Dynamic Insights into RMB Exchange Rate Risk Spillover and Its Determinants: A QVAR and Deep Learning Approach

Abstract

This study investigates RMB exchange rate risk spillovers and their underlying drivers across major currencies, highlighting time-frequency dynamics and structural asymmetries under different market regimes. First, we employ a quantile VAR model to evaluate the magnitude and direction of spillovers using return and volatility data under varying market conditions. The results reveal that RMB exchange rate risk spillovers rise sharply under extreme conditions, forming a U-shaped pattern across quantiles and highlighting sensitivity to tail risks. Return spillovers are short-term, while volatility spillovers are typically long-term but shift toward the short term during market turmoil. Return and volatility spillovers show clear heterogeneity under tail risks: returns remain balanced, while volatilities are strongly right-skewed. Moreover, we introduce a deep learning approach to explore the nonlinear, time-varying drivers of RMB exchange rate spillovers, with the Time Series Fusion Transformer (TFT) model outperforming traditional methods through effective variable selection and dynamic modeling in high-dimensional, non-stationary environments. The results reveal pronounced dynamic heterogeneity and structural breaks in RMB exchange rate spillovers, with key driving factors varying across market regimes—reflecting intricate risk transmission channels and adaptive market responses. The results offer actionable insights for risk management and policy design in exchange rate markets.

Keywords: RMB exchange rate; Quantile spillover; Deep learning; Driving factors; Asymmetry

1. Introduction

As a typical complex dynamic system, the degree of openness in the foreign exchange market plays a crucial role in enabling the free flow of global capital and improving resource allocation efficiency. Since the financial liberalization wave in the 1980s, many developing countries have actively reformed exchange rate regimes, increased exchange rate marketization, and gradually relaxed capital account controls, fostering a highly integrated global financial market. According to data from the Bank for International Settlements (BIS), as of April 2022, the global foreign exchange market recorded an average daily trading volume exceeding USD 7.5 trillion, approximately 30 times the global average daily GDP. This figure far surpasses the trading volumes of global stock and bond markets, reaffirming the foreign exchange market's dominance as the largest and most active financial market worldwide. Amid ongoing global trade liberalization and investment facilitation, China's integration with the international foreign exchange market has steadily deepened. Notably, the inclusion of the RMB in the IMF's Special Drawing Rights (SDR) basket in 2016 marked a significant milestone in aligning China's economy with the global financial system. This development not only substantially enhanced the RMB's status in the international monetary framework but also accelerated its internationalization process. The advancement of RMB internationalization not only strengthens China's economic integration with the world but also significantly contributes to the diversification and stability of the global financial system.

The accelerating transformation of the international economic and political landscape, coupled with deeper economic and financial integration, has elevated the foreign exchange market into a crucial channel for cross-border exchange rate risk transmission. While enhancing resource allocation and information flow, the market has become increasingly susceptible to systemic shocks. Growing currency interdependence raises the likelihood that local exchange rate fluctuations trigger "resonance" effects, amplifying risk spillovers and potentially escalating into systemic financial crises. This vulnerability is particularly pronounced amid heightened global uncertainties, such as U.S.-China trade tensions, the United Kingdom's withdrawal from the European Union, and the Russia-Ukraine conflict, which have significantly increased volatility and contagion risks in the global foreign exchange market. For China, this situation poses a dual challenge. On one side, the country must urgently strengthen its capacity to detect and manage externally induced financial shocks to prevent systemic risks (Song and Xiong, 2018). On the other, promoting RMB internationalization and achieving high-quality economic growth require enhanced exchange rate stability, emphasizing the need for an orderly foreign exchange market and a balanced exchange rate (Cui et al., 2024; He et al., 2024). Therefore, systematically investigating the structural features and dynamic evolution of risk spillovers in the RMB foreign exchange market, along with their transmission mechanisms, holds significant practical and strategic value.

Despite the rapid internationalization of the renminbi and the growing influence of its exchange rate fluctuations on global financial markets, academic research in this area remains relatively underdeveloped, with notable limitations in both scope and depth. On the one hand, much of the existing literature concentrates on a single bilateral exchange rate, such as the RMB-USD pair, while overlooking the potential multilateral interactions and risk transmission dynamics between the RMB and other major currencies (Du and Lai, 2017; Ding et al., 2020; Yu et al., 2024). On the other hand, a considerable number of studies treat the exchange rate merely as an exogenous variable used to explain the volatility of other market indicators, lacking a deeper investigation into its systematic role as a source of financial risk (Weiss and Wichowsky, 2018; Li et al., 2019; Long et al., 2022; Si et al., 2024). Furthermore, existing methodologies predominantly focus on mean value modeling (Tian et al., 2021; Sun et al., 2022; Wang et al. 2022; Yu et al., 2023), which limits their ability to effectively capture the asymmetric contagion mechanisms of tail risks under extreme market conditions. This also hinders a comprehensive reflection of the dynamic restructuring process of exchange rate risk in response to major unexpected events. Simultaneously, existing studies tend to focus on a single indicator, such as exchange rate returns or volatilities (Narayan, 2022; Huang and Zhang, 2024) , resulting in an incomplete and unsystematic portrayal of the heterogeneous spillover effects across different risk dimensions. As RMB marketization reforms deepen, exchange rate volatility has increased, along with rising vulnerability to external shocks. Consequently, prevailing frameworks increasingly fail to capture and address these emerging realities. This study provides fresh insights and empirical evidence by delineating RMB exchange rate spillover channels, characterizing tail risk spillovers, and analyzing their underlying drivers to inform policy formulation and risk management.

This study addresses the following core questions: First, what are the static and dynamic features of RMB exchange rate spillovers during major shocks? How do transmission mechanisms vary across time scales, and what heterogeneous effects do they have on market volatility and risk diffusion? Second, how do the connectivity patterns of returns and volatilities differ in terms of structure and behavior? Third, what are the key drivers of RMB exchange rate spillovers, and how do they affect risk transmission? Accordingly, this study first identifies spillover relationships across RMB exchange rates at different quantiles using generalized forecast error variance decomposition within a quantile vector autoregression (QVAR) framework. Second, it investigates spillover effects under varying shock intensities from both time and frequency domains, constructing static and dynamic spillover networks. Finally, leveraging identified effects of market states on gross and net spillovers, the Temporal Fusion Transformer (TFT) model is employed to examine the key drivers of spillover dynamics and their evolving transmission mechanisms.

This study makes three primary contributions beyond the existing literature. First, it jointly analyzes return and volatility dimensions of RMB exchange rate connectivity, differentiating their characteristics across distinct market regimes. Return connectivity reflects co-movements among returns, aiding in portfolio optimization and hedging strategy design, while volatility connectivity captures risk transmission pathways across markets, supporting dynamic risk management. By comparing these two forms of connectivity, the study enhances the understanding of spillover effects in the RMB exchange rate system and offers targeted tools for risk monitoring and informed decision-making. Second, it systematically investigates the determinants of return and volatility spillovers from both gross and net perspectives, thereby advancing the understanding of risk transmission mechanisms and pathways. This inquiry identifies key drivers of cross-market spillovers and provides both theoretical foundations and practical guidance for interpreting and managing their dynamics. By emphasizing the influence of different driving factors, the study extends existing research and marks significant progress in both its scope and analytical depth. Third, this study innovatively applies deep learning to financial analysis to explore the dynamic behavior of the RMB exchange rate. Adopting an inverse reasoning approach that infers explanations from predictions, the deep learning framework prioritizes forecasting accuracy over traditional model completeness, offering a novel and effective paradigm for identifying the drivers of exchange rate fluctuations. This also contributes to the broader exploration of RMB exchange rate "resonance" risk management, offering substantial theoretical and practical implications for related research areas and cross-domain risk management practices.

The remainder of the study is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the research methodology and data. Section 4 empirically quantifies the spillover effects of the RMB exchange rate in terms of returns and volatilities. Section 5 analyzes the dynamic impacts of various drivers on both gross and net spillovers. Finally, Section 6 concludes with a summary of the main findings.

2. Literature review

With the deepening of financial integration, the global financial system has become increasingly interconnected, and the transmission of risks across institutions, markets, and regions has grown more frequent, heightening the threat of systemic risk (Khalfaoui et al., 2022; Su et al., 2023; Wang et al., 2024). Financial contagion is increasingly shaped by network dynamics, prompting a shift toward revisiting and improving fragmented regulatory frameworks (Helbing, 2013). As a result, the traditional "too-big-to-fail" regulatory approach, which focuses on the resilience of individual institutions, is being replaced by a "too-connected-to-fail" paradigm that emphasizes systemic interlinkages and contagion channels (Kelly et al., 2016). In this context, exchange rate markets are recognized as key conduits for cross-border risk transmission due to their sensitivity to capital flows and trade shocks (Goldberg and Krogstrup, 2023). In recent years, frequent abrupt shocks have attracted increasing academic attention to the critical role of exchange rates in connecting global markets, with growing recognition that their high synchronicity amplifies cross-border financial spillovers (Tiwari et al. 2022) .

Against this backdrop, structural linkages within foreign exchange markets and their cross-border spillover channels have become key areas for evaluating exchange rate risk transmission. Existing studies can be broadly classified into two strands. The first focuses on return spillovers (Narayan, 2022; Kakran et al. 2025). The second strand investigates volatility spillovers (Hsu, 2022; Das and Roy, 2023; Liu et al., 2025). Together, these studies offer a dual perspective on exchange rate spillovers by elucidating the pathways and interaction patterns among global currencies. Return linkages reflect co-movements in currency returns, aiding hedging and cross-currency investment decisions (Malik, 2021). In contrast, volatility linkages capture risk transmission channels and support effective foreign exchange risk management (Gong et al., 2025). A joint analysis of return and volatility connectivity in the RMB market enables a more comprehensive understanding of spillover dynamics, investment implications, and market efficiency. In view of the preceding analysis, this study systematically investigates RMB exchange rate correlations from both return and volatility perspectives.

In the context of financial market risk contagion research, the Diebold-Yilmaz (DY) spillover index (Diebold and Yilmaz, 2012; 2014) has emerged as a widely adopted analytical framework. Compared with alternative spillover measures, the DY method systematically characterizes multi-market risk transmission paths, closely aligned with the logic of systemic risk transmission. When combined with rolling window techniques, it effectively captures time-varying spillover dynamics and has been widely applied in empirical studies (Antonakakis and Kizys, 2015; Zhang et al., 2021; Li et al., 2023), substantially advancing spillover research. Building on this, Baruník and Křehlík (2018) extended the DY framework into the frequency domain via the BK spillover index, which captures spillover heterogeneity across frequency bands. This methodology has since gained broad traction (Zhang and Chen, 2024; Ahmadian-Yazdi et al., 2025). However, both DY and BK approaches remain limited in capturing tail risk spillovers, as they fundamentally rely on conditional mean estimations. In response, complex network approaches have been introduced to better map the structure of cross-market risk transmission and enrich the analysis of exchange rate linkages

(Yu et al., 2024; Sun et al., 2025) . Nevertheless, these methods also primarily rely on mean-based estimations. To overcome these limitations, Chatziantoniou et al., 2022 proposed a quantile time-frequency framework that captures spillovers across market conditions and frequencies. Its robustness to extremes enhances risk assessment accuracy and strengthens policy adaptability (Gong et al., 2023).

While extensive research has explored the intensity, structure, and dynamics of exchange rate spillovers, the majority remains descriptive, emphasizing identification over the elucidation of economic logic and transmission mechanisms. To deepen understanding of exchange rate interlinkages and systemic risk evolution, recent studies focus on identifying key spillover drivers. This approach identifies key variables and channels influencing spillovers, including monetary policy, financial market interdependence, macro fundamentals, commodity prices, and global uncertainty. Regarding monetary stability, Kucharčuková et al. (2016) show that the ECB's unconventional policy significantly affects exchange rate volatility in non-euro countries through shifts in interest rate expectations and capital flows. Tian et al. (2023) find that the People's Bank of China's countercyclical policy alters information transmission between the onshore (CNY) and offshore (CNH) RMB markets, with spillovers exhibiting both directional and frequency heterogeneity. At the financial market level, Eraslan (2017) reports that sovereign credit rating downgrades intensify exchange rate linkages in emerging markets. Using risk network analysis, Huang and Liu (2023) further demonstrate that sovereign CDSs centralize cross-market contagion, amplifying volatility during external shocks. In terms of macro fundamentals, Ozkaya and Altun (2024) find that although global financial factors dominate, domestic variables such as inflation and interest rates remain significant in explaining Turkey's exchange rate dynamics. Global uncertainty events also act as spillover amplifiers. For instance, Kim et al. (2015) show that the 2008 global financial crisis heightened synchronization in exchange rate volatility across emerging Asian markets, primarily via capital flow disruptions and risk repricing. In sum, existing literature converges on the view that exchange rate spillovers are shaped by the interaction of multiple factors and propagate through a dynamic, multi-layered network of cross-market risk transmission.

To accurately uncover the causes of spillover effects, selecting appropriate research methods to analyze their driving forces has become a key focus in this field. Most existing studies rely on traditional econometric techniques to identify the determinants of spillovers. For example, Dai et al. (2024) and Li and Smallwood (2025) employed multivariate regression models to examine the core drivers of exchange rate connectivity from the perspectives of macroeconomic fundamental synchronization and the evolution of onshore–offshore market structures. Jia and Dong (2024) utilized impulse response analysis to investigate the dynamics of clean energy stock price spillovers at different stages of the pandemic. Zhang et al. (2025) applied the copula-CoVaR approach to identify the nonlinear spillover effects of energy and international carbon prices on China's carbon market. Chen et al. (2025) adopted the spatial Durbin model to explore the determinants of spatial spillovers in the sustainability of coastal fisheries in China.

With the rise of the digital economy, advancements in big data, artificial intelligence (AI), and computational power are no longer limiting factors to development. The interdisciplinary integration of scientific methodologies has transcended philosophical discussions and become a practical application (Ghoddusi et al., 2019). Given the strong alignment between AI technologies and socio-economic systems, machine learning has significantly improved predictive accuracy in the financial domain, particularly in forecasting economic indicators (Alexandridis et al., 2024), providing valuable insights for risk regulation. However, the application of machine learning, particularly deep learning, in finance has been criticized as a "black box" due to its complex and nonlinear internal structures, which hinder interpretability and obscure the relationships among variables. Additionally, mainstream interpretation techniques, such as post hoc analysis methods (Ribeiro et al., 2016), often fail to account for the temporal ordering of input variables, limiting their effectiveness in interpreting time-series predictions. The Transformer model (Ashish, 2017), which has gained prominence in recent years, captures the temporal significance of features. However, as it was originally designed for natural language processing and primarily handles univariate sequences, it struggles to differentiate the contributions of individual variables in multivariate time-series prediction tasks. Consequently, it does not meet the interpretability requirements for complex multivariate systems.

Building on the advanced Transformer architecture, the joint research team from Oxford University and Google introduced the TFT model in 2021, which achieved significant breakthroughs in both forecasting accuracy and interpretability (Lim et al., 2021). Moreover, the TFT model pioneers the exploration of quantitative relationships among variables from a global perspective and supports simultaneous multi-variable forecasting—making it particularly well-suited for complex economic systems comprising multiple markets. Accordingly, this study adopts the TFT model and employs a reverse analytical approach from prediction to explanation to systematically identify the key drivers of RMB exchange rate spillovers, thereby broadening the existing analytical framework and methodological foundation.

A review of the existing literature reveals that there remains considerable scope for further research on exchange rate spillovers. First, the RMB exchange rate spillover constitutes a complex and dynamic system, yet current research tends to adopt relatively narrow perspectives. For instance, no study has systematically compared spillover effects based on both returns and volatilities. Second, existing literature seldom investigates the coupling relationship between RMB exchange rate spillovers and their potential drivers, leaving the transmission mechanisms insufficiently explained. Third, empirical studies identifying the factors influencing spillovers still predominantly rely on traditional econometric methods, which struggle to capture complex features such as nonlinearity, high dimensionality, and time-varying dynamics. In addition, existing studies primarily concentrate on spillover effects among major international currencies (Kyriazis and Corbet, 2024), whereas systematic research on emerging markets, particularly the Chinese RMB, remains comparatively limited. Therefore, a quantitative analysis of RMB exchange rate spillover effects and their driving mechanisms under different market conditions, from the dual perspectives of returns and volatilities, will contribute to enriching and deepening existing research on exchange rate linkages.

3. Methodology

3.1 Quantile VAR Model

Building on the generalized forecast error variance decomposition of the QVAR model, we measure the RMB exchange rate spillover effects across different shock intensities and time horizons. Using a rolling window approach, it dynamically estimates total and directional risk spillovers, overcoming the limitations of the DY spillover index (Diebold and Yilmaz, 2012; 2014) and the BK spillover index (Baruník and Křehlík, 2018) in capturing tail risk behavior.

Specifically, the construction of the QVAR model proceeds as follows: First, define a p-order quantile vector autoregression process, $QVAR(p)$, involving n variables:

$$x_t = \mu_t(\tau) + \Phi_1(\tau)x_{t-1} + \Phi_2(\tau)_{t-2} + L + \Phi_p(\tau)x_{t-p}u_t(\tau) \tag{1}$$

Among them, x_t and x_{t-i} are N×1 dimensional vectors of endogenous variables; τ ranges between 0 and 1, representing the model-specific quantile; p denotes the lag order of the QVAR model; $\mu(\tau)$ is an N×1 dimensional conditional mean vector; $\Phi_j(\tau)$ is an N×N dimensional coefficient matrix of the QVAR model; and $\mu_t(\tau)$ represents an N×1 dimensional error vector. Based on Wald's theorem, Eq. (2) can be rewritten as an infinite order quantile vector moving average process, $QVMA(\infty)$:

$$x_t = \mu(\tau) + \sum_{i=0}^{\infty} \psi_i(\tau)u_{t-i} \tag{2}$$

The generalized forecast error variance decomposition (GFEVD) is computed following the approaches of Koop et al. (1996) and Pesaran and Shin (1998). For a forecast horizon H, the proportion of the H-step-ahead forecast error variance of variable i attributable to shocks from variable j, denoted by $\theta_{ij}^{g}(H)$, can be expressed as:

$$\theta_{ij}(H) = \frac{(\Sigma(\tau))_{ij}^{-1}\sum_{h=0}^{H}(\psi_h(\tau)\Sigma(\tau))_{ij}^{2}}{\sum_{h=0}^{H}(\psi_h(\tau)\Sigma(\tau)\psi'_h(\tau))_{ii}} \tag{3}$$

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{N}\theta_{ij}(H)} \tag{4}$$

Here, $\Sigma(\tau)$ denotes the variance-covariance matrix of the error vector. Since the row sums of $\theta_{ij}(H)$ do not equal one, they are normalized to $\tilde{\theta}_{ij}(H)$. The normalized value $\tilde{\theta}_{ij}(H)$ quantifies the directional spillover from variable i to variable j at the τ quantile. In this study, it is employed to measure spillover effects among different RMB exchange rate series. Moreover, the total directional spillover index from each variable to all others in the system is calculated as follows:

$$TO_i(H) = \sum_{i=1,i\neq j}^{N} \tilde{\theta}_{ij}(H) \times 100 \tag{5}$$

$$FROM_i(H) = \sum_{i=1,i\neq j}^{N} \tilde{\theta}_{ji}(H) \times 100 \tag{6}$$

Based on this, the total spillover index and net spillover index among the RMB exchange rate series at quantile τ are defined as follows:

$$TSI(H) = \frac{\sum_{i,j=1;i\neq j}^{N} \left(\tilde{\theta}_H\right)_{ij}}{N} \times 100$$
$$= N^{-1} \sum_{i=1}^{N} TO_i(H) \tag{7}$$
$$= N^{-1} \sum_{i=1}^{N} FROM_i(H)$$
$$NET(H) = TO_i(H) - FROM_i(H) \tag{8}$$

The above describes the calculation process of the time-domain spillover index based on the QVAR model. Next, we further compute the frequency-domain spillover index using the spectral decomposition method proposed by Stiassny (1996). First, based on the frequency response function $\psi\left(e^{-iw}\right) = \sum_{h=0}^{\infty} e^{-iwh} \psi_h$, the spectral density $S_x(\omega)$ of x_t at frequency ω is given by:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-iwh} = \psi(e^{-iwh}) \sum_t \psi'(e^{+iwh}) \tag{9}$$

Among them, $\psi(e^{-iwh})$ is obtained by taking the Fourier transform of ψ_h. It is worth noting that the frequency-domain GFEVD integrates the spectral density with the GFEVD. In the frequency domain, normalization of the frequency GFEVD is required, and the formula is as follows:

$$\theta_{ij}(\omega) = \frac{\Sigma(\tau)_{jj}^{-1} |\sum_{h=0}^{\infty} (\psi(\tau)(e^{-iwh})\Sigma(\tau))_{ij}|^2}{\sum_{h=0}^{\infty} (\psi(e^{-iwh})\Sigma(\tau)\psi(\tau)(e^{iwh}))_{ii}} \tag{10}$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N} \theta_{ij}(\omega)} \tag{11}$$

Among them, $\tilde{\theta}_{ij}(\omega)$ represents the portion of the spectrum of variable i attributable to the impact of variable j at a given frequency ω. To calculate the spillover index over different frequency bands, frequencies within a specified range $d = (a, b)$, where $a, b \in (-\pi, \pi)$ and $a < b$, are aggregated. Then, Eq. (12) can be expressed as:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(\omega)\, d\omega \tag{12}$$

$\tilde{\theta}_{ij}(d)$ measures the directional spillover from variable i to variable j within the frequency band d under the τ quantile. Similarly, since this study also focuses on the overall spillover level, we further calculate the total directional spillover index of each variable to all other variables in the system within the given frequency band d, which is computed as:

$$TO_i(d) = \sum_{i=1,i\neq j}^{N} \tilde{\theta}_{ij}(d) \times 100 \tag{13}$$

$$FROM_i(d) = \sum_{i=1,i\neq j}^{N} \tilde{\theta}_{ji}(d) \times 100 \tag{14}$$

Similarly, the total spillover index and net spillover index in the quantile frequency domain can be defined as follows:

$$\begin{aligned} TSI(d) &= \frac{\sum_{i,j=1;i\neq j}^{N} (\tilde{\theta}_d)_{ij}}{N} \times 100 \\ &= N^{-1} \sum_{i=1}^{N} TO_i(d) \\ &= N^{-1} \sum_{i=1}^{N} FROM_i(d) \end{aligned} \tag{15}$$

$$NET(d) = TO_i(d) - FROM_i(d) \tag{16}$$

3.2 Temporal Fusion Transformers

In time series forecasting, traditional deep learning algorithms often face difficulties processing heterogeneous input data, and their complex architectures impede clear interpretation of how meaningful information is extracted during prediction. These limitations have hindered the broader application of deep learning forecasting techniques in the financial sector. The spatiotemporal fusion transformer addresses these challenges through data integration and key variable identification, without compromising predictive accuracy. This advancement substantially enhances the applicability of deep learning in multiple fields. As illustrated in Fig.1, the main components of the TFT algorithm include: **(1) Gating Mechanism:** skips irrelevant components and automatically adjusts model depth and complexity to suit various data scenarios. **(2) Variable Selection Network:** dynamically selects relevant input variables at each time step. **(3) Static Covariate Encoder:** encodes static features into context vectors to guide temporal dynamics. **(4) Temporal Modeling:** integrates sequence layers with multi-head attention modules to capture both short-term local patterns and long-term dependencies. **(5) Interval Prediction:** estimates the possible range of target values using quantile predictions. Below, we analyze several key modules of the TFT model.

