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Exchange Rate Predictability Based on Market Sentiments

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I. Introduction

It is well-known that exchange rates are difficult to forecast using observed macro-fundamental variables. This discrepancy between economic theory and empirical results is called the Meese and Rogoff puzzle. According to early studies by Meese and Rogoff, a simple random walk model, which implies the best predictor of the exchange rate next period is the exchange rate today, has more explanatory power than models reflecting changes in economic fundamentals. A large body of literature has found that, in attempting to solve the Meese-Rogoff puzzle, the random walk generally beats macro-fundamentals-based models for periods up to a one-year forecasting horizon. Despite the fact that some studies have claimed success in forecasting exchange rates, the empirical evidence, which only applies to specific currencies during specific time periods, is not robust enough to be generalized (Cheung, Chinn, and Pascual 2005; Rossi 2013).

The purpose of this study is to address this puzzle from a new approach. Rather than pursuing a linkage between macro-fundamentals and exchange rates, we focus on the market sentiment index as a factor that could possibly enhance exchange rate predictability. The analysis folds into three phases. First, we conducted an assessment of the traditional exchange rate predictability model, as well as the augmented traditional model incorporating the market sentiment index. Second, we predicted the exchange rate by applying the market sentiment index, based on the contrarian opinion investment strategy commonly used by foreign exchange dealers. Finally, we analyzed if the machine learning model incorporating both economic fundamentals and market sentiment index could enhance the predictability of the exchange rate.

II. Traditional Exchange Rate Predictability Model

The traditional exchange rate prediction models include myriads of predictors. The predictors for exchange rate generally involved are differences in interest rate, price level, money supply, and real output between countries. First, based on the uncovered interest rate parity, the difference in interest rates between countries is used as a predictor (Meese and Rogoff 1988; Cheung et al. 2005; Alquist and Chinn 2008; Clark and West 2006; Molodtsova and Papell 2009). Second, the difference in the price level or inflation between countries is utilized as a predictor. This predictor stems from the purchasing power parity, which states that the purchasing power of the currencies in two countries determines the exchange rate (Rogoff 1996; Cheung et al. 2005). Third, the difference in interest rate, money supply, and GDP are predictors for exchange rate. This model counts on the traditional monetary model and asserts that the money demand determines the exchange rate (Meese and Rogoff 1983a; Meese and Rogoff 1983b; Chinn and Meese 1995; Mark 1995; Cheung et al. 2005; Alquist and Chinn 2008). In addition to these three traditional predictors, the difference in productivities, current accounts, net foreign assets, and commodity price indices are used as the predictor of the exchange rate.

While the macroeconomic approach could elaborate a long-run equilibrium of exchange rate, this approach faces a limit since the predictability of exchange rate varies significantly across predictors, currencies, and periods (Meese and Rogoff 1983a, 1983b, 1988; Cheung et al. 2005). Instead, the microeconomic approach recently came to the fore. This new approach predicts exchange rates by incorporating microeconomic information from the foreign exchange market. Also, the microeconomic approach assumes heterogeneous participants in the foreign exchange market and asymmetric information (Frankel and Rose 1995; O'Hara 1995; Lyons 1995). Lately, more emphasis has been placed on the sentiment of market participants, thereby leading to more institutes conducting studies on a prediction of the financial market using survey results and forecasts by institutes. However, many studies using the market sentiment cover the stock market (Das and Chen 2007; Ruiz et al. 2012; Sprenger and Welpe 2010; Zhang et al. 2011), while the studies on exchange rate prediction are limited. Hence, we conducted empirical analyses to convey how significantly market sentiment predicts the exchange rate.

