6. OUT-OF-SAMPLE FORECASTING PERFORMANCE OF A ROBUST NEURAL EXCHANGE RATE MODEL OF RON/USD

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Abstract

This paper aims to explore the forecasting accuracy of RON/USD exchange rate structural models with monetary fundamentals. I used robust regression approach for constructing robust neural models less sensitive to contamination with outliers and I studied its predictability on 1 to 6-month horizon against nonrobust linear and nonlinear regressions and, especially, random walk. The results show that robust model with low breakdown point improve the forecast accuracy of RW and AR models on 1- and 4-month horizon and performs better than RW at all time horizons.

Keywords: exchange rate, forecasting, neural networks, outliers

JEL Classification: E22, C22, C45, C53

I. Introduction

Estimation of exchange rate models is a very important task for any open small economy, especially because the development is based on competitiveness and international trade, and thus exposed the economy to exchange rate risk.

Exchange rates shows large changes over time as a result of crises in the market, changing in economic policies or due to economic cycles. The presence of outliers in the data series can disrupt the prediction, but their neglect can lead erroneously inadequate or poorly specified models (van Dijk, Franses & Lucas, 1999; Preminger & Frank, 2007).

Many studies show that exchange rates are unpredictable because the structural models do not perform better than random-walk (RW) models in predicting exchange rate.

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In a seminal paper, Meese and Rogoff (1983) compared structural linear models for different exchange rates with RW for one to twelve month horizons and reached the same conclusion. Linear monetary and portfolio models are studied and the result on their explanatory power are mixed (MacDonald & Taylor, 1991, 1994; Groen , 2000; Chinn, 2000; Alquist & Chinn, 2006). The literature suggests at least two important theoretical reasons for the poor results of structural linear models to estimate the exchange rate: the need for a more dynamic than that resulting from static money demand equation and a more complex mechanism for adjusting relative prices. Thus to improve forecasting accuracy Somanth (1986) proposed dynamic structural models with variable delay and obtained better results denying the conjecture of inability to beat the random walk model set by Meese & Rogof.

Later, more studies dedicated to this problem explained this negative result by the nonlinearity in the exchange rates and tried to capture this phenomenon using nonparametric models, such as kernel regression (Meese and Rose, 1991; Diebold and Nason, 1990), multivariate GARCH model using M-estimation (Boudt and Croux, 2007) or Markov-switching models (Engle, 1994; Yuan, 2011), but without obtaining more accurate models in terms of forecasting accuracy.

Also, the solution of neural models is applied to this problem with higher out-of-samples forecast accuracy. Kuan and Liu (1995) use a model based on a neural network for forecasting the daily exchange rates, which generates smaller MSE forecasting errors than RW models. Another recent article - that of Preminger and Frank (2007) - analyzes the forecasting performance of neural robust autoregressive models based on S-estimators. The results are encouraging indicate that robust models are better than classical ones. The conclusions regarding the comparison of the neural models relative to random walk are statistically significant in several cases with the amendment that on standard measures RMSE and MAE they show better results.

Some nonlinear models with monetary fundamentals are also employed. Qi and Wu (2003) studied short and medium term predictability of exchange rates using neural models with macroeconomic fundamentals and found out that cannot beat random-walk but occasionally exhibits limited market-timing ability. In general they concluded that neural models presents poor predictability when are more complex and when the horizon lengthens.

Yuan (2011) studies the dynamics of the exchange rate for four USD exchange rate using nonlinear models of Markov type processes with regime change in volatility where the transition probabilities from one state to another are determined by the fundamental values resulting from structural models based on macroeconomic variables (broad money, income, differences in interest rates and foreign trade balance of the two countries that corresponded to the exchange rate) and finds that the market responds to macroeconomic changes forcing regime change in the ARCH process.

In this paper, the idea of robust regression is also used in order to reduce the impact of outliers on the estimation. Due to major changes over time caused by the economic crises, market crashes or simply business cycles, the outliers may have a major effect on the exchange rates.

