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Investigation of emerging market stress under various frequency bands: Evidence from FX market uncertainty and liquidity

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A B S T R A C T

This study investigates the relationship between Emerging Markets Financial Stress Index (EMFSI) and currency returns, uncertainty and liquidity of eight emerging economies, using MODWT, Wavelet Coherence, TVP-VAR analyses. The results indicate that interactions become more pronounced during political events rather than economic developments. Energy market developments also appear to be significant periods for the interaction of variables, especially for Saudi Arabia and the UAE. Finally, the findings related to investment horizon suggest that short-term spillovers may be linked to medium- to long-term correlations between the EMFSI and currency pairs. This could serve as an early warning for policymakers and investors.

1. Introduction

The significant growth potential of emerging countries is key to the development of the global economy and to addressing future challenges. The natural resources they process and the responsibility for their sustainable development will require massive investment in these countries in the near future. As a representer of emerging economies, BRICS formation accounts for around 40% of the world's population, 33% of global GDP (by purchasing power parity) (Worldbank, n.d.). The importance of the BRICS countries is underlined by their diverse strengths, ranging from natural resources to advanced technological capabilities, and thus they play a key role in shaping international trade, investment and geopolitical dynamics. However, their relatively fragile economic structures and political risk factors make them vulnerable to specific risks, so it is crucial to understand the emergence and spread of financial stress in emerging financial markets. This study seeks to capture the dynamic relationship between the exchange rate components (returns, uncertainty, and liquidity) of eight emerging countries and the EMFSI. To account for the investment horizon, we employ methodologies that allow us to examine interactions across various frequency bands, including the maximal overlap discrete wavelet transform (MODWT), Wavelet Coherence analysis, and Time-Varying Parameter Vector Autoregression (TVP-VAR) frequency connectedness analysis.

Financial stress is defined by Hakkio and Keeton (2009) as an interruption to the normal functioning of financial system. It may apply to all or only some specific markets and may have different symptoms, such as a decline in asset prices, a decrease in liquidity and general uncertainty due to several factors. Stress measurement became a regulatory focus after the Global Financial Crisis (GFC) of

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2007–2009. The rapid spread and evolution of the crisis has spurred research on financial interconnectedness and contagion, as well as the development of stress indicators to help regulators monitor and intervene in financial markets and inform investors. In 2017, the Office of Financial Research (OFR) created a comprehensive stress indicator, the OFR Financial Stress Index (OFR FSI), to provide a daily market-based measure of stress in global financial markets (Monin, 2019). OFR FSI is constructed from 40 financial market variables, such as yield spreads, valuation measures, and interest rates. The FSI shows stress contributions by three regions: United States (USFSI), other advanced economies (OAFSI), and emerging markets (EMFSI). The OFR financial stress indicators are vital tools for monitoring the health of the financial system, serving as an early warning system for potential crises, guiding policy responses, and enhancing market confidence.

Studies in the literature (see, Rashid Sabri, 2004; Coudert et al., 2011; Walid et al., 2011; He et al., 2023) show that foreign exchange markets are a source of financial turbulence in many economic and financial crises. Thus, a meticulous examination of exchange markets is crucial for capturing financial stress stemming from contagion effects and spillovers. It is obvious that exchange rates no longer solely facilitate the trade of goods and services in global markets; their intricate interactions with domestic and international economic indicators allow them to reflect the impact of market developments and expectations across various maturities. Consequently, exchange rates function as barometers of market tension within domestic economies. This is particularly true in emerging markets, where market participants are more exposed to exchange rate depreciation through their foreign currency denominated debt (Pratap et al., 2003). The explosion of financial instruments associated with exchange rates has significantly increased market liquidity and attracted a diverse range of participants. Foreign exchange rate volatility, not just the level or returns of currency rates, plays a crucial role in understanding the risks and uncertainties of financial markets. It offers valuable insights into market expectations, economic stability, and investor sentiment. Volatility captures the market's outlook on future currency movements, particularly in relation to potential economic or political disruptions. It also reflects the confidence level in a currency or economy, with rising volatility often signaling declining confidence, which can trigger capital outflows and heighten financial stress. Another crucial indicator in the foreign exchange market is liquidity, which reflects transaction efficiency, market depth, investor sentiment, and the effectiveness of risk management strategies. High liquidity contributes to stability and resilience within the financial system, while low liquidity can exacerbate volatility and uncertainty, ultimately leading to increased financial stress.

In addition to the components outlined above, the investment horizon is a key element, as it impacts both market volatility and liquidity. For instance, short-term investors are more exposed to fluctuations, prompting them to focus on liquid, low-risk assets, while in the long term, asset prices exhibit more stable trends. This is highlighted by Cella et al. (2013) within the framework of investment horizon and diverse investor types. Investors with different time horizons respond to market information in distinct ways. Short-term investors often react quickly to news, economic reports, and price movements, which can increase volatility during periods of stress. Their rapid trading can amplify market fluctuations, creating a feedback loop of panic selling or buying. In contrast, long-term investors, who are less concerned with immediate price changes, tend to take a more measured approach, which can help stabilize the market during stressful times. These varying risk tolerances among investors shape the overall risk profile of the market, and the interaction between short-term and long-term investors significantly influences market volatility, liquidity, and overall stability. Ultimately, we can observe the interactions of variables relevant to speculative short-term investors and trend-chasing investors over various frequency bands, which may reveal different dynamics in both short-term and long-term perspectives (Koutmos and Payne, 2021).

Our research is related to the literature on financial market stress, but our approach is unique in several respects. The existing literature focuses on spillover effects of shocks from either developed markets to emerging markets (Balakrishnan et al., 2011; Park and Mercado Jr, 2014; Owusu Junior et al., 2020; Badshah et al., 2018; Das and Roy, 2023;) or on the co-movement of different financial markets, such as stock and currency market (Kaminsky and Reinhart, 2002; Rashid Sabri, 2004; Walid et al., 2011; Leung et al., 2017; He et al., 2023; Gunay et al., 2023). In contrast, we look at the sources of financial turbulence by analyzing the general stress in emerging markets and its relationship with the emerging market foreign exchange market components. Our contribution is twofold. First, unlike the existing literature (Kaminsky and Reinhart, 2002; Rashid Sabri, 2004; Walid et al., 2011; Das and Roy, 2023; He et al., 2023), our analysis integrates multiple components (returns, uncertainty, and liquidity) of exchange rates in exploring the relationship between currency markets and financial stress in emerging economies. Specifically, we utilize high-low spreads to account for uncertainty and bid-ask spreads to assess liquidity in currency rates. Liquidity is a key factor for market stability as it helps prevent large order flows from causing excessive price movements and contributes to the smooth functioning of the market. Bid-ask spreads reflect the depth of the order book and the cost of transactions, with higher bid-ask spreads indicating greater market vulnerability. Similarly, the difference between the highest and lowest exchange rate of a currency pair over a given period is an important indicator of market uncertainty, providing insight into market sentiment, with higher values indicating greater price volatility potential and higher risk exposure. Second, our analysis also considers the investment horizon by using different frequency bands that allows for the detection of stress transmission across both short-term and long-term horizons, reflecting the behavior of diverse investor groups. Thus, frequency-based analysis allows a more detailed understanding of changes in market interdependence over time and across different market conditions, which can be critical for investors and policymakers. Additionally, considering investment horizon provides insight into both uncertainty and liquidity developments in currency markets. Short-term investors face more pronounced price movements, while longer-term investors experience less volatile, trend-based price changes. As a result, these investors may seek low-risk, highly liquid assets that allow for quick cash-outs when necessary. These market dynamics can be effectively captured through frequency bands. While previous studies often categorize frequencies only for short, medium, or long terms (see Bredin et al., 2015; Owusu Junior et al., 2020; Ferrer et al., 2021; Aloui and Hamida, 2021; Chatziantoniou et al., 2023), we provide evidence across distinct frequencies: 4, 16, 64, 256, 1024, and the total in TVP-VAR model.

The structure of the study is as follows. Section 2 summarizes the existing literature, followed by the description of the data and methodology in Section 3. Section 4 presents the analysis with a discussion of the results. Finally, the conclusions are drawn.

2. Literature review

Financial stress typically results from a mix of factors, such as excessive borrowing, asset bubbles, and systemic risks within financial institutions (Reinhart and Rogoff, 2009). Financial markets are central to both the onset and spread of these crises through their roles in capital allocation, price discovery, and liquidity provision. In addition to these functions, financial markets also serve as indicators of financial stability, offering early warning signals of economic vulnerabilities (Frankel and Saravelos, 2012).

2.1. Financial stress in emerging markets

There is an extensive literature on the causes and spread of financial crises in emerging markets. The crises of the 21st century, though originating from different sources, have severely impacted emerging economies through financial stress and contagion. The 2008 Global Financial Crisis (GFC), which stemmed from the U.S. mortgage market, seemed to have limited direct effects on emerging markets due to their low exposure to toxic financial assets. However, these economies still faced falling export demand, capital outflows, and declining commodity prices (Claessens and Kose, 2013). Emerging economies were hit hard by the COVID-19 pandemic, with economic disruption caused by lockdowns leading to capital outflows, currency depreciation, and limited fiscal and monetary space due to increased healthcare spending and declining tax revenues (Baldwin and Di Mauro, 2020). El-Khatib and Samet (2021) investigated the performance of 45 emerging stock markets, showing that although COVID-19 caused sharp declines in stock market indices, increased volatility and widened CDS spreads, these movements were below the levels experienced during the GFC. The aftermath of the crises has highlighted the importance of understanding how crises develop and spread among different markets. Apostolakis and Papadopoulos (2015) found that securities markets in advanced economies, especially the U.S., primarily transmit financial stress to emerging markets. Conversely, Owusu Junior et al. (2020) highlighted that some emerging markets drive spillovers. Das and Roy (2023) observed significant co-movements between BRICS and developed country foreign exchange markets, with developed markets leading and BRICS markets being net receivers. Ozcelebi (2020) confirmed that contagion occurs during periods of high stress in markets like Brazil, China, and Russia. Feng et al. (2023) found that crises such as the GFC and COVID-19 led to regional risk spillovers, with interconnectedness amplifying market stress. Kenourgios et al. (2011) noted BRIC markets' vulnerability to contagion, while Hedström et al. (2020) argued that regional contagion in emerging markets is higher than global spillovers, suggesting diversification benefits.

2.2. Financial stress measures

The sources of financial stress stem from a variety of internal and external factors, like excessive indebtness, asset bubbles and busts, disruption in financial intermediation, external shocks. As such, financial crises are typically multidimensional events and can be hard to characterize using a single indicator (Claessens and Kose, 2013). The definition of stress may depend on the purpose for which the stress measurement is used, leading to differences in the construction of stress indices. This variation arises based on whether a comprehensive measurement is required or whether the user's activity is exposed to specific financial markets (Berlinger et al., 2016). Assessing the overall stability and health of the financial system requires a complex set of stress indicators covering different markets (equity, credit, foreign exchange) and variables (e.g., return, volatility, liquidity). The combination of these indicators provides a comprehensive picture of the overall stress level. Illing and Liu (2006) were the first to define financial stress not as a binary variable but as a continuum for the Canadian market, based on banking, debt, foreign exchange, and equity market variables. Other authors have developed their own financial stress indices, such as Hakkio and Keeton (2009) for the Federal Reserve Bank of Kansas City, Hollo et al. (2012) for European markets, Misina and Tkacz (2009) for selected advanced economies, and Yiu et al. (2010) for the Hong Kong Monetary Authority (Park and Mercado Jr, 2014). The Office of Financial Research (OFR), established by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, created a comprehensive stress indicator known as the OFR Financial Stress Index (OFR FSI) to provide a daily market-based measure of stress in global financial markets.

2.3. Stress transmission among financial markets

The empirical studies show that financial markets and asset returns or volatilities are liable to transmit stress and tension between them. This can be observed in both developed and emerging economies' markets. Both trade channels and cross-market linkages play a role in this stress transmission, according to the findings of Calvo and Reinhart (1996), Kaminsky and Reinhart (1999), Dornbusch et al. (2000), and Sydow et al. (2024). Kaminsky and Reinhart (2002) examined the international co-movement of different asset classes over the period 1997–1999 using data from 35 developed and emerging markets. They found that bond markets were the most synchronized, followed by equity and foreign exchange markets. The importance of currency markets in stock market volatility was highlighted by Rashid Sabri (2004). Leung et al. (2017) found a general increase in spillovers within equity markets and from foreign exchange markets to equity markets across countries during crisis periods in advanced markets. He et al. (2023) identified a negative relationship between foreign exchange rates and stock prices in the Turkish market, although the direction of causality and the strength of co-movement varied across different time and frequency bands. However, Walid et al. (2011) provided strong evidence that the relationship between stock and foreign exchange markets is regime-dependent, with stock price volatility responding asymmetrically to events in the foreign exchange market. The relationship between emerging equity markets (BRIC-T) and the OFR Emerging

Market Stress Index was examined by Gunay et al. (2023) over the period 2000–2023. They concluded that spillovers primarily occur during extreme positive and negative returns, with Brazil and Russia leading these spillovers due to the significance of energy-related and political factors.

The investment horizon influences the network structure of financial variables and investor behavior, with both short- and long-term risk perceptions tied to investment horizons (Bandi and Tamoni, 2017; Baruník and Nevrla, 2023; Ortu et al., 2013). Recent studies have focused on commodity markets, especially energy and green securities markets (Ferrer et al., 2021; Pham, 2021). Rehman and Vo (2021) observed low to moderate integration among energy commodities and metals, with increasing coherence over time. Li et al. (2023) found time-varying spillover effects between uncertainty and commodity markets. Aloui and Hamida (2021) noted that geopolitical risk affects the oil-stock market relationship, weakening in the short term. Investor horizons also affect market stress transmission. Short-term investors react quickly to volatility, while long-term investors provide stability by maintaining positions during turmoil (Bernardo and Welch, 2004; Morris and Shin, 2004). However, during prolonged crises, long-term investors' gradual withdrawal can lead to more widespread stress (Duffie, 2010). The interaction between short-term speculation and long-term repositioning creates cycles of volatility and market adjustments, making investor horizons essential for predicting how financial stress spreads across markets (Cella et al., 2013).

2.4. Methodology in stress related literature

There is significant interest in the literature regarding methods that allow for the examination of frequency, as they enable us to reveal differences between the short and long term. One such methodology, Wavelet Coherence, depicts patterns across varying frequency bands. Thus, the model is capable of capturing both short-term fluctuations and long-term trends, providing a more holistic picture of the underlying processes in the data. The wavelet coherency method has proven useful for analyzing the interrelationships between energy-related markets and other markets or financial stress (Vacha and Baruník, 2012; Aloui and Hamida, 2021; Li et al., 2023). Yang et al. (2017) used the wavelet coherency approach to investigate contagion and interdependence among large foreign exchange markets (GBP/USD, EUR/USD, and JPY/USD) and found that the spread of financial contagion is more pronounced during crises. Firouzi and Wang (2019) employed wavelet transform coherence to analyze the relationship between the movements of major currency pairs and the associated order flow over time and frequency, finding a strong negative correlation where order flow was the leading variable, suggesting it could be used to predict future currency movements. Mezghani and Boujelbène-Abbes (2023) found that financial stress strengthens long-term connectedness between the oil and stock-bond markets in the GCC, while Nguyen et al. (2021) highlighted the diversification benefits of green bonds, showing their low correlation with stocks and commodities even during crises.

The TVP-VAR model has gained attention in finance research for its ability to analyze time-varying relationships. Adekoya and Oliyide (2021) used it to study the impact of COVID-19 on financial asset connectedness, finding strong volatility spillovers, with gold and USD as net receivers. Kakran et al. (2025) applied TVP-VAR models to analyze APEC currencies, showing significant short-term impacts from crises, with long-term spillovers being more pronounced. Kyriazis et al. (2023) found that national currencies were key drivers of exports and inflation in developed and emerging markets. Cao (2012) investigated the effects of interest and exchange rates on the Chinese stock market, noting a short-term negative impact and a favorable effect from RMB appreciation. Yang and Zhang (2021) used TVP-VAR to explore the effects of U.S. Federal Reserve monetary policy on USD exchange rates, showing that contractionary policies lead to exchange rate appreciation.

2.5. Research gap

The role of foreign exchange markets in financial stability has been extensively studied in the literature, but the existing literature focuses on the interaction between foreign exchange markets and other markets that differ by region or asset type. The relationship between foreign exchange markets and a general financial stress index has been less studied. Unlike existing studies, we provide evidence on three components of exchange markets—currency returns, uncertainty, and liquidity—while also accounting for the investment horizon to capture emerging market financial stress, which has not been previously examined in this composition. To ensure robust results, we conduct an empirical investigation using both correlation-based tests (Wavelet Coherence) and spillover analysis (TVP-VAR frequency connectedness). This approach allows us to uncover patterns of short-, medium-, and long-term co-movements and spillovers. This modeling framework enables a comprehensive investigation of the currency market and financial stress index within the context of emerging markets.

3. Data and methodology

3.1. Data

In the empirical analysis section of this study, we examine the co-movements and spillovers between the EMFSI and the foreign exchange rate components of eight emerging economies: Brazil, Russia, India, China, South Africa, Saudi Arabia, the United Arab Emirates, and Türkiye. To deepen our analysis of various aspects of currency markets, we include the returns, uncertainty (measured by high-low spreads), and liquidity (measured by bid-ask spreads) for each exchange rate. As noted earlier, these components provide a comprehensive view of market dynamics. The EMFSI data, sourced from the OFR (n.d.), offers a market-based snapshot of stress in global financial markets. EMFSI is part of the aggregated Global Financial Stress Index and specifically reflects financial stress in emerging markets. Exchange rates data and their components were obtained from the LSEG Eikon platform (formerly Refinitiv Eikon).

