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# FORECASTING THE YUAN-TO-DOLLAR EXCHANGE RATE

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## ABSTRACT

As China play an increasingly important role in global trading, its economy raises serious attention all over the world. Accordingly, China's official currency, the yuan, an essential indicator of its economy health, has become one of the most valued currencies in the world. Therefore, it is useful to forecast the future value of the yuan. For this purpose, this paper proposes a model that can accurately forecast the exchange rate between the yuan and the dollar. As is known, the yuan-to-dollar exchange rate was as low as 6.08 in 2014. However, this spiked sharply to reach 6.9 in only two years. By analyzing related factors such as the consumer price index (CPI), market expectations, and interest rates, this paper proposes a model that predicts the yuan-to-dollar exchange rate to increase even more in the future, despite the consistent and dramatic escalation of the rate in the last two years. This result is reasonable in that the U.S. economy has mostly recovered from the 2008 market crash and stayed strong and robust, whereas the Chinese government has preferred the devaluation of the yuan to make its exports more competitive in the global market. The model suggests that investors should purchase more U.S. dollars (relative to the yuan).

**Keywords:** Forecasting, Yuan-to-dollar, Exchange rate

## INTRODUCTION

The exchange rate between the Chinese yuan and the U.S. dollar has gradually decreased since June 2005, when the Chinese government decided to loosen its control over the currency. However, the exchange rate has increased sharply in recent years. Around 2015, the rate was as low as 6.1, but it recently spiked above 6.9. A small change of the rate can make a huge difference, especially when making a large transaction such as paying college tuition. Therefore, it is useful for people such as international students and investors to better forecast the exchange rate between these two currencies.

This paper aims to build a model that can accurately forecast the exchange rate between the yuan

  

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and the dollar. Since this paper deals with the exchange rate, it checks whether the data are a unit root or not. If it is a unit root, then the reason behind it must be identified and addressed so that the data become stationary. This paper uses a cross-sectional model along with some ARIMA processes as necessary. According to the results, the model predicts that the exchange rate between the yuan and the dollar would continue to increase in the future, which is reasonable based on current economic situations in both countries.

**MODEL (Data)**

In order to predict future exchange rates, the factors influencing the exchange rate need to be determined. The exchange rate is defined as the value of one currency for the purpose of conversion to another. Thus, factors such as the interest rate and inflation, which cause changes in the value of currencies, can affect the exchange rate (Ijaz-ur-Rehman, 2017). For example, higher interest rates make it more attractive to save in the U.S., and therefore investors are more likely to use U.S. banks, causing the value of the dollar to increase. The result can be the same with a lower inflation rate, making U.S. products more competitive and thereby causing the currency to appreciate. Further, market expectations can also affect the exchange rate because, for instance, if the market expects the interest rate to increase, the value of the dollar will also increase because of the greater demand for the dollar. Therefore, this paper utilizes monthly data on the historical exchange rate between the yuan and the dollar, the consumer price index (CPI) as an indication of inflation, and both the Chinese and the U.S. stock market price indices[1] as an indication of market expectations from January 2001 to January 2017. Monthly data on both Chinese and the U.S. inflation surprise indices are also included to determine whether people's expectations affect the exchange rate. Table 1 shows the variables used in STATA.

[1] For the Chinese stock market price index, this paper picks the price index from the largest stock exchange in China, the Shanghai Stock Exchange, which better reflects market expectations. S&P 500 is selected to represent U.S. market expectations for a similar reason.

  

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| Name | Label |
|---|---|
| exrate | exchange rate |
| time | = trend |
| time2 | = trend square |
| cpius | consumer price index |
| interest | interest rate |
| CNStockPI | Chinese Stock exchange price index |
| SP500PI | S&P 500 Price index |
| usInfSuprise | US inflation surprise index |
| cnInfSuprise | Chinese inflation surprise index |
| yhat6 | forecasted exchange rate |

**Table 1. Variables used in STATA**

**MODEL (Selection)**

First investigate the time series plot of the y-variable (exrate) by using the "tsline" command in STATA (Fig. 1).

