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Predicting Exchange Rate under *UIRP* Framework with Support Vector Regression

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Abstract

This study aimed to forecast the exchange rate between the Vietnamese dong and the US dollar for the following month in the context of the COVID-19 pandemic. It used the Support Vector Regression (SVR) algorithm under the Uncovered Interest Rate Parity (UIRP) theoretical framework; the results are compared with the Ordinary Least Square (OLS) regression model and the Random Walk (RW) model under the rolling window method. The data included the VND/USD exchange rate, the bank interest rate for the 1-month term, and the 1-month T-bill from January 01, 2020, to September 11, 2021. The research discovered a linear link between the two nations' exchange rates and interest rate differentials. Interest rate differentials are input variables to forecast interest rate differentials. Furthermore, the connection between the exchange rate and interest rate differentials during this era does not support the UIRP hypothesis; hence, the error for OLS predictions remains large. The study provided a model to forecast future exchange rates by combining the UIRP theoretical framework and the SVR algorithm. The UIRP theoretical framework can anticipate exchange rate differentials using the input variable and the interest rates between two nations. Meanwhile, the SVR algorithm is a robust machine learning technique that enhances prediction accuracy.

Keywords:

Exchange Rate;
UIRP;
SVR;
Predicting;
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1- Introduction

In international finance, *Uncovered Interest Rate Parity* (UIRP) is one of the essential theories explaining interest rate and exchange rate differentials between two countries. However, it is challenging to apply UIRP in practice due to its limited assumptions [1]. The exchange rate forecast for a 1-month period is basic in theory. Many studies propose exchange rate forecast models, but the evaluation of the effectiveness of forecast models remains limited. Specifically, (1) some researchers used past information to evaluate, such as *Autoregressive Integrated Moving Average* (ARIMA); yet while the foreign exchange market is currently mostly efficient, ARIMA is outdated and cannot improve its effectiveness [2]; (2) forecast results only apply in the short term, for example, only for (t + 1) day(s) [3]. Moreover, many researchers have made proposals toward data mining without basis in underlying theories; hence, there are no novel contributions either in theory or practice. Much research has been done on forecasting exchange rates by academics and practitioners. The market for currency exchange rates is thought to be very efficient. As a result, making reliable short- and long-term forecasts is challenging. Overcoming the Random Walk model has necessitated many forecasting methods, including volatility estimation and exchange rate forecasting. These methods may be broken down into a few different groups.

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Although the economic theory may help discover structural links between the exchange rate and other variables, statistical techniques can detect a time series' serial correlation structure and non-linearity [4, 5]. The foreign currency market often uses economic and time-series models. These methods' predictive accuracy has been called into question in many studies. However, others have shown that random walk models perform better than time series and economic models [6, 7]. Non-linear time series models have a high chance of changing over time, including the series' mean and variance. Engle [8] introduces an autoregressive conditional heteroscedasticity (ARCH) model to address this issue, which is extended by Bollerslev [9]. A new implementation of GARCH models has been suggested to address non-linearities and long-term memory [10, 11]. Over the past decade, nonparametric models have been widely utilized. This work has been facilitated by the development of new methods in Machine Learning and the growing power of computers. These techniques have been used in various applications, including stock price prediction, option pricing, and credit risk assessment [12, 13].

Recurrent networks, radial basis functions, and multilayer perceptrons are the most common statistical techniques. Consequently, linear models should be avoided when forecasting dynamic time-series behavior using statistical methods. This result is due to the market's efficiency concerning foreign currencies. The RBF network predicted the $US/$NZ exchange rate better than the LAR models [14]. Prior studies adopted a neural network model for forecasting the exchange rate between the Swiss Franc and US Dollar, and researchers found that forecasting is difficult when the market is efficient.

The ANN and chaotic models have also been compared to the random walk model [15]. According to Lisi and Schiavo [16], the ANN and chaotic models outperform the random walk model. Several academics have utilized and debated neural networks in the literature on exchange rate market predictions [13, 14, 17]. Vapnik [18] has created a novel classification and regression technique called the *Support Vector Machine* (SVM), which has been effectively used for many classification and regression problems [18, 19]. Forecasts for stock market indices, such as the NASDAQ and Dow Jones, and short-term stock prices have been made using Support Vector Regression (SVR) [20, 21].

Ordinary Least Squares (OLS) is a classical algorithm for estimating parameters to infer statistics. However, OLS requires a lot of assumptions (precisely, Gauss-Markov assumptions), which are very difficult to achieve with streaming data and applied statistics in the finance field [22, 23]. SVR is an algorithm that can overcome the weaknesses of OLS through its ability to learn and determine linear and non-linear structures [24, 25]. Thus, SVR has become a popular algorithm across theoretical frameworks, including the financial sector. While traditional econometric models suffer from assumptions hardly met in practice, Machine Learning models suffer from the problem of the underlying theoretical framework.

