



Can skewness predict CNY-CNH spread?

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ABSTRACT

This paper aims to explore the predictive ability of skewness on CNY-CNH spread. We first prove positive effect of skewness with and without control variables under in-sample analysis. We further demonstrate the predictive power of skewness exists in the out-of-sample forecasts. This predictability becomes stronger when using longer skewness calculation windows but tends to decline at longer forecast horizon. And it is also robust even though adopting different measures of skewness and changing time horizons. Moreover, this predictability is realized through driving the changes in market liquidity. Our study illustrates skewness carries useful information for predicting CNY-CNH spread.

1. Introduction

The issue “one currency, two markets” has arisen with the establishment of Hong Kong offshore RMB market (the CNH market) since July 2010 (Li et al., 2020; Shu et al., 2015). Compared to the onshore RMB market (the CNY market) with center bank intervention and daily trade band regulation, the CNH market is totally free and includes a wider variety of participants and a more diversified range of RMB-linked products. In addition, investors in the CNH market are affected by the information from both China mainland and overseas fundamentals, thus causing information gap between the two markets (Han et al., 2018). Hence, the exchange rate spread between the CNY and CNH (the CNY-CNH spread) exists persistently (see Fig. 1). It is therefore necessary to analyze the CNY-CNH spread and further identify its drivers.

Unfortunately, there is little literature discuss this issue, and most of which focuses on the fundamentals (Funke et al., 2015), financial policies (Shu et al., 2015), EPU (Li et al., 2020) and investor attention (Han et al., 2018) etc. However, they ignore the information from the market itself. In this paper, we pay attention to the role of skewness, and detect its predictability on CNY-CNH spread. Skewness matters because investors are more likely to invest assets with positive skewness in order to get lottery-like returns, thus overvaluing the assets and earning low expect returns (Barberis and Huang, 2008). Moreover, investors with insufficiently diversified portfolio will sacrifice average variance efficiency pursuing high skewness exposure (Clark and West, 2007; Mitton and Vorkink, 2007). Subsequent literature has been proved the significant impact of skewness on financial assets, such as stocks (Amaya et al., 2015; Jondeau et al., 2019), currencies (Gkillas et al., 2019; Jiang et al., 2019a), and commodities (Fernandez-Perez et al., 2018) etc.

Notice that the empirical results for the relation between skewness and expected asset returns are mixed (Amaya et al., 2015; Jiang et al., 2019b; Xing et al., 2010), which makes it meaningful to study the relation between skewness and CNY-CNH spread. To explain this issue, we first conduct in-sample analysis with and without control variables and find significantly positive impact of skewness

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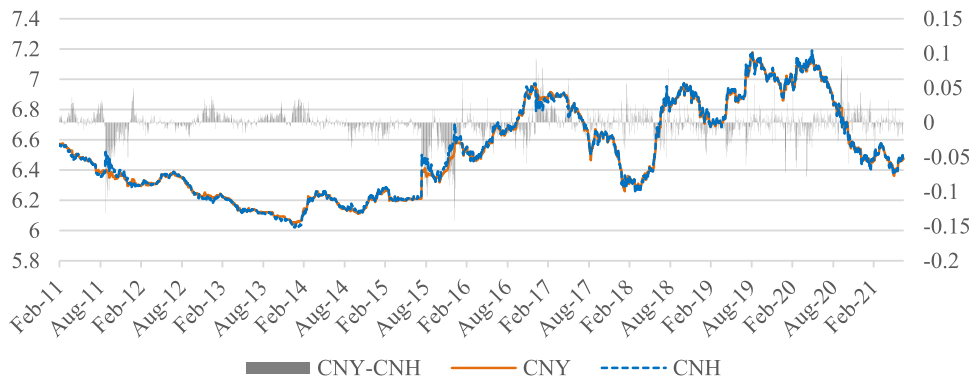


Fig. 1. The CNY and CNH spot exchange rates, and CNY-CNH spread (right axis) from February 2011 to June 2021.

over different calculation windows on CNY-CNH spread. We then perform out-of-sample forecasts, and demonstrate that skewness over longer windows can provide better predictive power than benchmark model although the predictability tends to decline at long forecast horizon. Moreover, considering the typical difference between positive and negative skewness, namely positive skewness captures market sentiment (Bevilacqua and Tunaru, 2021) while negative skewness can be viewed as a source of tail risk (Kelly and Jiang, 2014; Bollerslev et al., 2015) or crash risk (Kozhan et al., 2013), we further estimate the forecast performance of asymmetric skewness. Lastly, we conduct a subsample analysis, employing other measures of skewness and exploring possible economic mechanism as additional analyses of the predictability.

