

Study of Canada/US Dollar Exchange Rate Movements Using Recurrent Neural Network Model of FX-Market

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Abstract. Understanding exchange rate movements has long been an extremely challenging and important task. Unsatisfactory results produced by time series regression models have led to the claim by several authors that in foreign exchange markets, past movements of the price of a given currency have no predictive power in forecasting future movements of the currency price. In this paper, we build a recurrent neural network model for FX-market to explain exchange rate movements. Asset prices are discovered in the marketplace by the interaction of market design and agents' behaviour. The interaction is simulated by integrating 1) the FX-market mechanism; 2) an economic framework; and 3) the embedding of both tasks in neural network architectures. The results indicate that both macroeconomic and microeconomic variables are useful to forecast exchange rate changes. Results from regression model based on neural-fuzzy forecasting system are also included for comparison.

1 Introduction

Time series prediction is an important area of forecasting in which past observations of the prediction variable and other explanatory variables are collected and analyzed to develop a model describing the underlying relationship. The model is then used to extrapolate the time series into the future. One of the most important and widely used time series models is the autoregressive integrated moving average (ARIMA) model. The popularity of the ARIMA model is due to its statistical properties as well as the well known Box-Jenkins methodology [1] in the model building process. The major limitation of ARIMA models is the pre-assumed linear form of the model. That is, a linear correlation structure is assumed among the time series values and therefore, no nonlinear patterns can be captured by the ARIMA model. The approximation of linear models to complex real-world problems is not always satisfactory. Recently, neural networks (NN)

and fuzzy inference systems (FIS) have been extensively studied and used in time series forecasting [2,3]. The major advantage of these approaches is their flexible nonlinear modeling capability. With these soft computing tools, there is no need to specify a particular model form. Rather, the model is adaptively formed based on the features presented from the data. The data-driven time series modeling approaches (ARIMA, NN, FIS) are suitable for many empirical data sets where no theoretical guidance is available to suggest an appropriate data generating process, or when there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables. Our focus in this paper is on the study of exchange rate movements under the shadow of a long history of unsatisfactory results produced by time series models. Several authors have claimed that foreign exchange markets are efficient in the sense that past movements of the price of a given currency have no prediction value in forecasting future [4,5]. These results have helped popularize the view that the exchange rate is best characterized by a random walk. Recent papers that develop models based on long-term relationship between the real exchange rate and macroeconomic variables have found some encouraging results [6,7,8]. Macroeconomic models, however, provide no role for any market microstructure effects to enter directly into the estimated equation. These models assume that information is widely available to all market participants and that all relevant and ascertainable information is already reflected in the exchange rates. For the spot FX trader, what matters is not the data on any of the macroeconomic fundamentals, but information about demand for currencies extracted from purchases and sales orders, i.e., order flow. The work done at the Bank of Canada[9] demonstrates the strong link between macroeconomic and microeconomic variables, and real exchange rates. In this paper we examine whether introducing a market microstructure variable (that is, order flow) into a set of observations of macroeconomic variables (interest rate, crude oil price) can explain Canada/US dollar exchange rate movements. Our work looks at FX-market structure (or the trading process) : the arrival and dissemination of information; the generation and arrival of orders; and the market architecture which determines how orders are transformed into sales. Prices are discovered in the marketplace by the interaction of market design and participant behaviour. It is presumed that certain FX traders manage to get information that are not available to all the other traders and in turn, the market efficiency assumption is violated atleast in the very short term. It may be that, without these market microstructure frictions, markets would be efficient, but trading frictions impede the instantaneous embodiment of all information into prices.

2 FX-Market Mechanism

Basically, a market consists of various agents, which make their buying/selling decisions in accordance with their objective function (e.g., profit maximization). By summing up the individual decisions, the aggregated demand and supply is generated. Both aggregates can be used to describe an equilibrium condition

for the market. If the aggregated demand is equal to the aggregated supply, a market equilibrium is reached. Vice versa, if both aggregates are unequal, the market is in disequilibrium state. Since the aggregated demand as well as the aggregated supply are functions of the market price, a situation of a market disequilibrium can be corrected by adjusting the market price level. Therefore, one can anticipate upcoming price shifts by comparing these aggregates. For example if the aggregated demand is higher than the supply, a positive price shift will bring the market back into an equilibrium state [10,11].