The research question of this paper is to investigate the predictability of the exchange rate movements at different forecast horizons (1-6 months) using linear and nonlinear specifications, standard and robust estimation methods. The out-of-sample predictive ability of these models is compared and it is found out whether the robust regressions may provide better performance and whether models with monetary fundamentals work better than the autoregressive models.

The structure of the paper is the following. Section 2 presents a brief description of the specification of the models that are compared**;** Section 3 describes the neural models and robust estimation procedure; Section 4 introduces the data, the forecasting evaluation methods and the empirical results; and Section 5 concludes.

II. Exchange Rate Models

II.1. The Forecasting Problem

In this paper, an approach based on neural networks robust to outliers is conducted for predicting the monthly changes in the RON/USD exchange rate. It is based on structural models that use as determinants variables often used in the empirical models.

The monetary model with flexible prices of Frenkel-Bilson, the model with sticky prices of Dornbusch-Frankel or the Hooper-Morton model can be described by a reduced form specification (Meese and Rogoff, 1983):

$$s = a_0 + a_1(m_f - m) + a_2(y_f - y) + a_3(r_f - r) + a_4(\pi_f^e - \pi^e) + a_5 TB_f + a_6 TB + u \text{ ,} \quad (1)$$

where the variables are the logarithm of the exchange rate (s), the logarithm of the ratio of the money supply to the foreign money supply ($m_f - m$), the logarithm of the ratio of the two countries real income ($y_f - y$), the short-term interest rate differential ($r_f - r$), the expected long-time inflation differential ($\pi_f^e - \pi$) and TB_f; TB represent the foreign trade balances. The error term u may have serial correlation.

The Frenkel-Bilson model assumes the purchasing power parity, constraining to a_4=a_5=a_6=0. The Dornbusch-Frankel model allows for deviation from the purchasing parity assuming a_5=a_6=0, and the Hooper-Morton model does not impose any restriction on the coefficients.

Meese and Rogoff (1983) demonstrated that there is no gain in the out-of-sample forecast accuracy if the model considers separate coefficients for the variables corresponding to the two countries.

II.2. The Hooper-Morton Model

The Hooper-Morton model (as presented in Hooper and Morton, 1982) is based on both monetary and portfolio balance theories.

It is summarized by equations (2a) - (2f)[2].

$$(\Delta \log e)^e = r_f - r + \Phi \qquad (2a)$$

$$(\Delta \log e)^e = \theta(\log(\bar{e})^e - \log e) + (\Delta \log \bar{e})^e \qquad (2b)$$

$$(\Delta \log \bar{e})^e = \bar{\pi}_f^{\,e} - \bar{\pi}^{\,e} \qquad (2c)$$

$$\bar{e}^{\,e} = (\bar{P}_f^{\,e} / \bar{P}^{\,e}) * \bar{q}^{\,e} \qquad (2d)$$

$$M / P = y^{\alpha} \exp^{-\beta r} \qquad (2e)$$

$$M_f / P_f = y_f^{\;\alpha} \exp^{-\beta r_f} \qquad (2f)$$

The relation (2a) represents the open interest parity in an open economy adding the risk rate Φ .

The relation (2b) expresses the adjustment after a monetary shock (because prices are sticky) of the exchange rate. The difference between the expected values of the monthly changes in the exchange rate and the changes in the equilibrium value is proportional to the differential between the spot value and the market expectation value of the current equilibrium exchange rate, θ being the velocity of adjustment after the shock

The equation (2d) expresses the equilibrium nominal rate as a product of relative price and real component. With no changes in the equilibrium real exchange rate, relation (2d) becomes the long-run purchasing parity condition.

(2e) and (2f) represent the equilibrium relations (consistent with the monetary model) from the money market in the home and foreign country, assuming that parameters alfa and beta in the demand equation are identical for both countries.

The Hooper-Morton model is consistent with the long-run portfolio balance considering that the equilibrium real exchange rate is defined as the value expected to balance the current account in the long-run.

The model (1) for s=log(e) results from relations (2a-2f), by considering the dependence of exchange rate on the current account balance as well.