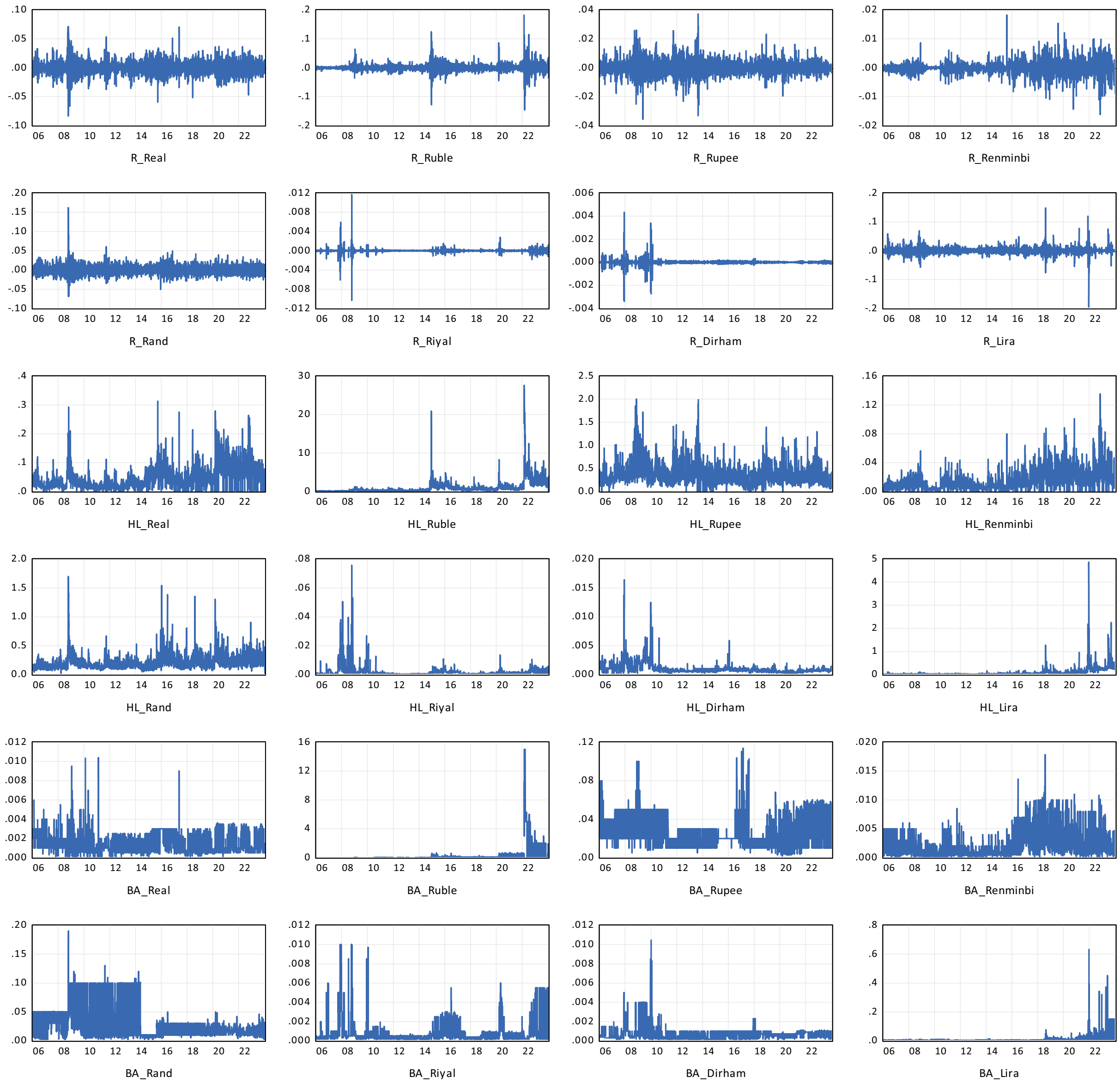


Fig. 1. Returns (R, first two rows), High-Low (HL, third and fourth rows) and Bid-Ask (BA, fifth and sixth rows) spreads of the variables.
Note: The figures present the daily return series (first two rows) High minus Low spreads (third and fourth rows) the Bid-Ask spread (the last two rows), of eight emerging currencies between 2006 and 2024.

In selecting the emerging economies for our analysis, we consider the BRICS formation (see Lattemann, 2014; Lehkonen and Heimonen, 2014; Asongu et al., 2018; Chkili and Nguyen, 2014) and align it with the MSCI (n.d.) emerging markets classification. To account for the recent updates to the BRICS group, now termed BRICS+, we include the countries invited to join during the 15th Summit in Johannesburg, specifically Saudi Arabia and the United Arab Emirates. However, we exclude Argentina and Ethiopia, as they are not listed in the MSCI classification, and Egypt due to significant missing data. Additionally, following the works of Becker (2014), Yıldırım et al. (2019), Yasir and Önder (2023), and Gunay et al. (2023), we include Türkiye, which is classified as an emerging market by MSCI and has formally applied to join BRICS (Bloomberg, 2024).

To assess the role of currency markets on the EMFSI, we decompose foreign exchange rates into two key components: liquidity and uncertainty. Both are critical elements in the dynamics of currency price movements. When liquidity is sufficient, currency values are established at prices with minimal deviation from the true market value, as the price shifts to a new equilibrium. However, insufficient liquidity leads to widening bid-ask spreads due to a reduced number of buyers and sellers compared to efficient market conditions. This misalignment results in currency prices diverging from their true value, causing abrupt and severe price changes, i.e., volatility. Empirical evidence supporting this relationship is presented by Bessembinder (1994) and Pham (2018). Poskitt (2005) investigates

Table 1
Descriptive statistics.

		EMFSI	REAL	RUBLE	RUPEE	RENMINBI	RAND	RIYAL	DIRHAM	LIRA
	Mean	0.0041	0.0002	0.0003	0.0001	0.0000	0.0002	0.0000	0.0000	0.0007
	Median	0.0000	0.0000	−0.0001	0.0000	0.0000	−0.0003	0.0000	0.0000	0.0004
	Std. Dev.	0.4002	0.0107	0.0124	0.0045	0.0020	0.0110	0.0004	0.0002	0.0105
	Skewness	0.1958	0.1880	0.5707	0.1942	0.0791	0.9349	2.0517	1.2904	−0.2214
	Kurtosis	20.236	7.780	38.097	9.720	12.209	15.914	384.409	185.049	48.337
	JB	56,339*	4358*	233,730*	8589*	16,079*	32,271*	27,576,370*	6,283,051*	389,633*
	ADF	−38.2304*	−71.5932*	−64.2206*	−32.4137*	−68.0334*	−69.2935*	−31.3051*	−385.5110*	−63.4812*
Returns (R)	PP	−62.2925*	−71.8682*	−64.1994*	−68.0200*	−69.0882*	−69.5588*	−141.3303*	−23.6768*	−63.4219*
	Mean		0.0466	0.9536	0.3645	0.0137	0.2074	0.0018	0.0010	0.0842
	Median		0.0372	0.4520	0.3200	0.0107	0.1800	0.0009	0.0009	0.0310
	Std. Dev.		0.0355	1.7036	0.2098	0.0123	0.1126	0.0036	0.0008	0.1630
	Skewness		1.6892	6.9876	2.0197	2.2686	3.4124	8.5029	5.7224	10.0349
	Kurtosis		7.577	75.665	10.454	12.440	28.693	109.159	68.405	205.741
	JB		6134*	1,037,831*	13,624*	20,794*	133,948*	2,190,884*	835,659*	7,867,236*
	ADF		−5.0808*	−7.2010*	−9.4140*	−7.8828*	−11.2297*	−8.3518*	−6.6402*	−4.8020*
High-Low Spreads (HL)	PP		−62.5970*	−15.9282*	−71.5369*	−59.4264*	−65.3639*	−47.8247*	−51.5275*	−41.3824*
	Mean		0.0015	0.2873	0.0254	0.0023	0.0291	0.0008	0.0007	0.0085
	Median		0.0012	0.0200	0.0200	0.0015	0.0156	0.0004	0.0007	0.0036
	Std. Dev.		0.0009	1.2274	0.0147	0.0021	0.0273	0.0011	0.0006	0.0222
	Skewness		1.3716	8.2935	1.2235	1.5694	1.7572	4.5085	5.0976	12.1970
	Kurtosis		9.019	88.320	4.956	5.656	5.216	30.610	49.424	240.691
	JB		8292*	1,431,903*	1860*	3205*	3272*	159,903*	428,205*	10,821,341*
	ADF		−8.2551*	−5.4844*	−7.8735*	−4.4090*	−4.5010*	−5.4844*	−8.1398*	−5.8070*
Bid-Ask Spreads (BA)	PP		−90.9045*	−19.0723*	−85.6255*	−72.8249*	−85.0859*	−19.0723*	−69.7030*	−95.4463*

[*] Indicates the significance at the 1% level. JB: Jarque–Bera, ADF: Augmented Dickey-Fuller test, PP: Phillips-Perron test.

whether these widening spreads are excessive during financial turbulence. To capture this aspect, we use bid-ask spreads as a proxy for exchange rate liquidity in our analysis. The second component of currency rates is uncertainty, reflected in volatility. Information disseminated during trading is incorporated into currency prices, and factors such as an economy's development, regulatory environment, and market efficiency influence how this information, along with expectations about inflation, interest rates, and government debt, drives fluctuations in exchange rates. In emerging markets, however, speculative operations and market sentiment often play a more significant role in currency value changes due to vulnerabilities related to foreign direct investment flows, reserves, and less efficient market structures. This has been empirically demonstrated by Frankel and Rose (1996) in their seminal study on emerging market economies. Thus, along with macroeconomic indicators (low-frequency information), we frequently observe severe intraday fluctuations in currency pairs driven by investor sentiment, political news, and other real-time developments. These fluctuations are captured by the high-low price spreads, making them an important measure of uncertainty in foreign exchange markets. Thus, in our empirical investigation, we incorporate both liquidity and uncertainty to provide a more comprehensive analysis of the currency markets.

The analysis period, spanning from January 4, 2006, to January 5, 2024, and containing 4549 data points, is extended to observe interactions during significant market developments over the last two decades. Statistical tests are carried out using R, Matlab, and *E*-views. The currency variables are listed as follows: Real (Brazil), Ruble (Russia), Rupee (India), Renminbi (China), Rand (South Africa), Riyal (Saudi Arabia), Dirham (United Arab Emirates), Lira (Türkiye). We present the variable plots in Fig. 1. The return series (Fig. 1, first two rows) exhibits varying degrees of fluctuation during the Global Financial Crisis (GFC) in 2008. In contrast to the other variables, the ruble displays significantly increased instability following the onset of the Russia-Ukraine conflict. The response of exchange rate variations to the COVID-19 pandemic seems relatively weak. Only the Chinese renminbi and Brazilian real show a reaction that can be attributed to the emergence of the outbreak. On the other hand, the currencies of three countries—Russia, Saudi Arabia, and the UAE—exhibit a short and abrupt fluctuation during this period, primarily associated with the negative oil price experience coinciding with the chaotic environment of the pandemic. Turning to the HL spreads (Fig. 1, third and fourth rows), it is evident that each currency manifests a certain level of uncertainty in daily price developments. These uncertainties appear to be relatively greater in the case of the ruble, lira, and rupee. While the rupee's oscillations remain stable across the years, jumps in the ruble can be linked to specific market events such as the annexation of Crimea in 2014 and the second conflict with Ukraine in 2022. Regarding the lira, uncertainties in the currency's value begin to grow after 2018 and spike during 2022. Finally, when examining the BA spread (Fig. 1, the last two rows), it becomes apparent that the currencies of the same two countries come to the forefront: the ruble and the lira. In both currencies, the liquidity crunch coincides with developments that also caused uncertainties in exchange rate movements.

Table 1 presents descriptive statistics for three data groups: returns (R) in panel one, high-low (HL) spreads in panel two, and bid-ask (BA) spreads in panel three. Results indicate that the highest fluctuations occur in the returns of the EMFSI index, with real, ruble, rand, and lira displaying relatively greater fluctuations than the other four currencies. Skewness statistics reveal that all variables are positively skewed, indicating that the frequency of above-mean returns is greater than their below-mean counterparts. Kurtosis statistics demonstrate fat tails in the return distributions, signifying departures from normality. This non-normal distribution is further confirmed by the statistically significant results of the Jarque–Bera test, supporting the choice of wavelet analysis. Finally, to examine the stationarity of the variables, we executed Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, revealing that all return series are stationary in their levels, denoted as I(0). Similarly, HL and BA spreads also exhibit departures from normality but are found to be stationary, akin to the case of returns.

3.2. Methodology

In our empirical study we apply the maximal overlap discrete wavelet transform (MODWT) as a preliminary analysis and investigate correlations of EMFSI and foreign exchange time series within each frequency band. Then, building on the evidence obtained, we employ Wavelet Coherence analysis (Grinsted et al., 2004; Bouri et al., 2020) to further examine the relationship and identify the variables leading to correlations. Wavelet analysis is a general empirical method in which a signal is decomposed into wavelets, which are localized functions that vary in frequency and time. Accordingly, wavelet analysis offers variable frequency resolution, allowing for localization of frequency components in both time and frequency domains. This makes wavelet analysis particularly useful for analyzing signals with non-stationary or transient behavior, which is we choose this empirical methodology for analyzing the impact of the foreign exchange market on emerging market stress. To better understand the relationships between variables and gain deeper insights into their associations, we also perform a Time-Varying Parameter Vector Autoregression (TVP-VAR) frequency connectedness analysis. This approach enables us to monitor the transmission of shocks between variable pairs across different investment horizons.

3.2.1. Maximal overlap discrete wavelet transform

Following the study of Zhu et al. (2014), we present the MODWT in this section. MODWT is a modified version of the Discrete Wavelet Transform (DWT). Both methodologies provide a scale-based additive decomposition of a time series $X = x(0),\ldots,x(n-1)$. The main technical difference is that standard DWT requires the length of the time series to be a power of 2 (for example the length of the time series must be divisible by 256 for an 8-level decomposition), whereas in the case of MODWT we face no such limitation.

Let $h_j(l)$ be the DWT wavelet filter for scale $j = 1,\ldots,J$, and $g_J(l)$ the scaling filter. For each scale j we have $l = 0,\ldots,L_{j-1}$, where $L_j = (2^j - 1)(L-1)+1$, where L is the length of the filter. The MODWT wavelet filters and scaling filter are defined directly: $\widetilde{h}_j(l) = \frac{h_j(l)}{2^{j/2}}$ and $\widetilde{g}_J(l) = \frac{g_J(l)}{2^{j/2}}$. The most common choice of wavelets are the Daubechies wavelets, which are a family of orthogonal wavelets with a maximum number of vanishing moments above some support. These wavelet functions cannot be expressed analytically, but most statistical software – such as R – have numerical implementations. The main output objects of this methodology are the MODWT wavelet coefficients of level j, which are the result of the convolution of the time series X and the MODWT filters:

$$W_j(t) = \sum_{l=0}^{L_j-1} \widetilde{h}_j(l) \cdot X(t - l \bmod n), j = 1, \ldots, J \tag{1}$$

$$V_J(t) = \sum_{l=0}^{L_J-1} \widetilde{g}_j(l) \cdot X(t - l \bmod n), \tag{2}$$

where mod stands for modulo division and is required for periodic boundary handling. From the definitions above it follows that each wavelet coefficient vector has the same length as the original time series itself. This calls for the following matrix-vector notation: $W_j = A_j X$ and $V_J = B_J X$, where A_j and B_J are n-by-n matrices filled with the values $\widetilde{h}_j(l)$ and $\widetilde{g}_J(l)$ respectively, and each row in the matrices is the copy of the one above, shifted by one to the right. For example:

$$A_j = \begin{pmatrix} \widetilde{h}_j(0) & \widetilde{h}_j(\mathrm{n}-1) & \cdots & \widetilde{h}_j(2) & \widetilde{h}_j(1) \\ \widetilde{h}_j(1) & \widetilde{h}_j(0) & \cdots & \widetilde{h}_j(3) & \widetilde{h}_j(2) \\ \vdots & \vdots & & \vdots & \vdots \\ \widetilde{h}_j(n-2) & \widetilde{h}_j(n-3) & \cdots & \widetilde{h}_j(0) & \widetilde{h}_j(n-1) \\ \widetilde{h}_j(n-1) & \widetilde{h}_j(n-2) & \cdots & \widetilde{h}_j(1) & \widetilde{h}_j(0) \end{pmatrix} \tag{3}$$

This filtering transformation has the property that the original time series can be reconstructed from its MOWDT:

$$X(t) = \sum_{j=1}^{J} A_j^T W_j + B_J^T V_J = \sum_{j=1}^{J} D_j + S_J, \tag{4}$$

where the n-length vectors $D_j = A_j^T W_j$ are called the level j MODWT details, and the n-length vector $S_J = B_J^T V_J$ is called the level J MODWT smooth. With the MODWT coefficient vectors W_j in hand, we can employ a scale-based cross-correlation analysis between two time series X and Y. Since the scale of MODWT is 2^j, where j is an integer, we consider this method a low resolution and preliminary method for examining the co-movement of the two variables. The following method provides a finer discretization of the scale parameter, and thus it enables us to understand the co-movement of two variables on a higher resolution.

3.2.2. *Wavelet coherence analysis*

In this section we follow the paper of Grinsted et al. (2004) and introduce the method of Wavelet Coherence analysis. The application of the wavelet coherence approach uncovers the co-movement between two time series at various frequencies. This approach is usually used when we may assume that the degree of co-movement between two time-series is frequency dependent. To employ the Continuous Wavelet Transform, we first need a mother wavelet, which is a function with zero mean and that is localized in both frequency and time (Grinsted et al., 2004). A common basis choice is the Morlet, defined as

$$\psi^M(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}} \tag{5}$$

whose localized and scaled version is

$$\psi_{\tau,s}(t) = s^{-\frac{1}{2}} \psi^M\left(\frac{t-\tau}{s}\right) = s^{-\frac{1}{2}} \pi^{-\frac{1}{4}} e^{\frac{i\omega_0}{s}(t-\tau)} e^{-\frac{(t-\tau)^2}{2s^2}} \tag{6}$$

where t is natural time, τ is the time localization parameter, s is scale (dilation parameter), ω_0 indicates the central frequency of the wavelet. The CWT of a time series $X = x(1), \ldots, x(n)$ with uniform time steps is defined as the convolution of the time series with the localized and scaled version of the Morlet:

$$W_X(\tau, s) = \sum_{t=1}^{n} x(t) \cdot \psi_{\tau,s}(t) \tag{7}$$

Note that $W_X(\tau, s)$ is a complex valued function of time localization and scale. The wavelet power of time series X is defined as the square of the absolute value of this complex valued function: $|W_X(\tau, s)|^2 = |W_X(\tau, s) \cdot W_X^*(\tau, s)|$, where * denotes complex conjugation. The measure of wavelet coherence is built upon the cross wavelet transform (XWT), which is constructed as

$$W_{XY}(\tau, s) = W_X(\tau, s) \cdot W_Y^*(\tau, s) \tag{8}$$

The cross wavelet power is defined analogously to its single time series counterpart: $|W_{XY}(\tau, s)|$. Cross wavelet power exposes time–frequency regions of high common power between time series X and Y. Lastly, wavelet coherence of two time series is defined similarly to a traditional correlation coefficient:

$$R_{XY}^2(\tau,s) = \frac{|S(s^{-1}W_{XY}(\tau,s))|^2}{S\left(s^{-1}|W_X(\tau,s)|^2\right)\cdot S\left(s^{-1}|W_X(\tau,s)|^2\right)} \tag{9}$$

where $S(.)$ is a smoothing operator. $R_{XY}^2(\tau,s)$ is the (squared) wavelet coherency measure of time localization and scale, and similarly to the square of a standard correlation coefficient, it has a value between 0 (no co-movement) and 1(high co-movement). Wavelet coherency can be thought of as the scale-specific local squared correlation of two CWTs. Wavelet coherency by itself has the issue that it cannot distinguish between a positive or a negative correspondence between two time series. Fortunately, the positive or negative relationship, and moreover, even the lead-lag relationship between the two CWTs can be uncovered by calculating the phase difference:

$$\theta_{XY}(\tau,s) = tan^{-1}\left(\frac{Im(W_{XY}(\tau,s))}{Re(W_{XY}(\tau,s))}\right) \tag{10}$$

where $Im(z)$ and $Re(z)$ denote the imaginary and real parts of the complex number z respectively. $\theta_{XY}(\tau,s)$ has the value between $-\pi$ and π, and shows the phase-locked behavior of X and Y for scale s and time localization τ. It is usually represented by arrows on a chart of time-scale wavelet coherence. A value of zero means that the two CWTs are in-phase (this behavior mostly resembles the usual positive correlation) and is represented by an arrow pointing to the right. A value of π or $-\pi$ means that the two CWTs are anti-phase (this behavior mostly resembles the usual negative correlation) and is represented by an arrow pointing to the left. A value of $\frac{\pi}{2}$ means that X leads Y by a quarter period (which is based on the actual scale s in question) and is represented by an arrow pointing upwards. The value $-\frac{\pi}{2}$ is defined and represented analogously.

