Prediction of Exchange Rates with Machine Learning

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ABSTRACT

In this study a macroeconomic model is considered to predict the next month's monthly average exchange rates via machine learning based regression methods including the Ridge, decision tree regression, support vector regression and linear regression. The model incorporates the domestic money supply, real interest rates, Federal Funds rate of the USA, and the last month's monthly average exchange rate to predict the next month's exchange rate. Monthly data with 148 observations from the US Dollar and Turkish Lira exchange rates are considered for the empirical testing of the model. Empirical results show that the Ridge regression offers accurate estimation for investors or policy makers with relative errors less than 60 basis points. Policy makers can obtain point estimates and confidence intervals for analyzing the effects of interest rate cuts on the exchange rates.

CCS CONCEPTS

• Applied computing • Law, social and behavioral sciences • Economics

KEYWORDS

Machine learning, Regression estimation, Foreign exchange rates

1 Introduction

The prediction of exchange rates is a challenging, but equally, an important problem for policy makers and investors. Exchange rates can be considered as the major gauge for the economy. Depending on the exchange rate regime different determinants might be dominant in the determination of the trends in the exchange rates. For example, in countries like China where the domestic currency is not convertible and capital account has controls the determination of exchange rates are more directly dependent on the domestic conditions and the extent of capital controls. However, if we consider the economies with floating exchange rate regimes, the exchange rates are highly dependent on the expectations of the international funds that highly effect the exchange rates. Macroeconomic theory suggests that when a country has current account surplus this would help the currency to appreciate against foreign currencies. However, the size of international funds is often so large that the current account mechanism might not work as expected in short periods of time.

For the market based exchange rate regimes the most significant relationship is based on the no-arbitrage condition between the capital markets of two countries denoted as the domestic and foreign. In this no-arbitrage mechanism, the domestic and foreign interest rates are major variables that also show in the interest parity condition or the so called no-arbitrage condition given by

$$E[S_{t+h}] = S_t * (\frac{1+i_d}{1+i_f}), \quad (1)$$

where $E[S_{t+h}]$ is the expected value of the exchange rate at time *t+k*, S_t is the spot exchange rate at time *t*, and i_d, i_f are the domestic and foreign interest rates. However, it should also be noted that when we consider Equation (1) between the USA and say, an emerging market, the condition is not expected to hold exactly as an equation due to a relatively large risk premium added to their implied interest rates of the emerging market. This is because the interest parity equation above ignores the financial crisis risk and the difference between the reserve currency and a local currency.

2 Background and Literature

Incorporating the idea of no-arbitrage condition with the data driven approach we utilize machine learning algorithms for the first time in the literature to predict the next month's average exchange rate. The seminal work of Meese and Rogoff [1] shows that various structural exchange rate models fail to beat the random walk model both within the forecasting and the estimation frameworks. However, in this study, we show that structural relations can provide better predictive power when combined with machine learning techniques rather than the ordinary least squares estimation as often utilized in these structural models.

Existing literature on machine learning considers a wide range of machine learning algorithms, where lagged values or technical based indicators are utilized in the prediction of exchange rates in short time periods. In the studies by Weigend et al [2, 3] the performance of neural networks is compared with

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that of random walk in predicting the Deutsche Mark/US dollar exchange rate, showing the superior performance of the artificial neural networks model. Shen et al. [4] forecasts GBP/USD exchange rate using deep belief networks and conjugate gradient method. Qian and Rasheed [5] considers machine learning classifiers such as artificial neural networks, decision trees and *k*-nearest neighborhood methods to test the predictability of exchange rates. Other examples of machine learning algorithms applied in exchange rate prediction problems can also be found in Panda and Narasimhan [6], Ince and Trafalis [7], and Kuan and Liu [8]. Furthermore, in Ni and Yin [9] proposed a hybrid model formed by a mixture of various regressive neural network models based on the technical analysis indicators used with the daily time horizon.

