Investigation of Chinese yuan/US dollar

exchange rates at high frequency

by

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**Abstract**

With the growth of China’s economy and the establishment of CNH market (the offshore market for the Chinese yuan), trade in the Chinese currency is growing rapidly. Consequently, it has become more and more important to understand the China’s foreign exchange market. This paper investigates the clustering pattern of CNH (the offshore currency) and CNY (the onshore currency). The goal is to show whether there exists a clustering pattern in the Chinese foreign exchange market similar to the clustering in discrete prices found by other researchers in the stock market (including Chinese stock market). Price clustering is of importance because previous studies of clustering have detected market maker collusion in the US stock market. This paper also investigates the forecastability of ARIMA models of CNH and CNY exchange rates, as ARIMA models have been widely applied to economic, stock and foreign exchange problems but not yet to the Chinese foreign exchange market. The aim is to test whether ARIMA models have good forecasting performance on CNH and CNY as well.

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**1. Introduction**

China has become the second largest economy in the world and a key influencer on the global economy. In the recent decades, China conducted a series of foreign exchange reforms. In 1994, China announced the first foreign exchange reform: it identified its currency regime as a managed float, and set a band of $\pm 0.3\%$ per day for the RMB/USD exchange rate. In the second foreign exchange reform, the RMB/USD exchange rate was moved by 2.1% (Ning, Wang and Su, 2017). This was under political pressure as China’s balance of payments surplus was misinterpreted by economists and politicians as an exchange rate problem, namely the RMB was artificially “undervalued” although the RMB/USD rate had been stable for almost 10 years (McKinnon and Schnabl, 2009). As part of the effort to develop RMB business outside China, on July 19th, 2010, the People's Bank of China (PBoC) and the Hong Kong Monetary Authority (HKMA) signed a Memorandum of Co-operation, creating the offshore CNH market for foreign individuals and institutions to trade CNH in Hong Kong. To further promote RMB’s internationalization, China announced a third reform on August 11, 2015, which is also known as the “8.11” reform. Before this reform, the Chinese yuan was kept pegged to the US dollar under the US dollar (Ogawa and Sakane, 2006). It is considered to be a historic move toward a market-determined exchange rate regime. This reform changed the determinization mechanism for the daily central parity, an important reference rate, which was thereafter based on the closing rate of the inter-bank foreign exchange market on the previous trading day (Ning, Wang and Su, 2017). According to the latest Triennial Central Bank Survey on the foreign exchange market in 2016, total daily turnover of RMB has reached over 200 billion dollars, which makes the Chinese currency the eighth most traded currency in the world (Bank for International Settlements, 2016).

With the establishment of CNH market (the offshore market) and rapidly growing trading activities of the Chinese currency, it has become more and more important to understand the China’s foreign exchange market. The CNY market (the onshore market) is deeper and more liquid than the offshore market, but the latter is growing rapidly (Funke, Shu, Cheng and Eraslan, 2015). CNH can be freely traded by offshore market participants, while the exchange rate of CNY is anchored by the official daily central parity rate and the trading band, which was widened to $\pm 1\%$ per day on April 14, 2012. The central parity is used to define the band within which the CNY exchange rate is allowed to fluctuate (Cheung and Rime, 2014). In contrast to the highly-regulated CNY market (the onshore market), there is no explicit management by the central bank nor are there trading restrictions in the CNH market. The exchange rate is freely driven by supply and demand, without the intervention of PBoC or HKMA. The offshore market is more closely linked with the global financial markets, and thus more vulnerable to changes in global liquidity conditions and the risk appetite of international investors. The distinctive features and continuing segmentation of the CNY and CNH markets may result in deviations between the two exchange rates (Funke, Shu, Cheng and Eraslan, 2015).

Against this backdrop, this paper aims to investigate price clustering in CNH and CNY on price clustering and exchange rate behavior at high frequency. Research into price clustering has been conducted in many different settings. Osborne (1962) initially documents price clustering in equity markets, for a sample of closing prices on the New York Stock Exchange (NYSE). Sopranzetti and Datar (2002) document the existence of price clustering in the foreign exchange spot market for the German mark, the Japanese yen, the United Kingdom pound, the French franc, the Italian lira, and the Swedish krona. Brown and Mitchell (2008) study the clustering of stock prices in China’s stock market. Although there has been growing interest in China’s foreign exchange market, few have studied price clustering in this market. For the behavior of the exchange rates, this paper uses the autoregressive integrated moving average (ARIMA) model to forecast exchange rates of CNH and CNY.