Wavelet coherence results are conventionally presented on a chart, featuring time and scale as the two axes. The coherences are depicted using a color scale, where warmer colors indicate higher coherence, while colder colors signify a weak or nonexistent relationship between series. To assess statistical significance, Monte Carlo simulations are employed, assuming a red noise (an AR(1) process). Statistically significant regions are highlighted by a thick black curve. Notably, the stretching of wavelets at larger scales introduces edge artifacts and impacts the validity of the results. For clarity, the cone of influence is incorporated into the charts, distinguishing between reliable (top) and less reliable (bottom) regions in the time-frequency space. This comprehensive visualization aids in interpreting the coherence patterns and their statistical significance across different scales and time intervals.

3.2.3. TVP-VAR frequency connectedness analysis

In this subsection, we introduce the TVP-VAR and its counterpart in the frequency domain. We follow the outline provided by Chatziantoniou et al. (2023) in describing this methodology. In this context, we use uppercase bold letters to denote vectors and matrices. A TVP-VAR (1) model is defined by the following equations:

$$\boldsymbol{X}(t) = \boldsymbol{\Phi}(t)\cdot\boldsymbol{X}(t-1)+\boldsymbol{\varepsilon}(t) \tag{11}$$

where $\boldsymbol{X}(t)$ is the N-dimensional vector of data, $\boldsymbol{\Phi}(t)$ is the time-dependent $N\times N$ dimensional coefficient matrix, $\boldsymbol{\varepsilon}(t)$ is the N-dimensional error term with zero mean and time-dependent covariance matrix $\boldsymbol{\Sigma}(t)$. The coefficient matrix $\boldsymbol{\Phi}(t)$ evolves according to

$$vec(\boldsymbol{\Phi}(t)) = vec(\boldsymbol{\Phi}(t-1))+\boldsymbol{\nu}(t) \tag{12}$$

where $vec(\boldsymbol{\Phi}(t))$ is the N^2-dimensional vectorized version of the coefficient matrix, $\boldsymbol{\nu}(t)$ is the N^2-dimensional error term with zero mean and time-dependent covariance matrix $\boldsymbol{R}(t)$. As the generalized forecast error variance decomposition (GFEVD) is based on the Wold representation, we transform our TVP-VAR (1) process to its moving average TVP-VMA(∞) form:

$$\boldsymbol{X}(t) = \boldsymbol{\Phi}(t)\cdot\boldsymbol{X}(t-1)+\boldsymbol{\varepsilon}(t) = \sum_{h=0}^{\infty}\boldsymbol{\Psi}_h\cdot\boldsymbol{\varepsilon}(t-k) \tag{13}$$

The GFEVD (denoted by $\theta_{ij}^H(t)$) represents the pairwise directional connectedness from j to i, and specifically measures the contribution of variable j to the variance of the forecast error of variable i at horizon H:

$$\theta_{ij}^H(t) = \frac{(\boldsymbol{\Sigma}(t))_{jj}^{-1}\cdot\sum_{h=0}^{H}\left((\boldsymbol{\Psi}_h\cdot\boldsymbol{\Sigma}(t))_{ij}\right)^2}{\sum_{h=0}^{H}\left(\boldsymbol{\Psi}_h\cdot\boldsymbol{\Sigma}(t)\cdot\boldsymbol{\Psi}_{\mathrm{h}}'\right)_{ii}} \tag{14}$$

Next, we normalize the rows of $\boldsymbol{\Theta}^H(t)$ so they sum up to one, which in turn means that the variables together account for 100% of the forecast error variance of variable i:

$$\widetilde{\theta}_{ij}^H(t) = \frac{\theta_{ij}^H(t)}{\sum_{i=1}^{N}\theta_{ij}^H(t)} \tag{15}$$

With the normalized values $\widetilde{\theta}_{ij}^{H}(t)$ in hand, we define the following connectedness measures according to Antonakakis et al. (2020): Total directional connectedness TO others:

$$TO_j^H(t) = \sum_{i=1, i\neq j}^{N} \widetilde{\theta}_{ij}^{H}(t) \tag{16}$$

Total directional connectedness FROM others:

$$FROM_i^H(t) = \sum_{j=1, j\neq i}^{N} \widetilde{\theta}_{ij}^{H}(t) \tag{17}$$

NET total directional connectedness:

$$NET_i^H(t) = TO_i^H(t) - FROM_i^H(t) \tag{18}$$

Net Pairwise Directional Connectedness:

$$NPDC_{ij}^H(t) = \widetilde{\theta}_{ji}^{H}(t) - \widetilde{\theta}_{ij}^{H}(t) \tag{19}$$

Total Connectedness Index (TCI):

$$TCI^H(t) = \frac{N}{N-1} \cdot \sum_{j=1}^{N} TO_j^H(t) = \frac{N}{N-1} \cdot \sum_{i=1}^{N} FROM_i^H(t) \tag{20}$$

Next, we can define similar connectedness measures in the frequency domain. First, we define the Fourier transform of the impulse response $\boldsymbol{\Psi}_h$:

$$\boldsymbol{\Psi}\left(e^{-i\omega}\right) = \sum\nolimits_{h=0}^{\infty} e^{-i\omega} \boldsymbol{\Psi}_h \tag{21}$$

where $i = \sqrt{-1}$ is the imaginary unit, and ω denotes the frequency.

$$\theta_{ij}^{\omega}(t) = \frac{(\boldsymbol{\Sigma}(t))_{jj}^{-1} \cdot \left| (\boldsymbol{\Psi}(e^{-i\omega}) \cdot \boldsymbol{\Sigma}(t))_{ij} \right|^2}{(\boldsymbol{\Psi}(e^{-i\omega}) \cdot \boldsymbol{\Sigma}(t) \cdot \boldsymbol{\Psi}(e^{i\omega}))_{ii}} \tag{22}$$

In the denominator of (22) we see the power spectrum $\boldsymbol{S}_{\boldsymbol{X}}^{\omega}$, which descibes how the variance of $\boldsymbol{X}(t)$ is distributed over the frequency components ω. Similarly to GFEVD, we normalize frequency GFEVD so the rows sum up to one:

$$\widetilde{\theta}_{ij}^{\omega}(t) = \frac{\theta_{ij}^{\omega}(t)}{\sum_{i=1}^{N} \theta_{ij}^{\omega}(t)} \tag{23}$$

To evaluate both short-term and long-term connectedness, rather than focusing on a single frequency, we aggregate frequencies across a defined range $d = (a, b) : a, b \in (-\pi, \pi), a < b$:

$$\widetilde{\theta}_{ij}^{d}(t) = \int_a^b \widetilde{\theta}_{ij}^{\omega}(t)\, d\omega \tag{24}$$

Lastly, we can define the connectedness measures in the frequency domain similarly to the previous definitions of (16)—(20). These values represent frequency connectedness measures that indicate spillovers within a specific frequency range d:

$$TO_j^d(t) = \Gamma_d \cdot \sum_{i=1, i\neq j}^{N} \widetilde{\theta}_{ij}^{d}(t) \tag{25}$$

$$FROM_i^d(t) = \Gamma_d \sum_{j=1, j\neq i}^{N} \widetilde{\theta}_{ij}^{d}(t) \tag{26}$$

$$NET_i^d(t) = \Gamma_d \cdot \left(TO_i^d(t) - FROM_i^d(t)\right) \tag{27}$$

$$NPDC_{ij}^d(t) = \Gamma_d \cdot \left(\widetilde{\theta}_{ji}^{d}(t) - \widetilde{\theta}_{ij}^{d}(t)\right) \tag{28}$$

$$TCI^d(t) = \Gamma_d \cdot \frac{N}{N-1} \cdot \sum_{j=1}^{N} TO_j^d(t) = \Gamma_d \cdot \frac{N}{N-1} \cdot \sum_{i=1}^{N} FROM_i^d(t) \tag{29}$$

Here we follow Baruník and Křehlík (2018) and weight all measures with respect to the overall system:

$$\Gamma_d = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{d}(t) \tag{30}$$

4. Empirical analysis

In this section of the study, we examine the relationship between the EMFSI and currency variables—returns, uncertainty, and liquidity—using Maximal Overlap Discrete Wavelet Transform (MODWT), Wavelet Coherence, and TVP-VAR frequency connectedness analyses.

As discussed by Percival and Walden (2000), wavelet and correlation analysis can be considered complementary methods. Therefore, before the execution of our primary methodology, Wavelet Coherence, as a preliminary investigation, we apply a correlation analysis under different time scales, recognizing that developments in financial markets may have varying degrees of effects in different frequencies. To accomplish this, we initially apply a scale-based multiresolution to the data through MODWT. The MODWT of level J_0 for a time series Y generates column vectors of $W_1, W_2, \ldots, W_{j0}$ and V_{j0} for each dimension utilized, N. W_j vectors present wavelet coefficients that are interconnected with the behavior of time series Y for the scales identified $\tau_j = 2^{j-1}$. For example, for $j = 11$, the first ten vectors will present the column vectors of wavelet coefficients, and the last series will be the scaling coefficient of V_{j0} that is related to variations at scales $\lambda_{j0} = 2^{j0}$ and higher. Unlike monoscale correlation analysis, this approach enables a deeper understanding of relationships by recognizing the most significant frequencies that incorporate the association of variables at different time scales, as exemplified by Saâdaoui (2023). Employing a correlation analysis on decomposed data (on multiple scales) may reveal interactions not apparent in aggregate data. For level $j = 10$ and the Daubechies wavelet with $N = 2$, overall wavelet decompositions correspond to d1 (0–2 days), d2 (2–4 days), d3 (4–8 days), d4 (8–16 days), d5 (16–32 days), d6 (32–64 days), d7 (64–128 days), d8 (128–256 days), d9 (256–512 days), d10 (512–1024 days). The wavelet coefficients of decomposed time series are presented in Appendix A and B.

This composition allows us to examine the relationship between variables for different investment horizons. For instance, while the low scales correspond to high frequency and short-term investment horizons, the high scales are associated with low frequency and long-term investment horizons. The results of the correlation analysis under four different scales[1] are presented in Table 2. According to the findings, the significant number of correlations between EMFSI and exchange rates increases along with the growing frequency bands. For instance, while in scale 16, we have only four significant correlations, in scales 64, 256, and 1024, we end up with five, seven, and eight significant co-movements, respectively. This result can be evaluated under the investment horizon, as discussed above. For instance, given that short-term investors or day traders focus more on rapid market changes, which corresponds to lower scales, the results in higher scales indicate the presence of long-term relationships between the variables. Long-term relationships can manifest during various economic phases and encompass both bullish and bearish market trends. A similar approach, using MODWT as a preliminary analysis, is employed by Arslan et al. (2024) in their use of deep learning methodologies to determine the best model performance among SVR, RNN, and LSTM. Regarding the correlations between currency rates, it is observed that the correlation rates are generally positive but less than 0.50 on scale 16. Unlike other variables, pairs of Riyal and Dirham display negative correlation statistics with the rest of the countries, except for the pair of Riyal and Renminbi. Similar to the case of EMFSI, correlations of currency rates also demonstrate higher co-movements on higher scales, and we observe statistics larger than 0.50. This development applies to the case of pairs formed with Riyal and Dirham. Higher scales yield larger correlation values and finally, in some cases, we end up with positive statistics in some pairs. This finding also indicates that investment horizon matters in the investigation of correlations in foreign exchange rates. When we focus on lower frequencies, namely long-term changes, we observe more positive and stronger correlations in the foreign exchange market.

As our preliminary analysis reveals, investigating correlations under various scales can be a crucial procedure for capturing unrevealed characteristics of market behavior. Given this finding, the following section employs wavelet coherence analysis to examine the relationship between the EMFSI and currency rates in both time and frequency domains. This analysis allows us to observe interactions within different scales and unlike multiresolution-based correlation analysis, wavelet coherence enables us to understand the dynamics of co-movements and verify whether long-term investor behavior remains influential or if immediate market dynamics play a more significant role in the relationship under investigation. In conclusion, this methodology facilitates monitoring how different scales are linked to periodic elements of the variables over the years.

In Figs. 2, 3, and 4, we present the results of the Wavelet Coherence analysis for log price changes, uncertainty and liquidity components of currency rates, respectively. Namely, Fig. 2 focuses on interactions between return variables, while Figs. 3 and 4 display the same results for high-low and bid-ask spreads of the exchange rates, respectively. To form pairs for analysis, we follow the previous procedure and pair each currency variable with the EMFSI. The horizontal and vertical axes represent time and frequencies, respectively. Considering the large number of observations and aiming for broad evidence in the frequency domain, we set the level to 10, corresponding to 1024 (2^{10}) in scales. The cone of influence (COI), indicating potential distortion caused by edge effects, is depicted in a softer shade separated by a white line. As discussed by Cazelles et al. (2008), the COI is crucial for evaluating analysis results, with the region beyond the cone of influence exhibiting reduced precision in spectral data. The heatmap visually demonstrates

[1] The scales are 16, 64, 256, and 1024. In the first panel, the results for scales 16 and 64 are displayed on the left and right sides of the diagonal matrix, respectively. Similarly, in the second panel, the results for scales 256 and 1024 are shown on the left and right sides of the diagonal matrix, respectively.

Table 2
The correlation matrix of the variables under different scales.

		EMFSI	REAL	RUBLE	RUPEE	RENMINBI	RAND	RIYAL	DIRHAM	LIRA	
						64					
EMFSI			-0.0544***	0.0193	-0.1523***	0.0408***	-0.0119	-0.0549***	0.0168	-0.1519***	
			[-3.6715	[1.3017]	[-10.3884]	[2.7530]	[-0.8049]	[-3.7054]	[1.1300]	[-10.3616]	
REAL		0.0234		0.2515***	0.5128***	0.2536***	0.6202***	0.1513***	-0.0529***	0.4750***	
		[1.5780]		[17.5188]	[40.2821]	[17.6754]	[53.3171]	[10.3242]	[-3.5712]	[36.3996]	
RUBLE		0.0269*	0.1970***		0.3185***	0.0001	0.2654***	0.1474***	0.0247*	0.2819***	
		[1.8140]	[13.5467]		[22.6566]	[0.0099]	[18.5629]	[10.0467]	[1.6661]	[19.8133]	
RUPEE		-0.0269*	0.3686***	0.1873***		0.1696***	0.5071***	0.0508***	-0.0332**	0.3613***	
		[-1.8147]	[26.7348]	[12.8574]		[11.6069]	[39.6704]	[3.4266]	[-2.2378]	[26.1266]	
RENMINBI	16	-0.0355**	0.1749***	0.0789***	0.1589***		0.2695***	-0.0092	0.0444***	0.1165***	64
		[-2.3966]	[11.9793]	[5.3361]	[10.8525]		[18.8728]	[-0.6210]	[2.9983]	[7.9069]	
RAND		-0.0058	0.4735***	0.2931***	0.4169***	0.2607***		0.0487***	-0.1695***	0.5210***	
		[-0.3893]	[36.2542]	[20.6699]	[30.9302]	[18.2089]		[3.2887]	[-11.6001]	[41.1573]	
RIYAL		-0.0496***	-0.0747***	-0.0110	-0.0733***	0.0598***	-0.0580***		0.5539***	0.0504***	
		[-3.3518]	[-5.0496]	[-0.7413]	[-4.9540]	[4.0405]	[-3.9181]		[44.8613]	[3.4033]	
DIRHAM		-0.0417***	-0.0675***	-0.0005	-0.1345***	-0.0021	-0.0878***	0.5810***		-0.1321***	
		[-2.8111]	[-4.5602]	[-0.0339]	[-9.1515]	[-0.1390]	[-5.9442]	[48.1357]		[-8.9848]	
LIRA		0.0311**	0.3551***	0.1845***	0.3774***	0.1240***	0.4869***	-0.0668***	-0.0572***		
		[2.0979]	[25.6176]	[12.657]	[27.4818]	[8.4296]	[37.5921]	[-4.5176]	[-3.8617]		
						16					

		EMFSI	REAL	RUBLE	RUPEE	RENMINBI	RAND	RIYAL	DIRHAM	LIRA	
						1024					
EMFSI			0.3263***	0.0969***	-0.3655***	-0.3382***	-0.2721***	0.1512***	0.2283***	-0.4504***	
			23.2761]	6.5656]	-26.4784]	-24.2345]	-19.0702]	10.3109]	15.8152]	-34.0174]	
REAL		0.1355***		0.6978***	0.4824***	-0.1335***	0.6791***	0.2577***	0.0245*	-0.1997***	
		[9.2196]		65.6820]	37.1374]	-9.0832]	62.3796]	17.9824]	1.6493]	-13.7406]	
RUBLE		-0.2164***	0.4930***		0.2333***	0.4125***	0.4434***	0.0706***	-0.2042***	0.1953***	
		[-14.9442]	[38.2139]		16.1807]	30.5336]	33.3581]	4.7759]	-14.0681]	13.4274]	
RUPEE		-0.0080	0.6684***	0.2990***		0.1745***	0.5658***	0.5695***	0.3811***	0.3955***	
		[-0.5407]	[60.6010]	[21.1302]		11.9516]	46.2720]	46.7185]	27.7938]	29.0390]	
RENMINBI	256	0.0978***	0.3121***	-0.1029***	0.3185***		0.0267*	-0.0976***	-0.2133***	0.6888***	1024
		[6.6289]	[22.1524]	[-6.9760]	[22.6546]		1.8039]	-6.6122]	-14.7226]	64.0720]	
RAND		0.1475***	0.7366***	0.4115***	0.5951***	0.3640***		0.0027	-0.2957***	-0.1307***	
		[10.0541]	[73.4508]	[30.4482]	[49.9384]	[26.3534]		0.1811]	-20.8699]	-8.8925]	
RIYAL		0.0534***	0.0234	-0.1545***	0.1877***	0.1391***	0.1683***		0.8371***	0.3378***	
		[3.6032]	[1.5790]	[-10.5433]	[12.8838]	[9.4747]	[11.5112]		103.1737]	24.1979]	
DIRHAM		-0.0552***	-0.1177***	-0.2177***	0.1693***	0.0950***	0.1095***	0.6188***		0.1858***	
		[-3.7246]	[-7.9947]	[-15.0378]	[11.5838]	[6.4332]	[7.4296]	[53.1117]		12.7504]	
LIRA		-0.0862***	0.5675***	0.3512***	0.4388***	0.4396***	0.5147***	-0.0061	0.0243		
		[-5.8318]	[46.4723]	[25.2903]	[32.9285]	[33.0000]	[40.4852]	[-0.4090]	[1.6371]		
						256					

Note: The table illustrates correlations across four different scales. The diagonal matrix separates the analysis into two groups on each panel. The left side of the diagonal matrix shows correlations in Scales 16 and 256 in Panels 1 and 2, respectively. Similarly, the right side of the diagonal matrix presents results for Scales 64 and 1024 in Panels 1 and 2, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Numbers within parentheses represent standard errors.