III. Neural Models and Robust Estimation Procedure

The type of models considered in this paper is nonlinear, based on feed-forward neural network with one hidden layer.

$$\hat{y} = y(x\;;w) \qquad (3)$$

[2] "e" denotes the expected value and "-" denotes the equilibrium value.

Due to the property of universal approximation (Cybenko, 19988 and Hornik, 1989) this type of networks can be used to solve nonlinear regressions of the form:

$$\hat{y} = f(x) = l(\sum_{j=1}^{n_h} w_{o[j,1]} h(w_{i[n+1,j]} + \sum_{i=1}^{n} w_{i[i,j]} x_i) + w_{o[n_h+1,1]}) \tag{4}$$

where: $h(.)$ is the sigmoid function (a smooth, monotonically increasing function $h(x) = 1/(1+e^{-x})$), w is the weights associated to each linked nodes, n_h is the number of hidden nodes and $l(x) = x$ is the activation function associated with output node. The nonlinear sigmoidal function $h(.)$ provides the computational flexibility allowing for the adjustment of the model to minimum errors on the data set.

Usually, the estimation of the neural model is based on minimization of the mean squared error (MSE):

$$\min_{\theta \in \Theta} \quad \left\{ \frac{1}{T} \sum_{t=1}^{T} (y_t - f(x_t, \theta))^2 \right\} \tag{5}$$

MSE, as a measure of dispersion of errors, is very sensitive to outliers, because even a single one can cause non-informative estimations, which is the definition of the breakdown point.

Neural models are especially suitable to encompass changes in the exchange rate that are rather frequent and sometimes dramatic due to major events in the market, business cycles or changes in the economic policy. These events can be viewed as causing the presence of outliers that may lead to misspecification, bias parameter estimates, deterioration of forecasting quality of the models (Chen and Liu, 1993; van Dijk, Franses and Lucas, 1999; Preminger & Frank, 2007).

The robust neural models that I use in this paper are based on the S-estimation method which minimizes a scale measure of the model errors, which is in the class of regular scales about the origin (Sakata and White, 2001):

$$\min_{\theta \in \Theta} \quad S(\theta) = \sup \left\{ s \in R_+ / \frac{1}{T} \sum_{t=1}^{T} \rho((y_t - f(x_t, \theta))/s) = K \right\} \tag{6}$$

for a function ρ that is even, bounded, continuously differentiable, has the property $\rho(0) = 0$ and strictly increases for every positive value before reaching supremum $\bar{\rho}$, $K \in (0, \frac{1}{2}\bar{\rho})$.

In the time series context the lower bound for breakdown point is determined by the ratio $K / \bar{\rho}/(nlag+1)$, where $nlag$ is the number of lags.

In this paper, the function ρ is the Tukey function:

$$\rho(x)=\begin{cases}\dfrac{x^2}{2}-\dfrac{x4}{2c^2}+\dfrac{x^6}{6c^4} & if \quad |x|\geq c\\ \dfrac{c^2}{6} & if \quad |x|\geq c\end{cases} \tag{7}$$

The S-estimators have a high breakdown point and the property of asymptotic normality (Rousseeuw and Zohai 1984) but the algorithms are intensive.

Another complication is caused by the fact that the minimization function is not convex and has more than one local minimum, so global optimization algorithms must be used (in this paper the adapted simulated annealing algorithms of Ingher ASA as in Sakata and White, 2001 and Preminger & Frank, 2007). This algorithm - and, implicitly, the robust regression approach - is more computationally demanding than other estimation procedures, but this is compensated by the gain in forecast ability.

IV. Empirical Neural Models for the RON/USD Exchange Rate

IV.1. The Data

The sample starts in January 2000 and ends in August 2012. For Romania, the data was collected from the Romanian National Institute of Statistics and for the USA the data were collected from the Federal Reserve Board database.

All the variables are logarithms of the indices. Thus, for the exchange rate the significance of the variable is that of continuously compounded return or log return, so we can use measures of the sign predictability that is important to investors who seek profit maximization and are not interested only in minimizing forecast errors.

