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Connectedness Between Natural Gas Price and BRICS Exchange Rates: Evidence from Time and Frequency Domains

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Abstract: In this paper, we investigate the connectedness between natural gas and BRICS (Brazil, Russia, India, China, and South Africa)'s exchange rate in terms of time and frequency. This empirical work is based on the approach of connectedness proposed by Diebold and Yilmaz, who provided an effective way of valuing how much variation in one variable is responsible for the value of other variables, and the method proposed by Baruník and Křehlík, who decomposed the results from Diebold and Yilmaz into different frequencies. We also use the rolling-window method to conduct time-varying analysis. The data used in this paper are from 23 August 2010 to 20 June 2019. We find that the natural gas price hardly influences BRICS's exchange rates, which provides an important practical implication for policymakers, especially in oil-dependent countries.

Keywords: BRICS; exchange rates; connectedness; time domain; frequency domain

1. Introduction

In light of the increasing attention being paid to environmental sustainability, energy systems are gradually transitioning from a dependence on non-renewable resources to the use of environment-friendly resources. This will have a great impact on day-to-day life, economies, businesses, manufacturers, and governments. Compared to coal or petroleum, natural gas has many qualities that makes it burn more efficiently. It also generates fewer emissions of most types of air pollutants, including carbon dioxide. With the expansion of gas pipelines, the increasing number of gas liquefaction plants, and the exploitation of natural gas fields, it is reasonable to consider that the natural gas trade will become more globalized. Natural gas has become a major part of the world's energy consumption, demand, and supply in recent years. In 2018, for example, natural gas consumption rose by 5.3%, one of the fastest rates of growth since 1984. With the continuing rapid expansion in liquefied natural gas (LNG), the inter-regional natural gas trade grew by 4.3%, which was more than double the 10-year average [1]. As reported in the Global Energy Perspective 2019: Reference Case [2], natural gas will be the only fossil fuel whose share of total energy demand continues to increase until 2035, and China will represent nearly half of the global demand growth. Other developing countries are also expected to increase their demand for natural gas.

Brazil, Russia, India, China, and South Africa (BRICS), a group of five fast-growing developing countries, play an important and expanding role in the world economy. In recent years, BRICS have represented an increasing share of global economic growth. According to the International Monetary Fund (IMF), as of 2018, the combined gross domestic product (GDP) of these five nations accounted for 23.2% of the gross world product (GWP). Given the growth of BRICS and the fact that energy is a crucial ingredient for economic development, these countries' relationship with natural gas will only become closer. According to the BP Statistical Review of World Energy [1], in 2018, the total consumption of natural gas in BRICS was 835.8 billion cubic meters (BCM), which accounted for 21.7% of the total global consumption. In terms of imports, China became the second largest importer of LNG, with imports increasing from 4.6 BCM in 2008 to 73.5 BCM in 2018. India was the fourth largest importer, with imports increasing from 11.3 BCM to 30.6 BCM over the same period. In terms of exports, Russia was the largest exporter of pipeline gas. It also accounted for nearly 6% of total LNG exports. As the trade of natural gas is usually settled in US dollars, it is meaningful to study the relationship between the natural gas price and the BRICS's exchange rates.

Against this backdrop, this paper investigates the interdependence between the natural gas price and the BRICS's exchange rate. In doing so, this study is expected to offer valuable insights for market operators, investors, and economists. We use the Henry Hub natural gas futures as the data for the natural gas price. There are two reasons behind this choice of dataset: First, the shale gas revolution in America has dramatically increased US production of shale gas since 2007. World Energy Outlook 2018 [3], produced by the International Energy Agency (IEA), has predicted that natural gas production in America will increase from 976 BCM in 2017 to 1328 BCM in 2040 and that this increase will be mainly due to the growth in shale gas production. Therefore, the Henry Hub natural gas price, which usually represents pricing for the North American natural gas market, has a great influence on the global energy market. We assume that this influence will become stronger over time. The second reason is that there are multiple natural gas price indexes in the world, such as the Japan Korea Marker and the UK National Balancing Point (NBP); however, we cannot predict which price index has strong connectedness with the BRICS's exchange rates. Therefore, we select the Henry Hub price given its characteristics of high liquidity and large trading volume.

Our contribution to the literature is twofold. First, we apply the connectedness methodology from Diebold and Yilmaz [4–6], which allows us to know how pervasive the risk is throughout the entire market by quantifying the contribution of each variable to the system. We also apply the time–frequency version of connectedness proposed by Baruník and Křehlík [7] to find the connectedness between different variables in the short, medium, and long term. Second, to the best of our knowledge, there is not much research on the relationship between the natural gas price and exchange rates. Nevertheless, there are many studies that analyzed the relationship between crude oil prices and foreign exchange rates, and almost all of them show that exchange rates are highly connected to the oil price. For example, in our previous research on the relationship between the West Texas Intermediate (WTI) crude oil price and BRICS's exchange rates using the copula method, we found a significant negative dependence between the two variables. Considering the globalization of natural gas trade, high demand growth (1.6% per year), and the expansive market share in the global energy market (World Energy Outlook 2018 [3] has predicted that, by 2030, natural gas will overtake coal and become the second largest source of energy after oil.), it is reasonable to compare the relationship between the crude oil price and exchange rates with that between the natural gas price and exchange rates. Therefore, in this study, we also aim to determine whether BRICS's exchange rates are closely linked to the natural gas price, as they are to the oil price.

The rest of this paper is organized as follows: A brief review of relevant literature is provided in Section 2. Section 3 introduces the empirical methodology used in this study. Section 4 reports empirical results. Section 5 gives the conclusion. Finally, a robustness analysis is presented in the Appendix A.

2. Literature Review

As we have mentioned above, there is not much literature that has analyzed the relationship between the natural gas price and exchange rates, as far as we know. However, there are many studies on the relationship between the exchange rate and other variables, such as the oil price and the stock market. Chen and Chen [8] investigated the long-term relationship between different crude oil price indexes and G7 countries' exchange rates using the monthly panel data between January 1972 and December 2005. They found that oil prices may account for the movements of the real exchange rate and there is a link between oil prices and real exchange rates. Additionally, from the results of panel predictive regression, they found that the crude oil price has the ability to forecast the future exchange rate. Andrieș et al. [9] identified the patterns of co-movement of the interest rate, stock price, and exchange rate in India using wavelet analysis. They used the data span from July 1997 to December 2010. The empirical results showed that exchange rates, interest rates, and stock prices are linked to each other and that the stock price fluctuations lag behind both the exchange rates and interest rates. Brahm et al. [10] used monthly data to investigate the relationship between the crude oil price and exchange rates in the long term and short term, respectively. The data span was from January 1997 to December 2009. Empirical results indicated exchange rates Granger-caused crude oil prices in the short term, whereas crude oil Granger-caused exchange rates in the long term. Furthermore, based on impulse response analysis, exchange rate shock had a significant negative effect on crude oil prices. Jain and Pratap [11] explored the relationship between global prices of crude oil and gold, the stock market in India, and the USD–INR exchange rate using the DCC-GARCH (dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity) model. They also examined the lead lag linkages among these variables using symmetric and asymmetric non-linear causality tests. They used daily data from the period of 2006 to 2016, finding that a fall in the value of the Indian Rupee and the benchmark stock index was caused by a fall in gold and crude oil prices.

On the empirical side, the methodology used in this paper has already been applied in many fields. Maghyereh et al. [12] used implied volatility indices (VIX) of the daily close price of crude oil in 11 countries. They found that the connectedness between oil and equity was dominated by the transmissions from the oil market to equity markets and most of the linkages between these two markets were established from mid-2009 to mid-2012, a period that witnessed the start of the global recovery. Lundgren et al. [13] studied the renewable energy stock returns and their relation to the uncertainty of currency, oil price, stocks, and US treasury bonds. They used data covering the period from 2004 to 2016, and found that the European stock market depends on renewable energy stock prices. Singh et al. [14] employed a dynamic and directional network connectedness between the implied volatility index (VIX) of the exchange rates of nine major currency pairs and the crude oil using the data between May 2017 and December 2017. They found that crude oil affected currencies more than currencies affected crude oil, but the reverse was true during the crude oil crisis period. Furthermore, their results revealed that EUR–USD is more sensitive to crude oil price fluctuation than others. Ji et al. [15] combined empirical mode decomposition with a connectedness methodology, and examined the dynamic connectedness among crude oil, natural gas, and refinery products using daily data between 3 January 2000 and 15 September 2017. Employing a constant analysis, they found that crude oil and its refinery product tend to be a net transmitter, while the natural gas tends to be a net receiver. In time-varying analysis, they found that the total connectedness generally increased until the 2014 crude oil crash, and then decreased sharply. Lovch and Perez-Laborda [16] used the connectedness method and frequency decomposition method to investigate the relationship between the natural gas and crude oil price during the period from 1994 to 2018. They found that the volatility connectedness varied over time; the connectedness became weak after the financial crisis; and the volatility had long-run effects, except during some specific periods, when volatility shocks transmitted faster but dissipated in the short-run.

3. Empirical Methodology

In this paper, we employ two methods to establish the nature of the relationship between exchange rates and natural gas price. The first method is provided by Diebold and Yilmaz (DY) [4–6], whose approach calculates the connectedness between different objects by introducing variance decomposition into vector autoregression (VAR) models. The second method is based on Baruník and Křehlík (BK) [7], who proposed a new framework to estimate connectedness by using a spectral representation of variance decomposition. In conclusion, the DY framework describes the connectedness as "when shocks are arising in one variable, how would other variables be changing?", whereas the BK framework estimates the connectedness in short-, medium-, and long-term financial cycles.

3.1. Connectedness Table

Based on Diebold and Yilmaz [6], a simplified connectedness table is presented in Table 1, which gives a clear picture of aggregated and disaggregated connectedness.

Table 1. Connectedness table.

	x_1	x_2	$\ldots$	x_N	From
x_1	d_{11}	d_{12}	$\ldots$	d_{1N}	$\sum_{j=1}^{N} d_{1j}\ j \neq 1$
x_2	d_{21}	d_{22}	$\ldots$	d_{2N}	$\sum_{j=1}^{N} d_{2j}\ j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$	$\vdots$
x_N	d_{N1}	d_{N2}	$\ldots$	d_{NN}	$\sum_{j=1}^{N} d_{Nj}\ j \neq N$
To	$\sum_{i=1}^{N} d_{i1}$ $i \neq 1$	$\sum_{i=1}^{N} d_{i2}$ $i \neq 2$	$\ldots$	$\sum_{i=1}^{N} d_{iN}$ $i \neq N$	$\frac{1}{N} \sum_{i,j=1}^{N} d_{ij}\ i \neq j$

Source: Diebold and Yilmaz (2015).

