ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 13 (2023) No. 6, pp.635-646
DOI:10.33168/JSMS.2023.0637

Forecasting Bilateral Exchange Rates under Uncertain Conditions Under Uncovered Interest Rate Parity Theoretical Framework A Machine Learning Approach

Phan Hong Hai[1], Tran Trong Huynh[2]

[1]Industrial University of Ho Chi Minh City, Ho Chi Minh City, Viet Nam
[2]FPT University, Hanoi, Viet Nam

phanhonghai@iuh.edu.vn (corresponding author), huynhtt4@fe.edu.vn

Abstract. This research aimed to forecast fluctuations in the exchange rate between the Vietnamese dong and the US dollar. The study utilized the Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) algorithm within the theoretical framework of Uncovered Interest Rate Parity (UIRP) in the context of economic policy uncertainty (EPU). Employing a rolling window methodology, the investigation compared results with those obtained from Ordinary Least Square (OLS) regression and Random Walk (RW) models. The dataset included the VND/USD exchange rate, 6-month bank interest rates, and 6-month T-bill rates from January 01, 2010, to July 31, 2023. The study revealed a direct correlation between exchange rates and interest rate differentials between the two countries. Interest rate differentials and EPU were used as input variables to forecast these differentials. Notably, the empirical evidence during this period did not support the UIRP hypothesis, resulting in substantial prediction errors in the OLS model. Consequently, this research proposed a predictive model for future exchange rates that combines the UIRP theoretical framework with the LSTM-RNN algorithm. The UIRP framework was employed to predict exchange rate differentials based on input variables and interest rates from both countries, while the LSTM-RNN algorithm, renowned for its robustness, contributed to enhanced prediction accuracy.

Keywords: UIRP, LSTM-RNN, EPU, Random Walk, exchange rate.

1. Introduction

The prediction of foreign exchange rates is a significant subject that garners the interest of both theoretical and empirical scholars. When considering the medium to long-term outlook, several models have been employed to elucidate exchange rate movements, including purchasing power parity, the international Fisher effect, and random walk models. Each of these models possesses its own set of advantages and drawbacks. Nevertheless, the challenge intensifies when addressing short-term forecasts, particularly disruptive factors like the COVID-19 pandemic and the conflict between Russia and Ukraine. These external uncertainties have rendered these models less reliable and effective in such contexts. Currencies in countries with high-interest rates tend to lose value due to a phenomenon known as Uncovered Interest Rate Parity (UIRP). Foreign currency investors may gain from engaging in trade manipulations when UIRP breaks down. To do this, you would borrow at low-interest rates and deposit at high interest rates. Several researchers have suggested that market flaws such as information asymmetry, uncertainty, and risk aversion play a role in why UIRP is often rejected (Husted *et al.*, 2018; Ismailov & Rossi, 2018). Although research on this subject has seen an uptick in recent years, there remains inconclusive evidence elucidating the underlying causes of UIRP's ineffectiveness. Consequently, empirical support is scarce for UIRP (Lothian, 2016).

In 2018, Ismailov and Rossi (2018) introduced an uncertainty scale, shedding light on short-term deviations from the Uncovered Interest Rate Parity (UIRP) model. In 2022, Khoa and Huynh (2022) utilized the Support Vector Regression (SVR) algorithm within the UIRP framework to project the bilateral exchange rates between Vietnam and the US based on the UIRP theoretical framework. While SVR demonstrated relatively strong forecasting performance compared to the Ordinary Least Square (OLS) method, it still exhibited vulnerabilities during crises such as the COVID-19 pandemic. Another study by Orellana and Pino (2021) encompassed 45 countries, including 35 high-income nations and 10 middle-income nations, offering empirical support for the UIRP hypothesis. They also brought attention to the fact that the amount of support for UIRP differs according on the country's income, with the policy being more popular in wealthy nations than in those with a more modest income. Uncovered Interest Parity may be broken in principle due to risk premiums, expectational mistakes, and shifting market assumptions (UIP) (Bacchetta & van Wincoop, 2021; Hashem, 2023). Risk premiums, expectational mistakes, and the shifting views of exchange rate factors have all been examined as potential answers to the mystery of UIP's failures (Engel *et al.*, 2019). Narayan (2022) introduced a novel present-value model to analyze the real exchange rate while incorporating a structured approach to the currency risk premium. This research allowed for the currency risk premium to be influenced by both the interest rate differential and a latent factor referred to as the elusive risk premium. In accordance with the empirical data, the present-value model suggested that the real exchange rate could function as an indicator for currency returns. The findings of this study revealed that the predominant source of variation in the real exchange rate was attributable to the elusive risk premium, rather than the interest rate differential. Additionally, the model offered valuable insights into the intricate interplay among the interest rate differential, the real exchange rate, and the currency risk premium.

Although the UIRP theoretical framework still possesses several limitations when explaining exchange rate fluctuations in real-world scenarios, its predictive potential remains viable if UIRP manifests itself. The studies conducted by Ismailov and Rossi (2018); Khoa and Huynh (2022) catalyzed this research. In this study, we extend the work of Khoa and Huynh (2022) by merging the uncertainty factor introduced by Ismailov and Rossi (2018) with the predictive capacity of the Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) algorithm for forecasting bilateral exchange rates between the US Dollar and the Vietnamese dong. This research utilizes VND/USD spot exchange rate data from January 2010 to January 2023, employing a rolling window approach, and conducts a comparative analysis with Random Walk, SVR, and Ordinary Least Squares (OLS) models.

