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Currency shocks spillovers and interconnectedness– evidence from emerging economies

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Abstract

This study examines how international monetary policy shocks from developed economies impact emerging market currencies, focusing on interconnectedness and spillovers. Using a time-varying parameter vector autoregressive (TVP-VAR) model, the study analyzes daily exchange rate data for USD currency pairs from six emerging markets (India, Brazil, Russia, South Africa, Thailand, and Indonesia) from January 1, 2001, to May 31, 2023. Results show that the South African Rand (ZAR) is the largest transmitter of return shocks (13.25%), while the Russian Ruble (RUB) is the largest transmitter of volatility shocks (6.48%). The Indian Rupee (INR), Indonesian Rupiah (IDR), and Thai Baht (THB) are significant receivers of shocks. Increased interconnectedness is observed during economic crises, such as the Global Financial Crisis and the COVID-19 pandemic. Emerging market currencies are highly interconnected and sensitive to global financial shocks, emphasizing the need for proactive monetary policies to mitigate international spillovers and maintain financial stability. Central banks in emerging economies should continuously monitor global financial dynamics and adopt macroprudential measures to enhance policy credibility and institutional strength, thereby mitigating the adverse effects of external shocks on domestic economies.

Keywords: Emerging economies, Exchange rates, Interconnectedness, Spillover, TVP-VAR.

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1. Introduction

Foreign exchange markets are the largest in the world, with an estimated daily turnover of $7.5 trillion as of 2022 [1]. The growth in foreign exchange markets is attributable to a host of factors that include a surge in trade and commerce in the recent past and geopolitical conditions necessitating market participants to hedge [2]. Apart from the obvious reactions and activities of market participants trading in currency markets, the attractiveness of emerging markets has propelled trade

[3].

The tremendous growth in trade value in forex markets has attracted the attention of various researchers and analysts. Various authors have argued that the returns in forex markets in emerging markets are highly attractive to portfolio investors [4, 5]. Although advanced economies dominate the foreign exchange market, the importance of currencies from emerging market economies (EMEs) is growing. TheFX turnover of EME currencies increased to 23% in April 2019 from 19% in 2016 and 15% in 2013 [6].

Economic interdependence among nations has grown tremendously as the world progresses towards globalization, and cross-border mobility of goods, capital, labor, and technology has increased. As a result, several challenges have arisen, including increased capital movement and exchange rate fluctuations in international market settings [7]. Consequently, some emerging market currencies have risen to prominence on a global scale. Despite divergent exchange rate policies that *inter alia* include a variety of managed floats, the central banks in emerging economies are struggling to provide a well-structured risk framework to market participants on a sustained basis.

The global factors such as wars, famines, pandemics, and the failure of major financial institutions, the linkage of exchange rates has significant implications for investors andregulators [8]. The large volume and volatility of capital flows maycause economic distortions and pose monetary authorities with exchange rate policy challenges [9].

Stability of their exchange rate is a burgeoning issue, emerging market regulators are bound tobe more interested in the connectedness of their home currency with regional currencies [10]. In contrast to mature markets, emerging economies have less diverse markets, less developed financial institutions, and a strong outward orientation. As a result, it is necessary to investigate the spillovers across currency markets in EMEs and advanced economies in order to identify information transmission channels for effective monetary policyformulation and investment strategy design.

The presence of asymmetric spillovers in returns has important implications for investors and policymakers since asymmetric spillovers may become a source of contagion [11]. When studying exchange rate connectedness, as with other financial markets, it is critical to account for potential asymmetry due to positive and negative spillovers in returns, weakening or strengthening of currencies against the US Dollar, Baruník et al. [12]. Baruník and Kočenda [13] have suggested that it is critical to investigate the time-varying nature of spillovers and identify time episodes when spillovers are attributed to positive and negative returns, as differences in return spillover may have markedly different effects across time horizons [13]. Furthermore, due to expanding (shrinking) demand and market participants' divergent investment horizons, the exchange rate in a specific country may not be related to the other exchange rate(s) over time [14].

The spillover effects leading to unprecedented changes in exchange rates carry a large impact on traders, investors, and macroeconomic indicators, particularly inflation rates [15]. Exchange rates and central bank policies are greatly influenced by spillover effects and vice versa [16]. The spillovers may affect the adoption of exchange rate management practices by central banks, leading to stylized regimes that subsequently affect the inflation and interest rates noted in various research studies [17, 18]. When major economies like the US or China adopt significant changes in monetary or fiscal policies, large portfolio shifts may occur, and policy uncertainty implies large spillovers [19].

We argue that in a given set of foreign exchange market, the players deploy a variety of measures to hedge and generate returns in their portfolios with varying investment horizons and trading frequencies [20]. Their actions result in turbulence in foreign exchange markets in addition to the conventional macroeconomic disturbances [21].

Using the time-varying parameter vector autoregressive (TVP-VAR) technique, we analyze the transmission of international monetary policy spillovers among emerging economies to investigate the interconnectivity of selected currencies. Understanding the spillover effects is crucial, given their rising vulnerability to global financial dynamics. Changes in US monetary policy have been demonstrated to create significant volatility in developing market currencies, threatening economic stability and growth. However, present research frequently overlooks the intricate connections between foreign monetary circumstances and domestic economic performance, leaving a void in understanding how these shocks affect local credit conditions and financial institutions. Addressing this gap would allow policymakers to devise more effective methods for mitigating negative impacts and improving financial resilience in these vulnerable economies. This understanding is critical for enhancing economic stability [22].

2. Materials and Methods

The study of the interconnectedness of foreign exchange markets can be ascertained through an examination of spillover effects computed using a variety of econometric and neural network measures used by authors in studies like Ahn et al. [23]; Wang et al. [24]; Andrieş et al. [25] and Lu et al. [26]. One widely used measure is [27] and Diebold and Yilmaz [28]. Their approach has been extended to compute joint conditional forecasts to decompose variance to study aggregate spillovers [29]. The use of a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to analyze exchange rate variables is justified by its ability to capture dynamic relationships and structural changes over time. This method allows for the estimation of time-varying coefficients, which account for changes in economic conditions that influence exchange rates. Linearity, variable stationarity, and the uncorrelated nature of system shocks over time are among the most important assumptions. Furthermore, the model assumes that previous variables' values influence future values, which is consistent with economic theories of exchange rate determination and macroeconomic interactions.