This paper proceeds as follows. The next section summarizes the relevant literature. Section 3 presents a description of the data. Section 4 explains the methodology used in this research. Section 5 presents results and analyses. Section 6 provides a concluding summary.

**2. Literature Review**

**2.1. Price clustering**

Price clustering is the ununiform distribution of the frequency of some number in price digits, for example, number “two” in the right-most digit (e.g., $6.82). A number of existing studies examine price clustering in different contexts. Harris (1991) characterizes stock price clustering and its relation to several observable characteristics of stock prices during a sample period when US stock prices were quoted in eighths (of a dollar). If prices were randomly selected from the discrete set of eights and price clustering did not exist, the distribution of fractional price remainders would be expected to be uniform. He shows that stock prices cluster on round fractions; integers are more common than halves, which are more common than odd quarters and odd eighths. Christie and Schultz (1994) present empirical evidence documenting an almost complete absence of odd-eighth quotes for 70 percent of the NASDAQ sample, including heavily traded stocks. Sopranzetti and Datar (2002) study the price clustering in the foreign exchange spot markets and find that the dollar exchange rate quotes tend to have right-most digits that end in either a “zero” or a “five”. They also suggest that clustering differs across different currencies. It is more prevalent for the French franc, Italian lira, UK pound and Swedish krona, and less prevalent for the German mark and Japanese yen.

There are two theories attempting to explain the phenomenon of even price clustering in financial markets. The first is the collusion theory. Christie and Schultz (1994) argue that market makers intentionally collude to avoid the use of odd-eighth quotes in order to widen bid-ask spreads for profits. However, in the foreign exchange market, since main players are large commercial banks that are trading currencies for their own accounts, it does not seem a plausible explanation that banks collude to set hefty bid-ask spreads (Sopranzetti and Datar, 2002). The second theory is the efficiency theory. Harris (1991) suggests that traders use discrete price sets to lower the costs of negotiating. A small set limits the number of different bids and offers that can be made, therefore, negotiations may converge more rapidly.

As for China’s financial market, Brown and Mitchell (2004) study trading on the Shanghai and Shenzhen stock exchanges to determine whether a culturally heuristic number preference exists. They find a ubiquitous avoidance of prices ending in 4 relative to 8, which is consistent with Chinese culture and “feng shui” superstition. Although scholars have investigated price clustering in China’s stock market and foreign exchange markets with different currencies, few have examined price clustering of CNY or CNH. With the rapid increase of trading activities in China’s foreign exchange market, it is vital to determine whether there exists similar number preference out of cultural factors or even clustering patterns in CNY and CNH.

**2.2. Exchange rate behavior**

Price prediction is an important topic in finance since useful predictive models could guide investors to make profitable investment decisions. The autoregressive integrated moving average (ARIMA) model was first introduced by Box and Jenkins in 1970 and has been widely applied to economic, stock and foreign exchange problems (Adebiyi, Adewumi and Ayo, 2014). Researchers have developed different predictive models based on the ARIMA model. Tseng et al. (2001) develop the fuzzy ARIMA model by combining advantages of time-series ARIMA(*p*,*d*,*q*) model and fuzzy regression model and test the model by forecasting the foreign exchange rate between the NTD (new Taiwan dollar) and the USD. Jarrett and Kyper (2011) implement ARIMA-Intervention analysis to assess the prediction and forecasting of Chinese stock market prices under the impact of serious economic interruptions. For empirical studies, Adebiyi, Adewumi and Ayo (2014) use published stock data obtained from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) and predict stock price with the ARIMA model. It turns out that the ARIMA model can perform reasonably well in short-term stock prediction. Although the ARIMA model has been applied to stock markets in different countries, including China, it has not been tested on China’s growing foreign exchange market. Since the trading of CNH and CNY is rapidly growing, it is of significance to test whether the ARIMA model has potential in predicting the exchange rates.

