Non-linear, Non-parametric, Non-fundamental Exchange Rate Forecasting

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Abstract

This paper employs a non-parametric method to forecast high-frequency Canada/U.S. dollar exchange rate. The introduction of a microstructure variable, order flow, substantially improves the predictive power of both the linear and non-linear models. The non-linear models outperform random walk and linear models based on a number of recursive out-of-sample forecasts. Two main criteria that are applied to evaluate model performance are: root-mean squared error (RMSE) and the ability to predict the direction of exchange rate moves. The artificial neural network (ANN) model is consistently better in RMSE to random walk and linear models for the various out-of-sample set sizes. Moreover, ANN performs better than other models in terms of percentage of correctly predicted exchange rate changes (PERC). The empirical results suggest that optimal ANN architecture is superior to random walk and any linear competing model for high-frequency exchange rate forecasting.

Keywords: Market Microstructure, Artificial Neural Networks, Foreign Exchange Rate Forecasting

JEL classification: F31, G14, C45, C52, C53

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1. Introduction

Understanding exchange rate movements has long been an extremely challenging and important task for academic and business researchers. Not only is the exchange rate a significant determinant of aggregate demand in a small open economy such as Canada's, but it also responds immediately and materially to monetary policy. However, the response is not always predictable. This makes it sometimes difficult to achieve the desired results of monetary policy implementation.

Efforts to deepen our understanding of exchange rate movements have taken on a number of approaches. Initially, efforts centred on the development of low-frequency macroeconomic (fundamental) empirical models. More recently, efforts have been aimed at the development of high-frequency models of the foreign exchange (FX) market, based on microeconomic (microstructure) variables. Throughout, however, forecasting models have been developed for obvious utilitarian purposes, but they have also served as a gauge of our understanding of exchange rate movements. Moreover, they can sometimes help to pinpoint where the gaps in our knowledge may lie, and therefore suggest new avenues of research. The exchange rate forecasting model developed in this paper serves all of these purposes.

Given the failure of traditional FX rate models to explain and predict exchange rate fluctuations correctly (Meese and Rogoff, 1983), we turn to the market microstructure of FX markets. In recent years there has been a lot of evidence that the behavior of dealers and other market participants can influence equilibrium exchange rates (Lyons and Evans, 2002, Covrig and Melvin, 1998). Inventory adjustments and bid-ask spread reactions to informative incoming order flows are two examples in which dealer behavior affects exchange rate determination. Indeed, given that different market participants trade based on private as well as public information sets, it is natural to assume that equilibrium exchange rate expectations are formed based on a combination of macroeconomic fundamentals and market microstructure variables (Goldberg and Tenorio, 1997). Moreover, it is most likely that the macroeconomic information and order flow information are processed in a non-linear fashion.

This paper contributes to the FX forecasting literature in the following aspects: First, we extend the empirical macroeconomic FX models to include "non-fundamental" variables such as order flow. Second, we employ a non-parametric method, artificial neural network (ANN) to capture the non-linear relationship between exchange rate and the informational content of trades and public information. Our study shows that non-linearities and order flows information play important roles for exchange rate determination and very short-term forecasting. In particular, the inclusion of additional microstructure variables and ANNs results in out-of-sample forecasts superior to those from random walk and linear models for daily Canada/U.S. dollar exchange rate movements. Three statistics are used to compare models: root-mean squared error (RMSE), mean squared prediction error (MSPE) and the percentage of correctly predicted exchange rate changes (PERC). Empirical findings are in favour of the ANN model, which yields a very robust out-of-sample forecasting improvement in RMSE, MSPE and PERC.

Our results generate important empirical and theoretical implications. Prior to this work, ANN exchange-rate models were built mostly on macroeconomic, technical trading or autoregressive foundations (Gencay, 1999, Kuan and Liu, 1995, Plasmans *et al.,* 1998) and the evidence from them was mixed. Our study suggests the importance of market microstructure variables in FX determination.

Moreover, we point to important implications beyond those given by Lyons and Evans (2002) and Lyons (2001). What makes their dynamic, temporary equilibrium structure relatively easy to characterize is its linear structure. However, we find that market participants (i.e., dealers) are likely to pursue more complex or even mixed strategies. This brings us to the notion of a non-linear equilibrium where market makers create a non-linear relation between public information, microstructure effects and exchange rates. One of the major strengths of this work is its strong empirical evidence that requires expansion of traditional microstructure linear characterization of equilibria as well as fundamental models of FX markets. We attempt to describe this new model only to a limited extent and more extensive research is required. In light of these findings, we challenge theoretical researchers to derive and explain this non-linear microstructure model more formally.