This study contributes interdisciplinary finance and data science knowledge based on international financial theory (UIRP) and a machine learning algorithm (Support Vector Regression). It (1) adopts SVR, a machine learning algorithm for research widely, resulting in more accurate results; (2) the forecast t + h period can extend further than in prior studies and facilitate investment with proper calculations for foreign exchange operations. In this case, the Random Walk (RW) model is considered the most effective. In the Vietnamese context, this study tested and rejected UIRP, but the linear relationship is statistically significant. Therefore, the RW and OLS models should be considered; the SVR model exploits the latent non-linearity in this relationship.

2- Literature Review

2-1- Uncovered Interest Rate Parity (UIRP)

The purchase of $1/S_t$ units of foreign bonds with one home currency would be possible if investors had complete foresight and a nominal bilateral exchange rate. The exchange rate of one currency versus another at a particular time t is represented by S_t. In the period h, the investor will receive an international interest rate i^*_{t+h}. Many investors expect to receive $S_{t+h}\frac{(1+i^*_{t+h})}{S_t}$ i_t after h day. Since there are no arbitrage or transaction costs, the expected return equals the home bond return $(1+i_{i+h})$. Hence, $E_t\frac{S_{t+h}}{S_t}(1+i^*_{t+h}) = 1+i_{t+h}$. The UIRP equation uses logarithms and disregards Jensen's inequality:

$$E_t(s_{t+h}-s_t) = \beta_0 + \beta_1(i_{t+h}-i^*_{t+h}) \tag{1}$$

where the $s_t = \ln(S_t)$, $s_{t+h} = \ln(S_{t+h})$, and the β_0 and β_1 parameters have the theoretical values $\beta_0 = 0$ and $\beta_1 = 1$.

Overall, the empirical data generates numerous conflicting views—for a recent review, see [26]. In some prior studies, the constant β_0 deviates from 0, the slope β_1 is less than zero, or the estimate gets zero value; furthermore, other research pointed out that β_1 has a higher value than 1. Either way, empirical evidence in out-of-sample prediction assessment does not support UIRP; it has been well known since Meese and Rogoff [27] that the Random Walk model better explains Equation 1 for out-of-sample data [12, 28, 29]. Clark and West [30] had somewhat more favorable results in the short term; the promising findings are attributable primarily to adopting an alternate measure of predictive capacity [30]. Ismailov and Rossi [1] have introduced an uncertainty index to explain the presence of UIRP. Consequently, UIRP continues under low-uncertainty circumstances; furthermore, there is a linear connection between exchange rate disparity and interest rate divergence.

2-2- The SVR Algorithm

In order to categorize the independent variables with N observations, a classification technique based on the Support Vector Machine (SVM) algorithm transfers them to a high-dimensional space using an SVM algorithm. This method was proposed by Vapnik [18], using the training set $\{(x_i, y_i)\}_{i=\overline{1,N}}$ to fit linear relationships with non-linear decision boundaries. The optimum hyperplane was calculated based on N observations to classify individuals, where **x** and **y** are the independent and categorical variables, and $(y_i \in \{-1,1\})$. Therefore, the subclass hyperplane is given by the Equation 2:

$$H: w^T \Phi(x_k) + b = 0 \tag{2}$$

where $\Phi: R^n \to R^m$ is the mapping from the original set to the higher dimensional space to facilitate classification.

By adjusting the weight w and the coefficient b, we can suppose that the shortest distance from the original set to the hyperplane (H) is equal to 1 for both classes. The SVM classification problem is finding the parameters w and b for the model.

For the k^th^ observation, if $w^T\Phi(x_k) + b \geq 1$, then $y_k = 1$, and if $w^T\Phi(x_k) + b \leq -1$ then $y_k = -1$, or we can combine to:

$$y_k(w^T\Phi(x_k) + b) \geq 1 \tag{3}$$

The model parameters are obtained by minimizing *w* and *b* with the constraint (3). The initial classification condition proposed by Vapnik [18] was $class(x) = sgn(w^T\Phi(x_k) + b)$. However, the mapping to a new space with Φ may still be imperfectly separated. Therefore, Vapnik [18] proposed a soft margin that allows some observations to be misclassified, using compensating variables ξ_k to measure the standard deviation of the k^th^ observation. Hence, constraint Equation 3 becomes:

$$y_k[w^T\Phi(x_k) + b] \geq 1 - \xi_k \tag{4}$$

Optimizing the objective function with constraint (Equation 4) to produce the following equation:

$$\min_{w,b}\left(\frac{1}{2}\|w\|^2 + C\sum_{k=1}^{N}\xi_k\right), \xi \geq 0 \tag{5}$$

where C is the correction parameter; the classification error is minimized in Equation 3.