We use thetotal connectedness index (TCI) proposed by Diebold and Yilmaz [30] for evaluating the level of connectedness. Diebold and Yilmaz [27] methodology for examining and quantifying the interdependencies and connectedness of the financial markets has been referredto as the "Diebold-Yilmaz Spillover Index," aids in determining how shocks or changes in onefinancial market can impact and spread to other markets and is especially useful forcomprehending systemic risk and the dynamics of financial contagion Diebold and Yilmaz [27]. [31] used a Kalman filter estimation with forgetting factors, as per Koop and Korobilis [32], to allow the variance-covariance matrix to vary. Kalman filtersassume a relatively simple form and require small computational power [33]. The total connectedness index (TCI) is defined as

$Ct(H) = \Sigma mi,j=1,i\tilde{=}j\Phi ij,t(H)\ \Sigma mi,j=\tilde{1}\Phi ij,t(H) * 100 = \Sigma mi,j=1,i\tilde{=}j\Phi ij,t(H)\ m * 100.$

The total directional connectedness to others, that is, i propagating its shock to all othervariables j is defined as $Ci\rightarrow j,t(H) = \Sigma nj=1,i\tilde{=}j\Phi ji,t(H)\ \Sigma nj=\tilde{1}\Phi ji,t(H) * 100.$

The total directional connectedness from others, that is, *i* receives from all other variables *j* isgiven as $Ci\leftarrow j,t(H) = \Sigma nj=1,\tilde{=}j\Phi ij,t(H)\ \Sigma ni=\tilde{1}\Phi ij,t(H) * 100.$ Net total directional connectedness

$Ci,t(H) = Ci\rightarrow j,t(H)\ \#\ Ci\leftarrow j,t(H).$

The total time-varying connectedness index (TCI) of the returns and volatility considers the time-varying connectedness dynamics.

2.1. The frequency-dependent TVP-VAR network connectedness

Time-varying variance decomposition matrices have been spectrally decomposed to create a dynamic network form proposed by Ellington and Baruník [34]. The network form shows theeffects of temporary (short-term) and long-term (permanent) shocks from variable *j* on the

expected variance of variable *i*. All information describing the network is contained in themodel's dynamic adjacency matrix.

2.2. Local network connectedness is defined as

$C(\gamma, d) = 100 \times \Sigma N\ j,k=1\ j{\not=}k\ [\tilde{\theta}(\gamma, d)]j,k/\ \Sigma N\ j,k=1\ [\tilde{\theta}(\gamma)]j,k.$

Local directional connectedness (FROM connectedness), which measures how much of eachindicator's *j* variance is due to shocks in other indicators $k \not= j$, is defined as

$Cj\leftarrow\cdot(\gamma, d) = 100 \times \Sigma N\ k=1\ k{\not=}j\ [\tilde{\theta}(\gamma, d)]j,k/\Sigma N\ j,k=1\ [\tilde{\theta}(\gamma)]j,k.$

Likewise, the contribution of *j* to variances in other indicators is calculated as

$Cj\rightarrow\cdot(\gamma, d) = 100 \times \Sigma N\ k=1\ k{\not=}j\ [\tilde{\theta}(\gamma, d)]k,j/\Sigma N\ k,j=1\ [\tilde{\theta}(\gamma)]k,j.$

"TO" and "FROM" used in our analysis, according to Diebold and Yilmaz [27], represent theaggregate impact of shock for a given variable and aggregate influence, respectively.

We use the currency pairs of India, Brazil, Russia, South Africa, Thailand, and Indonesia against the US dollar. The countries have been selected based on quantum of currency flows beingsignificant trade partners. China has been excluded from analysis since their currency monitoring via central bank intervention is altogether different from the sample set seen also in some studies like Chin [35] and Das and Song [36].

The daily data on exchange rates for the period 01 January 2001 to 31 May 2023 obtained fromBloomberg has been used for the analysis. We have used exponential smoothing for missingdata analysis, similar to Maniatis [37] and Wawale et al. [38]. We derive the daily logarithmic returns for the selected currency pairs for all computations.

3. Results

Table 1 and Table 2, respectively, show the return and volatility connectedness.

Table 1.
Returns Connectedness.

Currencies	BRL	IDR	INR	RUB	THB	ZAR	FROM
BRL	68.15	3.11	4.28	6.37	3.48	14.61	31.85
IDR	6.46	65.89	7.44	5.08	7.65	7.48	34.11
INR	6	7.22	66.37	6.25	6.59	7.58	33.63
RUB	7.06	3.25	5.44	69.76	3.99	10.5	30.24
THB	4.79	7.94	6.84	4.97	68.11	7.36	31.89
ZAR	13.67	3.25	4.15	9.14	4.07	65.72	34.28
TO	37.98	24.77	28.15	31.8	25.77	47.54	196.01
Incl. Own	106.13	90.66	94.52	101.56	93.88	113.25	cTCI/TCI
NET	6.13	-9.34	-5.48	1.56	-6.12	13.25	39.20/32.67

Table 2.
Volatility Connectedness

Currencies	BRL	IDR		INR	RUB	THB	ZAR	FROM
BRL	75.32	4.85		4.15	5.24	3.66	6.78	24.68
IDR	4.72	79.94		4.2	3.52	4.47	3.15	20.06
INR	3.81	5.38		76.48	6.69	3.67	3.97	23.52
RUB	4.5	2.8		3.99	82.74	1.97	3.99	17.26
THB	2.86	6.13		4.11	3.69	78.52	4.69	21.48
ZAR	6.94	2.85		2.59	4.58	2.8	80.23	19.77
TO	22.83	22.01		19.03	23.73	16.57	22.57	126.75
Incl. Own	98.15	101.96		95.52	106.48	95.1	102.8	cTCI/TCI
NET	-1.85	1.96		-4.48	6.48	-4.9	2.8	25.35/21.13

Figure 1(a) and Figure 1 (b) represent the total directional connectedness for a given currency pair from “others” for parameters of returns and volatility, respectively for the applied TVP-VAR model.