The market model discussed above can be represented by a block diagram of Fig.1. The inputs $x^1, \dots, x^n$ are the macroeconomic/microeconomic indicators. The decision behaviour of an agent a can be modeled by a single neuron.

$$z_t^a = \sigma \left(\sum_{i=1}^n w_i^a x_t^{(i)} + D^a \pi_{t+1} - \theta^a \right) \quad (1)$$

$$\pi_{t+1} = \lambda n \left(\frac{p_{t+1}}{p_t} \right); t = 1, 2, \dots, T \quad (2)$$

The external inputs $x_t^{(i)}$ and the feedback π_{t+1} (price shift; p_t : FX-rate) are weighted by adjusting the weights w_i^a and D^a , respectively. By summing up the weighted inputs and comparing the sum with a threshold value θ_a , the agents opinion is formed. Afterwards the result is transformed through a nonlinearity (e.g., $\tanh(\cdot)$) in order to generate the neurons output signal z_t^a which is analogous to the action carried out by the agent (e.g., buying / selling). A neural network consisting of A such neurons for agents $a = 1, 2, \dots, A$, describe the decision making process of agents. For simplicity, we assume that 1) no transaction costs are involved; 2) each agent is allowed to carry out one trading activity at a time, i.e., z_t^a can either be positive or negative; 3) agents have the same time horizon T , and 4) agents have the same risk aversion characteristic. Typically, the trading activities of a single agent are driven by a profit-maximization task, according to

$$\max \left[\frac{1}{T} \sum_t \pi_{t+1} z_t^a \right] \quad (3)$$

The market clearance condition, formulated as $\sum_a z_t^a = 0$ describes an equilibrium condition for the FX-market. Agents $a = 1, \dots, A$ interact with each other through the market clearance condition.

If we have reached an equilibrium, i.e., the excess demand/supply is equal to zero and market is cleared, there is no need to adjust the market price in order to balance demand and supply, Formally, in case of market equilibrium,

$$\sum_a z_t^a = 0 \Rightarrow \pi_{t+1} = 0 \quad (4)$$

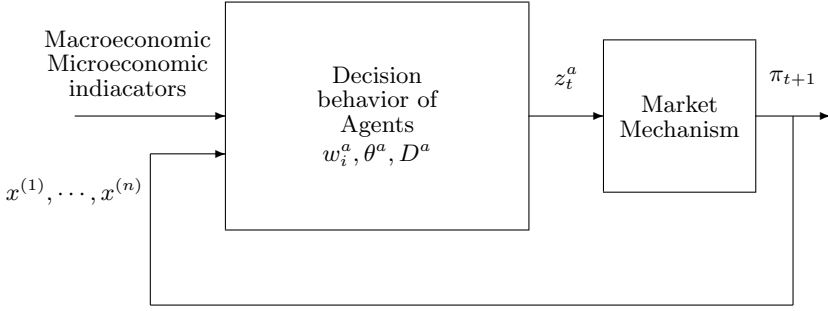


Fig. 1. Block diagram representation of FX-market model

In case the market clearance condition is violated, adjustments in market price will balance demand and supply. The price shift required to rebalance the market can be derived by

$$\sum_t z_t^a \neq 0 \Rightarrow \pi_{t+1} = C \sum_a z_t^a \quad (5)$$

where C is a positive constant. If there is excess demand, i.e., $\sum_a z_t^a > 0$ the FX-rate p_t tends to rise to re-balance the market $\pi_{t+1} > 0$. Since the excess demand tends to decrease when the price level p_t is marked up, the partial derivative of the excess demand with respect to price shift is negative. Therefore

$$\frac{\delta (\sum_a z_t^a)}{\delta \pi_{t+1}} < 0 \quad (6)$$

3 Recurrent Neural Network Model for FX-Market

Now we integrate the elementary trading mechanism of the agents, their decision behaviour and objective function, and the market mechanism discussed in Section II into a neural network architecture [10,11]. The proposed architecture distinguishes between a training and a test phase. The training phase is done by a feedforward neural network (Fig.2) while we use a fix-point recurrent network during the test phase (Fig.3). The weight matrix between the external inputs $x^{(i)}$ and the agents layer is sparse and spreads the information among the agents such that their decision behaviour is heterogeneous. This assumption clearly represents the underlying dynamics of the real world. In our experiments, the sparseness of weight matrix is initialized randomly, i.e., weights which should be turned to zero are randomly selected.

During the training phase of the network (Fig.2), the agents try to maximize their profits using both external input information $x^{(i)t}$ and the upcoming price shift. Simultaneous to agents profit maximization, the market mechanism adjusts the corresponding price level in order to vanish existing excess