Our paper fills a vital gap in the literature on CNY-CNH spread predictability. We employ skewness as a predictive indicator to forecast CNY-CNH spread, which promotes the application of skewness in exchange rate forecasts. More importantly, our paper can help to further understand CNY-CNH spread since its predictability contributes to capturing hedge and arbitrage opportunities for traders and investors (Chen and Xu, 2021; Zhao et al., 2021), assessing performance in risk control of cross-border capital flows (Funke et al., 2015; Zhang et al., 2021), and promoting the RMB's internationalization (Han et al., 2018).

The remainder is organized as follows. Section 2 describes data and skewness calculation. Section 3 and Section 4 present the results of in-sample and out-of-sample analyses, respectively. Section 5 provides robustness and additional tests. Section 6 concludes.

2. Data

We collect the daily exchange rates of CNY and CNH from July 2011 to June 2021 as sample. Specifically, they contain the exchange rates of spot, and 1-month, 3-month, 6-month and 1-year forwards. The CNY-CNH spread is defined as the difference of logarithmic on CNY and CNH for both spot and forward exchange rates in basis points. We then calculate the Pearson's moment coefficient of skewness of CNY-CNH spread. Like previous studies (Fernandez-Perez et al., 2018; Mo et al., 2019; Jiang et al., 2019a), we use the daily CNY-CNH spread of selected rolling windows to generate the time-series measures of spread skewness,

$$SK_t = \frac{1}{D} \sum_{d=1}^D \left(\frac{Y_{t-d} - \mu_t}{\sigma_t} \right)^3 \quad (1)$$

where D is the number of historical rolling window for skewness calculation and Y_{t-d} is the CNY-CNH spread in d day before t day. We let D equal to 60, 120 and 240 days respectively, so we can cover the information of past three months, half a year and one year on currency movements. μ_t and σ_t are the spread mean and its standard deviation over rolling window, respectively.

3. In-sample analysis

3.1. Baseline regressions

We start with in-sample predictive regression of skewness on CNY-CNH spread. The prediction model is as follows,

$$Y_{t+h} = \alpha + \beta SK_t + \varepsilon_{t+h} \quad (2)$$

where Y_{t+h} is the CNY-CNH spread in daily $t+h$, h is forecast period (we let $h=1$ here¹), SK_t is the skewness of CNY-CNH spread. α and β are estimated coefficients. ε_{t+h} is error term.

Table 1 presents the results for predictive regressions on one-day ahead CNY-CNH spread based on different calculation of skewness. Obviously, the skewness generates significantly positive effects on all CNY-CNH spreads. It means that an increase in

¹ The estimation results of $h=7, 30, 60$ are available upon request.

Table 1
In-sample estimation results.

	Y_{t+1} Spot	Y_{t+1} 1M Forward	Y_{t+1} 3M Forward	Y_{t+1} 6M Forward	Y_{t+1} 1Y Forward
Panel A: $D=60$					
SK_t	11.545*** (18.528)	13.469*** (17.687)	17.696*** (17.326)	22.044*** (17.140)	26.834*** (14.465)
constant	-3.449*** (-6.110)	-5.602*** (-8.774)	-13.017*** (-16.468)	-26.878*** (-27.900)	-56.514*** (-42.315)
adj. R^2 (%)	11.522	10.962	10.566	10.363	7.608
Panel B: $D=120$					
SK_t	11.683*** (21.492)	11.159*** (16.259)	15.593*** (16.770)	21.751*** (18.219)	33.917*** (18.277)
constant	-3.101*** (-5.473)	-4.390*** (-6.892)	-10.983*** (-13.724)	-23.704*** (-24.338)	-51.267*** (-38.001)
adj. R^2 (%)	15.205	9.630	10.182	11.800	11.867
Panel C: $D=240$					
SK_t	10.945*** (22.454)	16.953*** (25.964)	21.314*** (24.240)	26.454*** (23.787)	41.695*** (24.004)
constant	-2.994*** (-5.600)	-2.118*** (-3.402)	-4.671*** (-5.473)	-15.108*** (-14.002)	-37.951*** (-24.915)
adj. R^2 (%)	17.033	22.211	19.927	19.332	19.617