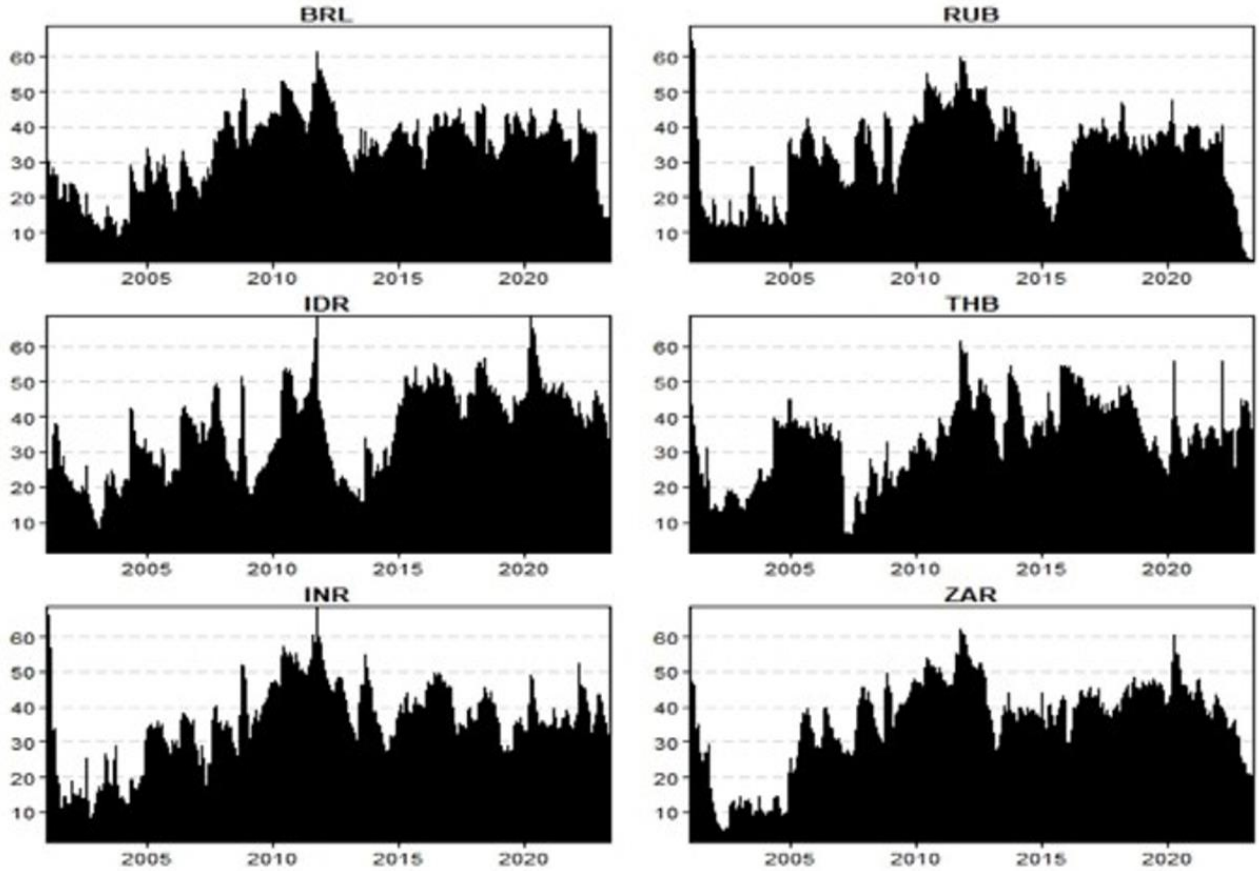

Figure 1(a).
Total Directional Connectedness from Others (Returns).

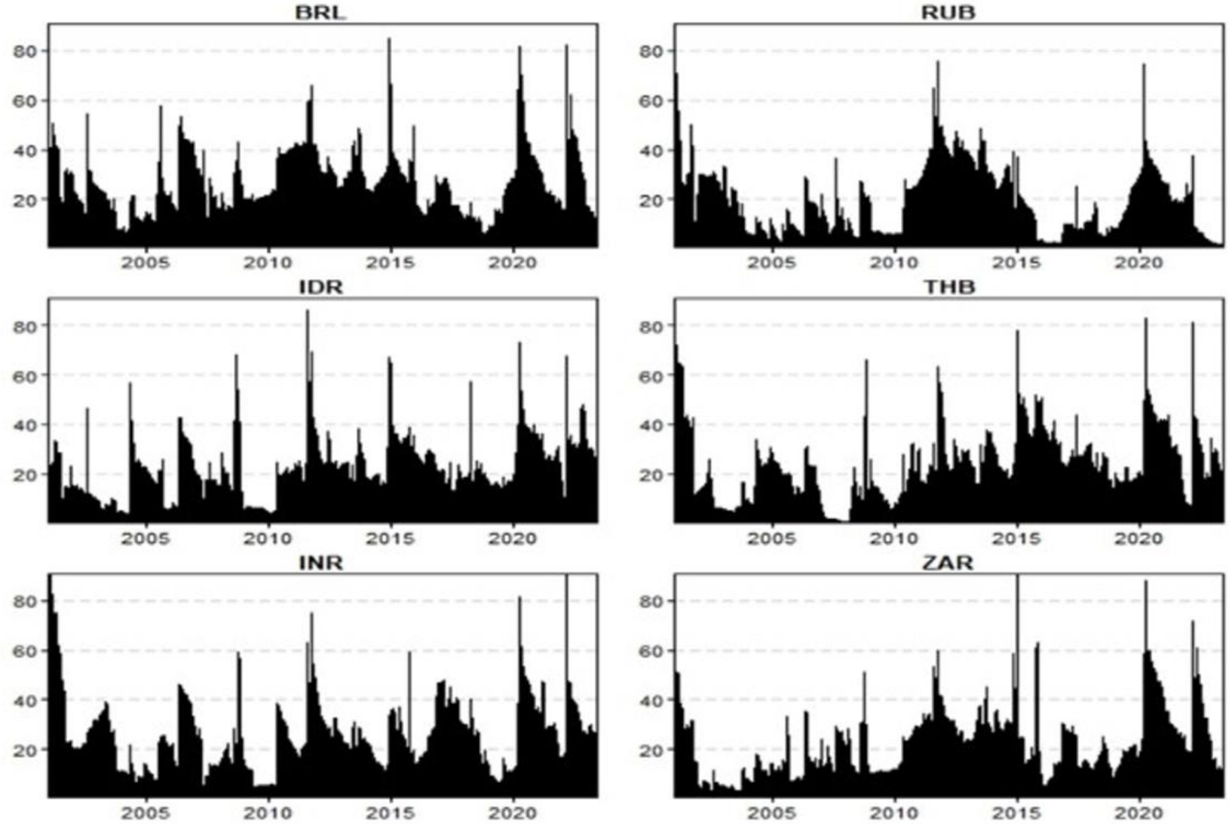

Figure 1(b).
Total Directional Connectedness from Others (Volatility).

The South African Rand (ZAR) receives the highest proportion of shocks in the return series, with a value of 34.28%, followed by the Indonesian Rupiah (IDR) at 34.11% and the Indian Rupee (INR) at 33.63%. This suggests that these currencies are extremely vulnerable to external monetary policy shocks and other economic disruptions.

The Brazilian Real (BRL) is the most vulnerable to shocks in the volatility series, with a value of 24.68%, followed by the Indian Rupee (INR) at 23.52% within the sample set of emerging economies. This finding highlights the significant impact of external shocks on the volatility of these currencies.

Figure 2(a) and Figure 2(b) represent the total directional connectedness for a given currency pair to “others” for parameters of returns and volatility, respectively for the applied TVP-VARmodel.

