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The forecast utility of onshore and offshore RMB spread skewness — Taking Hong Kong's offshore market as an example*

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Abstract

This paper investigates the dynamic effects of price skewness on the spread between offshore and onshore RMB exchange rates, an area underexplored in existing literature. As the RMB has gained increasing importance as a global currency, understanding its pricing mechanisms, particularly in the context of the offshore RMB market in Hong Kong, has become crucial. Using an autoregressive (AR) model, this study analyzes the persistence of skewness in the RMB price spread and its predictive power over both short and long-term horizons. Our findings reveal significant persistence in spread skewness, with peak predictive power occurring within a one-month window. Additionally, the analysis demonstrates that incorporating skewness into forecasting models improves predictive accuracy compared to random-walk models. The study also highlights the impact of market shocks, such as the 2018 trade war and the 2020 pandemic, on skewness-based predictions. This research provides valuable insights into the role of skewness in the RMB exchange rate market and contributes to the broader understanding of skewness strategies in currency markets.

JJEL Classification: C22, E43, F31

Keywords: offshore RMB, onshore RMB, skewness, predictive modeling

1. Introduction

In the post-financial crisis era, the international dominance of the U.S. dollar has been somewhat shaken, while China has accelerated its efforts to internationalize the RMB. In recent years, with the People's Bank of China signing currency swap agreements worth more than 3 trillion RMB with over 30 countries (regions) and benefiting from China's rapid trade growth worldwide, the importance of the RMB has gained recognition not only in emerging markets but also in developed countries. As a reserve currency, the RMB has played significant roles in investment, financing, and trade settlement, elevating its status to unprecedented heights in the global economic and financial system.

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The Hong Kong offshore RMB market is an essential outcome of the RMB's internationalization process. The market has continued to grow and expand, especially with the promotion of the "Belt and Road Initiative" (BRI), which seeks to enhance global trade and infrastructure links between China, Asia, Europe, and Africa. Launched in 2013, the BRI supports the increasing international use of the RMB. The offshore RMB market has gained significant influence, serving as a primary channel for the currency's expansion into neighboring regions. Following the "8.11" exchange rate reform in 2015, which made the RMB's central parity rate more market-driven, the offshore market's role in determining RMB pricing power became more prominent. This reform also heightened the volatility of the RMB exchange rate, underscoring the need for closer monitoring by scholars and regulators.

The onshore exchange rate refers to the RMB rate within mainland China, regulated by the People's Bank of China (PBOC) and subject to government policies. The offshore exchange rate, on the other hand, is determined in markets outside China, primarily in Hong Kong, and is more market-driven with less regulatory control. The difference between the onshore and offshore rates stems from government interventions, capital flow restrictions, and shifts in market sentiment. As China maintains strict capital controls, the free movement of money between the onshore and offshore markets is limited, leading to discrepancies in the supply and demand for the RMB. These discrepancies result in different exchange rates, which persist due to regulatory constraints and global market factors. Previous studies such as Fung & Yau (2012) and Cheung & Qian (2009) explore this price spread, showing that while arbitrage opportunities exist, they are often constrained by such regulatory factors.

Skewness strategies, which capitalize on asymmetry in asset return distributions, have gained considerable popularity in recent years. These strategies typically involve buying currencies with high positive skewness and selling those with low or negative skewness, hoping to profit from asymmetric return patterns. Jiang, Han, and Yin (2019) argue that investors are drawn to assets with lottery-like characteristics, while Chan, Yang, and Zhou (2018) demonstrate that skewness-based strategies can be effective in FX markets, especially for major currencies like the U.S. dollar and the Japanese yen. In particular, the skewness of returns has become an important factor for traders when identifying mispriced assets or exploiting market anomalies. Despite the prominence of skewness strategies in various markets, the effectiveness of skewness in predicting the price spread between offshore and onshore RMB remains largely underexplored.

The differences in investor behavior across regions also play a crucial role in shaping the onshore-offshore RMB spread. Chinese investors, influenced by capital controls and government policy guidance, tend to react more conservatively to external shocks (Fung & Yau, 2012). In contrast, U.S. investors, driven by market fundamentals, may respond more strongly to global risks, leading to greater volatility in the offshore market (Yan et al., 2017). Japanese investors, who are known for their risk aversion, often act as stabilizers during periods of uncertainty (Cheung & Rime, 2014). These behavioral differences impact the pricing mechanisms in both markets, influencing the role of skewness in forecasting future changes in the exchange rate spread. Understanding these dynamics is essential for improving predictive models of the RMB price spread.

While skewness has been extensively studied in equity markets, futures, and commodities, there is limited research on its role in the RMB exchange rate market, particularly in the context of the offshore RMB market in Hong Kong. For predicting the RMB spread, skewness in past spread distributions is believed to have effective explanatory power regarding the direction of changes, while kurtosis is expected to impact the accuracy of these changes rather than their direction. This led to the choice of skewness for analysis. This gap in the literature presents an opportunity to examine the dynamic effects of price skewness on the onshore-offshore RMB spread, as well as its spillover impacts. Previous research has largely overlooked the potential of skewness strategies in predicting exchange rate movements between the two RMB markets, making this a highly valuable area for further exploration.

To address this gap, we constructed an autoregressive (AR) model and conducted several tests, including cumulative mean-square prediction error (CSPE), robust testing, and structural breakpoint analysis, to validate the results. Our analysis revealed that the price spread skewness exhibits significant persistence. We found that incorporating lagged terms into the AR model improved its explanatory power, revealing a positive correlation between price spread skewness and the price spread itself, with the effect peaking within a one-month window. The CSPE analysis showed that our skewness-based model outperformed a random-walk model in terms of predictive accuracy.

Our analysis revealed three key findings: (1) spread skewness showed significant persistence with peak predictive power at one-month horizons (15.4% R^2); (2) while additional market factors improved 24-month explanatory power to 19.18%, they diluted short-term skewness effects; and (3) structural breaks precisely captured major shocks like the 2018 trade war and 2020 pandemic. These results provide the first systematic evidence that skewness contains valuable predictive information about RMB spread dynamics.

This study fills a critical gap by providing a comprehensive statistical analysis of the role of offshore-onshore RMB price skewness in the currency market, shedding light on its economic significance. It not only clarifies the role of skewness in RMB pricing but also contributes to the broader literature on skewness in currency markets. Moreover, the framework developed in this paper offers insights that can be extended to other asset markets, providing new empirical evidence on the overall study of return skewness. Thus, the predictive utility of offshore and onshore RMB price skewness for the price spread is a highly valuable research topic.

The structure of this paper is as follows: Section 2 reviews related studies on RMB spreads and skewness strategies; Section 3 describes the data and methodology; Section 4 presents the empirical results; and Section 5 concludes the study.