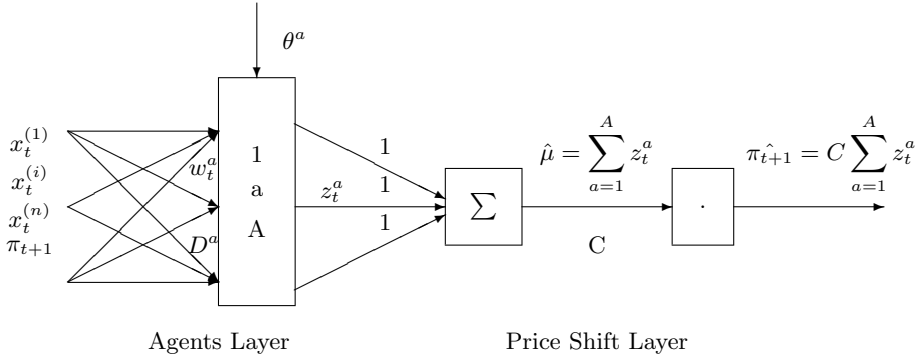


Fig. 2. Feedforward neural network for training phase

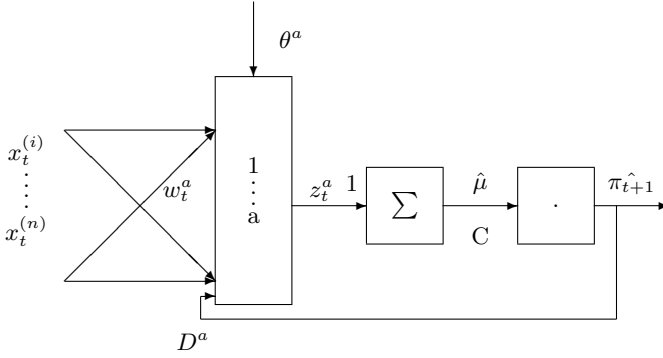


Fig. 3. Fix-point recurrent neural network for testing phase

demands/supplies. This is done indirectly by influencing the agents decision making using the related price shift π_{t+1} . The agents are provided with information concerning upcoming price movements by connecting an input terminal π_{t+1} to the agents layer. Since we have to guarantee that the partial derivative of excess demand with respect to price shift is negative (refer (6)) we only allow negative weights $D^a < 0$. The neural network of Fig.2 is trained with respect to the following error function :

$$E = \frac{1}{T} \sum_{T=1}^T \left(\pi_{t+1} - C \sum_{a=1}^A z_t^a \right)^2 - \lambda \sum_{a=1}^A \pi_{t+1} z_t^a \quad (7)$$

The first element in (7) is related to the market clearance condition. We use squared error function to minimize the divergence between the observed price shift π_{t+1} and the estimated price shift $\hat{\pi}_{t+1} = C \sum_a z_t^a$ which is derived from the

agents decision making process. The second element in (7) describes the neural network implementation of agents objective function, i.e., profit maximization. It should be noted that the solutions are not sensitive to the choice of the penalty parameter λ .

The learning parameters are w_i^a, θ^a and D^a . Parameter C varies between 0 and 1 ($0 < C \leq 1$). This is not taken as a learning parameter in our algorithm. It is a separate tunable parameter (C is initialized sufficiently small to guarantee convergence of fix-point recurrence). From Eqn.(7), we obtain

$$\frac{\delta E}{\delta w_i^a} = - \left[C(\pi_{t+1} - \pi_{t+1}^{\hat{}}) + \frac{1}{2} \lambda \pi_{t+1} \right] \left[(1 - (z_t^a)^2) x_t^{(i)} \right] \quad (8)$$

$$\frac{\delta E}{\delta \theta^a} = - \left[C(\pi_{t+1} - \pi_{t+1}^{\hat{}}) + \frac{1}{2} \lambda \pi_{t+1} \right] \left[(1 - (z_t^a)^2) \right] \quad (9)$$

Parameter D^a is tuned with respect to the following error function : $E' = \mu - \hat{\mu}$; $\mu = 0$ (Equilibrium condition)

$$\hat{\mu} = \sum_{a=1}^A z_t^a = \sum_{a=1}^A \tanh \left(\sum_{a=1}^A w_i^a x_t^{(i)} - \theta^a + D^a \pi_{t+1} \right) ; D^a < 0 \quad (10)$$

From this equation, we obtain

$$\frac{\delta E'}{\delta D^a} = - \frac{1}{2} [\pi_{t+1}] [(1 - (z_t^a)^2)] \quad (11)$$

Equations (9)-(11) provide the error derivatives for the gradient-descent back-propagation training of the neural network of Fig.2.

4 Simulation Results

For our empirical study, the database (www.economagic.com; www.bankofcanada.com) consists of monthly average values of FX-rate from January 1974 to November 2001 (335 data points) to forecast monthly price shifts of the FX-rate. Number of agents working in the market is assumed to be 40. As further decision of the empirical study, we had to assemble a database which serves as a raw input data for the agents taking part in the FX-market. The selection of raw inputs was guided by Gradojevic and Yang [9]. Besides the Canada/US dollar FX-rate itself, the agents may consider exports, imports, interest rate (Canada), interest rate (US), and crude oil price. We composed a data set of 5 indicators for the period of our empirical study. We trained the neural network until the convergence using incremental training. Following parameters were used in our model

- Excess demand constant $C=0.25$
- Discount rate $\lambda=0.05$
- Sparsity of parameter matrix $w_i^a = 0.35$
- Sparsity of parameter matrix $\theta^a = 0.8$
- Learning rate for training phase I ($parameter w_i^a, \theta^a$) = 0.01
- Learning rate for training phase II ($parameters D^a$) = 0.01
- Number of samples used for training=300

Figure 4 shows the simulation results for prediction of price-shift π (price=FX-rate).