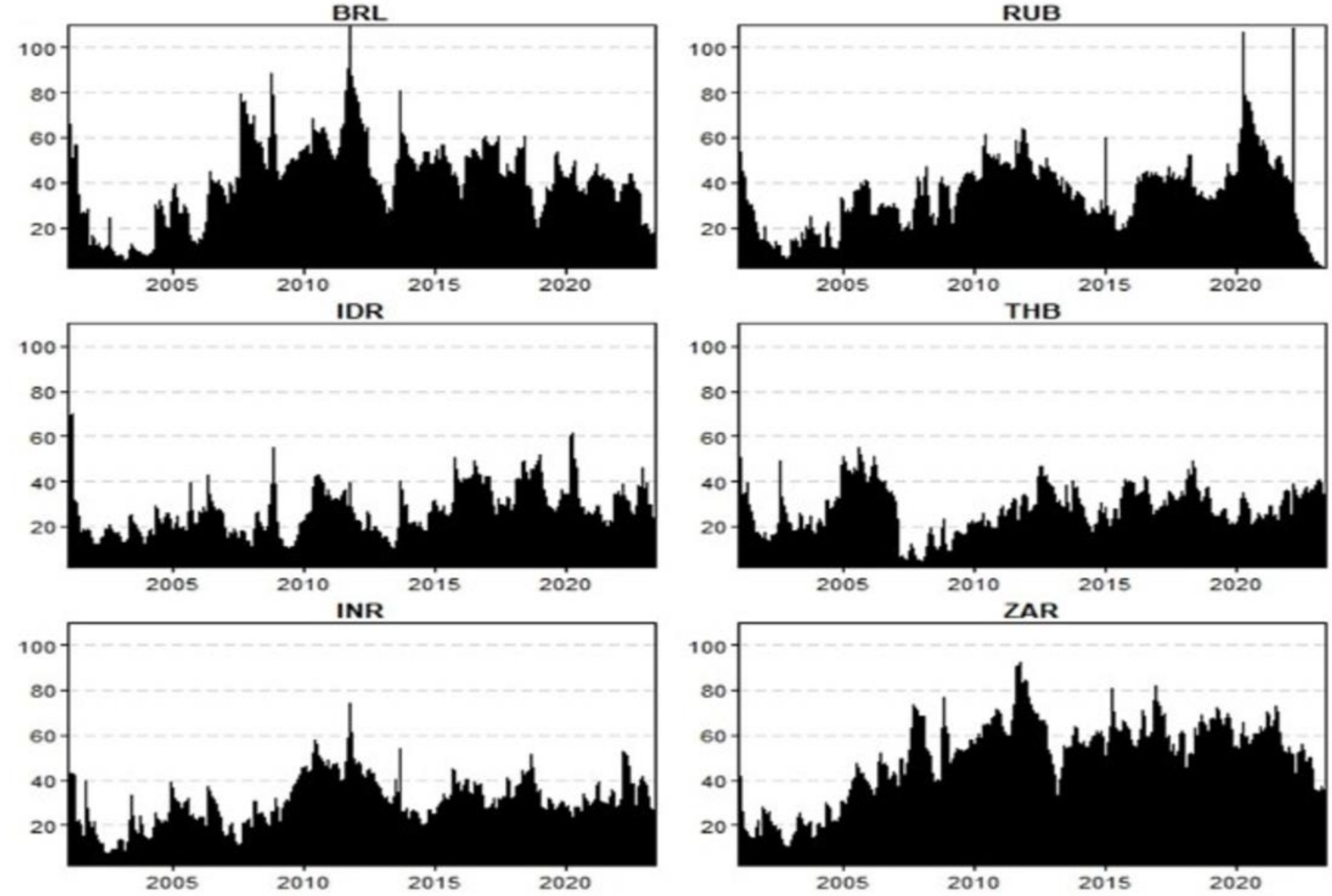

Figure 2(a).
Total Directional Connectedness to Others (Returns).

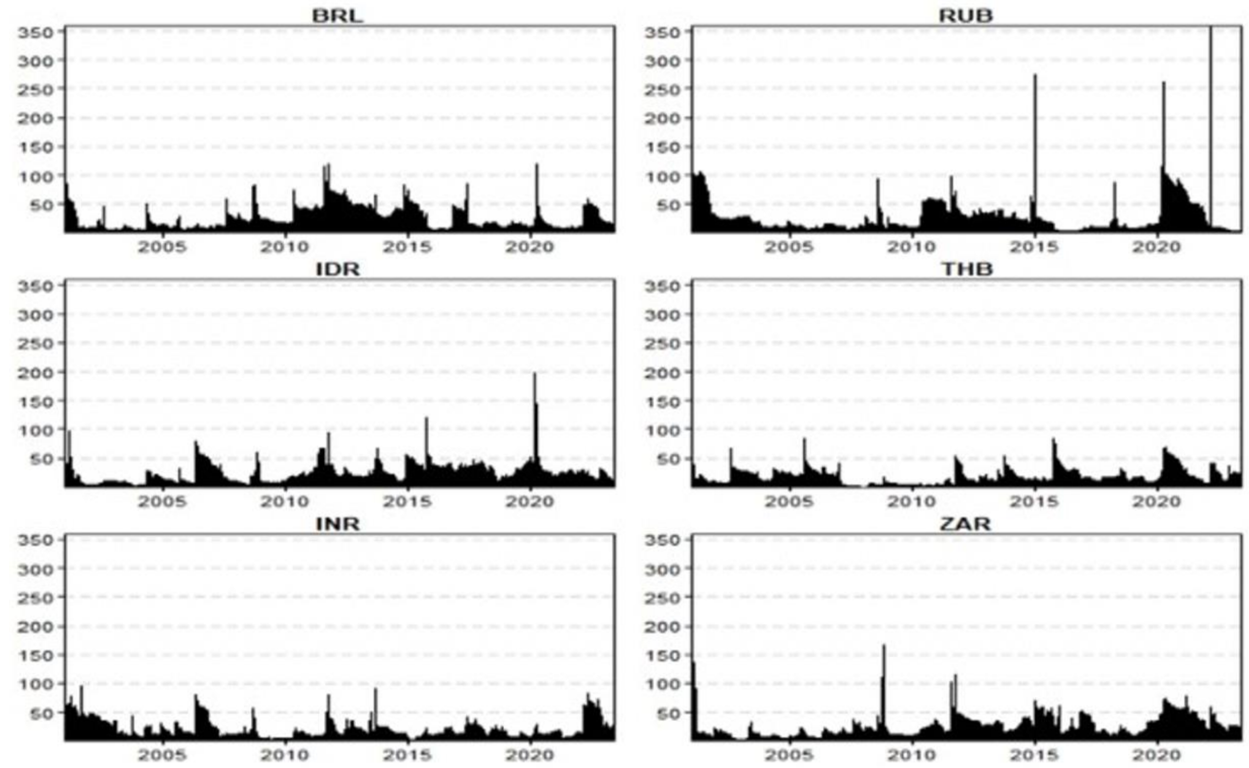

Figure 2(b).
Total Directional Connectedness to Others (Volatility).

According to the directional connectedness research, the South African Rand (ZAR) is the most significant transmitter of return shocks among the currencies evaluated, with a connectedness score of 14.61%. This suggests ZAR has a strong ability to impact other currencies, particularly in terms of returns. The Indian Rupee (INR) demonstrates relatively low transmission, with a value of only 7.58%, confirming its position as a net receiver of shocks, as supported by Sakthivel et al. [39].

The Total Directional Connectedness to Others (volatility) reveals RUB as the largest transmitter (23.73), followed by BRL (22.83), ZAR (22.57), IDR (22.01), INR (19.03), and THB (16.57). This highlights RUB's dominant role in volatility spillovers, with emerging markets exhibiting asymmetric transmission patterns, underscoring systemic risk vulnerabilities during financial stress.