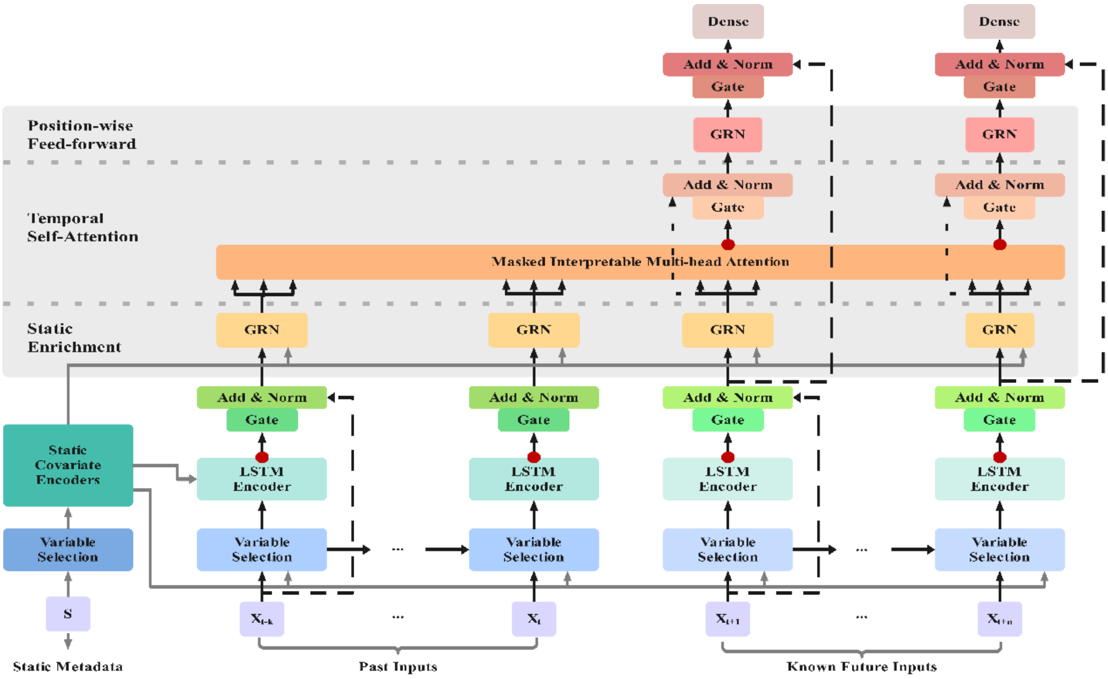


Fig.1. Basic Architecture of the TFT Model

3.2.1 Gating mechanisms in TFT

The gated residual network enhances the flexibility of nonlinear interactions between model variables and target outputs. The gated residual network takes two inputs: the primary input a and an optional context vector c. Its mathematical formulation is given by:

$$GRN_{\omega}(a,c) = LayerNorm(a + GLU_{\omega}(\eta_1)) \tag{17}$$

$$\eta_1 = W_{1,\omega}\eta_2 + b_{1,\omega} \tag{18}$$

$$\eta_2 = ELU(W_{2,\omega}a + W_{3,\omega}c + b_{2,\omega}) \tag{19}$$

Here, ELU denotes the exponential linear unit activation function; η_1 and $\eta_2 \in \mathbb{R}^{d_{model}}$ represent intermediate layers; ω stands for weight sharing; $W_{(\cdot)}$ is the weight matrix; and $LayerNorm$ refers to standard layer normalization. The gated linear unit component offers the flexibility to suppress unnecessary architectural elements for a given dataset, and is described as follows:

$$GLU_{\omega}(\gamma) = \sigma(W_{4,\omega}\gamma + b_{4,\omega}) \odot (W_{5,\omega}\gamma + b_{5,\omega}) \tag{20}$$

Here, $\gamma \in \mathbb{R}^{d_{model}}$ denotes the input; $\sigma(\cdot)$ is the sigmoid activation function;

$b_{(\cdot)} \in \mathbb{R}^{d_{model}}$ represents the bias term; $W_{(\cdot)} \in \mathbb{R}^{d_{model}}$ denotes the weight; and $\odot$ denotes the Hadamard product. The gated linear unit component enables the TFT model to regulate the influence of the gated residual network on the initial input.

3.2.2 Variable selection networks in TFT

The variable selection network identifies the most relevant variables for the prediction task and filters out noisy inputs in the TFT model that could degrade predictive performance. Let $[I]_t = [\xi_t^{(1)T}, \xi_t^{(2)T}, \ldots, \xi_t^{(m_x)T}]^T$ denote the flattened vector of all past inputs, where $\xi_t^{(j)}$ is the transformed input of the j-th variable. As illustrated in Eq. (21), $[I]_t$ and the external environment variable c_s are fed into the gated residual network, producing the variable selection weights V_{xt} after the $Softmax$ layer. According to Eq. (22), each $\xi_t^{(j)}$ undergoes nonlinear transformation via the gated residual network, and as per Eq. (23), these processed features are weighted and combined based on their respective variable selection weights.

$$V_{xt} = Softmax(GRN_{V_x}([I]_t, c_s)) \tag{21}$$

$$\tilde{\xi}_t^{(j)} = GRN_{\tilde{\xi}(j)}(\xi_t^{(j)}) \tag{22}$$

$$\tilde{\xi}_t = \sum_{j=1}^{m_x} v_{xt}^{(j)} \tilde{\xi}_t^{(j)} \tag{23}$$

3.2.3 Interpretable Multi-Head Attention in TFT

The TFT model employs a self-attention mechanism to capture long-range dependencies across time steps and enhances the basic Transformer's multi-head attention structure to improve the interpretability of the model. Specifically, the attention mechanism operates based on the relationship between "queries $Q \in \mathbb{R}^{N \times d_{attn}}$" and "keys $K \in \mathbb{R}^{N \times d_{attn}}$", and computes the "value" output using Eq. (24):

$$Attention(Q, K, V) = A(Q, K)V \tag{24}$$

Here, N denotes the number of time steps fed into the attention layer, and $A(\cdot)$ represents the normalization function. The attention scores are typically computed using a scaled dot-product mechanism, as shown below:

$$A(Q, K) = Softmax(QK^T / \sqrt{d_{attn}}) \tag{25}$$

The attention mechanism employs a multi-head attention strategy, enabling the model to capture information from different representation subspaces through multiple attention heads. Its mathematical formulation is as follows:

$$MultiHead(Q,K,V) = [H_1, \dots, H_{m_H}]W_H \tag{26}$$

$$H_h = Attention(QW_Q^{(h)}, KW_K^{(h)}, VW_V^{(h)}) \tag{27}$$

Among them, $W_K^{(h)} \in \mathbb{R}^{d_{model} \times d_{attn}}$, $W_Q^{(h)} \in \mathbb{R}^{d_{model} \times d_{attn}}$, and $W_V^{(h)} \in \mathbb{R}^{d_{model} \times d_v}$ denote the weight matrices for the "keys", "queries" and "values" in each attention head, respectively. $W_H^{(h)} \in \mathbb{R}^{(m_H \cdot d_V) \times d_{model}}$ represents the projection matrix that linearly combines the outputs from all attention heads.

Given that each attention head uses distinct value vectors, a single attention weight is insufficient to capture the importance of individual features. To address this, the multi-head attention mechanism is modified to share a common value representation across all heads, followed by additive aggregation of their outputs.

$$InterpretableMultiHead(Q,K,V) = HW_V \tag{28}$$

$$\begin{aligned} \widetilde{H} &= \tilde{A}(Q,K)VW_V \\ &= \left\{\frac{1}{m_H}\sum_{h=1}^{m_H} A\left(QW_Q^{(h)}, KW_K^{(h)}\right)\right\}VW_V \\ &= \left\{\frac{1}{m_H}\sum_{h=1}^{m_H} Attention\left(QW_Q^{(h)}, KW_K^{(h)}, VW_V\right)\right\} \end{aligned} \tag{29}$$

Among them, $W_H^{(h)} \in \mathbb{R}^{d_{attn} \times d_{model}}$ serves as the final linear projection matrix, while W_V denotes the shared value weight matrix across all attention heads.

3.2.4 Quantile Output and Loss Function in TFT

The TFT model produces prediction intervals by simultaneously forecasting multiple quantiles at each time step. These quantile forecasts are obtained through a linear transformation of the output from the temporal fusion decoder. Model training is performed by jointly minimizing the quantile loss, with the total loss computed as the sum of the individual quantile losses, as shown below:

$$Ł(\Omega, \mathrm{W}) = \sum_{y_t \in \Omega} \sum_{q \in Q} \sum_{T=1}^{T_{max}} \frac{QL(y_t, \hat{y}(q, t-T, T), q)}{MT_{max}} \tag{30}$$

$$QL(y_t, \hat{y}, q) = q(y - \hat{y})_+ + (1-q)(\hat{y} - y)_+ \tag{31}$$

Here, Ω denotes the domain of the training set containing M samples, y represents the true value, $\hat{y}$ the predicted value, Q the input quantile, $(\cdot)_+$ stands for max(0,.), and W represents the weights of the TFT model.

Unlike econometric and traditional machine learning models, the TFT model offers a significant advantage by accommodating three distinct input types: observed inputs, known inputs, and static inputs. Observed inputs are variables available only up to the present and cannot inform future values. Known inputs are features with predetermined future values, such as planned schedules or calendar variables. Static inputs represent immutable characteristics of the forecast entity, such as geographic region or sector classification. Conventional models typically rely solely on observed inputs, which limits their ability to exploit richer contextual information. The TFT's flexible input framework enables integration of diverse data types and more comprehensive feature extraction. To address the shortcomings of autoregressive structures, especially their poor performance on high-volatility sequences, the model intentionally excludes the historical values of the target variable y_i prior to time t when predicting $\hat{y}_i(t,\tau)$. This design improves forecast stability. Overall, the TFT model adopts a more adaptable and information-rich framework than traditional approaches.

$$\hat{y}_i(t,\tau) = f(\tau, O_{i,t-k:t}, k_{i,t-k:t+\tau}, s_i) \tag{32}$$

Among them, i denotes the target entity within the system, t represents the current time point, τ is the forecast horizon, and k indicates the step size. The observed information $O_{i,t-k:t} = \{O_{i,t-k}, \dots, O_{i,t}\}$ refers to historical data observed up to time t; the predicted information $k_{i,t-k:t+\tau} = \{k_{i,t-k}, \dots, k_{i,t+\tau}\}$ includes both past and future known variables within the forecasting window; and s_i denotes static features inherent to the target entity.

The TFT model decomposes forecasting results along two dimensions, "Spatial" and "Temporal", utilizing its embedded variable selection network and multi-head attention mechanism. This approach aims to pinpoint critical information locations within each forecast horizon. The "Spatial" dimension ranks the importance of different input variables, highlighting which indicators exert the greatest influence on predictions at specific time points, thereby helping to elucidate the economic dynamics driven by these variables. The "Temporal" dimension, on the other hand, identifies key time steps within the forecast window, reflecting how strongly the predictions depend on historical data, which aids in understanding the evolving stability of the production structure.

3.3 Data and Descriptive Analysis

Using exchange rate data from China's major trading partners, this study constructs an RMB exchange rate market network. Since the People's Bank of China adopted a managed floating exchange rate regime on July 21, 2005, which is primarily driven by market supply and demand and guided by a currency basket, significant marketization of the RMB exchange rate has occurred, increasing the influence of multiple currencies. Recent reforms and the internationalization of the RMB have further amplified exchange rate volatility. The currency basket reflects China's key economic partnerships, making RMB fluctuations more informative and predictable. Based on average weights from the past three years, this study selects the top ten RMB exchange rates in the basket, which together represent approximately 81.02% of its total weight, validating their suitability for analysis (see Table A1). The data, sourced from the Wind database, span daily observations from March 5, 2007, to October 11, 2024.

However, the RMB exchange rate is a quintessential complex system characterized by nonlinearities, non-stationarity, high volatility, irregular fluctuations, and emergent properties, with a wide range of influencing factors. The specific time series of the RMB exchange rate are illustrated in Fig.2. It is evident that different types of RMB exchange rates exhibit distinct trends across various periods, reflecting the impact of multifaceted political, economic, and other factors[1].

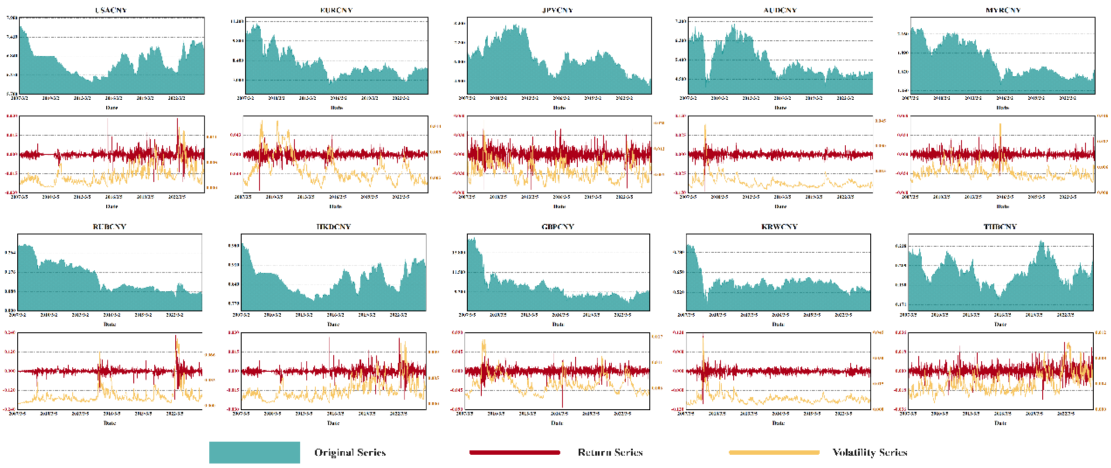


Fig.2. RMB Exchange Rate Line Chart from December 27, 2017 to October 11, 2024

Note: This chart shows the exchange rates of the top ten currencies in the RMB

[1] Among them, the exchange rates for the Japanese yen and the Korean won are relatively small, so they are uniformly quoted in units of 100 yen and 100 won, respectively.

currency basket. Rates are expressed using the direct quotation method, where a rise indicates RMB depreciation and a decline indicates appreciation.

In the foreign exchange market, return series directly reflect price changes and are significantly shaped by shocks from extreme events. To capture variations in exchange rates, we compute the daily returns of each RMB exchange rate using the logarithmic difference method, defined as $R_t = \ln{(P_{i,t}/P_{i,t-1})} \times 100$. Panel A of Table 1 presents descriptive statistics for the return series of ten RMB exchange rates. The average returns are slightly negative across all currency pairs, indicating a mild but negligible depreciation trend of the RMB. Return volatility is primarily measured by standard deviation, with higher values indicating greater fluctuations. Notably, RUBCNY exhibits the highest standard deviation, reflecting significantly higher volatility than other pairs. Most return series display positive skewness, indicating frequent small gains punctuated by occasional large losses. High kurtosis suggests heavy-tailed distributions with frequent extreme movements. Statistically significant Jarque-Bera statistics confirm the non-normality suggested by skewness and kurtosis. Both PP and ADF tests confirm that all return series are stationary. Ljung-Box Q statistics indicate significant autocorrelation, implying serial dependence and potential return predictability.

At the same time, under extreme shocks, exchange rates often exhibit volatility clustering, leptokurtosis, and heavy tails, with tail risk spillovers becoming especially pronounced. Tail risk spillovers refer to the transmission of extreme volatility shocks across variables, often amplifying overall instability. Thus, exchange rate research must account for both returns and volatility. As a key indicator of market risk and uncertainty, volatility captures underlying fluctuations and becomes especially important during extreme events.

To examine tail risk spillovers under extreme shocks, this study incorporates fat-tail features and stochastic volatility. It applies asymmetric GARCH models—including EGARCH (Nelson, 1991), TGARCH (Zakoian, 1994), and GJR-GARCH (Glosten et al., 1993)—to capture leverage effects and asymmetric volatility clustering. The optimal model is selected based on Akaike Information Criterion (AIC) and log-likelihood comparisons under both normal and Skew-t distributions. As shown in Table

A2, the EGARCH(1,1) model with a Skew-t distribution performs best for most RMB exchange rates, effectively capturing asymmetry and fitting empirical data. Accordingly, for consistency, this study employs the EGARCH model using the Skew-t distribution to capture the leptokurtosis and fat tails commonly observed in financial time series. Relevant descriptive statistics are presented in Panel B of Table 1.

From the data in Panel B, it is evident that RUBCNY exhibits higher average volatility compared to other RMB exchange rates, with the largest standard deviation, highlighting its pronounced volatility. The skewness coefficients indicate that the volatility distributions of all ten RMB exchange rates are positively skewed. Moreover, the kurtosis coefficients reveal that all volatility distributions exhibit leptokurtosis and heavy tails. Furthermore, Jarque-Bera test statistics confirm that the volatility series for all RMB exchange rates significantly deviate from normality. Both PP and ADF tests verify that all volatility series are stationary. Lastly, the Ljung-Box Q statistics indicate significant autocorrelation across all series.

Table 1

Descriptive statistics of RMB exchange rate fluctuations

	Mean	Sd	Median	Skew	Kurtosis	J-B	ADF	PP	Q(10)	Q(20)
Panel A. Return Series of RMB Exchange Rates										
USDCNY	-0.00003	0.00251	-0.000015	0.288	21.505	58881.42***	-11.329***	-57.384***	57.232***	95.685***
EURCNY	-0.00009	0.006616	0.000117	-0.621	10.915	15357.666***	-13.252***	-56.785***	9.245***	20.031***
JPYCNY	-0.00011	0.007615	-0.00027	-0.069	5.780	4255.295***	-13.936***	-58.280***	25.761***	43.839***
AUDCNY	-0.00008	0.009504	0.00015	-1.458	23.536	71558.198***	-13.706***	-58.367***	93.723***	128.420***
MYRCNY	-0.00010	0.00499	-0.00011	0.730	12.794	21101.371**	-13.624***	-57.328**	14.310***	33.734***
RUBCNY	-0.00046	0.01481	-0.00025	0.521	40.273	206474.365***	-13.967***	-56.866***	74.776***	112.510***
HKDCNY	-0.00003	0.00243	-0.00002	0.322	18.464	43430.382***	-10.981***	-57.293***	60.792***	103.020***
GBPCNY	-0.00016	0.00707	0.00003	-1.038	12.369	20015.745***	-13.854***	-53.928***	27.984**	56.736***
KRWCNY	-0.00015	0.00805	-0.00011	0.882	51.511	337958.948***	-13.733***	-53.941***	70.107***	129.300***
THBCNY	-0.00001	0.00395	-0.00012	0.272	6.770	5870.514***	-13.062***	-53.768***	16.545***	39.883***
Panel B. Volatility Series of RMB Exchange Rates										
USDCNY	0.002	0.002	0.002	1.710	4.024	3549.831***	-5.703***	-7.390***	23839.000***	40898.000***
EURCNY	0.006	0.003	0.005	1.269	1.059	962.899***	-3.506***	-3.460***	28656.000***	54061.000***
JPYCNY	0.008	0.002	0.007	0.854	1.299	586.638***	-5.666***	-6.498***	23125.000**	37854.000***
AUDCNY	0.009	0.005	0.007	4.119	22.503	73058.346**	-5.442***	-4.232***	27640.000***	49192.000***
MYRCNY	0.005	0.002	0.005	2.093	8.791	12063.338***	-5.209***	-6.119***	23376.000***	37516.000***
RUBCNY	0.012	0.009	0.009	3.782	20.158	58973.955***	-6.871***	-6.272***	24096.000***	36869.000***
HKDCNY	0.002	0.002	0.002	1.732	4.118	3685.986***	-5.663***	-7.118***	24025.000***	41147.000**
GBPCNY	0.007	0.002	0.006	1.643	3.625	3045.703***	-3.837***	-3.487***	28266.000***	52208.000***
KRWCNY	0.007	0.004	0.006	4.382	26.233	97317.022***	-5.158***	-4.490***	27099.000***	46724.000***

THBCNY	0.004	0.001	0.004	1.131	2.023	1172.158**	-6.240***	-7.269**	23194.000***	37922.000***

Note: ADF denotes the Augmented Dickey-Fuller unit root test statistic; J-B denotes the Jarque-Bera test statistic; PP denotes the Phillips-Perron test; Q(n) denotes the Ljung-Box Q statistic at lag n; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4. Empirical results

Based on the QVAR model, this study utilizes its generalized forecast error variance decomposition method to construct the risk spillover matrix for RMB exchange rate returns and volatilities, systematically capturing spillover effects across different market conditions. From a time-frequency perspective, it computes and visualizes the static tail risk spillover matrix among RMB exchange rates and quantifies each market's role in the risk propagation network using various metrics. Prior research has shown that tail risks during extreme upward or downward market movements intensify market irrationality and cause significant losses (Massacci, 2017). Analyzing spillovers only in normal markets is inadequate, emphasizing the necessity to study risk spillovers under extreme conditions. Accordingly, this study systematically contrasts RMB exchange rate spillovers across normal and extreme states to better capture systemic risk characteristics and transmission dynamics.