In the table, x_i is the interested variable, whereas d_{ij} is the pairwise directional connectedness from x_j to x_i, which shows what percentage of the h-step-ahead forecast error variance in x_i is due to the shocks in x_j (Equation (1)). We can simply understand d_{ij} as how much future uncertainty of x_i is due to the shocks in x_j:

$$C_{i \leftarrow j} = d_{ij}. \tag{1}$$

The column "From" is the total directional connectedness from x_j to others (Equation (2)), and the row "To" means the total directional connectedness from others to x_i (Equation (3)):

$$C_{\cdot \leftarrow j} = \sum_{\substack{i=1 \\ i \neq j}}^{N} d_{ij}, \tag{2}$$

$$C_{i \leftarrow \cdot} = \sum_{\substack{j=1 \\ j \neq i}}^{N} d_{ij}. \tag{3}$$

We were also interested in net pairwise directional connectedness (Equation (4)) and net total directional connectedness (Equation (5)), which are expressed as a negative value to indicate a net recipient and a positive value to indicate a net transmitter:

$$C_{ij} = C_{j \leftarrow i} - C_{i \leftarrow j}, \tag{4}$$

$$C_i = C_{\cdot \leftarrow i} - C_{i \leftarrow \cdot}. \tag{5}$$

Finally, the total connectedness (Equation (6)), calculated by the grand total of the off-diagonal entries of d_{ij}, is given in the lower-right cell of the connectedness table:

$$C = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} d_{ij}. \tag{6}$$

3.2. Generalized Forecast Error Variance Decomposition (GFEVD)

Diebold and Yilmaz [4] measured connectedness based on forecast error variance decompositions from VAR models, which were introduced by Sims [17] and Koop et al. [18]. However, the calculation of variance decomposition requires orthogonalized shocks and depends on ordering the variables, so Diebold and Yilmaz [5] exploited the generalized forecast error variance decomposition (GFEVD) of Pesaran and Shin [19] to solve those problems. In this paper, we employ the method of GFEVD to calculate the connectedness.

We will give a brief introduction to GFEVD, followed by an explanation of Lütkepohl [20] and Diebold and Yilmaz [6].

For easy understanding, we first consider a VAR (1) process with N-variable:

$$\begin{gathered} y_t = v + A_1 y_{t-1} + u_t, \quad t = 0, \pm 1, \pm 2 \ldots \\ E(u_t) = 0 \\ E(u_t u_t') = \Sigma_u \\ E(u_t u_s') = 0, \quad t \neq s. \end{gathered} \tag{7}$$

If the generation mechanism starts at time t = 1, we get:

$$\begin{gathered} y_1 = v + A_1 y_0 + u_1 \\ y_2 = v + A_1 y_1 + u_2 = v + A_1(v + A_1 y_0 + u_1) + u_2 \\ = (I_N + A_1)v + A_1^2 y_0 + A_1 u_1 + u_2 \\ \cdots \\ y_t = (I_N + A_1 + \cdots + A_1^{t-1})v + A_1^t y_0 + \textstyle\sum_{m=0}^{t-1} A_1^m u_{t-m} \cdot \ldots \end{gathered} \tag{8}$$

If all eigenvalues of A_1 have modulus less than 1 (VAR process is stable), we have:

$$\begin{gathered} (I_N + A_1 + \cdots + A_1^{t-1})v \ \rightarrow \ (I_N - A_1)^{-1} v \ \text{ as } t \rightarrow \infty \\ A_1^t y_0 \rightarrow 0 \ \text{ as } t \rightarrow \infty.. \end{gathered} \tag{9}$$

Then, we can rewrite Equation (7) as:

$$\begin{gathered} y_t = \mu + \textstyle\sum_{m=0}^{\infty} A_1^m u_{t-m}, \quad t = 0, \pm 1, \pm 2 \ldots \\ \text{where } \mu \equiv (I_N - A_1)^{-1} v. \end{gathered} \tag{10}$$

Secondly, let us consider a VAR (p) process:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \ t = 0, \pm 1, \pm 2, \ldots \tag{11}$$

By using matrices, we can rewrite the VAR (p) process as a VAR (1) process:

$$\begin{gathered} Y_t = \boldsymbol{v} + \boldsymbol{A}Y_{t-1} + U_t \\ \underset{(Np*1)}{Y_t} \equiv \begin{bmatrix} y_1 \\ y_2 \\ \ldots \\ y_{t-p+1} \end{bmatrix}, \quad \underset{(Np\times 1)}{\boldsymbol{v}} \equiv \begin{bmatrix} v \\ 0 \\ \ldots \\ 0 \end{bmatrix} \\ \underset{(Np\times Np)}{\boldsymbol{A}} \equiv \begin{bmatrix} A_1 & A_2 & \ldots & A_{p-1} & A_p \\ I_N & 0 & \ldots & 0 & 0 \\ 0 & I_N & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & 0 \\ 0 & 0 & \ldots & I_N & 0 \end{bmatrix}, \quad \underset{(Np\times 1)}{U_t} = \begin{bmatrix} u_t \\ 0 \\ \ldots \\ 0 \end{bmatrix}. \end{gathered} \tag{12}$$

Similar to Equation (10), Equation (12) can be rewritten as:

$$Y_t = \boldsymbol{\mu} + \sum_{m=0}^{\infty} \boldsymbol{A}^m U_{t-m}, \quad t = 0, \pm 1, \pm 2 \ldots \tag{13}$$

By pre-multiplying a $N \times Np$ matrix $J \equiv [I_N : 0 : \ldots : 0]$, we get:

$$\begin{gathered} y_t = JY_t = J\boldsymbol{\mu} + \sum_{m=0}^{\infty} J\boldsymbol{A}^m U_{t-m} = J\boldsymbol{\mu} + \sum_{m=0}^{\infty} J\boldsymbol{A}^m J' J U_{t-m} \\ = \mu + \sum_{m=0}^{\infty} \Phi_m u_{t-m} \\ \underset{(N\times 1)}{\mu} = J\boldsymbol{\mu}, \quad \underset{(N\times N)}{\Phi_m} \equiv J\boldsymbol{A}^m J', \quad \underset{(N\times 1)}{u_t} = JU_t. \end{gathered} \tag{14}$$

Finally, we get a moving average (MA) representation of the VAR(p) process:

$$\begin{gathered} y_t = \mu + \sum_{m=0}^{\infty} \Phi_m u_{t-m} \\ E(u_t) = 0 \\ E(u_t u_t') = \Sigma_u \\ E(u_t u_s') = 0, \quad t \neq s. \end{gathered} \tag{15}$$

The h-step GFEVD can be expressed as:

$$\omega_{ij,h}^{g} = \frac{\sigma_{jj}^{-1} \sum_{m=0}^{h-1} (e_i' \Phi_m \Sigma_u e_j)^2}{\sum_{m=0}^{h-1} (e_i' \Phi_m \Sigma_u \Phi_m' e_j)}, \tag{16}$$

where e_i is the i-th column of I_N and σ_{jj} is the j-th diagonal element of Σ_u.

Because the sums of the forecast error variance contribution are not necessarily in agreement, we contribute our generalized connectedness indexes as:

$$d_{ij} = \widetilde{\omega_{ij}^{g}} = \frac{\omega_{ij,h}^{g}}{\sum_{j=1}^{N} \omega_{ij,h}^{g}}. \tag{17}$$

3.3. Spectral Representation of GFEVD

Based on the DY framework, the BK framework defines the general spectral representation of GFEVD and uses it to define the frequency-dependent connectedness measure, which is inspired by the previous research of Geweke [21–23] and Stiassny [24].

We still consider the MA representation of the VAR(p) process (Equation (15)). The BK framework provides a frequency response function (Equation (18)), which can be obtained as a Fourier transform of the coefficient Φ_m:

$$\Psi(e^{-i\lambda}) = \sum_{m} e^{-i\lambda m}\Phi_m, \quad i = \sqrt{-1}. \tag{18}$$

The generalized causation spectrum over frequencies $\lambda \in (-\pi, \pi)$ is defined as:

$$(f(\lambda))_{j,k} = \frac{\sigma_{kk}^{-1}\left|(\Psi(e^{-i\lambda})\Sigma_u)_{j,k}\right|^2}{(\Psi(e^{-i\lambda})\Sigma_u\Psi'(e^{+i\lambda}))_{j,j}}, \tag{19}$$

where $(f(\lambda))_{j,k}$ represents the portion of the spectrum of x_j at a given frequency λ due to shocks in x_k. In order to obtain a natural decomposition of variance decomposition to frequencies, a weighting function is defined as:

$$\Gamma_j(\lambda) = \frac{(\Psi(e^{-i\lambda})\Sigma_u\Psi'(e^{-i\lambda}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Psi(e^{-i\lambda})\Sigma_u\Psi'(e^{-i\lambda}))_{j,j}d\lambda}, \tag{20}$$

where $\Gamma_j(\lambda)$ represents the power of the j-th variable at a given frequency.

The entire range of frequencies' influence of GFEVD from x_j to x_k is expressed as:

$$\omega_{jk}^{\infty} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_j(\lambda)(f(\lambda))_{j,k}d\lambda. \tag{21}$$

Additionally, the GFEVD on specified frequency band $d = (a, b)$, $a, b \in (-\pi, \pi)$, $a < b$, is defined as:

$$\omega_{jk}^{d} = \frac{1}{2\pi}\int_{d}\Gamma_j(\lambda)(f(\lambda))_{j,k}d\lambda. \tag{22}$$

As in Section 3.2, we contribute our scaled GFEVD on frequency band d as below, to make sure that the sums of variance contribution are in agreement:

$$d_{ij} = \widetilde{\omega_{jk}^{d}} = \frac{\omega_{jk}^{d}}{\sum_k \omega_{jk}^{\infty}}. \tag{23}$$

4. Empirical Results

4.1. Data

For this study, we collected daily data from Bloomberg, including the Henry Hub natural gas futures price (GASF), and the nominal dollar-denominated exchange rates for the Brazilian Real (BRL), Russian Ruble (RUB), Indian Rupee (INR), offshore Chinese Yuan (CNH), and South African Rand (ZAR). We used the offshore Chines Yuan instead of the onshore Chinese Yuan (CNY) for the reason that China has reformed its exchange rate regime twice, once in 2005 and the other in 2010. Before and after each reform, CNY kept its exchange rate steady for a long time, with almost no fluctuation or only change in a narrow range. Therefore, we chose CNH, which has more fluctuations, to conduct our analysis. In order to match the data availability for CNH, we used the data sample period from 23 August 2010 to 20 June 2019.

The stationary return series were obtained from Equation (18), and are in percentage points:

$$r_{i,t} = 100 \times ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right). \tag{24}$$

The return series for the natural gas price and exchange rate over time are plotted in Figure 1. Figure 1 shows that the GASF return had the highest volatility compared to the others. We consider that the natural gas price was largely affected by temperature, so most fluctuations occurred concentratedly during the winter season. A small number of fluctuations were recorded in the middle of the year, such as in 2012, when hot weather forecasts and elevated cooling demands created a great demand for natural gas. The RUB return fluctuated drastically at the end of 2014, when the crude oil crash happened, and caused the financial crisis in Russia.

Table 2 provides summary statistics for all return series. CNH has the lowest mean of all return series, as well as standard deviation. Therefore, in some way, CNH remained stable under government regulations. The GASF had the highest standard deviation, as shown in Figure 1. The distribution of all return series significantly deviated from normal, as demonstrated by the Jarque–Bera test.