Optimization (5) is transformed, according to Wolfe [31], to the form: $\min_{\alpha}\left(\frac{1}{2}\alpha^T P\alpha - e^T\alpha\right)$, where $\begin{cases} y^T\alpha = 0 \\ e^T = [1,2,\ldots,N] \\ 0 \leq \alpha_i \leq C \end{cases}$, and P is a square matrix with $P_{ij} = y_i y_j K(x_i, x_j)$. The function $K(x_i, x_j) = \Phi(x_i)^T\Phi(x_j)$ is called the kernel. The classification will be decided by $class(x) = sgn(w^T\Phi(x_k) + b)$.

Based on the same idea as the SVM algorithm, SVR is also similarly implemented, except that the dependent variable is continuous and takes on an actual value [32]. However, according to Qi and Wu [33], instead of finding the hyperplane, as in Equation 4, SVR finds a regression function, $f(x, w) = w^T x + b$. A boundary ε is introduced as follows:

$$|y - f(x,w)|_\varepsilon = \begin{cases} 0, \text{ if } |y - f(x,w)| \leq \varepsilon \\ |y - f(x,w)| - \varepsilon, if\ |y - f(x,w)| > \varepsilon \end{cases}$$

The SVR method minimizes L by ε and $\|w\|^2$ in the following expression:

$L = \|w\|^2 + c(\sum_{i=1}^{N}|y - f(x_i, w)|_\varepsilon)$, where c is the hyperparameter.

2-3- Relevant Studies

In an age of financial globalization and increasing connectivity among international markets, an exchange rate is crucial for defining a country's foreign policy [34]. However, since many factors may affect the exchange rate, it is very volatile. According to the "*Meese–Rogoff conundrum*," exchange rate models perform no better than a random walk, a finding well-documented in the literature. This result indicates that no basic structural model beats the random walk model in forecasting exchange rates [27]. No financial market strategy can consistently beat a strategy based only on chance. However, the literature has actively sought to develop models to forecast exchange rate behavior throughout the decades, a fiercely contested academic issue that has produced numerous contemporary scientific papers in high-impact journals [35].

The scientific literature regarding exchange rate forecasting can be divided into technical and fundamental analyses [36]. Mark [37] was one of the first to propose a basic model that outperformed the Random Walk, which served as the foundation for a slew of later research calling the Meese–Rogoff problem into doubt [38, 39]. Statistically, significant evidence from recent studies indicates that macroeconomic fundamentals have sufficient explanatory power to predict exchange rates and confirm a solid causal link between macroeconomic fundamentals and currency rates [40].

The financial literature increasingly uses machine learning techniques, which has led to excellent prediction outcomes and exciting research goals [41-43]. SVM models and their expansions (such as support vector regression or SVR) have produced acceptable results in many financial applications, as shown by papers outlining current best practices for exchange rate forecasting [15, 44, 45]. These models have been tested to see whether they can accurately forecast the spot nominal exchange rate of 10 currency pairs multiplied by the US dollar, Euro, British pound, and Japanese yen. These currencies were chosen because they are included in the SDR value basket of the International Monetary Fund, and the period under consideration was January 1, 2000–December 31, 2015. The leading independent variables are listed in table 1. Predictions used error measures such as root mean square error (RMSE) and mean absolute error (MAE), and White's Reality Check Test evaluated the statistical significance of the increased explanatory power of the model as compared to the Random Walk [46]. Most significant research on exchange rate forecasting has used monthly or quarterly data frequencies; the Random Walk without drift is the most challenging criterion to exceed, according to Rossi's findings [26]. Considering the highly dynamic nature of the FOREX market, data was gathered monthly, using the Random Walk without drift as a benchmark model to assess the SVR models' predictions.

Rossi [26] indicates that models with linear functional forms are still mainstream in exchange rate forecasting. However, Caginalp and DeSantis [47] discuss shreds of evidence of non-linearity patterns in financial data behavior. As a result, the models evaluated in this study included non-linear interactions between machine learning and Kernel techniques. The study uses White's test to determine which SVR models outperformed the Random Walk in explanatory power.

3- Research Method

Data were collected daily during the Covid-19 outbreak from January 01, 2020, to September 11, 2021, on the closing price of the VND/USD exchange rate, the 1-month deposit interest rate of Vietnamese-owned banks, and the interest rates of T-bills for a 1-month term. Data on the banks' deposit interest rates come from the official websites of the respective banks, while the VND/USD exchange rates and the 1-month T-bill rates are gathered from Datastream. The variables presented in the study are described in Table 1.