4.1 Static Spillover Effects of the RMB Exchange Rate

4.1.1 Time-Domain Perspective of the Results

To examine the spillover effects between the returns and volatilities of ten RMB exchange rates, this study sets the lag order of the QVAR model to 4 based on the AIC criterion. Following the approach of (Gabauer and Gupta 2020) , this study adopts a prediction horizon of 12 for the model variance decomposition. The results are presented in Tables 2 and 3, respectively.

Table 2

Time-Domain Static Spillover for RMB Exchange Rate Returns (Unit: %)

	τ=0.05				τ=0.50				τ=0.95			
	OWN	FROM	TO	NET	OWN	FROM	TO	NET	OWN	FROM	TO	NET
USDCNY	94.81	83.37	78.18	-5.19	101.44	49.43	50.87	1.44	98.58	82.1	80.67	-1.42
EURCNY	109.8	83.97	93.77	9.8	107.86	45.17	53.03	7.86	107.13	83.61	90.73	7.13
JPYCNY	93.34	80.94	74.28	-6.66	96.7	11.02	7.72	-3.3	95.83	81.34	77.17	-4.17
AUDCNY	105.26	82.98	88.24	5.26	109.75	44.81	54.56	9.75	104.21	82.9	87.11	4.21

MYRCNY	98.54	83.53	82.07	-1.46	89.21	30.32	19.53	-10.79	97.47	84.22	81.7	-2.53
RUBCNY	89.38	80.79	70.17	-10.62	97.04	15.27	12.31	-2.96	90.58	80.15	70.73	-9.42
HKDCNY	98.19	83.39	81.59	-1.81	101.69	49.62	51.31	1.69	99.91	82.31	82.22	-0.09
GBPCNY	105.52	83.12	88.64	5.52	100.59	40.9	41.49	0.59	102.79	83.3	86.08	2.79
KRWCNY	99.39	82.9	82.29	-0.61	97.32	34.51	31.82	-2.68	96.91	82.14	79.05	-3.09
THBCNY	105.77	83.34	89.11	5.77	98.4	33.11	31.51	-1.6	106.6	84	90.59	6.6
TCI	82.83				35.42				82.61			

Note: OWN denotes own variance shocks or idiosyncratic risk, NET measures net directional spillovers, and TCI stands for the total connectedness index. FROM refers to the receiver of return spillovers, while TO denotes the transmitter. Together, FROM and TO sum to the TCI. NET is calculated by subtracting TO spillovers from FROM spillovers. Positive or negative values in the NET row indicate whether an asset is a net source or net recipient of shocks.

Table 2 shows asymmetric return spillovers of RMB exchange rates across market states. It systematically analyzes the roles of currency pairs in the risk transmission network using various spillover indices, revealing the connectedness structure. The total spillover index (TCI) is markedly higher in extreme conditions than at the median, reflecting increased market interdependence and vulnerability to shocks. At the median quantile, AUDCNY shows the highest idiosyncratic risk, JPYCNY the lowest. Under extremes, EURCNY experiences the largest own variance shock, while RUBCNY shows the smallest, indicating diverse risk exposures across pairs. The risk reception index (FROM) indicates EURCNY is most vulnerable in downturns, USACNY leads in median markets, and MYRCNY dominates during upturns. This suggests EURCNY is sensitive in bearish markets, whereas USACNY and MYRCNY dominate risk reception in stable and bullish states. The risk transmission index (TO) identifies EURCNY as the main transmitter in extreme volatility, while AUDCNY leads in stable markets, likely reflecting its commodity market links. The net spillover index (NET) shows EURCNY as the key tail risk transmitter in turbulence, with AUDCNY dominant in stable conditions. This highlights market regimes' strong impact on spillover dominance: EURCNY leads in high volatility, AUDCNY in calmer markets. Overall, RMB return connectedness shows clear state dependence, with currency roles dynamically shifting as markets change.

Table 3

Time-Domain Static Spillover for RMB Exchange Rate Volatility (Unit: %)

	τ=0.05				τ=0.50				τ=0.95			
	OWN	FROM	TO	NET	OWN	FROM	TO	NET	OWN	FROM	TO	NET

USDCNY	103.63	69.95	73.58	3.63	105.66	56.7	62.36	5.66	73.47	87.87	61.34	-26.53
EURCNY	112.83	71.41	84.24	12.83	108.91	44.48	53.39	8.91	123.14	80.32	103.46	23.14
JPYCNY	106.69	69.8	76.49	6.69	106.64	43.69	50.33	6.64	105.9	88.2	94.1	5.9
AUDCNY	84.52	53.95	38.47	-15.48	108.43	44.62	53.05	8.43	104.85	80.25	85.09	4.85
MYRCNY	96.55	66.48	63.03	-3.45	88.01	37.49	25.5	-11.99	102.67	83.6	86.27	2.67
RUBCNY	86.81	59.38	46.18	-13.19	100.44	22.72	23.17	0.44	110.53	77.19	87.72	10.53
HKDCNY	104.97	70.56	75.53	4.97	106.54	56.87	63.4	6.54	79.47	87.29	66.75	-20.53
GBPCNY	102	68.09	70.08	2	96.16	48.48	44.63	-3.84	111.8	85.77	97.57	11.8
KRWCNY	98.11	65.7	63.81	-1.89	89.99	44.27	34.26	-10.01	110.46	79.86	90.32	10.46
THBCNY	103.9	70.49	74.39	3.9	89.23	44	33.23	-10.77	77.73	87.76	65.49	-22.27
TCI	66.58				44.33				83.81			

Note: OWN denotes own variance shocks or idiosyncratic risk, NET measures net directional spillovers, and TCI stands for the total connectedness index. FROM refers to the receiver of return spillovers, while TO denotes the transmitter. Together, FROM and TO sum to the TCI. NET is calculated by subtracting TO spillovers from FROM spillovers. Positive or negative values in the NET row indicate whether an asset is a net source or net recipient of shocks.

Table 3 shows that RMB exchange rate volatility spillovers have dynamic structures similar to return spillovers and are highly state-dependent. TCI values at the 0.05, 0.5, and 0.95 quantiles are 66.58%, 35.23%, and 83.81%, respectively, indicating stronger risk transmission under extreme market conditions, likely driven by increased tail risk correlations from global capital flows and uncertainty. Under neutral conditions, USDCNY and HKDCNY have the highest TO and FROM values, underscoring their central roles. Under extreme downside, EURCNY leads with TO and FROM at 84.24% and 71.41%, while in extreme upside, EURCNY and JPYCNY top the spillovers at 103.46% and 88.2%. This suggests that RMB rates linked to developed economies are key nodes in shock transmission during volatile periods. At the 0.95 quantile, most pairs show TO and FROM above 60%, reflecting stronger upside risk spillovers and possible contagion asymmetry. The NET index identifies EURCNY as a consistent net risk exporter, with elevated spillovers at both tails. Spillover roles shift across states: AUDCNY is a net exporter at median and high quantiles but a net recipient at the low quantile; USDCNY shows the opposite. These results also highlight that currency pairs' positions in the volatility network adjust dynamically with market conditions, revealing limitations of traditional conditional mean-based spillover metrics.

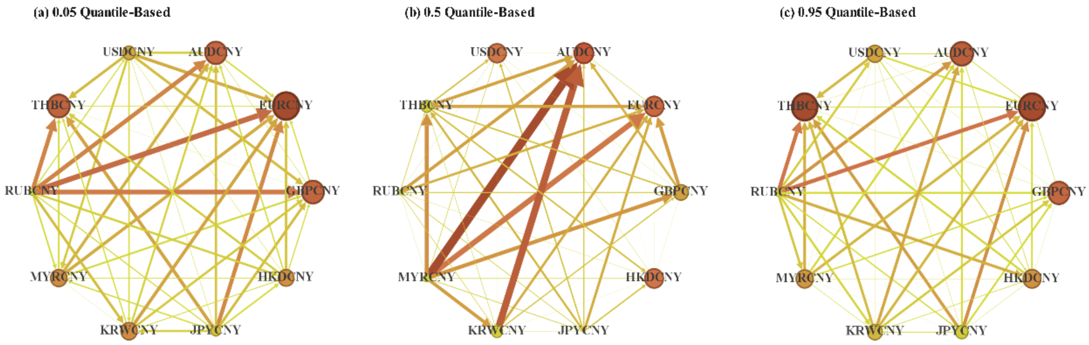


Fig. 3. Net pairwise spillover relationships among different RMB exchange rate returns across quantiles

To offer an intuitive view, this study constructs a tail risk spillover network for RMB using the generalized forecast error variance decomposition from the QVAR model. Ten RMB exchange rates form the nodes, with edges representing net volatility spillover relationships. Arrows show spillover direction toward net recipients, and edge weights indicate spillover intensity. Figs. 3 and 4 show notable heterogeneity in tail spillover patterns of returns and volatilities under different market conditions. During extreme downturns, RUBCNY exhibits the strongest net return spillover, reflecting its pronounced sensitivity to geopolitical events and energy price shocks, thus serving as a key transmitter of negative shocks. Under normal market conditions, MYRCNY is the primary net spillover source, while AUDCNY is the largest net recipient, indicating Malaysia's active influence within the RMB system and Australia's passive response as a commodity currency to external shocks. In extreme up markets, RUBCNY again leads as the main spillover source, suggesting its persistent role during rapid market recoveries or risk appetite increases. AUDCNY and EURCNY consistently act as stable net recipients across market states, likely due to commodity price cycles and the eurozone currency's relative robustness. Overall, in terms of returns, tail market states correspond with increased total system spillover effects, highlighting the heightened sensitivity of the RMB exchange rate system under extreme market conditions.

In the volatility dimension, market conditions exert a more pronounced influence on the spillover patterns. During low volatility periods, when the market is relatively stable, AUDCNY emerges as the primary net volatility spillover source, reflecting its role as a leading indicator of global commodity price movements and its continued significant volatility transmission effect in low-risk environments. Although the network structure adjusts under normal volatility, AUDCNY retains a dominant position. In high volatility periods, spillover interactions among currency pairs generally intensify, with RUBCNY transitioning from a source of return spillovers to a predominant contributor of net volatility spillovers. This may reflect its passive absorption of sharp market fluctuations, such as heightened risk aversion or delayed monetary policy responses. Meanwhile, EURCNY consistently acts as a stable net volatility receiver across all volatility states, underscoring its low volatility profile and resilience to shocks.

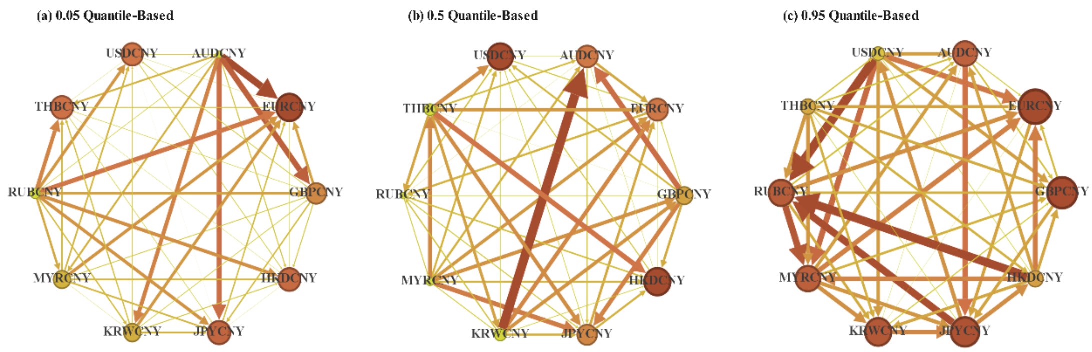


Fig. 4. Net pairwise spillover relationships among different RMB exchange rate volatilities across quantiles

4.1.2 Frequency-Domain Perspective of the Results

To analyze the spillover effects of the RMB exchange rate across different frequency domains, this study calculates the market spillovers in short-, medium-, and long-term horizons. Following Goswami et al. (2023), the sample frequency domain is divided into high frequency $d = (\pi/5, \pi)$, medium frequency $d = (\pi/20, \pi/5)$, and low frequency $d = (0, \pi/20)$, corresponding respectively to short-term (1-5 days), medium-term (5-20 days), and long-term (over 20 days) periods[2].

Table 4

Static frequency-domain spillover of RMB exchange rate returns under normal condition (unit: %)

	USDCNY	EURCNY	JPYCNY	AUDCNY	MYRCNY	RUBCNY	HKDCNY	GBPCNY	KRWCNY	THBCNY	FROM

[2] The RMB spot exchange rate data in the Wind database covers Monday through Friday, reflecting the structure of the global foreign exchange market. Trading centers located in major financial hubs worldwide operate 24 hours a day, five days a week, excluding weekends. Accordingly, we define the segments based on duration: 1-5 days as a trading week, classified as high-frequency; 5-20 days, spanning a trading week to a month, classified as medium-frequency; and periods over 20 days, exceeding a trading month, also classified as high-frequency.

Highest frequency (short-term): Frequency band of [1,5] days											
USDCNY	39.54	0.09	0.44	0.15	0.01	0.04	36.23	0.01	0.00	1.30	38.28
EURCNY	0.07	43.76	1.22	10.46	1.29	1.66	0.14	13.12	3.71	3.88	35.55
JPYCNY	1.00	2.00	70.25	1.05	0.19	0.67	1.09	0.03	0.07	2.88	8.98
AUDCNY	0.26	10.74	0.65	43.91	2.94	1.83	0.12	9.38	6.51	2.78	35.20
MYRCNY	0.23	1.83	0.34	3.77	54.83	1.88	0.25	1.57	4.88	2.67	17.42
RUBCNY	0.08	2.23	0.44	2.51	2.54	64.85	0.11	1.08	0.88	1.34	11.20
HKDCNY	35.78	0.20	0.52	0.09	0.04	0.06	38.70	0.05	0.02	1.36	38.12
GBPCNY	0.06	13.72	0.05	9.24	1.20	0.91	0.07	45.13	3.00	2.32	30.57
KRWCNY	0.05	3.48	0.13	7.57	4.67	0.64	0.04	2.98	51.67	4.80	24.35
THBCNY	1.84	3.94	2.00	2.87	2.41	1.09	1.90	2.53	4.81	51.13	23.40
TO	39.36	38.23	5.78	37.70	15.30	8.77	39.95	30.75	23.90	23.32	
NET	1.08	2.68	-3.20	2.50	-2.12	-2.43	1.83	0.19	-0.45	-0.08	TCI
NPT	7.00	8.00	3.00	5.00	1.00	1.00	8.00	4.00	5.00	3.00	26.31
Intermediate frequency (medium-term): Frequency band of [5,20] days											
USDCNY	7.00	0.01	0.09	0.05	0.01	0.03	6.60	0.00	0.00	0.29	7.07
EURCNY	0.01	7.52	0.22	2.11	0.24	0.23	0.02	2.53	0.51	0.69	6.55
JPYCNY	0.07	0.40	12.67	0.16	0.01	0.15	0.07	0.01	0.00	0.54	1.41
AUDCNY	0.01	2.13	0.09	7.70	0.52	0.27	0.01	1.84	1.32	0.53	6.72
MYRCNY	0.03	1.25	0.11	2.07	9.84	0.85	0.04	1.00	1.56	1.46	8.36
RUBCNY	0.03	0.49	0.07	0.64	0.48	13.07	0.04	0.33	0.16	0.34	2.59
HKDCNY	6.71	0.02	0.10	0.01	0.01	0.02	7.23	0.01	0.00	0.32	7.21
GBPCNY	0.01	3.05	0.00	2.47	0.20	0.17	0.02	9.51	0.64	0.52	7.09
KRWCNY	0.01	1.29	0.01	2.62	0.90	0.20	0.01	1.01	9.31	1.01	7.06
THBCNY	0.27	1.28	0.53	1.16	0.55	0.28	0.31	0.73	0.98	10.52	6.10
TO	7.14	9.92	1.24	11.28	2.91	2.20	7.12	7.47	5.18	5.71	
NET	0.08	3.38	-0.17	4.56	-5.45	-0.39	-0.09	0.38	-1.88	-0.40	TCI
NPT	6.00	7.00	4.00	8.00	0.00	3.00	5.00	5.00	1.00	6.00	6.02
Lowest frequency (long-term): Frequency band of [20,inf] days											
USDCNY	4.03	0.00	0.05	0.03	0.00	0.01	3.86	0.00	0.00	0.12	4.08
EURCNY	0.01	3.55	0.07	1.03	0.11	0.17	0.02	1.21	0.25	0.21	3.08
JPYCNY	0.05	0.14	6.07	0.07	0.01	0.00	0.06	0.00	0.00	0.29	0.62
AUDCNY	0.01	0.89	0.06	3.59	0.22	0.15	0.00	0.67	0.70	0.18	2.88
MYRCNY	0.01	0.70	0.04	1.18	5.01	0.61	0.01	0.41	0.79	0.78	4.54
RUBCNY	0.04	0.26	0.04	0.36	0.25	6.81	0.05	0.18	0.11	0.19	1.48
HKDCNY	4.09	0.00	0.06	0.01	0.00	0.01	4.44	0.00	0.00	0.12	4.30
GBPCNY	0.01	1.46	0.00	1.06	0.08	0.08	0.03	4.46	0.30	0.22	3.24
KRWCNY	0.00	0.67	0.01	1.16	0.35	0.09	0.01	0.44	4.51	0.38	3.10
THBCNY	0.16	0.76	0.37	0.66	0.31	0.22	0.20	0.35	0.58	5.24	3.61
TO	4.37	4.88	0.70	5.57	1.32	1.34	4.24	3.27	2.75	2.49	
NET	0.28	1.80	0.08	2.69	-3.21	-0.14	-0.06	0.03	-0.35	-1.12	TCI
NPT	7.00	6.00	6.00	9.00	0.00	2.00	6.00	5.00	3.00	1.00	3.09

Table 4 reports RMB exchange rate return spillovers of 26.31%, 6.02%, and 3.09% in high-, medium-, and low-frequency domains, respectively, with their sum representing total time-domain spillovers. The dominant high-frequency spillover highlights that risk transmission mainly occurs short-term, driven by short-term trading and speculation. Furthermore, factors such as high-frequency trading, market sentiment fluctuations, rapid information flow, and sudden economic events amplify these short-term effects (Liu et al., 2025). Conversely, long-term spillovers are weaker, reflecting that RMB returns are less affected by low-frequency shocks. Long-term fluctuations mainly stem from economic fundamentals, indicating RMB market stability and suitability for long-term investment. Central bank policies, capital account liberalization, and RMB internationalization likely mitigate long-term spillovers and enhance asset stability over extended horizons. Regarding net spillovers, USDCNY, EURCNY, AUDCNY, and GBPCNY consistently act as transmitters. The US dollar and euro, as key reserve currencies, exert strong influence, while the Australian dollar and British pound affect RMB via commodity ties and financial centers. Meanwhile, MYRCNY, RUBCNY, KRWCNY, and THBCNY are net recipients across frequencies, likely due to smaller market sizes, lower liquidity, and greater external dependence, making them vulnerable to RMB and major currency fluctuations. Additionally, capital flows in these emerging currencies are unstable and sensitive to global investor sentiment, reinforcing their passive role in spillover transmission.