Notes: This table reports the results for predictive regressions on all CNY-CNH spreads by using different calculation of skewness ($D=60, 120, 240$). The t -statistics are reported between parentheses. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

previous skewness may induce the expansion of future CNY-CNH spread. And a positive CNY-CNH spread indicates that spot exchange rate of CNY is higher than that of CNH which implies a depreciation of CNY against CNH (Han et al., 2018). Moreover, when rolling windows equal to 60 and 120 days, the adjusted R^2 of spot CNY-CNH spread is larger than that of other forward spreads, indicating that model (2) has a better ability on explaining spot spread. However, this phenomenon does not exist in 240 days window.

3.2. Regressions on adding control variables

To better detect the impact of skewness on the CNY-CNH spread, we introduce several control variables including interest rate differential (Ozmen and Yilmaz, 2017), liquidity differential (Funke et al., 2015), VIX (Funke et al., 2015), EPU (Li et al., 2020), and the realized volatility of CNY-CNH spread into baseline model. Specifically, we denote the interest rate differential (IR) as the spread between SHIBOR and HIBOR, the liquidity differential (LIQ) as the ratio between the CNY and CNH bid-ask spreads, and VOL as the realized volatility of CNY-CNH.

The model with skewness and control variables is expressed as follows,

$$Y_{t+h} = \alpha + \beta SK_t + \gamma X_t + \varepsilon_{t+h} \quad (3)$$

Where X_t denotes the vector of control variables. Here, Table 2 only reports the predictive regressions on one-day ahead CNY-CNH spread.

When forecasting spot CNY-CNH spread, the coefficients are significant for all control variables except for IR at $D=120$ and VOL at $D=60$. Moreover, the skewness over different windows still generates significantly positive effects on CNY-CNH spreads even introducing control variables, indicating that the information of skewness does not substantively overlap with traditional information (Yin and Wang, 2019). Remarkably, when comparing to the regressions only with control variables, the $\Delta adj.R^2$ for explaining all CNY-CNH spreads by incorporating skewness are positive, which further illustrates that the explanatory ability of CNY-CNH spread is better after introducing skewness.

4. Out-of-sample forecast

4.1. Linear specification

Comparing to in-sample analysis, the out-of-sample forecast is assumed to be more concerned in real time and avoid the over fitting issue (Yin, 2020). We next conduct the out-of-sample forecast based on the recursive estimation window by following Wang et al., 2018.

We split the sample observations T for both CNY-CNH spread and the corresponding skewness series into an in-sample part of M observations and an out-of-sample part of $T-M$ observations. We then run out-of-sample forecast by estimating the predictive regression including skewness and get the first forecast by,

$$\hat{Y}_{M+h} = \hat{\alpha}_M + \hat{\beta}_M SK_M \quad (4)$$

where $\hat{\alpha}_M$ and $\hat{\beta}_M$ are the OLS estimates from regression $\{Y_t\}_{t=h+1}^M$ on a constant and $\{SK_t\}_{t=1}^{M-h}$. And the second forecast is given by,

Table 2
In-sample estimation results with control variables.

