Econ 335 International Finance Final Report

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1. Abstract:

This paper constructed regression models on exchange rate prediction and conducted predicting process with different combinations of regressors. Identification was based on KRW-USD exchange rate data from June 2001 to December 2020. Comparisons of regression results suggest that the fitness of the model is significantly improved when the exchange rate in the former period is introduced as a regressor, but the fitted model does not seem to be desirable for prediction due to the lag of time. Whereas the both domestic and foreign inflation rates are significant for exchange rate prediction, the long run exchange rate is less important than short run exchange rate in most of the models. With respect to above findings and the failure of constructing a model with smaller RMSE than the benchmark model, this paper proposed that the undesirable result of exchange rate prediction may be attributed to ignoring short shocks and reference dependence.

2. Introduction

1) Importance of the exchange rate prediction

Export and import occupies a significant position in every open economy, and accordingly, the exchange rate is a determinative factor in international trade, both for evaluating nominal cash flows between nations and transaction of real products. Therefore, the exchange rate forecast is important as a medium of transaction, and further, an influencing factor of the international business environment.

2) Previous studies

Most studies in exchange rate prediction had focused on long memory property. Granger & Ding (1996) assumed that in volatility models, exaggerated and perpetual autocorrelations are gradually shrinking during a relatively long period of time. There is also long memory autoregressive conditional heteroskedasticity model of Baille et al. (1996) and Davidson (2004). At the same time, on the basis of long memory volatility process, scholars have shown interests in structural breaks, since the first discovery of robust and persistent structural breaks in conditional variance process (Lamoreaus & Lastrapes, 1990). Choi and Zivot (2007) also documented evidence for multiple structural breaks in the mean of the forward discount.

Combining the results of previous studies, the importance of applying long memory property with consideration of structural shocks in depreciation rate prediction is well stated.

However, exogenous accidental jumps are not with same amount of attention. As Goodhart and Giugale (1993) had noted that occasional shifts that occurs during long term also plays a significant role in the prediction process, although some ups and downs in the long run may offset each other, if the long memory property of depreciation rate is regarded as a weakly stationary model, the unexpected fluctuates of a small scale comparing to structural shock can also be fatal for the depreciation rate prediction. Therefore, it is worth discussing whether ignoring the possible small shifts matters for the creditability of depreciation rate prediction.

As for the prediction of KRW/USD exchange rate, most studies follow a practical method of analyzing relevant variables, such as fitting foreign exchange investment into the proposed model (see Kim, Lee, Kim & Ahn, 2018), while Lee and Lim (2018) used three numbers of technical indicators, including RSI (Relative Strength Index), CCI (Commodity Channel Index), and CPP (Current Price Position) to construct a model that can extract input features. However, as the number of relevant variable increases, the accuracy may be improved only by adding more data to the model rather than really making an effort. Moreover, the more regressors are considered, the more complex the model is, and the stricter the condition that the model can be applied to. As a result, to ensure the simplicity without loss of generality, it is necessary to start from fundamental theoretical equations, following by equation that holds empirically, for the possibility of being applied to a wider range.

3) contribution of this paper

Firstly, the paper well verified the long term and structural behavior of the fitting model in depreciation rate prediction. Because data is taken based on a relatively wide time range (June, 2001 to December, 2020), it is possible to read clear trends and structural shocks from the plots. Also, all models constructed in this paper are clearly coordinated to the structural shock of the tendency of the dependent variable, which reassured the structural shock characteristic of the depreciation.

Secondly, the paper is based on solid theoretical basis while taking empirically significant equations into consideration. Only relying on rigorous theoretical equations may lead to an unrealistic model, but on the other extreme, too many practices can lead to a complex model that is specifically applicable to a certain case. As a result, the paper combined both theoretical and practical equations to construct fitted models.

Thirdly, the paper revealed the importance of containing small shifts and jumps into fitting models. Although models of the paper behaved well accordance with the dependent variable with respect to long term shocks, none of them has a RMSE that is smaller than the benchmark model, and the paper argues that the difference can be attributed to not fully considering occasionally changes.

Fourthly, this paper takes behavioral economics into the financial field. It stands at the behavioral economic perspective, and uses the reference dependence theory to explain the fitness of the exchange rate predicting model, which promotes the research progress of determinants in exchange rate prediction.