Table 5

Static frequency-domain spillover of RMB exchange rate returns under extreme conditions (unit: %)

	USDCNY	EURCNY	JPYCNY	AUDCNY	MYRCNY	RUBCNY	HKDCNY	GBPCNY	KRWCNY	THBCNY	FROM
τ=0.05											
Highest frequency (short-term): Frequency band of [1,5] days											
USDCNY	13.71	7.17	7.51	5.97	7.10	6.05	13.18	6.80	6.38	7.85	68.00
EURCNY	5.64	12.19	6.83	8.42	6.64	5.89	6.02	8.93	6.82	7.62	62.82
JPYCNY	7.02	8.00	15.07	6.02	6.44	5.01	7.48	6.83	6.18	8.04	61.03
AUDCNY	4.83	8.49	5.37	12.28	7.01	5.82	5.18	8.23	7.55	7.03	59.53
MYRCNY	5.42	6.35	5.26	6.59	11.53	5.73	5.66	6.00	6.50	6.54	54.03
RUBCNY	6.21	7.65	5.6	7.12	7.07	14.46	6.39	7.13	6.45	7.35	60.97
HKDCNY	13.47	7.61	7.73	6.33	7.24	6.20	14.03	6.97	6.76	8.17	70.47
GBPCNY	5.79	9.51	6.49	8.77	6.82	5.80	6.21	12.84	7.41	7.47	64.27
KRWCNY	4.14	5.76	4.61	6.49	5.83	4.25	4.42	5.54	10.93	5.92	46.97
THBCNY	6.18	7.36	6.56	6.77	6.62	5.56	6.36	6.62	6.93	12.05	58.96
TO	58.7.	67.9.	55.97	62.48	60.77	50.32	60.90	63.04	60.98	66.00	
NET	-9.30	5.08	-5.05	2.94	6.74	-10.65	-9.57	-1.22	14.00	7.03	TCI
NPT	2.00	6.00	3.00	5.00	8.00	0.00	1.00	4.00	9.00	7.00	60.71
Intermediate frequency (medium-term): Frequency band of [5,20] days											
USDCNY	2.59	1.66	1.53	1.49	1.64	1.32	2.57	1.65	1.40	1.73	15.00
EURCNY	1.43	2.81	1.67	2.11	1.67	1.53	1.46	2.26	1.78	1.90	15.82
JPYCNY	1.39	1.74	2.61	1.28	1.26	1.18	1.38	1.48	1.37	1.60	12.68
AUDCNY	0.90	1.65	0.87	2.48	1.38	1.29	0.98	1.66	1.66	1.39	11.79
MYRCNY	1.50	2.20	1.58	2.48	2.98	1.91	1.64	2.02	1.97	2.07	17.37
RUBCNY	0.76	0.92	0.70	1.08	1.03	2.34	0.83	0.82	0.80	0.82	7.76
HKDCNY	2.17	1.38	1.28	1.27	1.37	1.08	2.25	1.36	1.18	1.47	12.57
GBPCNY	1.11	2.02	1.17	1.94	1.43	1.28	1.14	2.70	1.44	1.54	13.07
KRWCNY	1.71	2.64	1.65	3.00	2.34	2.00	1.81	2.68	3.47	2.42	20.26
THBCNY	1.46	1.85	1.58	1.81	1.72	1.45	1.52	1.79	1.65	2.82	14.83
TO	12.43	16.07	12.03	16.46	13.85	13.05	13.34	15.73	13.26	14.94	
NET	-2.56	0.25	-0.65	4.67	-3.53	5.28	0.77	2.67	-7.01	0.11	TCI
NPT	1.00	4.00	3.00	8.00	2.00	9.00	6.00	7.00	0.00	5.00	14.12
Lowest frequency (long-term): Frequency band of [20,inf] days											
USDCNY	0.34	0.01	0.01	0.00	0.00	0.00	0.33	0.01	0.00	0.00	0.37
EURCNY	0.55	1.03	0.58	0.68	0.57	0.49	0.55	0.75	0.61	0.55	5.34
JPYCNY	0.80	0.96	1.38	0.74	0.70	0.70	0.80	0.85	0.81	0.88	7.23
AUDCNY	0.87	1.64	0.82	2.26	1.26	1.21	0.91	1.85	1.76	1.35	11.66
MYRCNY	0.94	1.57	1.05	1.76	1.96	1.32	1.01	1.49	1.52	1.46	12.12
RUBCNY	0.83	1.45	1.03	1.79	1.50	2.42	0.90	1.50	1.55	1.50	12.05
HKDCNY	0.31	0.01	0.01	0.01	0.00	0.00	0.32	0.01	0.00	0.00	0.35
GBPCNY	0.54	0.90	0.47	0.88	0.55	0.58	0.55	1.34	0.71	0.62	5.79
KRWCNY	1.34	2.10	1.25	2.28	1.75	1.51	1.39	2.23	2.70	1.81	15.66
THBCNY	0.88	1.17	1.05	1.17	1.11	0.99	0.91	1.17	1.10	1.80	9.54
TO	7.04	9.81	6.28	9.30	7.45	6.80	7.35	9.87	8.06	8.17	

NET	6.67	4.47	-0.95	-2.36	-4.67	-5.25	6.99	4.08	-7.60	-1.37	TCI
NPT	8.00	7.00	5.00	3.00	2.00	0.00	9.00	6.00	1.00	4.00	8.01
τ=0.95											
Highest frequency (short-term): Frequency band of [1,5] days											
USDCNY	12.64	5.53	6.23	5.00	5.43	4.92	11.94	5.53	4.99	6.64	56.20
EURCNY	5.65	12.55	6.77	8.69	6.80	6.17	5.84	9.04	6.86	7.52	63.34
JPYCNY	6.81	7.55	13.03	5.84	6.23	5.10	6.87	6.47	5.80	7.65	58.32
AUDCNY	5.49	9.41	5.72	13.86	7.71	6.74	5.70	9.05	8.33	7.76	65.91
MYRCNY	4.10	5.05	4.18	5.50	9.38	4.74	4.18	4.97	5.33	5.55	43.60
RUBCNY	6.42	7.87	6.48	7.74	7.97	16.32	6.62	7.50	6.98	8.07	65.64
HKDCNY	12.40	6.14	6.70	5.53	5.93	5.18	12.90	5.92	5.27	6.96	60.03
GBPCNY	5.97	9.35	6.25	8.72	6.98	6.35	5.98	12.88	7.10	7.45	64.16
KRWCNY	5.25	7.24	5.56	8.47	7.44	5.76	5.33	7.31	13.51	7.54	59.91
THBCNY	5.91	6.68	6.40	6.26	6.20	5.36	5.92	6.41	6.24	10.84	55.39
TO	58.00	64.82	54.30	61.76	60.69	50.33	58.38	62.20	56.89	65.13	
NET	1.80	1.48	-4.02	-4.14	17.09	-15.31	-1.65	-1.96	-3.02	9.74	TCI
NPT	7.00	6.00	1.00	3.00	9.00	0.00	5.00	4.00	2.00	8.00	59.25
Intermediate frequency (medium-term): Frequency band of [5,20] days											
USDCNY	3.01	1.54	1.81	1.43	1.61	1.44	3.02	1.54	1.38	1.95	15.72
EURCNY	1.19	2.60	1.59	1.87	1.33	1.20	1.22	1.97	1.49	1.59	13.46
JPYCNY	1.59	1.90	3.55	1.40	1.49	1.17	1.61	1.55	1.47	1.89	14.08
AUDCNY	0.96	1.61	1.02	2.26	1.37	1.07	0.99	1.55	1.44	1.40	11.40
MYRCNY	2.33	3.04	2.69	3.23	4.02	2.52	2.31	2.90	3.05	3.21	25.28
RUBCNY	0.82	0.97	0.62	1.08	1.01	2.20	0.77	0.97	0.81	0.94	7.99
HKDCNY	2.59	1.31	1.62	1.23	1.39	1.24	2.70	1.29	1.19	1.68	13.54
GBPCNY	1.18	1.99	1.34	1.85	1.39	1.29	1.19	2.68	1.34	1.58	13.16
KRWCNY	1.40	1.93	1.43	2.19	1.68	1.25	1.43	1.82	2.97	1.90	15.03
THBCNY	1.92	2.40	2.16	2.34	2.27	1.92	1.97	2.20	2.11	3.51	19.31
TO	13.96	16.70	14.29	16.63	13.53	13.10	14.52	15.79	14.28	16.15	
NET	-1.76	3.24	0.21	5.23	-11.75	5.11	0.98	2.63	-0.74	-3.15	TCI
NPT	2.00	7.00	4.00	9.00	0.00	8.00	4.00	6.00	3.00	2.00	14.90
Lowest frequency (long-term): Frequency band of [20,inf] days											
USDCNY	2.25	1.04	1.20	0.84	0.97	0.94	2.35	0.76	0.88	1.21	10.18
EURCNY	0.61	1.24	0.85	0.89	0.69	0.64	0.63	0.96	0.72	0.82	6.80
JPYCNY	0.99	1.09	2.08	0.88	1.02	0.83	1.03	0.98	0.83	1.28	8.94
AUDCNY	0.49	0.76	0.63	0.98	0.66	0.48	0.51	0.75	0.67	0.66	5.60
MYRCNY	1.52	1.77	1.83	1.81	2.38	1.50	1.53	1.67	1.75	1.95	15.34
RUBCNY	0.94	0.73	0.50	0.75	0.72	1.34	0.95	0.54	0.67	0.69	6.51
HKDCNY	1.94	0.90	1.08	0.72	0.85	0.81	2.09	0.65	0.76	1.04	8.75
GBPCNY	0.60	0.83	0.68	0.78	0.63	0.59	0.62	1.14	0.56	0.70	5.98
KRWCNY	0.69	0.94	0.76	0.92	0.82	0.63	0.71	0.77	1.38	0.96	7.20
THBCNY	0.94	1.16	1.05	1.12	1.13	0.89	0.98	1.01	1.03	1.65	9.30
TO	8.71	9.22	8.58	8.72	7.47	7.30	9.33	8.10	7.87	9.31	
NET	-1.47	2.41	-0.36	3.12	-7.87	0.79	0.58	2.11	0.67	0.01	TCI
NPT	2.00	7.00	3.00	9.00	0.00	4.00	3.00	7.00	6.00	4.00	8.46

Table 5 reports spillover effects under extreme upside and downside conditions. Total spillovers are significantly higher during extreme states than at the median, indicating intensified cross-market risk transmission amid severe volatility. Despite increased spillovers in extremes, short-term effects remain dominant, consistent with median-state findings. This highlights rapid market reactions to shocks in the short term, while long-term effects stay limited. Further analysis of the net spillover effects reveals that EURCNY consistently acts as a net risk transmitter in both extreme upside and downside conditions, underscoring its strong influence over other RMB exchange rates during periods of market turbulence. JPYCNY exhibits notable state dependence and is the primary risk spillover recipient under extreme downside conditions, indicating heightened vulnerability to shocks from other RMB exchange rate markets amid market panic. Conversely, in extreme upside scenarios, no single dominant recipient emerges, suggesting a more balanced risk transmission pattern. This pattern may reflect that during broadly bullish markets, increased investor risk appetite reduces the reliance of any individual exchange rate on external shocks, thereby dispersing risk more evenly across markets.

Table 6

Static frequency-domain spillover of RMB exchange rate volatility under normal condition (unit: %)

	USDCNY	EURCNY	JPYCNY	AUDCNY	MYRCNY	RUBCNY	HKDCNY	GBPCNY	KRWCNY	THBCNY	FROM
Highest frequency (short-term): Frequency band of [1,5] days											
USDCNY	0.48	0.02	0.05	0.01	0.03	0.01	0.40	0.02	0.01	0.07	0.61
EURCNY	0.01	0.10	0.01	0.02	0.01	0.00	0.01	0.01	0.01	0.02	0.10
JPYCNY	0.13	0.07	0.82	0.10	0.07	0.03	0.12	0.08	0.05	0.12	0.77
AUDCNY	0.00	0.02	0.01	0.15	0.00	0.01	0.00	0.03	0.02	0.01	0.11
MYRCNY	0.01	0.01	0.01	0.02	0.44	0.01	0.01	0.00	0.03	0.01	0.12
RUBCNY	0.01	0.07	0.02	0.05	0.00	0.75	0.01	0.02	0.01	0.02	0.21
HKDCNY	0.41	0.02	0.07	0.00	0.02	0.01	0.52	0.03	0.01	0.09	0.67
GBPCNY	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.15	0.00	0.01	0.04
KRWCNY	0.01	0.03	0.02	0.05	0.01	0.00	0.01	0.01	0.38	0.02	0.16
THBCNY	0.05	0.03	0.06	0.02	0.04	0.00	0.04	0.04	0.01	0.44	0.29
TO	0.64	0.27	0.26	0.27	0.19	0.08	0.60	0.23	0.15	0.38	
NET	0.03	0.17	-0.51	0.16	0.07	-0.13	-0.07	0.19	-0.01	0.09	TCI
NPT	3.00	7.00	0.00	7.00	6.00	3.00	1.00	8.00	5.00	5.00	0.31
Intermediate frequency (medium-term): Frequency band of [5,20] days											
USDCNY	0.94	0.05	0.10	0.02	0.07	0.02	0.77	0.05	0.02	0.14	1.25
EURCNY	0.02	0.12	0.02	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.11
JPYCNY	0.21	0.13	1.25	0.10	0.11	0.05	0.17	0.06	0.05	0.16	1.05
AUDCNY	0.00	0.05	0.03	0.29	0.01	0.01	0.00	0.06	0.03	0.01	0.22
MYRCNY	0.05	0.04	0.07	0.06	0.83	0.02	0.05	0.02	0.10	0.09	0.51
RUBCNY	0.01	0.09	0.04	0.07	0.01	1.91	0.01	0.03	0.00	0.02	0.29
HKDCNY	0.74	0.05	0.11	0.01	0.06	0.02	0.91	0.05	0.01	0.16	1.22
GBPCNY	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.24	0.00	0.03	0.08
KRWCNY	0.01	0.07	0.04	0.09	0.01	0.00	0.01	0.01	0.64	0.02	0.26
THBCNY	0.11	0.07	0.22	0.05	0.09	0.05	0.10	0.06	0.06	0.85	0.81
TO	1.16	0.57	0.64	0.43	0.37	0.19	1.14	0.36	0.28	0.65	
NET	-0.09	0.46	-0.41	0.21	-0.13	-0.10	-0.08	0.28	0.02	-0.17	TCI
NPT	1.00	8.00	1.00	7.00	3.00	5.00	2.00	9.00	6.00	3.00	0.58
Lowest frequency (long-term): Frequency band of [20,inf] days											
USDCNY	41.88	1.91	4.35	0.66	0.96	1.33	37.67	2.00	0.78	5.18	54.84
EURCNY	1.39	55.30	7.69	9.35	3.69	3.99	1.79	9.44	4.10	2.84	44.27
JPYCNY	4.56	8.95	54.23	5.39	3.11	2.37	5.18	4.35	3.95	4.03	41.88
AUDCNY	0.47	10.71	6.26	54.94	2.09	2.02	0.59	10.04	10.01	2.11	44.30
MYRCNY	2.12	5.48	5.80	3.20	61.24	3.61	2.11	3.83	4.53	6.19	36.87
RUBCNY	2.10	2.69	2.93	1.81	4.16	74.62	2.17	3.17	1.23	1.97	22.22
HKDCNY	38.25	1.96	4.13	0.78	1.02	1.35	41.71	2.17	0.70	4.61	54.97
GBPCNY	3.05	9.94	6.90	13.15	1.83	2.83	3.57	51.14	4.37	2.71	48.35
KRWCNY	1.23	6.30	5.22	15.04	4.15	1.94	1.09	6.32	54.71	2.57	43.86
THBCNY	7.38	4.61	6.15	2.97	3.93	3.46	7.50	2.73	4.18	54.70	42.90
TO	60.56	52.55	49.43	52.36	24.93	22.90	61.66	44.03	33.83	32.21	
NET	5.73	8.28	7.55	8.06	-11.93	0.67	6.68	-4.32	-10.03	-10.69	TCI
NPT	7.00	8.00	6.00	6.00	1.00	4.00	6.00	4.00	2.00	1.00	43.45

Table 6 reports volatility spillover effects in the RMB exchange rate market under median conditions. TCI values are 0.31%, 0.58%, and 43.45% for high-, medium-, and low-frequency domains, respectively, contrasting sharply with return spillovers. Volatility spillovers are notably stronger in the low-frequency domain, indicating that long-term factors primarily drive volatility transmission. This suggests risk accumulates and dissipates over extended periods rather than through abrupt short-term shocks. Such dynamics likely stem from RMB fluctuations being influenced by macroeconomic cycles, international capital flows, and policy changes, while short-term market noise and sudden events exert limited cross-market volatility impact. Regarding NET, EURCNY and AUDCNY consistently serve as the primary risk exporters across all frequency domains, highlighting their dominant role in volatility transmission within the RMB exchange rate market. Conversely, JPYCNY serves as the largest net risk receiver in the high- and medium-frequency domains, likely absorbing external risks in the short run due to its safe-haven characteristics. However, under low-frequency conditions, JPYCNY transitions into a significant net risk exporter, reflecting that long-term economic structural factors enhance its capacity to transmit risk, thereby evolving from a risk absorber to a key risk transmitter in the RMB exchange rate market.

Table 7

Static frequency-domain spillover of RMB exchange rate volatility under extreme conditions (unit: %)

	USDCNY	EURCNY	JPYCNY	AUDCNY	MYRCNY	RUBCNY	HKDCNY	GBPCNY	KRWCNY	THBCNY	FROM
τ=0.05											
Highest frequency (short-term): Frequency band of [1,5] days											
USDCNY	1.90	0.33	0.47	0.06	0.31	0.30	1.76	0.30	0.23	0.63	4.41
EURCNY	0.05	0.30	0.11	0.07	0.09	0.07	0.05	0.12	0.09	0.09	0.74
JPYCNY	0.24	0.35	0.98	0.18	0.25	0.16	0.25	0.28	0.26	0.29	2.27
AUDCNY	0.01	0.04	0.03	0.19	0.02	0.01	0.01	0.04	0.04	0.02	0.22
MYRCNY	0.15	0.29	0.25	0.09	0.97	0.18	0.15	0.20	0.25	0.28	1.84
RUBCNY	0.37	0.46	0.37	0.14	0.41	2.23	0.37	0.34	0.26	0.43	3.15
HKDCNY	1.67	0.32	0.46	0.06	0.30	0.30	1.80	0.31	0.22	0.60	4.24
GBPCNY	0.03	0.07	0.05	0.04	0.04	0.03	0.03	0.20	0.04	0.04	0.39
KRWCNY	0.10	0.24	0.21	0.17	0.19	0.09	0.10	0.20	0.79	0.17	1.46
THBCNY	0.42	0.36	0.36	0.10	0.37	0.24	0.42	0.29	0.27	1.27	2.82
TO	3.03	2.47	2.31	0.91	1.97	1.38	3.16	2.09	1.65	2.55	
NET	-1.38	1.73	0.05	0.69	0.13	-1.77	-1.08	1.70	0.19	-0.27	TCI
NPT	1.00	7.00	4.00	9.00	5.00	0.00	2.00	8.00	6.00	3.00	2.15
Intermediate frequency (medium-term): Frequency band of [5,20] days											
USDCNY	2.93	0.50	0.71	0.10	0.46	0.47	2.71	0.47	0.36	0.95	6.73
EURCNY	0.09	0.52	0.21	0.12	0.16	0.12	0.09	0.20	0.17	0.14	1.31
JPYCNY	0.38	0.57	1.56	0.30	0.41	0.24	0.40	0.43	0.42	0.45	3.62
AUDCNY	0.01	0.07	0.05	0.31	0.03	0.02	0.01	0.07	0.07	0.03	0.37
MYRCNY	0.28	0.55	0.45	0.15	1.74	0.34	0.29	0.37	0.47	0.51	3.42
RUBCNY	0.59	0.74	0.61	0.24	0.67	3.62	0.61	0.57	0.42	0.69	5.14
HKDCNY	2.70	0.52	0.74	0.10	0.48	0.48	2.92	0.49	0.36	0.98	6.84
GBPCNY	0.05	0.12	0.08	0.08	0.06	0.05	0.05	0.34	0.07	0.07	0.63
KRWCNY	0.17	0.43	0.34	0.31	0.32	0.14	0.17	0.35	1.36	0.29	2.53
THBCNY	0.66	0.59	0.61	0.20	0.60	0.37	0.68	0.48	0.46	1.98	4.66