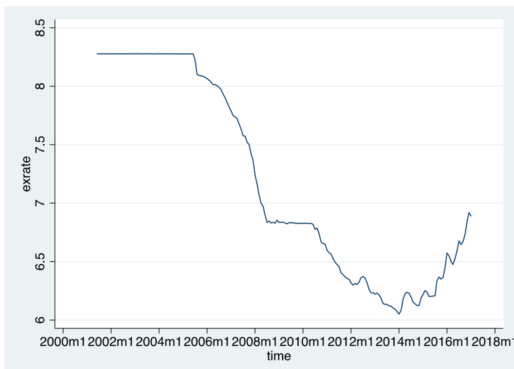


**Fig. 1. Exchange rate time series plot for 2001m1 – 2017m1**

The flat line from January 2001 to May 2005 indicates that the exchange rate is almost constant during that time period. This is caused by, as mentioned earlier, the Chinese government artificially pegging the currency around 8.2 (Seghezza, 2017). In this case, this part of data should be truncated. Fig. 2 shows a modified graph.

  

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**Fig. 2. Exchange rate time series plot for 2005m5 – 2017m1**

It can be easily seen that some nonlinear trends exist between the exchange rate and time, as indicated by the U-shaped graph. However, the question of whether this trend is deterministic or stochastic needs to be determined.

  

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| LAG | AC | PAC | Q | Prob>Q | -1 0 1 [Autocorrelation] | -1 0 1 [Partial Autocor] |
|---|---|---|---|---|---|---|
| 1 | 0.9943 | 0.9950 | 188.84 | 0.0000 | | |
| 2 | 0.9877 | -0.5296 | 376.17 | 0.0000 | | |
| 3 | 0.9803 | 0.0414 | 561.73 | 0.0000 | | |
| 4 | 0.9724 | -0.0594 | 745.28 | 0.0000 | | |
| 5 | 0.9637 | -0.2239 | 926.57 | 0.0000 | | |
| 6 | 0.9544 | -0.1647 | 1105.4 | 0.0000 | | |
| 7 | 0.9446 | -0.0905 | 1281.4 | 0.0000 | | |
| 8 | 0.9341 | 0.0500 | 1454.6 | 0.0000 | | |
| 9 | 0.9232 | -0.0973 | 1624.7 | 0.0000 | | |
| 10 | 0.9117 | -0.0826 | 1791.5 | 0.0000 | | |
| 11 | 0.8997 | -0.1510 | 1954.8 | 0.0000 | | |
| 12 | 0.8873 | -0.0406 | 2114.6 | 0.0000 | | |
| 13 | 0.8746 | 0.1370 | 2270.7 | 0.0000 | | |
| 14 | 0.8614 | -0.0315 | 2423 | 0.0000 | | |
| 15 | 0.8477 | -0.0440 | 2571.4 | 0.0000 | | |
| 16 | 0.8336 | -0.1099 | 2715.7 | 0.0000 | | |
| 17 | 0.8191 | -0.0474 | 2855.9 | 0.0000 | | |
| 18 | 0.8043 | 0.1010 | 2991.8 | 0.0000 | | |
| 19 | 0.7890 | 0.0050 | 3123.4 | 0.0000 | | |
| 20 | 0.7735 | 0.0775 | 3250.6 | 0.0000 | | |
| 21 | 0.7579 | -0.1056 | 3373.4 | 0.0000 | | |
| 22 | 0.7419 | -0.2978 | 3491.9 | 0.0000 | | |
| 23 | 0.7256 | 0.0318 | 3605.9 | 0.0000 | | |
| 24 | 0.7092 | 0.1658 | 3715.4 | 0.0000 | | |
| 25 | 0.6925 | 0.0615 | 3820.5 | 0.0000 | | |
| 26 | 0.6757 | 0.0637 | 3921.2 | 0.0000 | | |
| 27 | 0.6587 | -0.0495 | 4017.4 | 0.0000 | | |
| 28 | 0.6414 | -0.1858 | 4109.3 | 0.0000 | | |
| 29 | 0.6241 | 0.0076 | 4196.8 | 0.0000 | | |
| 30 | 0.6065 | -0.1001 | 4279.9 | 0.0000 | | |
| 31 | 0.5887 | -0.3359 | 4358.8 | 0.0000 | | |
| 32 | 0.5706 | -0.0160 | 4433.3 | 0.0000 | | |
| 33 | 0.5521 | -0.0154 | 4503.6 | 0.0000 | | |
| 34 | 0.5335 | 0.0651 | 4569.6 | 0.0000 | | |
| 35 | 0.5145 | 0.0412 | 4631.4 | 0.0000 | | |
| 36 | 0.4953 | -0.0102 | 4689 | 0.0000 | | |
| 37 | 0.4758 | 0.0437 | 4742.6 | 0.0000 | | |
| 38 | 0.4562 | 0.0786 | 4792.1 | 0.0000 | | |
| 39 | 0.4366 | 0.0184 | 4837.8 | 0.0000 | | |
| 40 | 0.4169 | -0.1462 | 4879.8 | 0.0000 | | |