Figure 3(a) and Figure 3(b) show the net time-varying connectedness for the sample currency pairs. A positive value indicates a net transmitter, whereas a negative value indicates a net receiver of spillover [40, 41].

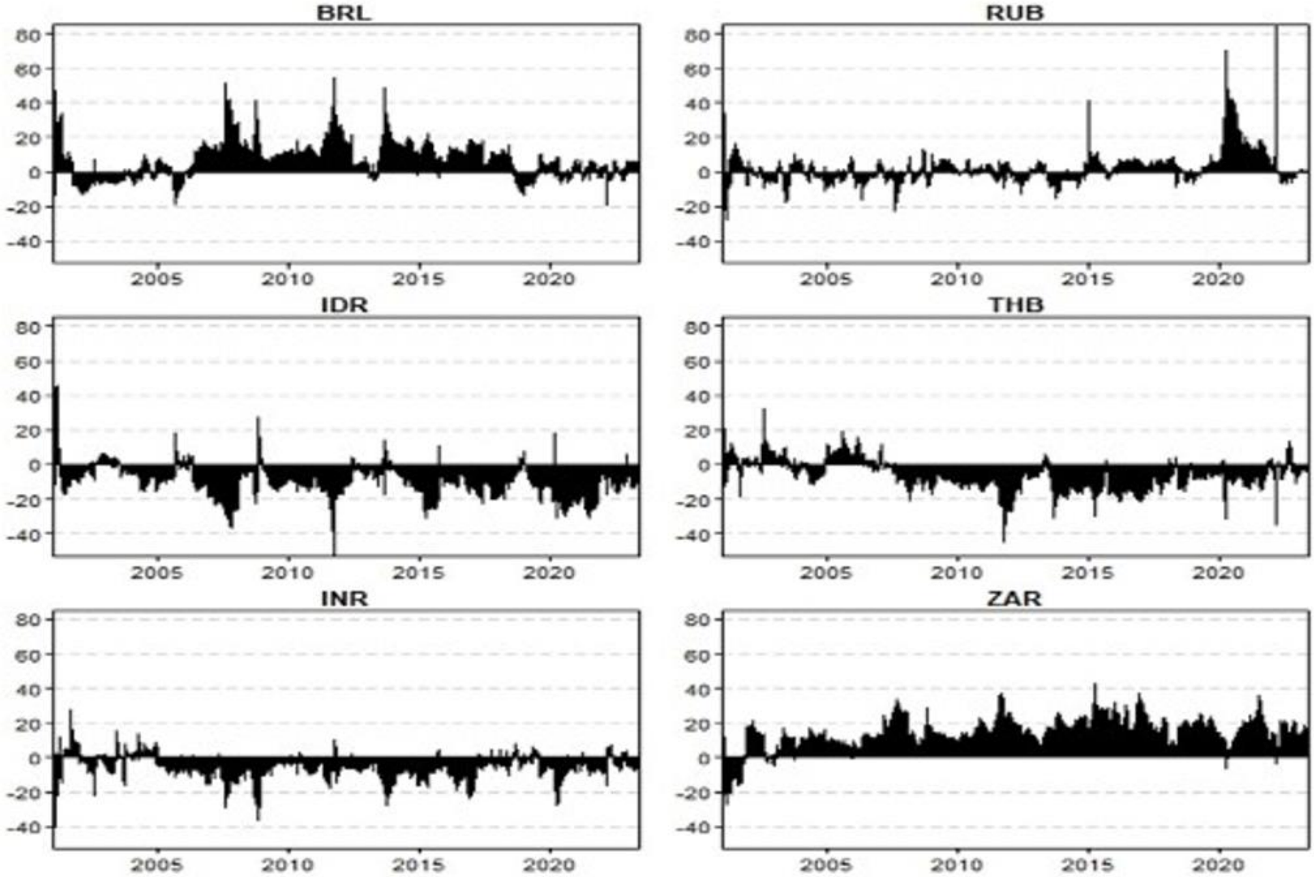

Figure 3(a).
Total Net time-varying connectedness (Returns).

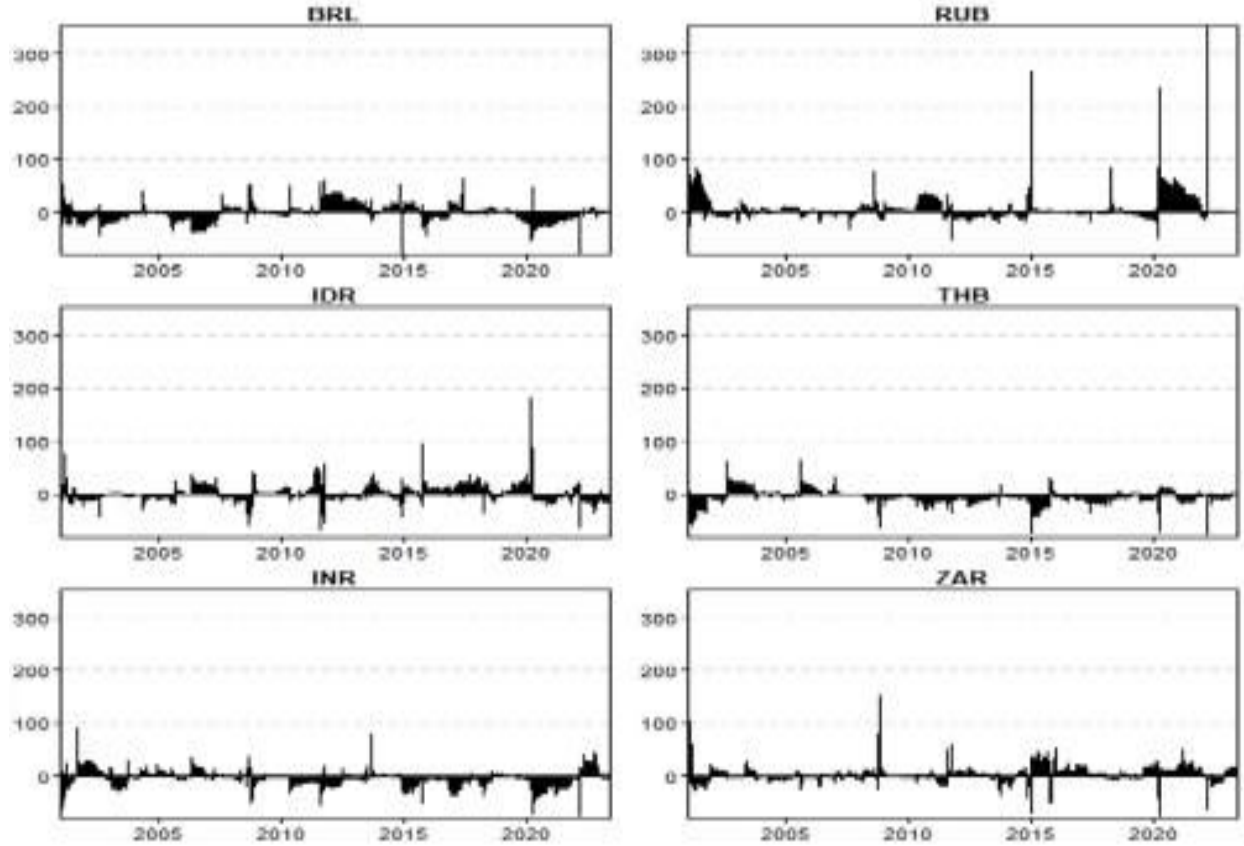

Figure 3(b).
Total Net time-varying connectedness (Volatility).