III. Market Sentiment and Exchange Rate Predictability

The exchange rate responded not only to economic fundamentals, represented as observable macroeconomic variables but also to market sentiments in the short run. The variables reflecting market sentiment, including order flow, momentum strategy, and carry trade, were found to be significant to a short-run exchange rate (Burnside et al. 2011). Through previous studies, we investigated the influence of market sentiment on exchange rate prediction using the Daily Sentiment Index (DSI)[1] and Bloomberg Foreign Exchange Forecast.[2]

According to the analysis, the Euro has a significant exchange rate predictability both on the DSI model and the Bloomberg FXFC model in the short run. Also, the Canadian dollar shows predictability in the Bloomberg FXFC (Y1) model. Although there are minor differences, the EU consistently shows a significant exchange rate predictability on tests including the Granger-Casualty test, RMSFER,[3] CW test, and fluctuation test.

Table 1. DSI Model and Bloomberg FXFC Model Comparison: Out-of-Sample Forecast Results

Country	DSI	DSI Difference	Bloomberg FXFC (Q1)	Bloomberg FXFC (Y1)	Bloomberg FXFC (Q2)	Bloomberg FXFC (Q3)	Bloomberg FXFC (Q4)	Bloomberg FXFC (Y2)
AUS							O	
CAN				O		O	O	
JPN								
CHE								
GBR								
EU	O*	O*	O*	O	O	O		O

Notes: (1) 'O' indicates that CW test is significant under the short run forecast period (h=1).
(2) '*' indicates that the model's prediction ability is superior to a random walk under the short run forecast period (h=1), as RMSFER is smaller than 1.
(3) Blank indicates neither (1) or (2) holds.
Source: Authors' calculation.

[1] The value of DSI represents the market optimism (%) among small traders. If the index value is above 90, market participants consider that the exchange rate, which is the price of a foreign currency against the US dollar, is heading towards a short-term high or has already reached a short-term high.

[2] Bloomberg FXFC is an aggregation of exchange rate forecasts from individual forecasting agencies and represents the relative influence of each currency.

[3] RMSFER indicates a ratio of the model's RMSFE over a random walk's RMSFE. If RMSFER is smaller than 1, the model is superior to a random walk model.

IV. Exchange Rate Predictability Based on Contrarian Opinion Strategy

We investigated the exchange rate predictability based on the contrarian opinion investment strategy which foreign exchange dealers apply. The future exchange rate was predicted by using four variables (Daily Sentiment Index, the distance between the current exchange rate and the maximum exchange rate, yield of the past exchange rate, and the exchange rate volatility.) First, through the Daily Sentiment Index of futures market participants to predict exchange rates, we analyze how well market participants' sentiments about market conditions are effective in predicting exchange rates. Second, in general, the closer (farther) the distance between the current exchange rates and the maximum of exchange rates in the period in which the exchange rate rises (decreases), the closer the future exchange rate becomes. This reveals a cyclical pattern that repeats rising and falling for a certain period, and can be used to predict exchange rates. Third, according to Fama and French (1988), it appears the past return of stock prices can predict future stock prices. Lastly, the volatility of exchange rates can measure the level of risk that exists in the foreign exchange market. If foreign exchange market risks are systematically reflected in exchange rates, exchange rate volatility helps predict future exchange rate movements.

According to our analysis, the distance between the current exchange rate and the maximum exchange rate was the best predictor of exchange rate. Specifically, under the forecast period of 1 week to 5 years, the in-sample estimation result showed a significant linear relationship between the distance between the current exchange rate and the maximum exchange rate. The out-of-sample forecast results showed that the model with the distance between the current exchange rate and the maximum exchange rate was superior to predicting the real-time exchange rate than a random walk model, under most forecast periods. This result is distinctive from the previous study, especially the out-of-sample forecast results that have contributed to providing a clue for solving the Meese and Rogoff puzzle.