The estimated relation is:

$$s=f(m_f-m, y_f-y, r_f-r, \pi_f-\pi, TB)+u \tag{8}$$

I used the industrial production index as proxy for output and the variable representing the current account deficit of the Hooper-Morton model was replaced by the net current export of Romania and was not considered for the USA. These are the restrictions imposed on the Hooper-Morton model due to the peculiarity of the model for Romania and to the availability of data.

IV.2. The Models

In this paper a robust neural models with macrodeterminants is constructed based on (8) with 3 lags. I employ two values $0.05\bar{\rho}$ and $0.10\bar{\rho}$ for K to produce models resistant to outliers with a low and a high breakdown point denoted RNN_MD5% and RNN_MD10%. For comparison reasons I also estimated the naive random walk (RW) model, an autoregressive model (AR) and a robust neural autoregressive model (RNN_ARR5%) for $K=0.05\bar{\rho}$.

The constructed neural networks have one hidden layer with 6 nodes (*n_h=6*). A reasonable number (n=100) for the initial random values was used in the process of selection of the best model.
The forecast horizon *h* is chosen to be from one month to 6 months.
37 experiments are conducted to estimate the models using a moving regression in a window with a fixed size of 105 observations. Based on each estimated model, the h-step forecast was generated, so the out-of-sample forecast consist of 37 observations. For each window, the models used 3 lags of the current return besides the chosen determinants of the exchange rate based on the Schwartz informational criterion, which was used to choose the lag order. This approach is used by Granger, King and White (1995), Swanson and White (1995, 1997).
In the time series context the lower bound for the breakdown point is determined by the ratio $K/\bar{\rho}/(nlag+1)$, where $nlag$ is the number of lags so we obtain a model (RNN_MD5%) resistant to 1.25% outliers and respectively to 2.25% outliers for RNN_MD10%.
The selection of the hidden nodes was based on heuristic methods of determination, basically consisting in the search conducted for the entire dataset from the simple network (with one unit in the hidden layer) to a more complex one adding a unit until the network fails to improve the error function. This approach is motivated by Occam's razor principle that implies preference for simpler models from the set of better ones.
In our experiments I set the number of hidden nodes to 6 as resulted from the selection procedure. The same choice of fixing the number of hidden nodes was made by White (1988) and Preminger and Franck (2007).

IV.3. Forecast Evaluation

The out-of-sample performances of the models are examined using measures based on RMSE (root mean square error), MAE (mean absolute error), and MAD (median of absolute deviation).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=t+1}^{t+n}(r_i - \hat{r}_i)}$$

$$MAE = \frac{1}{n}\sum_{i=t+1}^{t+n}\left|r_i - \hat{r}_i\right|$$

Also, the SR (success ratio) was used to assess the prediction accuracy of the models regarding the sign of the return. $SR = \frac{1}{n}\sum_{i=t+1}^{t+n}\mathbf{I}(r_i\, \hat{r}_i)$, where **I**(.) is the indicator function (I(a>0)=1; I(a<=0)=0).

Diebold-Mariano test (1995) (DM) is used to test whether the forecasts of the two models are equally accurate. This statistic is calculated as follows.

Suppose two models produce forecast errors:

$$\varepsilon^1_{t+h/t} = y_{t+h} - y^1_{t+h/t}\text{; and } \varepsilon^2_{t+h/t} = y_{t+h} - y^2_{t+h/t}$$

and since the accuracy of the forecast is measured by a function L($\varepsilon_{t+h/t}$) we test the null hypothesis $H_0 : E(L(\varepsilon^1_{t+h/t})) = E(L(\varepsilon^2_{t+h/t}))$ to the alternative $H_1 : E(L(\varepsilon^1_{t+h/t})) \neq E(L(\varepsilon^2_{t+h/t}))$.

