system.

The magnitude of the impulse response function corresponds, as highlighted in the methodology, to the increase of one standard deviation in the exchange rate being analyzed. All IRF estimated show that a contemporary shock to the Euro-Pound variable is negative to the other conditional correlations, which means that a shock of the exogenous variable decreases the conditional correlation of all estimates. The impulse-response function for of SVAR show a significant negative relationship between financial and economic policy uncertainty and exchange rate volatility in pairs of emerging exchange rates.

[1] Spike of S&P and Dow Jones Index
[2] Period in which most of the "dot com" companies ceased their activity, after burning their venture capital.
[3] Virus escalation in China
[4] Beginning of financial market collapse

Figure 4 –Impulse Response Functions: Euro-Pound shock



The greater the dynamic correlation of the Euro-Pound, the more unstable will be the proximity of the volatility of the other pairs. Which also means that the greater the correlation between Euro-Pound, more sensitive emerging countries will be. This result endorses the interpretation that the sustainability of exchange rate in emerging countries is more related to the fragility of the economic, financial, and political system. A good explanation derives of the contagion literature that conventionally highlights that volatility varies over time, with a surge during periods of increasing economic and financial instability. The Cholesky decomposition table is insert Appendix A determined by the most exogenous variable, the Euro-Pound pair.

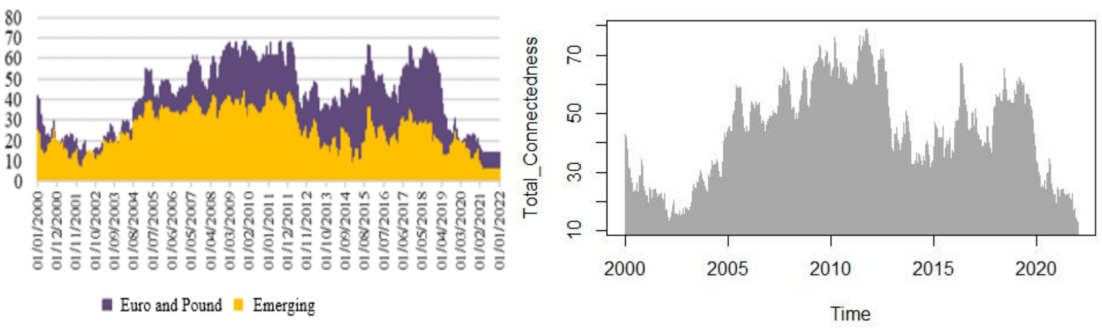
The growth of the conditional correlation of the developed countries exchange rates in this study implies greater economic, monetary, and financial union, which can usually represent prevention or mitigation strategies for systemic risks in financial markets. In emerging countries, however, as empirically demonstrated in Figure 3, there are a series of peaks and instabilities that, with an exogenous shock, can interrupt trade, investment, monetary and capital flows in developed countries, drastically damaging the conditional correlation of countries emerging and its connectedness. It is possible to affirm that Euro-Pound is a volatility transmitter. The transmission of these volatility of the most exogenous variable to the others highlighted is not lenient to a shock, revealing that in countries it did not occur, there are always more instabilities.

Increases on conditional correlation in Europe can create a severe and persistent contraction for emerging economies, BRICS+T, leaving them dependent on the conditions and expectations of responses from the US economy, since the estimated pairs are quoted on the same basis as the US dollar. This explanation derives from the fact that the crises of the emerging economies in the late 1990s – early 2000s were not able to drag the advanced economies into the crisis, while the 2008 crisis and trade disputes that emerged in the United States and extended widely spread to the Eurozone countries had a simultaneous strong impact on the BRICS+T economies. Finally, the shocks generated by conditional forecasts of different scenarios show that a deepening of dynamics in the Euro Zone with Pound would create a severe and persistent contraction for emerging currencies. A resurgence of capacity in the event of recessions suggests that a strong misalignment in emerging countries - would have a significant negative impact.

3.4 Exchange rates connectedness

Alternatively, we can assess the dynamics of total connectedness by unifying the pairs of exchange rates in separated blocs as Emerging (BRICS + T) and Developed (Euro and Pound) in the total connectedness index proposed in section 3.3.