2. Related Studies

The onshore RMB (CNY) refers to the currency used within Mainland China, with its exchange rate controlled by the People's Bank of China (PBOC). The PBOC's interventions play a key role in maintaining exchange rate stability. In contrast, the offshore RMB (CNH) is traded outside Mainland China, mainly in places like Hong Kong. The offshore market operates with greater flexibility, as it is less influenced by the PBOC, allowing market dynamics to drive the exchange rate. This difference is essential to understanding currency pricing and internationalization.

The offshore RMB market was established as part of China's effort to internationalize its currency. As China opened its capital account and promoted RMB use in global trade, a key milestone came on July 19, 2010, when the PBOC and the Hong Kong Monetary Authority launched RMB settlement services in Hong Kong.

This led to the creation of offshore RMB spot and forward exchange rates, officially establishing the Hong Kong RMB market (CNH) (Yan, Zhang and Liu, 2017). Over time, Hong Kong introduced the first offshore RMB interbank offered rate, and various RMB-denominated products such as stocks, bonds, and insurance began to be traded. The development of infrastructure, including the RMB clearing bank and payment systems, further expanded the offshore market's influence (Liu, Zhu and Li, 2016).

The offshore RMB market is crucial for RMB internationalization. It provides investment and hedging tools for offshore investors and allows the circulation of RMB without directly affecting the onshore market. The offshore market acts as a buffer, facilitating foreign capital flows while protecting China's domestic market from foreign capital volatility (Fung and Yau, 2012). The market's growing sophistication has significantly enhanced its global impact (Chen et al., 2016; Gao, 2017).

Despite the offshore market's growth, there remains a price difference between offshore and onshore RMB. This gap arises from factors such as capital controls, liquidity differences, and the more flexible nature of the offshore market. These discrepancies are influenced by the PBOC's management of the onshore rate and regulatory differences between the two markets. Improvements in liquidity in the Hong Kong market have reduced these differentials and eased exchange rate volatility (Yan, Zhang and Liu, 2017). However, issues persist due to varying degrees of openness and daily exchange rate fluctuations (Wang et al., 2016). These differences have created opportunities for arbitrage, which has been widely studied in relation to their impact on the onshore mark et.

Given China's control over the onshore RMB exchange rate, predicting the price gap between the onshore and offshore markets can offer valuable insights into currency market fluctuations. This approach helps forecast exchange rate changes and formulate timely responses. Since 2005, especially after the global financial crisis, China's monetary policy has increasingly influenced other emerging Asian economies, pushing the global monetary system towards a tri-polar structure. In this setup, the U.S. dollar remains dominant, while the euro and RMB have significant regional influence (Fratzscher and Mehl, 2013).

With capital account liberalization, the volatility of offshore RMB products has increased. The offshore market has not fully kept up with the rapid growth of offshore RMB stocks, leading to greater volatility (Yang, 2018). Shu, He and Cheng (2015), using the "Frankel-Wei" anchor currency framework, found that the Hong Kong offshore RMB market has become an important channel for RMB's influence on other currencies in the Asia-Pacific region. Offshore RMB fluctuations also affect domestic financial markets, including the stock market (Que and Li, 2018).

The development of the offshore RMB market is a key step in the RMB internationalization process, occurring alongside China's gradual move toward a market-driven exchange rate and capital account liberalization (Chen and Zhen, 2017). The offshore market plays a passive role in this process and relies on cooperation with the onshore market to facilitate RMB growth (Fung and Yau, 2012). This process gained momentum after August 11, 2015, when the PBOC reformed the RMB/USD exchange rate central parity mechanism. This reform was a major step toward improving the flexibility of the RMB exchange rate system and was followed by a series of measures, including the implementation of a central parity mechanism based on the closing price and changes in a basket of currencies (Peng, Luo and Li, 2018).

As the offshore RMB market deepens, its price discovery function has been improved. Unlike the "market

+ policy" approach of the onshore market, the offshore market's more flexible regulatory framework allows it to increasingly influence the onshore RMB exchange rate. This shift makes the offshore RMB market a key factor in predicting the RMB central parity rate (Cheung and Rime, 2014).

Finally, recent studies have focused on skewness strategies, which involve selling currencies with low skewness and buying those with high skewness. Skewness refers to the asymmetry in asset return distributions. A positively skewed asset has a higher likelihood of producing large positive returns, while a negatively skewed asset tends to have more frequent large negative returns. This approach challenges the traditional idea that investors prefer diversified assets to reduce risk. Some investors favor assets with a small chance of high returns, like lottery-like investments. This behavior suggests that factors like skewness should be considered in asset pricing (Jiang, Han and Yin, 2019). The foreign exchange market, with its high trading volume, low transaction costs, and sophisticated institutional investors, is well-suited for examining the profitability of skewness strategies. Chan, Yang and Zhou(2018) found that major currencies such as the U.S. dollar, Japanese yen, and Swiss franc exhibit positive skewness, making them effective hedges against global stock market volatility.

In conclusion, the exchange rate differential between offshore RMB (CNH) and onshore RMB (CNY) is common and significant. This gap is driven by factors such as capital controls, liquidity differences, and market dynamics. As the offshore market grows, predicting these differentials becomes increasingly important. Integrating strategies like the Skewness strategy into these predictions could offer valuable insights. Exploring its application to RMB exchange rate gaps may improve forecasting and risk management in the global RMB market.

3. Data Description

Based on the literature review, we recognize the significance of the offshore RMB market and the importance of skewness in capital market research. Next, we will study the role of skewness in predicting future RMB prices and confirm its importance in RMB pricing to enable timely control over the currency's price.

The onshore-offshore RMB spread in this paper is calculated using the spot exchange rate of RMB against USD:

$$r_t = \log\left(\frac{S_t}{O_t}\right) \tag{3.1}$$

Where r_t is the spread at time t, S_t is the onshore spot exchange rate of RMB against USD at time t, and O_t is the offshore spot exchange rate at time t.

The daily onshore-offshore RMB-USD spread skewness is calculated using the daily spread of the previous n trading days:

$$SK_t = \frac{1}{n}\sum_{i=0}^{n-1}\left(\frac{r_i-\bar{r}_i}{\sigma_i}\right)^3 \tag{3.2}$$

Here, SK_t represents the spread skewness at time t, r_t is the spread at time t, and n is the number of trading days in the rolling window. $\bar{r}_t = \frac{\sum_{i=1}^{n} r_{t-i}}{n}$ and $\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_{t-i} - \bar{r}_t)}$ represent the mean and standard deviation of the spread over the trading days in the rolling window.

In the foreign exchange market, the spread between onshore and offshore exchange rates is typically non-normally distributed. In such cases, skewness arises, meaning the mean, median, and mode of the spread do not coincide. If more data points lie to the left of the mean, it is called right skewed, indicating a smaller probability of the spread being above the mean. Conversely, if more data points lie to the right of the mean, it is called left skewed, indicating a higher probability of the spread being above the mean.