Today, foreign exchange investment is an open field expected to be effective for investors. Effective forecasting gives investors many opportunities to maximize the profits they bring. For foreign exchange-related businesses, the exchange rate risk is always on the porch; businesses can adopt forward contracts to reduce exchange rate risk. However, this solution can incur many costs for the business. Therefore, effective forecasting of exchange rates will help businesses save costs. For managers, stabilizing the exchange rate is one of the important goals of monetary policy. Effective exchange rate forecasts help policy-makers be more proactive in decision-making and fulfilling the set goals. Scientifically, this study contributes to the method of forecasting exchange rates by overcoming the limitations of previous research, incorporating the economic policy uncertainty index (EPU) to measure economic uncertainty and some powerful algorithms in Machine Learning, as in research by Khoa and Huynh (2023); Khoa *et al.* (2022)

2. Literature Review

2.1. UIRP theory

Uncovered interest rate parity states that, under perfect market conditions and a bilateral nominal exchange rate of S_t, investors can buy $1/S_t$ of foreign bonds in the domestic currency currently, where S_t is the value of the foreign currency in terms of the domestic currency at time *t*. Assume foreign bonds paid to a bond unit with foreign interest rates between time t and $(t+h)$ is i^*_{t+h}, with h being the term of the investment (Bonds). At the end of the period, the expected rate of return of foreign investments that can be converted into a local currency is $S_{t+h}\,[(1+\,i^*_{t+h})]/S_t$. In the absence of transaction costs, since there is no price difference business, this expected lucrative rate must be equal to the lucrative rate of domestic bonds, $(1+\,i_{t+h})$; therefore, $(1+\,i^*_{t\,+\,h})\,E_t(S_{t+h}/S_t) = (1\,+\,i_{t+h})$, which E_t represents the expected value at time *t*. By taking logarithms and ignoring Jensen's inequality, the equation is equivalent to the following: $E_t(s_{t+h} - s_t) = \beta_0 + \beta_1(i_{t+h} - i^*_{t+h})$ (1), in which: $s_t = ln\,(S_t)$, $s_{t+h} = ln\,(S_{t+h})$, value β_0, β_1 theoretically valuable is $\beta_0 = 0, \beta_1 = 1$.

Meese and Rogoff (1983) used the GMM method and the Random Walk model for exchange rate forecasts. The results showed that the Random Walk model had an RMSE (Root Mean Square Error) and a better sample in large countries during the floating rate period. Froot and Thaler (1990) synthesized 75 different studies on UIRP theory. In particular, the angular coefficients are largely negative or nearly zero; furthermore, the average of these coefficients is -0.88. This is strong evidence that rejects the UIRP theory in practice. Rossi (2006) studied the stability of parameters based on the difference in output, money supply, and interest rates of the two countries. The results show that there is evidence that regression coefficients change over time. This suggests that there exists a factor that causes coefficients to fluctuate over time. Continuing research, Ismailov and Rossi (2018) used uncertainty in the UIRP model. The results show that UIRP exists during a period of low uncertainty. Parot *et al.* (2019) used an artificial neural neuron network (ANN), ARIMA, self-regression vector (VAR), and vector error correction model (VEC) for forecasting EUR/USD, GBP/USD and JPY/USD rates for 1999-2015. Originally saved the proposal to incorporate VAR-VEC-ANN in exchange rate forecasts. The results show that the model combines the most effective forecast. Khoa and Huynh (2022) used the SVR algorithm to forecast VND/USD rates during the COVID-19 pandemic. Compared to the OLS method and the Random Walk model, the study proved the most effective SVR warning pattern by using the roll window method.

2.2. LSTM-RNN

The neural network in question is a recurrent neural network (RNN). As can be seen in Figure 1, the RNN network's output o_t at any given node is dependent not only on the input x_t at that node, but also on the output o_{t-1} of the node immediately before it. The function can express this: $o_t = f(W_{input}x_t + W_{output}o_{t-1} + b)$; where *f* is the cell's activate function; x_t, o_t are input, RNN output at time *t;* W_{input}, W_{output} is the matrix of parameters to find the model, and *b* is the model's vector bias. One limitation associated with the RNN model is its suboptimal performance in addressing long-term memory challenges. To address this limitation, Hochreiter and Schmidhuber (1997) introduced the

LSTM (Long Short-Term Memory) model, which represents an improved iteration of the RNN, effectively mitigating the inherent shortcomings of the original RNN model. A schematic representation of a typical LSTM architecture can be found in Figure 2. Within this model, each cell at time *t* receives not only the input value x_t but also incorporates the C_{t-1} state and the output value o_{t-1} from the preceding time step