**Table 2. Sample autocorrelations and partial autocorrelations of data**

Table 2 shows sample autocorrelations and partial autocorrelations of the data computed using STATA. Data appear likely to be a unit root in that the first values of autocorrelation (ac) and partial autocorrelation (pac) are extremely close to 1 and the values of ac functions decrease slowly. The paper applies the Dickey-Fuller test to further determine whether the data are a unit root or not.

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```
. dfuller exrate

Dickey-Fuller test for unit root                   Number of obs   =       139

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.202            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0007

. dfuller exrate,drift

Dickey-Fuller test for unit root                   Number of obs   =       139

                               ----------- Z(t) has t-distribution ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.202            -2.354            -1.656            -1.288
------------------------------------------------------------------------------
p-value for Z(t) = 0.0000

. dfuller exrate,trend

Dickey-Fuller test for unit root                   Number of obs   =       139

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)              1.804            -4.027            -3.445            -3.145
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 1.0000
```

**Table 3. Dickey-Fuller test results**

As shown in Table 3, the data pass the regular Dickey-Fuller test and the test with drift, but the data fail the test with trends. Thus, the data are determined to be a unit root with some trend, and the paper deletes the stochastic trend in the data to make it stationary.

The first approach is to create trends and trend$^2$ variables to capture nonlinear trends in the graph. However, these two variables are too closely correlated to the other x-variable, CPI, as shown by the scatterplot matrix (Fig. 3).

  

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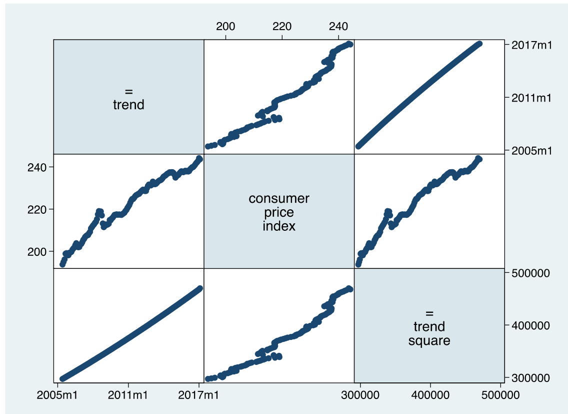


**Fig. 3. Scatterplot matrix**

Therefore, the paper turns to the second approach, where the nonlinear shape of the graph may be captured by the variable CPI. Under this assumption, the paper regresses the exchanged rate on CPI, the interest rate, Chinese and U.S. stock market price indices, and Chinese and U.S. inflation surprises. However, the regression output is not satisfactory in that its residuals remain a unit root (Table 4).

**. reg exrate CNStockPI SP500PI usInfSuprise cnInfSuprise cpius interest**

| Source | SS | df | MS |
|---|---|---|---|
| Model | 52.0050727 | 6 | 8.66751212 |
| Residual | 3.86036032 | 133 | .029025266 |
| Total | 55.865433 | 139 | .40190959 |

| | | |
|---|---|---|
| Number of obs | = | 140 |
| F(6, 133) | = | 298.62 |
| Prob > F | = | 0.0000 |
| R-squared | = | 0.9309 |
| Adj R-squared | = | 0.9278 |
| Root MSE | = | .17037 |

| exrate | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| CNStockPI | -.0000505 | .0000164 | -3.07 | 0.003 | -.000083 | -.0000179 |
| SP500PI | .0006779 | .0001029 | 6.59 | 0.000 | .0004744 | .0008814 |
| usInfSuprise | .0013538 | .0011177 | 1.21 | 0.228 | -.000857 | .0035647 |
| cnInfSuprise | .0018485 | .0007969 | 2.32 | 0.022 | .0002723 | .0034247 |
| cpius | -.0478359 | .0043429 | -11.01 | 0.000 | -.056426 | -.0392458 |
| interest | .0452424 | .0222505 | 2.03 | 0.044 | .0012318 | .0892531 |
| _cons | 16.52878 | .8518099 | 19.40 | 0.000 | 14.84393 | 18.21362 |

**. dfuller r7,trend**

Dickey-Fuller test for unit root Number of obs = 139

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -0.931 | -4.027 | -3.445 | -3.145 |

**Table 4. Regression output**

  

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Since it is not possible to predict the exchange rate itself, the paper regression on the change in the exchange rate (D.exrate) on all x-variables (note that D.cpi is used instead of CPI). This time, the output (shown below) is more reasonable. The graph of the model's residual presented in Table 5, Fig. 4, and Table 6 show no obvious traits of a unit root, and it passes all Dickey-fuller tests.