A machine learning based classification problem, i.e. the prediction of up and down moves, for the exchange rate between the USD versus Mexican Peso is considered in the study Rojan and Herman [10]. However, the classification accuracy is rather low with 56% in the best case test sample. Overall, our approach is similar to the study by Amat et al. [11] where macroeconomic factors and the interest parity condition is considered for the prediction of the end of month exchange rates for major currencies between 1973 and 2014. Although this study is a comprehensive one with RMSE up to 1.3%, which is still higher compared to our results, is not suitable for policy analysis. From a policy maker's perspective or even from a trader's perspective the prediction of the end of month value, i.e. a single value in one month's time has not much value since the value observed on a single day would be too noisy to be utilized for policy analysis or trading strategies.

Alternatively, a trader can utilize our predicted monthly average exchange rate values to trade whenever the daily rate is below the predicted value of the given month. For example, if the predicted value is higher than the value of the current month, which implies a depreciation in the local currency is predicted, the trader can purchase foreign currency on the day's with exchange rate below the predicted value, realizing an average cost of the FX position that is lower than the predicted value of that month.

Overall, there is a gap in the literature to consider the prediction of exchange rates with macroeconomic features via machine learning algorithms. Therefore, in this study we consider powerful machine learning algorithms in a macroeconomic framework which provides strong policy implications as a byproduct. The contributions and possible implications of this study for researchers and practitioners can be summarized as follows.

First, machine learning algorithms are applied within a macroeconomic framework that also has strong rationale in terms of explanatory power. In particular, we show that the Ridge regression method offers superior predictive power with the proposed model. Second, we show with an example that the effects of potential interest rate cuts on the exchange rates can be estimated dynamically, which can be considered as a new tool for the policy makers. Third, investors can utilize the predictive model to take long or short positions whenever the spot exchange rate deviates out of the confidence intervals of the predicted sport rates locking in the profit when the reversal occurs.

3 Data

The dataset includes the following macroeconomic variables USD Turkish Lira exchange rates, Federal Reserve Effective Funding Rates, Turkish Central Bank Real Effective Funding Rates, and the Money Supply in Turkey (M2) during the period from January 2007 to May 2019 with 148 monthly observations. Our data is obtained from the official electronic data service of the Turkish Central Bank (https://evds2.tcmb.gov.tr), whereas the FED rates are obtained from the FED St. Louis website (https://fred.stlouisfed.org). Descriptive statistics for the given set of variables is presented in Table 1.

Table 1: Descriptive Statistics of the Macroeconomic Variables Utilized for the Period from Jan 2007 to May 2019. *USD/TL is Defined as the Value of 1 US Dollar as Turkish Liras.

	USD/TL*	Real Rates	FED Rates	M2
Mean	2.40	8.89	0.92	9.25 e08
Stdev.	1.22	2.96	1.36	5.02 e08
Min	1.17	3.21	0.07	3.01 e08
25%	1.53	6.75	0.12	5.05 e08
50%	1.84	8.68	0.18	7.68 e08
75%	2.95	10.59	1.33	12.30 e08
Max	6.37	16.14	5.26	21.65 e08

Figure 1: Plot of the Exchange Rate (Defined as the Turkish Lira Value of 1 US Dollar) Dataset for the Period Jan 2007 to May 2019.

The plots for the USD/TL exchange rates is given in Figure 1. It is observed that there is a continuous depreciation of the Turkish Lira against the USD during this period, and in particular a currency crisis spike is observed around the August and September 2018 period. A closer look to this FX crisis period shows that a sudden capital outflow triggered the sudden depreciation and following hike in the inflation due to the associated increasing energy and imported raw material prices transmitted via exchange rates.

