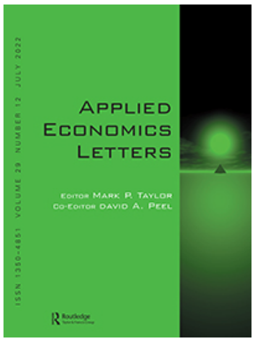

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Exchange rates forecasting and trend analysis after the COVID-19 outbreak: new evidence from interpretable machine learning

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ABSTRACT
We investigate the predictability of 12 exchange rates with machine learning, Deep Learning and interpretable machine learning (IML) models, based on a daily dataset from December 2019 to August 2021. We find that the appreciation and depreciation of exchange rates can be partly captured by Light Gradient Boosting Machine (LightGBM) and Long Short-Term Memory, especially for the developed currencies. Inconsistent with general perception, the LightGBM model performs the best in exchange rates forecasting since its short-term information extracting mode and great robustness on small datasets. Furthermore, by employing a representative global IML method, the Accumulated Local Effect algorithm, we find that the 1 ~ 3 lags of exchange rates provide more useful information for forecasting, which can help investors improve their models' predictive ability.

KEYWORDS
Exchange rates; forecasting; machine learning; interpretable machine learning

JEL CLASSIFICATION
C53; F37

I. Introduction

Exchange rates significantly affect real economic activities and financial markets (Kassi et al. 2019; Dupuy 2021). Therefore, forecasting exchange rates is of great significance. However, a Random Walk (RW) model can generally outperform any traditional models (Meese and Rogoff 1983) partly due to the non-linearity of exchange rates and the inadequacy of traditional models (Kilian and Taylor 2003; Taylor 2005). Scholars have tried various methods to challenge this conclusion (Bianco, Camacho, and Quiros 2012; Fuertes, Phylaktis, and Yan 2019). According to Rossi (2013), the predictability of exchange rates depends on the choice of predictor, forecast horizon, sample period, model, and forecast evaluation method.

Focusing on the types of models, many researches try to prove the feasibility of using different models to forecast exchange rates (Carriero, Kapetanios, and Marcellino 2009; You and Liu 2020). As AI technology advanced, scholars start to use machine learning (ML) such as Artificial Neural Network (ANN), Random Forest (RF) and Light Gradient Boosting Machine (LightGBM) to forecast exchange rates and successfully prove the predictive ability of these models (Zhao and Khushi 2020; Filippou et al. 2021). Deep Learning (DL) models including Recursive Neural Network (RNN) and Long Short-Term Memory (LSTM) have been used to forecast exchange rates (Ranjit et al. 2018; Yilmaz and Arabaci 2021). However, the low transparency of DL limits their use. Fortunately, interpretable machine learning (IML) methods can reveal the marginal effects of features, making us easily understand the forecasting processes of models (Molnar 2020). Till now, IML methods have been widely used (Liang and Cai 2022), but little focus on exchange rates except for Filippou et al. (2021), who adopt IML methods in multivariate exchange rates forecasting.

In this paper, we utilize a daily dataset containing 12 exchange rates from December 2019 to August 2021, aiming to expand the application of IML methods on univariate exchange rates forecasting. LightGBM, ANN and LSTM models are trained with window sliding methods, using Root Mean Square Error (RMSE) and Direction Accuracy (DA) as metrics. Furthermore, the Accumulated Local Effect (ALE) algorithm (Apley and Zhu 2020), one of the representative global IML methods, is employed to interpret the

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forecasting processes of our models, hoping to provide a quantitative analysis framework of exchange rates forecasting after the COVID-19 pandemic.

This paper contributes to the literature on exchange rates forecasting. Firstly, we prove the predictability of exchange rates' trend after the COVID-19 pandemic, especially for the developed currencies. Secondly, inconsistent with general perception, the LightGBM model performs better than deep learning since its short-term information extracting mode and great robustness on small datasets. Finally, according to ALE results, the 1 ~ 3 lags of exchange rates provide more useful information for forecasting. Our paper is the first to combine the ALE method with machine learning based on exchange rates forecasting, which can help investors improve their models' predictive ability.

The remainder is organized as follows. Section 2 describes data and models. Section 3 presents the results of forecast performances. Section 4 concludes.