TO	4.94	4.10	3.81	1.59	3.20	2.23	5.02	3.44	2.79	4.12	
NET	-1.79	2.79	0.20	1.23	-0.22	-2.91	-1.82	2.81	0.26	-0.54	TCI
NPT	1.00	7.00	5.00	9.00	4.00	0.00	2.00	8.00	6.00	3.00	3.52
Lowest frequency (long-term): Frequency band of [20,inf] days											
USDCNY	25.22	4.37	6.20	0.90	3.99	4.37	23.31	4.22	3.00	8.44	58.82
EURCNY	4.90	27.76	10.35	6.68	8.57	5.78	5.08	10.55	9.26	8.19	69.37
JPYCNY	6.78	10.53	27.66	4.21	7.41	4.76	7.10	7.65	7.32	8.17	63.92
AUDCNY	1.57	10.59	7.40	45.55	4.00	3.02	1.77	10.57	10.45	3.99	53.36
MYRCNY	5.26	9.73	8.27	2.76	30.81	6.10	5.38	6.77	7.74	9.21	61.22
RUBCNY	5.88	7.26	5.95	2.34	6.83	34.77	6.05	5.74	4.03	7.02	51.09
HKDCNY	23.01	4.55	6.46	1.06	4.10	4.34	24.72	4.45	3.12	8.39	59.48
GBPCNY	5.34	12.13	9.01	7.41	6.78	5.13	5.69	31.37	8.34	7.24	67.07
KRWCNY	3.79	10.50	8.45	7.85	8.09	3.72	3.93	8.31	32.16	7.07	61.71
THBCNY	9.09	8.00	8.27	2.77	8.08	5.36	9.05	6.30	6.10	26.26	63.01
TO	65.62	77.67	70.37	35.96	57.86	42.58	67.36	64.56	59.36	67.73	
NET	6.80	8.30	6.45	-17.39	-3.36	-8.52	7.87	-2.51	-2.35	4.71	TCI
NPT	8.00	6.00	6.00	0.00	4.00	1.00	9.00	2.00	3.00	6.00	60.91
τ=0.95											
Highest frequency (short-term): Frequency band of [1,5] days											
USDCNY	1.40	1.19	1.06	0.83	1.26	2.54	1.48	1.32	0.88	1.12	11.67
EURCNY	0.21	0.05	0.03	0.11	0.06	0.18	0.19	0.03	0.07	0.10	0.97
JPYCNY	1.06	0.60	0.63	0.40	0.61	1.66	1.07	0.71	0.41	0.60	7.11
AUDCNY	0.04	0.40	0.28	0.53	0.11	0.05	0.04	0.27	0.55	0.04	1.79
MYRCNY	0.03	0.47	0.36	0.48	0.34	0.04	0.03	0.27	0.51	0.08	2.26
RUBCNY	1.01	1.21	1.04	0.89	1.44	2.90	1.06	1.31	0.98	1.08	10.02
HKDCNY	1.28	1.13	0.98	0.81	1.15	2.36	1.36	1.24	0.82	0.98	10.75
GBPCNY	0.18	0.47	0.44	0.38	0.21	0.27	0.19	0.35	0.34	0.15	2.62
KRWCNY	0.02	0.56	0.39	0.81	0.23	0.04	0.03	0.39	0.85	0.08	2.54
THBCNY	0.93	0.93	0.83	0.66	1.08	1.34	1.01	0.96	0.79	0.95	8.51
TO	4.74	6.98	5.41	5.36	6.14	8.47	5.10	6.49	5.34	4.21	
NET	-6.93	6.00	-1.70	3.56	3.88	-1.55	-5.65	3.88	2.80	-4.30	TCI
NPT	0.00	9.00	2.00	8.00	5.00	4.00	3.00	7.00	6.00	1.00	5.83
Intermediate frequency (medium-term): Frequency band of [5,20] days											
USDCNY	1.95	1.67	1.47	1.16	1.75	3.57	2.06	1.84	1.23	1.55	16.31
EURCNY	0.33	0.22	0.15	0.27	0.20	0.33	0.31	0.17	0.22	0.17	2.17
JPYCNY	1.58	0.96	1.01	0.64	0.96	2.58	1.60	1.13	0.69	0.98	11.13
AUDCNY	0.22	0.75	0.57	0.90	0.36	0.26	0.21	0.56	0.91	0.21	4.06
MYRCNY	0.18	1.01	0.80	0.96	0.81	0.27	0.20	0.66	1.04	0.29	5.40
RUBCNY	1.43	1.82	1.54	1.34	2.14	4.16	1.52	1.96	1.46	1.60	14.80
HKDCNY	1.79	1.61	1.39	1.13	1.61	3.34	1.92	1.75	1.16	1.39	15.17
GBPCNY	0.35	0.78	0.78	0.65	0.41	0.46	0.38	0.62	0.60	0.28	4.69
KRWCNY	0.11	1.09	0.77	1.46	0.53	0.21	0.13	0.82	1.57	0.23	5.34
THBCNY	1.35	1.40	1.24	1.03	1.63	2.03	1.48	1.46	1.20	1.41	12.82
TO	7.33	11.08	8.71	8.64	9.60	13.05	7.90	10.36	8.53	6.69	
NET	-8.98	8.92	-2.42	4.59	4.20	-1.75	-7.27	5.67	3.19	-6.13	TCI
NPT	1.00	9.00	2.00	8.00	5.00	4.00	3.00	7.00	5.00	1.00	9.19
Lowest frequency (long-term): Frequency band of [20,inf] days											
USDCNY	8.78	5.99	5.82	4.04	6.28	11.31	9.07	6.66	4.46	6.25	59.89
EURCNY	2.83	19.40	11.89	13.68	9.25	4.34	3.40	12.11	13.52	6.17	77.18
JPYCNY	9.80	7.24	10.15	4.93	7.06	10.93	10.09	7.60	5.40	6.93	69.97
AUDCNY	2.31	13.90	10.89	18.32	8.12	4.71	2.76	12.00	15.15	4.56	74.39
MYRCNY	2.95	13.05	11.36	10.66	15.25	3.73	4.14	10.64	12.48	6.92	75.94
RUBCNY	5.82	6.11	5.37	4.45	7.31	15.75	6.03	6.67	4.87	5.74	52.37
HKDCNY	8.88	6.37	6.05	4.40	6.48	11.35	9.43	7.01	4.67	6.18	61.37
GBPCNY	5.84	13.03	11.42	10.14	8.54	6.76	6.35	13.25	9.80	6.59	78.47
KRWCNY	2.85	12.41	10.10	13.99	9.01	4.28	3.42	10.64	17.72	5.27	71.98
THBCNY	8.00	7.30	7.07	4.80	8.49	8.79	8.49	7.39	6.09	9.88	66.43
TO	49.27	85.40	79.98	71.09	70.54	66.19	53.75	80.72	76.44	54.59	
NET	-10.62	8.22	10.02	-3.30	-5.40	13.83	-7.61	2.25	4.47	-11.84	TCI
NPT	2.00	7.00	6.00	4.00	4.00	6.00	3.00	6.00	7.00	0.00	68.80

Table 7 reports RMB exchange rate volatility spillovers under extreme market conditions, showing patterns consistent with those in returns. The TCI is significantly higher during extreme states than in the median scenario, mainly concentrated in the low-frequency domain. In terms of NET spillovers, during low-volatility stable periods, RUBCNY acts as a pure risk receiver, while EURCNY and JPYCNY serve as primary risk exporters. Conversely, under high-volatility conditions, USACNY, HKDCNY, and THBCNY become risk receivers, with EURCNY, GBPCNY, and KRWCNY acting as exporters. Notably, EURCNY consistently functions as a risk exporter across all frequency domains and market regimes, while the identities of risk receivers vary by exchange rate and market condition. RUBCNY displays a distinctive pattern during extreme uptrends: it remains a risk receiver in short- and medium-term horizons but emerges as the largest risk exporter in the long-term domain when volatility spillovers peak. This underscores the significant intensification of RUBCNY's long-term spillover effect amid heightened market turbulence.

4.2 Dynamic Spillover Effects of the RMB Exchange Rate

Although static spillover effects under the three market states have been identified, their dynamic properties require further exploration. This study applies a rolling window method to analyze the time-varying spillovers of RMB exchange rate returns and volatilities. Following Hoque et al. (2024), a 200-day rolling window with a 12-day forecast horizon is used to precisely capture spillover dynamics. Prior studies reveal that return spillovers during extreme upside or downside states differ significantly from the median, indicating that models relying only on conditional mean or median may underestimate market dependence amid large shocks. This underscores the importance of tail dependence in financial supervision and risk monitoring. Accordingly, we extend the analysis across all quantiles to more comprehensively characterize the asymmetry of spillovers and transmission mechanisms of extreme risks.

4.2.1 Total Spillover Effects

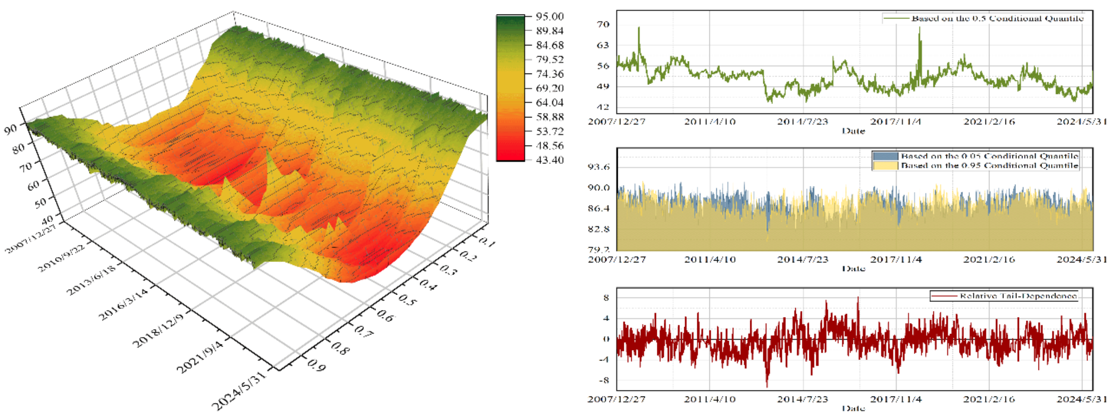


Fig. 5. Total risk spillover of RMB exchange rate returns across all quantiles

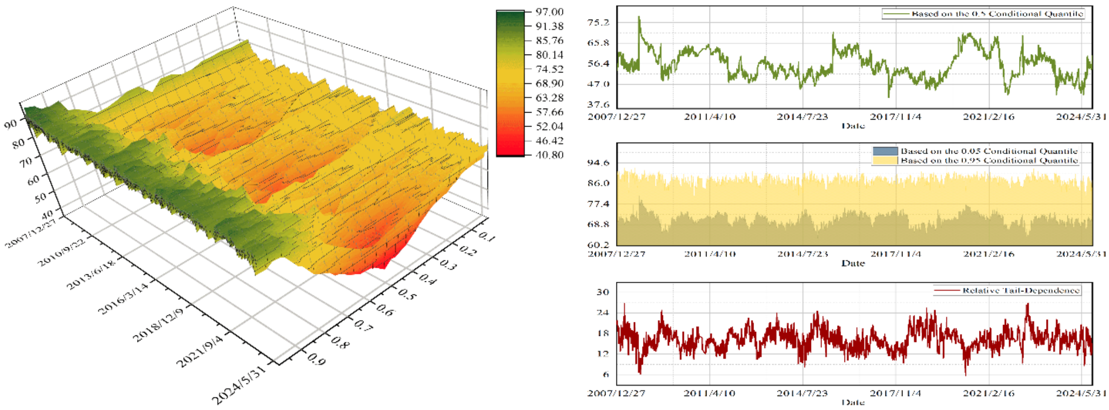


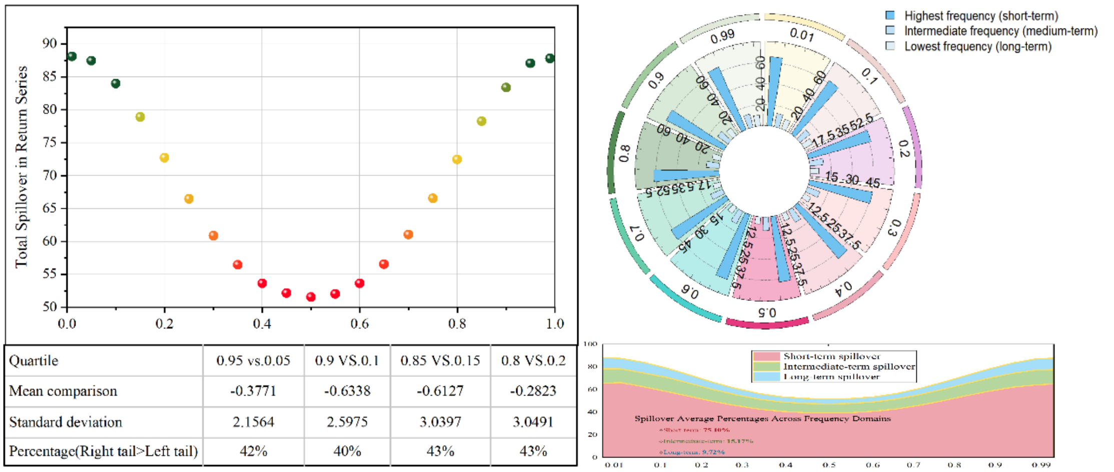
Fig. 6. Total risk spillover of RMB exchange rate volatility across all quantiles

The TCI based on the conditional median and conditional mean more accurately captures the overall spillover effects of RMB exchange rate tail risk under normal market conditions. However, the TCI varies across different levels of shock intensity, revealing significant heterogeneity in risk transmission. Fig. 5 and Fig. 6 illustrate the time-varying patterns of TCI for RMB exchange rate returns and volatilities across the full range of quantiles, offering a comprehensive view of how tail risk spillovers evolve over time and across different market states.

We first analyze risk spillovers in the return series as shown in Fig. 5. The left panel presents the TCI distribution across quantiles, revealing the lowest spillover intensity near the 0.5 quantile, indicating limited transmission under normal market conditions. In late 2008, large stimulus policies responding to the global financial crisis spurred investment and significantly increased spillovers. Between 2013 and 2015 and again in late 2017, sluggish global recovery, heightened political uncertainty, and tighter financial conditions depressed capital markets, causing a TCI decline. By early 2024, uneven global recovery and rising geopolitical tensions heightened volatility, yet TCI fell further, suggesting weakened systemic spillovers under uncertainty. The right panel's first subplot shows the median-based TCI fluctuating between 40% and 70%, reflecting pronounced time variation consistent with earlier trends. The second subplot reports TCI at the 0.05 and 0.95 quantiles, which capture sensitivity to extreme negative and positive shocks. These tail values significantly exceed the median, ranging mostly from 80% to 95% with limited volatility. This indicates the RMB exchange rate system's heightened sensitivity to extreme shocks and stronger risk transmission in tail events. The third subplot, based on Ando et al. (2018), presents relative tail dependence

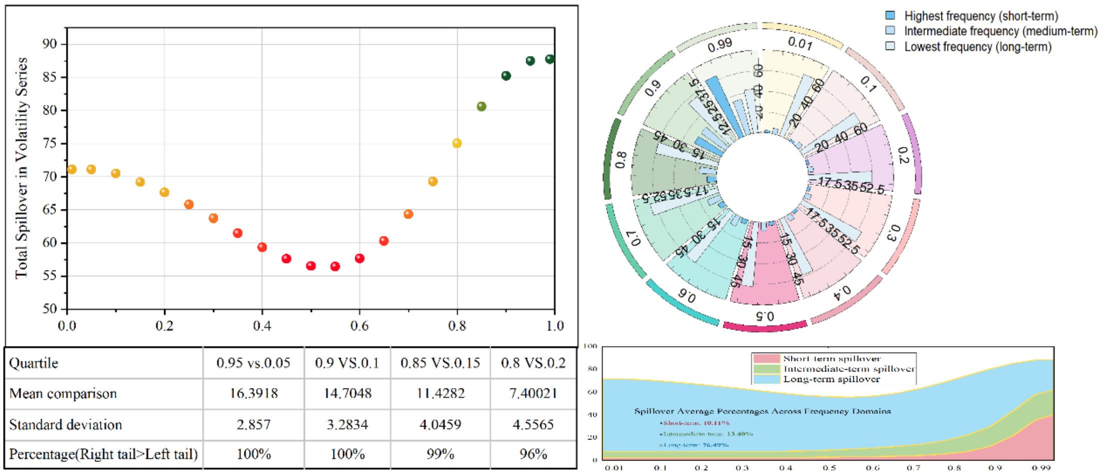
($RTD = TCI_{\tau=0.95} - TCI_{\tau=0.05}$). Our results align with Massacci (2017), revealing clear asymmetry between upper and lower tails and strong tail connectivity. Positive (negative) RTD signals greater (weaker) dependence on positive (negative) shocks, correlating with financial vulnerability. Overall, RTD oscillates near zero, indicating balanced transmission of extreme positive and negative shocks. Yet, RTD deviates significantly in specific periods, reflecting cyclical shifts in tail risk sensitivity. For instance, late 2007 showed negative RTD, signaling stronger sensitivity to negative shocks; during late 2015's exchange rate reform, RTD was positive, indicating greater dependence on positive shocks. These dynamics highlight evolving market sensitivity and offer key insights for risk monitoring.

Secondly, we analyze risk spillover in the volatility series (see Fig. 6). The left panel's 3D distribution shows that risk spillover near the 0.5 quantile remains low, indicating low volatility spillover under neutral market conditions. Color intensity reveals risk spillover in the right tail significantly exceeds the left, indicating stronger contagion during extreme upward movements. The first two right panels confirm this pattern, showing pronounced dynamic evolution of total RMB exchange rate risk spillover over time. Key event analysis shows the 2008 US subprime crisis triggered global turmoil, pressuring the RMB downward and causing prolonged export decline. China's stock market saw severe volatility in 2015. Despite a non-market-oriented exchange rate mechanism, the RMB was notably impacted. Sino-US trade tensions escalation in 2018 intensified RMB depreciation expectations. The 2020 COVID-19 outbreak and lockdowns severely disrupted the global economy, markedly increasing RMB risk spillover. The 2022 Fed rate hikes strengthened the US dollar, renewed RMB pressure, and elevated risk spillovers. The third right panel shows relative tail dependence from volatility, assessing asymmetry in tail risk spillover. Positive (negative) RTD values indicate stronger (weaker) spillovers during high versus low volatility periods. Volatility-based RTD remains consistently positive, implying heightened market interdependence in volatile periods. This suggests greater systemic risk under high-volatility shocks and relative stability in calmer conditions. This may reflect asymmetry between market behavior and policy: investor herding amplifies upward momentum during appreciations, while regulatory actions curb declines, reinforcing right-tail dependence. Asymmetries in global capital flows and external shocks also play key roles. For example, Fed policy adjustments often intensify RMB upward pressure but have limited impact on depreciation. Markets typically leverage upward moves but turn risk-averse during declines. This amplifies right-tail dependence, highlighting market fragility under high volatility.



Quartile	0.95 vs.0.05	0.9 VS.0.1	0.85 VS.0.15	0.8 VS.0.2
Mean comparison	-0.3771	-0.6338	-0.6127	-0.2823
Standard deviation	2.1564	2.5975	3.0397	3.0491
Percentage(Right tail>Left tail)	42%	40%	43%	43%

Fig. 7. Total dynamic spillover effects of RMB exchange rate returns across quantile-based frequency domains



Quartile	0.95 vs.0.05	0.9 VS.0.1	0.85 VS.0.15	0.8 VS.0.2
Mean comparison	16.3918	14.7048	11.4282	7.40021
Standard deviation	2.857	3.2834	4.0459	4.5565
Percentage(Right tail>Left tail)	100%	100%	99%	96%

Fig. 8. Total risk spillover effects of RMB exchange rate volatility across quantile-based frequency domains

Moreover, this study further examines risk spillover across quantiles. Figs. 7 and 8 depict the tail risk spillover of the RMB exchange rate measured across different quantiles and frequency domains, offering a detailed view of its dynamic evolution under extreme market volatility and across time scales. The left panel shows that, regardless of whether the total spillover index derives from returns or volatilities, spillover effects across quantiles form a distinct U-shaped curve, reflecting intensified spillovers during extreme market conditions. Return-based total spillovers display symmetry between left and right tails, while volatility-based spillovers exhibit pronounced asymmetry, with right-tail spillovers notably exceeding those on the left. To validate this, statistical tests on average spillovers at four extreme quantile pairs (0.95-0.05, 0.9-0.1, 0.85-0.15, and 0.8-0.2) were conducted. Results for returns show the mean difference near zero and the proportion close to 50%, confirming approximate balance between upper and lower tail spillovers. This balance under extreme shocks likely reflects the interplay of systemic risk, common drivers such as market sentiment, and regulatory equilibrium between policy intervention and market forces. Conversely, volatility results reveal consistently greater right-tail spillovers at these quantiles, with differences statistically significant. This indicates stronger contagion during extreme upswings than downturns. Frequency analysis supports this asymmetry, as upper-tail spillovers exceed lower-tail ones more frequently. The asymmetry may arise from amplified irrational market sentiment driven by factors such as trade frictions, domestic economic conditions, global currency settlements, and central bank policies, which intensify RMB exchange rate uncertainty and exacerbate volatility spillovers.

The right panel shows that the TCI from the return series is mainly driven by the high-frequency component across all quantiles, reflecting the market's acute sensitivity to short-term shocks. Conversely, the TCI from the volatility series is largely dominated by the low-frequency component, indicating that volatility spillovers tend to be more stable and linked to long-term risks. With increasing quantiles, high- and medium-frequency spillovers increase substantially, sometimes matching or exceeding the low-frequency component at extreme quantiles. This suggests that during sharp market fluctuations, risk responses extend beyond short-term shocks to include sustained oscillations, creating a complex interplay between short- and medium-term risks. This heterogeneity in spillover dynamics can be explained by the differing nature of return and volatility fluctuations. Return fluctuations mainly arise from short-term trading behavior, information shocks, and investor sentiment, leading to rapid and intense risk transmission. In contrast, volatility reflects broader market uncertainty evolving gradually under the influence of long-term macroeconomic trends, policy shifts, and structural changes. During extreme episodes, sharp short-term volatility spikes coexist with accumulating medium-term risks, amplifying both medium- and short-term components of volatility spillovers. This pattern highlights the complex and evolving nature of volatility risk transmission over time, consistent with previous findings.