The offshore and onshore exchange rates used in this study are daily data. The offshore RMB-USD exchange rate in the Hong Kong offshore market and the onshore exchange rate data are sourced from the Wind database.

This paper uses data from January 1, 2017, to June 30, 2024. Figure 1 illustrates the fluctuations in the onshore exchange rate, offshore exchange rate, and the spread r_t over a one-month rolling window during this period.

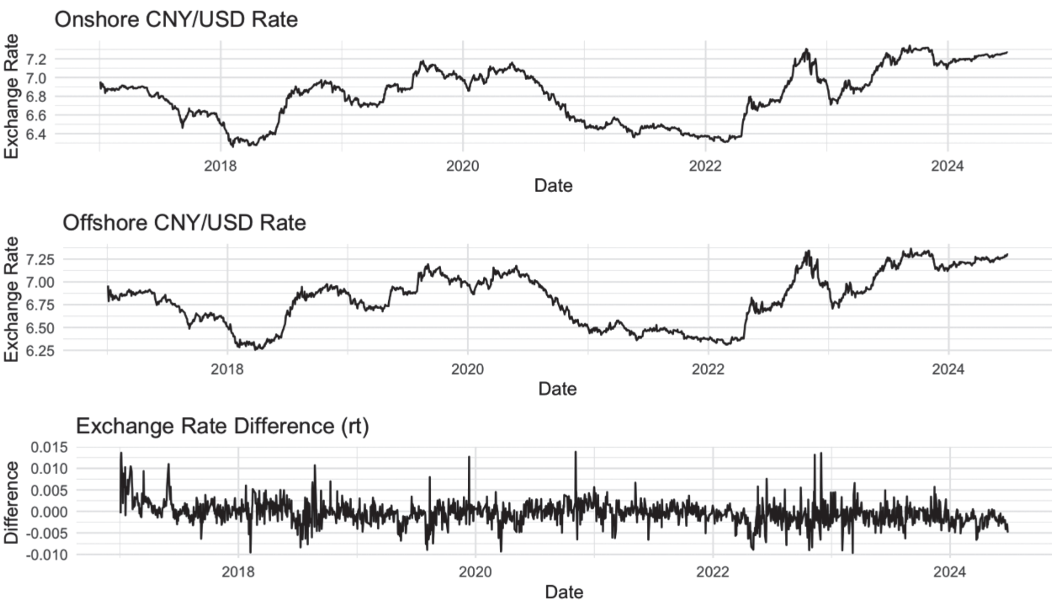

Figure 1 Data Fluctuation

4. Methodology and Empirical Results

The previous research has proved that in-sample forecasting, RMB onshore price skewness has very limited ability to predict onshore prices, but in out-of-sample testing, the skewness testing method is significantly better than random walk models. Therefore, for further analysis, combined with the previous test results, we will further examine how predictable the spread skewness is on the onshore-offshore RMB spread.

4.1 Linear Pricing Model with Spread Skewness

To determine the effect of the onshore-offshore spread skewness on the spread, we still first use the univariate linear regression containing only the spread skewness to study:

$$r_{t+1} = \alpha + \beta SK_t + \varepsilon_{t+1} \tag{4.1}$$

Wherer_{t+1} is the price difference between the onshore RMB and offshore RMB in period $t + 1$, and SK_t is the price skewness between the onshore RMB and offshore RMB in period t. The statistical results of the model's next month sample are shown in Table 1:

Table 1 Regression results of the spread linear model under 1-month window

Variable	σ	sd	t-value	P-value	Sample	R^2	F-value
α	0.0003	3.633e-05	8.849	0.0000***	1768	0.0914	88.91
β	-0.0005	5.616e-05	-9.458	0.0000***	1768		0.0000

The results show that the spread skewness has a significant negative effect on the spread in the next period, the coefficient is about -0.0005. The F-statistic is 88.91, indicating that at least one independent variable has a significant impact on the dependent variable. But under the linear model, the R^2 level is only 9.15%, which shows that the model under the next one-month window period, the skewness of the price difference is very weak in explaining the price difference of the next period, and other factors should be included in the model.

Table 2 Regression results of the spread linear model

Rolling window	α	β	$R^2(\%)$
1 month	0.0003*** (8.849) (0.0000)	-0.0005*** (-9.458) (0.0000)	9.15
2 months	0.0003*** (6.151) (0.0000)	-0.005*** (-9.736) (0.0000)	8.24
3 months	0.0002*** (4.902) (0.0000)	-0.0005*** (-9.282) (0.0000)	7.60
6 months	-0.0002** (3.015) (0.0026)	-0.007*** (-11.138) (0.0000)	9.48
9 months	0.0004** (6.587) (0.0000)	-.0007*** (-10.938) (0.0000)	12.11
12 months	0.0003** (2.632) (0.0086)	-0.0007*** (-9.827) (0.0000)	8.66
18 months	0.0008* (4.731) (0.0000)	-0.0010*** (-12.174) (0.0000)	20.41
24 months	0.0018* (3.362) (0.0009)	-0.0010* (-8.409) (0.0000)	26.57

To examine the different predictive effects of skewness in exchange rate differences over various rolling windows and determine the optimal rolling period for prediction, we tested the forecasting performance under rolling windows of 1 month, 2 months, 3 months, 6 months, 9 months, 12 months, 18 months, and 24 months.

The relevant statistical properties of the univariate linear regression model are shown in Table 2.

Under all rolling windows, the onshore-offshore spread skewness coefficients in the sample are significantly negative, with coefficient values ranging from -0.0010 to -0.0005. The absolute values of the spread skewness coefficients under the eight rolling windows are relatively small, with no significant differences; among them, the coefficients for the 18-month and 24-month windows are the smallest, while the spread skewness is largest for the 1-month, 2-month, and 3-month windows. The R-Square level of the model is not high, ranging from 7.60% to 26.57%, with the highest coefficient of determination for the 24-month window. During the transition from smaller to larger window periods, the R-Square first decreases, then increases, and after reaching a relatively low level at the 12-month window, the explanatory power rapidly rises for the 18-month and 24-month windows, showing a pronounced trend of change.

Overall, the spread skewness has a significant negative impact on the onshore-offshore RMB spread, indicating that the greater the spread skewness, the smaller the current spread. The explanatory power of this effect is limited, with the best explanatory ability around the 2-year window, explaining the onshore-offshore RMB spread to an extent of 26.57%.

In summary, although the spread determination model including spread skewness has a relatively low overall explanatory power, it demonstrates a significant negative impact on the spread across all window periods. Therefore, in this context, we will continue to explore the role of lagged terms in the spread skewness pricing model.