II. Data and models

Data

Obtained from Datastream, our dataset covers 12 spot exchange rates under the U.S. dollar quotation from December 2019 to August 2021. We calculate the difference of logarithmic on exchange rates as a daily return. The descriptive statistics are reported in Table 1.

During the sample period, the average returns of almost all developed currencies are negative, which means they have appreciated against the U.S. dollar. By contrast, most developing currencies are depreciated. Moreover, the Jarque-Bera test rejects the null hypothesis that the returns of exchange rates follow a normal distribution.

Models

The benchmark model of short-term exchange rates prediction is the RW, which depends on time-series information only. Following the concept of RW, we use univariate sequences data and introduce the nonlinear framework of ML algorithms, trying to verify the predictability of time-series from the perspective of AI technology without interference from various features. Therefore, we choose the most mainstream tree, neural network and recurrent neural network algorithms to achieve various analysis perspectives. The representative models of these algorithms, the ANN, LSTM and LightGBM models, are built for our empirical study. Furthermore, following Liang and Cai (2022), we introduce the ALE method to interpret models' forecasting processes, thus revealing their time-series extracting modes and the importance of different features.

The constructions of models include four steps. Firstly, the dataset is split into train (365 days) and test (60 days) datasets based on the order of their trading dates. Secondly, the hyperparameters of models are tuned on the train dataset under different sliding window lengths using the 'TimeSeriesSplit'[1] method. Thirdly, models with

Table 1. Descriptive statistics.

	Obs.	Mean	Std.	Min	Max	Skewness	Kurtosis	JB_statistics
USDAUD	425	−0.0001	0.0072	−0.0294	0.0359	0.5515	3.3098	209.2313***
USDBRL	425	0.0006	0.0124	−0.0378	0.0443	0.0090	0.6451	6.8897**
USDCAD	425	−0.0001	0.0047	−0.0203	0.0239	0.4419	2.9327	161.0414***
USDCHF	425	−0.0002	0.0043	−0.0142	0.0188	0.4813	2.1079	92.0994***
USDCNH	425	−0.0002	0.0028	−0.0091	0.0113	0.4399	1.4410	48.8129***
USDEUR	425	−0.0001	0.0043	−0.0175	0.0175	0.0774	1.8388	57.9993***
USDGBP	425	−0.0001	0.0062	−0.0314	0.0270	0.0204	3.0011	154.3252***
USDINR	425	0.0001	0.0032	−0.0100	0.0188	0.9006	5.6411	604.6356***
USDJPY	425	0.0000	0.0045	−0.0269	0.0202	−0.4606	5.6207	558.5512***
USDNZD	425	−0.0001	0.0073	−0.0256	0.0337	0.5867	2.4461	126.4976***
USDRUB	425	0.0004	0.0100	−0.0305	0.0814	1.9975	14.2275	3774.6090***
USDZAR	425	0.0001	0.0098	−0.0228	0.0363	0.4191	0.3451	14.2484**

[1] Https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.TimeSeriesSplit.html.

the best hyperparameter configs are tested on the test dataset under different sliding window lengths. Finally, we extract the relationship between input features and target variable with the ALE method. For forecasting accurately, the best hyperparameter configs of models vary differently according to window length. Therefore, we give the grid-search spaces instead of the final hyperparameter configs in Appendix Table A1.

III. Results

We first compare the performance of three models on forecasting sample currencies' returns under 30, 60, 90, 120, 180 and 365 sliding window lengths. Furthermore, we investigate their different forecasting processes with the ALE method. With the RMSE and DA metrics, the forecasting results on the test dataset are given in Appendix Table A2, Figures 1 and 2.

For all the window lengths and currencies, the forecasting performance of the LSTM and LightGBM models are obviously better than that of the ANN model. The losses of all models decrease when the window length increases, but the losses are too large to build currency portfolios based on these models. The DA of models is also improved when the window length increases, which can reach over 75% (LightGBM) and 63% (LSTM) on average. Despite the different data volume requirements of models, this result reveals the strong trend capturing ability of ML and DL models.