Section 2 describes the competing theoretical models. Section 3 offers a short discussion on the backpropagation ANNs. Section 4 describes the data and the method used to assess the predictive performance of the models. Section 5 describes the empirical results of the models. Section 6 concludes the paper and recommends further research.

2. Models of Exchange Rate Determination

Various models aiming at explaining exchange rate fluctuations have been proposed. Meese and Rogoff (1983) found that a simple random walk model performed no worse than any of competing representative time series and structural exchange rate models. Out-of-sample forecasting power in those models was surprisingly low for various forecasting horizons (from 1 to 12 months).

Subsequent attempts to determine exchange rates shed very little light on the problem. Baillie and McMahon (1989) pointed out that exchange rates are in general not linearly predictable. They are described as highly volatile with an elusive data generating process (DGP). Similarly, Hsieh (1988), Boothe and Glassman (1987) and Diebold and Nerlove (1989) observed that exchange rate changes are leptocurtic and may be non-linearly dependent. Further, the observed exchange rates seem to exhibit volatility clustering, i.e., high (low) volatility periods tend to be followed by high (low) volatile periods. This conditional heteroskedasticity evidence was reported in Hsieh (1989) and Engle *et al.* (1990). Nevertheless, excess kurtosis and conditional heteroskedasticity in the residuals may not improve point forecasts because these effects operate through even-ordered moments. To model the observed effects, parametric non-linear models such as ARCH (Hsieh, 1989) and GARCH (Bollerslev, 1990) were applied to exchange rates modeling, but with very little success. Gencay (1999) examined the predictability of spot foreign exchange rate returns using moving average technical trading rules and GARCH, nearest neighbours (NN) and ANN models. GARCH models generated insignificant sign forecasts improvement (and less than 1 per cent mean-squared error improvement) over a simple random walk. As noted in Diebold and Nason (1990), the pre-specification of the GARCH model form may neglect other possible non-linearities resulting from a true DGP. Meese and Rose (1991) examined macroeconomic exchange rate models and found that poor explanatory power of the models cannot be attributed to non-linearities. They considered five non-linear structural exchange rate models in order to capture possible non-linearities. The application of several parametric and non-parametric techniques on these fundamentally-driven models did not show any improvement in our ability to understand the exchange rate fluctuations.

Meese and Rose (1990) and Diebold and Nason (1990) used a NN non-parametric method called locally-weighted regression to estimate non-linearities in exchange rates. As a results, Meese and Rose (1990) rejected the existence of non-linearities. Diebold and Nason (1990) could not significantly improve upon a simple random walk in the out-of-sample exchange rate predictions. In contrast, using a NN method, Gencay (1999) and Lisi and Medio (1997) were able to generate predictions superior to those generated by the random walk model. This mixed evidence could suggest an existence of non-linear patterns in the exchange rates which, if revealed, could be exploited to improve both point and sign predictions.

Kuan and Liu (1995) used backpropagation and recurrent ANNs, a very powerful tool for detecting non-linear patterns, to investigate the ANN's out-of-sample forecasting ability on five exchange rates (British pound, Canadian dollar, Deutsche mark, Japanese yen, and Swiss franc) against the US dollar. The data were daily opening bid prices of the NY Foreign Exchange Market and the model of interest was a non-linear autoregressive model where its performance against random walk and ARMA processes was measured. Their results showed the presence of non-linearities in exchange rates time series. For the Japanese yen and British pound, ANNs exhibited significant sign predictions and/or significantly lower out-of-sample MSPE (relative to the random walk model); for the remaining three currencies ANNs had inferior forecasting performance. Some other studies involving ANNs were less encouraging. Plasmans *et al.* (1998) and Verkooijen (1996) used macroeconomic models, but they could not produce any satisfactory monthly forecasts. However, Zhang and Hu (1998) modeled exchange rate as depending non-linearly on its past values, and their model outperformed simple linear models, but they never compared it to a random walk. Hu *et al.* (1999) showed (using daily and weekly data) that ANNs are a more robust forecasting method than a random walk model. Hence, the application of ANNs to short-term currency behavior was successful in numerous cases and the results suggest that ANN models may have some advantages when frequent short-term forecasts are required.[1]