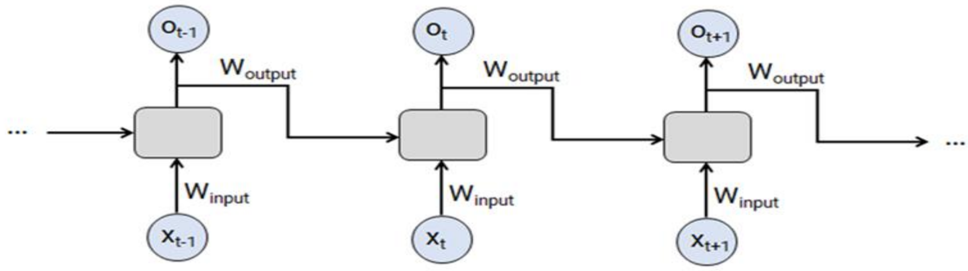

Fig.1: RNN structure

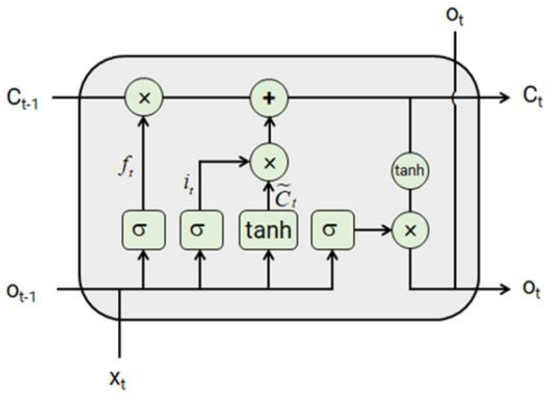

Fig.2: A typical LSTM cell

The long-term information about the cell's output is included in its state, or C_t, in addition to its output value, o_t. This makes it feasible for LSTM to learn more successfully when learning relies on long-term memory, which is an advantage over the RNN model. The model makes use of the following mathematical functions:

$$f_t = \sigma\left(W_f \cdot [o_{t-1}, x_t] + b_f\right) \ (2)$$

$$i_t = \sigma(W_i \cdot [o_{t-1}, x_t] + b_i) \ (3)$$

$$\tilde{C}_t = tanh(W_C \cdot [o_{t-1}, x_t] + b_C) \ (4)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \ (5)$$

$$o_t = \sigma(W_o \cdot [o_{t-1}, x_t] + b_o) \ (6)$$

Internally, LSTM employs a forget gate connected to a sigmoid (logistics function as in) to choose which input data will be remembered and which will be dismissed (2). This function's computation of ft will be utilized to derive o_t, C_t using the formula (5). (6). C_t cell state is updated with the information from (3) and (4), which specify which new information will be merged with the information maintained to generate a new state, $\tilde{C}_t$. In the realm of financial forecasting, deep learning has recently attracted increased interest. Ding *et al.* (2015) implemented a convolution neural network (CNN) to handle events collected from news websites to predict the S&P index. H. Chen *et al.* (2017) implemented a recurrent neural network to analyze news content on social media. Maneejuk and Srichaikul (2021) used machine learning models to forecast foreign exchange markets. This study used SVR, ANN, LSTM-RNN, and ARIMA algorithms to forecast several currency pairs such as JPY/USD, USD/GBP, EUR/USD, CHF/USD, and CAD / USD, period 2012-2018; the results showed that the LSTM-RNN model is most effective. Khoa and Huynh (2023); Khoa *et al.* (2022); Khoa *et al.* (2023b) applied several algorithms in machine learning such as SVR, LSTM-ANN in the pricing model and obtained some important results. Lu (2022) studied the GBP/CNY exchange rate forecast for 1/2020 – 12/2021. Comparing 3 models, ARIMA, LSTM, and GRU, the study concludes that the LSTM model is the most effective.

3. Methodology

The data collected includes the daily closing price of the VND/USD exchange rate between January 1, 2010, and July 31, 2023, and 6-month government bond rates of the US and Vietnam. The variables in the model are summarized in Table 1.

Table 1. The variable description

Variables	Formula	Description
S_t		The spot currency rate's closing price (VND/USD) at time t.
S_{t+h}		The exchange rate's closing price at time t+h
ivn6m		Vietnamese government bond interest rate for 6 months
ius6m		US government bond interest rate for 6 months
DS_t	$\ln(S_{t+h}) - \ln(S_t)$	Exchange rate fluctuations
Di_t	ivn6m – ius6m	Interest rate variations in two nations
EPU		Index based on the number of newspaper articles.

Firstly, this study tests whether the UIRP theory is empirically appropriate; then, it made the S_{t+h} forecast using the rolling window method and used F-Test to verify the effectiveness of the forecasting models, where h is 6 months. For UIRP theory testing, this research follows the sequence: The Engle-Granger cointegration test, regression according to equation (1), and simultaneous testing. $\beta_0 = 0, \beta_1 = 1$. UIRP theory predicts that DS_t and Di_t are cointegrated and $\beta_0 = 0, \beta_1 = 1$. The coefficient related to economic policy uncertainty (EPU) in Vietnam elucidates the connection between disparities in interest rates and exchange rates between two nations. EPU, in this context, arises from factors such as inflation, negative economic growth, financial crises, unconventional adjustments in lending rates, pandemics, elevated unemployment rates, foreign exchange fluctuations, and unforeseen shifts in monetary policy. EPU can manifest itself through unexpected alterations in monetary, fiscal, and regulatory policies, largely stemming from uncertainties surrounding potential policy changes. It characterizes the uncertainty surrounding the potential impacts of new policies on both the economy and the private sector. This research leveraged the EPU index in conjunction with the UIRP theoretical framework to project exchange rates.