Observing Table 2, the DA of three models on developed currencies approaches to 77.94%, 66.35% and 56.51% on average, which are higher than that of developing currencies at 73.67%, 60.28% and 55.11%. It's maybe attributed to the difference in liquidity and turnover between them. This result proves that forecasting developing currencies are becoming relatively difficult after the COVID-19 pandemic (Gunay 2021), and provide evidence for investors who manage portfolios prefer to hold developed currencies after the COVID-19 pandemic (Bazán-palomino and Winkelried, 2021).

Table 2. DA of developed and developing currencies.

	Developed			Developing		
Window	LightGBM	LSTM	ANN	LightGBM	LSTM	ANN
30	77.38%	62.14%	50.95%	74.67%	58.67%	52.33%
60	79.29%	67.86%	53.10%	74.33%	59.33%	50.00%
90	78.10%	67.86%	54.05%	74.67%	61.33%	53.67%
120	77.14%	65.24%	58.33%	73.33%	65.00%	54.00%
180	78.10%	68.33%	60.95%	73.33%	57.33%	58.00%
365	77.62%	66.67%	61.67%	71.67%	60.00%	62.67%
Average	77.94%	66.35%	56.51%	73.67%	60.28%	55.11%

We further adopt the ALE method to interpret models' forecasting processes, trying to find the reasons for their different performance and trend capturing ability. The ALE results of three models under 365 sliding window length are given in Appendix Table A3, Table A4 and Table A5. The results of ALE range percentage on different lags are summarized in Table 3.

Different emphases on lags make the three models have various time-series extracting modes, which lead to their differences in RSME and DA

Table 3. ALE range percentage of three models.

Lags	LightGBM	LSTM	ANN
1 ~ 3	0.61	0.59	0.55
4 ~ 5	0.39	0.41	0.45

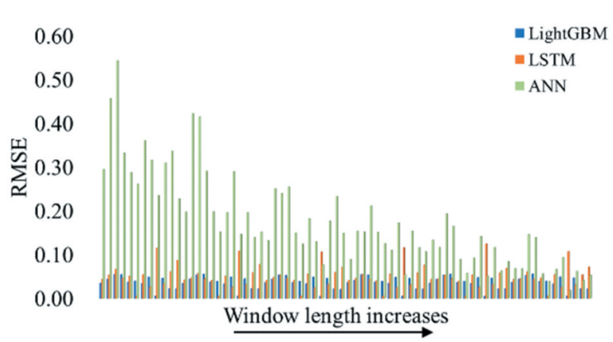

Figure 1. Test loss.

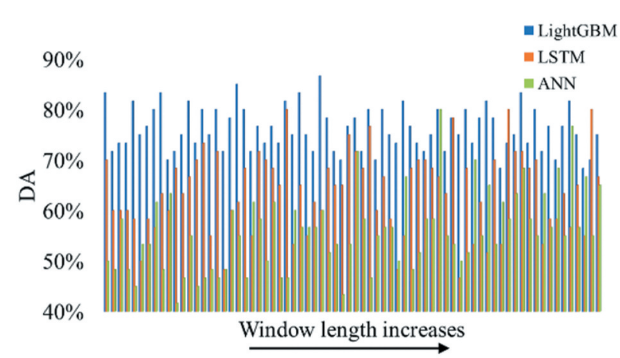

Figure 2. Test DA.

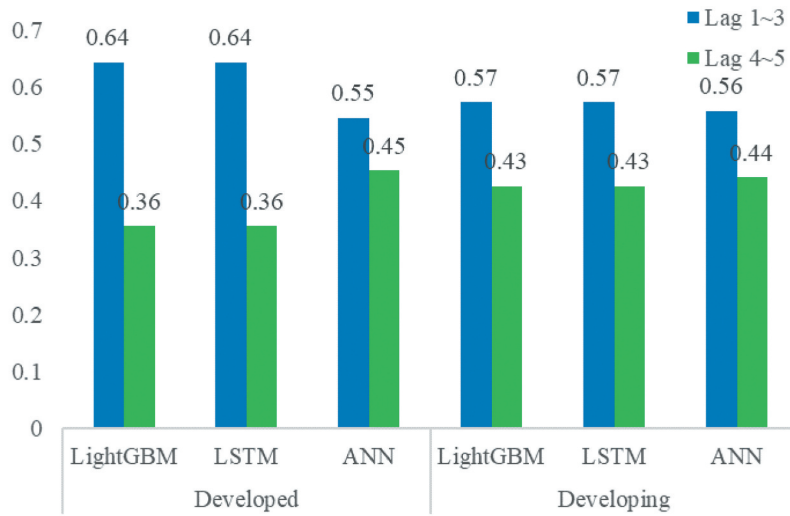

Figure 3. ALE range percentage of developed and developing currencies.

results. LightGBM and LSTM are more inclined to learn 1 ~ 3 lags short-term information while ANN is more inclined to extract information in 4 ~ 5 lags. Moreover, the forecasting processes of developed and developing currencies are also summarized in Figure 3.