**3. Data**

The research chooses CNH and CNY exchange rates associated with USD as measurements of RMB exchange rates. The data is from Olsen Financial Technologies, a commercial provider of one of the largest databases of tick-by-tick prices for financial institutions and researchers alike. It has collected and compiled bid and ask historical data from different live market sources. The data used in this research are constructed over one-minute interval in the time period of April 2013 and April 2016. The representative months are chosen in accordance with the triennial Bank for International Settlements (BIS) surveys of foreign exchange and OTC derivatives markets. Since the CNH market was established in July 2010, only two months of sample data are available. Each observation represents indicative quotes of bid and ask associated with date and timestamp within each interval. Table 1 shows a statistics summary for the bid and ask quotes, including counts, median, mean and standard deviation. Table 2 presents a statistics summary for the first difference of bid and ask quotes, with same measures as Table 1.

**4. Methodology**

**4.1. Frequency distribution**

Price clustering is the tendency for prices to congregate around some specific set of values, for example whole digits ($6.00) or half digits ($6.50) (Sopranzetti and Datar, 2002). To examine the clustering of CNH and CNY exchange rates, this research measures the frequencies of pip, the fourth decimal place for a quote. For example, if the bid is 6.2042 and the ask is 6.2077, then the bid pip digit is 2 and the ask pip digit is 7. For the data in April 2013, pip is the rightmost digit of denominated exchange rate quotes, while for the data in April 2016, pip is the second to the rightmost digit since the exchange rates are quoted to the fifth decimal place. The reason for the selection of pip is that clustering is constrained by the minimum tick size available (Brown and Mitchell, 2008) and traditionally exchange rates were quoted to a tick size of 0.0001 (Hasbrouck and Levich, 2019).

This paper also applies a chi-square test in order to test whether non-uniformity in the frequency distribution of digits is statistically significant. The null hypothesis is that all digit frequencies are equal to 10 percent. The test compares the observed frequencies from sample data with the expected frequency of 10 percent.

**4.2. ARIMA Model**

The ARIMA model was introduced by Box and Jenkins in 1970. The model is most prominent methods in financial forecasting. ARIMA models have shown efficient capability to generate short-term forecasts (Adebiyi, Adewumi and Ayo, 2014). ARIMA stands for auto regressive integrated moving average and is specified by these three order parameters: *(p, d, q)*. The auto-regressive parameter *p* specifies the number of lags used in the model. For example, ARIMA (2,0,0) is as follows:

$$Y\_{t}=c+ϕ\_{1}y\_{t-1}+ϕ\_{2}y\_{t-2}+e\_{t}$$

where $ϕ\_{1}$,$ ϕ\_{2}$ are coefficients. The order *d* is the degree of differencing in the integrated (*I(d)*) component. The order *q* represents the moving average component where the error of the model is a combination of previous error terms $e\_{t}$:

$$Y\_{t}=c+θ\_{1}e\_{t-1}+θ\_{2}e\_{t-2}+…+θ\_{q}e\_{t-q}+e\_{t}$$

ARIMA models rely on the past values and past errors to predict the future value of a variable. The expression is as follows:

$$Y\_{t}=ϕ\_{0}+ϕ\_{1}Y\_{t-1}+ϕ\_{2}Y\_{t-2}+…+ϕ\_{p}Y\_{t-p}+ϵ\_{t}-θ\_{1}ε\_{t-1}-θ\_{2}ε\_{t-2}-…-θ\_{q}ε\_{t-q}$$

where $Y\_{t}$ is the actual value and $ϵ\_{t}$ is the random error at *t*.

This research uses the ARIMA model to forecast foreign exchange rate. The software used for implementation is R. To identify the best ARIMA model for forecasting, these steps are followed:

1. Identification of the order of differencing. Use the augmented Dickey-Fuller (ADF) test, a formal statistical test for stationarity, to produce a stationary time series model. The null hypothesis assumes that the series is non-stationary. The details of ADF test is in table 6.
2. Identification of the order *p* and *q*, the auto-regressive and moving-average component of the model with the training set. Use the autocorrelation function (ACF) and partial autocorrelation function (PACF) for parameters estimation.
3. Evaluation of the fitted model. Examine ACF and PACF plots for model residuals. If model order parameters and structure are correctly specified, it is expected that no significant autocorrelations present. Compare AIC (Akaike Information criterion) and BIC (Bayesian or Schwarz Information Criterion).
4. Forecast with the selected model on the test set and evaluate the out-of-sample forecast performance.