3. Prediction models
   1) Theoretical basis

Suppose

P_i is the unit price of a good i measured in currency in country A

P_i^* is the unit price of a good i measured in currency in country B

S is the exchange rate between currency in country A and currency in country B.

From empirical experience, there exist a constant k such that

$$kS_t = \frac{P_i}{P_i^*}$$

$$P_t = kP_t^* S_t$$

$$P_{t+1} = kP_{t+1}^* S_{t+1}$$

$$\log P_{t+1} - \log P_t = \log P_{t+1}^* - logP_t^* + logS_{t+1} - logS_t$$

$$s_{t+1} = \pi_{t+1} - \pi_{t+1}^*$$

$$s_t = \pi_t - \pi_t^*$$

Where s_t is the depreciation rate.

The exchange rate driven from the relative PPP equation is determined by present period domestic and foreign inflation rate

From the theoretical perspective, the exchange rate can be driven from the Uncovered Interest Rate Parity equation as the following:

If there is no transaction cost and agents are risk-neutral,

$$S_t = \frac{1 + i_t^*}{1 + i_t} S_{t+1}^e$$

$$\log S_{t+1}^e - \log S_t = i_t - i_t^*$$

$$\log S_{t+2}^e - \log S_{t+1} = i_{t+1} - i_{t+1}^*$$

$$\log S_t^e = (i_0 - i_0^*) + (i_1^e - i_1^{*e}) + (i_2^e - i_2^{*e}) + \cdots$$

$$S_t = \frac{1 + i_t^*}{1 + i_t} S_{t+1}^e$$

And when the UIP is realized

$$s_{t+1} = logS_{t+1} - logS_t = i_t - i_t^* + error$$

$$s_t = i_{t-1} + i_{t-1}^* + error$$

Where s_t is the depreciation rate.

According to the UIRP, the depreciation rate is determined by previous period domestic and foreign interest rate.

Combining the two expressions, it is possible to assume that the depreciation rate is correlated to current period domestic and foreign inflation rate, and previous period domestic and foreign interest rates.

2) Choice of variables

i) Dependent variable

The dependent variable of the paper is

s_t: depreciation rate (KRW/USD) from June 2001 to December 2020

ii) Independent variables

The independent variables of the paper are

$i_{S,t-1}$: previous period domestic short time interest rate

$i^*_{S,t-1}$: previous period foreign short time interest rate

$i_{L,t-1}$: previous period domestic long time interest rate

$i^*_{L,t-1}$: previous period foreign long time interest rate

π_t: current period domestic inflation

π^*_t: current period foreign inflation

s_{t-1}: previous period depreciation rate

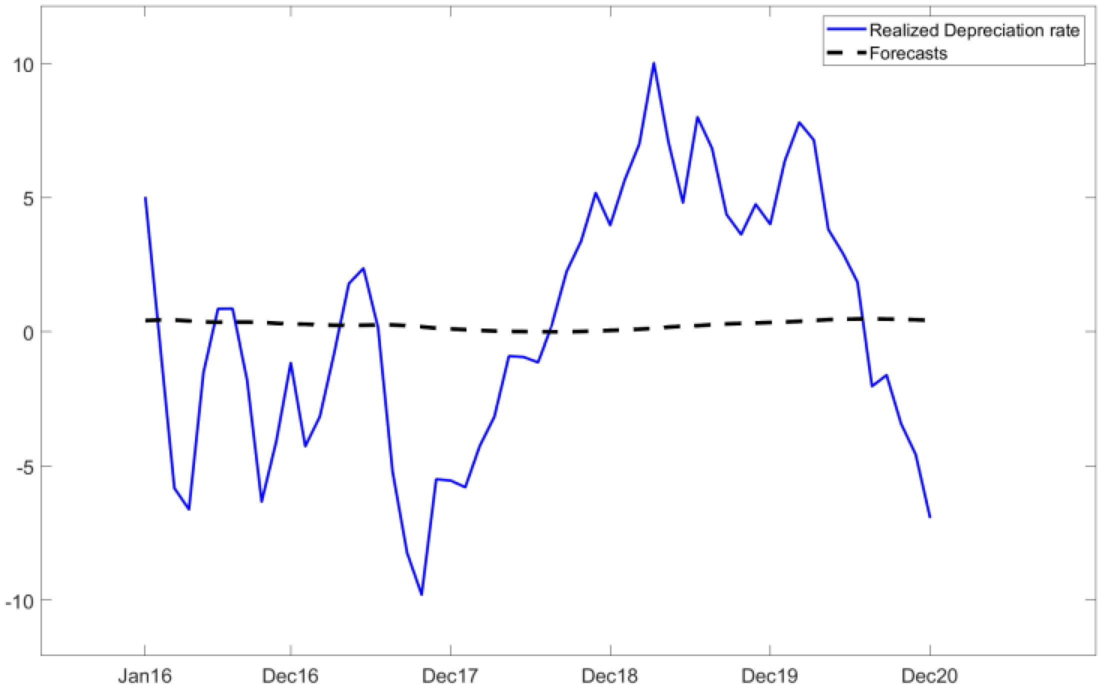
And data are generated from OCED statistics.