Compared with developing currencies, models prefer to absorb more short-term information while forecasting developed currencies, which leads to their better DA performance. Therefore, more attention should be paid to 1 ~ 3 lags short-term information when forecasting exchange rates, especially for the developed currencies.

IV. Conclusion

In this paper, we investigate the predictability of exchange rates by using LightGBM, ANN, LSTM and IML models. The forecasting DA of LightGBM and LSTM models reach over 75% and 63% on average respectively, indicating that the appreciation and depreciation of exchange rates can be partly captured. Inconsistent with general perception, the LightGBM model performs better than the ANN and LSTM models in forecasting exchange rates, since its short-term information extracting mode and great robustness on small dataset. Moreover, there is a significant change in the model's reliance on short/long term information during forecasting exchange rates. Model's preference for 1 ~ 3 lags short-term information leads to a better forecasting DA, especially for the developed currencies. This result is helpful for improving the predictive ability of investors' models. For further study, following Filippou et al. (2021), we would like to use more advanced ML and IML models to better fit data and improve models' robustness, and build various currency portfolios to verify models' efficiency.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A.1. Tuning results of three models.

Models	Hyperparameters	Search Space
ANN	lag	[5][2]
	hidden_layers	[3, 4, 5]
	nodes	[32, 64, 128]
	learning_rate	[0.0005, 0.001]
	epochs	Earlystop
	mini_batch	[16, 32]
LSTM	lag	[5]
	hidden_layers	[2, 3][3]
	nodes	[32, 64, 128]
	learning_rate	[0.0005, 0.001]
	epochs	Earlystop
	mini_batch	[16, 32]
LightGBM	lag	[5]
	max_depth	[8, 16]
	num_leaves	[32, 64, 128]
	subsample	[0.5, 0.75]
	learning_rate	[0.0001, 0.0005, 0.001]
	n_estimators	Earlystop
	min_data_in_leaf	[10, 20]

[2]We take the 5 lags as an example, aiming to make input features include the trading information of exchange rates in one week.
[3]In order to compare the performance of algorithms under similar model complexity, we set the search space of LSTM to be consist with that of ANN.

Table A2. Models' performance on the test dataset.