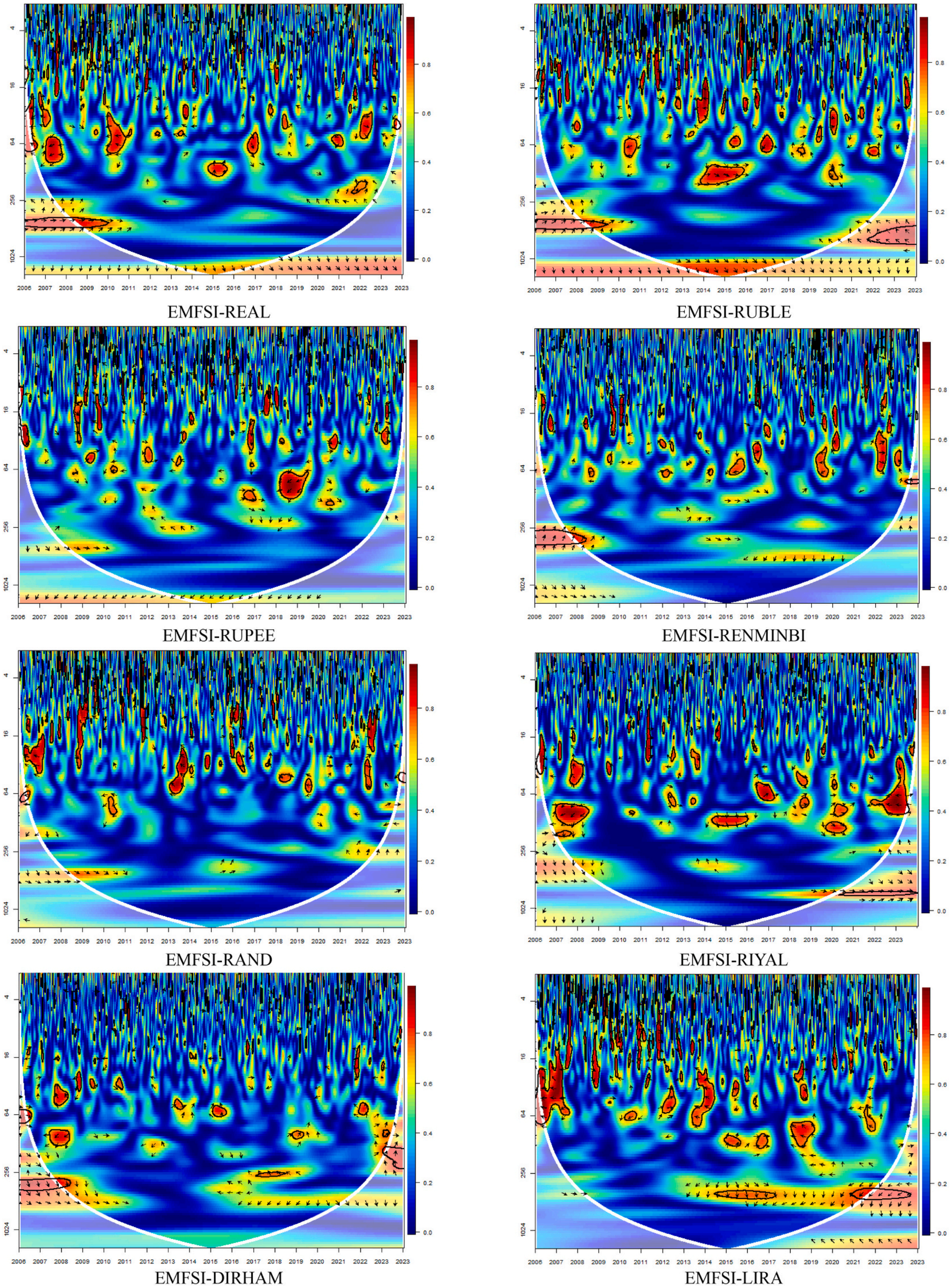


Fig. 2. Wavelet coherency between currency market returns and EMFSI.

Note: The figures feature time as the horizontal axis, and scale as the vertical axis. Coherences are depicted with a color scale, where warmer colors indicate higher coherence, colder colors signify lower coherence. The cone of influence distinguishes between reliable (top) and less reliable (bottom) regions in the time-frequency space. Phase is demonstrated by arrows: → (←) indicates significant positive (negative) correlations. Arrow ↑ (↓) shows that EMFSI (Currency) leads the Currency (EMFSI) in these correlations. A combination such as ↗ (↘), demonstrates the presence of positive correlations when EMFSI (Currency) leads the Currency (EMFSI).

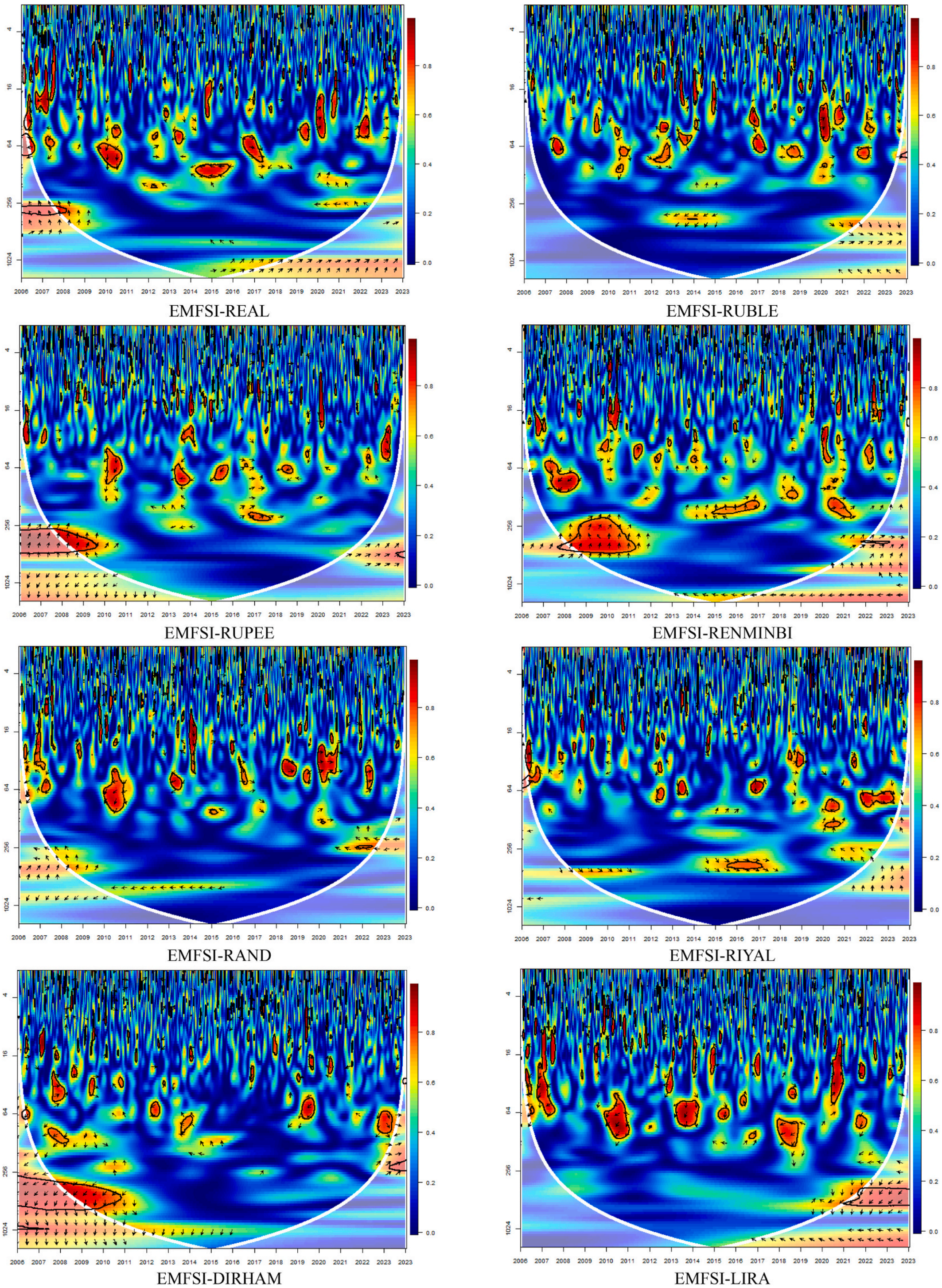


Fig. 3. Wavelet coherency between currency market uncertainty and EMFSI.
Note: The figures feature time as the horizontal axis, and scale as the vertical axis. Coherences are depicted with a color scale, where warmer colors indicate higher coherence, colder colors signify lower coherence. The cone of influence distinguishes between reliable (top) and less reliable (bottom) regions in the time-frequency space. Phase is demonstrated by arrows: → (←) indicates significant positive (negative) correlations. Arrow ↑ (↓) shows that EMFSI (Currency) leads the Currency (EMFSI) in these correlations. A combination such as ↗ (↘), demonstrates the presence of positive correlations when EMFSI (Currency) leads the Currency (EMFSI).

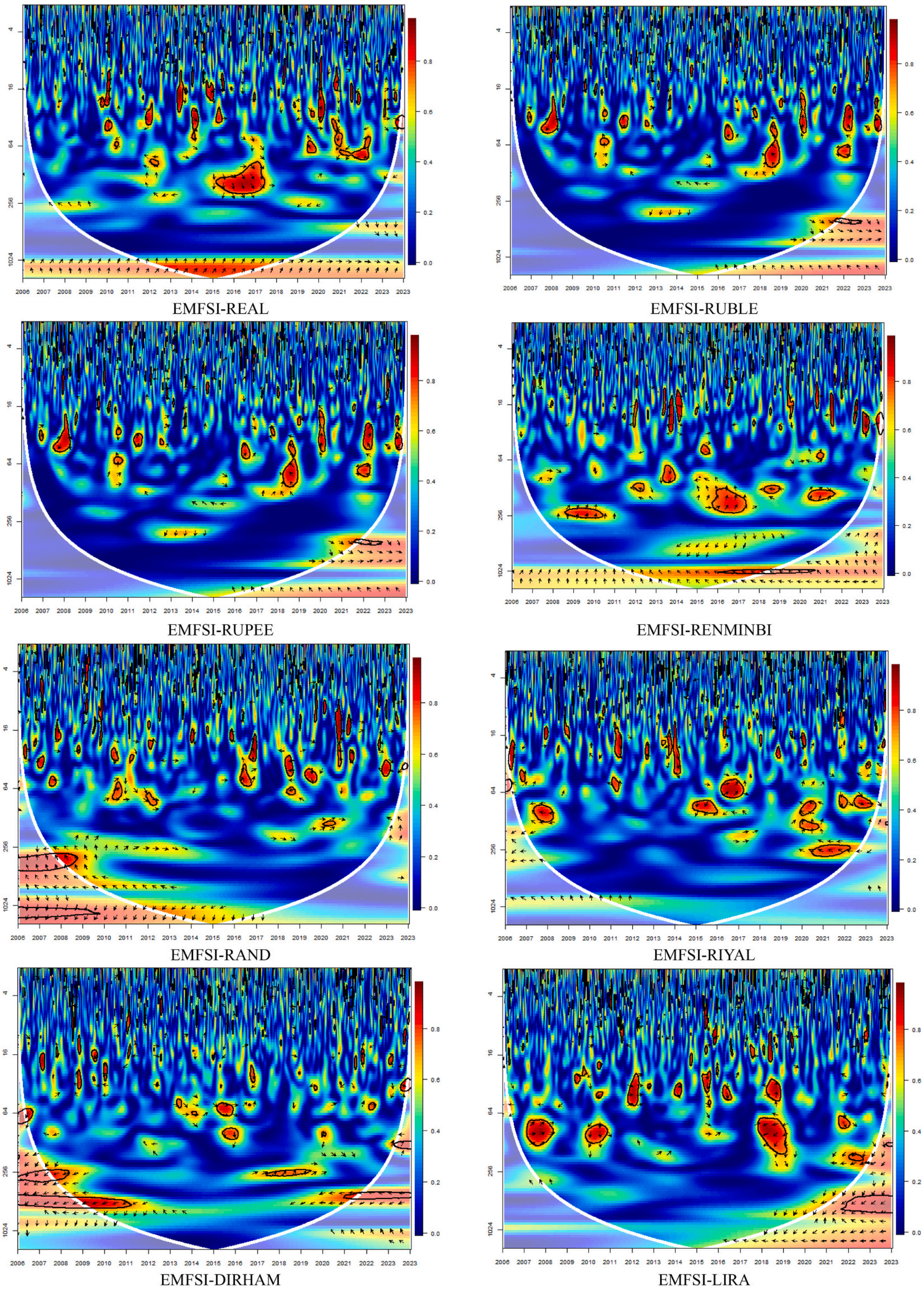


Fig. 4. Wavelet coherency between currency market liquidity and EMFSI.
Note: The figures feature time as the horizontal axis, and scale as the vertical axis. Coherences are depicted with a color scale, where warmer colors indicate higher coherence, colder colors signify lower coherence. The cone of influence distinguishes between reliable (top) and less reliable (bottom) regions in the time-frequency space. Phase is demonstrated by arrows: → (←) indicates significant positive (negative) correlations. Arrow ↑ (↓) shows that EMFSI (Currency) leads the Currency (EMFSI) in these correlations. A combination such as ↗ (↘), demonstrates the presence of positive correlations when EMFSI (Currency) leads the Currency (EMFSI).

the degree of coherence, ranging from weak (shown by warm blue) to precise (indicated by warm red) relationships. Additionally, significant relationships are illustrated within the thick black contour at the 5% level. Standard deviations of correlation coefficients obtained through 1000 iterations in Monte Carlo simulations.

As known, correlation coefficients provide information about the strength of the relationship between two variables but do not reveal which variable leads this connection. However, as suggested by Grinsted et al. (2004), the Wavelet Coherence approach within the context of causality links enables us to determine the variable that dominates these co-movements. Following the study of Vacha and Baruník (2012), we use the wavelet coherence phase differences to be able to determine the variable that dominates these co-movements. In this approach the phase is demonstrated by the arrows within Wavelet Coherence plots. For instance, arrows →, ←, ↑, ↓, ↗, ↘, ↖, ↙ convey different information regarding the interaction of variables for a data pair like EMFSI-Real. For example, → and ← indicate significant positive and negative correlations between EMFSI and Real variables, respectively. Arrow ↑ (↓) show that EMFSI (Real) leads Real (EMFSI) in these correlations. The combinations of these arrows, such as ↗ (↘), demonstrate the presence of positive correlations when EMFSI (Real) leads Real (EMFSI). Changing the direction and angle, for example, ↖ (↙), implies negative correlation with EMFSI (Real) leading the Real (EMFSI). In interpreting the results, we categorize the ranges as short-term, medium-term, and long-term investment horizons in the figures: 0–64, 64–256, and 256–1024. As theorized in finance, investment horizon can significantly influence the network structure of financial variables and investor behavior. For instance, short-term traders operate in high-frequency bands corresponding to short-term horizons, while long-term investors are active in lower frequency bands associated with longer horizons. Additionally, long-term investors' perception of news falls within the domain of systematic risk rather than the elements governing unsystematic risk (Aloui and Hamida, 2021; Ferrer et al., 2021; Omane-Adjepong et al., 2019; Pham, 2021; Bredin et al., 2015). Hence, an investor's risk perception in both the short and long term is linked to their investment horizon, as demonstrated by Bandi and Tamoni (2017), Baruník and Nevrla (2023), and Ortu et al. (2013).

Results for EMFSI-Real in Fig. 2 indicate that significant correlations are primarily intensified in the frequency band of 32–128. We observe negative correlations led by Real before and after the GFC. However, during the GFC, there are no significant co-movements between the variables. This could be attributed to the nature of the crisis, which originated in the sub-prime mortgage market and primarily impacted countries with sophisticated credit derivatives in their markets. Our results indicate that emerging market stress is not connected to the Brazilian Real in this period. Looking at other currency rates, we obtain the same result regarding the GFC period, with two exceptions: South Africa and Türkiye. We observe a very short period of co-movements toward the end of 2008 at the frequency band of 16–32, corresponding to short-term cycles. In both cases, local currencies appear to be a source of correlations with EMFSI.

These results might be related to concerns about the economic resilience of these countries during the GFC. As for the Russian Ruble, the most significant and sound correlations appear during the period of the annexation of Crimea in 2014 in the frequency band of 64–128. The positive correlations of the period indicate co-movements between depreciations in the value of the Russian Ruble and growing tension in overall emerging markets. It is interesting that wavelet coherence does not demonstrate a significant correlation during the Russia-Ukraine war, unlike the case of the annexation of Crimea. This finding can be accounted for by market expectations and priced (purchased) information in the exchange rates and market stress of emerging economies. Regarding the third currency variable, the Indian Rupee, we do not observe widespread and consistent interactions. The only exception, demonstrating significant correlations, emerges in 2018 and is negative and led by India. These results can be linked to the escalated tension between India and Pakistan during 2018–2019. In terms of the connection between emerging market stress and the currency value of China, we do not observe a durable and consistent period or frequency band, although China was the epicenter of the global pandemic and subject to trade war and tariff disputes with the US that emerged in 2018. This implies that emerging market stress is mostly governed by political risk factors rather than economic and natural developments. Significant correlations between Saudi Arabia and emerging market stress mostly have negative correlations and are clustered at the beginning and end of the analysis period, namely around 2007–2008 and 2022–2023. These two periods coincide with two important periods regarding oil prices. While in the first one, oil prices are in a steep upward trend just before the GFC, the second one corresponds to the plunge in oil prices that occurred after the Russian invasion of Ukraine. While the direction of oil prices in these two periods differs according to Wavelet Coherence analysis, in both cases, we observe negative correlations between EMFSI and Riyal. This observation implies that the relationship between Saudi Riyal and EMFSI is indirectly linked to the value of oil prices and its expectational impact on the Riyal. In the first period, we witness an appreciation in the value of the Riyal and consistently climbing oil prices. However, in the second period, we observe depreciation in the value of the Riyal and again a consistent plunge in oil prices. While these two movements are economically consistent, the exchange rates' negative relationship with EMFSI indicates that the main reason behind the sign of correlation might be the oil price developments.