**5. Results**

**5.1. Price clustering**

Harris (1991) suggests that price clustering occurs because traders use a discrete set of prices to specify the terms of their trades. With the use of a smaller set of prices, the costs of negotiating may be lower, as negotiations may converge more rapidly since frivolous offers and counteroffers are restricted. If there is no price clustering, one would expect a uniform frequency distribution of the pip digit, the fourth decimal place of a quote. This means that the frequency of pip digit with a “zero” would be identical to the frequency of any other single digit, equal to ten percent. Table 3 presents the frequency distribution of the sample data in the CNH and CNY market. Table 4 shows the chi-square test results for the sample data. Table 5 presents the standard deviation of the frequency distribution.

For CNH bid and ask quotes, the pip frequency distribution is more uniform in 2016 than in 2013. For CNH bid, the standard deviation of the pip frequency declines from 0.60 in 2013 to 0.23 in 2016. For CNH ask, the standard deviation also declines from 0.40 in 2013 to 0.22 in 2016. In addition, from the table 3, although frequencies are close to ten percent, digits of “0” and “5” occur more frequently, for example, in 2013, 10.31% and 10.52% for “0” pip digit of bid and ask quotes, and 11.05% and 10.49% for “5” pip digit of bid and ask quotes. Specifically, the frequency of “5” in bid quotes declines from 11.05% to 10.10% over the years. Overall, the results indicate decline in price clustering for CNH exchange rates. Such decline in price clustering could also be associated with the rise in algorithmic trading (Hasbrouck and Levich, 2019).

However, for CNY exchange rates, the clustering pattern is much different. For bid and ask quotes, the pip frequency distribution was overall more clustered in 2016 than in 2013. For CNY bid, the standard deviation of the pip frequency increases from 0.34 in 2013 to 0.57 in 2016. For CNY ask, the standard deviation also increases from 0.27 in 2013 to 0.52 in 2016. In addition, both bid and ask quotes are more clustered on “0” and “5” in 2016, for example, the frequency of “0” in bid pip digits increases from 10.24% in 2013 to 11.28% in 2016, and the occurrence of “5” in ask pip digits increases from 9.92% to 10.69%.

In previous literatures of stock price clustering, Brown and Mitchell (2008) find that there was a strong preference for number “8” in China’s stock market. They show that the prices of A-shares (mostly held by Chinese organizations or individuals) traded on the Shanghai stock exchange during their sample period (1994 – 2002) were more than twice as likely to end in “8” as “4”. However, preference for “8” was much weaker for B-shares, largely held by foreigners. This was due to the cultural preference as, to many Chinese, “8” is considered “lucky”, while “4” is “unlucky” and to be avoided. However, from the results in table 3, there no longer exists such cultural preference for “8” in either the CNH or CNY market. The frequencies of “8” and “4” in pip digits are close to each other for bid and ask quotes in both 2013 and 2016. For the CNH market, this is consistent with the participation of foreign investors. For CNY market, this shows that cultural preferences are less influential in trading than a decade ago.

**5.2. ARIMA forecast**

To forecast the exchange rates with ARIMA model and evaluate the forecast performance, the dataset in each sample period is split into two halves. The first half of the data is served as the training set and is used to fit ARIMA model. The second half of the data is served as the test set to evaluate the forecast performance of the fitted ARIMA model. Measures of root mean squared error (RMSE) and mean absolute error (MAE) are calculated to compare the forecast exchange rates with the actual quotes.

To determine the order of differencing, Augmented Dicky Fuller (ADF) test has been conducted for original bid and ask quotes and quotes after first differencing. The test results confirm that the series becomes stationary after taking the first-difference of original quotes. Table 7 shows the parameters of ARIMA model for bids and asks respectively and the root mean squared error (RMSE) and mean absolute error (MAE) of the fitted values. For CNY, in both 2013 and 2016, same model is fitted for bid and ask in that year. For CNH, the fitted models are similar for bid and ask, except the moving average component. For example, in 2016, the ARIMA models for CNH bid and ask are (3,1,1) and (3,1,2), with *q* equal to 1 and 2 respectively.