Table 1. Variable description

Variable	Formula	Description
S_t		The closing price of the spot exchange rate (VND/USD) at the point of time t.
S_{t+h}		The closing price of the rate at the point of time t+h
i_t	$i = \frac{1}{n}\sum_{j=1}^{n} i_j$	Average deposit interest rates of state-owned banks at the point of time t.
i_t*		The 1-month T-bill interest rate at the point of time t.
$deltaS_t$	$ln(S_{t+h}) - ln(S_t)$	Changes in the exchange rate
$deltai_t$	$i_t - i_t^*$	Changes in the interest rates of two countries

Figure 1 check whether the UIRP theory is valid in empirical reality; then, it performs S_{t+h} forecasts using the rolling window method and uses the T-Test to evaluate the efficacy of the forecasting models. To test the theory of UIRP, it tests for cointegration [48], then regresses the Equation 1 and simultaneously tests if $\beta_0 = 0, \beta_1 = 1$. UIRP theory predicts that deltaS and deltai should be cointegrated, with $\beta_0 = 0, \beta_1 = 1$.

The SVR model is $deltaS_t = f(deltai_t)$, applying a linear kernel function at the cost of 0.001. The OLS regression model is $deltaS_t = \widehat{\beta_0} + \widehat{\beta_0} deltai_t$. The forecast value of both models is $S_{t+h} = exp(deltaS_t + S_t)$. The RW model is $E(S_{t+h}) = S_t$, with a forecast value of S_t, as in Figure 2.

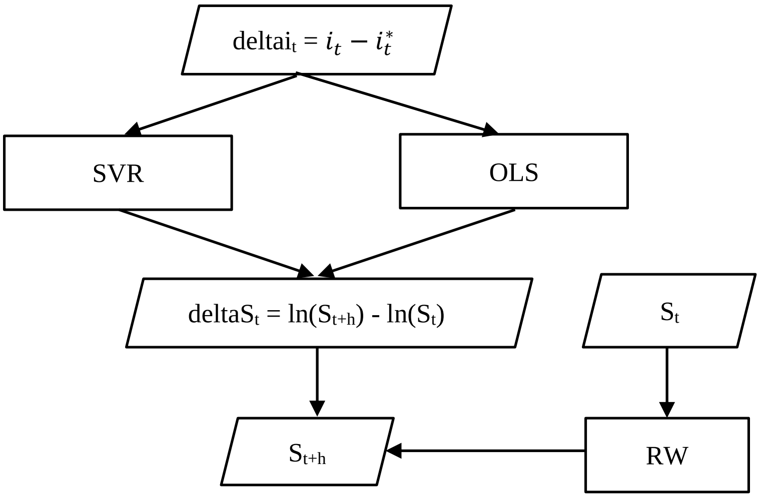

Figure 1. The research process

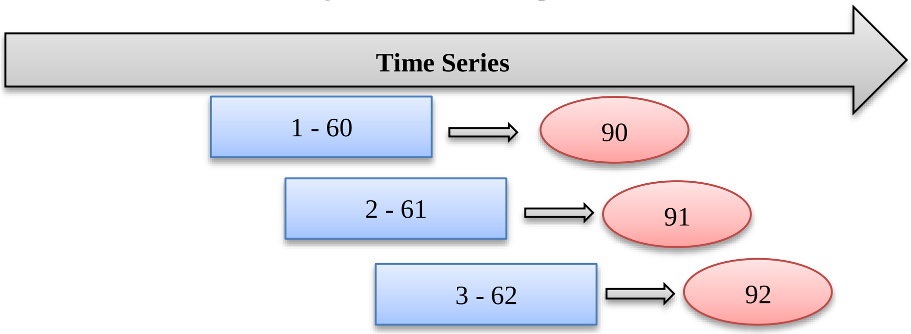

Figure 2. The rolling window method

This research used the MAE, RMSE, and MAPE (Mean Absolute Percent Error) to compare forecast results (100-104). Finally, it adopted the T-Test to check the actual performance of the models. In the following formulas, $Y_t, \hat{Y}_t$ represent the actual and anticipated values, respectively.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|, RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}}, MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t}$$

4- Results and Discussion

4-1- Descriptive Statistics

From Table 2, the VND/USD exchange rate was relatively stable during the Covid-19 pandemic outbreak period, ranging from 22,809 to 23,643.

Table 2. Variable statistics

Statistics	S_t	tb	rf	deltaS	Deltai
min	22,809	0.0001	2.9	-0.0097	2.819
median	23,057	0.081	3.5	-0.001	3.417
max	23,643	1.608	5.1	0.0171	3.537
mean	23,160	0.2372	3.51	-0.0009	3.277
standard deviation	138.9778	0.4626	0.6	0.0043	0.251

The exchange rate started to increase sharply from March 2020 due to the Covid-19 outbreak in Vietnam; investors were afraid of the impact of the pandemic, so they tended to hoard foreign currency. The purchasing power of foreign currency increased, pressuring the VND to depreciate relative to the USD, a situation that reached its peak in early April 2020 and then trended down, as shown in Figure 3.