```
. reg D.exrate CNStockPI SP500PI usInfSuprise cnInfSuprise D.cpius interest
```

| Source | SS | df | MS | | | |
|---|---|---|---|---|---|---|
| | | | | Number of obs | = | 139 |
| | | | | F(6, 132) | = | 10.11 |
| Model | .070035053 | 6 | .011672509 | Prob > F | = | 0.0000 |
| Residual | .152357713 | 132 | .001154225 | R-squared | = | 0.3149 |
| | | | | Adj R-squared | = | 0.2838 |
| Total | .222392766 | 138 | .001611542 | Root MSE | = | .03397 |

| D.exrate | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| CNStockPI | -3.53e-06 | 3.27e-06 | -1.08 | 0.282 | -.00001 | 2.94e-06 |
| SP500PI | .0000421 | 9.65e-06 | 4.36 | 0.000 | .000023 | .0000612 |
| usInfSuprise | .0001113 | .000227 | 0.49 | 0.625 | -.0003377 | .0005604 |
| cnInfSuprise | -.0004606 | .0001643 | -2.80 | 0.006 | -.0007856 | -.0001356 |
| cpius | | | | | | |
| D1. | -.0081349 | .004234 | -1.92 | 0.057 | -.01651 | .0002403 |
| interest | -.0038843 | .0018213 | -2.13 | 0.035 | -.007487 | -.0002815 |
| _cons | -.0549032 | .0152666 | -3.60 | 0.000 | -.0851022 | -.0247043 |

**Table 5. Regression Output**

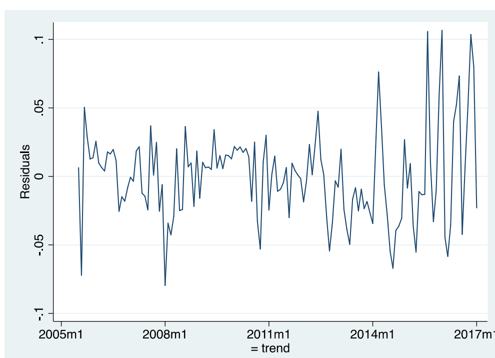


**Fig. 4. Model residuals**

  

```
. dfuller r5

Dickey-Fuller test for unit root                   Number of obs   =       138

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.260            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller r4,drift

Dickey-Fuller test for unit root                   Number of obs   =       138

                               ---------- Z(t) has t-distribution -----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.174            -2.354            -1.656            -1.288
------------------------------------------------------------------------------
p-value for Z(t) = 0.0000

. dfuller r4,trend

Dickey-Fuller test for unit root                   Number of obs   =       138

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.148            -4.027            -3.445            -3.145
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

**Table 6. Dickey-Fuller test results**

However, the residual does not look random. Therefore, there must be more to model, and the paper addresses this issue by first investigating its graphs of autocorrelations (ac) and partial autocorrelations (pac) at the 95% confidence interval (Fig. 5).