When we examine the price developments of each variable, the respective periods demonstrate opposite directions between oil prices and EMFSI, not with the Riyal. Although UAE is one of the leading oil producers, its interactions with the EMFSI seem considerably weak compared to Saudi Arabia. Looking at the case of Türkiye, we observe that significant co-movements are clustered around 2006–2007 (pre-GFC), 2013, and 2015–2016. It is interesting, but at the same time consistent with our pre-arguments, that each of these dates is relevant to various political developments in Türkiye. For instance, the period of 2006–2007 marked significant developments in Türkiye's political landscape. In 2007, the country held both parliamentary and general elections, leading to heightened political tension during this time, which seems to have been reflected in market indicators. This is evident because immediately after these elections in 2008 and 2009, we do not observe a comparable level of correlation between the Turkish lira and emerging market stress, even though this period encompasses one of the most significant financial turbulences in the history of the world, the GFC. Similarly, we also note significant interactions between the variables in 2013, during which the country experienced another political event: the Gezi Park Demonstrations, a protest against the government. Similarly, during the 2016 coup attempt, we observe significant correlations, aligning with the findings of He et al. (2023) on the interaction between the Turkish stock market and

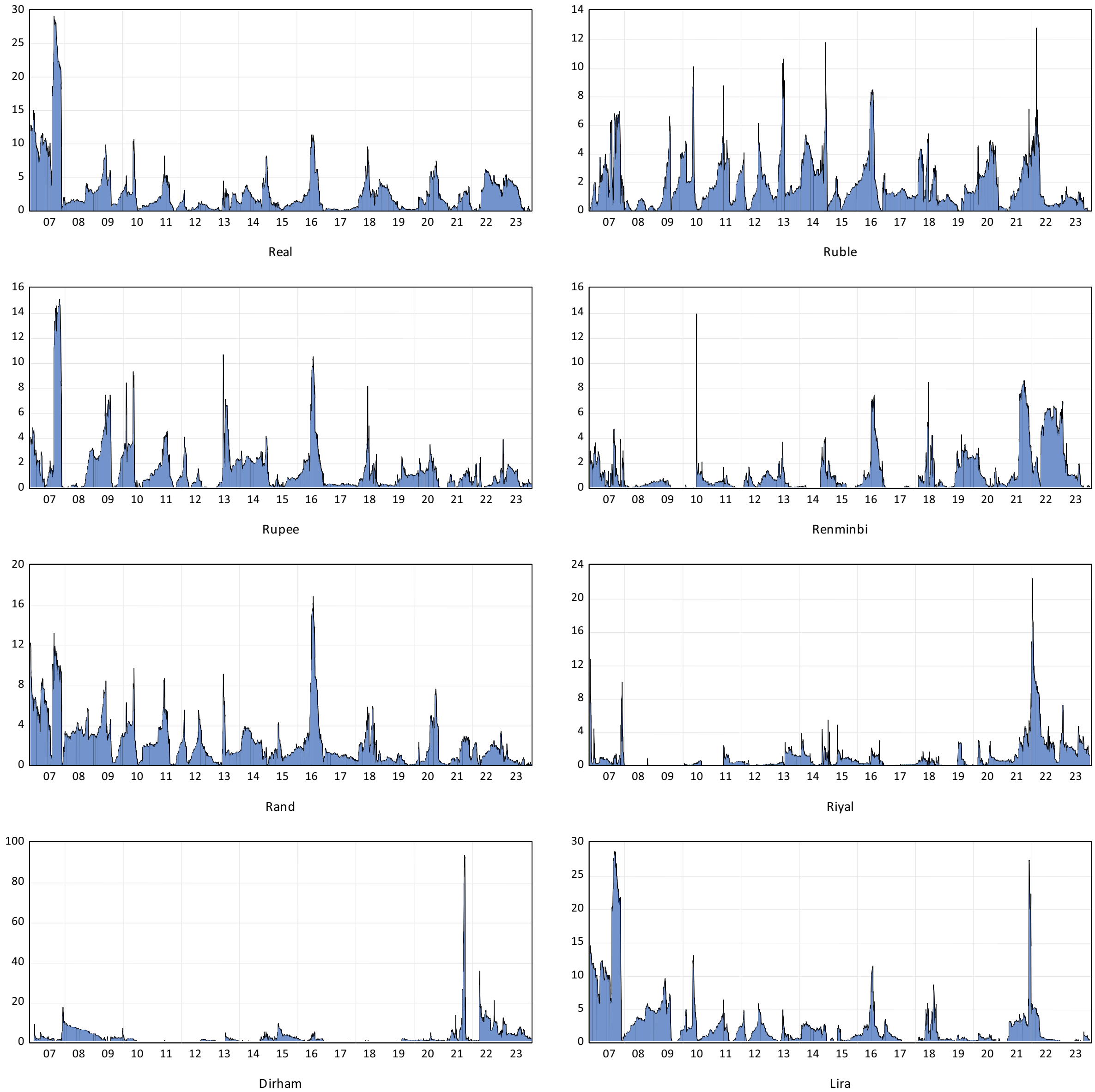


Fig. 5. Total spillovers transmitted from currency returns TO EMFSI index.
Note: The figure above indicates the total spillovers from all frequency bands TO EMFSI. Since the analysis is conducted on a pairwise basis—between each respective currency returns and the EMFSI—the values can also be interpreted as spillovers received from each currency's returns by the EMFSI. The optimal lag-lengths are determined as follows: 1 for Real (SIC), 1 for Ruble (SIC), 1 for Rupee (SIC), 1 for Renmibnbi (SIC), 1 for Rand (SIC,), 8 for Riyal (AIC and HQ,), 7 for Dirham (AIC, SIC, HQ), 1 for Lira (SIC).

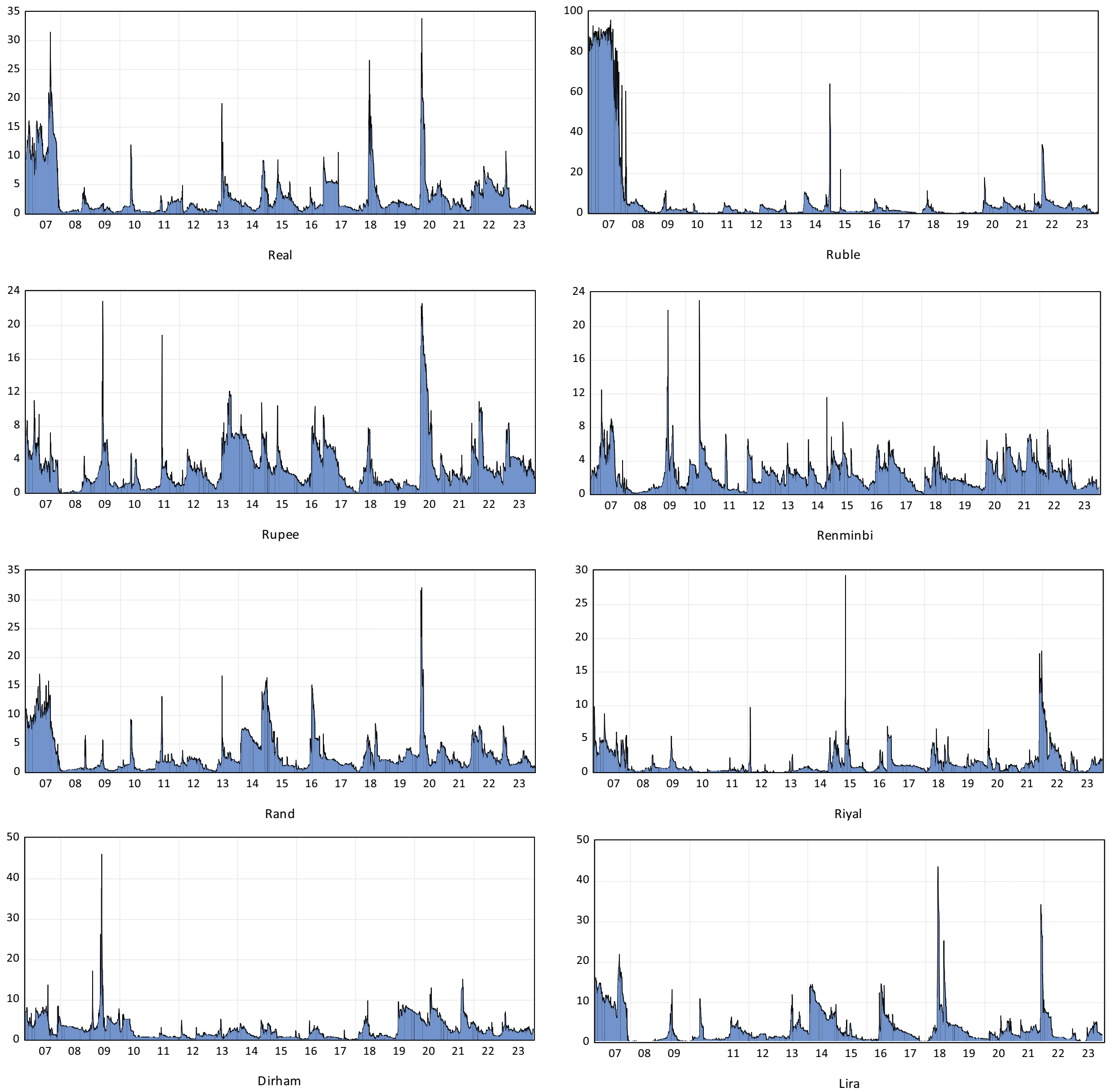


Fig. 6. Total spillovers transmitted from currency uncertainty TO EMFSI index.
Note: The figure above indicates the total spillovers from all frequency bands TO EMFSI Index. Since the analysis is conducted on a pairwise basis—between each respective currency uncertainty and the EMFSI—the values can also be interpreted as spillovers received from each currency's uncertainty by the EMFSI The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 8 for Ruble (AIC and HQ), 8 for Rupee (AIC and HQ), 8 for Renmibnbi (AIC and HQ), 7 for Rand (AIC and HQ), 4 for Riyal (SIC and HQ), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

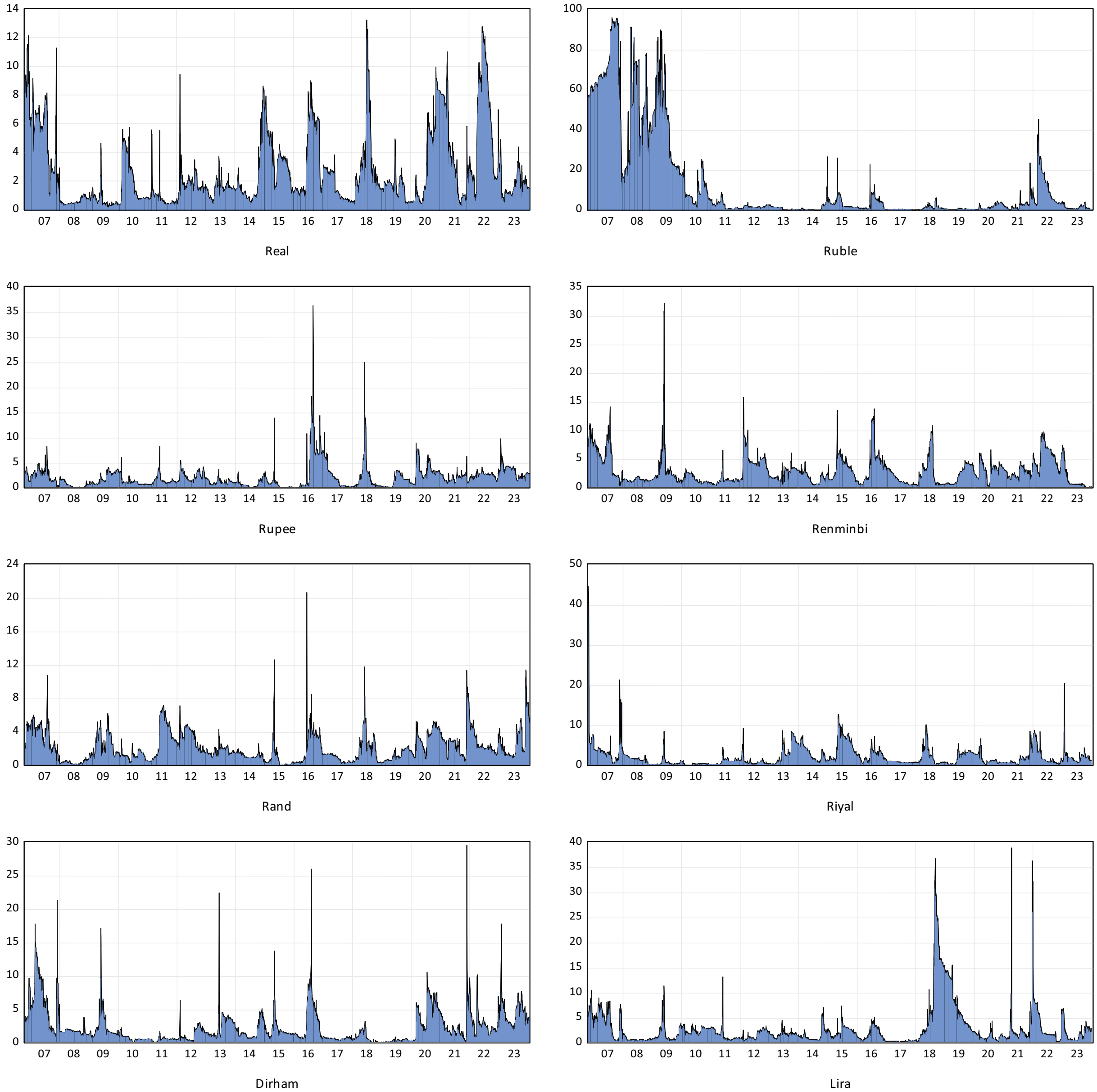


Fig. 7. Total spillovers transmitted from currency liquidity TO EMFSI index.
Note: The figure above indicates the total spillovers from all frequency bands TO EMFSI Index. Since the analysis is conducted on a pairwise basis—between each respective currency liquidity and the EMFSI—the values can also be interpreted as spillovers received from each currency's liquidity by the EMFSI The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renmibnbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

Table 3
Weights of short term investment horizon on total spillovers.

Components	Real	Ruble	Rupee	Renminbi	Rand	Riya	Dirham	Lira
Returns	0.9539	0.9477	0.9524	0.9510	0.9503	0.9691	0.9778	0.9522
Uncertainty	0.9013	0.8950	0.8851	0.8518	0.8831	0.7621	0.8849	0.8846
Liquidity	0.8780	0.9029	0.8735	0.8908	0.8629	0.8071	0.8667	0.8472

Note: The numbers in the table illustrate the weight of the 1–32 frequency band on the total spillovers transmitted from the respective currency variables—namely returns, uncertainty, or liquidity—to the EMFSI. For instance, the weight of the 1–32 frequency band on the total spillovers from the Brazilian Real to the EMFSI in the return component is 0.9539, indicating a strong association with a short-term horizon characterized by high-frequency changes. This means that 95.39% of the spillovers from currency market returns to the EMFSI are primarily driven by short-term price fluctuations resulting from daily market developments.

currency rates in 2016. Gunay (2016, 2019) also highlights the impact of political developments on Türkiye's credit risk. Unlike the previous events, this finding is observed in two different frequency bands: mid-term (two months) and long term (one and a half years). The last pattern that emerges in 2018–2019 is the beginning of the government's peculiar approach to monetary policy: managing inflation by lowering interest rates and conveying messages regarding the (in)dependence of the central bank.

In the second stage of the analysis, we investigate the decomposition of the relationship between foreign exchange rates and the EMFSI, aiming to investigate the potential impact of uncertainty (Fig. 3) and liquidity (Fig. 4) risk in this interaction. Results obtained for Real reveal that daily uncertainties play a crucial role in the emergence of co-movements between the Brazilian Real and EMFSI after the GFC. However, it is noteworthy that the uncertainty in the value of the Brazilian Real starts positively leading the EMFSI during 2015–2017. The developments in this period, such as the sharp decline of GDP, economic recession, and political risk factors like the Petrobras Scandal, one of the biggest political scandals in the history of Brazil, appear to be significant contributors to this result. Examining the source of significant positive correlations between the Ruble and EMFSI, it becomes apparent that neither daily uncertainties nor liquidity issues are elements in the co-movements stemming from the annexation of Crimea in 2014. This result may be attributed to the political risk perception of the markets, aligning with our previous arguments. Bilson et al. (2002) also find that return variations in the financial markets of emerging countries are significantly influenced by political events, while developed economies do not show such evidence. When exploring the sources of negative correlations between the Rupee and EMFSI through uncertainty and liquidity elements, it is observed that neither of them plays a significant role in the previous pattern of correlations. However, it is found that uncertainty in price developments had a positive correlation during the GFC, and EMFSI was leading this relationship. Similarly, a correlation is observed during 2010 on the scale of 64, where liquidity risk in the Rupee appears to lead the EMFSI. Concerning China, acknowledged globally as a manufacturing hub owing to its cost-effective workforce, efficient manufacturing capabilities, favorable population characteristics, and competitive currency policies (Giffi et al., 2016), the results indicate that uncertainty in the value of Renminbi was influenced by emerging market stress during the GFC for approximately three years, from 2008 to 2011, within the scale of 256. The impact of Renminbi on EMFSI is also witnessed in the early stages of the GFC in lower frequencies (64 days). Regarding Rand, it does not display significant co-movements with EMFSI over the years for uncertainties and liquidity risk, except for the period of 2010, in which it demonstrates negative correlations leading EMFSI. In contrast to the previous discussion about the Riyal, there is substantial resemblance between the patterns of correlations in return series and the patterns of correlations in uncertainty and liquidity components. Results indicate that both liquidity and uncertainties in daily price developments play a significant role in interactions with EMFSI. It appears that as a leading country in the energy market, developments stemming from the volatility and liquidity of the Riyal have a significant linkage with market tension. However, considering the previous argument in the return series, we still assert that this connection is highly associated with developments in the oil market. This observation underscores the significance and role of the energy market in influencing emerging market stress. In line with our argument for Saudi Arabia, results from the UAE also confirm this connection. While the extent of overlapping is relatively lower, the results for the Dirham show that both liquidity and uncertainty components align with the return series' results. Consequently, we deduce that the impact of energy markets on emerging market stress is conveyed through the local currencies. It is noteworthy that, despite not being an energy supplier country unlike Saudi Arabia and the UAE, both the uncertainty and liquidity models of the Turkish Lira exhibit similarities in the formation of correlation patterns with the return series models. In both components (uncertainty and liquidity), the warmer shades in the scologram figures align with the patterns of return series in both time and frequency domains. As we have concluded for all variables, political developments play a significantly impactful role in the relationship we are investigating. Thus, we infer that as an emerging market subject to a substantial extent of political uncertainties due to its geographical location and domestic instabilities, the liquidity and uncertainty of the Turkish Lira are significantly associated with emerging market stress.

At this stage of the study, to provide further evidence and enhance the robustness of our findings, we employ frequency connectedness analysis for the variable pairs analyzed earlier. While MODWT and Wavelet Coherence analyses allowed us to identify the comovements of pairs and the variables potentially driving these comovements, they do not provide insights into how one variable reacts to shocks in another. To address this gap—specifically, to uncover how shocks in the examined currencies influence emerging market stress and how these shocks evolve over time and across frequency bands—we apply the methodology of Baruník and Křehlík (2018) and Chatziantoniou et al. (2023) using a TVP-VAR model.