	Y_{t+1} Spot	Y_{t+1} 1M Forward	Y_{t+1} 3M Forward	Y_{t+1} 6M Forward	Y_{t+1} 1Y Forward
Panel A: $D=60$					
SK_t	8.997*** (14.082)	11.479*** (15.270)	13.697*** (14.587)	19.762*** (15.881)	23.706*** (12.931)
constant	10.174** (1.777)	17.790*** (2.743)	7.452 (1.077)	-34.294*** (-3.891)	-98.884*** (-7.359)
IR_t	1.192** (2.021)	2.169*** (3.336)	4.298*** (5.241)	7.302*** (5.638)	21.685*** (9.024)
LIQ_t	1.880*** (3.175)	1.851*** (2.853)	4.274*** (4.827)	4.413*** (3.731)	3.196** (2.105)
VIX_t	-23.314*** (-11.758)	-29.110*** (-12.656)	-28.578*** (-11.601)	-31.084*** (-9.832)	-31.747*** (-6.682)
EPU_t	11.292*** (11.425)	12.170*** (11.195)	13.073*** (10.480)	18.476*** (11.549)	22.970*** (9.977)
VOL_t	0.476 (1.153)	0.050*** (3.001)	-4.917*** (-17.821)	10.925*** (9.11)	16.102*** (7.312)
adj. R^2 (%)	16.439	17.976	27.213	18.681	15.968
$\Delta adj.R^2$ (%)	6.561	7.578	6.134	8.128	5.558
Panel B: $D=120$					
SK_t	8.586*** (14.245)	10.389*** (14.823)	12.043*** (13.983)	18.279*** (15.279)	34.900*** (18.543)
constant	4.292 (0.730)	24.590*** (3.380)	-5.557 (-0.785)	-42.726*** (-4.664)	-47.261*** (-3.248)
IR_t	0.524 (0.840)	2.337*** (3.596)	4.640*** (5.532)	10.505*** (7.425)	21.015*** (8.974)
LIQ_t	2.206*** (3.731)	2.715*** (4.216)	2.865*** (3.285)	4.090*** (3.511)	4.269*** (2.952)
VIX_t	-16.012*** (-7.672)	-27.384*** (-11.149)	-20.013*** (-7.893)	-28.205*** (-8.722)	-40.388*** (-8.324)
EPU_t	8.862*** (8.853)	9.917*** (8.818)	11.068*** (8.968)	17.670*** (11.216)	17.428*** (7.720)
VOL_t	-0.415* (-1.462)	0.066*** (4.992)	-4.032*** (-20.159)	8.935*** (9.832)	21.292*** (12.965)
adj. R^2 (%)	15.237	16.583	29.085	20.751	24.155
$\Delta adj.R^2$ (%)	6.977	7.438	5.624	7.509	10.600
Panel C: $D=240$					
SK_t	12.588*** (21.040)	16.445*** (25.339)	17.715*** (20.418)	21.263*** (18.849)	37.202*** (22.888)
constant	-2.887 (-0.489)	62.006*** (8.241)	2.785 (0.387)	-57.773*** (-6.354)	10.749 (0.694)
IR_t	-1.423** (-2.127)	1.611*** (2.772)	5.034*** (5.918)	18.381*** (12.156)	21.312*** (9.546)
LIQ_t	1.286** (2.158)	2.424*** (4.025)	2.008** (2.248)	3.044*** (2.706)	6.189*** (4.371)
VIX_t	-7.636*** (-3.580)	-31.648*** (-13.090)	-24.113*** (-9.415)	-28.591*** (-9.130)	-59.733*** (-11.939)
EPU_t	6.225*** (6.235)	4.350*** (4.012)	12.524*** (9.992)	19.290*** (12.841)	18.068*** (8.351)
VOL_t	-1.133*** (-5.587)	0.121*** (13.300)	-1.819*** (-11.708)	8.148*** (11.538)	17.660*** (14.537)
adj. R^2 (%)	22.974	31.440	30.932	30.821	35.014
$\Delta adj.R^2$ (%)	14.583	18.839	12.313	10.505	14.564

Notes: This table reports the results for predictive regressions on all CNY-CNH spreads with different calculation of skewness and control variables. The t -statistics are reported between parentheses. Moreover, the $\Delta adj.R^2$ denotes the change of adjusted R^2 for model (3) relative to the model without skewness. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

$$\hat{Y}_{M+h+1} = \hat{\alpha}_{M+1} + \hat{\beta}_{M+1} SK_{M+1} \quad (5)$$

where $\hat{\alpha}_{M+1}$ and $\hat{\beta}_{M+1}$ are the estimates from regression $\{Y_t\}_{t=M+1}^{M+1}$ on a constant and $\{SK_t\}_{t=1}^{M-h+1}$.

Proceeding in this way until the end of forecasting, we can obtain $T-M$ forecasts of CNY-CNH spread. We employ R^2_{OOS} (Campbell and Thompson, 2008) and $MSFE$ -adjusted statistics (Clark and West, 2007) to evaluate the out-of-sample forecast performance. In line with Welch and Goyal (2008), we adopt historical average as benchmark.

Table 3 shows the forecasts results on the CNY-CNH spread. When $h=1$, the skewness provides significantly predictive power since almost all R^2_{OOS} are positive and the null hypothesis of $MSFE$ -adjusted statistics are rejected, indicating that the forecast performance of skewness over selected windows are better than that of historical average. Moreover, the predictability tends to be stronger with the

Table 3

Out-of-sample forecasts performance.