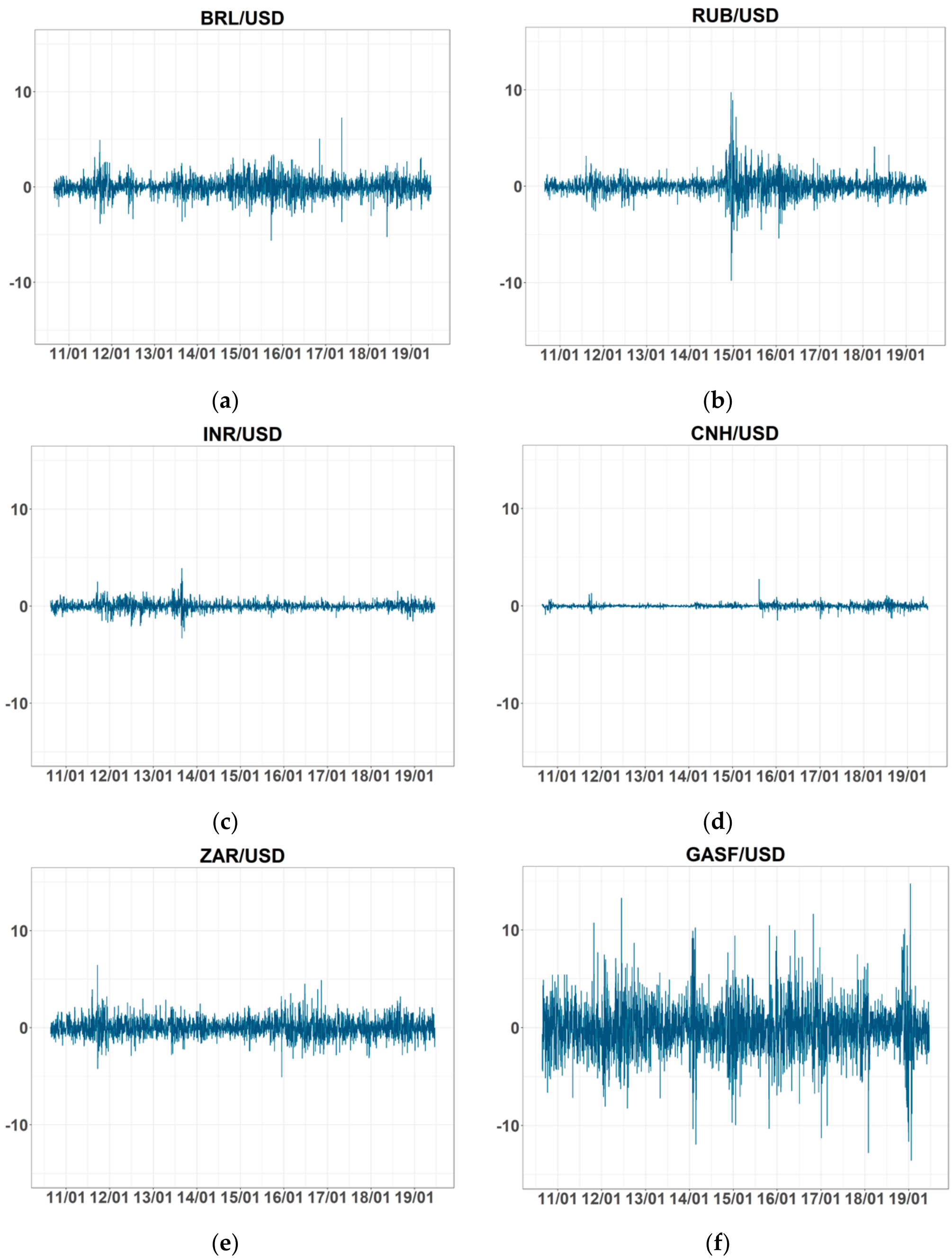


Figure 1. Daily return. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. (**a**–**f**) refer to BRL, RUB, INR, CNH, ZAR, and GASF return series, respectively.

Table 2. Summary statistics for daily returns.

	Min	Max	Mean	Std Dev	Skewness	Kurtosis	JB-Test
BRL	−5.601	7.270	0.034	0.949	0.140	3.784	1386.046 ***
RUB	−9.771	9.731	0.032	1.024	0.440	13.933	18,741.359 ***
INR	−3.294	3.904	0.017	0.451	0.286	7.546	5509.334 ***
CNH	−1.471	2.747	0.001	0.227	0.473	14.522	20,365.878 ***
ZAR	−5.081	6.444	0.029	0.986	0.271	1.994	411.515 ***
GASF	−18.055	16.691	−0.025	2.759	0.116	4.080	1607.127 ***

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. The sample period is from 23 August 2010 to 20 June 2019. The JB-Test refers to the Jarque–Bera test for normality. *** indicates rejection of the null hypothesis that the data are normally distributed at the 1% level of significance.

We were interested in not only the connectedness of the return series, but also the volatility connectedness, because volatility can provide a measure of risk and is particularly crisis-sensitive [25]. As volatility is unobserved and must be estimated, we used generalized autoregressive conditional heteroscedasticity (GARCH) models to obtain the volatilities of BRL, INR, CNH, and GASF return series, and Glosten–Jagannathan–Runkle GARCH (GJR-GARCH) models to obtain the volatility of RUB and ZAR return series (for the sake of brevity, the results of the GARCH model and GJR-GARCH model are omitted).

The plots of volatility are presented in Figure 2. For simplicity's sake, we used a different scale for the y-axis in RUB and GASF. The GASF fluctuated violently and most fluctuations accumulated during the winter season, which is consistent with the return series. The volatilities of the five exchange rates reached a high level at the end of 2011, compared to the period before and after, when the eurozone debt crisis reached its peak. The BRL's volatility was turbulent after 2010, especially between 2015 and 2017, when Brazil experienced a severe economic crisis and faced a dramatic economic recession. The volatility of INR reached its peak at the end of 2013, as the Indian rupee had depreciated greatly. The description statistics for volatility are reported in Table 3. Similar to the return series, GASF has the highest standard deviation, whereas CNH has the lowest. All volatilities were skewed and had high kurtosis, indicating that the distributions showed obvious non-normality characteristics. The Jarque–Bera test also verifies our opinion.

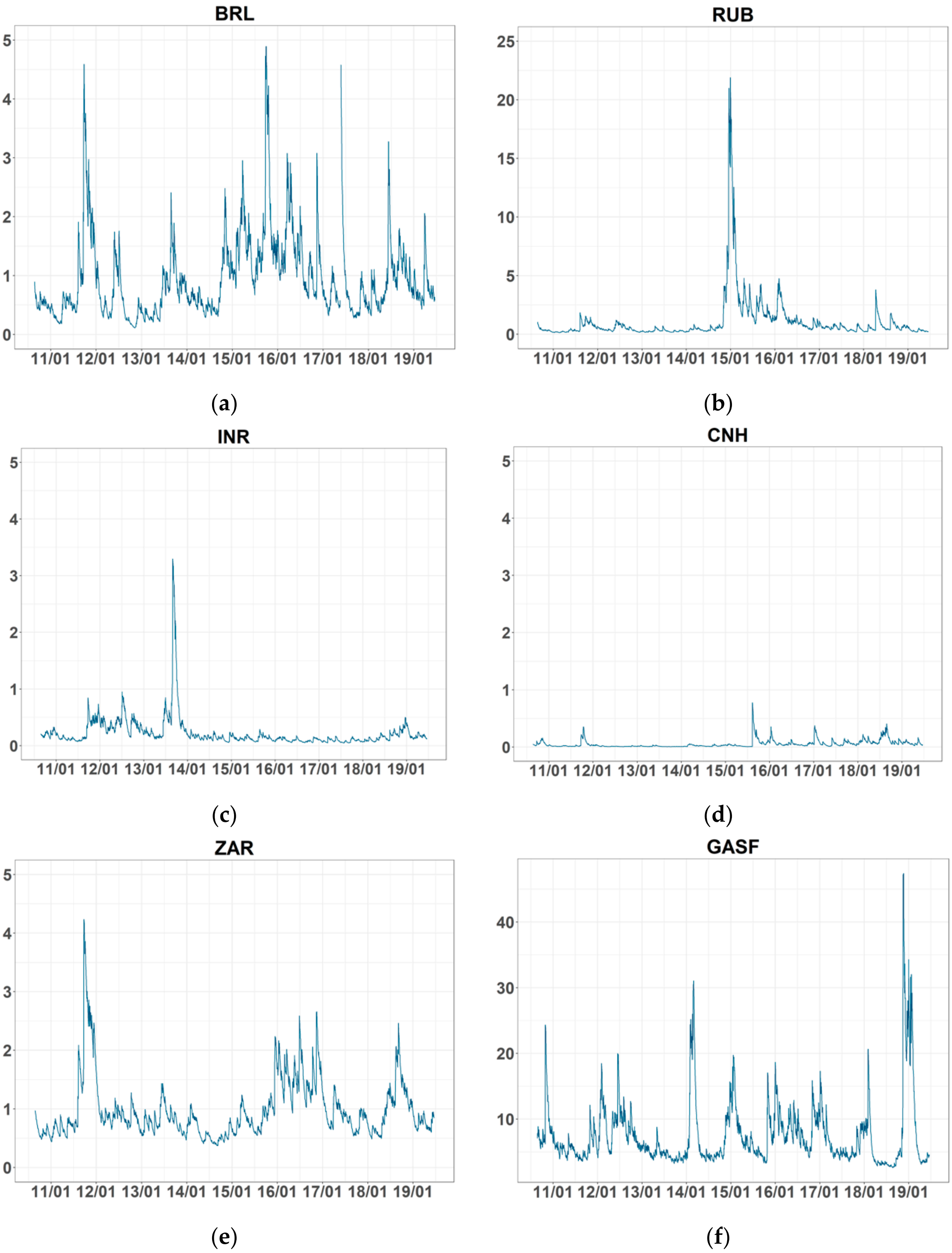


Figure 2. Volatility. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. (**a**–**f**) refer to the volatility of BRL, RUB, INR, CNH, ZAR, and GASF return series, respectively.

Table 3. Summary statistics for volatilities of daily returns.

	Min	Max	Mean	Std Dev	Skewness	Kurtosis	JB-Test
BRL	0.111	5.466	0.957	0.707	2.127	6.536	5847.958 ***
RUB	0.135	21.907	1.061	2.044	6.108	44.688	206,321.592 ***
INR	0.048	3.297	0.223	0.277	6.275	52.188	276,967.370 ***
CNH	0.005	0.775	0.055	0.068	3.675	21.737	50,619.087 ***
ZAR	0.372	4.234	0.978	0.506	2.205	6.796	6312.786 ***
GASF	2.596	47.407	7.547	5.102	2.837	11.266	15,299.202 ***

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. The volatilities of BRL, INR, CNY, and GASF return series were calculated by the generalized autoregressive conditional heteroscedasticity (GARCH) (1,1) model, and the volatilities of RUB and ZAR return series were calculated by the Glosten–Jagannathan–Runkle (GJR)-GARCH (1,1) model. The sample period is from 23 August 2010 to 20 June 2019. *** indicates rejection of the null hypothesis that the data are normally distributed at the 1% level of significance.

4.2. Connectedness and Frequency Decomposition

As the calculation of the connectedness index is based on the VAR model, we conducted an augmented Dickey–Fuller (ADF) test for the unit root before applying the data to the VAR model.

However, it is well-known that the unit root hypothesis can be rejected if the data series contain structural break(s) [26–28]. As our sample period is long, from 2010 to 2019, which is almost 9 years, and several big events happened during the sample period, such as the 2014 crude oil crush, which may have had an impact on the economies and caused structural breaks, it is well-founded to consider that structural breaks may exist. Therefore, a Bai–Perron test for structural breaks was conducted. The p-values of the Bai–Perron test for the return series are presented in Table 4. All numbers indicate the acceptance of null hypothesis that no break exists. These results confirm the reliability of the ADF test.

Table 4. Bai–Perron breakpoint test on return series.

	BRL	RUB	INR	CNH	ZAR	GASF
p-value	0.769	0.448	0.316	0.190	0.773	0.536

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. Each number indicates the p-value of the Bai–Perron breakpoint test.

The results of the ADF test are presented in Table 5. All results show that no unit root exists. The p lags of the VAR model were chosen by the Akaike information criterion (AIC). Return series used the VAR (1) model, whereas volatilities used the VAR (2) model (for the sake of brevity, the results of the VAR model are omitted).

Table 5. Augmented Dickey–Fuller (ADF) test on return series and volatilities.