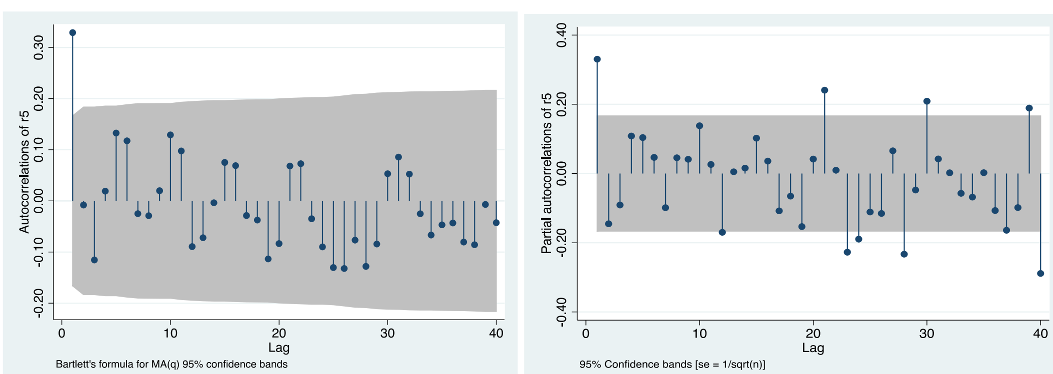


**Fig. 5. Autocorrelations (ac) and partial autocorrelations (pac) at the 95% confidence interval**

Based on the graphs of autocorrelations and partial autocorrelations, models such as MA(1), AR(1), AR(2), and ARMA(1,1) are considered. The paper decides on the model MA(1), which

  

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has the lowest AIC (= -564.14) and BIC (= -555.33) values.[2] The output, ac, and pac graphs are shown in Table 7.

```
Sample:  2005m7 - 2017m1                        Number of obs     =        139
                                                Wald chi2(1)      =      24.48
Log likelihood =   285.068                      Prob > chi2       =     0.0000
```

| r5 | Coef. | OPG Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **r5** | | | | | | |
| _cons | -9.17e-06 | .003752 | -0.00 | 0.998 | -.007363 | .0073446 |
| **ARMA** | | | | | | |
| ma L1. | .3442957 | .0695866 | 4.95 | 0.000 | .2079084 | .480683 |
| /sigma | .0311094 | .001537 | 20.24 | 0.000 | .028097 | .0341219 |

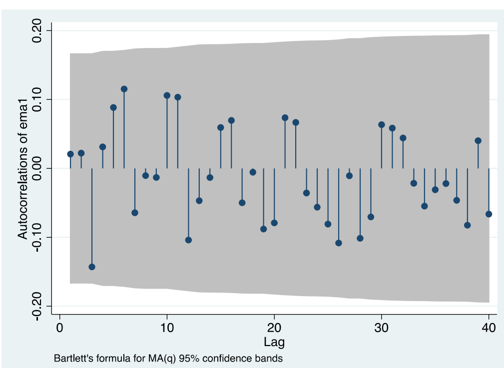
```
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.

. estat ic

Akaike's information criterion and Bayesian information criterion
```

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 139 | . | 285.068 | 3 | -564.1359 | -555.3325 |

**Table 7. MA(1)**



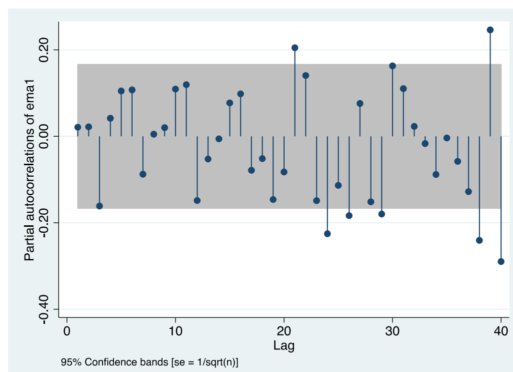




**Fig. 6. Graphs of ac and pac**

The autocorrelation graph looks good in that all values are within the confidence interval (Fig. 6). In the partial-autocorrelation graph, there are some values slightly beyond the confidence interval, but they do not show up in the autocorrelation graph. Therefore, these may be some

[2] $AIC_{AR1}$ = -562.84, $BIC_{AR1}$ = -554.0403
$AIC_{AR1}$ = -563.71, $BIC_{AR1}$ = -551.98
$AIC_{ARMA1}$ = -562.50, $BIC_{ARMA1}$ = -550.77, thus the AIC and BIC of MA(1) is the lowest.