3) Model building

The benchmark model M1

$$s_t = F(\text{constant})$$

The benchmark model M1 includes constant terms only.



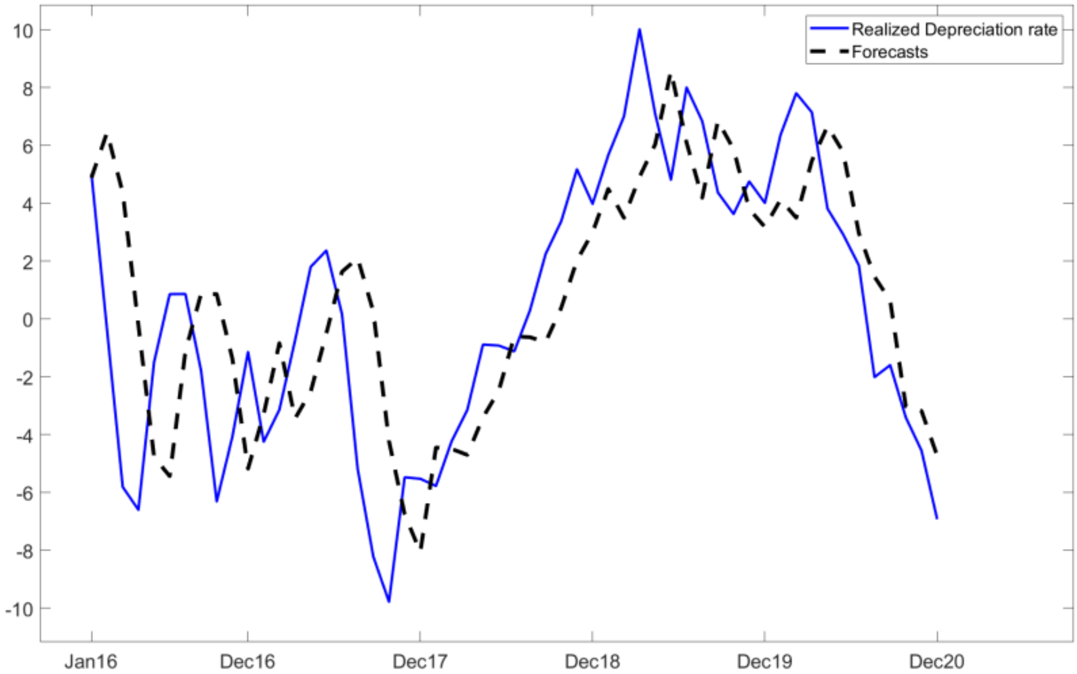
The RMSE of the benchmark model is 5.1983.

Comparison 1: previous period depreciation rate

1) Full model

$$s_t = F(i_{S,t-1}, i^*_{S,t-1}, i_{L,t-1}, i^*_{L,t-1}, \pi_t, \pi^*_t, s_{t-1})$$