	BRL	RUB	INR	CNH	ZAR	GASF
			Return			
Dickey–Fuller	−12.050 ***	−11.581 ***	−11.718 ***	−11.470 ***	−14.284 ***	−13.837 ***
			Volatility			
Dickey–Fuller	−5.493 ***	−4.983 ***	−5.471 ***	−6.763 ***	−4.013 ***	−5.422 ***

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. Each number indicates that Dickey–Fuller is the ADF test statistic. *** indicates rejection of the null hypothesis that a unit root is present in the time series at the 1% level of significance.

The connectedness index based on DY and its spectral representation based on BK of short-, medium-, long-term are reported in Tables 6–9, respectively. The frequency band of short term, medium term, and long term in Table 6 roughly corresponds to 1 day to 5 days, 5 days to 21 days, and more than 21 days, respectively. The diagonal elements in both tables represent the own-market connectedness and are not important in our paper. We have more interest in the off-diagonal elements, which indicate pairwise connectedness between two variables: the values of the To row, which show when one variable receives a shock; how much influence would be exerted on other variables; the values of the "From" column, which measure the composition of one variable's change; and the values of the "Net" row, which reveal whether a variable is a net recipient or a net transmitter. The "GAS-FX" column, which exhibits the net pairwise directional connectedness between GAS and the five exchange rates, is the most critical for our study.

Table 6. Connectedness among the natural gas future price and BRICS's exchange rates.

	BRL	RUB	INR	CNH	ZAR	GASF	From	GAS-FX
				Return				
BRL	69.719	7.790	1.360	3.129	17.692	0.310	30.281	−0.124
RUB	8.335	73.334	2.658	3.303	12.248	0.122	26.666	−0.113
INR	5.502	3.814	77.817	3.686	9.165	0.017	22.183	0.016
CNH	3.609	3.693	3.391	81.305	7.998	0.004	18.695	−0.024
ZAR	16.241	10.551	3.255	6.237	63.673	0.043	36.327	−0.012
GASF	0.433	0.235	0.001	0.028	0.055	99.248	0.752	
To	34.119	26.083	10.665	16.383	47.158	0.496	**22.484**	
Net	3.838	−0.583	−11.517	−2.312	10.831	−0.257		
				Volatility				
BRL	75.206	3.630	0.723	0.092	19.230	1.118	24.794	0.989
RUB	1.040	97.472	0.783	0.060	0.393	0.252	2.528	−3.667
INR	4.205	0.174	91.702	0.446	3.466	0.006	8.298	−0.026
CNH	3.768	0.197	2.853	86.083	6.943	0.156	13.917	−0.107
ZAR	12.265	0.244	1.080	0.449	85.171	0.791	14.829	−0.682
GASF	0.129	3.920	0.032	0.263	1.473	94.183	5.817	
To	21.407	8.165	5.471	1.310	31.506	2.324	**11.697**	
Net	−3.387	5.637	−2.826	−12.607	16.677	−3.493		

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. From column reports the total directional connectedness from others to x_i. To row reports the total directional connectedness from x_i to others. Net row reports the net total directional connectedness. GAS-FX column reports the net pairwise connectedness between the GASF and exchange rates, which is calculated by the GASF to others minus the others to GASF. The number in red represents the largest value in this system. The number in bold means the total connectedness. All results are expressed as a percentage.

Table 7. Connectedness among the natural gas future price and exchange rates in the frequency domain (short term).

	BRL	RUB	INR	CNH	ZAR	GASF	From	GAS-FX
				Return				
BRL	58.271	6.229	1.130	2.701	14.487	0.282	24.829	−0.111
RUB	6.470	58.659	2.207	2.684	9.513	0.096	20.969	−0.134
INR	3.796	2.569	62.837	2.626	5.975	0.016	14.982	0.015
CNH	2.838	3.122	2.748	65.387	6.316	0.004	15.029	−0.015
ZAR	13.332	8.809	2.767	5.097	51.584	0.042	30.048	0.004
GASF	0.393	0.229	0.001	0.020	0.039	82.464	0.682	
To	26.829	20.958	8.853	13.128	36.330	0.440	**17.756**	
Net	1.999	−0.010	−6.129	−1.901	6.283	−0.242		

Table 7. *Cont.*

	BRL	RUB	INR	CNH	ZAR	GASF	From	GAS-FX
				Volatility				
BRL	2.783	0.001	0.027	0.000	0.193	0.001	0.222	−0.001
RUB	0.002	1.226	0.011	0.000	0.022	0.000	0.036	−0.010
INR	0.012	0.006	1.107	0.006	0.039	0.001	0.063	−0.002
CNH	0.012	0.000	0.029	5.085	0.057	0.005	0.103	0.003
ZAR	0.085	0.012	0.019	0.004	1.181	0.000	0.120	−0.007
GASF	0.001	0.010	0.004	0.002	0.008	3.005	0.025	
To	0.112	0.030	0.090	0.012	0.319	0.008	**0.095**	
Net	−0.110	−0.006	0.026	−0.091	0.199	−0.017		

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. From column reports the total directional connectedness from others to x_i. To row reports the total directional connectedness from x_i to others. Net row reports the net total directional connectedness. GAS-FX column reports the net pairwise connectedness between the GASF and exchange rates, which is calculated by the GASF to others minus the others to GASF. The number in red represents the largest value in this system. The number in bold means the total connectedness. The frequency band of short term roughly corresponds to 1 day to 5 days. All results are expressed as a percentage.

Table 8. Connectedness among the natural gas future price and exchange rates in the frequency domain (medium term).

	BRL	RUB	INR	CNH	ZAR	GASF	From	GAS-FX
				Return				
BRL	8.454	1.149	0.170	0.318	2.363	0.020	4.020	−0.009
RUB	1.372	10.802	0.334	0.457	2.011	0.019	4.193	0.015
INR	1.250	0.912	11.041	0.777	2.332	0.001	5.272	0.001
CNH	0.567	0.423	0.474	11.721	1.237	0.000	2.701	−0.006
ZAR	2.148	1.289	0.361	0.840	8.913	0.001	4.639	−0.011
GASF	0.030	0.005	0.000	0.006	0.012	12.391	0.053	
To	5.367	3.777	1.339	2.398	7.956	0.042	**3.480**	
Net	1.347	−0.416	−3.933	−0.303	3.316	−0.012		
				Volatility				
BRL	8.452	0.018	0.091	0.002	0.712	0.006	0.829	−0.002
RUB	0.012	4.530	0.035	0.000	0.082	0.002	0.130	−0.059
INR	0.072	0.034	4.791	0.020	0.193	0.001	0.320	−0.003
CNH	0.075	0.001	0.093	15.124	0.275	0.009	0.452	0.004
ZAR	0.273	0.036	0.062	0.004	3.877	0.001	0.375	−0.032
GASF	0.008	0.061	0.005	0.005	0.033	9.896	0.111	
To	0.440	0.150	0.285	0.029	1.296	0.019	**0.370**	
Net	−0.389	0.020	−0.035	−0.423	0.920	−0.092		

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas future price. From column reports the total directional connectedness from others to x_i. To row reports the total directional connectedness from x_i to others. Net row reports the net total directional connectedness. GAS-FX column reports the net pairwise connectedness between the GASF and exchange rates, which is calculated by the GASF to others minus the others to GASF. The number in red represents the largest value in this system. The number in bold means the total connectedness. The frequency band of medium term roughly corresponds to 5 days to 21 days. All results are expressed as a percentage.

Table 9. Connectedness among the natural gas future price and exchange rates in the frequency domain (long term).

	BRL	RUB	INR	CNH	ZAR	GASF	From	GAS-FX
				Return				
BRL	2.994	0.412	0.060	0.111	0.842	0.007	1.432	−0.003
RUB	0.493	3.873	0.118	0.162	0.724	0.007	1.504	0.006
INR	0.456	0.333	3.940	0.282	0.857	0.000	1.929	0.000
CNH	0.204	0.148	0.169	4.198	0.444	0.000	0.965	−0.002
ZAR	0.761	0.453	0.126	0.299	3.176	0.000	1.640	−0.004
GASF	0.010	0.001	0.000	0.002	0.004	4.392	0.017	
To	1.923	1.347	0.473	0.857	2.872	0.014	**1.248**	
Net	0.491	−0.157	−1.455	−0.108	1.232	−0.003		
				Volatility				
BRL	63.970	3.611	0.606	0.090	18.324	1.111	23.742	0.991
RUB	1.026	91.716	0.737	0.059	0.289	0.250	2.361	−3.598
INR	4.121	0.134	85.804	0.421	3.235	0.003	7.914	−0.020
CNH	3.681	0.196	2.731	65.874	6.611	0.142	13.361	−0.114
ZAR	11.906	0.196	1.000	0.442	80.113	0.790	14.334	−0.642
GASF	0.120	3.848	0.023	0.257	1.432	81.282	5.680	
To	20.855	7.985	5.097	1.269	29.891	2.297	**11.232**	
Net	−2.888	5.624	−2.817	−12.093	15.558	−3.384		

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas future price. From column reports the total directional connectedness from others to x_i. To row reports the total directional connectedness from x_i to others. Net row reports the net total directional connectedness. GAS-FX column reports the net pairwise connectedness between the GASF and exchange rates, which is calculated by the GASF to others minus the others to GASF. The number in red represents the largest value in this system. The number in bold means the total connectedness. The frequency band of long term roughly corresponds to more than 21 days. All results are expressed as percentages.

As shown in Table 6, the total connectedness of the return series is 22.484%, which is almost twice as much as the connectedness between volatilities (11.697%), but both of them are modest. In this system, no matter what the connectedness from the return series or volatilities was, the shocks transmitted from ZAR to BRL contributed the largest value. The BRL was a net transmitter in return connectedness, but a net recipient in volatility connectedness. The RUB was opposite to BRL in that it was a net recipient in the return case, but a net transmitter in the volatility case. Furthermore, INR, CNH, and GASF were net receivers in both cases, whereas ZAR was a net transmitter. By obtaining the absolute value of the “Net” row, we found that INR had the strongest influence (11.517%) in all return series and ZAR was the most powerful variable (16.677%) in volatilities.

In Tables 7–9, we note that the sum of total connectedness in the short term, medium term, and long term is equal to the total connectedness shown in Table 6, which is in agreement with the definition of frequency decomposition for connectedness. It is interesting to find that the total connectedness from the return series is highest in the short term (17.756%), followed by the medium term (3.480%) and long term (1.248%). By contrast, from volatilities, the value is highest in the long term (11.232%), followed by the medium term (0.370%) and short term (0.095%), which means that the uncertainty transmitted by the shock has a long-term impact on the market, rather than the shock itself.

From the values of the GAS-FX column, we found that the net pairwise connectedness between GAS and the exchange rate was higher in volatilities than return series, but both were very weak. All values were almost zero. The possible reason for this is that the GASF data we have chosen are for Henry Hub natural gas, which could be seen as representative of the North American natural gas market. However, as the natural gas pipeline in North America can hardly reach any BRICS countries, and the distance between North America and BRICS countries makes the transportation cost of LNG expensive, whether as an import or export, North American natural gas is not the primary selection for

BRICS countries. Our opinion is also supported by statistics from the BP Statistical Review of World Energy [1]. Whether natural gas is traded by a pipeline or LNG, the quantity being directed from the US, Mexico, and Canada to BRICS countries is very low. Consequently, we could say that the natural gas price is unrelated to the exchange rate in BRICS countries.