Since this method is based on a VAR model, we first determine the optimal lag lengths for the variable pairs using the AIC, SIC, and HQ information criteria. We adopt the majority rule: if two or more criteria suggest the same lag length, we use that lag; otherwise, following Lütkepohl (1985, 2005), we defer to the SIC's suggestion. The optimal lag lengths are reported alongside the figures presenting the analysis results. In line with our earlier analysis and the objectives of our study, we examine the spillovers transmitted from currency variables to the EMFSI, indicated by "TO" in the methodology. Since the spillover analysis is conducted using a bivariate VAR model—between each respective currency and the EMFSI—the values can also be interpreted as spillovers received by the EMFSI from each currency. To provide further insights, we also present the net directional spillovers and the Total Connectedness Index (TCI) in the Appendices C - H. The results in Figs. 5, 6 and 7 exhibit total spillovers across all frequency bands.

These findings align with the observations from the Wavelet Coherence analysis. For example, we do not observe substantial spillovers from the Brazilian Real to the EMFSI during the peak of the GFC in 2008. However, as seen in the Wavelet analysis, significant spillovers occur just before and after this major market downturn, from the Real to the EMFSI. According to Fig. 5, this pattern is also evident with the Ruble, Rupee, Renminbi, Riyal and Dirham, the only currency showing a growing spillover effect to the EMFSI during the GFC is the Turkish Lira.

These results prompt further investigation into other potential drivers of the spillovers, similar to the comovements revealed by the Wavelet Coherence analysis. When examining the potential threats posed by political risks, it becomes evident that they can also lead to spillovers across variable pairs. For instance, the initial allegations surrounding the Petrobras scandal in 2007 can be clearly observed in the impact of the Brazilian Real on the EMFSI, with a significantly greater effect in 2007 than in any other year, as shown in Figs. 6 and 7. Similarly, in the same figures, while spillovers from the Russian Ruble to the EMFSI remain consistently high throughout the analysis period, notable increases occur during major political risk events, such as the tensions between Russia and Georgia in 2007–2008, the annexation of Crimea in 2014, and the Ukraine war in 2022. As concluded earlier, given Russia's critical role as a global energy provider, fluctuations in the Ruble strongly influence the transmission of shocks to the EMFSI over the years.

Unlike in the Wavelet Coherence analysis, the Russia-Ukraine war also appears to have influenced the spillover effects of four other currencies on the EMFSI: the Renminbi, Riyal, Dirham, and Lira. For the first three currencies, this is likely tied to developments in the energy market, considering their economies' dependence on oil prices as consumers and exporters. Relatively less spillovers between the variables during the period of GFC might be accounted for by the origin of crisis. The GFC, by nature, is linked to complex financial instruments in the credit market, such as Credit Default Swaps (CDS) and Collateralized Debt Obligations (CDO), which are primarily associated with developed markets. The reduced spillover effects during 2008 may be related to this fact. At the same time, the slowdown in global economic activity during the GFC could be seen as a critical factor affecting the EMFSI and its interaction with emerging market currencies. However, the absence of notable spillovers in 2008 reinforces the key findings from both the Wavelet and spillover analyses, which highlight the strong impact of political events and their influence on the relationship between emerging market currencies and the EMFSI.

Our comprehensive analysis of the variables provides important insights in this regard. For example, while the stress transmission from the Russian Ruble to the EMFSI during the GFC is relatively low in terms of returns (Fig. 5), when we examine this through the lenses of uncertainty and liquidity (Figs. 6 and 7), it becomes clear that spillovers from the Ruble to the EMFSI reach historic highs and remain highly persistent. Notably, this period also coincides with the growing political tension between Russia and Georgia over South Ossetia and Abkhazia, which culminated in the Russo-Georgian War in 2008. Thus, we conclude that analyzing currency returns alone may be insufficient to fully capture the potential interactions between variables. The liquidity and uncertainty components must also be considered to uncover effects that operate within deeper dynamics.

To highlight the primary frequency band driving the total spillovers, we present in Table 3 the weights corresponding to the short-term investment horizon. According to the results, the evidence derived from the high-frequency components (frequency band of 1–32), aligns with the nature of spillover analysis and findings from Mensi et al. (2023) and Kang et al. (2021). On the other hand, it is worth remembering that the co-movements observed in previous analyses (Table 2 and Figs. 2, 3, 4) intensified at medium- to long-term frequencies. This suggests that, unlike the correlations between emerging market currency behaviors and EMFSI, the spillovers primarily occur in short-term market developments. Therefore, we can conclude that long-term correlations may be driven by the short-term interactions shaped and influenced by spillovers. Monitoring short-term spillover effects could provide significant predictive insights regarding the long-term associations between the variable pairs investigated in this study. Using technical analysis tools, Pojarliev (2005) shows that strategies following long-term trends in the currency markets of emerging economies can yield better performance. This highlights the importance of tracking long-term co-movements in the currency markets of these countries.

5. Discussion

The findings of this study reveal that political risk plays a crucial role in the interactions between currency markets and the financial stress levels of emerging markets. The results confirm this observation through the analysis of exchange rate price components—returns, uncertainty, and liquidity—and their association with various investment horizons related to different frequency bands, namely short- and long-term price movements. We obtained this evidence through correlation and spillover analyses. Both Wavelet Coherence and TVP-VAR connectedness analyses demonstrated significant interactions between these two variables during such events. These findings align with the definition of emerging markets. As noted in the seminal study by Hoskisson et al. (2000), political shocks are a significant factor for emerging economies and can increase uncertainty for both domestic and foreign stakeholders, in addition to economic developments. Therefore, we conclude that it is essential to prioritize political stability alongside economic stability. This can also be observed in the findings of Mei and Guo (2004). The authors report that eight out of nine economic crises in 22 emerging countries occurred during periods of political tension. This underscores the importance of political risk in emerging economies, which our results also support. Based on our findings, we suggest the need for close monitoring of political developments to hedge against currency risk linked to market stress. This also necessitates the tracking of political tensions through indicators in these countries, although high-frequency data for such indices may not be available. However, as suggested by the findings of this work, the EMFSI can serve as a useful tool for monitoring market tension, even if it cannot be decomposed at the country level. In addition to the importance of the political risk factor, it is worth mentioning that investment horizons exhibit different characteristics under various examinations. For instance, while relatively lower frequencies demonstrate significant correlation-based relationships (as observed in Wavelet Coherence), we find that higher frequencies associated with short-term price movements play a critical role in the transmission of market stress, as suggested by the TVP-VAR connectedness analysis. This finding suggests that different elements should be monitored in these markets. For example, short-term investors may consider hedging strategies linked to the network obtained from spillover analyses, while long-term investors may focus on co-movements that emerge primarily in medium- to long-term frequency bands. This approach would facilitate better protection and more efficient management of invested funds.

6. Conclusion

6.1. Empirical findings

In this study, we explore the relationship between the foreign exchange rates of eight emerging countries (Brazilian Real, Russian Ruble, Indian Rupee, Chinese Renminbi, South African Rand, Saudi Riyal, United Arab Emirates Dirham, Turkish Lira) and the Emerging Market Financial Stress Index (EMFSI). The analysis covers the period from January 4, 2006, to January 5, 2024.

To account for the impact of investment horizon, our analysis incorporates various frequency bands. As a preliminary step, we employ the MODWT technique to implement a scale-based multiresolution. Using the MODWT-generated time series, we conduct a correlation analysis between the returns of currency variables and EMFSI. Results indicate that the number of significant correlation coefficients increases with the scales utilized. Although only four significant correlations are observed at the scale of 16, reaching the scale of 1024 shows that all pairs in the analysis exhibit significant coefficients. This finding suggests that market interactions may vary based on the investment horizon, specifically within different frequency bands. Considering this information, we proceed to the Wavelet Coherence analysis. To provide additional evidence, we incorporate uncertainty and liquidity indicators from the currency market, utilizing high-low and bid-ask spreads, respectively. Results suggest that the interactions between EMFSI and currency market returns are predominantly influenced by political events rather than domestic, regional, or global economic developments. For instance, when focusing on two major events over the last two decades that disrupted global economic stability—the GFC and the COVID-19 pandemic—we observe mainly insignificant correlations during these economic upheavals. However, delving into market developments linked to political events reveals an augmentation in the extent of co-movements between EMFSI and exchange rates. Significant correlations are notably observed during specific political events. The results of the wavelet analysis further confirm that associations between the variables strengthen with increasing scales, particularly intensifying within the frequency band of 64–128, which corresponds to a medium- to long-term investment horizon. To provide new insights and elaborate on our arguments, we employed the TVP-VAR frequency connectedness analysis. This methodology confirms that spillovers from currency returns, liquidity, and uncertainty to the EMFSI are primarily linked to political and energy market developments in these economies, including the Russia-Ukraine war, the Petrobras scandal, the India-Pakistan conflict, the trade war between China and the U.S., and civil demonstrations. However, in contrast to the observed co-movements of the variables, this analysis indicates that spillovers from currency variables to the EMFSI are predominantly driven by higher frequencies, which are associated with short-term price fluctuations. Thus, it can be stated that short-term spillovers may govern long-term correlations, thereby offering predictive power in the currency market.

6.2. Policy implications

The results of this study suggest three important directions for stakeholders in financial markets, including investors, regulators, and the public. As emerging economies play a vital role in global economic activity and seek to increase their influence, their relatively fragile economic structures, financial instability, inflationary pressures, and vulnerability to external shocks necessitate close monitoring of investment portfolios, effective market regulation to mitigate risks, and meticulous financial management by households.

Our findings indicate that emerging market financial stress is significantly associated with fluctuations in the currency values of these economies. We evaluate our findings through two frameworks: a time-varying perspective to reveal the influence of key market developments and an analysis of frequency bands to uncover the impact of different investment horizons. Regardless of the components of currency value—returns, liquidity, and uncertainty—financial stress in emerging markets is heavily linked to political developments. For example, the most pronounced correlations between the Russian Ruble and EMFSI occur during the annexation of Crimea in 2014. Similarly, substantial co-movements between the Indian Rupee and EMFSI becomes apparent during the period of 2018–2019, coinciding with the India and Pakistan conflict. In the case of China, significant co-movements between the Chinese Renminbi and EMFSI are observed not during the pandemic period but rather during the trade war and tariff disputes with the US around 2018. Likewise, interactions between the Turkish Lira and EMFSI become more apparent and significant during specific political events, including presidential and parliamentary elections in 2007, the 2013 Gezi Park protests, the 2016 coup attempt, and 2018—an impactful year marked by discourses about economic policy that deviated from the general acceptance imposed by the government. In contrast to other currencies, the relationship between the Riyal and Dirham with EMFSI seems more associated with periods of oil price shocks, aligning with our theoretical expectations. These findings suggest that investors seeking relatively higher returns in emerging economies may need to adjust their required rates of return according to the levels of political risk. This adjustment would lead to more accurate and realistic Net Present Value calculations in capital budgeting. Additionally, identifying assets closely associated with political risk factors and diversifying portfolios in line with these findings may offer more stable yields on investments. It is also evident that, due to the nature of data used to measure political risks, such indices are primarily constructed using low-frequency data. However, our results indicate that these indices may be insufficient to capture the evolving dynamics of currency markets. Therefore, introducing indices that reflect the changing nature of political risk could provide better and more timely signals for both investors and the public. Furthermore, since currency markets are utilized as investment instruments in emerging economies by households, especially given the inflationary pressures on domestic currencies, providing early warning indicators may enhance public financial management. For instance, during the period of the Turkish central bank's unconventional monetary strategy, which involved managing inflation by lowering interest rates—a political decision—average citizens suffered the side effects of these political choices.

The second significant finding from our investigation pertains to the role of the investment horizon across different frequency bands. Our results indicate that the investment horizon displays distinct characteristics in wavelet and spillover analyses, aligning with our theoretical expectations. For example, we observe that the co-movements between emerging market financial stress and currency value components (returns, uncertainty, and liquidity) manifest in long-term fluctuations, influenced by political risk factors and developments in the energy market. This suggests that, in the long run, movements in the currency market and emerging market stress are closely linked. However, as revealed by the spillover analysis, the transmission of shocks related to returns, uncertainty, and liquidity to emerging market stress primarily occurs over short time periods. This indicates that the mechanism through which disseminated information in the market affects currency values first induces stress transmission to emerging market financial stress in the short run, which then leads to significant co-movements in the long run. From this, we can conclude that political risks emerging in developing economies have implications that extend beyond short-term market concerns. The consequences are not only immediate stress transmissions but also create lasting effects over time. This finding underscores the threat posed by political risk factors and their influence in both the short and long run. To mitigate the adverse effects of short-term spillovers that ultimately result in long-term co-movements between currency values and market stress, we recommend prioritizing comprehensive regulations in emerging markets that focus on political risk management along with implementing economic strategies. It appears that the effectiveness of economic policies might be insufficient if political risks are overlooked or underestimated.

6.3. Limitations and future research directions

Although this study aims to conduct a comprehensive analysis of currency market-based parameters associated with financial stress—focusing on returns, uncertainty, liquidity, and investment horizon—the evidence obtained solely from emerging economies may not be sufficient to develop portfolio management strategies from a broader perspective. Examining similar parameters in developed markets could provide more general insights into the characteristics of emerging economies. Additionally, our findings indicate that the association between the EMFSI and currency rates primarily occurs during political risk events. The lack of a high-frequency index for political risk in the countries examined prevents us from comparing our arguments with relevant data points. Therefore, the future availability of country-specific high-frequency political risk indices may offer an opportunity to compare empirical research findings with market-based data. Future research could also extend this analysis to other markets, such as equity, credit, and fixed income, allowing policymakers to gain deeper insight into developing appropriate measures.

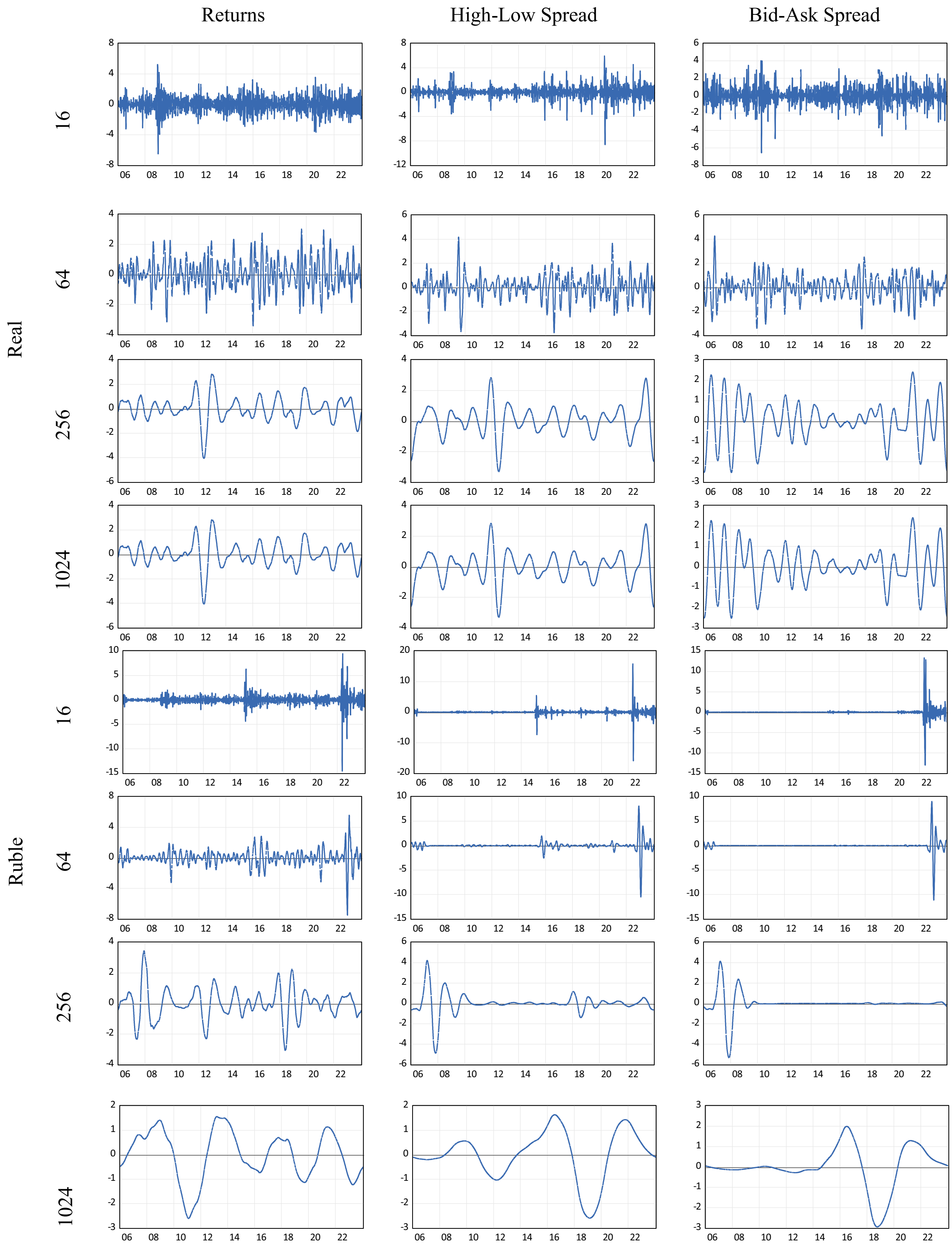
Authorship information

Samet Gunay: Study of conception and design, data curation, empirical analysis and interpretation of results, writing original manuscript and revision **Barbara Dömötör:** Introduction, Literature Review, writing original manuscript and revision **Attila András Víg** Literature Review, Methodology, writing original manuscript and revision.