The analysis shows that BRL, ZAR, and RUB are net shock transmitters in returns, whereas IDR, INR, and THB are net receivers. BRL sends shocks with a net magnitude of 6.13%, ZAR with 13.25%, and RUB with 1.56%. In contrast, IDR experiences shocks with a net magnitude of -9.34%, INR with -5.48%, and THB with -6.12%. These findings highlight the directional flow and intensity of return shocks among these currencies, emphasising their interconnected nature. The magnitudes point to significant transmission effects from BRL, ZAR, and RUB to the other currencies in the system.

The analysis of total net time-varying connectedness in volatility reveals that IDR and RUB are the primary sources of volatility shocks. Specifically, IDR transmits with a net magnitude of 1.96%, whereas RUB transmits with a significant magnitude of 6.48%. In contrast, BRL, INR, and THB are identified as net recipients of volatility shocks. BRL receives shocks with a net magnitude of -1.85%, INR -4.48%, and THB -4.9%. ZAR also acts as a transmitter, albeit to a lesser extent (net magnitude of 2.8). These findings highlight the directional flow and intensity of volatility shocks across these currencies, emphasizing their interconnected volatility dynamics.

Figures 4(a) and 4(b) show the net pairwise directional connectedness of the returns and volatility for the TVP-VAR model.

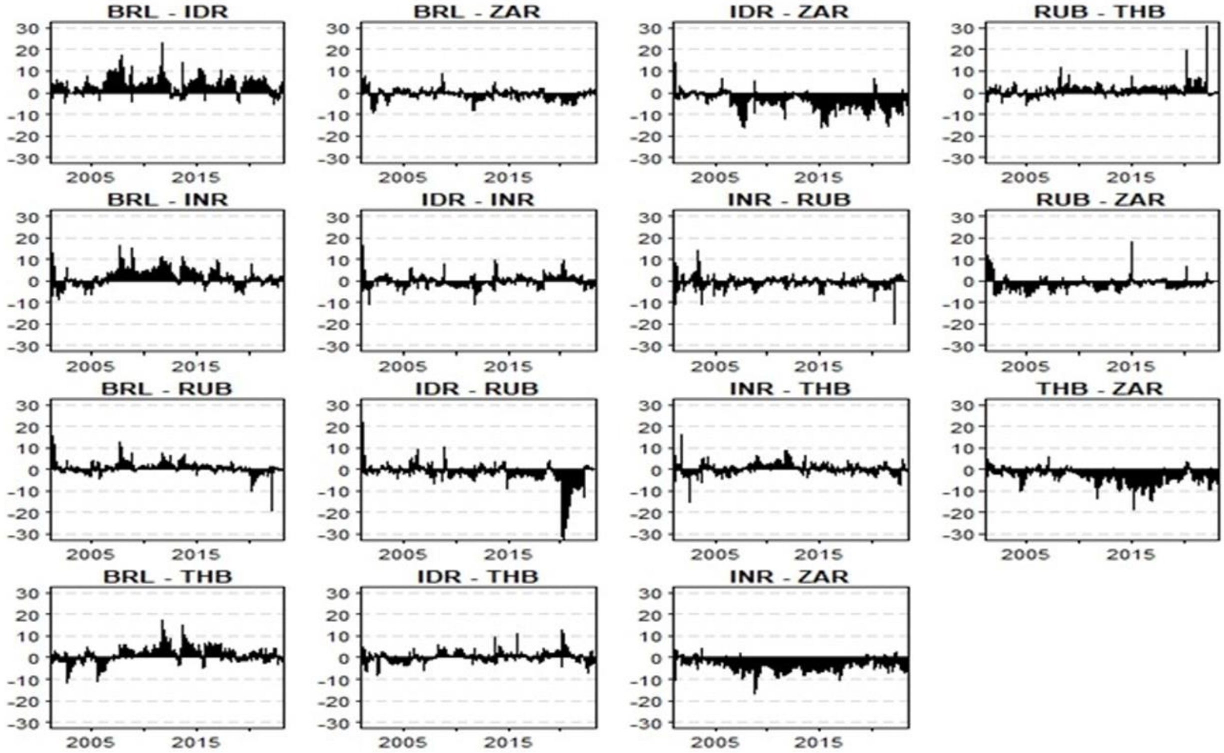

Figure 4(a).
Net pairwise directional connectedness (Returns).