4.2 Intra-sample prediction effect of spread skewness under autoregressive model

From Section 4.1, we can see that the skewness of the spread has a certain negative effect on the spread, and this predictive effect is best explained under a 24-month rolling window. However, the explanatory power of the univariate linear model in Section 4.1 is limited. Therefore, to avoid model specification errors and to determine whether it is necessary to include independent variables that can incorporate information from the previous period's spread skewness, we will use an AR model to test whether the spread skewness exhibits persistence:

$$SK_t = \alpha + \sum_{l=1}^{L} b_{t-l} \times SK_{t-l} + \varepsilon_t \tag{4.2}$$

Among them, SK_t is the onshore-offshore RMB spread skewness of t period, and SK_{t-1} is the spread skewness of $t-1$ period. We use the modified Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine the model lag order. The optimal lag order of the autoregressive model for the spread skewness under these eight rolling windows is greater than or equal to 1. Based on the principle that smaller AIC and BIC values indicate a better model, we determine that the maximum lag order for the 1-month window is 4. Therefore, we set the model as a 4-lag AR model, with the regression results shown in Table 3.

In all window periods, the skewness of the return spreads in the AR model at the first lag is significantly positive. For the 6-month window periods, the coefficients remain significant even at the fourth lag. This indicates that we cannot ignore the persistence of return skewness, and the information about lagged return skewness must be included in the predictive model.

Table 3 AR regression of spread skewness

	α	b_{t-1}	b_{t-2}	b_{t-3}	b_{t-4}	R^2(%)
1 month	-0.12	0.19***	0.05**	0.03	0.04	
	(-0.55)	(8.06)	(1.96)	(1.30)	(1.62)	
	(0.5800)	(0.0000)	(0.0500)	(0.1930)	(0.1040)	4.79
2 months	-0.20	0.15***	0.04	0.02	0.06	
	(-0.71)	(6.22)	(1.53)	(1.47)	(1.42)	
	(0.4770)	(0.0001)	(0.1260)	(0.1400)	(0.1570)	2.95
3 months	-0.29	0.13***	0.05**	0.02	0.05**	
	(-0.95)	(5.61)	(2.26)	(0.73)	(1.96)	
	(0.3410)	(0.0000)	(0.0240)	(0.4630)	(0.0500)	2.76
6 months	-0.28	0.15***	0.08***	0.02	0.05**	
	(-0.8)	(5.91)	(3.11)	(0.97)	(2.16)	
	(0.4220)	(0.0000)	(0.0019)	(0.3330)	(0.0309)	3.79
9 months	-0.22	0.13***	0.06**	0.01	0.05**	
	(-0.55)	(5.25)	(2.48)	(0.20)	(2.13)	
	(0.5840)	(0.0000)	(0.0132)	(0.8390)	(0.0328)	2.84
12 months	0.04*	0.13***	0.05*	-0.002	0.04*	
	(1.69)	(4.92)	(1.89)	(-0.08)	(1.69)	
	(0.0904)	(0.0000)	(0.0589)	(0.9380)	(0.0904)	2.31
18 months	-0.12	0.11***	0.05*	-0.01	0.03	
	(-0.30)	(3.86)	(1.68)	(-0.44)	(1.17)	
	(0.7645)	(0.0001)	(0.0937)	(0.6631)	(0.2432)	1.59
24 months	-0:04	0.12***	0.03	-0.02	0.03	
	(-0.11)	(4:00)	(0.91)	(-0.49)	(0.96)	
	(0.9140)	(0.0000)	(0.3610)	(0.6240)	(0.3360)	1.67

Since the AR regression results indicate that we should include lagged spread information in the predictive model, and we know that the lag order is at least one, we will use the first lagged spread as one of the explanatory variables. This effectively adds the lagged spread information to the predictive model with certain weights. Thus, the prediction formula is adjusted from equation (4.1) to:

$$r_{t+1} = \alpha + \gamma r_t + \beta SK_t + \varepsilon_{t+1} \tag{4.3}$$

where r_{t+1} is he spread between onshore and offshore RMB at time $t+1$, r_t is the spread at time t, and SK_t is the skewness of the spread at time t. The model results for the one-month window period are shown in Table 4.

In the one-month window period, both the current spread and the skewness of the spread have a significant positive relationship with the next period's spread. The model's fit has improved, with an R^2 level of 15.4%. Compared to the model without autoregressive terms, this represents an enhancement, indicating that lagged terms play a crucial role in predicting the spread.

Table 4 Regression results of autoregressive model under 1-month window

Variable	Estimate	sd	t-value	P-value	Sample	R^2
α	-0.0003	0.0005	-5.47***	0.0000	1797	0.154
r (1)	0.4270	0.0287	14.91***	0.0000	1797	
β	0.00002	0.0000	-2.02**	0.0440	1797	

After confirming the model's explanatory power has improved, we will continue to use this model for in-sample forecasting of the time series. The prediction results are shown in Table 5.

Table 5 The intra-sample predictive utility of the spread skewness on spread

Rolling window	α	β	γ	$R^2(\%)$
1 month	-0.0003***	0.4270***	0.00002**	
	(-5.47)	(14.91)	(-2.20)	
	(0.0000)	(0.0000)	(0.0440)	15.4
2 months	-0.0003***	0.4020***	-0.0001	
	(-6.81)	(14:04)	(-1.42)	
	(0.0000)	(0.0000)	(0.1600)	14.2
3 months	-0.0004***	0.3850***	0.00001	
	(-6.38)	(13.76)	(-0.67)	
	(0.0000)	(0.0000)	(0.5000)	14..0
6 months	-0.0004***	0.3700***	0.00001***	
	(-6.80)	(12.50)	(-0.69)	
	(0.0000)	(0.0000)	(0.0000)	12.8
9 months	-0.0004***	0.3710***	0.00001	
	(-6.97)	(12.48)	(-0.84)	
	(0.0000)	(0.0000)	(0.4000)	12.7
12 months	-0.0005***	0.3620***	0.00001	
	(-7.63)	(11.59)	(-0.66)	
	(0.0000)	(0.0000)	(0.5100)	12.2
18 months	-0.0005***	0.3980***	0.0001	
	(-6.92)	(12.22)	(-1.29)	
	(0.0000)	(0.0000)	(0.200)	14.0
24 months	-0.0004***	0.3870***	0.0001	
	(-6.13)	(10.89)	(-0.76)	
	(0.0000)	(0.0000)	(0.4500)	13.7

It can be observed that compared to a simple univariate linear regression model, the model with lagged terms shows that the skewness of the exchange rate spread is only significantly positive in the one-month window; in other windows, it is not significant. The R^2 values of the model have improved to varying degrees across different rolling windows, with the one-month rolling window showing the best explanatory power. In this case, the R^2 is 15.4%, indicating that the skewness model with the first-order lag term can predict the next period's onshore-offshore RMB exchange rate spread at a level of 15.4%.