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noise in the data.

In order to determine whether there is more to model, the paper performs a White-Noise q-test on its residuals (Table 8).

```
. wntestq ema1

Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    30.2038
 Prob > chi2(40)           =     0.8695
```

**Table 8. White-Noise q-test**

According to the results, white noise is achieved, indicating a good model.

Then the final model is formulated by combining the trend model with the MA(1) process:

$$D.exrate = \beta_1 CNStockPI + \beta_2 \mathrm{SP500PI} + \beta_3 \mathrm{usInfSuprise} + \beta_4 \mathrm{cnInfSuprise} + \beta_5\ \mathrm{D.cpius} + \beta_6\ \mathrm{interest\ rates} + \beta_0 + \mathrm{MA(1)}$$

```
Sample:  2005m7 - 2017m1                        Number of obs     =        139
                                                Wald chi2(7)      =      93.47
Log likelihood =  285.2064                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
    D.exrate |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
exrate       |
   CNStockPI |  -3.16e-06   3.66e-06    -0.86   0.388    -.0000103    4.02e-06
     SP500PI |   .0000397   .0000136     2.91   0.004      .000013    .0000663
usInfSuprise |   .0000338   .0003288     0.10   0.918    -.0006107    .0006783
cnInfSuprise |  -.0004756   .0002436    -1.95   0.051    -.0009531    1.81e-06
             |
       cpius |
         D1. |  -.0067619   .0049907    -1.35   0.175    -.0165434    .0030196
             |
    interest |  -.0036547   .0036918    -0.99   0.322    -.0108904    .0035811
       _cons |  -.0536384   .0232554    -2.31   0.021    -.0992181   -.0080587
-------------+----------------------------------------------------------------
ARMA         |
          ma |
         L1. |   .3485122   .0780037     4.47   0.000     .1956278    .5013966
-------------+----------------------------------------------------------------
      /sigma |   .0310762   .0018718    16.60   0.000     .0274076    .0347449
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.

. estat ic

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |        139         .   285.2064       9   -552.4128  -526.0025
-----------------------------------------------------------------------------
```

**Fig. 7. Final model regression output**

  

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Note that even though some of variables in the final model are nonsignificant, the paper retains them because these x-variables are intuitively important in explaining the y-variable (Fig. 7).

The residual of the final model is shown in Fig. 8.

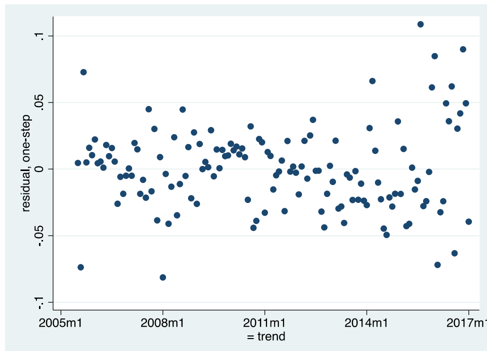


**Fig. 8. Residuals of final model**

The residuals are random, and the model passes the White-Noise q-test, indicating it to be complete and sound (Table 8).

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    30.2699
 Prob > chi2(40)           =     0.8676
```

**Table 8. White-Noise q-test**

**Forecasting Model Selection and Results**

For forecasting, since some of the newest data are yet to be released, the paper runs the regression using the first 136 observations (from May 2005 to September 2016) and forecasts the exchange rate in the last four months (from October 2016 to January 2017). The modified model output is shown in Table 9.

  