All the above-mentioned approaches try to find the exchange rate determinants among macroeconomic variables such as interest rates, money supplies, inflation rates, and trade balances. Flood and Rose (1995) concluded that exchange rate modeling based only on macroeconomic fundamentals might be insufficient to explain the exchange rate volatility. Recently, Cheung and Wong (2000) conducted a survey of practitioners in the

[1] In this context, ANNs focus on daily (weekly) or less-than-a monthly forecasting frequency, while typical macroeconomic models are at a monthly or quarterly frequency.

interbank foreign exchange markets in Hong Kong, Tokyo, and Singapore. A majority of participants view short-term exchange rate variability closely related to non-economic forces including bandwagon effects, over-reaction to news, speculation, and technical trading. Only 1 per cent of the traders look at economic fundamentals to determine daily exchange rate movements.

Given the partial empirical success of the macroeconomic models, there is an increasing interest in the exchange rate microstructure. The microstructure approach investigates how specific trading mechanisms affect the exchange rate formation. Lyons and Evans (2002) incorporated a variable reflecting the microeconomics of asset pricing into a model of the exchange rate. They introduced the most important microstructure variable, "order flow" as the proximate determinant of the exchange rate (using daily data over a four-month period) and were able to significantly improve on existing macroeconomic models. More precisely, they managed to capture about 60% of the exchange rate daily changes using a linear model.

In general, there are two broad theories of exchange rate modeling: traditional macroeconomic models and the more recently developed market microstructure models. Macroeconomic models aim at modeling and estimating exchange rates at monthly or lower frequency. These models are in general of the following form:

$$\Delta rpfx_t = \phi(M_t) + \varepsilon_t \text{ , } t=1,..,N. \quad (1)$$

where $\Delta rpfx_t$ is the change in the logarithm of the real exchange rate over the month or some lower frequency of observations, and M_t is a vector of typical macroeconomic variables such as the difference between home and foreign nominal interest rates, the long-run expected inflation differential, and relative real growth rates.[2] To control for the key Canadian macroeconomic variables, this paper uses a variation of the model developed by Amano and van Norden (1995):

$$\Delta rpfx_t = \varphi\,(rpfx_t, com_t, ene_t, intdiff_t) + \delta_t \text{ , } t=1,..,N. \quad (2)$$

where $rpfx_t$ is real Canada/U.S. exchange rate deflated by GDP deflators, com_t is the logarithm of non-energy commodity price index (deflated by the U.S. GDP deflator), ene_t

[2] See Meese and Rogoff (1983).

is the logarithm of energy commodity price index (deflated by the U.S. GDP deflator) and $intdiff_t$ represents the nominal 90-day commercial paper interest rate differential (Canada-U.S.).

Macroeconomic models provide no role for any "market microstructure" effects to directly enter into the estimated equation which are thus incorporated through the error term δ_t.[3] These models assume that markets are efficient in the sense that information is widely available to all market participants and all relevant and ascertainable information is already reflected in exchange rates. In other words, from this point of view, exchange rate changes are not informed by microstructure variables. However, typical macroeconomic models perform poorly. Moreover, empirical evidence from Lyons and Evans (2002), Covrig and Melvin (1998), and this paper suggests that a microstructure variable 'order flow' contains information relevant to exchange rate determination.[4]

For the spot FX trader, what really matters is not the data on any of the macroeconomic fundamentals, but information about demand for currencies extracted from purchases and sales orders, or order flow (Cheung and Wong, 2000). Any short-term exchange rate determinant such as portfolio shifts, over-reaction to news, or speculative trading would be recorded in order flow. It is presumed that certain FX traders observe trades that are not observable to all the other traders and, in turn, the market efficiency assumption is violated at least in the very short term.[5]

Microstructure models directly rely on information regarding the order flow. Lyons and Evans (2002) approach an order flow/exchange rate relation through a very realistic framework - portfolio shifts model. They use the perfect Bayesian-Nash Equilibrium and explicitly derive an equilibrium price change (between period t-1 and t) and equilibrium trading strategies. Intuitively, equilibrium price is determined from the common information set (macroeconomic fundamentals, denoted r_t) and aggregate interdealer order flow (denoted IB_t):

[3] Microstructure literature examines the elements of the security 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 trades. Prices are discovered in the marketplace by the interaction of market design and participant behavior.