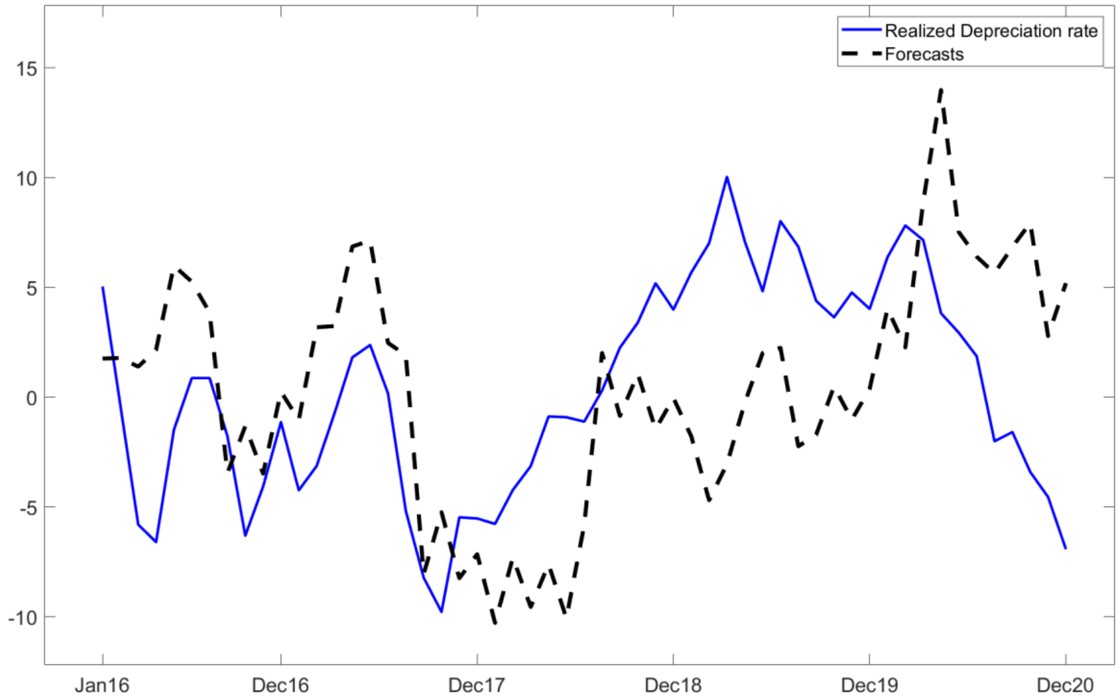
includes all variables mentioned in the list 3 (2).



RMSE=3.7241

Variables that are statistically significant at 95% confidence level include previous period domestic short and long interest rates, with previous period depreciation ($\mathrm{i}_{\mathrm{S,t-1}}, i_{L,t-1}, s_{t-1}$)

2) Full Model without previous period depreciation rate



RMSE=6.4611

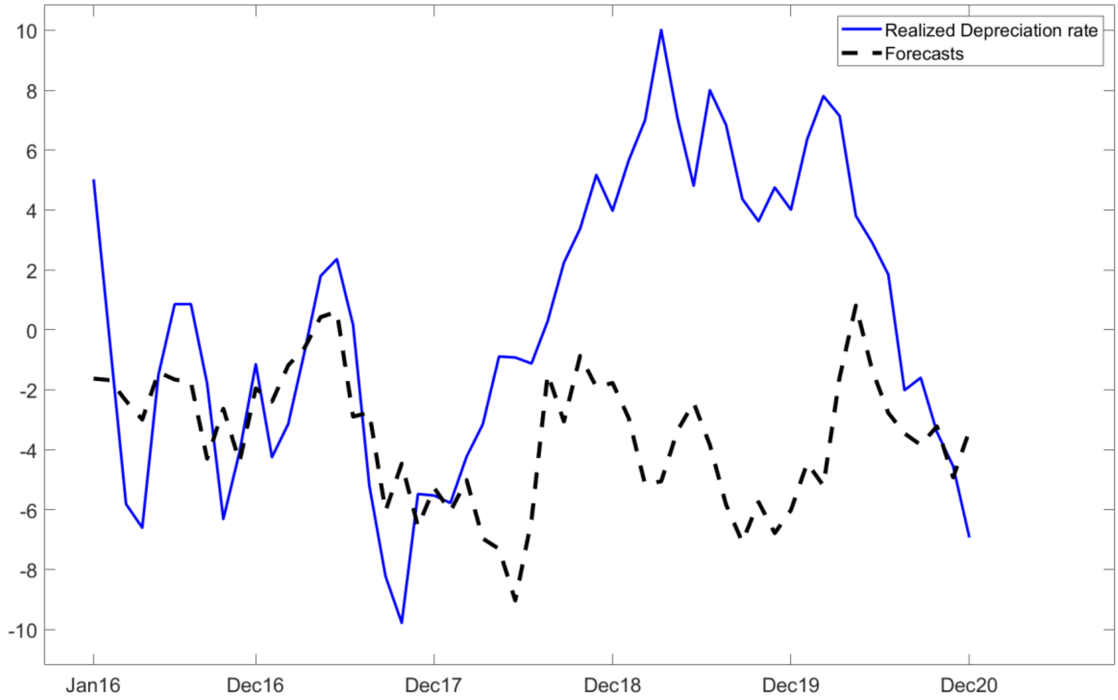
Variables that are statistically significant at 95% confidence level include are previous period foreign short and long interest rates, with domestic and foreign inflation rates ($\mathrm{i}^{*}_{\mathrm{S,t-1}}, i^{*}_{L,t-1}, \pi_t, \pi^{*}_t$).