4.3. Rolling-Window Analysis

We also conducted a rolling-window analysis to investigate the time-varying connectedness between GAS and exchange rates. The window size was 300 (we also obtained the dynamic connectedness from a window size of 400 and obtained similar results to the result produced from the 300 window size). Figure 3 plots the dynamic total connectedness. From Figure 3, we can see that the total connectedness from the return series begins with a high level (around 40%) in the first few windows, and then falls after 2011 (around 25%), when South Africa joined the BRICS group and the period in which the European debt crisis was at its peak. After a temporary rise in late 2012, the connectedness falls again at the beginning of 2013 (around 20%). From 2013 to mid-2015, the connectedness fluctuates between 20% and 25%, and then rises again to over 30% after mid-2015. The connectedness drops dramatically between 2017 and 2018, from almost 35% to around 20%, and then recovers slowly. The trend of dynamic connectedness from volatilities is similar to that of return series. There are several unusual peaks and troughs in the plot, which we think are related to big events, like the Russian financial crisis (2014), the Brazilian economic recession (2015), and the US–China trade war (2018). Figure 4 presents the frequency decomposition of dynamic connectedness. We find that, whether in the short, medium, or long term, the trend of return connectedness is similar to the dynamic total connectedness. However, for volatilities, in the short and medium term, the connectedness exhibits almost no change (except for some abrupt rises and falls), and the long term has a similar trend to total connectedness. We think that long-term connectedness exerts the most influence in the case of volatility.

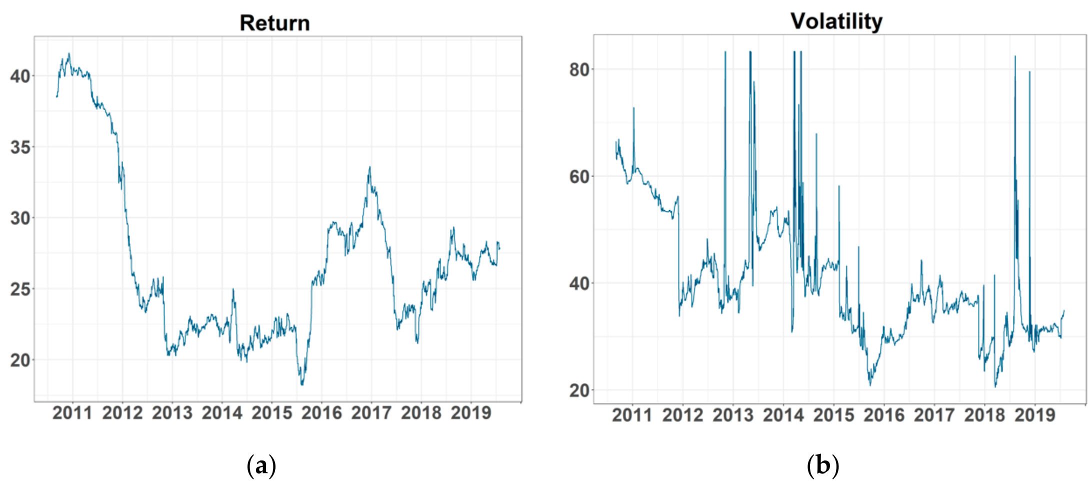
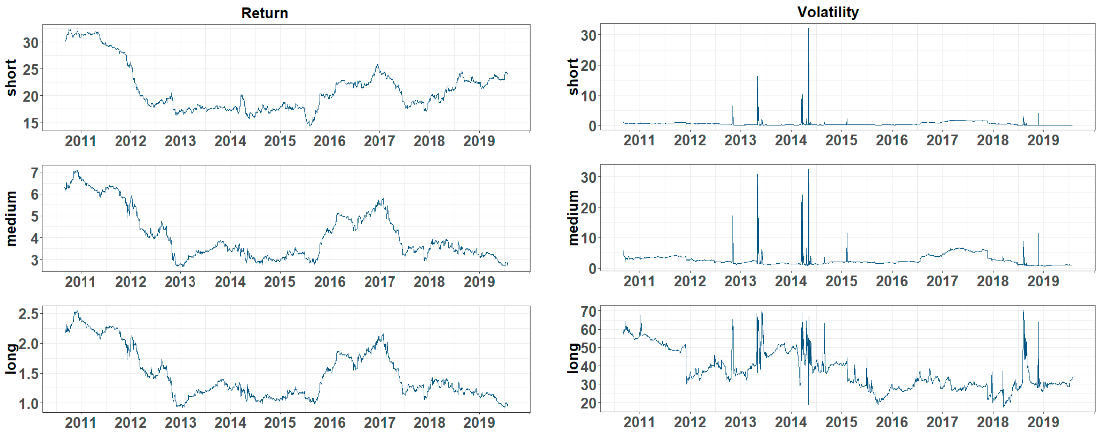


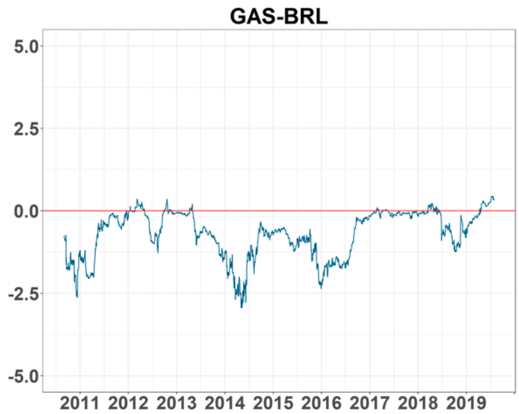
Figure 3. Dynamic connectedness: (**a**) total connectedness of return series and (**b**) total connectedness of volatilities. BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively.



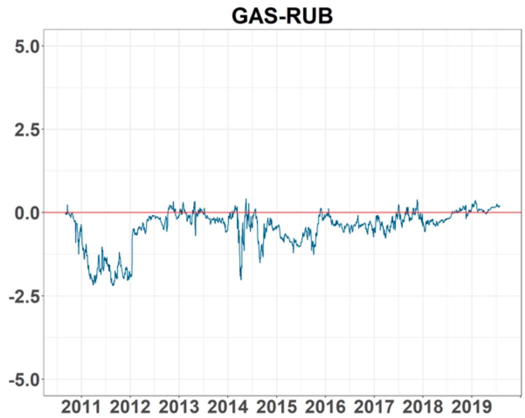
(**a**) (**b**)

Figure 4. Frequency decomposition of dynamic connectedness: (**a**) frequency decomposition of total connectedness for return series and (**b**) frequency decomposition of total connectedness for volatilities. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

The time-varying net pairwise connectedness between GAS and exchange rates return series is plotted in Figure 5. Like the result in Section 4.2, all values were low and almost all of them were below 2.5% in terms of the absolute value, so were negligible. The results from volatilities are presented in Figure 6. There are also several sudden rises and falls, which is consistent with the plot of total connectedness. In the net pairwise connectedness of GAS-BRL, GAS-INR, and GAS-ZAR pairs, except for the abnormal value at some points, the values were almost insignificant; thus, we can hardly say that the GAS has an influence on the exchange rate or vice versa. However, in GAS-RUB and GAS-CNH pairs, there are some significant positive or negative periods during our data span. Before 2014, GAS was a net transmitter to RUB, and then turned into a net recipient after 2014, when Russia was undergoing an economic crisis caused by the oil price crash. After 2016, GAS was a net transmitter to CNH, when Australia became the largest supplier of LNG to China instead of Qatar, and the trade kept increasing after that.



(**a**)



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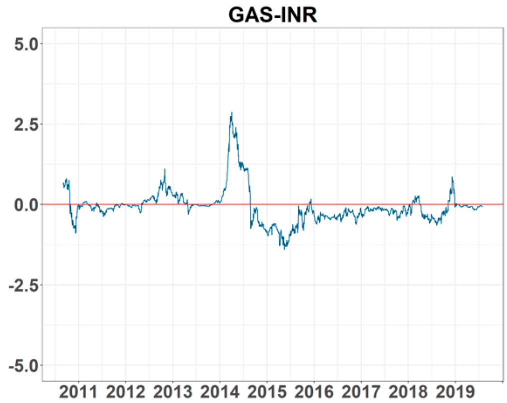

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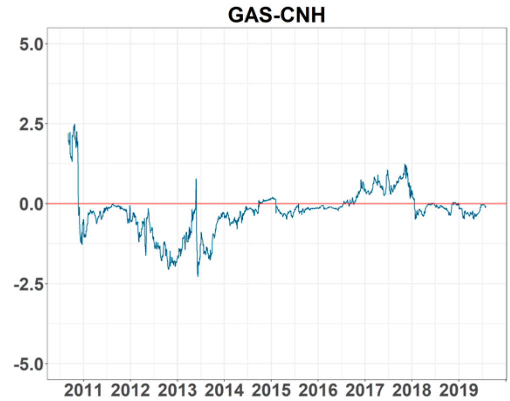

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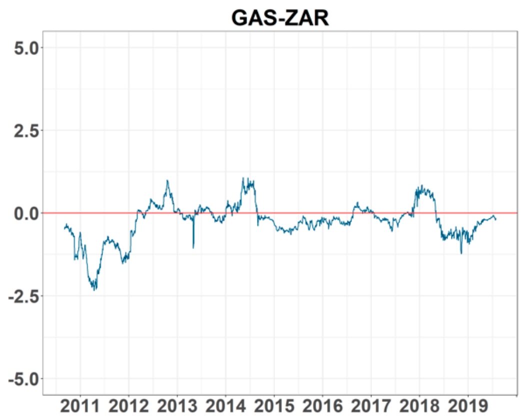

(**e**)

Figure 5. Net pairwise connectedness of return series. (**a**–**e**) refer to the net pairwise connectedness between GASF and BRL, RUB, INR, CNH, and ZAR return series, respectively. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