	D=60 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=120 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=240 R^2_{OOS} (%)	$MSFE_{adjusted}$
Panel A: $h = 1$						
Spot	7.446	9.188***	11.776	10.56***	17.892	13.217***
1M Forward	9.172	8.713***	9.954	9.269***	21.864	11.615***
3M Forward	8.078	8.626***	10.656	9.720***	19.323	11.886***
6M Forward	7.225	9.475***	12.361	12.413***	19.676	14.852***
1Y Forward	6.596	9.966***	12.598	15.291***	19.928	19.815***
Panel B: $h = 7$						
Spot	3.973	7.343***	9.664	9.393***	15.958	12.284***
1M Forward	6.288	7.635***	8.268	8.157***	20.628	10.849***
3M Forward	6.607	7.976***	9.229	8.520***	18.338	11.030***
6M Forward	7.109	9.238***	10.928	10.945***	18.557	13.766***
1Y Forward	6.968	10.116***	10.848	14.489***	17.892	19.672***
Panel C: $h = 30$						
Spot	2.115	7.023***	2.419	7.083***	8.088	9.085***
1M Forward	3.809	8.607***	4.242	7.311***	14.074	10.024***
3M Forward	3.746	8.525***	4.851	7.564***	11.339	9.788***
6M Forward	4.759	9.451***	5.894	9.806***	12.107	11.758***
1Y Forward	5.594	10.373***	5.422	12.665***	12.027	16.531***
Panel D: $h = 60$						
Spot	-0.911	-1.783	0.861	4.603***	5.399	6.484***
1M Forward	0.012	1.954**	2.811	5.558***	11.472	7.854***
3M Forward	0.732	4.110***	4.445	6.439***	10.651	7.929***
6M Forward	2.607	7.395***	6.012	8.116***	10.898	9.061***
1Y Forward	2.416	7.318***	4.385	8.391***	9.940	11.874***

Notes: This table reports the out-of-sample forecasts for predictive regressions on all CNY-CNH spreads with different calculation of skewness ($D=60, 120, 240$) and forecast horizons ($h=1, 7, 30, 60$). Moreover, the R^2_{OOS} and $MSFE_{adjusted}$ statistics are calculated with historical average as benchmark. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

extension of calculation windows. The R^2_{OOS} reaches the maximum when $D=240$, which is consistent with the window used in calculating the skewness of commodity futures returns (Fernandez-Perez et al., 2018) and oil returns (Mo et al., 2019) to some extent. Furthermore, the R^2_{OOS} gradually decreases with forecast horizon increase, indicating that the forecast performance of skewness tend to

Table 4

Out-of-sample forecasts performance with control variables.

	D=60 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=120 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=240 R^2_{OOS} (%)	$MSFE_{adjusted}$
Panel A: $h = 1$						
Spot	6.801	7.813***	7.627	9.382***	16.225	12.581***
1M Forward	-19.007	0.016	-30.870	-0.260	19.479	15.486***
3M Forward	7.072	7.202***	7.750	8.550***	15.438	12.749***
6M Forward	8.967	9.467***	9.411	9.712***	13.833	11.809***
1Y Forward	6.418	8.131***	12.852	13.828***	18.939	15.211***
Panel B: $h = 7$						
Spot	3.581	6.386***	6.364	8.642***	16.121	12.367***
1M Forward	-11.215	0.716	-25.878	-0.149	16.335	12.415***
3M Forward	5.648	6.554***	6.258	7.362***	14.133	11.305***
6M Forward	8.625	9.788***	8.076	8.570***	13.033	11.010***
1Y Forward	6.699	8.515***	10.304	12.372***	16.596	13.850***
Panel C: $h = 30$						
Spot	1.629	6.706***	1.611	5.542***	8.359	9.860***
1M Forward	-15.819	-0.701	-17.781	-0.502	18.852	4.394***
3M Forward	1.761	6.116***	2.684	6.165***	7.956	10.464***
6M Forward	4.492	9.703***	3.725	7.401***	8.747	10.032***
1Y Forward	4.735	8.772***	4.520	9.354***	11.032	11.242***
Panel D: $h = 60$						
Spot	0.033	1.927**	0.954	4.564***	5.417	9.495***
1M Forward	-2.047	-0.867	-3.188	2.999***	18.313	2.551***
3M Forward	0.028	1.622*	2.860	7.219***	10.037	8.565***
6M Forward	2.479	6.614***	4.042	7.878***	9.752	9.695***
1Y Forward	1.681	5.043***	4.548	8.725***	9.998	10.563***