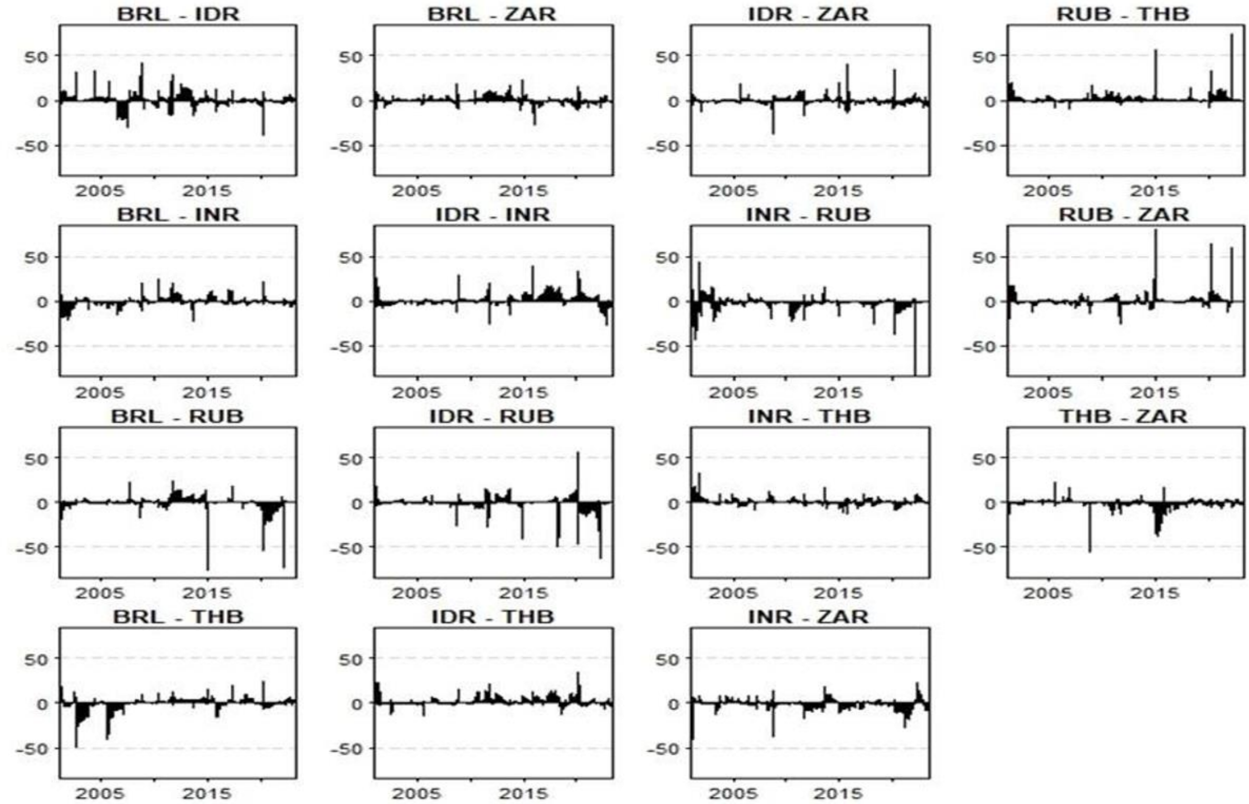

Figure 4(b).
Net pairwise directional connectedness (Volatility).

The net pairwise directional connectedness analysis in returns reveals that ZAR and BRL are the largest shock transmitters. ZAR transmits with a net magnitude of 13.25%, whereas BRL transmits with 6.13%. In contrast, INR has been identified as a significant recipient of spillover effects, particularly in its pairwise connections with ZAR, BRL, and RUB. INR experiences shocks with a net magnitude of -5.48%, indicating that these currencies are more affected than others. This dynamic emphasizes the directional flow and intensity of return shocks, highlighting ZAR and BRL's dominant transmission roles and INR's receptive nature.

When net pairwise directional connectedness in volatility is analyzed, IDR, RUB, and ZAR emerge as the leading transmitters. IDR transmits 1.96%, RUB 6.48%, and ZAR 2.8%. In contrast, INR is identified as the primary recipient of spillover connectedness, particularly in pairwise connections with IDR, RUB, ZAR, and BRL. The INR experiences volatility shocks with a net magnitude of -4.48%, indicating that it is significantly impacted by these currencies. This dynamic emphasizes the directional flow and intensity of volatility shocks, highlighting IDR, RUB, and ZAR's transmission roles, as well as INR's receptive nature.

Finally, Figures 5(a) and 5(b) depict the TCI for the sample currency pairs for returns and volatility.

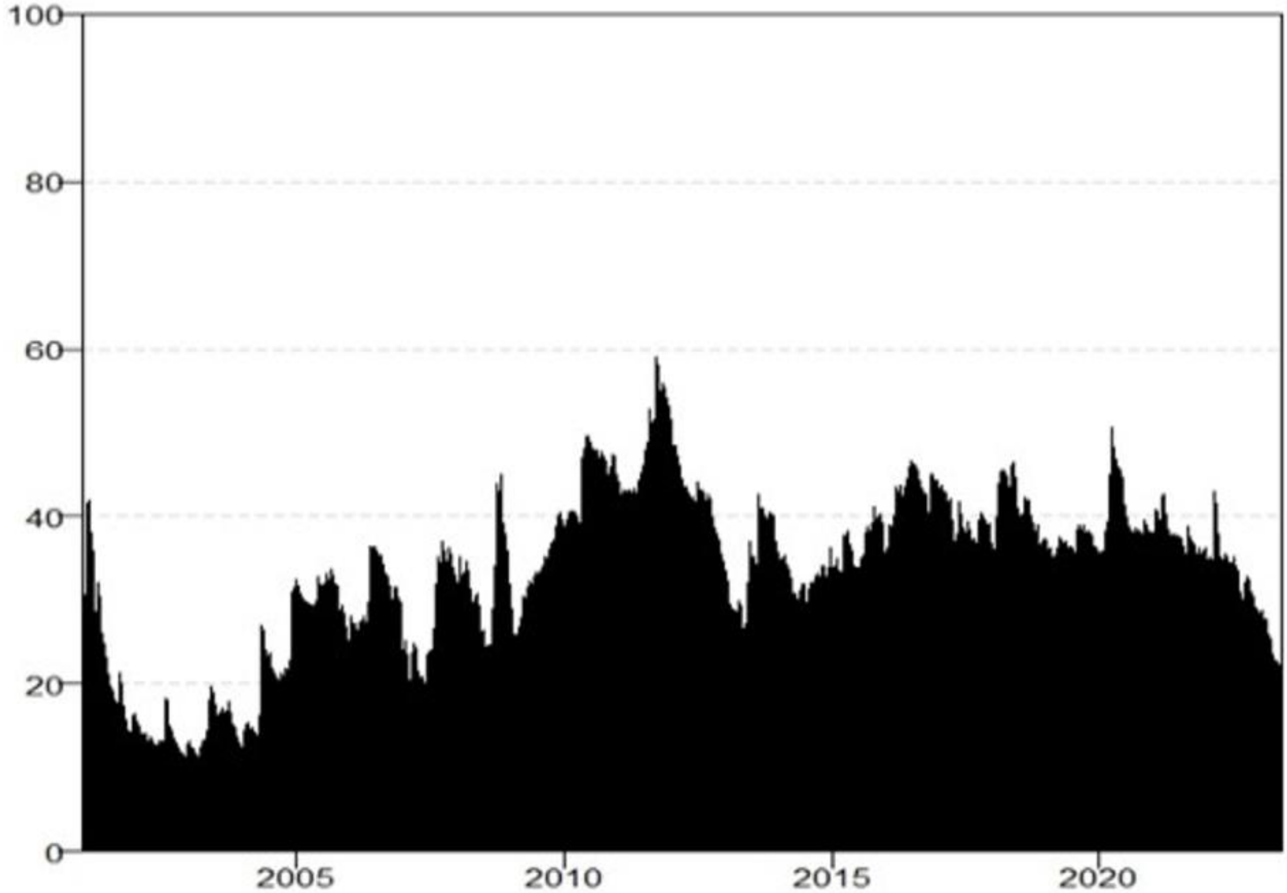

Figure 5(a).
TCI (Returns).