Window Length	Exchange Rate	LightGBM_ RMSE	LightGBM_DA	LSTM_ RMSE	LSTM_ DA	ANN_ RMSE	ANN_ DA
30	USDAUD	0.03494	83.33%	0.04365	70.00%	0.29413	50.00%
60	USDAUD	0.03466	81.67%	0.04221	66.67%	0.19710	55.00%
90	USDAUD	0.03543	76.67%	0.04163	68.33%	0.13133	61.67%
120	USDAUD	0.03562	78.33%	0.04157	71.67%	0.08916	71.67%
180	USDAUD	0.03497	80.00%	0.04406	66.67%	0.13297	80.00%
365	USDAUD	0.03694	83.33%	0.04283	71.67%	0.06808	68.33%
30	USDBRL	0.04403	71.67%	0.05335	60.00%	0.45563	48.33%
60	USDBRL	0.04411	73.33%	0.04705	70.00%	0.42121	45.00%
90	USDBRL	0.04361	73.33%	0.04769	65.00%	0.24980	46.67%
120	USDBRL	0.04177	71.67%	0.04557	68.33%	0.15325	58.33%
180	USDBRL	0.04388	71.67%	0.04473	63.33%	0.11620	55.00%
365	USDBRL	0.04447	73.33%	0.04489	68.33%	0.06788	58.33%
30	USDCAD	0.05437	73.33%	0.06624	60.00%	0.54196	58.33%
60	USDCAD	0.05387	80.00%	0.05712	73.33%	0.41406	46.67%
90	USDCAD	0.05372	81.67%	0.05344	80.00%	0.23939	46.67%
120	USDCAD	0.05444	80.00%	0.05473	76.67%	0.15152	46.67%
180	USDCAD	0.05283	78.33%	0.05315	78.33%	0.19272	53.33%
365	USDCAD	0.05245	80.00%	0.06103	70.00%	0.14602	55.00%
30	USDCHF	0.02218	71.67%	0.06108	68.33%	0.33561	41.67%
60	USDCHF	0.02248	76.67%	0.05883	71.67%	0.13870	58.33%
90	USDCHF	0.02157	70.00%	0.05933	65.00%	0.23228	43.33%
120	USDCHF	0.02185	71.67%	0.05842	70.00%	0.11571	58.33%
180	USDCHF	0.02200	73.33%	0.05769	80.00%	0.06311	58.33%
365	USDCHF	0.02219	70.00%	0.05399	80.00%	0.04109	55.00%
30	USDCNH	0.05456	73.33%	0.04683	60.00%	0.33138	48.33%
60	USDCNH	0.05484	75.00%	0.04525	55.00%	0.28989	48.33%
90	USDCNH	0.05245	75.00%	0.04663	53.33%	0.25403	60.00%
120	USDCNH	0.05361	70.00%	0.04408	60.00%	0.21104	55.00%
180	USDCNH	0.05514	75.00%	0.04531	46.67%	0.16407	50.00%
365	USDCNH	0.05562	71.67%	0.04451	53.33%	0.13837	63.33%
30	USDEUR	0.03744	81.67%	0.05099	58.33%	0.28684	45.00%
60	USDEUR	0.03751	80.00%	0.04059	71.67%	0.19772	46.67%
90	USDEUR	0.03630	83.33%	0.04121	65.00%	0.14900	56.67%
120	USDEUR	0.03739	80.00%	0.04008	66.67%	0.15057	56.67%
180	USDEUR	0.03675	80.00%	0.03960	68.33%	0.08902	51.67%
365	USDEUR	0.03831	76.67%	0.04691	58.33%	0.05637	56.67%
30	USDGBP	0.02175	75.00%	0.08710	63.33%	0.22673	46.67%
60	USDGBP	0.02196	73.33%	0.07774	70.00%	0.15143	50.00%
90	USDGBP	0.02069	76.67%	0.07106	75.00%	0.14847	53.33%
120	USDGBP	0.02159	75.00%	0.07641	68.33%	0.10645	58.33%
180	USDGBP	0.02220	75.00%	0.06856	71.67%	0.08417	63.33%
365	USDGBP	0.02156	75.00%	0.07123	66.67%	0.05275	65.00%
30	USDINR	0.03970	75.00%	0.00555	50.00%	0.26105	53.33%
60	USDINR	0.03918	71.67%	0.00560	48.33%	0.15144	48.33%
90	USDINR	0.03900	75.00%	0.00578	55.00%	0.12342	56.67%
120	USDINR	0.03908	75.00%	0.00575	58.33%	0.12509	56.67%
180	USDINR	0.03870	73.33%	0.00571	53.33%	0.05740	70.00%
365	USDINR	0.03969	70.00%	0.00576	58.33%	0.03964	68.33%
30	USDJPY	0.03377	76.67%	0.05420	58.33%	0.35921	53.33%
60	USDJPY	0.03303	78.33%	0.05124	60.00%	0.19566	60.00%
90	USDJPY	0.03339	71.67%	0.05555	61.67%	0.18204	56.67%
120	USDJPY	0.03464	73.33%	0.05561	48.33%	0.10992	50.00%
180	USDJPY	0.03372	78.33%	0.05359	61.67%	0.09228	55.00%
365	USDJPY	0.03279	76.67%	0.05457	63.33%	0.06618	55.00%
30	USDNZD	0.04896	80.00%	0.02637	56.67%	0.31488	61.67%
60	USDNZD	0.04881	85.00%	0.02580	61.67%	0.28910	55.00%
90	USDNZD	0.04891	86.67%	0.02487	60.00%	0.12876	60.00%
120	USDNZD	0.04789	81.67%	0.02517	55.00%	0.17183	66.67%
180	USDNZD	0.04747	81.67%	0.02550	51.67%	0.14073	65.00%
365	USDNZD	0.04912	81.67%	0.02555	56.67%	0.09298	76.67%
30	USDRUB	0.00509	83.33%	0.11503	63.33%	0.23444	48.33%
60	USDRUB	0.00503	80.00%	0.10797	68.33%	0.14621	46.67%
90	USDRUB	0.00477	78.33%	0.10596	68.33%	0.07675	51.67%
120	USDRUB	0.00495	76.67%	0.11570	68.33%	0.05411	48.33%
180	USDRUB	0.00470	78.33%	0.12434	70.00%	0.05127	53.33%
365	USDRUB	0.00490	75.00%	0.10678	65.00%	0.01845	56.67%
30	USDZAR	0.04570	70.00%	0.03381	60.00%	0.30881	63.33%
60	USDZAR	0.04493	71.67%	0.03218	55.00%	0.19532	61.67%
90	USDZAR	0.04527	71.67%	0.03251	65.00%	0.17597	53.33%
120	USDZAR	0.04528	73.33%	0.03108	70.00%	0.15321	51.67%
180	USDZAR	0.04645	68.33%	0.03244	53.33%	0.11594	61.67%
365	USDZAR	0.04690	68.33%	0.03071	55.00%	0.06153	66.67%