To evaluate the selected ARIMA model, one-step-ahead forecast is generated as the fitted values. In both years, the out-of-sample forecast performance of the onshore currency, CNY, is worse than the offshore currency, CNH. More specifically, in 2013, the RMSE and MAE for CNH bid are 0.00028 and 0.00017, while the same measures for CNY bid are 0.01893 and 0.01213. In 2016, for CNH bid, the RMSE and MAE report 0.00034 and 0.00023, while the same measures for CNY bid report 0.00426 and 0.00348. One possible reason is that exchange rate of CNY is anchored by the official daily central parity rate and the fluctuation of CNY is constrained by its daily trading band while CNH is freely traded in the market without intervention of PBoC (Cheung and Rime, 2014).

**6. Summary**

This paper examines the price clustering pattern of CNH and CNY exchange rates. For CNH, the pip frequency distribution was overall more uniform in 2016 than in 2013. Such decline in price clustering could be associated with the rise in algorithmic trading. However, for CNY exchange rates, the clustering pattern is much different. The pip frequency distribution was overall more clustered in 2016 than in 2013. In addition, both bid and ask quotes are more clustered on “0” and “5” in 2016. The chi-square test also shows that the clustering pattern is statistically significant, except for the CNY ask. The difference in clustering pattern of CNH and CNY could be attributed to the different systematic design as CNH is freely traded in the market while CNY market is under governmental intervention. In contrast to the previous findings of preference for number “8” in China’s stock market, there no longer exists such cultural preference for “8” in either CNH or CNY market.

For the ARIMA forecasts, the first difference of the data is used in order to produce stationary time-series model. The ADF test is applied to the original data and the first difference of the quotes to show the stationarity. The ARIMA model is generated on the first half of the data set, the training set, and produces one-step-ahead forecasts for the second half of the data set, the testing set. The forecast performance is evaluated by comparing the predicted values with the actual values and measured by RMSE metrics. Overall, the out-of-sample forecast performance of the onshore currency, CNY, is worse than the offshore currency, CNH. One possible reason is that exchange rate of CNY is anchored by the official daily central parity rate and the fluctuation of CNY is constrained by its daily trading band while CNH is freely traded in the market without intervention of PBoC. The government intervention and the trading band make the CNY rates less predictable than CNH. Though one-step-ahead ARIMA forecasts demonstrate good predictability on both CNH and CNY, this has limited practical use for investors and traders since market moves fast and multiple steps ahead forecasts are needed for trading. In future research, rolling estimation and multiple step ahead forecasts with ARIMA models could be conducted to further investigate the ability of ARIMA models to predict CNH and CNY exchange rates.

**Table and Figure**

Table 1. Summary statistics for bid and ask quotes

|  |
| --- |
| **2013** |
|  |  | n | median | mean | std. dev |
| **CNH** | bid | 10,891 | 6.181 | 6.181 | 0.011453 |
| ask | 10,891 | 6.183 | 6.184 | 0.011500 |
| **CNY** | bid | 21,843 | 6.195 | 6.200 | 0.027857 |
| ask | 21,843 | 6.196 | 6.200 | 0.028644 |

|  |
| --- |
| **2016** |
|  |  | n | median | mean | std. dev |
| **CNH** | bid | 1,147,628 | 6.485 | 6.486 | 0.011340 |
| ask | 1,147,628 | 6.486 | 6.487 | 0.011308 |
| **CNY** | bid | 299,690 | 6.479 | 6.480 | 0.012206 |
| ask | 299,690 | 6.481 | 6.482 | 0.012220 |

Table 2. Summary statistics for the first differences of bid and ask quotes

|  |
| --- |
| **2013** |
|  |  | n | mean | std. dev |
| **CNH** | bid | 10,890 | -3.930E-06 | 0.000303 |
| ask | 10,890 | -3.930E-06 | 0.000303 |
| **CNY** | bid | 21,842 | -2.340E-06 | 0.025110 |
| ask | 21,842 | -2.340E-06 | 0.025110 |
| **2016** |
|  |  | n | mean | std. dev |
| **CNH** | bid | 1,147,628 | 1.900E-08 | 0.000429 |
| ask | 1,147,628 | 1.900E-08 | 0.000429 |
| **CNY** | bid | 299,690 | 9.000E-08 | 0.006222 |
| ask | 299,690 | 9.000E-08 | 0.006222 |