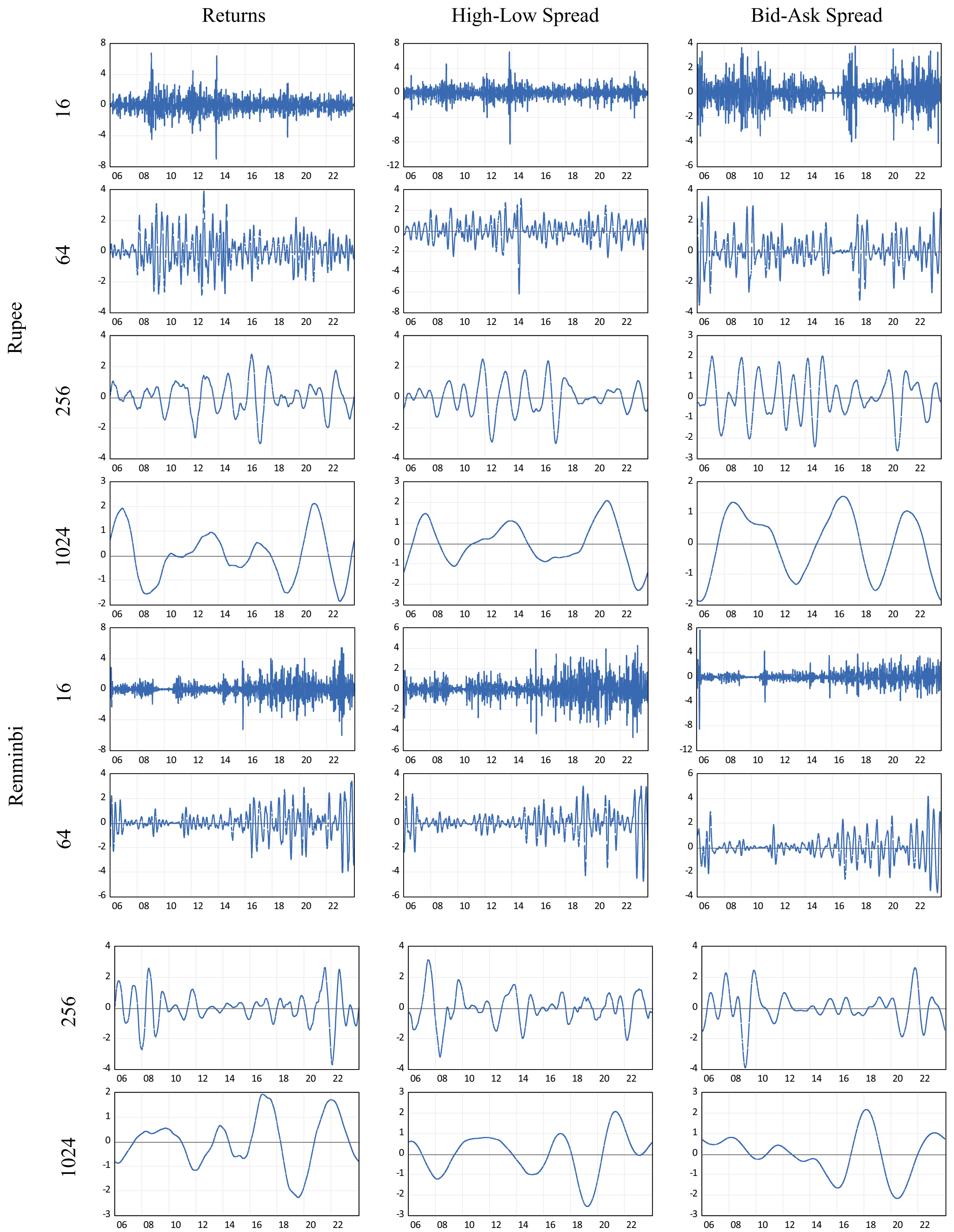
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

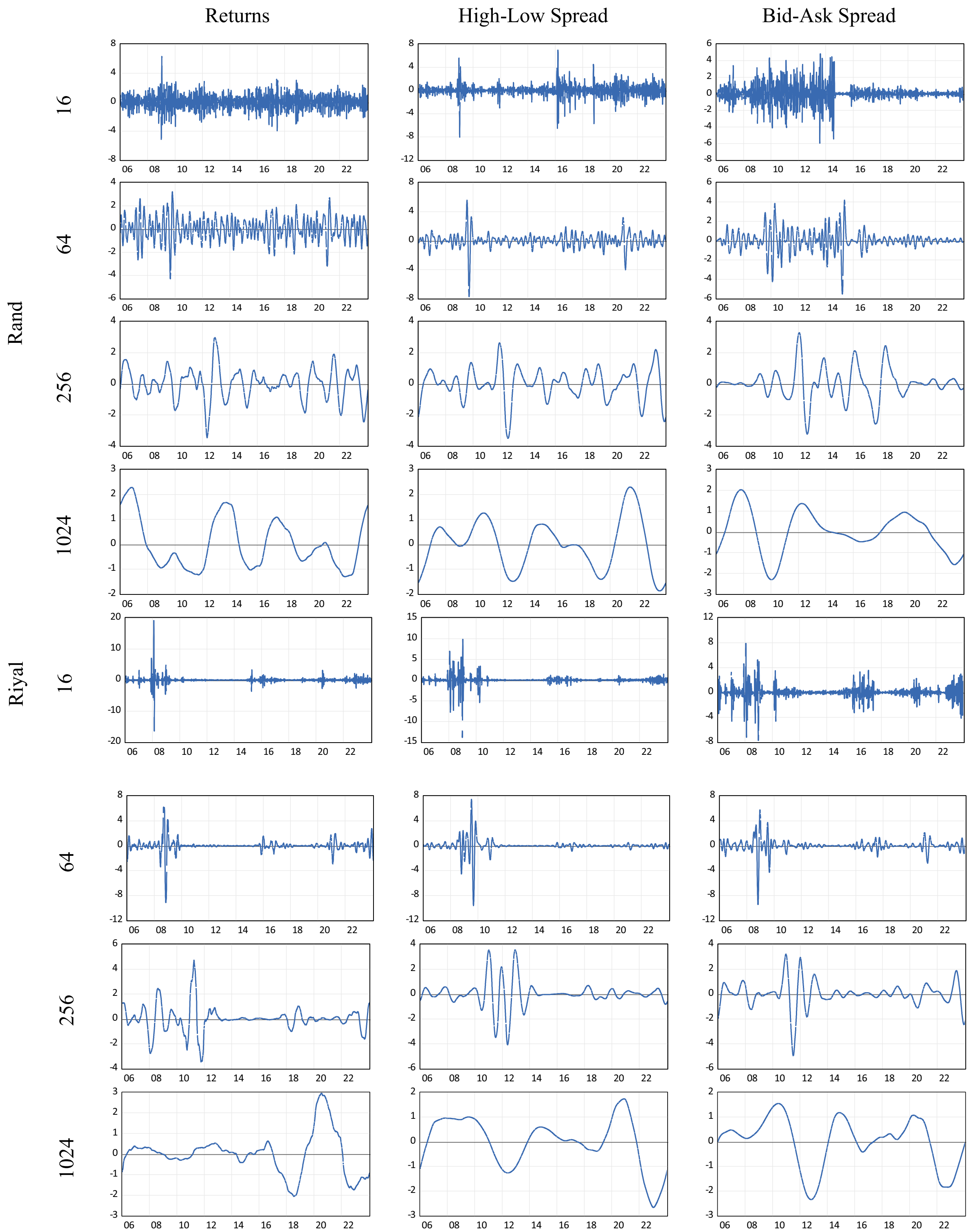
Appendix A. Scale-based Multiresolution of FX-Variables



Scale-based Multiresolution of FX-Variables

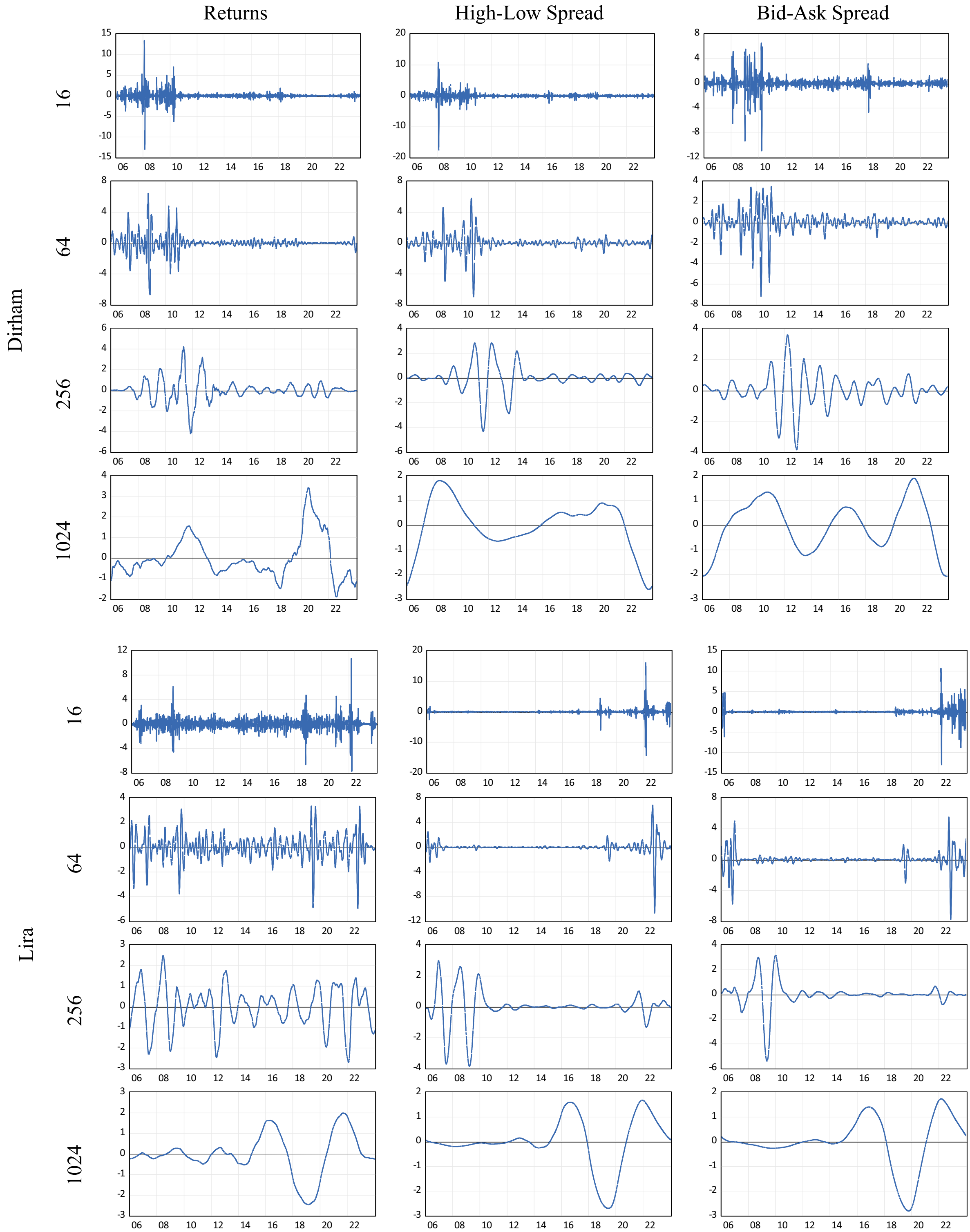

Returns
High-Low Spread
Bid-Ask Spread
Rupee
Renminbi
16
64
256
1024
06 08 10 12 14 16 18 20 22

. (*continued*).



Returns
High-Low Spread
Bid-Ask Spread
Rand
Riyal
16
64
256
1024
06 08 10 12 14 16 18 20 22

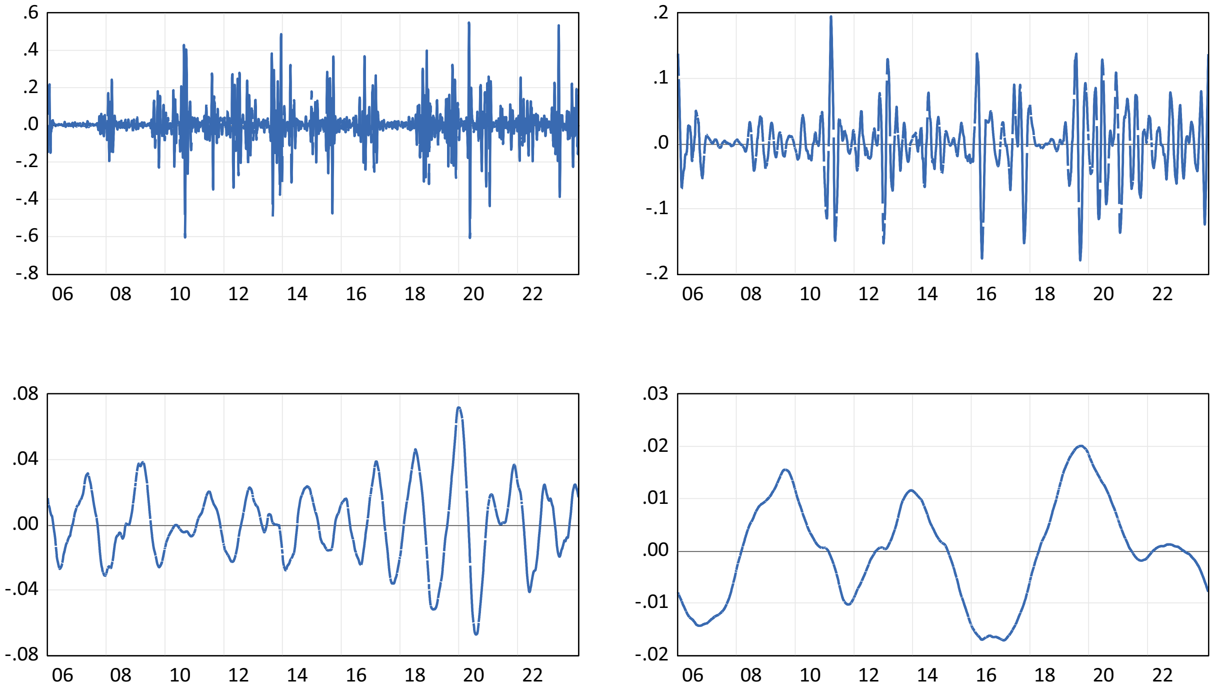
. (*continued*).


Returns
High-Low Spread
Bid-Ask Spread
Dirham
Lira
16
64
256
1024

. (*continued*).

Note: The figures depict time-varying wavelet coefficients at different scales (16, 64, 256, 1024). The vertical axis represents the scales used, while the horizontal axis illustrates the timeline. For comparative analysis, each plot's left axis is scaled with normalized data.

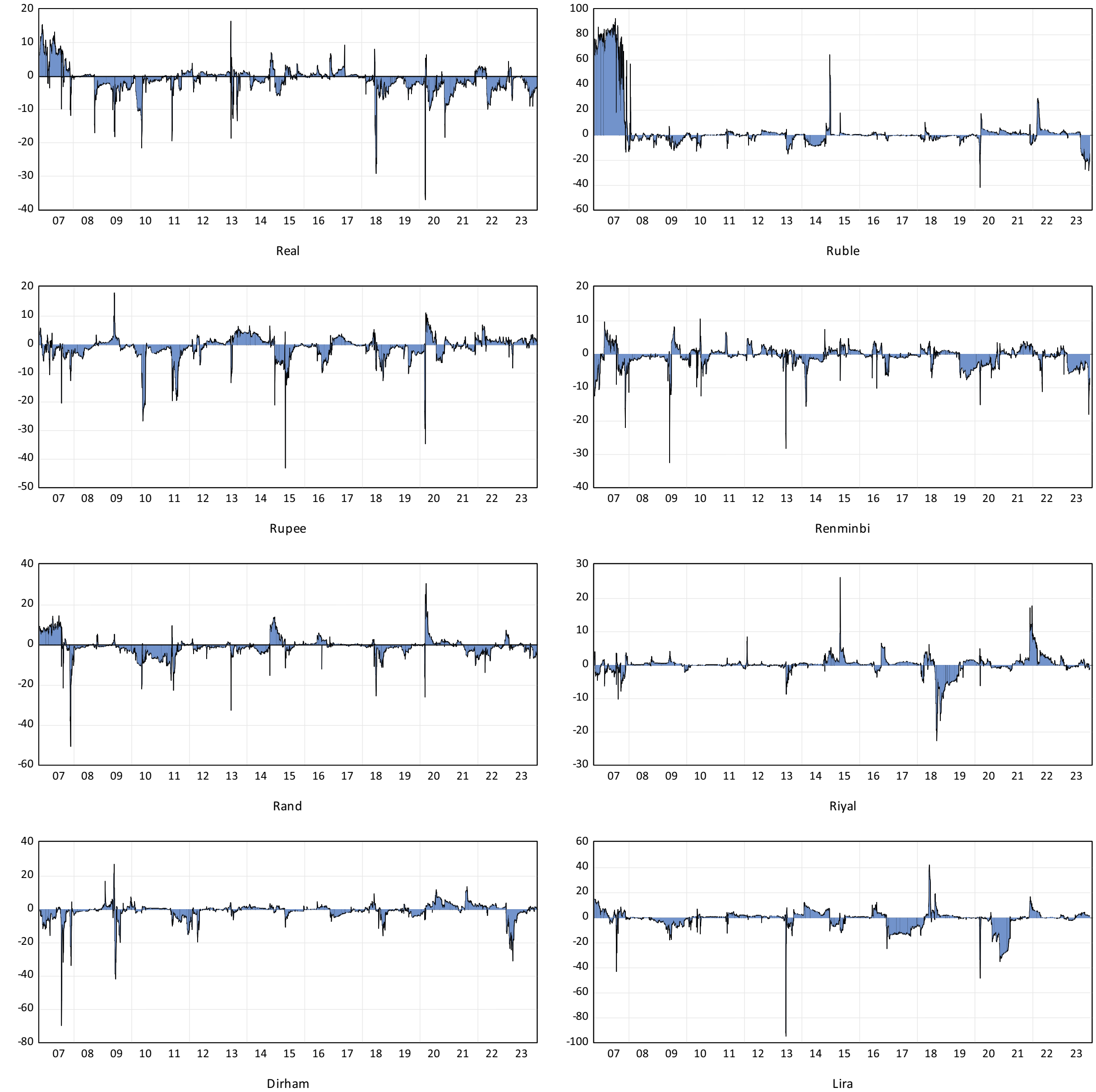
Appendix B. Scale-based Multiresolution of EMFSI



Scale-based Multiresolution of EMFSI

Note: The respective scales, from the top-left to the top-right corner, are 4, 16, 256, and 1024.