Table 2. Distance between the Exchange Rate and the Maximum Exchange Rate (in-sample estimation result)

	CHF	EUR	JPY	GBP	CAD	KOR	SWE
Forecast Period: 1 day (obs: 6,886)							
α	-8.213	-9.793	-10.864	-8.196	-4.472	-24.920	-11.086
	(-1.616)	(-1.683)	(-1.873)	(-1.596)	(-1.657)	(-1.212)	(-1.992)
β	-0.144	-0.263	-0.336	-0.273	-0.172	-0.443	-0.322
	(-1.386)	(-1.738)	(-2.000)	(-1.827)	(-1.558)	(-1.405)	(-2.153)
R^2	0.000	0.001	0.001	0.001	0.000	0.001	0.001
Forecast Period: 1 week (obs: 6,882)							
α	-8.267	-9.840	-10.845	-8.330	-4.395	-23.976	-10.593
	(-1.972)	(-2.013)	(-2.216)	(-1.951)	(-2.004)	(-2.187)	(-2.301)
β	-0.146	-0.264	-0.334	-0.278	-0.171	-0.427	-0.309
	(-1.687)	(-2.080)	(-2.419)	(-2.217)	(-1.895)	(-2.626)	(-2.522)
R^2	0.001	0.003	0.003	0.003	0.002	0.005	0.003
Forecast Period: 1 month (obs: 6,866)							
α	-7.730	-9.996	-10.790	-7.522	-3.909	-25.952	-10.106
	(-1.830)	(-2.039)	(-2.208)	(-2.099)	(-1.933)	(-2.986)	(-2.396)
β	-0.133	-0.268	-0.332	-0.252	-0.152	-0.459	-0.295
	(-1.560)	(-2.078)	(-2.354)	(-2.256)	(-1.851)	(-3.431)	(-2.600)
R^2	0.005	0.011	0.014	0.010	0.006	0.022	0.012
Forecast Period: 6 months (obs: 6,761)							
α	-6.242	-10.296	-11.428	-7.512	-4.087	-28.544	-11.063
	(-1.786)	(-2.198)	(-2.433)	(-1.841)	(-1.956)	(-3.366)	(-2.255)
β	-0.102	-0.279	-0.356	-0.255	-0.157	-0.503	-0.326
	(-1.532)	(-2.217)	(-2.404)	(-1.800)	(-1.813)	(-3.062)	(-2.281)
R^2	0.023	0.070	0.089	0.057	0.041	0.146	0.080
Forecast Period: 1 year (obs: 6,635)							
α	-5.709	-9.971	-10.215	-5.920	-3.771	-27.058	-10.695
	(-1.519)	(-2.170)	(-2.669)	(-1.595)	(-1.806)	(-3.157)	(-2.283)
β	-0.096	-0.277	-0.323	-0.218	-0.147	-0.480	-0.320
	(-1.454)	(-2.521)	(-2.510)	(-1.637)	(-1.824)	(-2.878)	(-2.608)
R^2	0.042	0.138	0.164	0.088	0.075	0.282	0.150
Forecast Period: 5 years (obs: 5,627)							
α	-5.150	-8.351	-7.199	-2.940	-4.620	-13.652	-8.890
	(-2.772)	(-6.975)	(-3.476)	(-1.517)	(-2.482)	(-12.690)	(-8.456)
β	-0.091	-0.230	-0.220	-0.219	-0.170	-0.243	-0.258
	(-4.413)	(-7.031)	(-5.468)	(-3.664)	(-3.300)	(-17.089)	(-6.973)
R^2	0.217	0.579	0.600	0.358	0.452	0.855	0.598

Note: ( ) indicates t-value.
Source: Authors' calculation.