[4] Order flow is explained in the next section.

[5] It may be that markets, absent these market microstructure frictions would be efficient, but trading frictions impede the instantaneous embodiment of all information into prices.

$$\Delta P_t = r_t + \lambda\, IB_t \qquad (3)$$

where λ is a positive constant.

This model was estimated over a four-month span of daily observations controlling for a key macroeconomic variable, interest rate differential. The results were in favor of microstructure approach with R^2 statistic over 50 per cent.

However, there are several unanswered questions which require further research. First, can this model be used for out-of-sample forecasting? Lyons and Evans (2002) model is based on realized order flow information which is not available ex-ante.[6] Secondly, is there a non-linear conditional mean function that characterizes a true DGP? By employing ANNs and relaxing the restrictions of the model by Lyons and Evans (2002), we attempt to find another equilibrium, non-linear by its structure.[7] Indeed, in this new setting there is a possibility that other types of order flow might play a role in setting the price. Finally, can we restrict our model to only one macroeconomic determinant? In this paper, we try to control (among other candidates available on a daily basis) for another fundamental variable: crude oil price. We address all of these issues and provide adequate answers based solely on empirical grounds.

In general, the market microstructure approach assumes the following relationship between the exchange rate and the driving variables:

$$\Delta rpfx_t = \psi\,(\Delta x_t, \Delta I_t, N_t\,) + \chi_t\ ,\ t=1,..,N. \qquad (4)$$

where Δx_t represents order flow, ΔI_t is a change in net dealer positions, while N_t is any other microeconomic variable. Order flow can be positive (net dollar purchases), or negative (net dollar sales). Macroeconomic effects are incorporated into error term χ_t. A positive relationship between the exchange rate and order flow is expected since informational asymmetries gradually affect the price until it reaches equilibrium. Figure 1

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[6] We also experimented with the linear regression and realized order flow information as explanatory variables and obtained the R^2 statistic around 40 per cent. However, we choose to use lagged order flow variables throughout the study since the same-period order flow information is not available ex-ante and it, therefore, can not be used in a forecasting model.

[7] For example, Bhattacharya and Spiegel (1991) and Rochet and Vila (1994) show that microstructure models can have multiple or non-linear equlibria. Lyons and Evans (2002) add a squared order flow term into their regression, but find it insignificant.

illustrates the explanatory power of an aggregate order flow and its IB component (the data cover the period from January 1990 to June 2000 at a daily frequency).

Insert Figure 1 about here

As the solid line indicates, the Canadian dollar has depreciated throughout most of the sample. The relationship between the exchange rate and order flow is quite clear as a positive correlation between cumulative purchases of U.S. dollars and the depreciation. This relationship is more obvious from the three-month sample (December, 1999 – February, 2000) of IB order flow and log Canada/U.S. real exchange rate. However, it would be inappropriate to assume that order flow contains all the information that is relevant for exchange rates.

This paper combines macroeconomic and microstructure approaches into a single high-frequency data model.[8] More specifically, it embodies modified models from Amano and van Norden (1995, 1998) and Lyons and Evans (2002):

$$\Delta \mathrm{rpfx}_t = \Psi(\Delta \mathrm{intdiff}_{t-1}, \Delta \mathrm{oil}_{t-1}, \Delta \mathrm{x}_{t-1}) + \eta_t,\ t=1,..,N. \tag{5}$$

where $\Delta \mathrm{intdiff}_t$ is the change in the differential between the Canada and U.S. nominal 90-day commercial paper rates, $\Delta \mathrm{oil}_t$ is the daily change in the logarithm of the crude oil price, and order flow is denoted by $\Delta \mathrm{x}_t$. Later in the paper, $\Delta \mathrm{x}_t$ is substituted by either a vector of three different order flow types or aggregate order flow. ANNs are employed to estimate a non-linear relationship between exchange rate movements and these variables.