Accordingly, three forecasting models, including the RW model, OLS regression, and LSTM-RNN using the rolling window method, were used to forecast for S_{t+h}.

- LSTM-RNN model: $DS_t = f(Di_t, EPU_t)$; OLS regression model: $DS_t = \widehat{\beta_0} + \widehat{\beta_1} Di_t + \widehat{\beta_2} EPU_t$. The forecast values of both models are: $S_{t+h} = exp(DS_t + S_t)$;
- RW model: $E\left(S_{t+h}\right) = S_t$ the forecast value is also S_t.

RMSE (Root Mean Squared Error) is applied as evaluation criteria to compare forecast results $RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}}$; in which, Y_t, Y_t respectively, are actual values and forecast values.

Finally, the F-Test is used for true efficiency testing of models.

4. Results

Faced with a significant surge in inflation during 2010 and 2011, the State Bank of Vietnam adopted a stringent monetary policy to combat inflation. However, this period also witnessed the emergence of several financial and monetary issues that had lasting consequences, including tightening monetary policy, reduced money supply growth, mobilization and credit decreased sharply; banking system liquidity was tense, interbank interest rates were high; loan interest rates skyrocketed; the bad debt ratio of the banking system increased; the problem of cross-ownership between banks is increasing; the asset market (stock market, real estate market) declined sharply. From 2011 to 2014, this period was marked by significant fluctuations, particularly concerning issues within the banking sector, notably the rising problem of bad debt. However, since 2014, following a period of decline and stability at a low level, Vietnam's Economic Policy Uncertainty Index began to rise again in the fourth quarter of 2020 and the second quarter of 2021. The impact of the Covid-19 pandemic can explain this increase. Nevertheless, in the second quarter of 2022, Vietnam's Economic Policy Uncertainty Index increased once more, nearly reaching the levels seen in the third quarter of 2010. This escalation in the index can be attributed to external factors, such as the rising global inflation and the US Federal Reserve's policy of increasing interest rates, which exerted pressure on exchange rates, as shown in Figure 3.

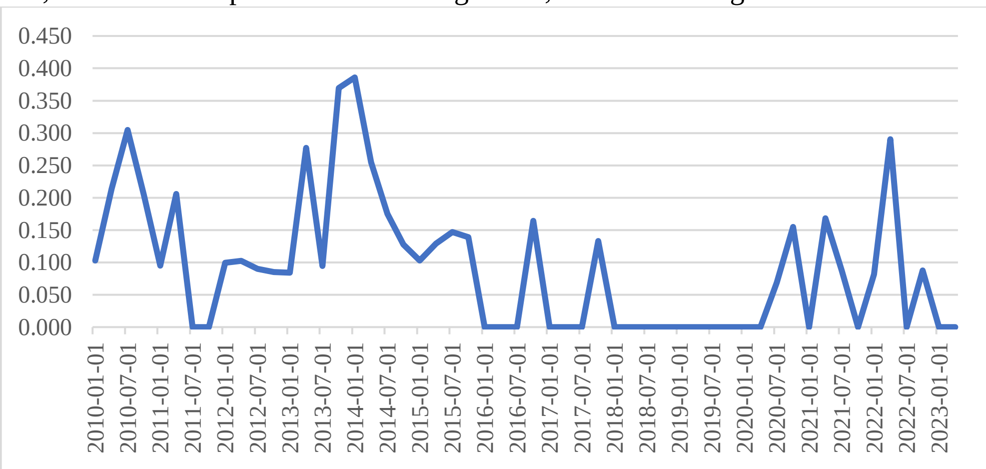

Fig.3: EPU fluctuations

Descriptive statistics in Table 2 show that the VND/US exchange rate is very stable, ranging from 19,050 VND/1 USD to 24,840 VND/1 USD, with an average value of 22,168,936 VND/1 USD due to Vietnam's monetary policy. From 2010 to 2014, due to the impact of the global financial crisis, Vietnam's central bank implemented a policy to control inflation and boosted interest rates mobilized through bond and savings channels. Compared to Vietnam, interest rates in the US during this period were stable at a low level. In contrast to Vietnam, the US government implemented many stimulus measures to restore the economy, resulting in low-interest rates at this stage in the US (Figure 2). In the next step, while interest rates in Vietnam continue to decrease, the FED increases interest rates to tighten monetary policy to curb inflation. From 2022 to 2023, under pressure from global inflation due to the impact of the COVID-19 pandemic and the energy crisis, both Vietnam and the US will increase interest rates to curb inflation.

Table 2. Descriptive statistics of variables.