The Diebold-Mariano test is based on the difference of the cost function $d_t = L(\varepsilon^1_{t+h/t}) - L(\varepsilon^2_{t+h/t})$ and the statistics $DM = \dfrac{\bar{d}}{\sqrt{\hat{LVR}_d / T}}$, where: $\bar{d}$ is the mean of the values d_t and $\hat{LVR}_d$ is a consistent estimator of the asymptotic variance of $\sqrt{T}\,\bar{d}$ (it is used because the series {d_t} is serially correlated for h>1). $LVR_d = \gamma_0 + 2\sum_{j=1}^{\infty}\gamma_j, \quad \gamma_j = \mathrm{cov}(d_t, d_{t-j})$.

Under the null hypothesis of equal predictive accuracy, *DM* is standard normally distributed, *N(0,1)*.

IV.4. Empirical Results

Table 1 reports the results of the out-of-sample forecasting performance of the models for the movements in the RON/USD exchange rate, one panel for each forecast horizon (1-6-month horizon). Table 2 displays the DM statistics for the null of equal predictive reported to the RW.

The forecast accuracy measures indicate that the out-of-sample performance of the models varies with the forecast horizon.

At the 1-month horizon all models either liner or nonlinear, robust or non-robust outperforms RW in terms of RMSE and MAE. The robust neural model with low breakdown point (RNN_MD5%) shows the best out-of-sample accuracy in terms of both standard measures (RMSE and MAE) and we can reject the hypothesis of equal accuracy (benchmark model is RW) at 10% significance level. Also it predicts better the direction of change for the exchange rate.

As the forecast horizon lengthens the linear models accuracy improved and performs better than the neural models on 3-, 5- and 6-month horizon.

The results of the DM test (table 2) indicate that all the models performs better than RW, but we cannot reject the hypothesis of equal forecast accuracy between the RW and the other models for all forecast horizons.

Table 2 shows that on the 2-, 3-, 4- and 5-month horizon the AR model performs better than random-walk at 5% significance level. At 4-month forecast horizon the robust neural model with low breakdown point (RNN_MD5%) shows better accuracy than RW at 10% significance in terms of RMSE respectively at 5% level in terms of MAE and at 5-month forecast horizon both robust models with macrodeterminants performs better than RW at 10% level of significance in terms of RMSE.

The results of the DM test show that for one-month horizon we cannot reject the null of equal predictive accuracy between all models and RW models at 10%, but the robust nonlinear models with low breakdown point is significantly better than the random-walk model. For the 4- and 5-month horizon the robust models with macrodeterminants beat RW at 10% significance, but so does the autoregressive model robust or non-robust.

The null of equal predictive ability cannot be rejected and for the 6-month horizon for neural models and for the AR, which is to be expected because the neural models must be retrained to maintain their performance.

Table 1

Out-of-sample Forecasting Performance Based on Forecast Accuracy Measures

Model	RMSE	MAE	SR
1-month horizon			
RW	0.03887	0.027621	
ARR	0.031404	0.023613	0.649*
RNN_AR5%	0.034481	0.027583	0.541
RNN_MD5%	0.028037*	0.02255*	0.622
RNN_MD10%	0.032881	0.02447	0.568
2-month horizon			
RW	0.046749	0.035863	
ARR	0.031661	0.025004	0.514
RNN_AR5%	0.037273	0.030931	0.514
RNN_MD5%	0.031428*	0.023411*	0.541*
RNN_MD10%	0.034855	0.029056	0.432
3-month horizon			
RW	0.044798	0.034652	
AR	0.031151*	0.024283*	0.541
RNN_AR5%	0.035288	0.026689	0.595*
RNN_MD5%	0.034759	0.026011	0.541
RNN_MD10%	0.033488	0.025929	0.541
4-month horizon			
RW	0.047569	0.036711	
AR	0.030577	0.02323*	0.568*
RNN_AR5%	0.051872	0.037593	0.378
RNN_MD5%	0.028965*	0.023828	0.514
RNN_MD10%	0.036758	0.031164	0.405
5-month horizon			
RW	0.048011	0.035424	
AR	0.02949*	0.02322*	0.405
RNN_AR5%	0.043494	0.03465	0.405
RNN_MD5%	0.039233	0.030523	0.486
RNN_MD10%	0.03279	0.026094	0.568*

Model	RMSE	MAE	SR
6-month horizon			
RW	0.040702	0.031163	
AR	0.028419*	0.022425*	0.405
RNN_AR5%	0.035806	0.027577	0.405
RNN_MD5%	0.034773	0.027848	0.352
RNN_MD10%	0.032705	0.025623	0.595*

Note: RMSE, MAE are forecast accuracy measures, SR is the statistics regarding the sign of the actual return. NN5% and NN10% refer to robust neural models with 5% and 10% outliers, respectively. Asterisk (*) represents the lower value on the column for forecast accuracy measures and the highest value for SR.