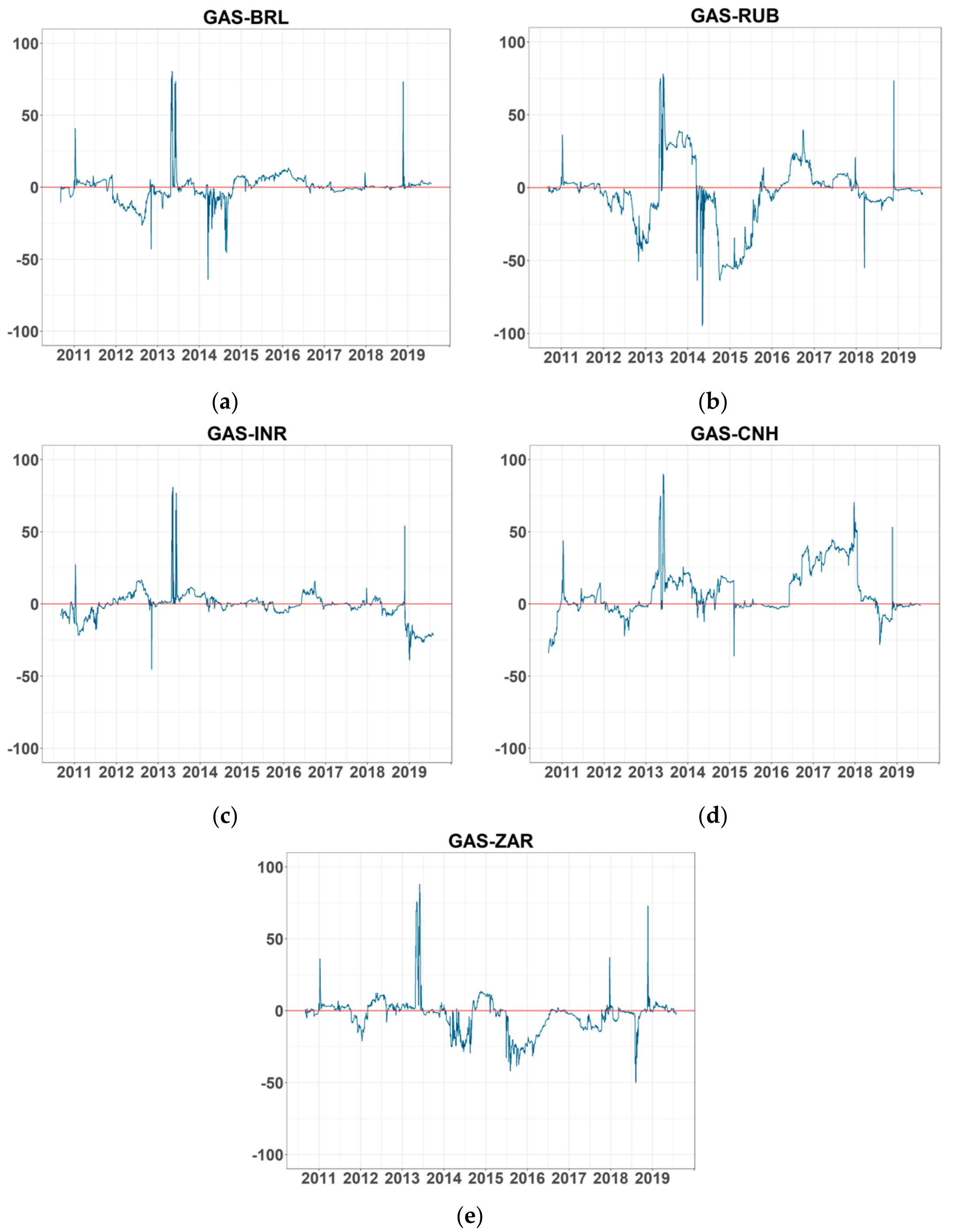

Figure 6. Net pairwise connectedness of volatility. (**a**–**e**) refer to net pairwise connectedness between the volatility of GASF and BRL, RUB, INR, CNH, and ZAR, respectively. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

5. Conclusions

This paper examined the connectedness between the Henry Hub natural gas price and the BRICS's exchange rates. To that end, the connectedness methodology from Diebold and Yilmaz (2009, 2012, 2015) as well as frequency decomposition of connectedness proposed by Baruník and Křehlík (2018) were used. We collected data from 23 August 2010 to 20 June 2019 and tested both return series and volatilities from GARCH models.

Our empirical results show that the total connectedness was 22.5% in the return series and 11.7% in volatilities. Compared to results from previous studies—such as Lundgren et al. [13] who found that the total volatility connectedness among renewable energy stock returns, investment assets, and several sources of uncertainty is 67.4%—our results are modest, which means that most variation was due to the variation in the variables themselves. By taking the frequency decomposition of connectedness, we found that, in the return series, the short term contributes to the total connectedness the most, whereas the long term contributes most in relation to volatility. From the results of net pairwise connectedness between the natural gas price and exchange rates, we obtained a value of almost zero in each natural gas and exchange rate pair, which means that natural gas does not play an important role in explaining movements in the exchange rates. We also applied a rolling-window approach to conduct the time-varying analysis. In short, the results are similar to those of the constant analysis and we cannot say for certain that the natural gas price had a great influence on exchange rate movement. Only in the plot of volatility connectedness were there several dramatic fluctuations, which we consider to be connected to some notable events, such as economic crises and trade frictions.

Our results are obviously different from the results of the studies on the relationship between the oil price and exchange rates, such as that conducted by Singh et al. (2018), who found that the total volatility connectedness between the oil price and nine exchange rates reached 72.96%. The shocks transmitted from crude oil to each exchange rate are also significant. We consider some possible reasons for the difference. First, crude oil can be used more widely across different fields than natural gas. For example, it can fuel our cars and make plastics, rubbers, and the like, which are uses that cannot be replaced by natural gas. As indicated in the BP Statistical Review of World Energy [1], crude oil has the highest share in global energy consumption, and its consumption is almost double that of natural gas. Second, the production of crude oil far exceeds that of natural gas. Therefore, whether for energy import countries or energy export countries, crude oil is more easily traded. Third, compared to developed countries, awareness of the environment in developing countries is at a lower level. As the BRICS are the focus of our study, although their consumption of natural gas has increased in recent years, natural gas is still not the primary energy source for these countries (with the exception of Russia). India, China, and South Africa consumed coal the most in 2019, while Brazil consumed oil the most [1].

Although crude oil plays an irreplaceable role in the energy market now, with increasing environmental awareness, we believe that natural gas will become more important and the connectedness between the natural gas price and exchange rates will become stronger in the future.

The empirical evidence in this study may have important implications for policymakers, especially those in oil-dependent countries. As much of the literature shows that exchange rates are highly dependent on the oil price, turbulence in the crude oil market could have a great impact on the foreign currency market, thus causing exchange rate pressure and even economic instability. In order to solve the foreign exchange fluctuation, monetary authorities need to accumulate or reduce foreign exchange reserves, which is not considered desirable in the real world. Changing the dependence structure in relation to energy—from depending on energy that is closely connected with the currency market, such as crude oil, to depending on energy that is hardly connected to the currency market, such as natural gas—could provide an efficient way of maintaining economic stability and reducing exchange rate pressure. By contrast, because of the low connectedness between the natural gas price and exchange rates, foreign exchange fluctuation may barely be affected by the natural gas price. Therefore, for investors, it is less risky to invest in gas-related financial products than oil-related financial products, which are highly connected with currency.

Although this paper conducted thorough research, there were several limitations in the empirical work. First, although we found that natural gas did not have a significant impact on the exchange rate, this result could be influenced by the data selection. We used Henry Hub as our natural gas price data, which represents the North American natural gas market. However, given the restriction of pipelines and high transportation cost, North American countries that produce natural gas may not be the primary selection for BRICS. Second, with technological improvements in exploiting natural gas and the increasing number of gas liquefaction plants, we assumed that the LNG price would have more influence on the exchange rate than the pipeline natural gas price did. However, owing to data limitations, we could only focus on the whole natural gas market, which may be the reason why the connectedness between the natural gas price and exchange rates was modest. Therefore, for further extension of this research, first, we want to collect different natural gas price data, such as the Netherlands Title Transfer Facility (TTF) index and Japan Korea Marker, to exclude the impact of data selection on the results. Second, we want to analyze the relationship between the crude oil price and exchange rates and the relationship between the crude oil price and natural gas price. This would allow us to compare the connectedness between the crude oil price and exchange rates with that between the natural gas price and exchange rates more rationally. Finally, if the data permit, we want to use the data on only LNG to find the connectedness between the natural gas price and foreign exchange rates more precisely.

Author Contributions: Conceptualization, S.H.; investigation, Y.H.; writing—original draft preparation, Y.H.; writing—review and editing, T.N.; project administration, S.H.; funding acquisition, S.H.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A Robustness Analysis

We used the Henry Hub natural gas spot price (GASS) as the natural gas price data to examine the robustness of our results. (The natural gas futures index in the United Kingdom, which is known as the UK National Balancing Point (NBP), was also used to conduct the robustness check, but the results were quite similar to those from GASS, so we only present the connectedness table of NBP and exchange rates (Table A2) in Appendix A).

The plot of GASS's return and volatility series are reported in Figure A1. We found that some values of volatility were extremely large (the maximum is over 800). We think that the reason for this is that the natural gas spot price was more easily affected by the change of demand and supply than the future price, even though the change was small.

We summarize the results of connectedness and the frequency decomposition of short, medium, and long term in Table A1, Table A3, Table A4, Table A5, respectively. The result is quite similar to that of GASF and exchange rates. We also used a 300 rolling-window to conduct the time-varying analysis. The dynamic connectedness and its spectral representation are plotted in Figures A2 and A3, respectively. The net pairwise connectedness of return series and volatilities are illustrated in Figures A4 and A5, respectively. All results are consistent with those from the analysis using the natural gas future price, except for the net pairwise connectedness of return series (Figure A4). Some values are opposite to the result above, but all of them are low, even the maximum value, which is less than 5% and negligible.

The results of robustness confirm the suitability of our proposed approach, which aimed to capture the relationship between the natural gas price and exchange rates.

Table A1. Connectedness between the natural gas spot price and BRICS's exchange rates.

	BRL	RUB	INR	CNH	ZAR	GASS	From	GAS-FX
				Return				
BRL	69.839	7.714	1.456	3.124	17.688	0.179	30.161	−0.249
RUB	8.323	73.405	2.681	3.276	12.230	0.085	26.595	−0.058
INR	5.571	3.833	77.727	3.652	9.066	0.152	22.273	0.040
CNH	3.588	3.648	3.378	81.296	7.953	0.137	18.704	0.136
ZAR	16.233	10.559	3.252	6.206	63.643	0.108	36.357	0.094
GASS	0.429	0.143	0.113	0.001	0.014	99.301	0.699	
To	34.143	25.896	10.879	16.259	46.951	0.660	**22.465**	
Net	3.983	−0.699	−11.394	−2.444	10.593	−0.039		
				Volatility				
BRL	75.533	3.660	0.288	0.354	20.138	0.025	24.467	−0.377
RUB	0.890	97.569	0.750	0.298	0.479	0.014	2.431	−0.006
INR	3.133	0.494	92.791	0.277	3.235	0.070	7.209	−0.234
CNH	3.679	0.213	2.713	85.576	7.123	0.696	14.424	0.678
ZAR	11.251	0.282	0.801	1.067	86.363	0.236	13.637	0.208
GASS	0.402	0.020	0.304	0.018	0.028	99.229	0.771	
To	19.356	4.669	4.856	2.015	31.003	1.041	**10.490**	
Net	−5.111	2.238	−2.354	−12.410	17.367	0.270		

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price. From column reports the total directional connectedness from others to x_i. To row reports the total directional connectedness from x_i to others. Net row reports the net total directional connectedness. GAS-FX column reports the net pairwise connectedness between the GASS and exchange rates, which is calculated by the GASS to others minus the others to GASS. The number in red represents the largest value in this system. The number in bold means the total connectedness. All results are expressed as a percentage.

Table A2. Connectedness between the UK NBP and BRICS's exchange rates.

	BRL	RUB	INR	CNH	ZAR	GASS	From	GAS-FX
				Return				
BRL	69.761	7.791	1.352	3.139	17.707	0.249	30.239	−0.099
RUB	8.337	73.395	2.660	3.307	12.251	0.049	26.605	−0.014
INR	5.472	3.796	77.446	3.686	9.115	0.485	22.554	0.134
CNH	3.600	3.676	3.391	80.904	7.971	0.458	19.096	−0.088
ZAR	16.162	10.491	3.227	6.215	63.346	0.559	36.654	−0.286
GASS	0.348	0.062	0.352	0.546	0.845	97.847	2.153	
To	33.919	25.816	10.983	16.893	47.889	1.800	**22.883**	
Net	3.680	−0.788	−11.571	−2.204	11.236	−0.353		
				Volatility				
BRL	75.164	3.509	0.542	0.277	20.254	0.254	24.836	−0.041
RUB	0.947	96.034	0.952	0.188	0.549	1.329	3.966	1.213
INR	3.494	0.244	90.752	0.328	3.404	1.778	9.248	−1.243
CNH	3.879	0.269	2.684	85.577	6.804	0.788	14.423	0.611
ZAR	11.028	0.318	0.775	0.822	86.380	0.677	13.620	−0.742
GASS	0.295	0.116	3.021	0.177	1.419	94.971	5.029	
To	19.643	4.456	7.974	1.792	32.430	4.827	**11.854**	
Net	−5.193	0.491	−1.274	−12.631	18.810	−0.202		

Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. NBP is the UK National Balancing Point. From column reports the total directional connectedness from others to x_i. To row reports the total directional connectedness from x_i to others. Net row reports the net total directional connectedness. GAS-FX column reports the net pairwise connectedness between the NBP and exchange rates, which is calculated by the NBP to others minus the others to NBP. The number in red represents the largest value in this system. The number in bold means the total connectedness. All results are expressed as a percentage.