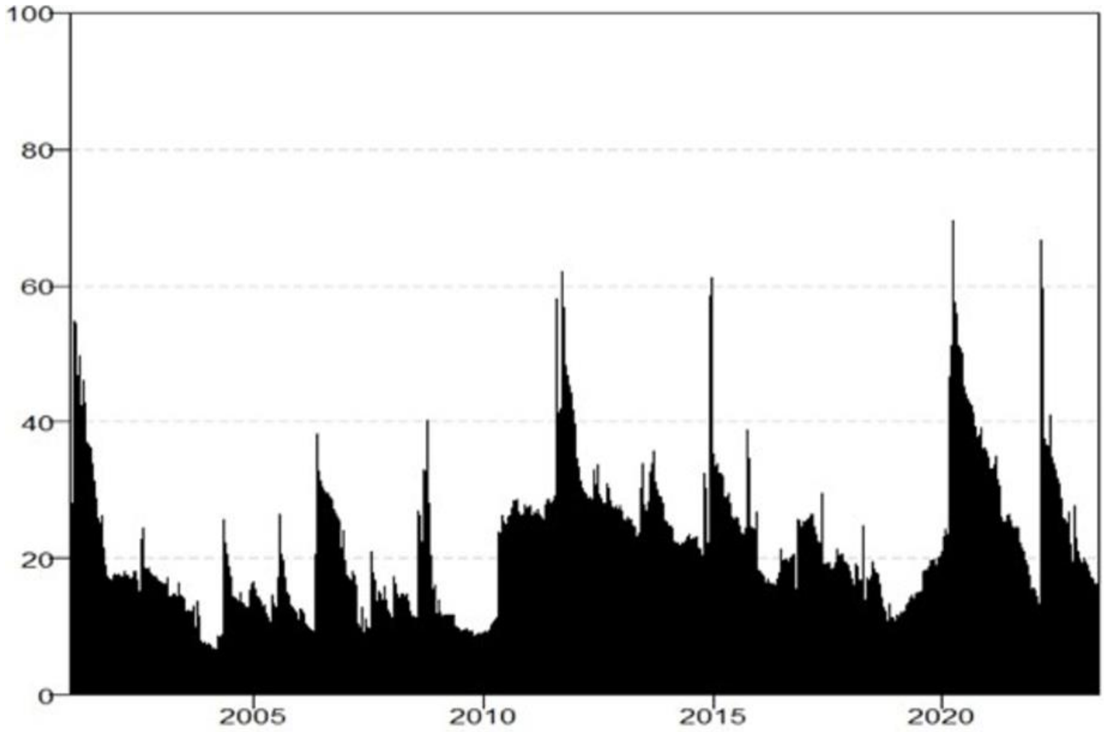

Figure 5(b).
TCI (Volatility).

Figure 5(a) illustrates the TCI for returns, showing moderate fluctuations with peaks around 60. Figure 5(b) shows the TCI for volatility, which exhibits more pronounced spikes, reaching up to 100. These peaks suggest periods of heightened interconnectedness and potential market stress. The volatility TCI generally shows greater fluctuations than the returns TCI, indicating that currency pairs are more interconnected in terms of volatility. This analysis highlights the dynamic nature of financial markets and the varying degrees of influence currency pairs have on each other.

The system-wide connectedness in the return series is reported to be 39.20%, indicating a high level of currency interdependence. ZAR is the leading transmitter with a net magnitude of 13.25%. This significant transmission effect highlights ZAR's important role in the system. Furthermore, BRL and RUB serve as transmitters, albeit to a lesser extent, with net magnitudes of 6.13% and 1.56%, respectively. In contrast, IDR, INR, and THB are identified as net shock receivers, with magnitudes of -9.34%, -5.48%, and -6.12%. These findings emphasize ZAR's dominant transmission role and the receptive nature of IDR, INR, and THB in the return series.

The volatility series has a system-wide connectedness of 25.35%, indicating a high level of currency interdependence. RUB emerges as the largest transmitter, accounting for 6.48% of the net magnitude. This significant transmission effect emphasizes RUB's important role in volatility spillovers. Furthermore, IDR and ZAR serve as transmitters, albeit to a lesser extent, with net magnitudes of 1.96% and 2.8%, respectively. In contrast, BRL, INR, and THB have been identified as net receivers of volatility shocks, with magnitudes of -1.85%, -4.48%, and -4.9%, respectively. These findings emphasize RUB's dominant transmission role and the receptive nature of BRL, INR, and THB in the volatility series.

4. Conclusion

The spillover effects in currency markets due to various monetary policy shocks and extreme events from developed markets to emerging economies are a matter of concern for central banks. Our study investigates the transmission of international monetary policy spillovers among emerging economies using a time-varying parameter vector autoregressive (TVP-VAR) technique to examine currency connectedness for USD currency pairs of Brazil, Russia, India, South Africa, Thailand, and Indonesia. Summarization of results indicates that ZAR is the largest receiver of shocks in the return series, followed by IDR and INR. In the volatility series of 'from' analysis, BRL is the highest receiver of shocks in the sample set of emerging economies, followed by INR. ZAR is the largest transmitter of shocks on returns, while INR transmission is relatively low in comparison to other pairs. RUB is the largest transmitter of volatility, while INR transmission is minimal.

In terms of pairwise connectedness, the INR has a greater impact on the sampling of emerging currencies and a lesser impact on other currencies in the return series. Furthermore, the INR is the major currency that receives spillover connectedness in pairwise analysis with the IDR, RUB, ZAR, and BRL. In the return series of system-wide connectedness, ZAR is the leading transmitter, while RUB is the largest transmitter in total connectedness in the volatility series. Analysis of the time-varying dynamics of financial markets in recent times shows that connectedness is sparked during times of economic stress [42, 43]. The results shown in the above figures indicate several spikes primarily due to economic or policy shocks, and troughs show the normalized circumstances of connectedness in money markets. The initial spike in the graph from 2008 to 2010 represents the GFC's aftershocks, and it is well established that markets are highly interconnected at this time [44].

The increase between 2010 and 2012 links to the time when the European economy suffered a downturn as a result of balance sheet errors, which ultimately led to the high degree of interconnectedness of the world's financial markets and the anti-inflation measures by the central banks limited the flow of resources abroad [45]. It is implied thata greater degree of interconnectedness among the world's financial markets reveals different investor perspectives on sudden changes in business conditions [46, 47].

Overall, time-varying dynamics show that market volatility is caused by stress periods and thatglobal financial markets are sensitive to economic uncertainty and crisis periods. Thus, system-wide connectedness increases under abnormal market conditions and decreases under the emergence of a new normal.

Our study infers an important implication for central banks. The implementation of independent monetary policies by central banks may be hampered by spillover effects [48]. In order to balance national and international interests, central banks frequently need to make difficult decisions. Continuous examination and monitoring of spillovers through a reliable index are absolutely essential for emerging economies so that the relative strength of currencies and the competitiveness of international trade can be ensured. Inflation targeting on a short-term and long-term basis requires delineation of the spillover and other factors.

The findings suggest that sudden changes in business conditions have a significant impact on investor perspectives, resulting in increased interconnectedness among global financial markets during crisis periods [46, 47]. This increased interconnectedness during stress periods highlights global financial markets' vulnerability to economic uncertainty and crises.

Future research should aim to broaden the scope to include a wider range of economies, as well as incorporate real-time data to better predict future market behaviors. Investigating the impact of non-economic factors on financial market connectedness, such as geopolitical tensions or technological innovations, could also yield useful information. Furthermore, developing more sophisticated models that account for the complex interactions between various financial instruments and markets may improve our understanding of global financial interconnectedness. Overall, this study emphasizes the importance of monitoring and analyzing financial market connectivity in order to anticipate and mitigate potential risks during times of economic stress.

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