4 Regression with Machine Learning

Machine learning offers a wide range of algorithms and methods to handle both small or large scale prediction problems. However, financial prediction problems are hard in terms of model construction due to noisiness of the data and potential non-stationary behavior. Given the fact that most macroeconomic variables are at the monthly frequency, it is technically not possible to utilize sophisticated deep learning models within the macroeconomic framework. Within the category of supervised machine learning predictions, one can either consider the classification or regression methods. In our setting, we prefer to consider the regression method since the target variable is the monthly average exchange rates. Furthermore, for policy makers or traders the predicted level should be known for scenario analysis rather than the discrete labels. Therefore, models that consider discrete choices, such as logit or mixed logit with examples in Train [12] or Tsagkanos [13], are not suitable in our framework. Predicted values, which are real numbers, and the sensitivities respect to the changes in the input features are of interest without any distributional assumptions. Finally, the monthly re-calibration of all model parameters in an expanding window yields a problem that is more suitable for machine learning based techniques with no distributional assumptions.

In the regression method we utilize four powerful machine learning regression algorithms, namely, Linear Regression, Ridge Regression, Support Vector Regression, and Decision Trees Regression. The results from artificial neural networks method is not reported due to the un-stability of the method with respect to the hyper parameters of the model. As described artificial neural networks involve many parameters in the estimation and the macroeconomic data is limited. In particular, simpler models are expected to perform better in our framework.

5 Exchange Rate Prediction Model

For any economy with floating exchange rates, the uncovered interest parity condition in economic theory tells us that the difference between the real interest rates between two countries should equal the expected depreciation of the two currencies. In other words, if we consider the exchange rate of the domestic country with respect to the US Dollar, then the natural choice of variables to include in the prediction of exchange rates should include the domestic interest rates, FED rates. However, it should also be noted that the interest parity is a theoretical equation. International funds often compare the real interest rates between countries and depending on the inflation expectations which might drive the expected depreciation in the exchange rate simultaneously, might play a significant role in the direction of exchange rates. It is common to calculate the real interest rates by subtracting the current inflation rate from the nominal benchmark interest rates of the Central Banks. Notice that the interest parity condition assumes perfect capital mobility between these countries. However, the actual predictive performance alternative major macroeconomic variables also determine the flow of funds between countries. To predict the next month's average foreign exchange rate against the USD we propose the following prediction model:

$$X_{t+1} = f\left(X_t, R_t^{Domestic}, R_t^{Foreign}, M_t\right), \tag{2}$$

where $X_t, R_t^{Domestic}, R_t^{Foreign}, M_t$ represents the exchange rates, domestic real interest rates, interest rates abroad such as the FED rates, and money supply (M2) in month *t*. The monthly exchange rate is calculated as the average exchange rate over the trading days of the month. The target variable is the next month's average exchange rate. The major benefit of using the monthly exchange rates is the smoothing effect since many countries such as emerging markets often have very volatile exchange rates. Therefore, if a single day's value is taken to represent the month such as the last day of the month, then the variation of the exchange rates might be extremely high. This reduces the effectiveness of the predictive models.

Furthermore, the regulators are not interested in a single day's value for the prediction of exchange rates. For example, a Central Bank would like to see the effect of their interest rate decision on the next month's average exchange rate value rather than the value at a single day. Together with the confidence bands around the point forecast obtained, predicted exchange rates can be utilized both by traders and Central Banks in different ways. A trader can also utilize the average value of the next month's value to take long or short position whenever the exchange rate falls below or above the predicted level.

6 Empirical Results

To verify the performance of the proposed predictive model we consider an extensive out-of-sample back-testing exercise to compare the relative performance of different machine learning algorithms over different out-of-sample time periods. For this purpose, we consider the last 30, 60, 90, and 120 months as the out-of-sample test size with the remaining observations utilized with an expanding window of training sets to re-train our model month by month as new data arrives. Since our features are at the monthly frequency utilizing an expanding window for the re-training of model is preferred.