Table A3. Connectedness between the natural gas spot price and exchange rates in the frequency domain (short term).

	BRL	RUB	INR	CNH	ZAR	GASS	From	GAS-FX
				Return				
BRL	58.953	6.079	1.107	2.772	14.530	0.118	24.606	−0.295
RUB	6.713	58.808	2.160	2.705	9.511	0.057	21.146	−0.060
INR	4.027	2.716	64.161	2.696	6.053	0.150	15.641	0.075
CNH	2.969	3.124	2.809	66.238	6.361	0.096	15.357	0.095
ZAR	13.475	8.616	2.769	5.042	51.620	0.089	29.991	0.081
GASS	0.414	0.118	0.075	0.001	0.008	81.932	0.615	
To	27.597	20.653	8.919	13.216	36.463	0.510	17.893	
Net	2.991	−0.494	−6.722	−2.141	6.472	−0.106		
				Volatility				
BRL	2.698	0.002	0.028	0.002	0.205	0.002	0.238	−0.003
RUB	0.001	1.256	0.011	0.002	0.026	0.001	0.041	−0.003
INR	0.016	0.009	1.099	0.006	0.030	0.000	0.061	−0.001
CNH	0.010	0.002	0.022	5.130	0.056	0.004	0.093	0.001
ZAR	0.090	0.011	0.014	0.006	1.193	0.000	0.121	−0.001
GASS	0.005	0.004	0.001	0.004	0.001	8.637	0.015	
To	0.123	0.028	0.076	0.019	0.318	0.007	**0.095**	
Net	−0.116	−0.014	0.015	−0.075	0.197	−0.008		

Note: The frequency band of short term roughly corresponds to 1 day to 5 days. All results are expressed as a percentage. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

Table A4. Connectedness between the natural gas spot price and exchange rates in the frequency domain (medium term).

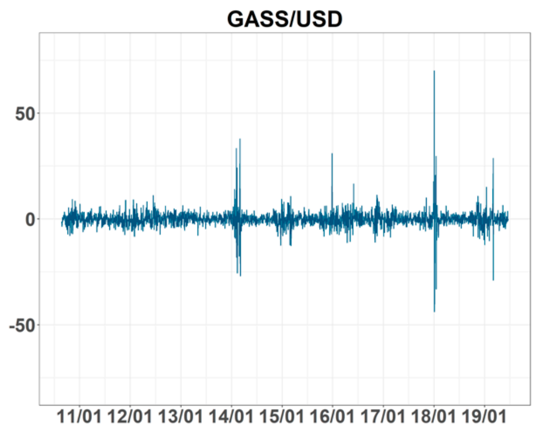
	BRL	RUB	INR	CNH	ZAR	GASS	From	GAS-FX
				Return				
BRL	8.061	1.197	0.254	0.265	2.325	0.045	4.086	0.032
RUB	1.195	10.750	0.382	0.423	1.997	0.020	4.018	0.001
INR	1.143	0.821	10.068	0.705	2.216	0.003	4.888	−0.025
CNH	0.465	0.392	0.426	11.137	1.177	0.030	2.489	0.030
ZAR	2.045	1.423	0.359	0.856	8.868	0.014	4.697	0.010
GASS	0.013	0.019	0.028	0.000	0.004	13.017	0.065	
To	4.861	3.852	1.448	2.250	7.720	0.113	**3.374**	
Net	0.775	−0.166	−3.440	−0.240	3.023	0.048		
				Volatility				
BRL	9.181	0.005	0.052	0.020	1.331	0.005	1.413	−0.030
RUB	0.007	3.981	0.043	0.013	0.090	0.002	0.155	−0.003
INR	0.253	0.076	5.828	0.015	0.084	0.002	0.430	−0.012
CNH	0.090	0.003	0.086	14.160	0.385	0.093	0.657	0.087
ZAR	0.486	0.050	0.049	0.005	4.430	0.006	0.596	0.002
GASS	0.036	0.005	0.014	0.007	0.004	35.740	0.065	
To	0.872	0.139	0.244	0.059	1.894	0.108	**0.553**	
Net	−0.541	−0.016	−0.186	−0.598	1.298	0.044		

Note: The frequency band of medium term roughly corresponds to 5 days to 21 days. All results are expressed as a percentage. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

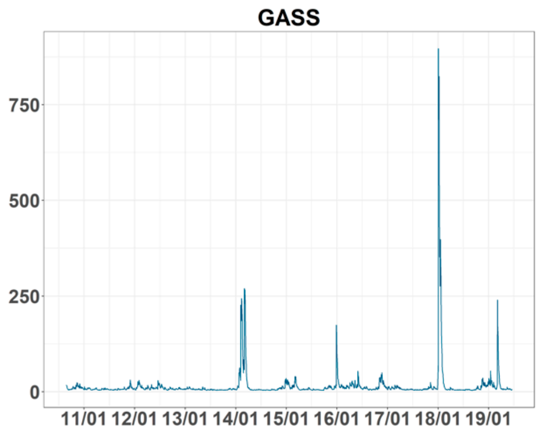
Table A5. Connectedness between the natural gas spot price and exchange rates in the frequency domain (long term).

	BRL	RUB	INR	CNH	ZAR	GASS	From	GAS-FX
				Return				
BRL	2.825	0.437	0.095	0.087	0.833	0.016	1.468	0.014
RUB	0.415	3.847	0.138	0.149	0.722	0.007	1.431	0.001
INR	0.401	0.296	3.498	0.250	0.797	0.000	1.744	−0.010
CNH	0.155	0.132	0.144	3.921	0.415	0.010	0.857	0.010
ZAR	0.713	0.520	0.124	0.308	3.155	0.005	1.669	0.003
GASS	0.001	0.006	0.010	0.000	0.002	4.352	0.019	
To	1.685	1.391	0.512	0.793	2.769	0.038	**1.198**	
Net	0.217	−0.040	−1.232	−0.063	1.099	0.019		
				Volatility				
BRL	63.654	3.654	0.208	0.333	18.603	0.018	22.815	−0.343
RUB	0.882	92.332	0.696	0.283	0.362	0.011	2.234	0.001
INR	2.864	0.409	85.864	0.257	3.121	0.068	6.719	−0.221
CNH	3.580	0.209	2.605	66.285	6.682	0.598	13.674	0.591
ZAR	10.675	0.220	0.738	1.056	80.740	0.230	12.919	0.207
GASS	0.361	0.011	0.289	0.008	0.023	54.851	0.691	
To	18.362	4.502	4.535	1.937	28.790	0.926	**9.842**	
Net	−4.454	2.268	−2.183	−11.737	15.872	0.235		

Note: The frequency band of long term roughly corresponds to more than 21 days. All results are expressed as a percentage. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

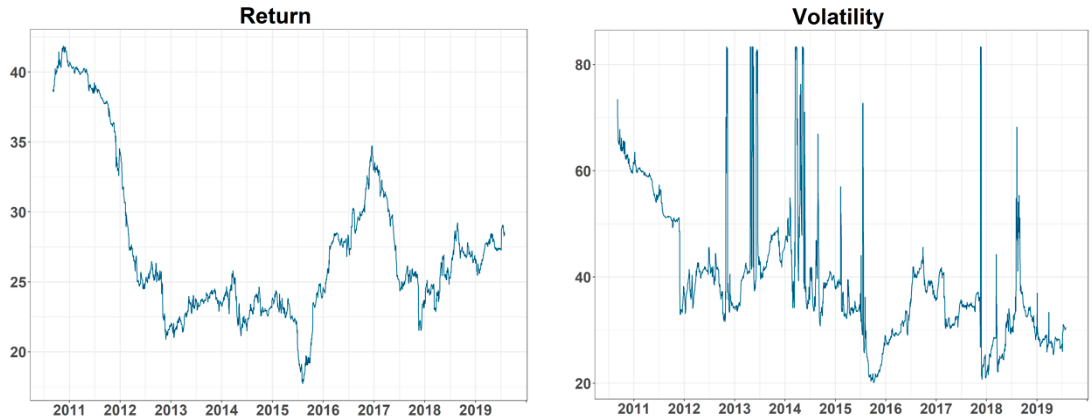


(**a**)



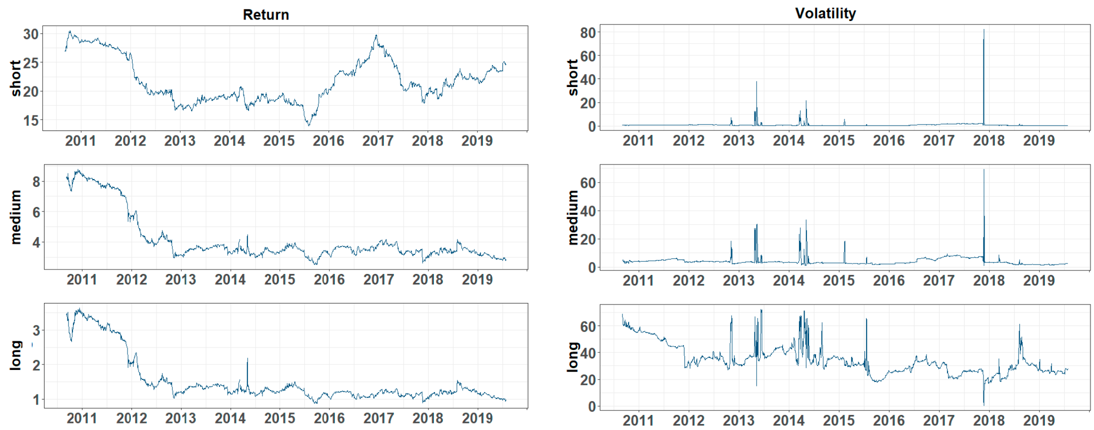
(**b**)

Figure A1. Daily return and volatility: (**a**) return series and (**b**) volatility.



(**a**) (**b**)

Figure A2. Dynamic connectedness: (**a**) total connectedness of return series and (**b**) total connectedness of volatilities. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.