4.3 Out-of-sample prediction effect of spread skewness under autoregressive model

In section 4.2, we established that the skewness of the price difference has predictive power for the onshore-offshore RMB price difference using in-sample data. However, we need to examine whether this predictive effect still holds in out-of-sample predictions and whether it offers advantages over commonly used benchmark prediction models. In this chapter, we will use data from January 1, 2012, to December 31, 2016, to test the out-of-sample predictive performance.

In addition to utilizing statistical measures, we also study the changes in out-of-sample prediction accuracy by comparing the Cumulative Square Prediction Error (CSPE) of the skewness-based spread prediction model and the random walk benchmark prediction model.

To provide a more intuitive view of the differences in CSPE between the model in this paper and the random walk (RW) model across different window periods, we plotted Figure 2. When the cumulative squared prediction error of the random walk benchmark prediction model is greater than that of the model in this paper, indicated by the CSPE being above zero throughout the sample period, it demonstrates that the onshore-offshore spread prediction model in this paper has more accurate predictive power. Conversely, when the CSPE is below zero, it indicates that the predictive ability of the model in this paper is weaker than that of the random walk

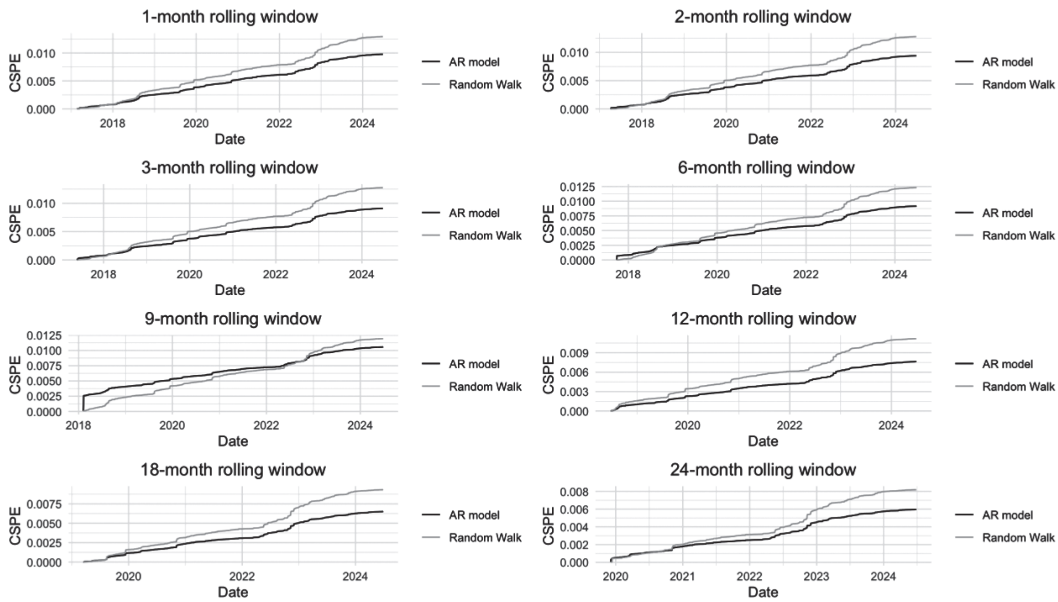

Figure 2 CSPE under 8 window periods

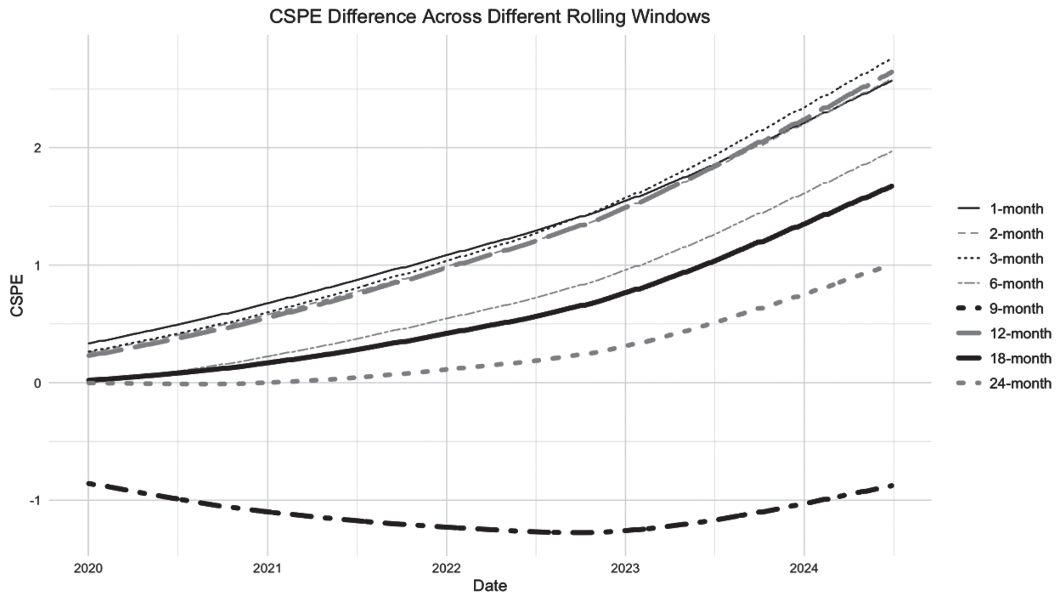

Figure 3 Differences of CSPE under 8 window periods

benchmark model for out-of-sample predictions.

It can be observed that in the 12-month and 18-month window periods, the cumulative squared prediction error (CSPE) of the model in this paper is consistently lower than that of the random walk model. For the 1-month, 2-month, 3-month, 6-month, and 12-month window periods, although the two models did not show significant differences in the initial stages and at certain times, the mean squared prediction error of the model in this paper is even higher than that of the random walk model, this disadvantage is quickly corrected within a few months, and the model showed better predictive ability in later periods. However, in the 9-month window period, the model's performance is not as good as in other window periods. From the beginning of 2018, the 9-month window period model shows significant prediction errors, and it isn't until around September 2022 that this gap is closed. During this process of reducing the gap, the model's fitting ability compared to the random walk model has also improved.

Figure 3 illustrates the differences of CSPE under eight rolling window periods: 1-month, 2-month, 3-month, 6-month, 9-month, 12-month, 18-month and 24-month. It can be observed that, apart from the 9-month window period, all other graphs show a relatively stable upward trend, without significant fluctuations. In the early stages of the sample period, the 1-month window period displayed the best predictive performance, with the largest CSPE difference. This advantage is surpassed by the 12-month window period around September 2022 and further overtaken by the 3-month window period around July 2023. However, overall, these three window periods demonstrated the best predictive ability. The 24-month window period initially fluctuated around zero in the early stages but then quickly rose, showing an increasing difference in prediction errors between the two models. The 9-month window period remained an outlier, exhibiting a relatively flat "U" shape around -1. Although the curve began to tilt upwards later on, whether it can stay above zero in the future remains uncertain.