Comparison 2: for short and long run

1) Short-run model

The short run model includes variables are previous period domestic and foreign short run interest rates, with present period domestic and foreign inflation rates.

$$s_t = F(i_{S,t-1}, i^*_{S,t-1}, \pi_t, \pi^*_t)$$



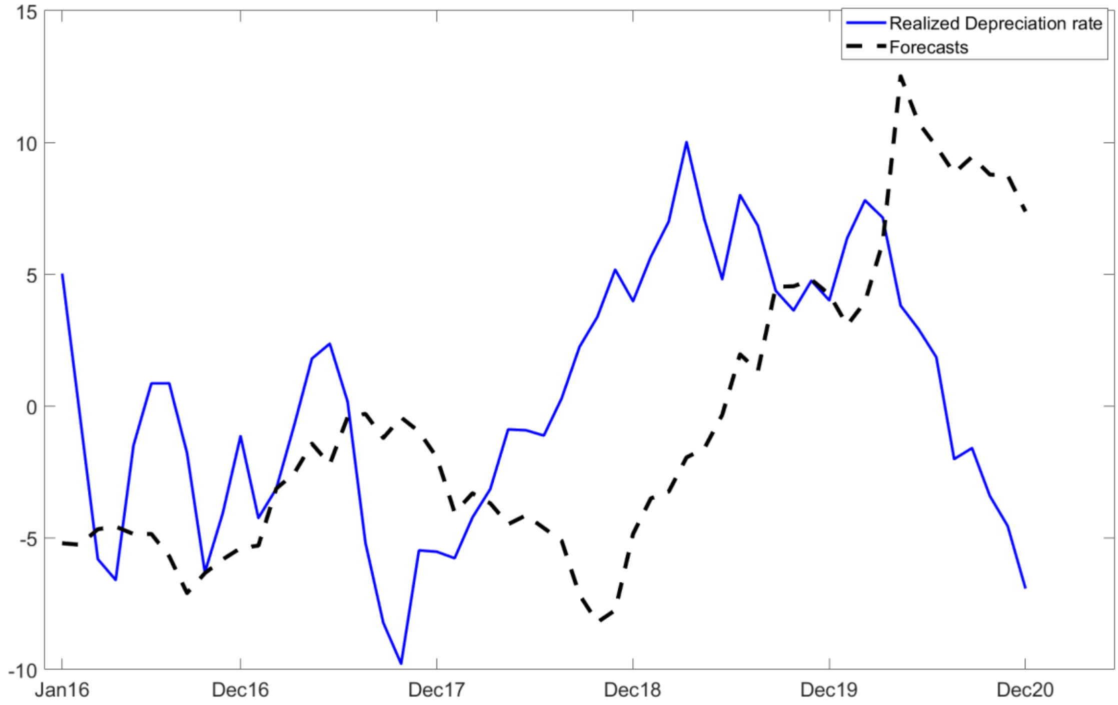
RMSE=6.9491

Variables that are statistically significant at 95% confidence level include previous period foreign short interest rate, with current period domestic and foreign inflation rates ($i^*_{S,t-1}, \pi_t, \pi^*_t$)

2) Long-run model

The long run model includes previous period domestic and foreign long run interest rates, with present period domestic and foreign inflation rates.