For example, when we utilize the last 30 months the expanding window starts with a set of 118 (148-30=118) months to start training the model parameters. As we progress to the next month we add one more month's information to the training set and obtain the next predicted value. Mean absolute relative error (MARE) is calculated as the metric to compare and report the prediction performance of the model. The calculation for the mean absolute relative error is given as

$$MARE = \frac{1}{N}\sum_{t=1}^{N} \left| \frac{Forecast_t - Real\ value_t}{Real\ value_t} \right|$$

where N denotes out-of-sample test size. Following the described out-of-sample back-testing methodology we present the comparative results in Table 2 for the linear regression (LR), Ridge regression, support vector regression (SVR), decision tree regressor (DTR) for the 30, 60, 90, and 120 months as the out-of-sample test sizes. The standard deviation of the estimators is provided in parenthesis. It can be noted that the lowest standard deviation of the estimation errors is obtained with the Ridge regression.

Table 2: Mean Relative Errors Obtained from the Back-testing with Different Algorithms and Out-of-sample Testing Periods. Standard Deviations of the Estimators are Given in Parenthesis.

Out of Sample Size	LR	Ridge	SVR	DTR
30	0.0106	0.0078	0.0127	0.0071
	(0.0799)	(0.0396)	(0.0640)	(0.1021)
60	0.0080	0.0065	0.0121	0.0100
	(0.0599)	(0.0305)	(0.0471)	(0.1083)
90	0.0066	0.0058	0.0149	0.0104
	(0.0507)	(0.0254)	(0.0487)	(0.0925)
120	0.0069	0.0054	0.0206	0.0129
	(0.0464)	(0.0225)	(0.0523)	(0.0843)

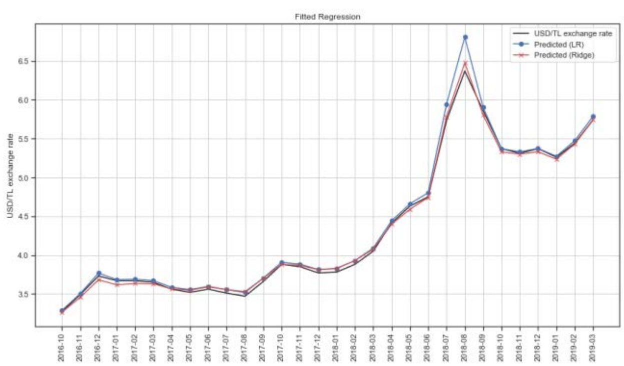

Figure 2: Fitted and Actual USD/TL Exchange Rate Values are Plotted for the Linear Regression and Ridge Regression Algorithms for the Last 30 Months of Out-of-sample Back-testing Period.

In Table 2, we observe that for all the out-of-sample sizes considered Ridge regression algorithm performs the best both in terms of the MARE and standard deviation of the estimators. SVR and DTR are not performing well compared to the Ridge and linear regression algorithms.

In Figure 2, fitted values for the Ridge and linear regression algorithms are provided together with the actual values. As observed the fitted and actual values are close. Furthermore, confidence bands that are obtained within one standard deviation of the predicted values of the Ridge regression is plotted in Figure 3. It is important to note that vast majority of the months the actual values are within one standard deviation of the predicted values. In few instances, whenever the actual monthly exchange rate exceeds the one standard deviation level, such as in the recent spike around September 2019, this indicates a foreign exchange driven financial crisis and sudden capital outflow in the economy.

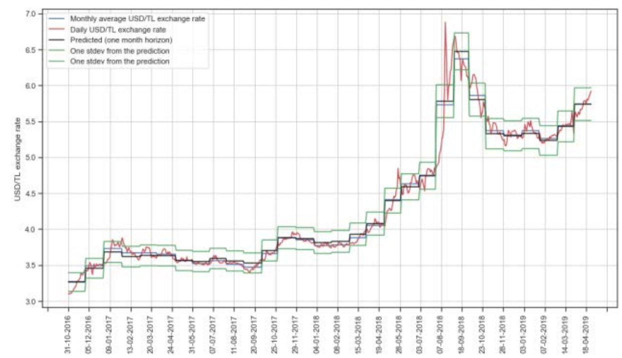

Figure 3: Daily USD/TL Exchange Rates Versus the Predicted Monthly Exchange Rates together with the Plus and Minus One Standard Deviation Confidence Bands around Point Estimates.