Table A3. ALE range of LightGBM.

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5
USDAUD	0.0173	0.0124	0.0214	0.0130	0.0057
USDBRL	0.0306	0.0157	0.0136	0.0171	0.0319
USDCAD	0.0159	0.0195	0.0171	0.0126	0.0092
USDCHF	0.0061	0.0028	0.0034	0.0072	0.0052
USDCNH	0.0192	0.0202	0.0351	0.0209	0.0197
USDEUR	0.0284	0.0066	0.0157	0.0104	0.0156
USDGBP	0.0152	0.0087	0.0083	0.0100	0.0086
USDINR	0.0228	0.0121	0.0079	0.0128	0.0182
USDJPY	0.0215	0.0189	0.0224	0.0172	0.0075
USDNZD	0.0263	0.0204	0.0139	0.0252	0.0231
USDRUB	0.0033	0.0055	0.0059	0.0050	0.0052
USDZAR	0.0169	0.0107	0.0119	0.0196	0.0196

Table A4. ALE range of LSTM.

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5
USDAUD	0.0187	0.0577	0.0775	0.0231	0.0430
USDBRL	0.0102	0.0076	0.0090	0.0087	0.0189
USDCAD	0.0119	0.0240	0.0285	0.0189	0.0214
USDCHF	0.0049	0.0038	0.0042	0.0050	0.0053
USDCNH	0.0224	0.0279	0.0185	0.0238	0.0295
USDEUR	0.0233	0.0135	0.0158	0.0145	0.0220
USDGBP	0.0155	0.0240	0.0277	0.0171	0.0169
USDINR	0.0234	0.0101	0.0208	0.0202	0.0190
USDJPY	0.0256	0.0242	0.0106	0.0158	0.0192
USDNZD	0.0173	0.0211	0.0573	0.0467	0.0239
USDRUB	0.0018	0.0013	0.0029	0.0022	0.0028
USDZAR	0.0077	0.0144	0.0111	0.0108	0.0118

Table A5. ALE range of ANN.

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5
USDAUD	0.0651	0.0898	0.0850	0.0862	0.0806
USDBRL	0.0847	0.0730	0.0615	0.0560	0.0858
USDCAD	0.1731	0.0981	0.1769	0.3246	0.1393
USDCHF	0.0276	0.0237	0.0342	0.0618	0.0219
USDCNH	0.0709	0.0488	0.0722	0.1387	0.0710
USDEUR	0.0577	0.0616	0.0846	0.0642	0.0744
USDGBP	0.0392	0.0328	0.0587	0.0986	0.0386
USDINR	0.0461	0.0928	0.0578	0.0941	0.0638
USDJPY	0.0592	0.0705	0.0412	0.0688	0.0774
USDNZD	0.0745	0.1002	0.1047	0.1057	0.0694
USDRUB	0.0413	0.0553	0.0827	0.0909	0.0481
USDZAR	0.0432	0.0715	0.0364	0.0529	0.0520