Table 3. Distance between the Exchange Rate and the Maximum Exchange Rate (out of sample forecast result)

	CHF	EUR	JPY	GBP	CAD	KOR	SWE
Forecast Period: 1 day							
RMSFE	1.000	1.000	0.999	1.001	1.000	0.999	1.000
DM p-value	0.475	0.159	0.009	0.797	0.076	0.023	0.531
CW p-value	0.383	0.100	0.003	0.557	0.056	0.010	0.270
Forecast Period: 1 week							
RMSFE	0.999	0.998	0.996	1.002	0.998	0.997	0.999
DM p-value	0.089	0.066	0.001	0.690	0.008	0.007	0.406
CW p-value	0.052	0.034	0.000	0.384	0.005	0.003	0.168
Forecast Period: 1 month							
RMSFE	0.996	0.992	0.984	1.007	0.994	0.985	0.997
DM p-value	0.064	0.011	0.000	0.803	0.000	0.001	0.330
CW p-value	0.026	0.002	0.000	0.370	0.000	0.000	0.061
Forecast Period: 6 months							
RMSFE	0.980	0.943	0.890	1.074	0.966	0.903	0.981
DM p-value	0.004	0.000	0.000	0.999	0.000	0.000	0.152
CW p-value	0.000	0.000	0.000	0.370	0.000	0.000	0.000
Forecast Period: 1 year							
RMSFE	0.949	0.873	0.796	1.122	0.945	0.834	0.948
DM p-value	0.000	0.000	0.000	1.000	0.000	0.000	0.023
CW p-value	0.000	0.000	0.000	0.548	0.000	0.000	0.000
Forecast Period: 5 years							
RMSFE	1.017	0.641	0.447	0.937	0.621	0.370	0.700
DM p-value	0.762	0.000	0.000	0.008	0.000	0.000	0.000
CW p-value	0.001	0.000	0.000	0.000	0.000	0.000	0.000

Note: Items with RMSFE less than 1 or significant p-values of DM and CW at 10% (or 5%) are shaded.
Source: Authors' calculation.

V. Exchange Rate Predictability Based on Machining Learning

Recently, as the development of machine learning algorithms gains momentum and the quantity and quality of data available for analysis have improved, many studies that attempt to analyze the market by introducing machine learning algorithms are being conducted. Weigend et al (1991, 1992) found that artificial neural networks have higher explanatory power than a random walk model in predicting the exchange rate of the German mark/US dollar (DEM/USD).

This study incorporated both macroeconomics variables of economic fundamentals and market sentiment variables. Also, we applied the machine learning analysis methodology to predict the exchange rate. We used several different models to examine the explanatory power of the machine learning model (e.g., a baseline model, a linear model, a dense artificial neural network model, a multi-step fully connected artificial neural network model, a convolutional neural network model, and an LSTM model).

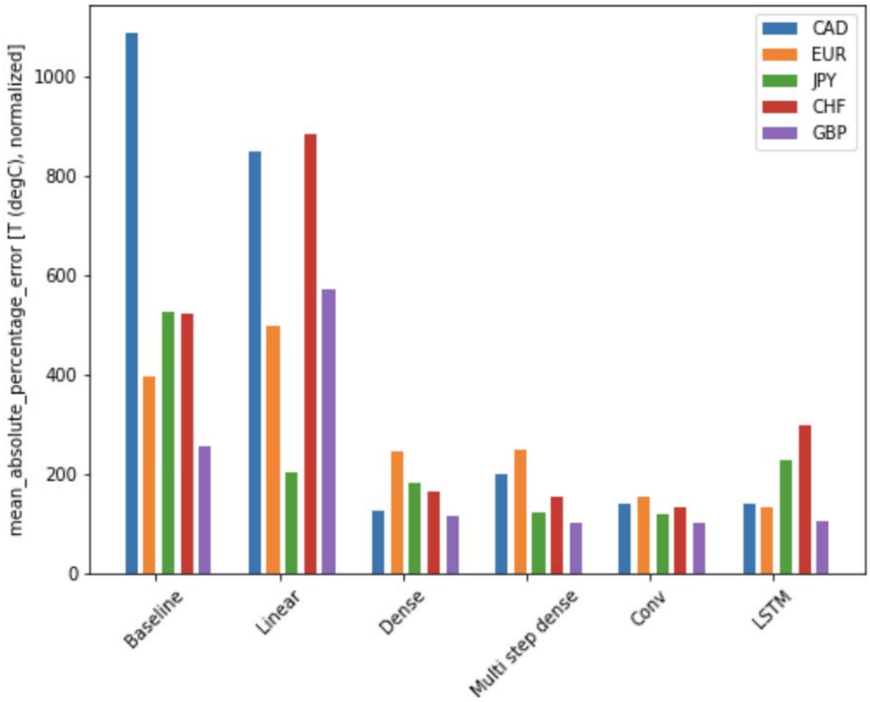
According to the results of our study, the various machine learning models showed higher explanatory power than the linear models. The linear model tends to overfit, and the market sentiment variable is not significant in the model. Among the machine learning models, the convolutional neural network model showed higher explanatory power than the LSTM model, which is known to be suitable for time-series data analysis. Selvin et al. (2017) showed that convolutional neural networks are generally more predictive than LSTM models specialized for time series data.