Notes: This table reports the out-of-sample forecasts for predictive regressions on all CNY-CNH spreads with different calculation of skewness and control variables based on different forecast horizons. Moreover, the R^2_{OOS} and $MSFE_{adjusted}$ statistics are calculated with the model without skewness ($Y_{t+h} = \alpha + \gamma X_t + \varepsilon_t$) as benchmark. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

decline in longer horizons.

Table 4 reports the out-of-sample forecasts results of the model with skewness and control variables. We find that incorporating skewness into the model containing traditional predictors can significantly improve the predictability of all CNY-CNH spreads except for 1-month forward spread. It means that skewness cannot be replaced by any of these traditional predictors and indeed brings additional information. Moreover, the incremental predictive power performs better over longer calculation windows and shorter forecast horizon since the R^2_{OOS} on all spreads achieves the maximum when $D=240$ and tends to decrease when horizon increases. In summary, skewness indeed plays an important role for forecasting CNY-CNH spread.

4.2. Non-linear specification

It is possible that the impact of skewness on CNY-CNH spread is asymmetric as investors tend to long assets with positive skewness and short assets with negative skewness (Jondeau et al., 2019). Thus, we decompose the skewness into two parts, namely a component containing positive skewness (SK_t^+) and a component containing negative skewness (SK_t^-). The asymmetric model is expressed as follows.

$$Y_{t+1} = \alpha + \beta^+ SK_t^+ + \beta^- SK_t^- + \varepsilon_{t+1} \quad (6)$$

Table 5 reports the out-of-sample forecast results of model (6). We find that the asymmetric model outperforms historical average since the R^2_{OOS} is almost positive and the null hypothesis of *MSFE_adjusted* statistics are rejected. However, comparing to the R^2_{OOS} of model (2) when $h=1$, the most of ΔR^2_{OOS} are negative, especially for spot and 3-month forward spreads over different windows. This result suggests that the forecast performance of model (6) are weaker than model (2). Thus, predicting CNY-CNH spread by taking asymmetry skewness into consideration may not bring the enhancement of predictive ability.

5. Robustness and additional tests

5.1. Subsample analysis

The RMB central parity formation mechanism reform on August 11, 2015 (811 reform) remarkably alters the behavior of the onshore RMB exchange rates, and thus changes the CNH-CNY spread dynamics (Liang et al., 2019). Hence, we further explore the predictive ability of skewness by comparison the out-of-sample forecasts before and after 811 reform. The results are reported in Table 6. Obviously, skewness appears predictive power on all CNY-CNH spreads before 811 reform, which is similar to the full sample results. However, the predictability is largely decline after 811 reform since the R^2_{OOS} is negative for spot and one-month forward spreads. This maybe ascribe to the increased fluctuations in either the CNY or the CNH market stemming from the reform, which eventually leads to greater volatility in the spread (Liang et al., 2019). And thus, the predictability mainly reflects on the forecasting of forward spreads rather than spot spread with more volatility (Li et al., 2021).

Furthermore, considering the outbreak of COVID-19 deeply influence the currency markets (Xu and Lien, 2021), we next conduct the out-of-sample forecasts during this period to explore whether the predictability remains robust. Observing Table 7, skewness can still effectively forecast the CNY-CNH spreads, indicating that our results are robust enough to despite the currency markets are facing serious uncertainty.

Table 5
Out-of-sample forecasts performance for the asymmetric model.