Statistics	S_t	*DS*	*ivn6m*	*ius6m*	*EPU*
Mean	22168.936	0.142	4.878	0.785	0.090
Median	22645.000	0.000	4.211	0.112	0.084

Standard Deviation	1170.307	0.928	3.399	1.253	0.104
Kurtosis	-0.542	24.367	0.051	3.421	0.592
Skewness	-0.495	2.884	0.868	1.966	1.120
Minimum	19050.000	-4.140	0.270	-0.010	0.000
Maximum	24840.000	7.080	13.543	5.372	0.386

An important point from Figure 4 is that there is a breaking point between interest rates in the US and Vietnam at the time of the Covid-19 pandemic. Specifically, before this period, interest rates in the US and Vietnam tended to go in opposite directions, but they correlated in the same direction after this period.

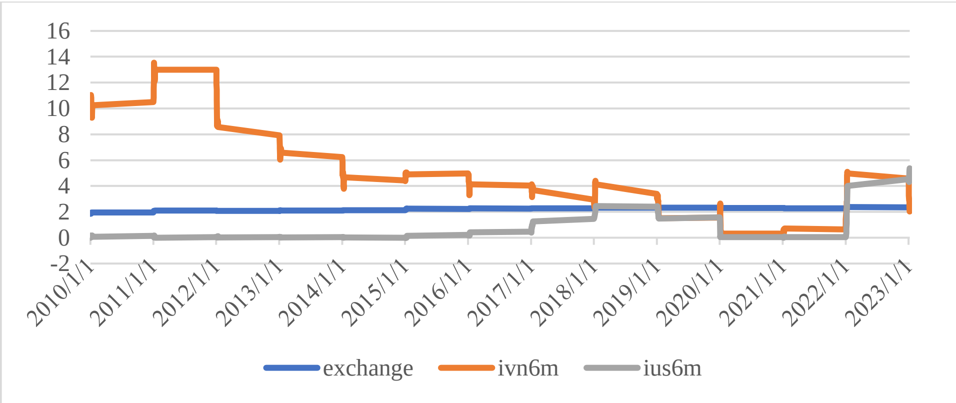

Fig.4: Exchange rate fluctuations (divided by 10,000), the 1-month interest rate in America and Vietnam.

Time series analysis cannot proceed without first checking for cointegration. There may be major repercussions, like false regression, if a time series is neither stable or cointegrated (Eryiğit & Durmuşoğlu, 2022). The alternative, "stationary," hypothesis is supported since the p-value in Table 3 is less than 0.05. The findings of the tests in Table 3 indicate that *DS* and *Di* are cointegrated.

Table 3. The Augmented Dickey-Fuller Test result

Augmented Dickey-Fuller Test
data: resid(reg)
Dickey-Fuller = -5.3817, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

The outcomes of applying regression to Equation 1 are shown in Table 4. At the 0.05 level of significance, the findings of the regression indicate a linear connection between the interest rate disparity and the exchange rate differential. The slope, however, b1 = 0.193, is much less than 1. Indeed, use the T-test to test whether the slope is equal to 1 or not. Specific calculation $t\_stat = (b1 - 1)/SE = -22.5$, and the corresponding p-value is approximately 0. This result proved that the UIRP model is invalid.

Table 4. Regression results of UIRP model

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.047	0.203	0.233	0.816
Di	0.193	0.036	5.381	0.000

This study used three models (LSTM-RNN, OLS, RW) to forecast the VND/US exchange rate from January 1, 2010 to July 31, 2023. Due to the characteristics of the time series, we use the rolling window method instead of dividing the data into 2 train-test sets. Furthermore, the financial market is efficient, so the older the information, the less effective it becomes in forecasting (Aslam *et al.*, 2020). Three years of historical data were analyzed to forecast the next observation. The forecast results of the three models are summarized in Table 5 and Figure 5.

According to Figure 5, all three models make predictions quite close to the actual value, in which the LSTM-RNN curve (predicted by the LSTM-RNN model) is closer to the exchange rate curve than the OLS curve (predicted by the LSTM- RNN model) using OLS model). and RW (predicted using the RW model). These results can be explained by the uncertainties affecting the equilibrium in UIRP theory.

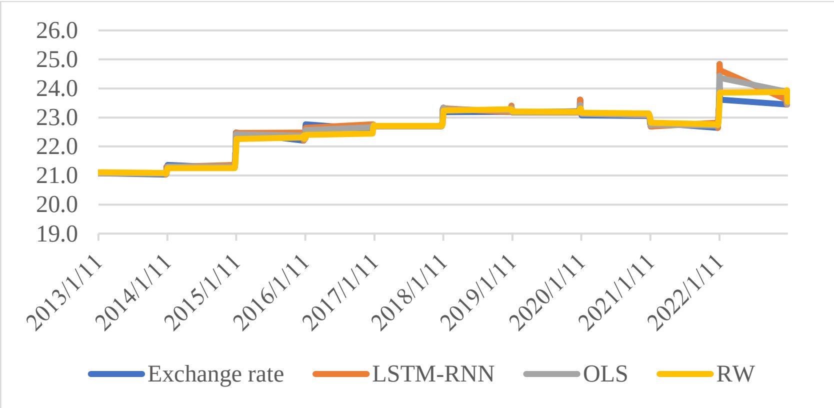

Fig.5: Actual exchange rate and model forecast value (thousand VND/USD)

Table 5 summarizes the forecast errors and tests the performance of the models, showing that the LSTM-RNN model is the best forecasting model, the RW model is the worst forecasting model among the three models with an RMSE of only 143.4254 and the least efficient RW model with an RMSE of 182.7282.