Table2

Out-of-sample Diebold-Mariano Test for Equal Accuracy with Random Walk

Model	DM	
	RMSE	MAE
1-month horizon		
ARR	0.844	0.801
RNN_AR5%	0.632	0.796
RNN_MD5%	0.934*	0.877
RNN_MD10%	0.665	0.622
2-month horizon		
ARR	0.985**	0.984**
RNN_AR5%	0.946*	0.815
RNN_MD5%	0.910	0.891
RNN_MD10%	0.878	0.870
3-month horizon		
ARR	0.984**	0.997*
RNN_AR5%	0.618	0.640
RNN_MD5%	0.784	0.941
RNN_MD10%	0.790	0.814
4-month horizon		
RW		
ARR	0.977**	0.903*
RNN_AR5%	0.640	0.603
RNN_MD5%	0.967**	0.991**
RNN_MD10%	0.818	0.783
5-month horizon		
ARR	0.994**	0.657
RNN_AR5%	0.681	0.601
RNN_MD5%	0.954**	0.564
RNN_MD10%	0.914*	0.818
6-month horizon		
ARR	0.928*	0.561
RNN_AR5%	0.851	0.602

Model	DM	
	RMSE	MAE
RNN_MD5%	0.770	0.531
RNN_MD10%	0.743	0.681

Note: DM is p-values for Diebold-Mariano test (1995) for different costs. P-values lower or equal to 0.005 signifies that the reference model (RW) yields a lower forecast error with 5% significance. Values greater or equal to 0.95 indicate that RW yields higher errors with 5% significance level. .(*) and (**) represents better performance than RW at 10% respectively 5% level.

V. Conclusions

The prediction of exchange rate movements is a major subject for economic policy application. A number of researchers tried to capture the structural breaks in the exchange rate due to market events, financial crises or changes in business cycles by incorporating nonlinearities in their models. They used non-parametric kernel regression, Markov-switching models, but found that the models do not perform better than the random-walk model.

There are some other researchers that used neural networks and obtained some evidence of better performance in out-of-sample forecasts. They applied the methodology to the daily exchange rates (Kuan and Liu, 1995, Gencay, 1999) and found some improvements in the mean squared forecast errors. Preminger and Franck (2007) used neural autoregressive models robust to outliers and found out that these models can provide better out-of-sample forecast in comparison with non-robust models and better market timing ability at all time horizons. However the hypothesis of equal accuracy in comparison to RW cannot be rejected in most cases except for JPY/USD at one-month horizon, 15% level of significance.

In this paper, we follow the same robust regression approach based on S-estimators as in Preminger and Franck (2007) to forecasting exchange rates with macro determinants of Hooper-Morton's structural model. We found out that in terms of forecast accuracy measures the robust neural models with other determinants than the history of the exchange rate show better performance than the random-walk model and the robust purely autoregressive neural model for 1-, 2-, 3- and 4-month horizon. The predictive accuracy measures presented in Table 1 show that the out-of-sample measures of accuracy of each model vary with the forecast horizon, but the general conclusion is that all models either linear or nonlinear are better than RW for all 1-6 month horizon. At one-month horizon the best forecasts are those provided by the robust nonlinear models with monetary fundamentals (RNN_MD5% is better according to accuracy measures RMSE and MAE and also in terms of the forecast success rate, SR).

We can conclude that an important cause of lower performance of the models that predict the exchange rate, besides nonlinearities, is the presence of outliers in the data. The solution could be the robust neural models that are trained frequently to incorporate new information.

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