	Spot	1M Forward	3M Forward	6M Forward	1Y Forward
Panel A: $D=60$					
R^2_{OOS} (%)	4.713	8.257	7.463	6.191	7.116
<i>MSFE_adjusted</i>	6.551***	6.446***	7.499***	8.720***	9.712***
ΔR^2_{OOS} (%)	-2.734	-0.915	-0.614	-1.034	0.521
Panel B: $D=120$					
R^2_{OOS} (%)	8.523	10.179	10.600	12.724	14.219
<i>MSFE_adjusted</i>	7.861***	6.981***	8.460***	11.827***	16.505***
ΔR^2_{OOS} (%)	-3.253	0.225	-0.056	0.363	1.621
Panel C: $D=240$					
R^2_{OOS} (%)	16.643	23.461	20.227	20.934	19.899
<i>MSFE_adjusted</i>	12.953***	11.472***	11.648***	13.471***	17.531***
ΔR^2_{OOS} (%)	-1.250	1.597	0.905	1.258	-0.029

Notes: This table reports the out-of-sample forecasts for the asymmetric predictive model on all CNY-CNH spreads with different calculation of skewness. The ΔR^2_{OOS} denotes the change of R^2_{OOS} for Eq. (6) relative to the baseline model. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 6

Out-of-sample forecasts performance before and after 811 reform.

	D=60 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=120 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=240 R^2_{OOS} (%)	$MSFE_{adjusted}$
Panel A: subsample before 811 reform						
Spot	2.389	10.588***	10.213	11.969***	2.139	5.221***
1M Forward	3.849	10.189***	15.617	12.994***	24.937	11.334***
3M Forward	1.888	9.612***	13.489	11.329***	27.599	11.334***
6M Forward	-5.694	9.496***	12.669	9.729***	7.786	5.898***
1Y Forward	-6.433	7.196***	3.571	4.817***	9.653	6.231***
Panel B: subsample after 811 reform						
Spot	-0.944	4.418***	-1.839	3.727***	-3.432	2.926***
1M Forward	-0.043	4.236***	2.316	4.646***	-7.100	1.288*
3M Forward	3.696	5.535***	4.905	7.656***	4.475	7.798***
6M Forward	7.59	8.382***	8.26	8.348***	15.41	12.992***
1Y Forward	5.642	7.345***	11.504	10.365***	29.973	18.056***

Notes: This table reports the out-of-sample forecasts ($h=1$) before and after 811 reform with different calculation of skewness. Moreover, the R^2_{OOS} and $MSFE_{adjusted}$ statistics are calculated with historical average as benchmark. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 7

Out-of-sample forecasts performance during the COVID-19 period.

	D=20 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=40 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=60 R^2_{OOS} (%)	$MSFE_{adjusted}$
Spot	8.196	3.096***	5.273	2.510***	7.142	2.675***
1M Forward	12.450	3.756***	12.183	3.246***	12.287	3.091***
3M Forward	20.121	5.037***	25.216	4.620***	24.893	4.120***
6M Forward	25.374	5.648***	33.215	5.066***	33.025	4.443***
1Y Forward	27.314	6.025***	38.954	5.776***	42.966	5.485***

Notes: This table reports the out-of-sample forecasts ($h=1$) during the COVID-19 (from December 30, 2019 to July 30, 2021) with different calculation of skewness. Here, the calculation windows are reduced to ensure the forecasting accuracy since the sample during the COVID-19 is relative smaller. Specifically, the windows are set as 20, 40 and 60 days, which are corresponding to the information of past one month, two months and three months. Moreover, the R^2_{OOS} and $MSFE_{adjusted}$ statistics are calculated with historical average as benchmark. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

5.2. Other proxies for skewness

We introduce other measures of skewness to smooth extreme observations and improve forecast accuracy as the Pearson's moment coefficient of skewness involves many jumps in its dynamics. Following Jiang et al. (2019b) and Ghysels et al. (2016), we adopt the difference between upside and downside semi-variance, and quantile-based measures of skewness.

Related results are concluded in Table 8, which denotes that the R^2_{OOS} of almost all CNY-CNH spreads are obviously larger than the corresponding results in Table 3. Thus, our main results are robust, and the predictability is enhanced by adopting the two measures.

5.3. Economic mechanism

According to Funke et al. (2015), the liquidity plays an important role in explaining the CNY-CNH spread. And Wang et al. (2021) find that stocks with asymmetry distribution have less liquidity. Thus, we explore the impact of skewness on liquidity of different RMB markets to explore the possible economic mechanism for the predictive ability of skewness.