Table 5. Comparison of RMSE of models

Groups	*Count*	*Sum*	*Average*	RMSE
LSTM-RNN	121	9451	78.10744	**143.4254**
RW	121	18012.57	148.8642	**236.207**
OLS	121	11713	96.80165	**182.7282**

To support the conclusion, F-test was used to test the difference between different forecasting models. The results of analysis of variance (ANOVA) is shown in Table 6. The F-test results show that the p-value = 0.001 < 5%, so we can conclude that there is a difference in the forecasting effectiveness of the models. In other words, the ANOVA table supports the conclusion that LSTM-ANN is the most effective model.

Table 6. ANOVA analysis table

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	325349.2	2	162674.6	6.655688	**0.001451**	3.0208
Within Groups	8798918	360	24441.44			
Total	9124267	362				

5. Conclusions

5.1. Discussion

The foreign exchange market is one of the largest financial markets in the world. Reasonable exchange rate forecasts can help investors increase profits and minimize risks. However, the foreign exchange market is one of the most efficient markets and is affected by many factors, such as national economy, politics, society, and certain economic conditions. Therefore, researchers find exchange rate forecasting challenging (Khadjeh Nassirtoussi *et al.*, 2015). The trend to replace traditional forecasting models is to use advanced algorithms in machine learning. There are two approaches to forecasting models: technical analysis and fundamental analysis. Therefore, technical analysts believe that exchange rates will trend and use several indicators and charts to make decisions (W. Chen *et al.*, 2021); some researchers use fundamental analysis based on the intrinsic value of currency pairs, including various economic conditions, monetary policy, country risks to predict exchange rate quotes (Fasanya *et al.*, 2021). However, the relationships between variables are complex and non-linear, making it difficult for traditional forecasting models to be effective. Several studies have shown that machine learning techniques are more effective than traditional econometric techniques (Khoa *et al.*, 2023a; Khoa *et al.*, 2023b).

The RNN family of models includes the LSTM model. Its main contribution is the introduction of a self-loop design for producing a gradient's route that can flow continuously for a long time. The gradient vanishing issue that is naturally created by the RNN model updating the weights is avoided by additionally updating the weight of the self-loop in each iteration (Fazeli & Houghten, 2019). Non-linear parameter fitting is the backbone of time series modeling. The LSTM model does well in both achieving its predictive goal and revealing the correlation of a non-linear time series in the delay state space (He & Droppo, 2016). This research combined the UIRP theoretical framework and the LSTM-RNN algorithm to forecast exchange rates. The effectiveness of this model is shown in that UIRP will provide some important inputs, and the LSTM-RNN algorithm will exploit the complex relationships between variables. As a result, when compared with RW and OLS models, LSTM-RNN is the most effective, with the lowest value of RMSE. This result is consistent with previous studies such as Qu and Zhao (2019).

Although many studies build exchange rate forecasting models, these studies reveal many shortcomings. Such as, Australian Dollar/Japanese Yen (AUD/JPY), New Zealand Dollar/U.S. Dollar (NZD/USD), and British Pound/Japanese Yen (GBP/JPY) exchange rate predictions were made using Convolutional Neural Networks (CNNs) by Panda *et al.* (2022) between January 1, 2003 and May 31, 2020.. Panda *et al.* (2022) divided the data set in a ratio of 80:20 to the train-test set. Splitting this data will reduce predictive ability because the data is too old to estimate the parameters in the model. Furthermore, the input variables have not been proven to impact prediction, and finally, the effectiveness of the CNN model has not been tested through tests such as T-test or F-test. Some other studies also have similar shortcomings as using flags as input and splitting the dataset into training tests (W. Chen *et al.*, 2021); they did not demonstrate that the inputs had predictive value, and there were no statistical tests to demonstrate the effectiveness of the predictive models.

According to the study's findings, the gap between Vietnam and the United States' interest rates and their respective exchange rates is linear, supporting the UIRP framework. Furthermore, the regression results also demonstrate that UIRP is invalid. This result is consistent with previous studies (Ismailov & Rossi, 2018; Khoa & Huynh, 2022). However, compared to the study of Khoa and Huynh (2022), this study result has an initial coefficient close to 0. This result is consistent with the intercept coefficient of the UIRP theoretical model. The research of Khoa and Huynh (2022) can explain that during the COVID-19 period, the structure was broken, causing the intercept coefficient to deviate from 0.

The Random Walk (RW) model demonstrates proficiency in short-term forecasting (Meese & Rogoff, 1983); however, its efficacy diminishes when applied to longer-term predictions. On the other hand, Ordinary Least Square (OLS) regression models represent an intermediary approach bridging theoretical models and Machine Learning algorithms. They furnish empirical evidence of statistical relationships among variables present in theoretical models, particularly establishing a linear association between interest rate and exchange rate differentials. Although all error metrics in Table 5 support the LSTM-RNN model, its reliability still requires rigorous testing. A novel aspect of this study is the amalgamation of the Uncovered Interest Rate Parity (UIRP) theoretical framework with the LSTM-RNN algorithm to construct a forecasting model. The efficacy of this approach has been substantiated through a comparative analysis with two models, OLS and RW, where the F-test corroborates the superior predictive performance of the LSTM-RNN model over OLS and RW.