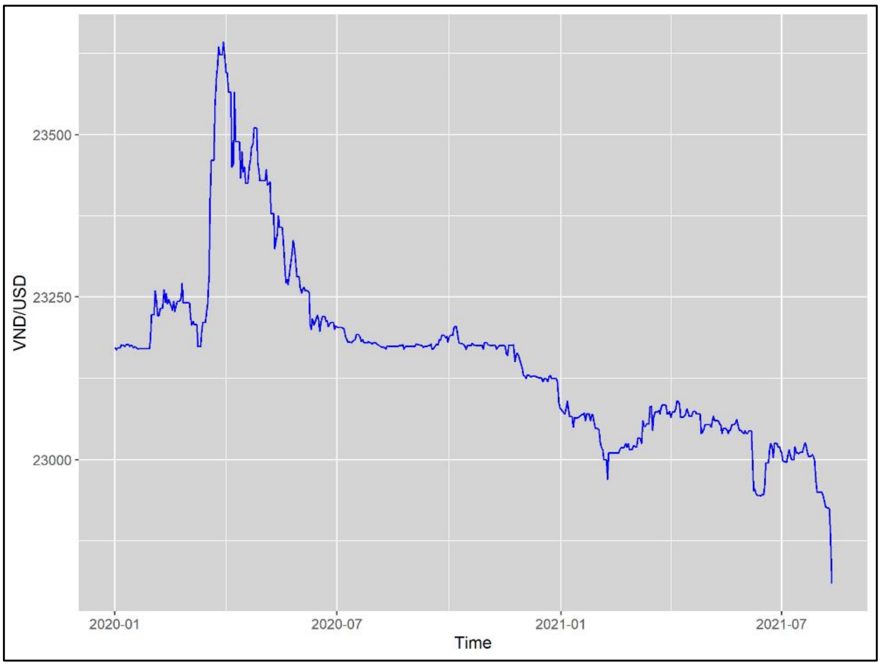

Figure 3. **The VND/USD exchange rate**

In early March, the deposit rates of Vietnamese banks fell harshly, along with T-bill interest rates; the cause may have been the excess supply of capital among the population. Investors were afraid the pandemic would affect production activities, so bank savings or government bonds were considered the optimal investment channel in this period, as shown in Figure 4. The research shows that lowering interest rates to stimulate economic growth is also a solution for national monetary policy during the Covid-19 pandemic. The Covid-19 outbreak created breakpoints in interest rates. This effect was most evident at the beginning of February 2020, when interest rates in the two countries fell suddenly and then stabilized. However, in Vietnam, a second Coronavirus outbreak occurred in early 2021, leading to a sudden drop in interest rates. Meanwhile, interest rates in the US also showed a slight decrease. This is because interest rates are shallow, close to zero, but unable to fall below it, as shown in Figure 4.

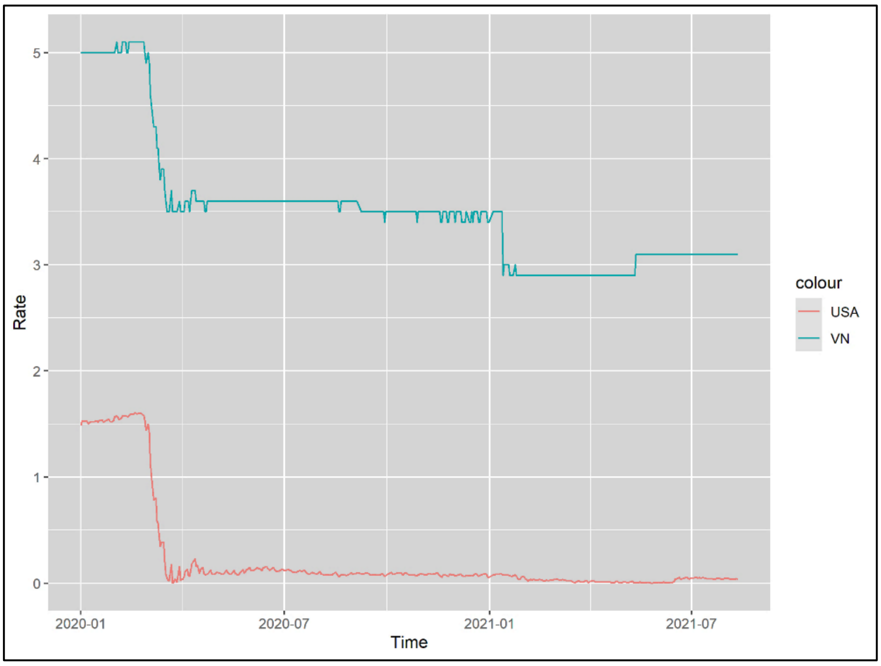

Figure 4. **Deposit and T-bill interest rate**

Based on Figure 5, the relationship between interest rate differential and exchange rate difference is complicated to explain in terms of UIRP. The result indicates that UIRP predicts a linear relationship with a slope of 1 and an intercept of 0. This relationship is shaped like a parabola, with a peak in the range *deltai* of 3.1, which means that the further the interest rate differential is from 3.1, the larger the exchange rate differential should be.