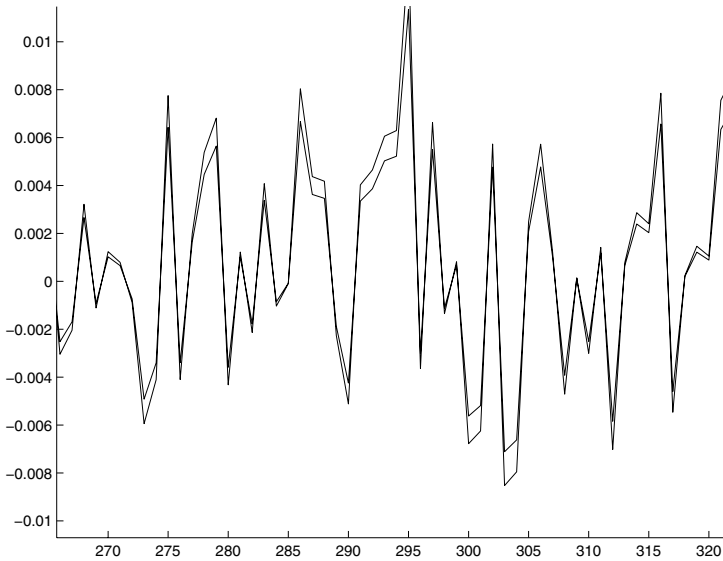


Fig. 4. Price-shift prediction using FX-market model

For evaluation of the performance of recurrent neural network model of the FX-market, we built a regressor model for forecasting using neuro-fuzzy strategy (fuzzy inference system with backpropagation tuning). As inputs of the neuro-fuzzy network, we utilized the database of our multiagent approach. The results obtained using the neurofuzzy method (NFIS) of [12], are shown in Fig 5. As expected, the regressor model has poor forecasting power for the FX-rate.

5 Conclusions

The goal of this paper was to study the predictability of exchange rates with macroeconomic and microeconomic variables. A variable from the field of microstructure (order flow) is included in a set of macroeconomic variables (interest

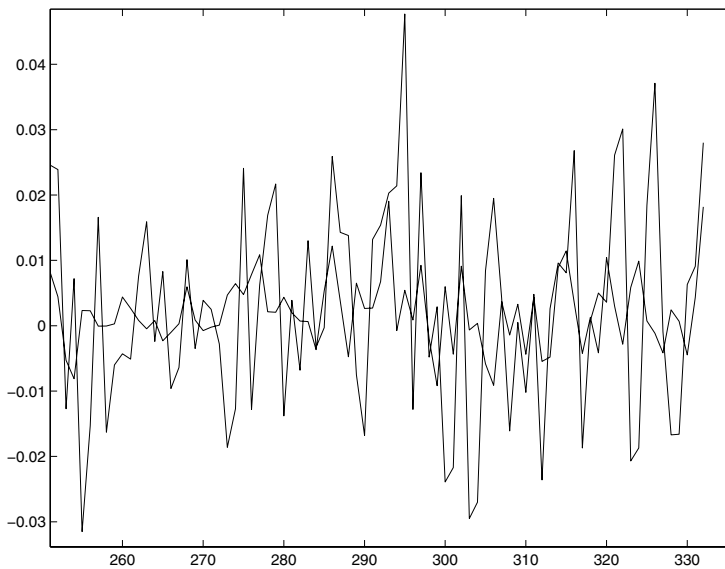


Fig. 5. Price-shift prediction using regression model

rate, and crude oil price) to explain Canada/US dollar exchange rate movements. Fuzzy Inference Systems with backpropagation tuning are employed to estimate a nonlinear relationship between exchange rate movements and these variables. The results confirm the poor performance of the time series regression models for exchange rate forecasting.

The prime focus of the paper is on a recurrent neural network model for FX-market to explain exchange rate movements. Asset prices are discovered in the marketplace by the interaction of market design and agents behaviour. The interaction is simulated by integrating 1) the FX-market mechanism; 2) an economic framework; and 3) the embedding of both tasks in neural network architectures. The results indicate that both macroeconomic and microeconomic variables are useful to forecast exchange rate changes. The inclusion of other microeconomic and macroeconomic variables could improve these findings. The power of this approach should be tested on other currencies.

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