4.2.2 Net Spillover Effects

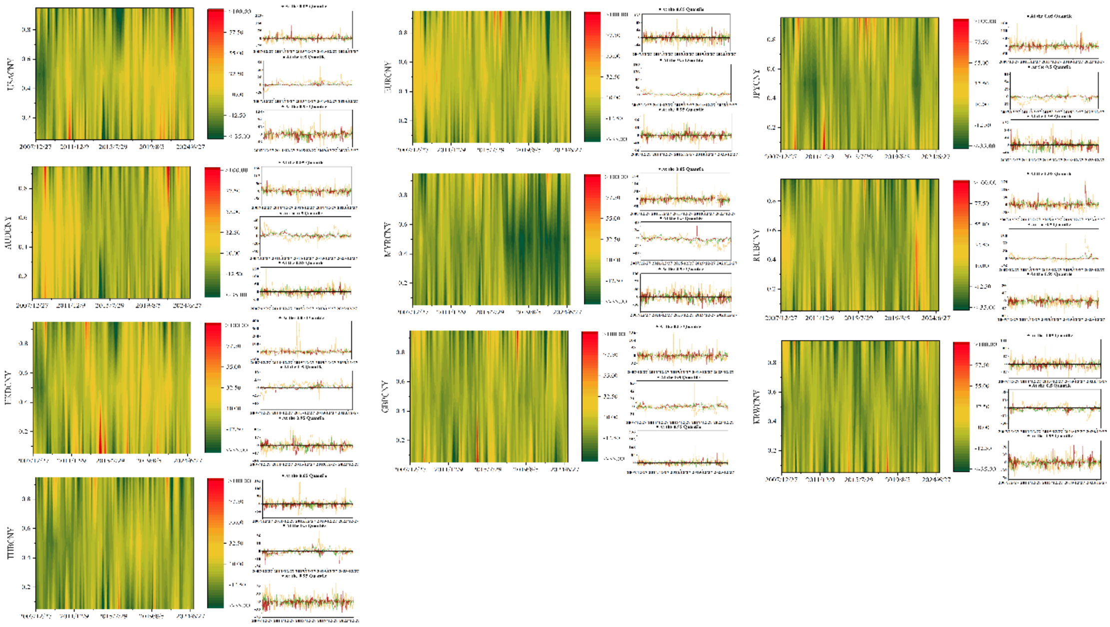


Fig. 9. Net Risk Spillover of RMB Exchange Rate Returns Across Quantile-Frequency Domains

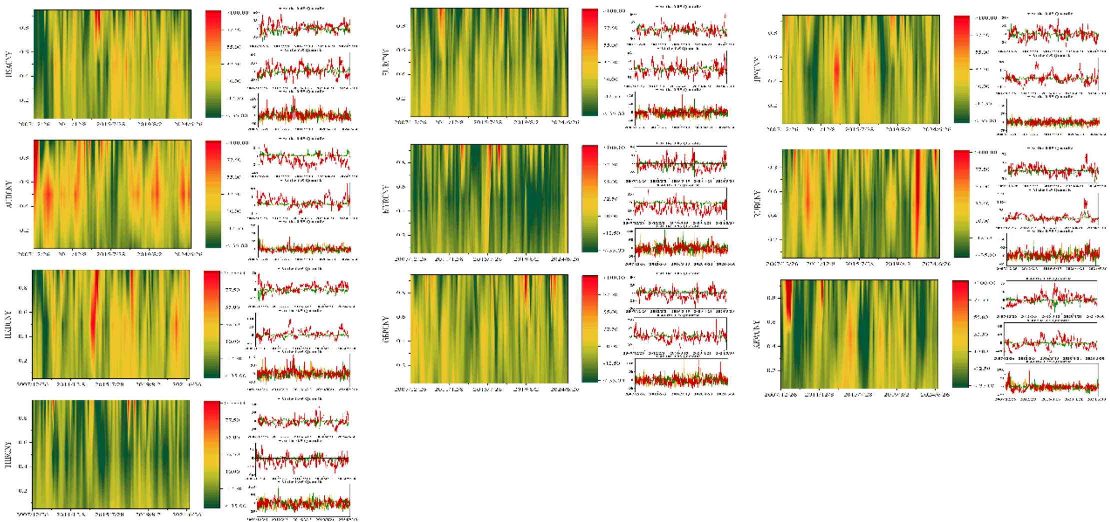


Fig. 10. Net Risk Spillover of RMB Exchange Rate Volatilities Across Quantile-Frequency Domains

Note: In the line charts across different quantiles, the yellow line represents the short-term spillover effect, the green line indicates the medium-term spillover effect, and the red line signifies the long-term spillover effect.

In the following analysis, this study primarily examines the network's overall connectivity to investigate interactions among system variables. Prior studies recognize net interest rate shocks as key indicators of connectivity (Khalfaoui et al., 2022; Zhang and Wei, 2024). Figs. 9 and 10 display net spillover effects of the RMB exchange rate, derived from returns and volatilities across quantiles, and analyze their frequency-domain characteristics. Fig. 9 shows that spillover effects at the distribution tails of RMB returns markedly exceed those near the median, suggesting more pronounced net spillover effects in extreme cases. Net spillover analysis across three quantiles underscores short-term spillover dominance. However, in Fig. 10, net spillover effects in extremes do not consistently surpass median levels, with even the net spillover at the 0.5 quantile for RUBCNY exceeding that of the extremes. While long-term spillovers typically dominate in the volatility series, we hypothesize that short-term spillovers become exceptionally prominent during extreme upward movements. This hypothesis is supported by the empirical results. Overall, while spillover patterns in both figures are similar, volatility-based net spillover indices show greater volatility. Notably, each RMB exchange rate exhibits distinct spillover profiles, influenced differently by varying market volatility patterns. In extreme events, net spillover patterns across the two quantiles differ markedly, with no consistent net volatility transmitter or receiver over time. Therefore, investors and policymakers must closely monitor the evolving net spillover dynamics of the RMB exchange rate under such extreme conditions.

5. Further analysis

Building on the time-varying results above, the evidence indicates that external risk shocks play a significant role in shaping the extreme spillover effects among RMB exchange rates, affecting both return and volatility dimensions. This prompts a central question: what risk factors drive the dynamic evolution of interconnectedness across the ten RMB exchange rate markets? In practice, market participants often rely on these underlying drivers to anticipate or assess the magnitude of extreme risk spillovers in the global RMB exchange rate system. Identifying these determinants not only enhances the forward-looking effectiveness of risk management strategies but also offers valuable policy implications for investors and regulators seeking to evaluate evolving risk conditions. This section therefore aims to empirically identify the key drivers of both total and net spillover effects, in order to deepen understanding of RMB exchange rate risk transmission mechanisms and to uncover the structural logic behind spillover patterns in returns and volatilities across different market regimes.

Drawing on existing literature, this study identifies eight potential time series drivers of dynamic total tail spillovers. These include: **1. Geopolitical Risk Index, 2. Real Interest Rate, 3. Gold ETF Volatility Index, 4. Crude Oil ETF Volatility Index, 5. Short-Term Capital Flows, 6. Exchange Rate Intervention, 7. S&P 500 Index, 8. Shanghai Composite Index.** The corresponding data were obtained from the Wind database and the National Bureau of Statistics of China. Below is a brief theoretical rationale for the selection of each variable:

（1） **Global Uncertainty Factor: Geopolitical Risk Index**

Geopolitical events frequently trigger increased risk aversion in financial markets, leading to a flight of capital toward safer assets, which subsequently influences the spillover effects of the RMB exchange rate. This indicator captures how external sudden risks exacerbate volatility within the exchange rate market, thereby altering the interconnectedness among different currencies. Accordingly, it is reasonable to hypothesize a significant relationship between the Geopolitical Risk Index and exchange rate spillovers (e.g., Hui, 2022; Iyke et al., 2022).

（2） **Monetary Stability Indicators: Real Interest Rate and Exchange Rate Intervention**

Real interest rates and exchange rate interventions, as key indicators of monetary stability, jointly shape the dynamic evolution of exchange rates through market forces and policy actions. In the RMB exchange rate system, real interest rates reflect domestic financial conditions, influencing capital flows, market expectations, and the internal linkage among exchange rates. Higher real interest rates enhance the appeal of RMB assets, attract capital inflows, and reinforce exchange rate equilibrium (Edison and Pauls, 1993). Meanwhile, central bank interventions guide market sentiment and correct short-term misalignments, especially when rates deviate from fundamentals. Through foreign reserve adjustments and countercyclical policies, such interventions mitigate the impact of one-sided expectations (Dominguez, 1998). Together, these mechanisms form a dual foundation—market-based and policy-driven—for sustaining internal exchange rate stability and explaining the spillover patterns across RMB exchange rates.

（3） Commodity Market Factors: Gold ETF Volatility Index and Crude Oil ETF Volatility Index

Commodity prices are closely linked to exchange rate markets. Gold, recognized as a safe-haven asset, serves as an indicator of market risk expectations (Iqbal, 2017). Crude oil, as a major global commodity, directly influences inflation expectations and economic growth, thereby impacting currency markets (Ayres et al., 2020). Hence, incorporating the Gold ETF Volatility Index and Crude Oil ETF Volatility Index allows for a more comprehensive assessment of how external commodity factors affect spillover effects in the RMB exchange rate.

（4） Influence of Capital Dynamics: Short-Term Capital Flows

Short-term cross-border capital flows primarily influence exchange rate fluctuations through two key mechanisms: interest rate arbitrage and sentiment transmission. Capital flows are highly sensitive to the differential between domestic and foreign interest rates, and according to the uncovered interest parity theory, arbitrage transactions adjust the supply and demand balance via the spot foreign exchange market, which can lead to short-term exchange rate overshooting. Furthermore, abrupt shifts in market risk preferences can trigger a “herd effect,” meaning that during periods of increased uncertainty, short-term capital flows tend to exacerbate exchange rate fluctuations, and their self-reinforcing trading inertia significantly amplifies the fragility of the exchange rate market. Consequently, these dynamics may actively promote the risk spillover effect of the exchange rate (Li et al., 2021).

（5） Financial Market Impact: S&P 500 Index and Shanghai Composite Index

The performance of global equity markets often reflects investors’ risk appetite and market liquidity conditions. Significant fluctuations in stock markets can trigger capital reallocations between RMB-denominated assets and other asset classes, thereby influencing exchange rate interconnectedness (Cenedese et al., 2016; Nusair and Olson, 2022). Accordingly, this study selects the S&P 500 Index as a proxy for the global market and the Shanghai Composite Index to represent the Chinese market, aiming to analyze how financial market volatility impacts the spillover effects of the RMB exchange rate.

5.1 Determinants of Total Spillover Effects

After identifying the core variables, this study analyzes the dynamic impact on the internal linkage relationships and spillover structure within the RMB exchange rate system. Given the complexity and pronounced time-varying nature of the exchange rate system, it is essential to employ methodologies capable of handling nonlinear, multivariate, and temporal dependencies for effective modeling and analysis. To this end, this study employs the TFT model [3] to empirically examine the dynamic relationships between the selected variables and exchange rate spillovers, aiming to more comprehensively characterize their mechanisms and temporal heterogeneity across varying market conditions. To enhance the model's ability to capture long-term trends, all variables undergo X-5 filtering to mitigate the influence of short-term fluctuations. In the modeling process, the approach adopts an inter-temporal perspective, using several lagged periods of variables to predict outcomes for a single period, making the window length a crucial hyperparameter. The macroeconomic environment is complex, and the optimal lag length is unknown in advance. To address this, this study tests various lag settings and selects the best-performing one to ensure both predictive accuracy and economic interpretability.

To systematically and rigorously assess the forecasting performance advantages of the TFT model, this study selected several representative classical AI models—including Support Vector Machine (SVM), Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM)—as benchmark

[3] In this study, we conducted a systematic hyperparameter search and optimization process during the training of the TFT model. By iteratively traversing the hyperparameter space, we identified the optimal configuration: 300 training epochs, a batch size of 32, a learning rate of 0.7, 115 hidden units, a dropout rate of 0.1, and Ranger activation functions. These settings were validated through extensive experimentation, achieving a sound balance between convergence stability and predictive performance, and were employed as the standard setup in all subsequent analyses.

methods. Prediction experiments were conducted focusing on the total and net spillovers of RMB exchange rate returns and volatilities. To enhance the comparability of results across models, all benchmark models incorporated the full set of input features used by the TFT model, and the inter-temporal lag length parameter was uniformly fixed at 5 periods in the forecasting setup to ensure consistency and fairness in comparison.

Table 8 presents the forecasting performance of the TFT model compared with several traditional benchmark models across five key evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Logarithmic Error (MSLE), and Median Absolute Error (MEDAE). The comparative analysis of forecast results for the two types of series at the 0.05, 0.5, and 0.95 quantiles demonstrates that the TFT model consistently outperforms the baseline models across most indicators and quantiles. This highlights its superior predictive performance and robustness in handling complex time series dynamics. It is worth noting that the coefficient of determination (R^2) was excluded from the evaluation framework due to the limited variability in some target variables, which could otherwise lead to misleading interpretations.

Table 8

Forecasting Performance of Different Models on Total Risk Spillovers

	TSI Based on Return Series					TSI Based on Volatility Series				
	RMSE	MAE	MAPE	MSLE	MEDAE	RMSE	MAE	MAPE	MSLE	MEDAE
τ=0.05										
SVM	1.411	1.1463	0.0131	0.0003	0.9963	3.7366	2.9009	0.0558	0.0049	2.2155
MLP	1.3711	1.0964	0.0125	**0.0002**	0.9619	3.3779	2.5455	0.0469	0.0038	2.0095
RNN	1.1967	0.9644	0.011	**0.0002**	0.8525	2.6809	1.9827	0.037	0.0024	1.7077
LSTM	1.1842	0.929	0.0106	**0.0002**	0.7495	2.3603	1.6427	0.0309	0.0019	1.2261
TFT	**1.1696**	**0.8927**	**0.0102**	**0.0002**	**0.6979**	**1.725**	**1.2241**	**0.0226**	**0.001**	**0.9137**
τ=0.5										
SVM	3.7366	2.9009	0.0558	0.0049	2.2155	1.5363	1.1882	0.0241	0.0009	0.9656
MLP	3.3779	2.5455	0.0469	0.0038	2.0095	1.3935	1.0488	0.0211	0.0007	0.8017
RNN	2.6809	1.9827	0.037	0.0024	1.7077	1.2001	0.8923	0.0177	0.0005	0.6873
LSTM	2.3603	1.6427	0.0309	0.0019	1.2261	1.0082	0.724	0.0145	0.0004	**0.5392**
TFT	**1.725**	**1.2241**	**0.0226**	**0.001**	**0.9137**	0.94	**0.6906**	**0.0139**	**0.0003**	0.5484
τ=0.95										
SVM	2.1233	1.7568	0.02	0.0006	1.6419	2.0561	1.6926	0.0193	0.0005	1.5442
MLP	2.3116	1.908	0.0218	0.0007	1.7715	1.8996	1.4943	0.0172	0.0005	1.2373

RNN	1.7876	1.4116	0.0161	0.0004	1.1959	1.6988	1.3449	0.0154	0.0004	1.1596
LSTM	1.6487	1.3435	0.0153	0.0004	1.1531	1.1812	0.9044	0.0104	0.0002	0.7088
TFT	**1.6096**	**1.1578**	**0.0135**	**0.0003**	**0.8802**	**1.0114**	**0.7640**	**0.0088**	**0.0001**	**0.5864**

Note: Bolded values are the best-predicted evaluation indicator data.

Based on the model's predictive outputs for the total spillover of return and volatility series across ten RMB exchange rates from May 2021 to September 2024, this study utilizes the variable selection network and multi-head attention mechanisms of the TFT model to extract the relative importance of each explanatory variable in contributing to the spillover indices over time and across quantiles, as detailed in Table 9. It is important to note that the attention weights primarily reflect the relative ranking of variable importance at each time step, and should not be directly interpreted as the actual quantitative contribution to the forecasting results (Clark et al., 2019; Kovaleva et al., 2019). Therefore, this study organizes the weights of the eight primary influencing factors over the forecast window and integrates them with the predicted values of the spillover index to conduct a comprehensive analysis of their relative importance and dynamic evolution. This approach aims to uncover the behavioral characteristics of the RMB exchange rate system during the sample period, rather than drawing conclusions based on individual indicators or isolated time points.

An analysis of the total spillover within the return series indicates that, under normal market conditions, the S&P 500 Index holds the greatest relative importance, suggesting that RMB exchange rate returns exhibit strong sensitivity to fluctuations in global capital markets. As a widely recognized indicator of investor risk appetite and market liquidity, variations in the S&P 500 Index are rapidly transmitted to emerging market currencies, thereby influencing movements in the RMB exchange rate. Under extreme downside scenarios, the Geopolitical Risk Index becomes the most influential factor. This reflects the heightened importance of risk aversion and the dominant role of geopolitical uncertainty in driving foreign exchange market volatility when negative shocks intensify. Conversely, under extreme upside conditions, the Crude Oil ETF Volatility Index holds the highest relative weight. This finding suggests that during periods of positive global economic expectations and increased risk appetite, fluctuations in commodity prices, especially in energy markets, exert the strongest and most direct influence on the RMB exchange rate by altering trade conditions and shaping expectations of imported inflation.

The total spillover of the volatility series exhibits distinct characteristics compared to its return counterpart. Under normal market conditions, short-term cross-border capital flows carry the highest weight, suggesting that variations in short-term liquidity serve as a primary driver of RMB exchange rate volatility. This pattern likely arises because cross-border capital flows directly reflect shifts in investor sentiment, risk appetite, and global liquidity, all of which exert immediate and sensitive influence on exchange rate fluctuations. In scenarios characterized by extremely low volatility, the Crude Oil ETF Volatility Index emerges as the most influential factor. This indicates that even during periods of market calm, marginal changes in commodity prices can disrupt expectations and exert a measurable impact on the foreign exchange market. Conversely, under conditions of extremely high volatility, exchange rate intervention becomes the dominant variable. This suggests that during periods of heightened market stress, official intervention in the foreign exchange market constitutes a critical tool for stabilizing expectations and mitigating excessive fluctuations.

Table 9

Importance Rankings of Input Variables

Variables	τ=0.05		τ=0.5		τ=0.95	
	Coefficient	Percentage	Coefficient	Percentage	Coefficient	Percentage
Return Series Metrics						
Geopolitical Risk Index	**33.0442**	**23.29%**	7.6074	10.54%	8.4700	12.37%
Real Interest Rate	3.8513	2.71%	8.3007	11.50%	8.8748	12.96%
Gold ETF Volatility	19.5933	13.81%	11.2449	15.58%	10.0608	14.70%
Crude Oil ETF Volatility	6.9057	4.87%	5.0780	7.04%	**16.4095**	**23.97%**
Short-term Capital Flows	21.9175	15.45%	8.7392	12.11%	4.3259	6.32%
Exchange Rate Intervention	23.0717	16.26%	8.8893	12.32%	3.8672	5.65%
S&P 500 Index	6.7625	4.77%	**11.3787**	**15.77%**	10.3752	15.16%
Shanghai Composite Index	26.7276	18.84%	10.9155	15.13%	6.0697	8.87%
Volatility Series Metrics						
Geopolitical Risk Index	14.8129	14.86%	15.4359	13.28%	16.0813	8.81%
Real Interest Rate	14.3101	14.35%	14.5784	12.54%	22.2295	12.18%
Gold ETF Volatility	9.4719	9.50%	13.6203	11.71%	8.0352	4.40%
Crude Oil ETF Volatility	**16.4531**	**16.50%**	16.0662	13.82%	23.1651	12.69%
Short-term Capital Flows	10.6912	10.72%	**18.1103**	**15.58%**	36.3679	19.93%
Exchange Rate Intervention	15.5757	15.62%	13.4997	11.61%	**40.9651**	**22.44%**
S&P 500 Index	10.5680	10.60%	14.0220	12.06%	15.9166	8.72%
Shanghai Composite Index	7.8264	7.85%	10.9400	9.41%	19.7627	10.83%

Note: Bolded values indicate that under equal conditions, the variable has the highest coefficients and percentages.

Combined with the analysis results of Fig. 11, it can be seen that the figure illustrates the dynamic evolution of the importance ranking of the influencing factors related to the total spillover of returns and volatilities over time at three quantiles. The results indicate that under different market scenarios, the core variables with the highest weights consistently maintain a significant leading position and dominate the trend of changes in the total spillover level of the RMB exchange rate. However, aside from these dominant variables, the relative importance of the remaining factors exhibits clear time-varying characteristics, showing a ranking structure that adjusts continuously over time. This pattern reflects that at different stages, evolving macroeconomic environments, global financial market fluctuations, and policy interventions lead to a phased restructuring of the exchange rate spillover framework. These features highlight the high sensitivity and adaptability of the spillovers of RMB exchange rate returns and multiple volatilities in responding to complex macro-financial scenarios.

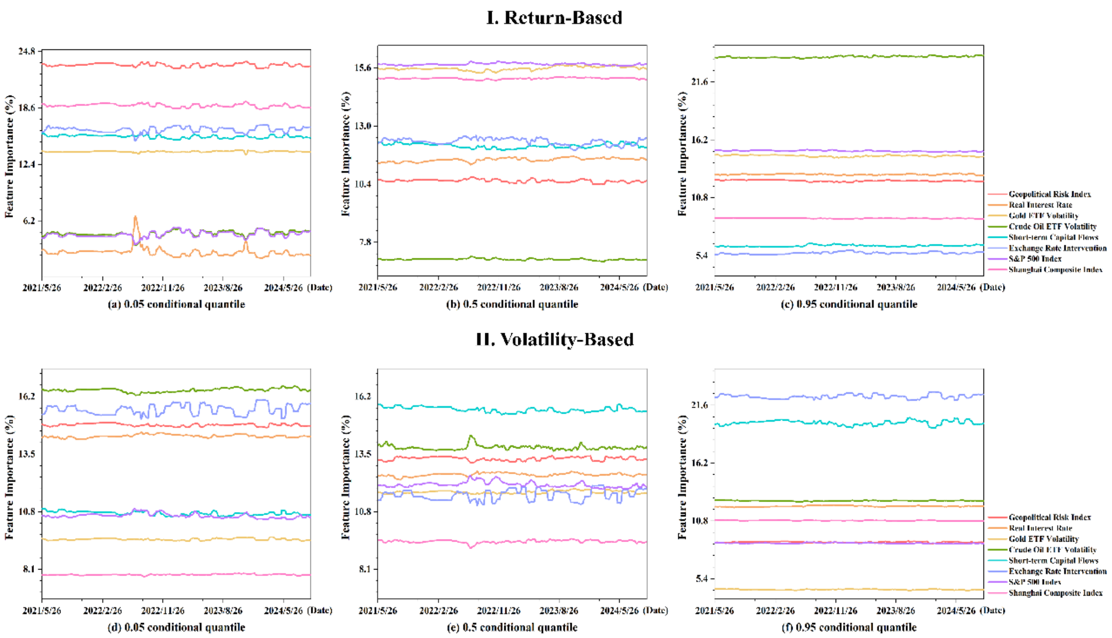


Fig. 11. Historical Dynamic Evolution of Variable Importance Rankings

By further decomposing and analyzing the multi-head attention weights of the forecast results for the total spillover of RMB exchange rate returns and volatilities, this study reveals that the total spillover is not excessively dependent on the most recent influencing factors (see Figs. 10-11). Taking the extreme downside scenario as an example, for both returns and volatility, the relative importance of historical information within the five-period window used for daily forecasts is distributed relatively evenly and stably. Notably, the historical data from period T-5, which is temporally more distant from the forecast point T, occasionally contributes more to predictions at certain time points than the immediately preceding T-1 period. This indicates the absence of a simple “closer in time, higher weight” pattern, thereby highlighting a temporal lag in the actual influence of input variables on the total spillover level.