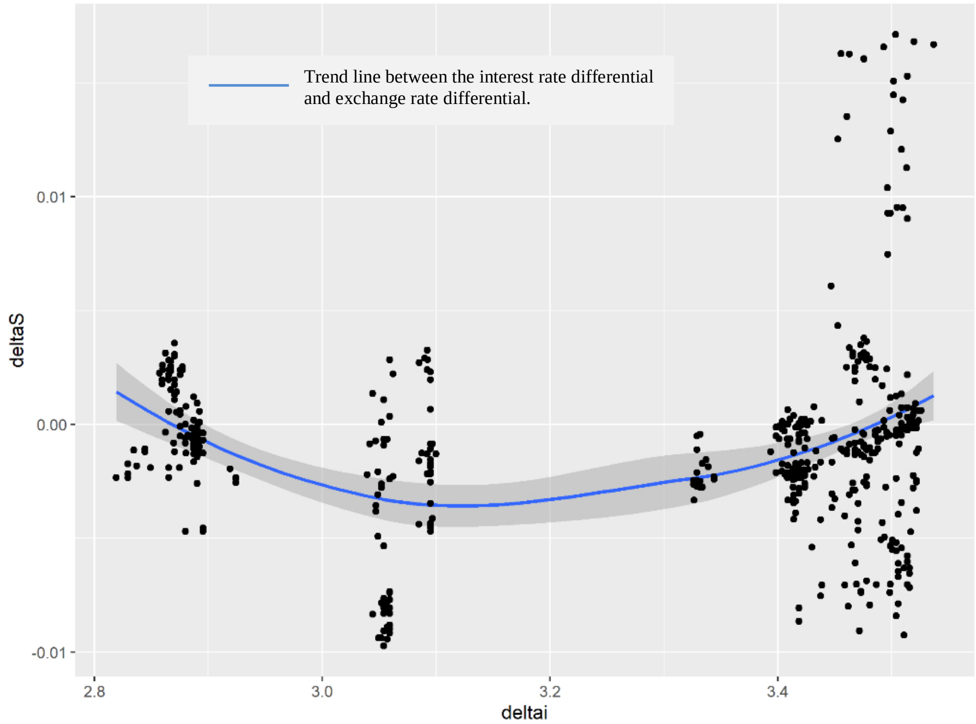

Figure 5. The interest rate differential and exchange rate differential

4-2- Testing for Cointegration

The cointegration test is essential in time series analysis. If a time series is neither stationary nor cointegrated, the consequences could be severe, possibly a spurious regression [48]. In table 3, the p-value is 0.01, which is less than 0.05; hence, the alternative hypothesis, "stationary," is supported. The test results show that deltaS and deltai are cointegrated.

Table 3. Testing for cointegration

data: resid(reg),
Dickey-Fuller index = -4.0926,
Lag order = 7, p-value = 0.01

4-3- OLS Regression

Performing a regression on Equation 1 gives the results in Table 4. Regression results show a linear relationship between interest rate differential and exchange rate difference at a significance level of 0.05. However, the slope b1 = 0.0016 is insignificant and far from 1. Indeed, this research can conduct a T-Test for the null hypothesis; the corresponding p-value is approximately 0. Moreover, the value of intercept b0 is less than 0 and statistically significant at 0.05, implying that the experiment does not support the UIRP theory.

Table 4. Regression results of Equation 1

Call: lm(formula = y ~ x, data = dta)

Residuals:

- Min = -0.0087753 ,
- 1Q = -0.0018499, 3Q = 0.001149,
- Median = -0.0000003, Max = 0.0176254

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0060981	0.0026143	-2.333	0.0201 *
x	0.0015985	0.0007954	2.010	0.0450 *