(**a**) (**b**)

Figure A3. Frequency decomposition of dynamic connectedness: (**a**) frequency decomposition of total connectedness for return series and (**b**) frequency decomposition of total connectedness for volatilities. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

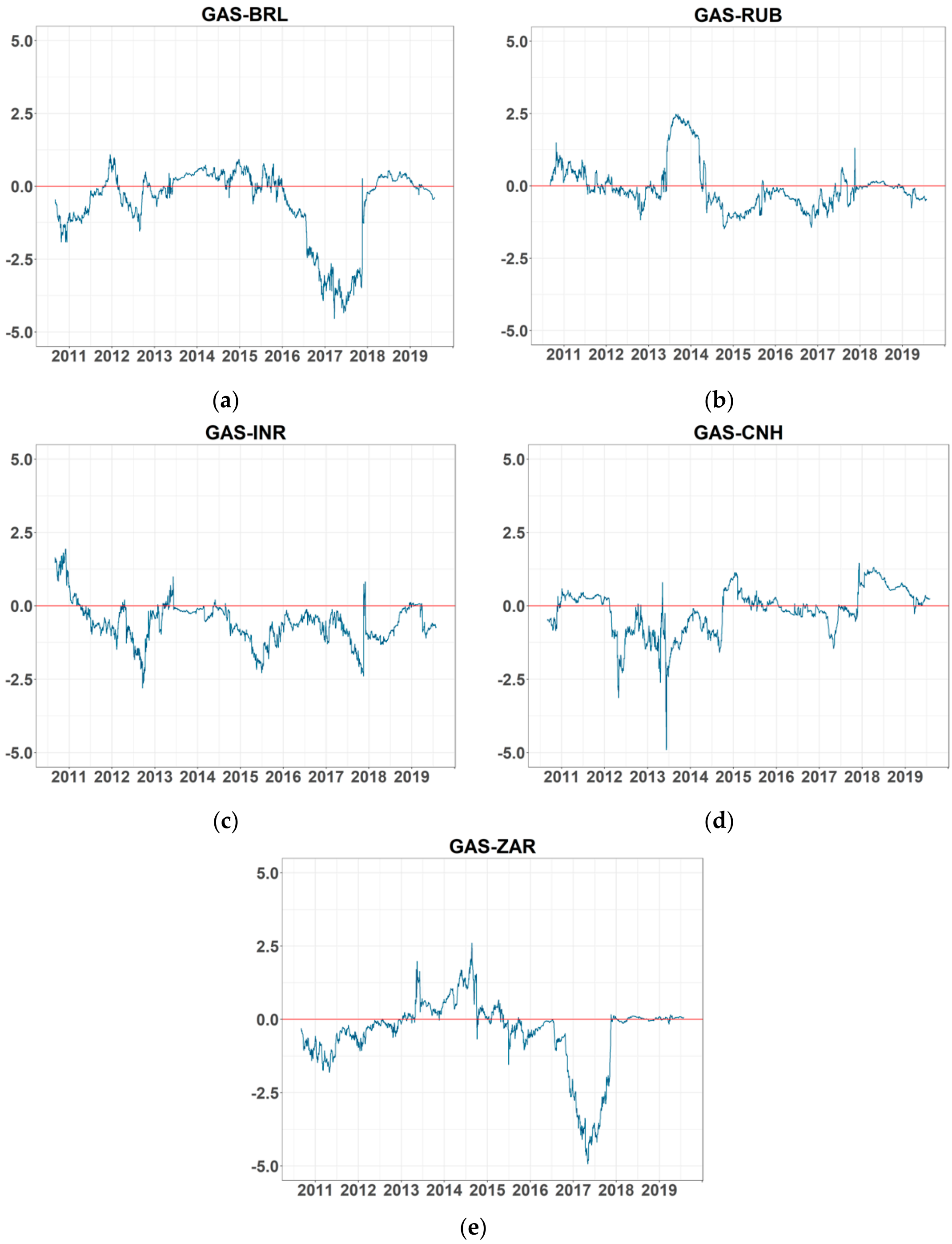
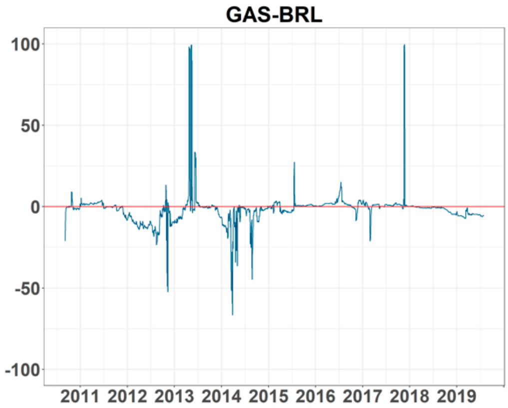
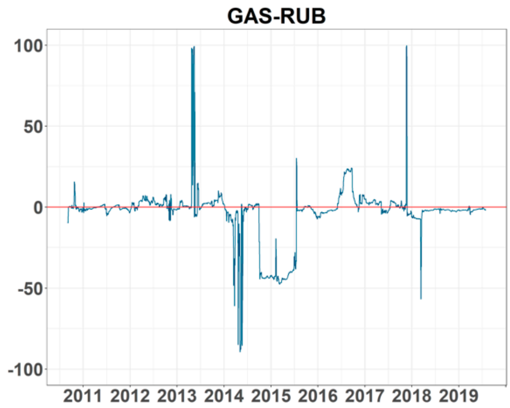
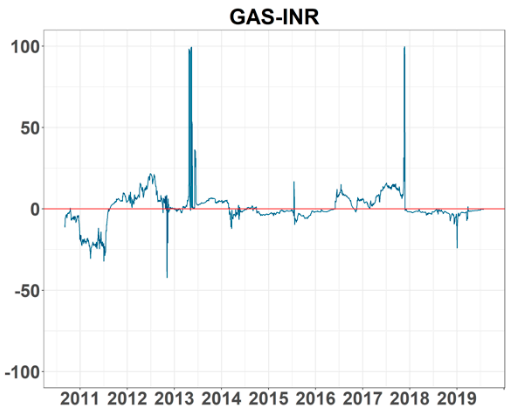


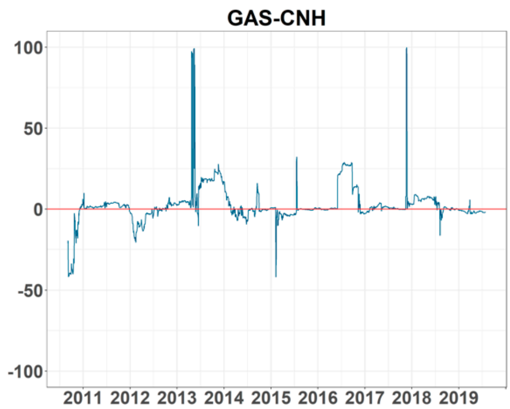
Figure A4. Net pairwise connectedness of return series: (**a**–**e**) refer to the net pairwise connectedness between GASS and BRL, RUB, INR, CNH, and ZAR return series, respectively. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.



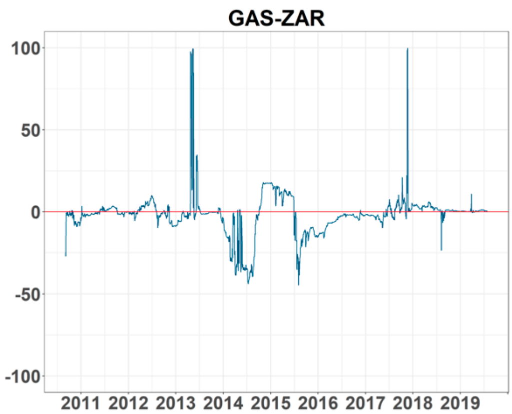


(**a**) (**b**)





(**c**) (**d**)



(**e**)

Figure A5. Net pairwise connectedness of volatility. (**a**–**e**) refer to the net pairwise connectedness between the volatility of GASS and BRL, RUB, INR, CNH, and ZAR, respectively. Note: BRL, RUB, INR, CNH, and ZAR are Brazilian Real, Russian Ruble, Indian Rupee, offshore Chinese Yuan, and South African Rand, respectively. GASF is the Henry Hub natural gas futures price.

References

1. BP p.l.c. BP Statistical Review of World Energy 2019. Available online: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2019-full-report.pdf (accessed on 1 July 2019).
2. Mckinsey & Company. Global Energy Perspective 2019: Reference Case. Available online: https://www.mckinsey.com/~{}/media/McKinsey/Industries/Oil%20and%20Gas/Our%20Insights/

Global%20Energy%20Perspective%202019/McKinsey-Energy-Insights-Global-Energy-Perspective-2019_Reference-Case-Summary.ashx (accessed on 22 September 2019).
3. International Energy Agency. World Energy Outlook 2018. 2018. Available online: https://www.iea.org/weo/ (accessed on 22 September 2019).
4. Diebold, F.X.; Yilmaz, K. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Market. *Econ. J.* **2009**, *119*, 158–171. [CrossRef]
5. Diebold, F.X.; Yilmaz, K. Better to give than to receive: Predictive directional measurement of volatility spillovers. *Int. J Forecast.* **2012**, *28*, 57–66. [CrossRef]
6. Diebold, F.X.; Yilmaz, K. *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*; Oxford University Press: Oxford, UK, 2015.
7. Baruník, J.; Křehlík, T. Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *J. Financ. Econ.* **2018**, *16*, 271–296. [CrossRef]
8. Chen, S.-S.; Chen, H.-C. Oil prices and real exchange rates. *Energy Econ.* **2007**, *29*, 390–404. [CrossRef]
9. Andrieș, A.M.; Ihnatov, I.; Tiwari, A.K. Analyzing time–frequency relationship between interest rate, stock price and exchange rate through continuous wavelet. *Econ. Model.* **2014**, *41*, 227–238. [CrossRef]
10. Brahm, T.; Huang, J.-C.; Sissoko, Y. Crude oil prices and exchange rates: Causality, variance decomposition and impulse response. *Energy Econ.* **2014**, *44*, 407–412.
11. Jain, A.; Pratap, B. Dynamic linkages among oil price, gold price, exchange rate, and stock market in India. *Resour. Policy* **2016**, *49*, 179–185. [CrossRef]
12. Maghyereh, A.I.; Awartani, B.; Bouri, E. The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. *Energy Econ.* **2016**, *57*, 78–93. [CrossRef]
13. Lundgren, A.I.; Milicevic, A.; Uddin, G.S.; Kang, S.H. Connectedness network and dependence structure mechanism in green investments. *Energy Econ.* **2018**, *72*, 145–153. [CrossRef]
14. Singh, V.K.; Nishant, S.; Kumar, P. Dynamic and directional network connectedness of crude oil and currencies: Evidence from implied volatility. *Energy Econ.* **2018**, *76*, 48–63. [CrossRef]
15. Ji, Q.; Geng, J.B.; Tiwari, A.K. Information spillovers and connectedness networks in the oil and gas markets. *Energy Econ.* **2018**, *75*, 71–84. [CrossRef]
16. Lovch, Y.; Perez-Laborda, A. Dynamic frequency connectedness between oil and natural gas volatilities. *Econ. Model.* **2019**. [CrossRef]
17. Sims, C.A. Macroeconomics and Reality. *Econometrica* **1980**, *48*, 1–48. [CrossRef]
18. Koop, G.; Pesaran, M.H.; Potter, S.M. Impulse response analysis in nonlinear multivariate models. *J. Econ.* **1996**, *74*, 119–147. [CrossRef]
19. Pesaran, H.H.; Shin, Y. Generalized impulse response analysis in linear multivariate models. *Econ. Lett.* **1998**, *58*, 17–29. [CrossRef]
20. Lütkepohl, H. *New Introduction to Multiple Time Series Analysis*; Springer: Berlin/Heidelberg, Germany, 2005.
21. Geweke, J. Measurement of Linear Dependence and Feedback between Multiple Time Series. *J. Am. Stat. Assoc.* **1982**, *77*, 304–313. [CrossRef]
22. Geweke, J. Measures of Conditional Linear Dependence and Feedback between Time Series. *J. Am. Stat. Assoc.* **1984**, *79*, 907–915. [CrossRef]
23. Geweke, J. The Superneutrality of Money in the United States: An Interpretation of the Evidence. *Econometrica* **1986**, *54*, 1–21. [CrossRef]
24. Stiassny, A. A spectral decomposition for structural VAR models. *Empir. Econ.* **1996**, *21*, 535–555. [CrossRef]
25. Diebold, F.X.; Yilmaz, K. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *J. Econ.* **2011**, *182*, 119–134. [CrossRef]
26. Perron, P. The great crash, the oil price shock, and the unit root hypothesis. *Econometrica* **1989**, *57*, 1361–1401. [CrossRef]

27. Papell, D.H.; Lumsdaine, R.L. Multiple trend breaks and the unit-root hypothesis. *Rev. Econ. Stat.* **1997**, *79*, 212–218.
28. Andrews, D.W.K.; Zivot, E. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *J. Bus. Econ. Stat.* **2002**, *20*, 25–44.