```
Sample:  2005m7 - 2016m9                          Number of obs     =        135
                                                  Wald chi2(7)      =      90.31
Log likelihood =   283.115                        Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
    D.exrate |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
exrate       |
   CNStockPI |  -2.91e-06   3.35e-06    -0.87   0.385    -9.47e-06    3.66e-06
     SP500PI |   .0000334   .0000126     2.65   0.008     8.69e-06    .0000582
usInfSuprise |   .0000443   .0002975     0.15   0.882    -.0005388    .0006274
cnInfSuprise |  -.0005705   .0002474    -2.31   0.021    -.0010554   -.0000856
             |
       cpius |
         D1. |  -.0067294    .004607    -1.46   0.144     -.015759    .0023002
             |
    interest |  -.0031249   .0033575    -0.93   0.352    -.0097054    .0034556
       _cons |  -.0475737   .0209307    -2.27   0.023    -.0885971   -.0065502
-------------+----------------------------------------------------------------
ARMA         |
          ma |
         L1. |   .2929246   .0746854     3.92   0.000     .1465438    .4393054
-------------+----------------------------------------------------------------
      /sigma |   .0297064   .0017774    16.71   0.000     .0262228    .0331901
------------------------------------------------------------------------------
```

**Table 9. Modified model output**

Predicted and real exchange rates and their time series plots using the modified model are shown in Table 10 and Fig. 9, respectively.

| | time | exrate | yhat6 |
|---|---|---|---|
| 137 | 2016m10 | 6.7303 | 6.678839 |
| 138 | 2016m11 | 6.8402 | 6.742736 |
| 139 | 2016m12 | 6.9198 | 6.857595 |
| 140 | 2017m1 | 6.8907 | 6.920435 |

**Table 10. Predicted and real exchange rates**

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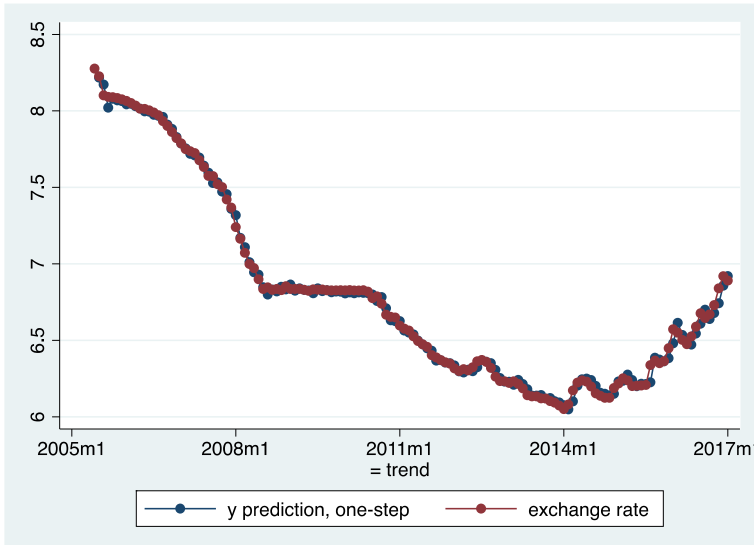


**Fig. 9. Time series plots**

The predicted exchange rate (yhat6) fits the real exchange rate well.

It can be calculated that Out – of sample Root MSE = $\sqrt{(\sum_{h=1}^{H}(forecast\ residual_h)^2)/H}$ $\sqrt{\frac{((6.7303-6.678839)^2+(6.8402-6.742736)^2+(6.9198-6.85795)^2+(6.8907-6.920435)^2)}{4}}$ =0.06491736775.

suggests that the proposed model is accurate in that the out-of-sample root MSE is very small. This model can predict the exchange rate between the yuan and the dollar for the decision to purchase the dollar or the yuan. Further, the model suggests an upward trend, suggesting that the exchange rate between the yuan and the dollar is likely to keep increasing in the future. This model suggests that the rate is likely to climb and thus the benefits of purchasing the dollar relative to the yuan.

## CONCLUSIONS

This paper proposes a cross-sectional model with the MA(1) process to predict the exchange rate between the yuan and the dollar. The predicted value of the exchange rate fits the real value of the exchange rate well. The model suggests that the yuan-to-dollar exchange rate will keep increasing in the future as long as the economy remains stable. Overall, this is a reasonable model in that the U.S. economy has mostly recovered from the 2008 financial crisis and is getting more vigorous (Bergsten, 2013). On the other hand, the Chinese government prefers a lower yuan-to-dollar exchange rate, which would allow Chinese exports to be more competitive in the international market (Seghezza, 2017). All this suggests that the exchange rate will likely follow its upward path.

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