RSE: 0.004375, df = 480

R^2: 0.008344, Adjusted R^2: 0.006278

F-statistic: 4.039 on 1 and 480 DF, p-value: 0.04503

4-4- Forecast Results

From Figure 6, all three models have provided predictions quite close to the actual values, with the SVR line (forecast by the SVR model) being closer to the St line than those of OLS (forecast by the OLS model) and RW (forecast by the RW model). Specifically, during the outbreak period (from the beginning of 2020 to 7/2020 and 1/2021 to 7/2021), the forecast results of the RW and OLS models were further from the actual value than the SVR model. All three models predict very well in the stable period (7/2020 to 1/2021). These results can be explained by the uncertainty affecting the equilibrium in the UIRP theory [1]. Tables 5 and 6 summarize the models' forecasting errors and efficiency testing, showing that the SVR model is the best predictor and the RW model is the worst predictor of the three models. For the MAE criterion, the average forecast errors in the SVR, OLS, and RW models are 37.868, 45.763, and 57.74 VND/USD, respectively. There is a similar result when considering the RMSE criterion: the SVR model has the lowest mean error, with a value of 51.792 VND/USD, and the RW model is the least effective, with an error of 81.554 VND/USD. We know that the average exchange rate in this period is 23,160 VND/USD (Table 2), so the relative MAPE is deficient: 0.0016, 0.002, and 0.0025 for the SVR, OLS, and RW prediction models, respectively. Moreover, this study uses a T-Test for the output error series to consider the effectiveness of the three algorithms:

Hypothesis H1: There is no difference between SVR and OLS;

Hypothesis H2: There is no difference between SVR and RW;

Hypothesis H3: There is no difference between OLS and RW.

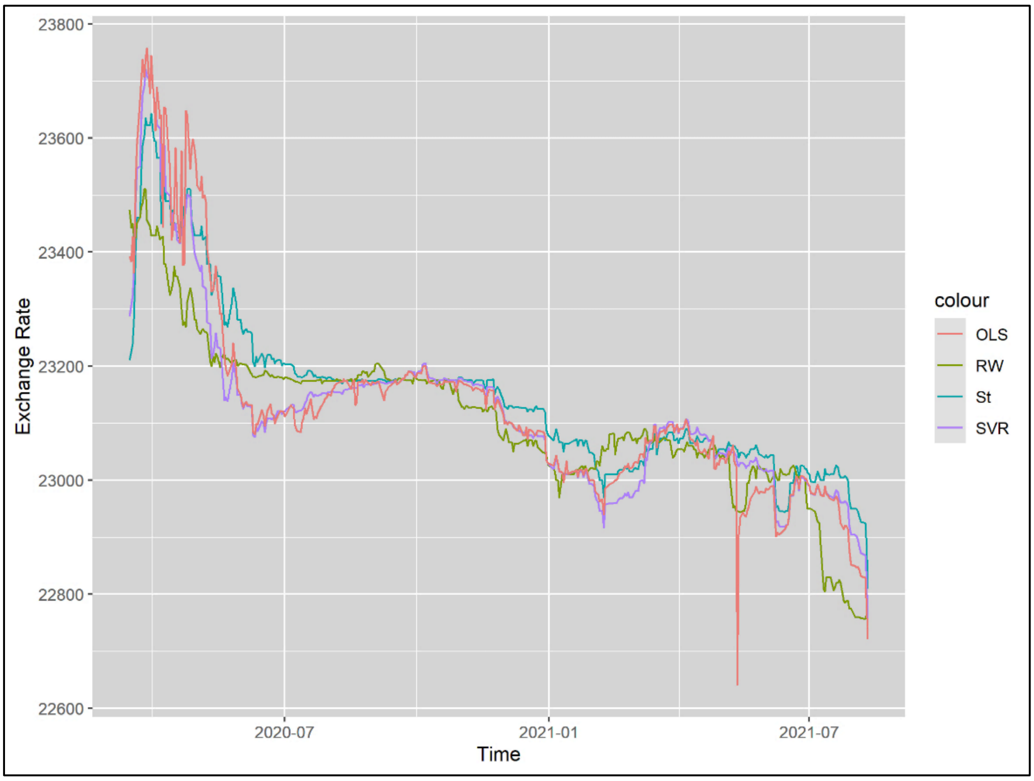

Figure 6. **Forecast results of VND/USD exchange rate**

Table 5. **Statistics of MAE, MRSE và MAPE**

Model	SVR	OLS	RW
MAE	37.868	45.763	57.74
RMSE	51.792	64.606	81.554
MAPE	0.0016	0.0020	0.0025

Table 6. **Results of T-Test**

T-Test	SVR vs. OLS	SVR vs. RW	OLS vs. RW
t-value	-2.8048	-6.0285	-3.3422
p-value	0.0026	0.0000	0.0004

5-1- Discussion

Empirical data during the Covid-19 period did not support the existence of UIRP; this result is consistent with Ismailov and Rossi [1], probably because either the uncertainty index was high or the UIRP assumptions were not met during this period. However, there is still a positive linear relationship between interest rate differential and exchange rate difference. Therefore, part of the changes in the exchange rate can be explained by changes in the interest rate differential between the two countries (Table 4). Ismailov and Rossi [1] used 3-month interest rates and experimented on developed countries; the results also proved that the non-zero intercept is statistically significant and the coefficient angle is either negative, close to 0, or too large relative to 1. Furthermore, deviations from the UIRP theory arise due to uncertainty. During the pandemic, interest rates in both countries tended to decrease (Figure 4). Interest rates in the US sometimes dropped to approximately zero during May 2021 (and obviously could not go below zero), while deposit interest rates in Vietnam were still high; this is why foreign capital was attracted to Vietnam, especially in the form of remittances. Under the pressure of an abundant USD supply, the spot rate tended to drop, which meant that the VND appreciated relative to the USD during this period.