Figure 5 – Connectedness Index for BRCS+T vs. Developed Countries Exchange Rate Pairs



As shown in Figure 5, it was decided to evaluate the dynamics of connectedness separately between emerging and developed currencies, only indexing the connectedness of foreign exchange rates of BRICS+T against Euro and Pound through the mechanism defined in the *Empirical Strategy*. There is a period that the connectedness index of emerging countries presented a great relationship between the volatilities closer to 50 percent - from 2009 to 2012, the period after the subprime crisis. However, despite the peak close to 50%, during the crisis there is a greater cumulative increase than in periods that did not register a crisis. When we evaluate the Euro and Pound connectedness, we notice that the index is higher in the entire estimation, even if very close in some periods. This result shows, under this methodology, that the exchange rate volatility of developed markets it is closely related to emerging countries presenting very similar and correlated movements, even if in higher proportions in practically the entire test. This does not imply assuming causalities or interpretations about the declines and growths of one set over the other but indicates a presence of regional currency contagion. European currencies TCI it is aligned to DCC-GARCH estimated, which found a strong conditional correlation between Euro-Pound indicating that shocks of exchange rates over correlated and connected create an adverse scenario for emerging currencies.

The dynamics of the total connectedness records an average of 42%, with emphasis on peaks of over 70% in 2012. It is noted that in the years corresponding to world financial crises there is a peak of relevant connectedness, as well as Dot-com crisis (2000), subprime crisis (2007, 2008, 2009), Greek bailout (2012) – higher level of connectedness - and COVID-19 (2019). The TCI indicates more pertinent pressure from Euro and Pound connectedness than from emerging markets identifying similar peaks and sensitivity, but which may result in a lenient decline in conditional correlation in times of crisis. Emerging economies are now more integrated into global production and trade chains, which strongly inserts them into the transmission of economic shocks. Thus, with greater interconnectivity in developed economies, the greater must be the fall on the connectivity and conditional correlation of emerging economies in global markets. This could be a result of what we commented above: a greater transmission of economic and financial shocks due to greater exposure to foreign capital flows, which left them vulnerable to sudden changes in investor sentiment and the volatility of global financial markets.

4 Conclusion

The objective of this paper was to investigate the dynamic effects of shocks on exchange rates conditional correlations and evaluate the connectedness between pairs of exchange rates. We considered the BRICS countries plus Turkey (BRICS+T) as emerging countries and developed countries exchange rates are represented by the UK pound and EZ Euro, all quoted against the US dollar. The sample covers the period from January 2000 to March 2022 in a daily basis. We applied the DCC-GARCH model to obtain the dynamics of the conditional correlations for exchange rates pairwise and estimated a Structural Autoregressive Vector model (SVAR) to account for exogenous shocks. The connectedness index was used to express the dependence among the selected currencies exchange rates.

The results indicated that pairs with strong positive correlation of 0.5 points or more in some periods of intensive financial crisis, but none of these pairs correspond to estimations with Turkish Lira. Since Euro and Pound are valued more than the quote basis (US Dollar), these two exchange rates became the most exogenous pair of conditional correlation for the SVAR framework, precisely because they presented the highest conditional volatility correlation of all DCC- GARCH.

The outcomes of the econometric model became inputs for the SVAR estimation, where pairs with conditional correlation excluding “Euro” or “Pound” were selected. The Euro-Pound pair shocks generate a drop in conditional correlation in all estimations of emerging pairs, exemplifying a reverse trend between center and periphery of the global financial and economic system, in line with the contagion literature and insights of Fernández-Rodriguez and Sosvilla-Rivero (2019). This indicates, in other words, that a greater concentration of volatility in core countries increases instabilities in emerging countries.

We also estimated a total connectedness index to contrast the DCC-GARCH conditional correlation results by separating the model's own estimated pairs into emerging pairs versus Euro or Pound ensemble pairs. TCI for European currencies indicates that there is a great relationship between Euro or Pound, the dynamics denotes something like what we saw in the DCC-GARCH conditional volatility and SVAR – exogeneity relation. From a political economy perspective, this finding would be evidence of a strong relationship of vulnerability.

These results may enhance the understanding of volatility dynamics in times of either boom or burst in financial markets and may help to assess the risks of crisis transmission among the BRICS+T countries. They may also be support policy-makers decisions, who should take into consideration the volatility effects explained by the dynamic interdependences and connectedness among the foreign exchange markets, especially in emerging countries. Indeed, the connectedness measure can be used in a dynamic context, by showing the potential volatility transmission by shocks or correlations, allowing us to identify systemically relevant markets that can be a source of systemic risk and vulnerability. A natural extension would be to explore the effects of commodity boom on macroeconomic variables and its implications for monetary policy in emerging markets and/or in Latin America. This should be object of further research.

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