We use the bid-ask spread of CNH (CNY) market to measure the offshore (onshore) RMB market liquidity. As shown in Table 9, the regressions are mainly reflected by significantly negative effects, namely a decreasing in skewness will cause high bid-ask spread in CNH (CNY) market and generate a worse liquidity. Then, it will lead to a discount of the CNH relative to the CNY (Funke et al., 2015; Sun et al., 2020), and further diminish the difference between CNY and CNH, which is consistent with our main results. Moreover, this phenomenon is more prominent in the CNH market, which is not surprised since the CNH market is likely more prone to swings in risk appetite of global financial markets (Funke et al., 2015).

6. Conclusions

With in-sample and out-of-sample analyses, we demonstrate the predictive ability of skewness on CNY-CNH spread exists with and without control variables. The predictability is stronger by using longer calculation windows. And it still endures over longer horizons but tends to decline when horizon increase. Moreover, considering asymmetry skewness does not improve the predictability. Our findings are also robust to using alternative skewness measures and changing time horizons. Furthermore, the deviation of skewness indicates the changes in market liquidity, especially the CNH market, then act on the prediction of CNY-CNH spread. In summary, our

Table 8

Out-of-sample forecasts performance based on other measures of skewness.

	D=60 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=120 R^2_{OOS} (%)	$MSFE_{adjusted}$	D=240 R^2_{OOS} (%)	$MSFE_{adjusted}$
Panel A: skewness measures by subtracting the downside from the upside semi-variance						
Spot	14.498	9.873***	15.228	8.927***	9.513	8.292***
1M Forward	16.952	9.493***	18.019	8.369***	12.847	8.823***
3M Forward	23.965	10.527***	21.22	9.443***	16.914	9.707***
6M Forward	32.011	11.449***	25.177	10.958***	23.54	11.158***
1Y Forward	43.877	13.61***	39.788	14.72***	38.126	15.827***
Panel B: quantile-based measures of skewness referring to Ghysels et al. (2016)						
Spot	11.774	9.808***	14.782	12.624***	15.006	12.254***
1M Forward	17.266	10.392***	17.166	11.812***	26.034	11.787***
3M Forward	14.402	10.271***	13.360	11.695***	30.389	12.317***
6M Forward	13.234	10.402***	11.885	13.794***	28.297	15.043***
1Y Forward	6.419	7.764***	9.302	13.284***	25.479	21.303***

Notes: This table reports the out-of-sample forecasts ($h=1$) for predictive regressions on all CNY-CNH spreads with skewness calculation following Jiang et al. (2019b) and Ghysels et al. (2016), respectively. Moreover, the R^2_{OOS} and $MSFE_{adjusted}$ statistics are calculated with historical average as benchmark. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 9

Results for the impact of skewness on liquidity.

	D=60 Coeff.	t -statistic	D=120 Coeff.	t -statistic	D=240 Coeff.	t -statistic
Panel A: the impact of skewness on liquidity of the CNH market						
Spot	-0.086***	(-5.900)	-0.062***	(-5.000)	-0.066***	(-5.608)
1M Forward	-0.051***	(-4.255)	-0.078***	(-7.367)	-0.152***	(-14.705)
3M Forward	-0.059***	(-4.793)	-0.093***	(-8.507)	-0.178***	(-17.585)
6M Forward	-0.076***	(-6.644)	-0.115***	(-11.039)	-0.156***	(-16.297)
1Y Forward	-0.059***	(-5.580)	-0.101***	(-9.669)	-0.134***	(-14.008)
Panel B: the impact of skewness on liquidity of the CNY market						
Spot	0.009	(0.379)	-0.039**	(-1.964)	-0.064***	(-3.379)
1M Forward	0.057**	(2.332)	-0.042*	(-1.891)	-0.117***	(-5.219)
3M Forward	-0.016	(-0.743)	0.005	(0.267)	-0.025	(-1.327)
6M Forward	-0.040*	(-1.856)	-0.012	(-0.615)	-0.050***	(-2.605)
1Y Forward	-0.002	(-0.098)	-0.016	(-0.643)	-0.037	(-1.590)

Notes: This table reports the results for regressions of $BID_t = \alpha + \beta SK_t + \varepsilon_t$ (BID denotes the bid-ask spread) by using different calculation of skewness. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

study illustrates that skewness carries meaningful and distinctive information for predicting CNY-CNH spread.

CRediT author statement

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Yiye Liu implements the empirical process and writes the original manuscript. Liyan Han provides research funding and polishes the manuscript. You Wu provides the idea and polishes the manuscript.

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