The SVR model has firmly demonstrated its ability to forecast the exchange rate, with the lowest error of all three models. This result is also consistent with previous studies, such as Ince and Trafalis [49], Lu et al. [50], Yaohao and Albuquerque [51]; all of these studies show that the SVR model is adequate. However, unlike previous studies, this study made forecasts for the next 30 days, so the forecast accuracy decreased significantly. In addition, comparing absolute errors such as MAE and RMSE will not be possible when studies are carried out in different countries and measuring units. The MAPE could alternatively be used, as it is a relative measure effective for different studies. Ince and Trafalis (2008) [20] used the models ARIMA, VAR, ANN, and SVR, with daily exchange rates for Euro/Dollar, Pound/Dollar, JPY/Dollar, and AUD/Dollar, from January 1, 2000, to May 26, 2004. The results also show that the most effective SVR with MAE error for these four currency pairs is 0.001400, 0.003200, 0.098700, and 0.001600. Of course, it is not easy to compare the results of the two studies because of the difference in the units of calculation. A limitation of this study is that it does not use the rolling window method in forecasting, which reduces the signal in the estimation of input parameters due to the characteristics of the time series. Yaohao and Albuquerque [51] used 13 macro variables to forecast for ten currency pairs; their models include SVR with different input parameters and RW; consequently, they also had excellent SVR results.

The RW model can effectively forecast in the short term [27], but it gradually loses its inherent advantage when forecasting a more extended period. The OLS regression model is an intermediary between the theoretical model and the Machine Learning algorithm. It provides evidence for a statistical relationship between the variables in the theoretical model; specifically, a linear relationship exists between interest rate differential and exchange rate difference. Although the error indicators all support the SVR model, as seen in Table 5, it is still necessary to test its efficacy for more reliability. Table 6 is a statistically significant demonstration of the superior performance of the SVR model.

5- Conclusion

The main contribution of this study is to provide a method to forecast the next month's exchange rate by combining UIRP theory and the SVR algorithm. The combination of theoretical models and Machine Learning algorithms, especially SVR, has shown its effectiveness in forecasting. However, the effectiveness may still be within a specific range, so future studies need to extend to more countries and extended periods to increase the model's reliability. The UIRP theory explains the relationship between interest rate differential and exchange rate difference; empirical results in Vietnam during the Covid-19 pandemic do not support UIRP. However, there is still a positive linear relationship between interest rate differential and exchange rate difference in the Vietnamese dong and the US. The SVR model combines UIRP theory and the SVR Machine Learning algorithm that has been effective in forecasting. The SVR model gave the lowest error results, and the T-Test showed that it surpasses the other two models examined, OLS regression and RW.

Besides the theoretical contribution, this study offers some managerial implications for investors and businesses. First, for investors, foreign currency trading has long been a specialized operation of commercial banks that has become an investment and business channel for those seeking profit from changes in exchange rates. With the current solid international integration speed, the foreign exchange sector will become one of the economy's more official and essential investment channels. Accurate forecasting will help investors maximize returns in their portfolios. For businesses, exchange rate risk is always present in foreign currency-related businesses, incurring costs and maybe even leading to the risk of bankruptcy. This risk can be hedged using a derivative contract with hidden risk. The solution based on the forecasting method in this research will help businesses significantly save costs arising from exchange rate risk, thereby helping them maximize their value.

Some research limitations of this study provide opportunities for further research. The theoretical UIRP model does not fully forecast the relationship between two countries' exchange rates and interest rate differentials. Therefore, building a more suitable theoretical model in practice is necessary. The solution may include the uncertainty index in the UIRP model.

6- Declarations

6-1- Author Contributions

Conceptualization, B.T.K., and T.T.H.; methodology, B.T.K. software, T.T.H.; validation, B.T.K., and T.T.H.; formal analysis, B.T.K.; investigation, B.T.K.; resources, B.T.K.; data curation, T.T.H.; writing—original draft preparation, B.T.K.; writing—review and editing, B.T.K.; visualization, T.T.H. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6-5- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the authors have completely observed the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies.

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