Overall, except for the 9-month window period, the cumulative squared prediction error of the onshore-offshore spread skewness prediction model shows an advantage over the benchmark model. Moreover, this advantage increases over time, with the spread skewness prediction model displaying stronger out-of-sample predictive power for the spread. Among these, the predictive accuracy under the 1-month window period (early stage) and the 3-month window period (later stage) is the most optimal.

Through the comparison with the random walk benchmark model, the CSPE graphs all demonstrate that the onshore-offshore RMB spread skewness model has superior out-of-sample predictive ability. Combined with the findings from Section 4.2, we know that the in-sample predictions during the eight rolling window periods are also significant. Therefore, we believe that in the Hong Kong offshore RMB market, the onshore-offshore RMB spread skewness exhibits significant in-sample and out-of-sample predictive power for the spread. Both the in-sample and out-of-sample studies indicate that the 1-month rolling window period provides the best predictive performance, with the model's explanatory power reaching 15.4%. However, the predictive performance across other window periods does not differ significantly. Therefore, when forecasting the onshore-offshore RMB spread, it is essential to examine the spread skewness at least within the preceding 1-month period to obtain valuable information.

4.4 Robustness test

In the previous two sections, the in-sample and out-of-sample predictive performance of the spread skewness on the spread has been confirmed. However, the explanatory power of the model is not high, with the maximum R^2 value reaching only 15.4%. Therefore, in order to improve the explanatory power of the model and enhance the robustness of the linear model, we will attempt to add other variables to the model containing lagged information. Factors that typically affect the RMB exchange rate include stocks, bonds, and market volatility. Thus, we use the S&P 500 stock index to represent the global stock market volatility trend, and the VIX index from the Chicago Board Options Exchange to represent the market's expectations for volatility over the next 30 days. Additionally, we include the impact of the bond market by using the 10-year Treasury bond yield and the 10-year U.S. Treasury yield. The predictive model is adjusted from the regression prediction model shown in formula (4.3) as follows:

$$r_{t+1} = \alpha + \gamma r_t + \mu SP_t + \delta V_t + \eta S_t + \zeta B_t + \beta SK_t + \varepsilon_{t+1} \tag{4.4}$$

Among them, r_{t+1} is the price difference between the onshore RMB and offshore RMB in period $t+1$, r_t is the onshore-offshore RMB spread in period t, and SK_t is the spread skewness in period t. SP_t is the t-period S & P 500 index, V_t is the t-period VIX index, S_t is the t-period 10-year U.S. Treasury bond rate, and B_t is the t-period 10-year Chinese Treasury bond rate. Similarly, in order to determine the rolling window with the best prediction effect, we have tested the rolling window for 1 month, 2 months, 3 months, 6 months, 9 months, 12 months, 18 months and 24 The prediction effect under the monthly situation, the time series intra-sample prediction results under this model are shown in Table 6.

Table 6 Robustness Test

Rolling Window	1 month	2 months	3 months	6 months	9 months	12 months	18 months	24 months
α	-0.0022.	-0.0035**	-0.0038**	-0.0041**	-0.0050***	-0.0040*	-0.0038*	-0.0018
	(-1.73)	(-2.70)	(-2.83)	(-2.96)	(-3.334)	(-2.55)	(-2.15)	(-0.91)
β	0.3244***	0.3025***	0.2890***	0.2730***	0.2793***	0.2773***	0.3141***	0.2467***
	(10.32)	(9.628)	(9.53)	(8.46)	(8.68)	(8.20)	(8.62)	(6.35)
γ	-1.1450	2.5680	7.2460	6.5300	0.9429	1.0670	-3.3890	9.5210
($\times 10^{-6}$)	(-0.10)	(0.30)	(0.973)	(0.88)	(0.14)	(0.15)	(-0.44)	(1.18)
μ	-3.4790	-16.87	18.98	-22.30	26.28*	22.38	18.64	-46.00*
($\times 10^{-8}$)	(0.31)	(1.43)	(1.57)	(1.77)	(2:03)	(1.71)	(1.30)	(-2.24)
δ	-1.3450	-0.7336	-0.6449	-0.4681	-0.2311	-0.7181	-0.8833	-4.1770**
($\times 10^{-5}$)	(-1.55)	(-0.83)	(-0.72)	(-0.50)	(-0.24)	(-0.73)	(-0.85)	(-3:07)
η	-2.2870***	-2.3150***	-2.3470***	-2.3990***	-2.1810***	-2.4660***	-2.2710**	-1.3310
($\times 10^{-4}$)	(-3.78)	(-3.85)	(-3.89)	(-3.94)	(-3.49)	(-3.69)	(-2.85)	(-1.65)
ζ	8.2270**	10.60***	11.01***	11.43***	13.65***	11.65***	11.43**	15.36***
($\times 10^{-4}$)	(3.22)	(4:03)	(4.13)	(4.24)	(4:48)	(3.43)	(2.82)	(8.72)
$R^2(\%)$	17.96	17:04	16.9	15.40	15.30	14.65	16.67	19.18

Based on the observed data; after adding more explanatory factors, the in-sample impact of the onshore-offshore spread skewness was completely removed across all window periods. The coefficient of spread skewness became extremely close to zero in a positive direction, with its value significantly reduced compared to the original model, showing no meaningful digits when rounded to four decimal places. Similarly, the coefficient of the S&P 500 Index was also very small, and it was only significant at the 90% confidence level during the 9-month and 24-month window periods. The coefficient of the VIX index was also low, showing a negative impact on the onshore-offshore spread in most window periods, but this effect was only significant during the 24-month window period. The influence of the 10-year U.S. Treasury yield and the 10-year Chinese Treasury yield on the spread was opposite.

Considering the bond yield, the U.S. Treasury yield had a negative effect on the spread-when the U.S. yield increased, the spread decreased, and when the U.S. yield decreased, the spread increased. This negative correlation can be explained by several factors related to capital flows, global risk sentiment, and investor preferences. When U.S. Treasury yields rise, they make U.S. assets more attractive, leading to capital flowing out of offshore RMB markets and reducing demand for offshore RMB resulting in an oversupply of RMB. The capital inflow into the US can also lead to the appreciation of the U.S. dollar and the depreciation of the RMB, thereby narrowing the spread. Additionally, rising yields signal tighter financial conditions, reducing liquidity and increasing risk aversion, which can increase the premium for holding offshore RMB assets. Furthermore, as a global benchmark, U.S. Treasury yields influence investor portfolio adjustments, impacting the supply and demand dynamics of onshore and offshore RMB. When U.S. yields decline, riskier assets, including RMB-denominated products, become more appealing, which can widen the spread between onshore and offshore RMB. In contrast, the Chinese Treasury yield had the opposite effect.