5.2. Conclusion

The primary contribution of this research lies in its innovative approach to forecasting exchange rates over the next six months by combining the Uncovered Interest Rate Parity (UIRP) theory with the UIRP algorithm in the context of economic policy uncertainty. The integration of theoretical models and Machine Learning algorithms, particularly the LSTM-RNN, has demonstrated its effectiveness in predictive accuracy. However, it's worth noting that the efficacy may still be contingent on specific circumstances. Hence, future research endeavors should expand to encompass a broader spectrum of countries and longer timeframes to bolster the model's reliability.

UIRP theory elucidates the connection between interest rate differentials and exchange rate disparities. In the Vietnamese dong and the US context, empirical findings do not align with UIRP; nevertheless, a positive linear relationship between interest rate differentials and exchange rate disparities persists. The LSTM-RNN model, which amalgamates UIRP theory with the LSTM-RNN algorithm, has proven to be highly effective in forecasting. Notably, the LSTM-RNN model yielded the lowest error rates, with the F-test affirming its superiority over the two alternative models examined, namely OLS regression and RW.

Beyond its theoretical contributions, this study offers valuable managerial insights for investors and businesses. Firstly, foreign currency trading, previously the domain of commercial banks, has evolved into a viable investment and business avenue for those seeking profits through exchange rate fluctuations. Given the rapid pace of international integration, the foreign exchange sector is becoming increasingly essential as an investment channel. Accurate forecasting can assist investors in optimizing returns within their portfolios. For businesses, exchange rate risk is a perpetual concern in foreign currency-related operations, incurring costs and potentially even jeopardizing solvency. This risk can be mitigated through derivative contracts with hidden risks. The forecasting method proposed in this research offers a solution that can substantially reduce costs associated with exchange rate risk, thus enabling businesses to maximize their value.

Several research limitations in this study open up avenues for further exploration. The existing UIRP model does not fully capture the dynamics governing exchange rates and interest rate differentials between two countries. Consequently, there is a pressing need to develop more suitable theoretical models in practice.

Acknowledgment

This research is funded by the Industrial University of Ho Chi Minh City under Contract for Scientific Research and Technology development No. 73/HĐ-ĐHCN signed on March 03rd, 2023.

References

Aslam, F., Aziz, S., Nguyen, D. K., Mughal, K. S., & Khan, M. (2020), On the efficiency of foreign exchange markets in times of the COVID-19 pandemic, *Technol Forecast Soc Change,* Vol. *161*, 120261. doi:10.1016/j.techfore.2020.120261

Bacchetta, P., & van Wincoop, E. (2021), Puzzling exchange rate dynamics and delayed portfolio adjustment, *Journal of International Economics,* Vol. *131*, 103460. doi:10.1016/j.jinteco.2021.103460

Chen, H., Xiao, K., Sun, J., & Wu, S. (2017), A Double-Layer Neural Network Framework for High-Frequency Forecasting, *ACM Transactions on Management Information Systems,* Vol. *7*, No. 4, 1-17. doi:10.1145/3021380

Chen, W., Xu, H., Jia, L., & Gao, Y. (2021), Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants, *International Journal of Forecasting,* Vol. *37*, No. 1, 28-43. doi:10.1016/j.ijforecast.2020.02.008

Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015). *Deep learning for event-driven stock prediction.* Paper presented at the Twenty-fourth international joint conference on artificial intelligence.

Engel, C., Lee, D., Liu, C., Liu, C., & Wu, S. P. Y. (2019), The uncovered interest parity puzzle, exchange rate forecasting, and Taylor rules, *Journal of International Money and Finance,* Vol. *95*, 317-331. doi:10.1016/j.jimonfin.2018.03.008

Eryiğit, K. Y., & Durmuşoğlu, V. (2022). The Joint Tests of the Parity Conditions: Evidence from a Small Open Economy. In *Advances in Econometrics, Operational Research, Data Science and Actuarial Studies* (pp. 63-79): Springer.

Fasanya, I. O., Adekoya, O. B., & Adetokunbo, A. M. (2021), On the connection between oil and global foreign exchange markets: The role of economic policy uncertainty, *Resources Policy,* Vol. *72*, 102110. doi:10.1016/j.resourpol.2021.102110

Fazeli, A., & Houghten, S. (2019). *Deep learning for the prediction of stock market trends.* Paper presented at the 2019 IEEE International Conference on Big Data (Big Data). doi:10.1109/BigData47090.2019.9005523

Froot, K. A., & Thaler, R. H. (1990), Anomalies: Foreign Exchange, *Journal of economic perspectives,* Vol. *4*, No. 3, 179-192. doi:10.1257/jep.4.3.179