We begin by examining the dynamics of returns, as depicted in Fig. 12. Under baseline market conditions, the spillover effects in RMB exchange rate returns exhibit relative stability. However, exogenous shocks disrupt this equilibrium, precipitating a dynamic reorganization of the spillover architecture. Specifically, at the median quantile, the contribution magnitudes across forecasting horizons were relatively homogeneous with limited volatility throughout the first half of 2022 and prior periods, indicative of rational market expectations and subdued external disturbances. Since late 2022—most notably in the final quarter of the year and during June and July 2023—these contribution values have manifested substantial fluctuations. This period coincides with a confluence of critical macro-financial events, including the accelerated tightening of U.S. monetary policy by the Federal Reserve, recalibration of China’s COVID-19 containment measures, and the ongoing unwinding of risks within the real estate sector. Such compounded shocks have engendered pronounced shifts in both global and domestic financial conditions, eliciting heightened volatility in market risk sentiment and triggering a rapid repricing and temporal differentiation of the relative importance across forecast horizons.

In the extreme downside scenario, the volatility of contribution values across forecast horizons further intensifies, exhibiting more pronounced and abrupt fluctuations. Notably, the weight associated with the T-5 period consistently surpasses those of other lags, underscoring the heightened significance of more distant historical information in shaping market expectations during severe negative shocks. This pattern reflects the prevalence of inertia-driven trading and momentum continuation within the foreign exchange market. Market participants tend to anchor their expectations on prior trends, thereby amplifying short-term volatility and reinforcing the influence of historical trajectories on prevailing market sentiment and trading dynamics. Such behavior highlights a pronounced path dependence and collective behavioral tendency in the RMB exchange rate's response to adverse external shocks under extreme downside conditions.

In the extreme upside scenario, the spillover structure exhibits pronounced asymmetry and heterogeneity, characterized by episodic concentration in specific forecast periods. Notably, from May to September 2021, late 2022, April 2023 to February 2024, and August 2024, spillover contributions were heavily concentrated, reflecting temporary impacts of distinct events or market sentiment. Between May and September 2021, RMB broadly appreciated, supported by strong exports, capital inflows, and intermittent US dollar weakness. Regulatory adjustments in technology and real estate caused short-term sentiment shifts, driving spillover changes. Late 2022 saw "triple pressure" from COVID outbreaks, real estate corrections, and Fed hikes, increasing risk aversion and market volatility with concentrated spillovers. From April 2023 to February 2024, weak domestic data, Fed tightening, and real estate risks led to phased RMB depreciation, followed by a rebound as the Fed paused hikes and domestic policies aimed to stabilize growth—spurring volatile spillover patterns. In August 2024, factors including China's Q2 GDP, Fed decisions, Chinese political signals, and US election-related policy shifts intensified market volatility, triggering another spike in spillover concentration.

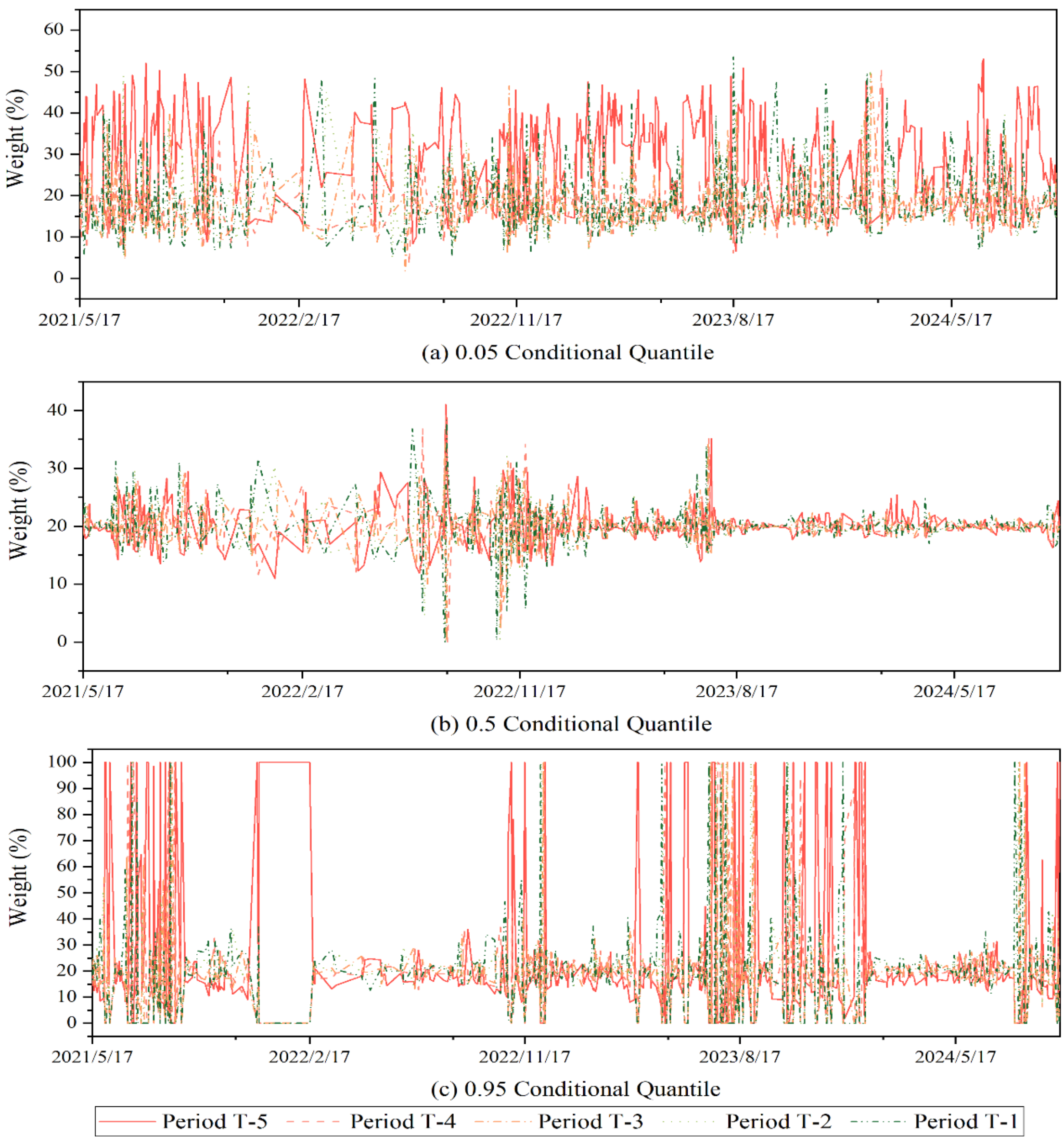


Fig. 12. Lagged weight distribution of historical information in total return spillover prediction

Unlike returns, RMB exchange rate volatility spillovers display more complex, regime-dependent dynamics (see Fig. 13). Under normal and extreme downside conditions, volatility spillover weights concentrate mainly in two periods: February to August 2022 and June 2023 to December 2024. In these intervals, the T-5 lag dominates, indicating a delayed reflection of past information. During these periods, the Federal Reserve accelerated interest rate hikes, the escalation of the Ukrainian crisis drove up energy and food prices, China's economic growth decelerated, and global supply chains remained strained—factors that collectively exerted sustained but moderate external pressure. Investor perceptions and risk pricing evolve gradually, reflecting that under normal and mild fluctuations, capital flows, risk assessments, and portfolio reallocations exhibit inertia. Consequently, volatility is primarily driven by long-term shifts in macroeconomic fundamentals rather than by isolated events. Overall, in stable or mildly volatile markets, exchange rate volatility mirrors the gradual integration of slow-moving macroeconomic changes into expectations, representing a natural economic cycle.

Under extreme upside scenarios, variable importance weights show pronounced and volatile shifts. Notably, during mid-2021, from September 2022 to September 2023, and between May and December 2024, amid external shocks such as accelerated Fed rate hikes, changes in domestic macro policies, and rising geopolitical tensions, exchange rate volatility surged with weights concentrated in the T-1 period, reflecting strong market sensitivity to recent information. For example, in June 2021, the Fed's tapering announcement triggered rapid US dollar strengthening and RMB depreciation pressure, sharply heightening investor risk sentiment and short-term volatility. After the Fed's November 2022 rate hike, the US dollar index rose steadily, intensifying depreciation expectations and market uncertainty, leading to abrupt capital flow reversals. These episodes reveal a tight link between capital flow imbalances and shifting policy expectations. Market responses to major policy shifts or crises often display nonlinear dynamics with overshooting, large short-term capital movements, and elevated volatility—hallmarks of market irrationality.

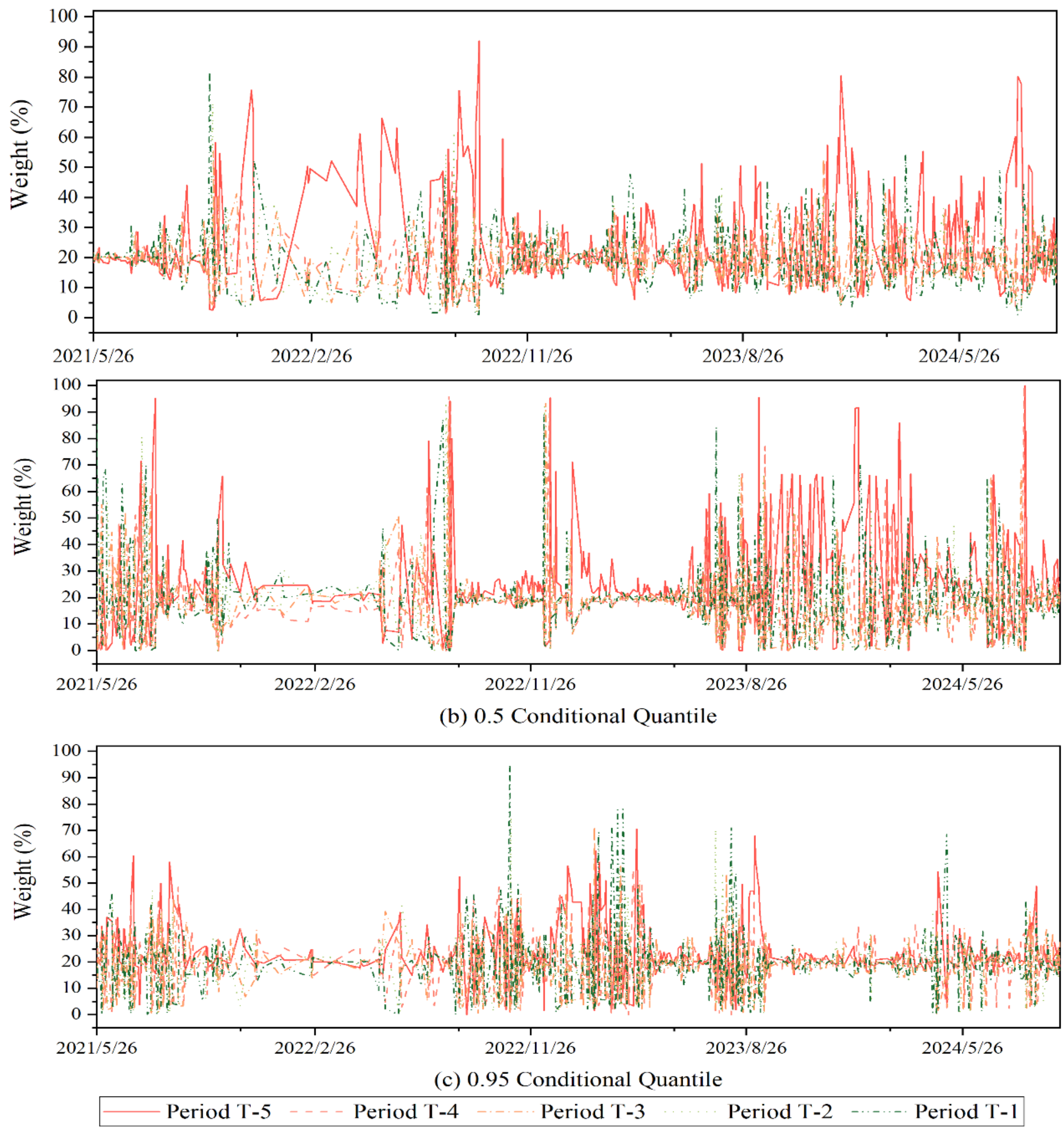


Fig. 13. Lagged weight distribution of historical information in total volatility spillover prediction

Overall, fluctuations in the external environment disrupt the steady evolution of spillover effects seen under normal conditions by altering market risk preferences and liquidity expectations. This disturbance causes a significant temporal redistribution of spillover contributions across forecast horizons. Such dynamic shifts reveal the nonlinear, state-dependent nature of total RMB exchange rate return spillovers and underscore differences in transmission channels and amplification mechanisms across market regimes. Under normal conditions, RMB exchange rate return spillovers respond to information moderately and gradually, with risk adjustments unfolding steadily. In contrast, during extreme episodes, specific events or prevailing sentiment can swiftly dominate expectation formation, reshape the return spillover structure, and trigger sharp short-term adjustments. Similarly, RMB exchange rate volatility spillovers exhibit structural heterogeneity depending on market states. In both normal and extreme downside scenarios, volatility spillovers mainly reflect a long-term, stable adjustment process driven by macroeconomic fundamentals. Conversely, extreme upside scenarios intensify short-term shocks, often accompanied by abrupt capital flow shifts and rapid policy expectation revisions, highlighting heightened market stress sensitivity and nonlinear adjustment mechanisms amid significant external uncertainties.

5.2 Determinants of Net Spillover Effects

Subsequently, this study undertakes a detailed examination of the driving factors influencing the net extreme spillovers in the RMB exchange rate system. The weight coefficients and their corresponding proportional contributions of the principal determinants based on returns and volatilities are systematically reported in Tables 10 and 11, respectively.

Under different market conditions, each variable significantly and dynamically influences the net spillover of RMB exchange rate returns (see Table 10). At the 0.05 quantile, representing extreme downturns, geopolitical instability from the Russia-Ukraine conflict is the main shock driver, with RUBCNY bearing substantial risk. Real interest rate fluctuations due to global monetary tightening notably affect JPYCNY and KRWCNY. Short-term capital flow volatility increases pressure on USACNY and EURCNY, while commodity market uncertainties strongly impact AUDCNY and RUBCNY. Exchange rate interventions and S&P 500 Index changes further amplify RMB exchange rate pressures. At the 0.5 quantile, reflecting normal conditions, geopolitical risk influence wanes amid stable global politics, though real interest rates and commodity prices continue to affect the RMB moderately. Short-term capital flows and exchange rate interventions remain relevant, with interventions stabilizing exchange rate returns between 2.64% and 16.33%. At the 0.95 quantile, indicating extreme upward markets, all variables' effects intensify, with larger coefficients amplifying their combined impact on exchange rate returns.

Table 10

Importance Ranking of Input Variables for Net Spillover in Return Series

	USACNY	EURCNY	JPYCNY	AUDCNY	MYRCNY	RUBCNY	HKDCNY	GBPCNY	KRWCNY	THBCNY
Extreme Cases: Based on the 0.05 Quantile										
Geopolitical Risk Index	26.2769 (12.39%)	**31.8839 (20.92%)**	2.3898 (4.29%)	20.1673 (11.55%)	14.9639 (9.66%)	**35.3336 (21.43%)**	4.2382 (10.79%)	21.6849 (14.44%)	9.3666 (14.37%)	12.2872 (13.03%)
Real Interest Rate	32.0912 (15.13%)	23.09140 (15.15%)	**12.4856 (22.44%)**	23.2469 (13.32%)	14.1912 (9.16%)	5.76526 (3.50%)	6.01534 (15.31%)	16.8852 (11.24%)	7.46498 (11.45%)	9.49101 (10.06%)
Gold ETF Volatility	29.1114 (13.73%)	17.8484 (11.71%)	5.0276 (9.04%)	5.4420 (3.12%)	14.8409 (9.58%)	25.2130 (15.29%)	1.62420 (4.14%)	7.4968 (4.99%)	**11.2637 (17.28%)**	**17.7475 (18.82%)**
Crude Oil ETF Volatility	26.0642 (12.29%)	9.7425 (6.39%)	5.54670 (9.97%)	27.1115 (15.53%)	19.2829 (12.45%)	25.0526 (15.19%)	5.29604 (13.48%)	15.7451 (10.48%)	3.42319 (5.25%)	10.1179 (10.73%)
Short-term Capital Flows	32.5372 (15.34%)	19.3082 (12.67%)	8.7867 (15.79%)	18.2186 (10.44%)	**30.7122 (19.83%)**	18.4439 (11.19%)	5.8590 (14.92%)	21.1378 (14.07%)	9.0748 (13.92%)	11.2650 (11.94%)
Exchange Rate Intervention	21.7574 (10.26%)	17.9956 (11.81%)	10.4710 (18.82%)	26.0540 (14.93%)	23.8143 (15.38%)	6.44967 (3.91%)	6.3221 (16.10%)	**24.8582 (16.55%)**	8.9767 (13.77%)	11.8842 (12.60%)
S&P 500 Index	**39.1490 (18.46%)**	16.9621 (11.13%)	7.2680 (13.06%)	**31.8541 (18.25%)**	8.4042 (5.43%)	20.7651 (12.59%)	**8.4818 (21.59%)**	17.8924 (11.91%)	9.0773 (13.93%)	9.8930 (10.49%)
Shanghai Composite Index	5.0532 (2.38%)	15.6061 (10.24%)	3.6684 (6.59%)	22.4459 (12.86%)	28.6340 (18.49%)	27.8558 (16.89%)	1.4420 (3.67%)	24.4805 (16.30%)	6.5356 (10.03%)	11.6272 (12.33%)
Normal Cases: Based on the 0.5 Quantile										
Geopolitical Risk Index	6.404879 (9.87%)	7.1273 (5.73%)	10.7620 (7.74%)	12.3847 (10.76%)	8.5458 (6.97%)	10.8004 (18.98%)	8.4426 (7.17%)	5.9163 (5.75%)	4.6328 (8.27%)	10.3572 (9.58%)
Real Interest Rate	8.347584 (12.86%)	6.4221 (5.17%)	15.7498 (11.32%)	16.3707 (14.22%)	8.3601 (6.82%)	**13.4186 (23.58%)**	13.7218 (11.66%)	17.9379 (17.42%)	6.6962 (11.95%)	9.8886 (9.14%)
Gold ETF Volatility	8.06875 (12.43%)	19.4102 (15.61%)	18.5652 (13.35%)	5.8880 (5.11%)	11.3590 (9.27%)	5.4863 (9.64%)	17.3527 (14.74%)	2.9345 (2.85%)	9.0889 (16.22%)	16.5925 (15.34%)
Crude Oil ETF Volatility	2.36889 (3.65%)	**26.8496 (21.60%)**	17.6373 (12.68%)	17.3646 (15.08%)	18.8358 (15.37%)	5.4509 (9.58%)	10.3746 (8.81%)	14.7601 (14.34%)	5.8133 (10.38%)	**24.0238 (22.21%)**
Short-term Capital Flows	7.1671 (11.04%)	5.6026 (4.51%)	14.4476 (10.39%)	15.3018 (13.29%)	18.3931 (15.01%)	5.5125 (9.69%)	19.7475 (16.78%)	12.6887 (12.33%)	7.3925 (13.20%)	18.5999 (17.20%)
Exchange Rate Intervention	6.7068 (10.33%)	19.3491 (15.56%)	**22.3304 (16.05%)**	16.6246 (14.44%)	15.3045 (12.49%)	1.5005 (2.64%)	19.2163 (16.33%)	14.2150 (13.81%)	6.5009 (11.60%)	8.4201 (7.79%)
S&P 500 Index	10.0930 (15.55%)	23.8126 (19.16%)	18.5248 (13.32%)	8.4288 (7.32%)	17.6083 (14.37%)	6.4198 (11.28%)	3.7196 (3.16%)	16.4005 (15.93%)	4.0034 (7.15%)	10.8576 (10.04%)
Shanghai Composite Index	**15.7547 (24.27%)**	15.7387 (12.66%)	21.0710 (15.15%)	**22.7722 (19.78%)**	**24.1540 (19.71%)**	8.3178 (14.62%)	**25.1335 (21.35%)**	**18.0952 (17.58%)**	**11.8927 (21.23%)**	9.4062 (8.70%)
Extreme Cases: Based on the 0.95 Quantile										
Geopolitical Risk Index	13.9186 (12.20%)	1.9304 (8.63%)	16.9080 (10.51%)	4.9767 (13.55%)	20.5781 (9.76%)	7.6727 (16.39%)	26.5043 (15.66%)	1.8911 (12.34%)	4.5199 (8.48%)	26.9965 (11.54%)
Real Interest Rate	16.6341 (14.58%)	3.2616 (14.58%)	11.7255 (7.29%)	2.7737 (7.55%)	**40.7271 (19.32%)**	5.3802 (11.49%)	13.1304 (7.76%)	1.8517 (12.08%)	3.8823 (7.28%)	24.3619 (10.41%)
Gold ETF Volatility	5.4567 (4.78%)	1.0076 (4.50%)	**33.5028 (20.83%)**	**6.3125 (17.19%)**	17.5937 (8.34%)	4.3120 (9.21%)	10.5470 (6.23%)	1.6893 (11.02%)	3.3309 (6.25%)	**51.3631 (21.96%)**
Crude Oil ETF Volatility	13.9745 (12.25%)	**5.6290 (25.16%)**	15.4488 (9.61%)	3.6444 (9.92%)	25.7004 (12.19%)	6.0051 (12.83%)	35.7537 (21.13%)	1.8229 (11.89%)	**24.6831 (46.29%)**	18.0101 (7.70%)
Short-term Capital Flows	**17.5980 (15.43%)**	2.3385 (10.45%)	24.7641 (15.40%)	5.5135 (15.01%)	38.2258 (18.13%)	**8.6085 (18.39%)**	25.5105 (15.07%)	1.9777 (12.90%)	1.3110 (2.46%)	22.1395 (9.46%)
Exchange Rate Intervention	14.6897 (12.88%)	2.5508 (11.40%)	11.8072 (7.34%)	4.3366 (11.81%)	21.8241 (10.35%)	4.2903 (9.16%)	**40.3910 (23.87%)**	1.9400 (12.66%)	1.8842 (3.53%)	29.4811 (12.60%)
S&P 500 Index	15.7645 (13.82%)	4.7144 (21.07%)	29.5569 (18.38%)	3.3346 (9.08%)	19.5962 (9.29%)	5.0217 (10.73%)	12.5637 (7.42%)	1.7465 (11.40%)	6.3216 (11.85%)	29.6534 (12.68%)
Shanghai Composite Index	16.0328 (14.06%)	0.9396 (4.20%)	17.1201 (10.64%)	5.8315 (15.88%)	26.5866 (12.61%)	5.5306 (11.81%)	4.8392 (2.86%)	**2.4063 (15.70%)**	7.3944 (13.87%)	31.9180 (13.64%)