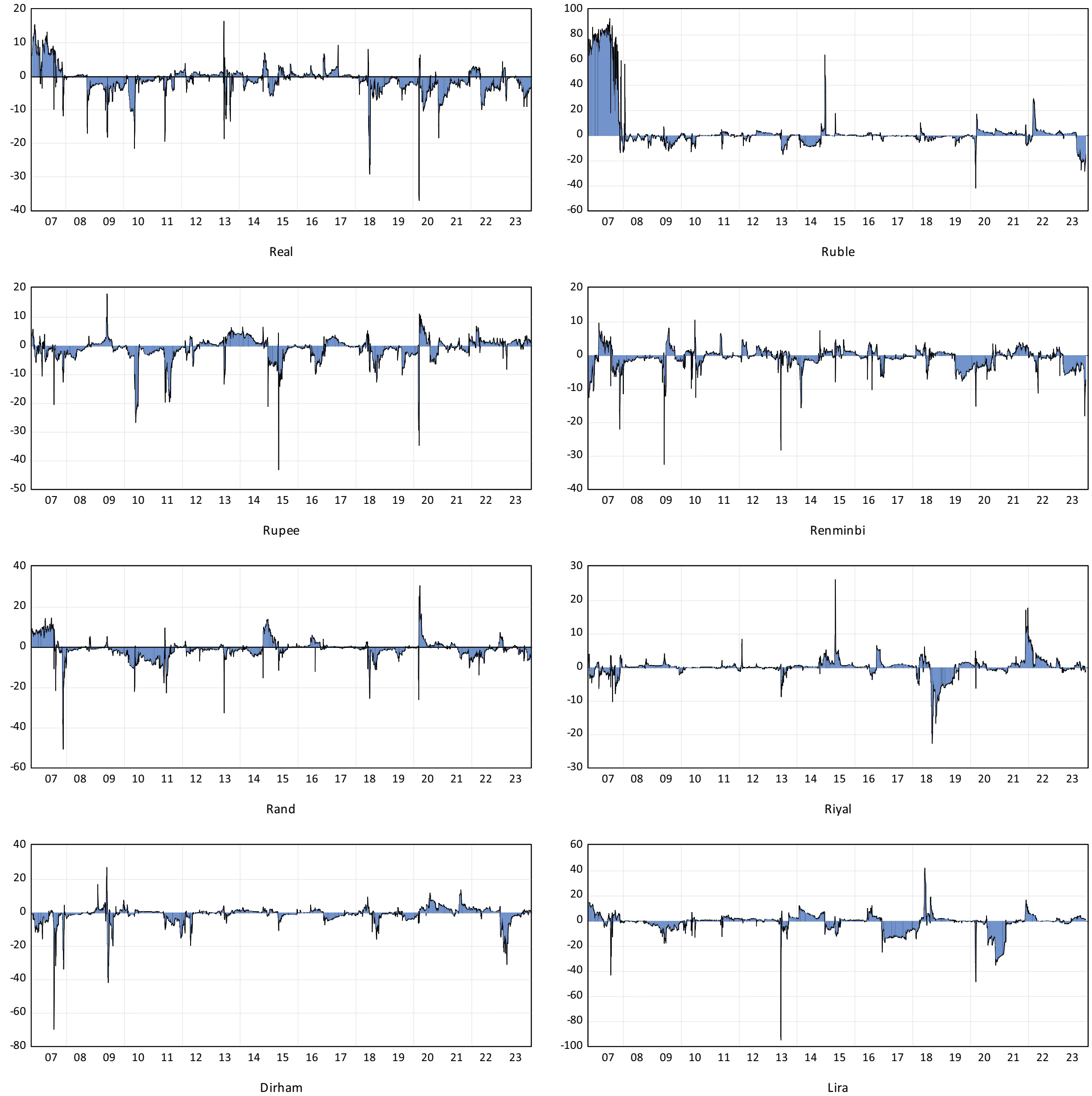
Appendix C. Net directional spillovers of currency returns and EMFSI



Net directional spillovers of currency returns and EMFSI

Note: The values above the zero line indicate that the returns of the currencies act as net transmitters of spillovers across the total frequency bands to EMFSI. Likewise, the values below the zero line indicate that EMFSI is the net transmitter of spillovers to currencies. The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renminbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

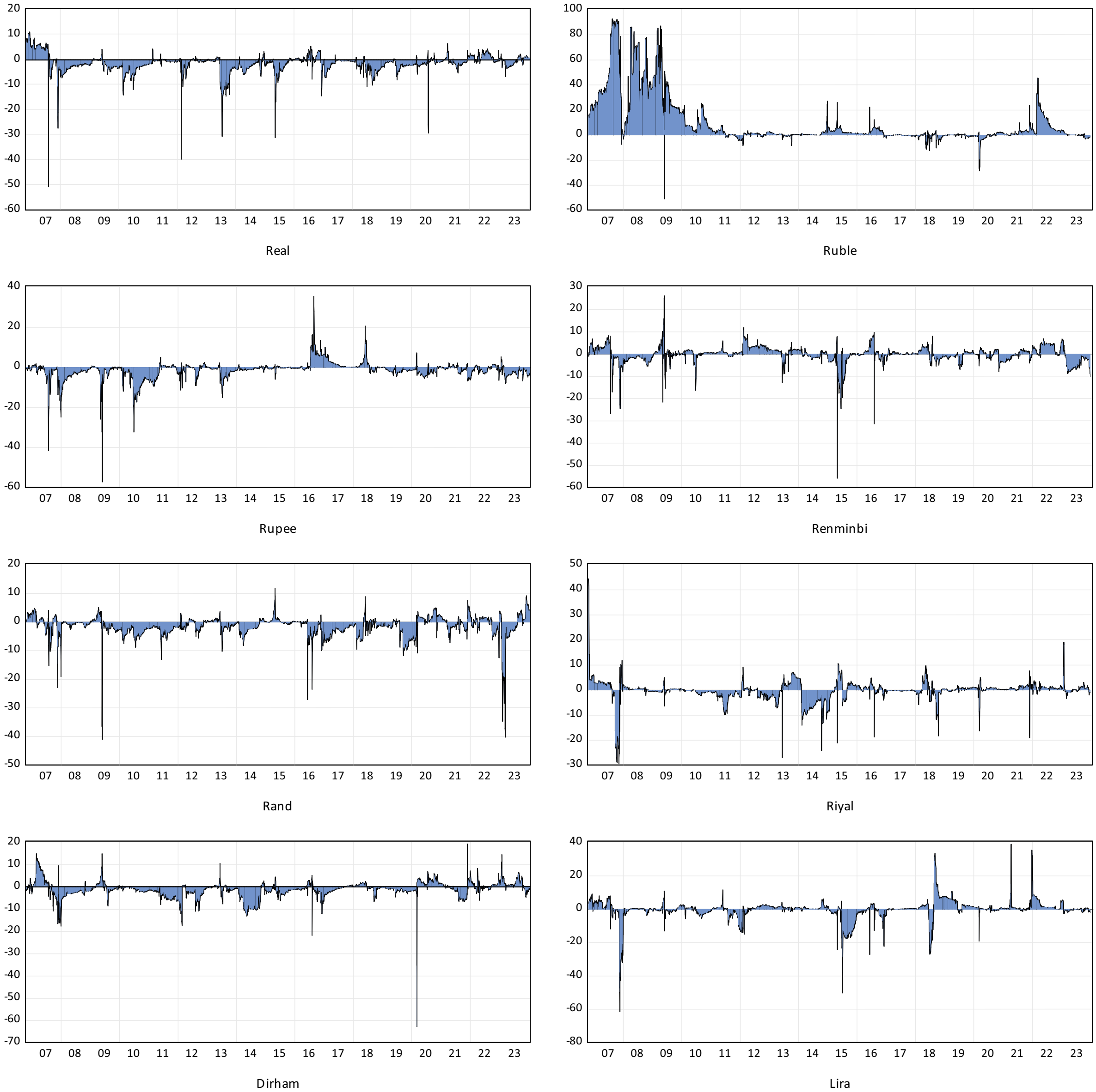
Appendix D. Net directional spillovers of currency liquidity and EMFSI



Net directional spillovers of currency liquidity and EMFSI

Note: The values above the zero line indicate that the liquidity of the currencies act as net transmitters of spillovers across the total frequency bands to EMFSI. Likewise, the values below the zero line indicate that EMFSI is the net transmitter of spillovers to currencies' liquidity. The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renminbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

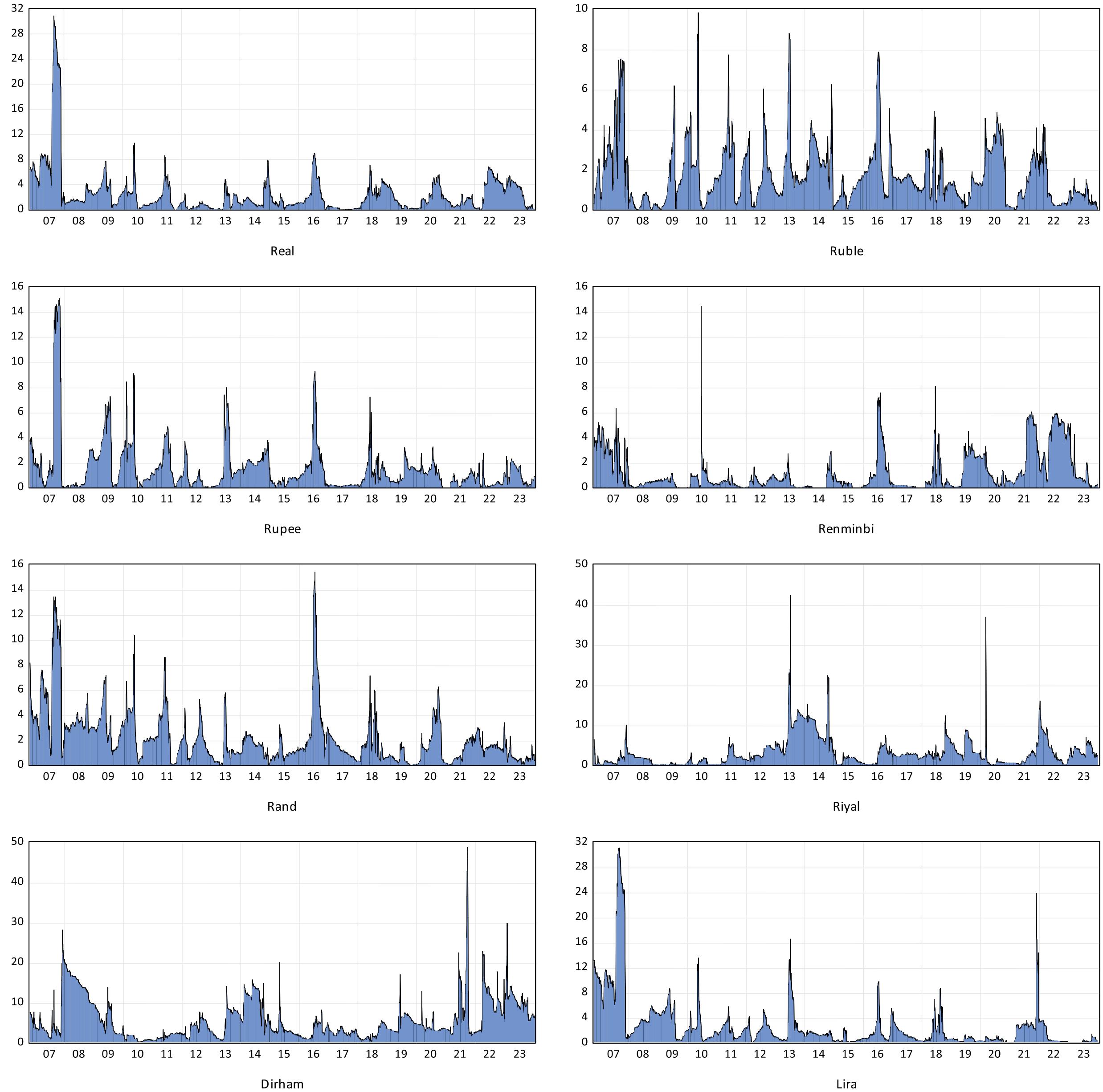
Appendix E. Net directional spillovers of currency uncertainty and EMFSI



Net directional spillovers of currency uncertainty and EMFSI

Note: The values above the zero line indicate that the uncertainty of the currencies act as net transmitters of spillovers across the total frequency bands to EMFSI. Likewise, the values below the zero line indicate that EMFSI is the net transmitter of spillovers to currencies' uncertainty. The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renminbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

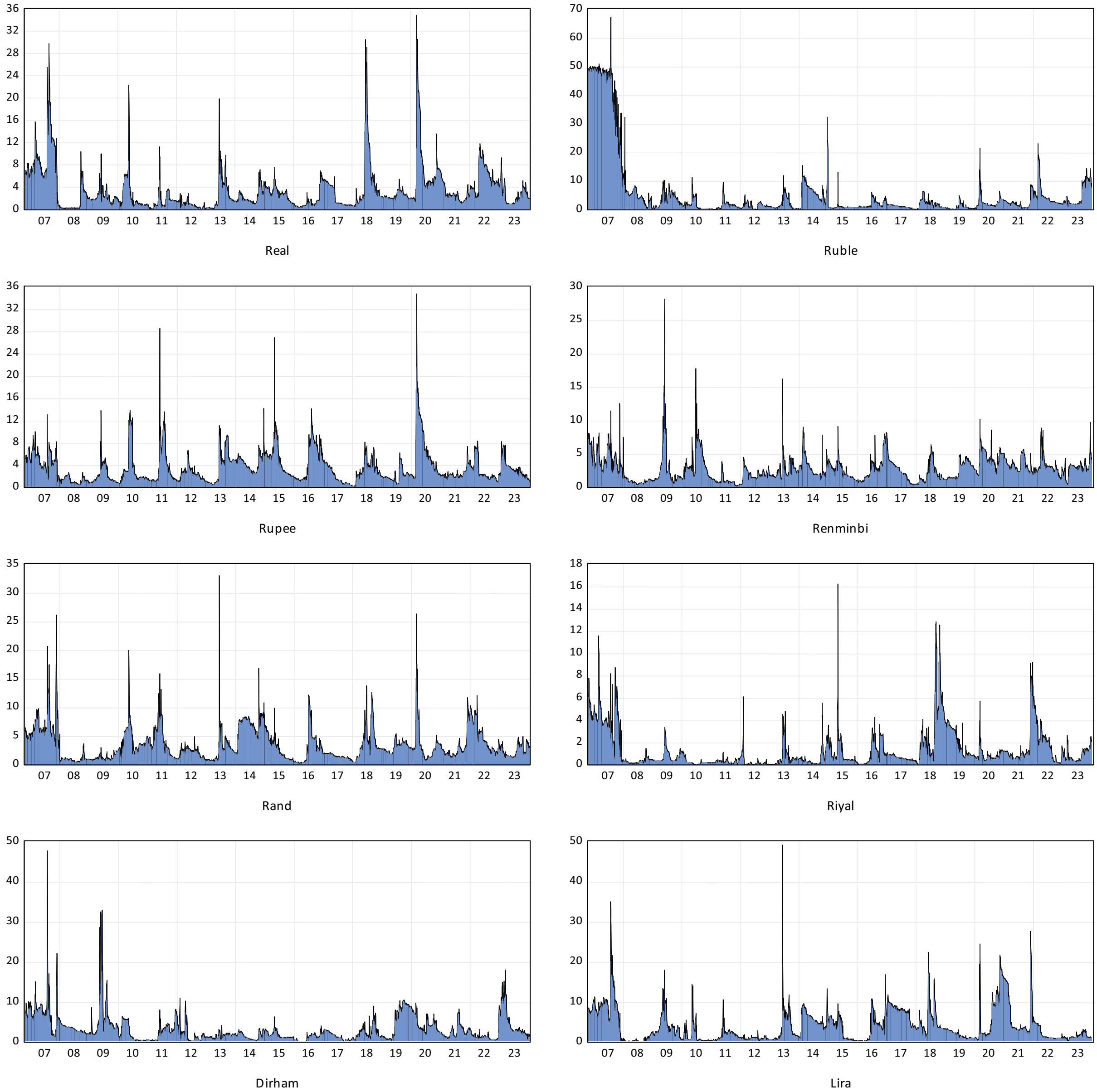
Appendix F. Total connectedness index (TCI) of currency returns and EMFSI



Total connectedness index (TCI) of currency returns and EMFSI

Note: The values indicate the degree of interconnectedness between the currency returns and EMFSI, capturing the extent of shock transmission between them. A higher value suggests greater spillovers, reflecting stronger linkages and potential financial stress within each pair over time. The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renminbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

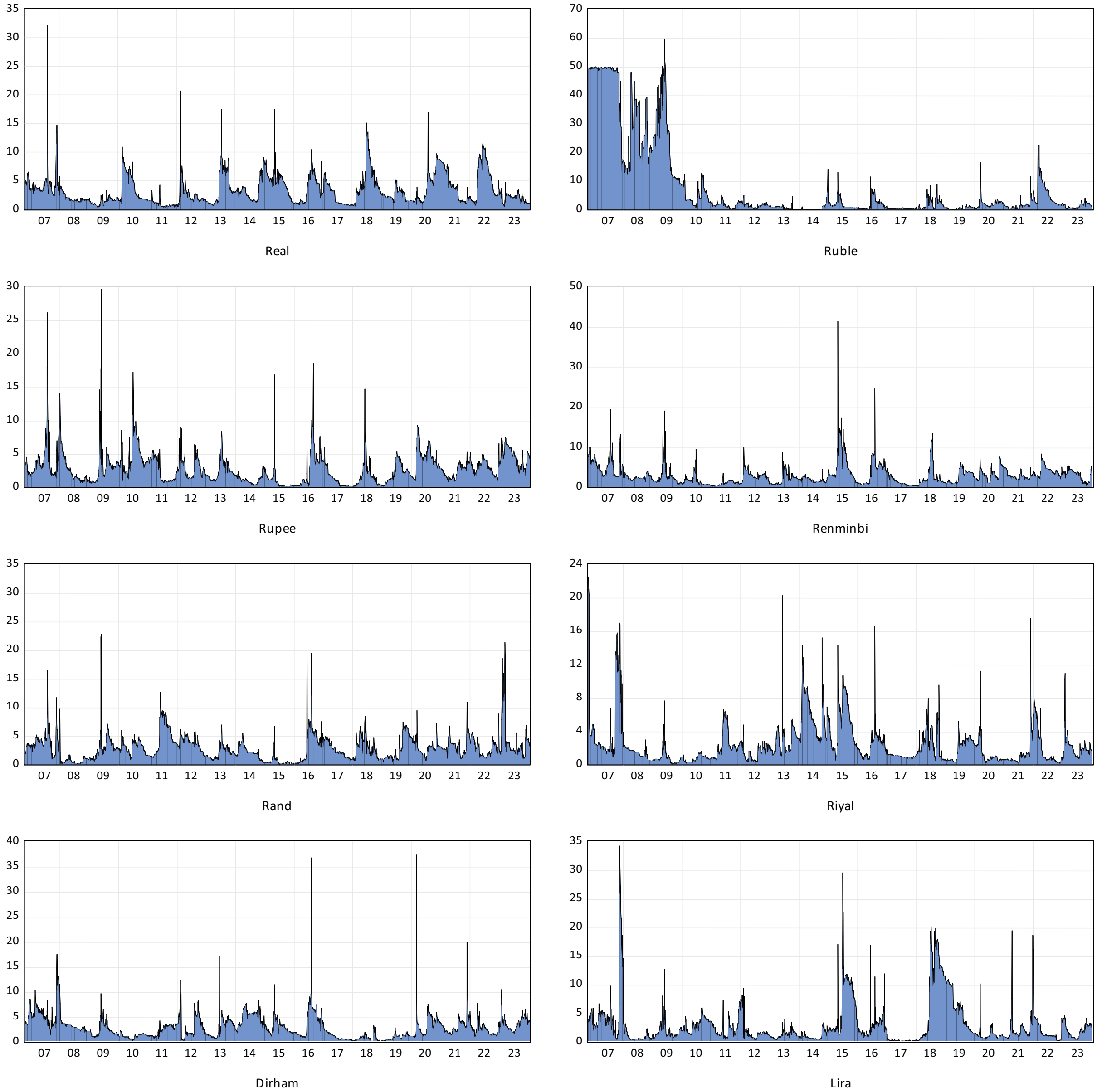
Appendix G. Total connectedness index (TCI) of currency liquidity and EMFSI



Total connectedness index (TCI) of currency liquidity and EMFSI

Note: The values indicate the degree of interconnectedness between the currency liquidity and EMFSI, capturing the extent of shock transmission between them. A higher value suggests greater spillovers, reflecting stronger linkages and potential financial stress within each pair over time. The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renminbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

Appendix H. Total connectedness index (TCI) of currency uncertainty and EMFSI



Total connectedness index (TCI) of currency uncertainty and EMFSI

Note: The values indicate the degree of interconnectedness between the currency uncertainty and EMFSI, capturing the extent of shock transmission between them. A higher value suggests greater spillovers, reflecting stronger linkages and potential financial stress within each pair over time. The optimal lag-lengths are determined as follows: 8 for Real (AIC and HQ), 5 for Ruble (SIC and HQ), 8 for Rupee (AIC, SIC and HQ), 8 for Renminbi (AIC and HQ), 8 for Rand (AIC, SIC and HQ), 6 for Riyal (SIC), 8 for Dirham (AIC and HQ), 8 for Lira (AIC and HQ).

Appendix I. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ememar.2025.101262.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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