Additionally, compared to the original model, although the R^2 level of the new model is still not very high, ranging between 14.65% and 19.18%, there is a certain degree of improvement across all eight rolling windows. The most significant improvement in explanatory power occurred under the 24-month window period, where R^2 increased from 13.7% to 19.18%, marking the highest explanatory power in the sample. It is worth noting that the range of R^2 in the new model has widened, and compared to the original model, it forms a more fitting "U-shaped" trend. This indicates that the newly added explanatory factors have different impacts on the predictive power of spread skewness across various rolling window periods.

Overall, the inclusion of new factors removed the previously significant in-sample positive predictive effect of spread skewness on the onshore-offshore RMB spread, and the model's explanatory power has increased. This suggests that the newly added factors have replaced the original role of spread skewness, but on the other hand, it also shows that spread skewness reflects the effects of these factors. Moreover, the significance of the S&P 500 and VIX indices is not high, indicating that more factors should be considered. The model can predict the onshore-offshore spread with an accuracy of 19.18% when the rolling window period is two years. This implies that stock, bond, and market volatility factors weaken the short-term effect of spread skewness and emphasize its long-term impact.

4.5 Structural breakpoints in spread skewness

In the previous chapter, we incorporated market factors into the autoregressive model to enhance its robustness, and we observed a certain degree of improvement in the model's explanatory power. Considering that the impact of market factors on the model has been further amplified, the foreign exchange market may experience shocks from external factors during certain periods. Exchange rates are highly influenced by major international events, and during the observation period, several significant events occurred that theoretically should have impacted the price spread.

After the exchange rate reform on August 11, the Federal Reserve raised interest rates four times in 2018, the U.S.-China trade war broke out, the Russia-Ukraine war began, and the COVID-19 pandemic emerged. All of these events likely influenced the spread between onshore and offshore RMB. At the same time, we also recognize that the rolling window approach may cause changes in the model's structure. This potential influence was overlooked in the previous analysis, so it is essential to test for structural breaks in the model. Therefore, this chapter aims to investigate whether these shocks cause changes in the skewness coefficient of price spreads during the generation process, resulting in structural breaks. Following Bai and Perron (2003), we set up a partially structural change model with mm structural breaks as follows:

$$r_{t+1} = \alpha + \gamma r_t + \beta_j SK_t + \varepsilon_{t+1} \tag{4.5}$$

In this model, α , γ are constant over time. The parameter estimation is based on all observations within the sample period. β_j $(j = 1, \dots, m+1)$ represents the coefficients of the price spread skewness, and there are $m+1$ values corresponding to mm structural breaks. The structural breaks of the price spread skewness coefficients and the coefficient values between the breaks are shown in Table 7.

Based on the empirical results of structural breakpoints, it can be observed that the coefficient of skewness for the spread under the one-month rolling window exhibits three structural breakpoints on June 13, 2018, May 28, 2020, and December 8, 2021. Before the first structural breakpoint, during the first phase, the skewness coefficient for the spread is $\beta_{1,1} = 5.7555 \times 10^{-5}$, which is significant at the 5% significance level. In the second phase, the skewness coefficient for the spread is $\beta_{1,2} = -0.7988 \times 10^{-5}$, with a lower absolute value compared to the previous phase. In the third phase, the skewness coefficient for the spread is negative, $\beta_{1,3} = -2.1044 \times 10^{-5}$, with a higher absolute value than the previous phase. In the fourth phase, the skewness coefficient becomes positive again, $\beta_{1,4} = 0.3573 \times 10^{-5}$. Overall, the explanatory power of skewness in returns under the one-month rolling window was strong before June 2018, then significantly decreased and became negative, before gradually rising again to a positive value.

Additionally, it can be observed that the 2-month, 3-month, 6-month, and 9-month rolling windows all contain three structural breakpoints. For the most part, the skewness of the spread has a positive impact on the next period's spread, while significant negative shifts in the coefficients mostly occurred between 2018 and 2019. During these negative phases, the explanatory power of the coefficients was relatively strong. In both the 12-month and 24-month rolling windows, two structural breakpoints appeared, with the skewness coefficients shifting from negative to positive, although their explanatory power decreased. Under the 24-month rolling window, only one structural breakpoint was detected, on February 28, 2022.

Upon examining the structural breakpoints that emerged across different rolling windows, a high degree of overlap in the timing of these breakpoints becomes evident. Structural breakpoints are detected around June 13, 2018, in the 1-month, 2-month, and 3-month rolling windows. All rolling windows, except for the 24-month window, experienced significant structural changes on May 28, 2020. In five rolling windows—1-month, 6-month, 9-month, 12-month, and 18-month—there are notable fluctuations on December 28, 2021. Additionally, three rolling windows exhibited structural breakpoints on February 28, 2022. Apart from these key dates, the period between 2018 and 2019 saw frequent structural changes. The emergence of these structural breakpoints often coincides with major political or market events, which introduce external factors not captured by the model, thereby affecting the value of the RMB. As such, the events that occurred during these periods warrant further attention.

Table 7 Structural Breakpoints of Spread Coefficient

Rolling window	*Structural Breakpoints and* β_j ($\times 10^{-5}$)			
1 month	*Structural Breakpoints* (3):	2018/6/13	2020/5/28	2021/12/8
	$\beta_{1,1}$	$\beta_{1,2}$	$\beta_{1,3}$	$\beta_{1,4}$
	5.7555**	-0.7988	-2.1044	0.3573
2 months	*Structural Breakpoint* (3):	2018/6/13	2019/8/12	2022/2/28
	$\beta_{2,1}$	$\beta_{2,2}$	$\beta_{2,3}$	$\beta_{2,4}$
	3.7593**	6.0554*	1.8414*	2.3372
3 months	*Structural Breakpoint* (3):	2018/6/13	2020/5/28	2022/2/28
	$\beta_{3,1}$	$\beta_{3,2}$	$\beta_{3,3}$	$\beta_{3,4}$
	2.4350	-1.7173	0.0060	3.7742**
6 months	*Structural Breakpoints* (3):	2018/12/12	2020/5/28	2021/12/8
	$\beta_{6,1}$	$\beta_{6,2}$	$\beta_{6,3}$	$\beta_{6,4}$
	4.0908	-4.6122***	0.8134	3.8437***
9 months	*Structural Breakpoint* (3):	2019/1/15	2020/5/28	2021/12/8
	$\beta_{9,1}$	$\beta_{9,2}$	$\beta_{9,3}$	$\beta_{9,4}$
	1.9150	-4.0826***	0.5270	2.9979***
12 months	*Structural Breakpoints* (2):	2020/5/28	2021/12/8	
	$\beta_{12,1}$	$\beta_{12,2}$	$\beta_{12,3}$	
	-0.3320**	0.0604	2.0511**	
18 months	*Structural Breakpoint* (2):	2020/5/28	2021/12/8	
	$\beta_{18,1}$	$\beta_{18,2}$	$\beta_{18,3}$	
	-5.4869***	0.4147	1.9223*	
24 months	*Structural Breakpoints* (1):	2022/2/28		
	$\beta_{24,1}$	$\beta_{24,2}$		
	-1.3081	1.8110		