Table 4. Exchange Rate Forecast by Currency

FX		Baseline Model	Linear Model	Dense Artificial Neural Network Model	Multi-step Fully Connected Artificial Neural Network Model	Convolutional Neural Network Model
CAD	Val_MAPE	565.266	197.424	142.166	112.077	110.574
	Test_MAPE	1088.636	850.726	126.514	201.978	141.041
EUR	Val_MAPE	408.907	266.598	160.231	175.969	127.291
	Test_MAPE	396.110	497.197	244.871	250.048	154.071
JPY	Val_MAPE	559.515	275.314	154.523	149.627	110.334
	Test_MAPE	527.928	203.090	183.962	123.499	121.843
CHF	Val_MAPE	630.534	366.113	132.984	131.770	124.648
	Test_MAPE	524.523	882.574	165.423	153.762	133.035
GBP	Val_MAPE	521.799	538.663	157.046	109.307	125.755
	Test_MAPE	255.224	572.123	116.273	101.657	103.395

Notes: Val_MAPE: Verification Data Mean Average Percentage Error, Test_MAPE: Test Data Mean Average Percentage Error
Source: Authors' calculation.

Figure 1. Exchange Rate Forecast Results by Currency



Source: Authors' calculation

VI. Policy Implication

This study investigated the influence of sentiment on predicting exchange rates by incorporating the market sentiment index on traditional exchange rate prediction models. According to the analysis, in the short run, the market sentiment effectively predicted the euro exchange rate, while it was not significant for other currencies. However, we assume that the loss of information could have interfered while we transformed the daily market sentiment index into monthly data. This transformation was inevitable for the daily sentiment index to be comparable to the traditional models constructed on monthly data.

In addition, this study investigated if the contrarian investment strategy used by current foreign exchange investors could improve the forecasting power of the exchange rate. Specifically, we examined whether we could improve the exchange rate forecasting power by incorporating the market sentiment index of futures market participants, based on several theories (the contrarian opinion theory, the relative position of the current exchange rate, and the historical exchange rate return based on the momentum strategy). In the case of the model using the relative position of the current exchange rate, the linear relationship between this variable and the rate of return of the exchange rate was statistically significant for all exchange rate forecast periods from 1 week to 5 years, excluding only forecasts of one day ahead.

Furthermore, this study investigated if the machine learning model could improve the forecasting power of the exchange rate. In doing so, we constructed diverse exchange rate prediction models based on the machine learning model. We found that the machine learning model incorporating UIRP and Daily Sentiment Index shows better predictability on the exchange rate than a random walk model without a constant. This result could corroborate the predictability of the exchange rate as the dataset expands.

Though we investigated diverse models to examine the exchange rate predictability, there is a limit on explaining the cause of fluctuation in the exchange rate. For instance, it is difficult to empirically support why, among the traditional models, the Taylor rule model shows high exchange rate predictability. Also, the emerging countries do not seem to experience the forward premium puzzle (Bansal and Dahlquist 2000). As this is assumed to correspond to the exchange rate prediction model, further study on theoretical models incorporating a market investor and a market structure is needed. KIEP

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