$$s_t = F(i_{L,t-1}, i^*_{L,t-1}, \pi_t, \pi^*_t)$$



RMSE=7.8827

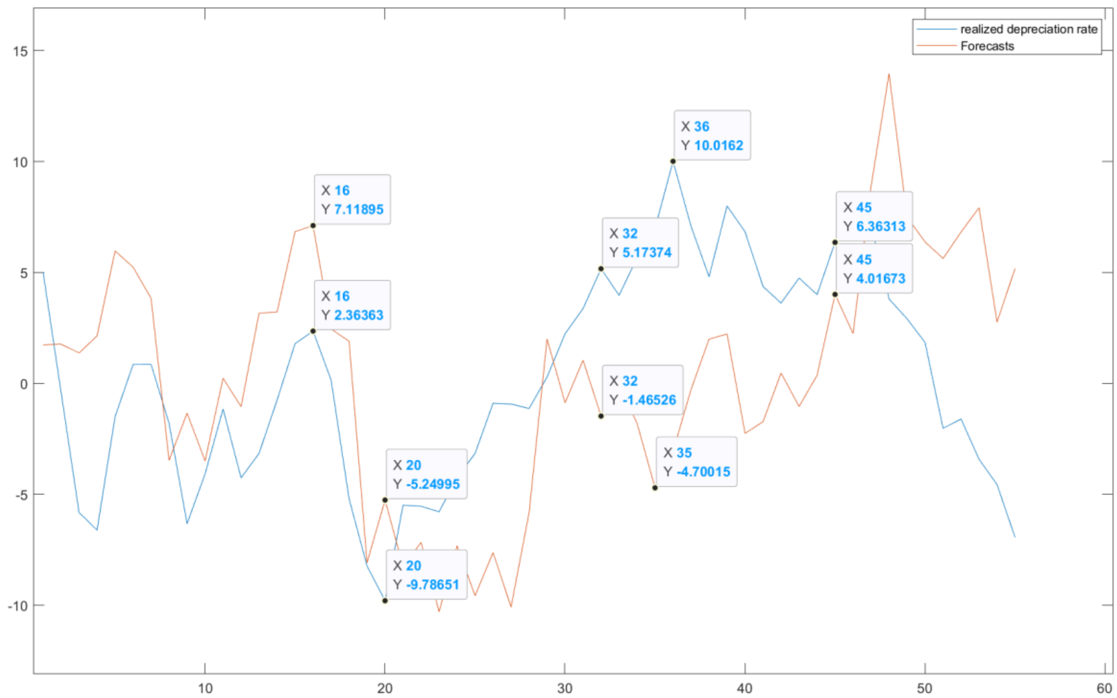
Variables that are statistically significant at 95% confidence level include present period domestic interest rate and foreign inflation rates ($i_{L,t-1}, \pi_t^*$).

4. Results

Result for comparison 1:

Full Model seems to be quite accurate judging from the RMSE. However, this may due to the characteristic of data structure. In other words, since the depreciation rates are highly correlated with each other in a timely manner, the fitness of model increases as the previous period depreciation rate is included as a regressor. However, judging from the plotted graph, Model 1 does not seem to be a proper depreciation rate prediction, because it does not accurately forecast the present period value of depreciation rate.

To compare with, Full Model without previous period depreciation rate has similar structure shocks with the real data, but does not tightly follow the same manner with respect to small, accidental shocks, as showed in the following graph.



This may reveal the fact that leaving occasional changes can cause a model;s decreased fitness even with the similar trend and structural shocks.

Result for comparison 2:

As the short term model has a smaller RMSE(6.949) than that of the long term model (7.882), the short term model seems to be a better exchange rate prediction model comparing to the long term one.

Also, the foreign inflation rate is statistically significant at 95% confidence level in both models

5. Conclusion:
6. Result interpretation:
   i) Full Model has the smallest RMSE. It considered current period domestic and foreign inflation rate, previous period domestic and foreign interest rates and previous period depreciation rate. However, the plotted trend does not seem to be practical in forecasting the depreciation rate.
   ii) Although RMSEs of other models that had excluded the previous period depreciation rate are all larger than the benchmark model, the model that only excluded the previous period depreciation rate has the smallest RMSE.
   iii) Short-run model has smaller RMSE than long run model.
7. Explanation:

   From the analysis stated above, fitted models show three tendencies:

   i) Short run factors are more influencing than long run factors

ii) The previous period depreciation rate is statistically significant but may not be useful in exchange rate prediction.

It is possible to explain the above three trends with the reference dependence theory. As one fundamental theory of behavioral economics, the reference dependence theory states that people evaluate outcomes relative to a reference point or status quo (McDermott, 2001), and then classify gains and losses (Kahneman & Tversky, 1979). Since the exchange rate prediction always involves risk and uncertainty, and thus, is accompanied with profit and gains, the most available and convenient reference point is the previous period exchange rate. However, the reference point may be misleading in the exchange rate prediction, since potential small, accidental changes are ignored. And this can also explain why short term model has a smaller RMSE than the long run model but is still not perfect.

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