Since August 11, 2015, China initiated a currency reform, allowing the RMB's central parity rate to float for the first time. This marked the first time in history that PBOC conceded to depreciation pressures on the RMB. Following the second half of 2015, China's foreign exchange reserves continued to decline, with July and August seeing the most significant drops. This indicated that the central bank had substantially reduced the amount of RMB used to purchase foreign exchange assets, signaling weak demand for RMB and clear downward pressure on its value.

From the start of the exchange rate reform until the end of 2015, the mechanism for determining the RMB exchange rate was a freely floating system, entirely dictated by market supply and demand. Thus, after the "8.11"reform, the PBOC introduced the "closing price + currency basket" mechanism to prevent sharp depreciation of the RMB against the U.S. dollar. The central parity rate mechanism, which uses two equally weighted factors, was introduced to determine the RMB's exchange rate against the U.S. dollar. The first factor is the previous day's closing price, while the second factor is maintaining the exchange rate index of the RMB against the CFETS (China Foreign Exchange Trade System) currency basket within a 24-hour period.

In the short term, the change in the interest rate differential between China and the United States can better explain the fluctuations in the RMB/USD exchange rate. Influenced by the Federal Reserve's tightening monetary policy, PBOC's quantitative easing policy, announced in April 2018, further narrowed the interest rate gap between the two countries, bringing new depreciation pressure on the RMB against the USD. However, by that time, the RMB exchange rate formation mechanism had effectively evolved into a combination of "free-floating + pegging to a basket of currencies + countercyclical factor." Therefore, the structural breaks that occurred after June 2018 indicate that in order to maintain the RMB/USD exchange rate near the "7" threshold in the short term and stabilize the exchange rate, the central bank took measures such as strengthening capital outflow controls, using foreign exchange reserves, and even intervening in the offshore RMB market in Hong Kong.

The fluctuation of the RMB exchange rate around May 28, 2020, was the result of multiple interwoven factors. During this period, relations between China and the United States significantly deteriorated, particularly with widespread attention focused on the discussion of Hong Kong's national security law. The U.S. government strongly opposed this and imposed a series of sanctions on China. This tension not only affected market confidence in China's economic outlook but also heightened concerns among investors about the potential depreciation of the RMB. At the same time, the ongoing impact of the COVID-19 pandemic posed numerous challenges to the global economic recovery. Although some countries had begun to gradually lift lockdown measures, the recurrence and resurgence of the virus made the pace of recovery uncertain, and investors became more cautious toward risk assets.

To cope with the economic shock brought about by the pandemic, PBOC implemented a series of accommodative monetary policies, including interest rate cuts and liquidity injections. While these measures aimed to stimulate economic growth, the looser policies may have led to an increase in RMB liquidity, thereby exerting downward pressure on the exchange rate.

At the end of 2021, the Federal Reserve signaled in its monetary policy meeting that it would accelerate the tapering of bond purchases and consider raising interest rates starting in 2022. This signal heightened market expectations of Fed rate hikes, leading to a stronger U.S. dollar. At the same time, China's economy faced challenges toward the end of 2021, particularly due to the real estate crisis (such as Evergrande Group's debt issues), which negatively impacted economic growth. Weak economic data, along with the recurring COVID-19 outbreaks affecting Chinese ports and manufacturing, and the global supply chain crisis, also hurt investor confidence.

Additionally, between late 2021 and February 2022, global geopolitical risks-especially tensions with Russia and the potential economic sanctions that could arise-sparked market concerns about risk assets. In times of heightened uncertainty, investors may prefer to hold U.S. dollars, thereby driving up the value of the dollar. This further contributed to the formation of structural breakpoints at the end of 2021 and early 2022.

The coefficient of spread skewness will fluctuate greatly in the face of major financial events, which is basically consistent with the common sense we have learned. However, the response to different events is not the same, and there may be cases where the explanatory power increases or decreases. However, considering the fluctuation of the spread before and after the structural breakpoint, the fluctuation of the explanatory power in the context of this major external event will quickly decline. Or achieve balance and stability at a new level.

The spread skewness coefficient tends to experience significant fluctuations during major financial events, which aligns with what we commonly understand from theory. However, the response to different events varies, and the explanatory power may increase or decrease. When looking at the spread fluctuations before and after structural breakpoints, it becomes evident that such fluctuations in explanatory power caused by external significant events tend to quickly subside or reach a new level of balance and stability.

5. Conclusion

The Hong Kong offshore RMB market plays a crucial role in the internationalization of the RMB, influencing currency demand, domestic monetary policy, and the macroeconomy. This market is expected to grow further due to the Belt and Road Initiative and the improvement in market interconnectivity, although its development presents challenges for domestic economic stability, necessitating further reforms in the onshore market.

Key findings from this study include Predictive Power of Skewness: The skewness of the onshore-offshore RMB spread demonstrates strong predictive ability, especially in the 1-month (15.4%), 3-month, and 2-year rolling windows. The model performs best in the 1-month window, outperforming the benchmark model in both short and long terms.

(2) Impact of Additional Explanatory Variables: When factors like the S&P 500, VIX, and bond yields are included, the model's explanatory power improves in the long-term, with the highest accuracy reaching 19.18% in the 2-year rolling window. However, the short-term predictive power of spread skewness diminishes with the addition of these factors.

(3) Structural Breaks and External Shocks: Key international events, including the U.S.-China trade war, the Russia-Ukraine war, and COVID-19, may led to structural breaks in the model. Significant breakpoints were identified in June 2018, May 2020, December 2021, and February 2022, highlighting the possible influence of these external factors on the onshore-offshore RMB spread.

(4) Volatility and Stabilization: Despite the increased volatility caused by these events, the RMB exchange rate eventually stabilized, providing valuable insights into future predictions.

Overall, the study emphasizes the combined use of skewness models with market factors to improve long-term forecasting of the RMB exchange rate. Future research should explore other offshore RMB markets beyond Hong Kong and examine the interactions between onshore and offshore exchange rates globally.

Future research should expand to other offshore RMB markets and examine the interactions between onshore and offshore markets globally. Analyzing the relationship between kurtosis and the prediction of exchange rate spreads also seems to be a promising direction

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