7 Policy Implications and Scenario Analysis

Empirical evidence shows that the proposed macroeconomic model can predict the next month's average exchange rates with relatively high precision given the fact that standard deviation of the estimators is tight enough to capture most of the actual variations in the exchange rates in the monthly time horizon. It is important to note that at least two of the variables in our predictive model are policy variables for the Central Bank of the domestic economy. The Central Bank's funding rate for the banking industry basically leads the short term rates in the yield curve of the domestic economy. Similarly, the money supply M2 is controlled by the Central Bank. Therefore, a natural consideration is to consider scenario analysis based on the potential policy choices of the Central Bank. For example, if the Central Bank or the government is targeting to lower the rates over time to stimulate the economy, our model helps to capture the potential increase in the USD/TL exchange rate and provide confidence levels for the decision makers.

To demonstrate the policy implication, we consider an example scenario. In our numerical example, we continue to predict the USD/TL exchange rate using the new data added to our dataset under the assumption that all the other variables are constant except the Central Bank rates. We consider a linear month by month interest rate cut with increments of 1% each time. This way we can consecutively predict the next month's USD/TL exchange rates month by month, building upon the previous predicted exchange rates and the new interest rates. This way we construct the possible path that USD/TL exchange rate follows in response to regular interest rate cuts at monthly time frequencies. However, different speed of interest rate cuts or non-uniform time intervals can be considered easily in our framework.

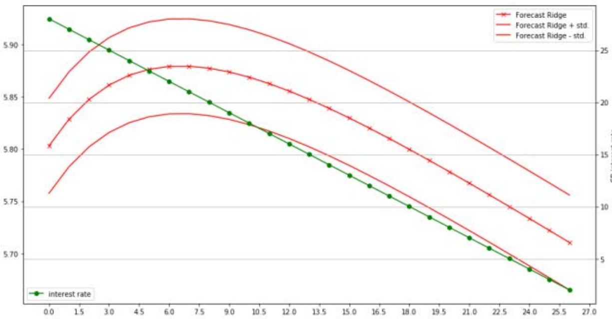

Figure 4: USD/TL Response as a Function of Linear Interest Rate Cuts by the Central Bank with 1% Monthly Increments.

As given in Figure 4, we observe that in the first few months the exchange rate shows stronger depreciation in response to the interest rate cuts. However, after a saturation point the exchange rate starts to go down with the autoregressive term, that is the lagged value of the exchange rate showing mean reversion behavior. This result is intuitive since exchange rates cannot depreciate unlimited when only the interest rates are changing over time even if the domestic interest rates goes all the way down to zero. There is a saturation level in the predictive model, where further interest rate cuts do not result in USD/TL continuous exchange rate depreciations in the Turkish Lira. This shows that ceteris paribus, i.e. while we keep the money supply, FED rates constant, the Central Banks can easily consider more complex scenarios given potential changes in the FED rates and money supply.

8 Conclusions

A machine learning based model is tested for the prediction of exchange rates based on the interest parity condition. Different machine learning regression methods are tested with various out-of-sample back-testing sample sizes. The results show that Ridge regression algorithms outperforms the support vector regression, decision tree regression, and linear regression methods. The relative performance of the Ridge regression in comparison to the support vector regressor or decision trees indicates that the non-linearity in the forecasting problem is weak. On the other hand, Ridge regression outperforming the linear regression shows the need to penalize the coefficients to avoid overfitting. As a result of our analysis we provide a generic model for open economies with flexible exchange rate regimes with the key macro-economic features in the determination of exchange rates are interest rates (domestic and foreign), money supply and lagged values of the exchange rate. By considering the USD/Turkish Lira exchange rate we show that high precision forecasts can be obtained to predict the next month's average exchange rate.

Furthermore, regression based machine learning algorithms allow for scenario analysis where potential effects of the Central Bank interest rate decisions are analyzed in terms of effects on the exchange rate. Investors or policy makers can potentially benefit from machine learning based prediction models for macroeconomic management and regulation.

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