Hashem, A. (2023), The Impact of Blockchain Technology on Financial Services: Mediating Role of Big Data Analytics, *Journal of Logistics, Informatics and Service Science,* Vol. *10*, No. 2, 91-107. doi:10.33168/JLISS.2023.0207

He, T., & Droppo, J. (2016). *Exploiting LSTM structure in deep neural networks for speech recognition.* Paper presented at the 2016 IEEE international conference on acoustics, speech and signal processing (ICASSP). doi:10.1109/ICASSP.2016.7472718

Hochreiter, S., & Schmidhuber, J. (1997), Long short-term memory, *Neural Comput,* Vol. *9*, No. 8, 1735-1780. doi:10.1162/neco.1997.9.8.1735

Husted, L., Rogers, J., & Sun, B. (2018), Uncertainty, currency excess returns, and risk reversals, *Journal of International Money and Finance,* Vol. *88*, 228-241. doi:10.1016/j.jimonfin.2017.07.011

Ismailov, A., & Rossi, B. (2018), Uncertainty and deviations from uncovered interest rate parity, *Journal of International Money and Finance,* Vol. *88*, 242-259. doi:10.1016/j.jimonfin.2017.07.012

Khadjeh Nassirtoussi, A., Aghabozorgi, S., Ying Wah, T., & Ngo, D. C. L. (2015), Text mining of news-headlines for FOREX market prediction: A Multi-layer Dimension Reduction Algorithm with semantics and sentiment, *Expert Systems with Applications,* Vol. *42*, No. 1, 306-324. doi:10.1016/j.eswa.2014.08.004

Khoa, B. T., & Huynh, T. T. (2022), Predicting Exchange Rate under UIRP Framework with Support Vector Regression, *Emerging Science Journal,* Vol. *6*, No. 3, 619-630. doi:10.28991/esj-2022-06-03-014

Khoa, B. T., & Huynh, T. T. (2023), The value premium and uncertainty: An approach by support vector regression algorithm, *Cogent Economics & Finance,* Vol. *11*, No. 1, 2191459. doi:10.1080/23322039.2023.2191459

Khoa, B. T., Huynh, T. T., & Huong, N. T. D. (2023a, 7-9 April 2023). *Predicting Returns of Exchange Rate from Oil Prices: Machine Learning Approach.* Paper presented at the 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), Lonavla, India. doi:10.1109/I2CT57861.2023.10126372

Khoa, B. T., Huynh, T. T., & Qin, L. (2022), Long Short-Term Memory Recurrent Neural Network for Predicting the Return of Rate Underframe the Fama-French 5 Factor, *Discrete Dynamics in Nature and Society*, Vol. *2022*, 1-8. doi:10.1155/2022/3936122

Khoa, B. T., Huynh, T. T., & Thang, L. D. (2023b), Effectiveness of OLS and SVR in Return Prediction: Fama-French Three-factor Model and CAPM Framework, *Industrial Engineering & Management Systems,* Vol. *22*, No. 1, 73-84. doi:10.7232/iems.2023.22.1.073

Lothian, J. R. (2016), Uncovered interest parity: The long and the short of it, *Journal of empirical finance,* Vol. *36*, 1-7. doi:10.1016/j.jempfin.2015.12.001

Lu, C. (2022). *The Long Short-Term Memory of GBP/CNY Exchange Rate Forecasts.* Paper presented at the 2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022). doi:10.2991/aebmr.k.220405.196

Maneejuk, P., & Srichaikul, W. (2021), Forecasting foreign exchange markets: further evidence using machine learning models, *Soft Computing,* Vol. *25*, No. 12, 7887-7898. doi:10.1007/s00500-021-05830-1

Meese, R. A., & Rogoff, K. (1983), Empirical exchange rate models of the seventies, *Journal of International Economics,* Vol. *14*, No. 1-2, 3-24. doi:10.1016/0022-1996(83)90017-x

Narayan, P. K. (2022), Understanding exchange rate shocks during COVID-19, *Financ Res Lett*, Vol. *45*, 102181. doi:10.1016/j.frl.2021.102181

Orellana, V., & Pino, G. (2021), Uncovered interest rate parity: A gravity-panel approach, *Heliyon*, Vol. *7*, No. 11, e08350. doi:10.1016/j.heliyon.2021.e08350

Panda, M. M., Panda, S. N., & Pattnaik, P. K. (2022), Forecasting Foreign Currency Exchange Rate using Convolutional Neural Network, *International Journal of Advanced Computer Science and Applications,* Vol. *13*, No. 2. doi:10.14569/ijacsa.2022.0130272

Parot, A., Michell, K., & Kristjanpoller, W. D. (2019), Using Artificial Neural Networks to forecast Exchange Rate, including VAR - VECM residual analysis and prediction linear combination, *Intelligent Systems in Accounting, Finance and Management,* Vol. *26*, No. 1, 3-15.

Qu, Y., & Zhao, X. (2019). *Application of LSTM neural network in forecasting foreign exchange price.* Paper presented at the Journal of Physics: Conference Series.

Rossi, B. (2006), Are exchange rates really random walks? Some evidence robust to parameter instability, *Macroeconomic dynamics,* Vol. *10*, No. 1, 20-38.