Examining the net spillover effects of RMB exchange rate volatility across quantiles reveals a multifaceted interaction of factors. At the 0.05 quantile, representing relatively stable markets, heightened global geopolitical conflicts increase demand for safe-haven assets, strengthening RMB’s linkages with other emerging market currencies. Under the Federal Reserve’s high interest rate regime, capital increasingly flows into US dollar assets, raising volatility sensitivity in currencies like MYRCNY and THBCNY. Commodity price fluctuations, reflecting inflation and supply risks, contribute as well—for example, gold price shifts boost volatility in resource-based currencies such as AUDCNY and THBCNY, while geopolitical tensions and OPEC+ cuts raise crude oil ETF volatility, reinforcing spillovers between RUBCNY and THBCNY. Exchange rate interventions stabilize markets for HKDCNY, RUBCNY, and GBPCNY, though frequent interventions may raise transparency concerns. At the 0.5 quantile, net spillovers remain driven by multiple overlapping factors. Geopolitical risks—including the Russia-Ukraine war, Middle East tensions, and Sino-US strategic rivalry—strengthen volatility links among EURCNY, GBPCNY, and others. Real interest rate differentials continue to influence, while frequent cross-border capital flows tied to Sino-US policies sustain RMB volatility. Commodity market fluctuations further amplify RMB exchange rate swings, notably impacting energy-dependent currencies. Short-term capital flows and interventions remain effective in dampening volatility, especially in Asia. Stock market dynamics, reflecting expectations of a US soft landing, also heighten volatility correlations between the RMB and major currencies. At the 0.95 quantile, marking extreme market turbulence, intensified geopolitical risks worsen capital flow uncertainty and risk aversion, pressuring RMB depreciation. Short-term capital flows, interventions, and sharp commodity price swings compound this pressure.

Overall, the net extreme spillover of the RMB exchange rate is dynamically shaped by multiple factors across market conditions. Policymakers and regulators must continuously monitor global geopolitical developments, major economies' monetary policy shifts, and commodity market fluctuations to enhance early risk detection. Exchange rate interventions should focus not only on market stabilization but also on transparent communication to effectively guide expectations. Additionally, strengthening oversight of cross-border capital flows and improving macroprudential regulations are crucial to enhance the RMB exchange rate's resilience in a complex international environment. These measures will support orderly financial market development and protect systemic stability.

Table 11

Importance Ranking of Input Variables for Net Spillover in Volatility Series

	USACNY	EURCNY	JPYCNY	AUDCNY	MYRCNY	RUBCNY	HKDCNY	GBPCNY	KRWCNY	THBCNY
Extreme Cases: Based on the 0.05 Quantile										

Geopolitical Risk Index	19.2560 (13.66%)	6.3601 (15.95%)	15.7181 (13.98%)	17.9233 (11.37%)	24.2549 (15.85%)	8.8039 (7.84%)	11.4743 (10.92%)	12.7703 (10.67%)	8.2789 (7.64%)	30.4645 (13.99%)
Real Interest Rate	19.1283 (13.57%)	4.2692 (10.70%)	13.1837 (11.73%)	**30.2407** **(19.18%)**	23.6874 (15.48%)	21.1191 (18.81%)	13.8514 (13.19%)	**19.6644** **(16.44%)**	14.6221 (13.50%)	**36.5633** **(16.79%)**
Gold ETF Volatility	**19.8446** **(14.08%)**	4.3015 (10.78%)	14.6262 (13.01%)	24.2346 (15.37%)	12.9981 (8.50%)	10.2956 (9.17%)	16.6488 (15.85%)	12.8294 (10.72%)	7.6245 (7.04%)	27.0765 (12.43%)
Crude Oil ETF Volatility	14.6671 (10.41%)	3.6005 (9.03%)	13.5330 (12.04%)	7.8329 (4.97%)	15.2206 (9.95%)	**22.6645** **(20.19%)**	12.3518 (11.76%)	12.4714 (10.42%)	**24.0370** **(22.20%)**	27.8029 (12.77%)
Short-term Capital Flows	16.1616 (11.47%)	3.6376 (9.12%)	14.3271 (12.74%)	19.7128 (12.50%)	**27.2283** **(17.80%)**	5.2601 (4.68%)	1.3342 (1.27%)	14.1634 (11.84%)	10.9365 (10.10%)	24.4190 (11.21%)
Exchange Rate Intervention	19.5728 (13.89%)	5.6549 (14.18%)	**16.3315** **(14.53%)**	5.7274 (3.63%)	20.2435 (13.23%)	10.1309 (9.02%)	**20.9316** **(19.92%)**	16.6660 (13.93%)	12.0025 (11.08%)	26.6707 (12.25%)
S&P 500 Index	17.6027 (12.49%)	**7.0505** **(17.68%)**	8.7266 (7.76%)	26.5442 (16.84%)	14.4277 (9.43%)	21.7668 (19.39%)	11.8369 (11.27%)	16.9905 (14.20%)	11.6984 (10.80%)	18.9722 (8.71%)
Shanghai Composite Index	14.6886 (10.42%)	5.0117 (12.57%)	15.9749 (14.21%)	25.4488 (16.14%)	14.9327 (9.76%)	12.2417 (10.90%)	16.6239 (15.82%)	14.0839 (11.77%)	19.0944 (17.63%)	25.7868 (11.84%)
Normal Cases: Based on the 0.5 Quantile										
Geopolitical Risk Index	12.8576 (14.09%)	24.4572 (15.97%)	18.0544 (10.59%)	11.7360 (10.59%)	7.9530 (9.21%)	11.4857 (9.55%)	17.1779 (15.30%)	17.0190 (12.34%)	11.3829 (9.27%)	**18.3348** **(16.76%)**
Real Interest Rate	8.7502 (9.59%)	16.2916 (10.64%)	20.8866 (12.25%)	11.0375 (9.96%)	3.9535 (4.58%)	13.1581 (10.94%)	13.4827 (12.01%)	14.7167 (10.67%)	10.4670 (8.53%)	12.8246 (11.72%)
Gold ETF Volatility	13.1015 (14.36%)	21.7334 (14.19%)	21.3730 (12.53%)	14.6740 (13.24%)	8.7300 (10.11%)	14.1593 (11.77%)	18.3545 (16.35%)	13.6471 (9.90%)	17.4762 (14.23%)	13.9074 (12.71%)
Crude Oil ETF Volatility	**16.5052** **(18.09%)**	11.7398 (7.67%)	**29.6872** **(17.41%)**	**26.2235** **(23.65%)**	14.8491 (17.19%)	**19.4557** **(16.17%)**	12.9637 (11.55%)	14.6258 (10.61%)	**25.2994** **(20.61%)**	7.6771 (7.02%)
Short-term Capital Flows	9.1766 (10.06%)	20.5722 (13.43%)	15.4230 (9.04%)	15.0986 (13.62%)	12.9984 (15.05%)	14.3287 (11.91%)	6.6200 (5.90%)	20.9303 (15.18%)	16.0897 (13.11%)	13.3056 (12.16%)
Exchange Rate Intervention	7.8343 (8.59%)	16.7791 (10.96%)	28.6918 (16.82%)	12.0956 (10.91%)	**17.7021** **(20.94%)**	18.2350 (15.16%)	**18.4109** **(16.40%)**	20.1947 (14.64%)	11.4063 (9.29%)	13.8120 (12.63%)
S&P 500 Index	9.1779 (10.06%)	**32.3007** **(21.09%)**	18.9787 (11.13%)	10.5732 (9.54%)	5.6876 (6.58%)	13.7931 (11.47%)	11.2139 (9.99%)	13.8504 (10.04%)	12.1564 (9.90%)	13.1609 (12.03%)
Shanghai Composite Index	13.8295 (15.16%)	9.2546 (6.04%)	17.4632 (10.24%)	9.4296 (8.51%)	14.5153 (16.80%)	15.6821 (13.04%)	14.0587 (12.52%)	**22.9162** **(16.62%)**	18.4921 (15.06%)	16.3566 (14.95%)
Extreme Cases: Based on the 0.95 Quantile										
Geopolitical Risk Index	6.8382 (3.14%)	6.228 (11.07%)	14.6789 (8.99%)	17.4270 (10.49%)	**38.9061** **(20.20%)**	2.7111 (10.65%)	16.5901 (17.58%)	18.0859 (7.73%)	**27.2760** **(16.49%)**	15.0387 (10.12%)
Real Interest Rate	27.6282 (12.67%)	**10.6325** **(18.90%)**	12.5148 (7.67%)	11.2741 (6.78%)	26.1765 (13.59%)	0.6464 (2.54%)	5.3929 (5.71%)	23.0230 (9.84%)	22.8672 (13.82%)	19.3400 (13.01%)
Gold ETF Volatility	**43.3894** **(19.90%)**	5.7615 (10.24%)	22.2065 (13.61%)	19.9616 (12.01%)	24.6545 (12.80%)	3.2114 (12.61%)	7.7091 (8.17%)	24.3478 (10.41%)	24.4446 (14.78%)	23.0068 (15.48%)
Crude Oil ETF Volatility	28.3387 (13.00%)	3.3933 (6.03%)	27.1100 (16.61%)	**49.4354** **(29.75%)**	20.5219 (10.66%)	4.1755 (16.40%)	14.8077 (15.69%)	**65.1902** **(27.87%)**	4.7969 (2.90%)	**34.3497** **(23.11%)**
Short-term Capital Flows	21.5745 (9.89%)	6.5115 (11.58%)	21.1385 (12.95%)	21.6078 (13.00%)	20.0783 (10.43%)	3.3295 (13.07%)	10.4533 (11.07%)	22.3089 (9.54%)	15.9818 (9.66%)	10.7199 (7.21%)
Exchange Rate Intervention	36.2883 (16.64%)	6.7422 (11.99%)	**48.4403** **(29.63%)**	12.1223 (7.29%)	29.8902 (15.52%)	2.0538 (8.06%)	10.2158 (10.82%)	36.5829 (15.64%)	20.6308 (12.47%)	20.7881 (13.98%)
S&P 500 Index	14.7643 (6.77%)	10.3289 (18.36%)	12.1707 (7.46%)	23.6145 (14.21%)	24.0359 (12.48%)	4.5876 (18.01%)	10.4511 (11.07%)	26.4269 (11.30%)	24.1010 (14.57%)	17.3204 (11.65%)
Shanghai Composite Index	39.2285 (17.99%)	6.6513 (11.82%)	4.9436 (3.03%)	10.7359 (6.46%)	8.3294 (4.32%)	**4.7522** **(18.66%)**	**18.7702** **(19.89%)**	17.9682 (7.68%)	25.3414 (15.32%)	8.0963 (5.45%)

6. Conclusion

In recent years, as China deepens its global economic integration, trade and cross-border capital flows have become increasingly active. Consequently, exchange rate risks transmit more frequently across currencies through complex financial linkages, creating widespread "resonance" effects in global markets. In this context, this study takes the RMB exchange rate and its top ten counterparties in a representative currency basket as the research sample, and applies a quantile-based VAR spillover index to construct a risk spillover network based on return and volatility series across multiple quantiles. This framework allows for a comprehensive assessment of the intensity and direction of RMB exchange rate risk spillovers under both normal and extreme conditions, as well as their evolution over time and frequency domains. Furthermore, the study employs an advanced deep learning model equipped with a multi-head attention mechanism and embedded variable selection functions to analyze the driving forces and dynamic influence mechanisms of RMB exchange rate spillovers. The model effectively captures the contributions of diverse influencing factors and reveals their time-varying importance under different market states, thus offering new insights into the complex interaction structure and dynamic propagation path underlying exchange rate risk. On this basis, the study arrives at the following major conclusions:

The RMB exchange rate's risk spillovers, based on returns or volatility, show clear state dependence and a distinct U-shaped pattern, with intensities rising sharply in extreme market conditions. This highlights the system's sensitivity to tail risks. Frequency analysis reveals that return spillovers are mainly short-term, while volatility spillovers are dominated by long-term components. Yet, during market turbulence, long-term volatility effects shift toward shorter horizons, reflecting temporal changes in risk transmission. Notably, tail risk spillovers differ between returns and volatility: return spillovers are balanced across tails, whereas volatility spillovers skew strongly to the right tail, indicating more severe contagion in high-volatility periods. Moreover, individual RMB exchange rates respond heterogeneously to external shocks; under extremes, net spillovers vary widely among pairs, with no single currency consistently dominating risk transmission.

Furthermore, in studying the driving factors of RMB exchange rate spillover, the TFT model demonstrates excellent capabilities in dynamically capturing and identifying mechanisms within the high-dimensional, nonlinear, and time-varying characteristics of the RMB exchange rate system. Compared to traditional AI models, it offers superior prediction accuracy and adapts better to heterogeneous market conditions. Its multi-head attention and variable selection enhance the detection of key variables and relevant historical information. RMB exchange rate spillovers show significant dynamic heterogeneity, with spillover structures varying across market states. Notably, long-term historical data can outweigh recent data, challenging the common assumption that more recent information always matters most. Under extreme downturns, path dependence and inertia dominate, while extreme upturns bring sudden spillover shifts with concentrated weights. Key drivers also shift by scenario: the S&P 500 index leads during normal periods, geopolitical risks dominate downturns, and crude oil ETF volatility stands out in upturns. For volatility spillovers, short-term cross-border capital flows prevail normally, energy market shocks matter in low volatility, and exchange rate interventions stabilize during high volatility, highlighting policy's regulatory role. Moreover, the driving factors of the net spillover of the RMB exchange rate also display dynamic multi-factor superposition across different market scenarios, reflecting the complex mechanisms of risk transmission and market responses.

This study offers valuable implications for both policymakers and investors. For policymakers, adopting a global perspective is crucial since the RMB exchange rate functions within a complex multi-market network. Its fluctuations are influenced not only by the US dollar but also by interactions among major global currencies and financial markets. Thus, exchange rate policies must go beyond focusing solely on the US dollar and emphasize managing transmission channels across diverse markets. Enhancing resilience to external shocks calls for better policy coordination and forecasting, stronger strategic reserves to address geopolitical tensions and commodity volatility, and greater policy flexibility to mitigate market disruptions from uncertainty. Market-oriented reforms are equally important, including increasing transparency and flexibility in exchange rate formation, optimizing intervention strategies to avoid procyclical extremes, and strengthening real-time monitoring with countercyclical regulation of cross-border capital flows. Together, these actions improve the flexibility and stability of the RMB exchange rate system. For investors, keen awareness of tail risks and the ability to adjust asset allocations with shifting market regimes are vital. Tracking key variable changes and allocating prudently to safe-haven assets strengthen portfolio resilience. Investors should also leverage advanced analytics, such as high-frequency data and AI methods, to quickly identify and respond to risk channels and anomalies. These tools support more robust, adaptive strategies amid growing market uncertainty.

Appendix A

Table A1

Average Weights of Currency Basket in the CFETS RMB Exchange Rate Index (2022-2024)

No.	**Currency type**	**Weights in 2022**	**Weights in 2023**	**Weights in 2024**	**Average Weights Over Three Years**
1	USD	0.1983	0.1983	0.1890	**0.1952**
2	EUR	0.1821	0.1821	0.1790	**0.1811**
3	JPY	0.0976	0.0976	0.0858	**0.0937**
4	KRW	0.0951	0.0951	0.0837	**0.0913**
5	AUD	0.0607	0.0607	0.0595	**0.0603**
6	MYR	0.0464	0.0464	0.0512	**0.0480**
7	RUB	0.0385	0.0385	0.0490	**0.0420**
8	HKD	0.0360	0.0360	0.0347	**0.0356**
9	THB	0.0344	0.0344	0.0343	**0.0344**
10	GBP	0.0296	0.0296	0.0271	**0.0287**
11	SGD	0.0247	0.0247	0.0297	0.0264
12	SAR	0.0229	0.0229	0.0282	0.0247
13	MXN	0.0227	0.0227	0.0260	0.0238
14	CAD	0.0215	0.0215	0.0240	0.0223
15	AED	0.0190	0.0190	0.0247	0.0209
16	ZAR	0.0143	0.0143	0.0144	0.0143
17	CHF	0.0116	0.0116	0.0155	0.0129
18	PLN	0.0111	0.0111	0.0113	0.0111
19	TRY	0.0090	0.0090	0.0112	0.0097
20	NZD	0.0065	0.0065	0.0057	0.0062
21	SEK	0.0055	0.0055	0.0051	0.0054
22	DKK	0.0047	0.0047	0.0037	0.0044
23	HUF	0.0041	0.0041	0.0040	0.0041
24	NOK	0.00395	0.00400	0.00207	0.00334

Source: China Money Network

Table A2

Model Selection and Estimation Results for RMB Exchange Rates Using Asymmetric GARCH Models

Variables	**Models**	**Distribution**	**AIC**	**LogLikelihood**
USACNY	EGARCH	norm	-5.989	8637.523
		skew-t	**-6.430**	**9274.124**
	TGARCH	norm	-5.796	8359.468
		skew-t	-6.388	9214.437
	GJR-GARCH	norm	-5.768	8318.294

		skew-t	-6.359	9172.619
EURCNY	EGARCH	norm	-3.188	4600.899
		skew-t	**-3.309**	**4777.766**
	TGARCH	norm	-3.186	4597.480
		skew-t	3.309	4776.721
	GJR-GARCH	norm	-3.191	4605.631
		skew-t	-3.308	4775.143
JPYCNY	EGARCH	norm	-3.362	4850.889
		skew-t	-3.533	5100.156
	TGARCH	norm	-3.281	4734.428
		skew-t	**-3.533**	**5100.696**
	GJR-GARCH	norm	-3.355	4841.915
		skew-t	-3.527	5090.777
AUDCNY	EGARCH	norm	-3.467	5002.462
		skew-t	-3.538	5106.523
	TGARCH	norm	-3.467	5002.391
		skew-t	-3.538	5107.722
	GJR-GARCH	norm	-3.470	5007.104
		skew-t	**-3.540**	**5109.749**
MYRCNY	EGARCH	norm	-6.789	9789.790
		skew-t	**-6.917**	**9975.832**
	TGARCH	norm	-6.692	9650.269
		skew-t	-6.916	9975.182
	GJR-GARCH	norm	-6.795	9798.002
		skew-t	-6.915	9974.061
RUBCNY	EGARCH	norm	-10.292	14838.350
		skew-t	**-10.475**	**15103.690**
	TGARCH	norm	-10.092	14549.620
		skew-t	-10.474	15101.490
	GJR-GARCH	norm	-10.269	14803.970
		skew-t	-10.458	15079.630
HKDCNY	EGARCH	norm	-10.112	14578.420
		skew-t	**-10.499**	**15138.490**
	TGARCH	norm	-10.023	14450.800
		skew-t	-10.461	15083.520
	GJR-GARCH	norm	-8.484	12232.830
		skew-t	-10.434	15044.250
GBPCNY	EGARCH	norm	-2.576	3719.416
		skew-t	**-2.774**	**4006.711**
	TGARCH	norm	-2.522	3640.622
		skew-t	-2.774	4005.573
	GJR-GARCH	norm	-2.614	3773.106
		skew-t	-2.764	3991.949
KRWCNY	EGARCH	norm	-8.503	12259.900

		skew-t	**-8.573**	**12362.610**
	TGARCH	norm	-8.421	12141.210
		skew-t	-8.572	12361.460
	GJR-GARCH	norm	-8.505	12262.210
		skew-t	-8.570	12357.950
THBCNY	EGARCH	norm	-11.675	16830.140
		skew-t	**-11.821**	**17042.970**
	TGARCH	norm	-11.594	16714.080
		skew-t	-11.820	17042.210
	GJR-GARCH	norm	-11.653	16798.600
		skew-t	-11.805	17020.090

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