Table 3. Price clustering in bid and ask quotes

|  |  |  |
| --- | --- | --- |
| **2013** |  | **2016** |
| 　 | CNH | CNY |  | 　 | CNH | CNY |
| Digit | bid pip | ask pip | bid pip | ask pip |  | Digit | bid pip | ask pip | bid pip | ask pip |
| 0 | 10.31 | 10.52 | 10.24 | 10.01 |  | 0 | 10.36 | 10.16 | 11.28 | 10.88 |
| 1 | 9.50 | 10.37 | 10.32 | 9.73 |  | 1 | 10.27 | 9.85 | 10.26 | 9.34 |
| 2 | 9.34 | 9.99 | 9.81 | 10.28 |  | 2 | 9.78 | 9.68 | 9.88 | 9.63 |
| 3 | 10.28 | 10.24 | 9.50 | 10.04 |  | 3 | 9.81 | 9.88 | 9.59 | 9.97 |
| 4 | 10.57 | 9.71 | 10.58 | 10.20 |  | 4 | 9.87 | 10.23 | 9.41 | 10.49 |
| 5 | 11.05 | 10.49 | 10.00 | 9.92 |  | 5 | 10.10 | 10.44 | 10.62 | 10.69 |
| 6 | 9.12 | 9.19 | 9.65 | 9.93 |  | 6 | 10.15 | 10.06 | 10.20 | 9.54 |
| 7 | 9.47 | 10.08 | 9.94 | 9.94 |  | 7 | 9.73 | 9.80 | 9.65 | 9.36 |
| 8 | 10.50 | 9.71 | 10.32 | 9.46 |  | 8 | 9.73 | 9.85 | 9.60 | 10.10 |
| 9 | 9.85 | 9.70 | 9.65 | 10.47 |  | 9 | 10.19 | 10.05 | 9.50 | 10.00 |

Table 4. Chi-square test for price clustering

|  |  |  |
| --- | --- | --- |
|   | CNH | CNY |
| Year | bid pip | ask pip | bid pip | ask pip |
| 2013 | 0.0000 | 0.0401 | 0.0031 | 0.0710 |
| 2016 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Table 5. Standard deviation of frequency distribution

|  |  |  |
| --- | --- | --- |
|   | CNH | CNY |
| Year | bid pip | ask pip | bid pip | ask pip |
| 2013 | 0.603 | 0.402 | 0.338 | 0.269 |
| 2016 | 0.226 | 0.219 | 0.566 | 0.519 |

Table 6. ADF Test

|  |
| --- |
| **2013** |
|   | CNH bid | CNH ask | CNY bid | CNY ask |
| Dickey-Fuller | -3.3717 | -3.4225 | -11.342 | -11.399 |
| p-value | 0.05814 | 0.04965 | 0.01 | 0.01 |
| Dickey-Fuller (diff) | -80.435 | -32.458 | -80.435 | -32.458 |
| p-value (diff) | 0.01 | 0.01 | 0.01 | 0.01 |
| **2016** |
|   | CNH bid | CNH ask | CNY bid | CNY ask |
| Dickey-Fuller | -2.9135 | -2.9737 | -8.197 | -8.3549 |
| p-value | 0.1883 | 0.1626 | 0.01 | 0.01 |
| Dickey-Fuller (diff) | -80.435 | -32.458 | -80.435 | -32.458 |
| p-value (diff) | 0.01 | 0.01 | 0.01 | 0.01 |

Table 7. ARIMA Model and Forecast Errors

|  |
| --- |
| **2013** |
|   | CNH bid | CNH ask | CNY bid | CNY ask |
| ARIMA Model | (1,1,4) | (1,1,3) | (2,1,2) | (2,1,2) |
| RMSE | 0.00028 | 0.00028 | 0.01893 | 0.01955 |
| MAE | 0.00017 | 0.00017 | 0.01213 | 0.01298 |
| **2016** |
|   | CNH bid | CNH ask | CNY bid | CNY ask |
| ARIMA Model | (3,1,1) | (3,1,2) | (5,1,4) | (5,1,4) |
| RMSE | 0.00034 | 0.00034 | 0.00426 | 0.0044 |
| MAE | 0.00023 | 0.00024 | 0.00348 | 0.00362 |

Note: Rows “RMSE” and “MAE” reports the Root Mean Squared prediction Errors and Mean Absolute prediction Errors for differences between the actual quotes and the forecast of the exchange rates.

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