3. Backpropagation ANNs

The backpropagation ANN, a network type applied in this paper, is probably the most commonly used ANN. Backpropagation learning algorithm requires continuous

[8] For example, Goldberg and Tenorio (1997) and Osler (1998) also follow this approach.

differentiable non-linearities and the most commonly used type is the sigmoid logistic (or logsig) function: [9]

$$f(w) = \frac{1}{1+e^{-w}} \tag{6}$$

Studies by Cybenko (1989) and Funahashi (1989) show that the backpropagation non-linear representation with sigmoid non-linearities can approximate a large number of mappings between inputs and outputs reasonably well. This makes ANN a very useful non-parametric technique and there is no need for any unjustified restrictions often present in econometric modeling.

Backpropagation estimation techniques are important for large samples and real-time applications since they allow for adaptive estimation. However, they may not fully utilize the information in the data. White (1989) showed that the recursive estimator is not as efficient as the non-linear least squares estimator. An important aspect of the backpropagation methods is the choice of the learning rate η. The inefficiency of the backpropagation originates in keeping the learning rate constant in an environment where the influence of random movements in inputs are not accounted by the target. This would lead the parameter vector to fluctuate indefinitely, i.e., there would be no convergence. A minimum requirement is to gradually drive the learning rate to zero to achieve convergence. In fact, White (1989) demonstrated that η_t has to be chosen not as vanishing scalar, but as a gradually vanishing matrix of a very specific form. These arguments on learning rates are only valid if the environment is stationary, which is the case in this work (as well as the constant learning rate). However, instead of tuning the network's learning rate, we attempt to balance the bias and variance and avoid non-convergence with early stopping. This may slightly deteriorate the model's performance and we acknowledge that probably by following White (1989) an optimal estimator would be achieved.

[9] Other types of transfer functions used in this research are tan - sigmoid ($f(w) = \frac{e^{w} - e^{-w}}{e^{w} + e^{-w}}$) and purelin ($f(w) = w$).

4. Model Specification

4.1 Data description

The order flow data were obtained from the Bank of Canada's unique Daily Foreign Exchange Volume Report, which is coordinated by the Bank and organized through the Canadian Foreign Exchange Committee (CFEC). Details about the trading flows (in Canadian dollars) for six major Canadian commercial banks are categorized by the type of trade (spot, forward, and futures) and transaction type (i.e., with regard to trading partner).[10] Because this paper focuses on a short-term exchange rate forecast, spot transactions are of interest. In a spot transaction, a currency is traded for immediate delivery and payment is made within two business days of the contract entry date. Spot transactions vary, as follows:

- Commercial client transactions (CC) include all transactions with resident and non-resident non-financial customers.
- Canadian-domiciled investment transactions (CD) include all transactions with non-dealer financial institutions located in Canada.
- Foreign institution transactions (FD) include all transactions with foreign financial institutions, such as FX dealers.
- Interbank transactions (IB) include transactions with other chartered banks, credit unions, investment dealers, and trust companies in the interbank market.

Because it was unavailable prior to 1994, CD transactions are excluded as an explanatory variable in this work. Moreover, according to Reuters Dealing 2000-1 electronic dealing system, IB transactions account for about 75 per cent of total trading in major spot markets (Lyons and Evans, 2002). Thus, the CD transactions contribution in daily exchange rate explanation is relatively small and our results support this conjecture.

Individual order flows (CC, FD, IB) are measured as the difference between the number of currency purchases (buyer-initiated trades) and sales (seller-initiated trades).

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[10] The six banks used in this research account for approximately 83 per cent of all Canada/U.S. dollar transactions. The remaining transactions occur within Canada (4 per cent) and in the US and the rest of the world (13 per cent). Source: Bank of Canada.

Aggregate order flow (aggof) is the sum of individual order flows. As noted earlier, the other variables of interest are the crude oil closing price (in U.S. dollars) deflated by the U.S. consumer price index (CPI) (Δoil) and the change in the difference between nominal 90-day commercial paper rates in Canada and the United States (Δintdiff). The dependent variable data set comprises the logarithm of real Canada/U.S. exchange rate daily changes (Δrpfx) between January 1990 and June 2000. The real exchange rate was calculated from the nominal exchange rate and CPI for the United States and Canada.

All variables are considered in first-difference terms, because the daily change (positive or negative) prediction is of interest. Also, by using the first differences we avoid theoretical problems of estimation of non-stationary non-parametric functions (see Diebold and Nerlove, 1990). To support this claim, standard Dickey-Fuller unit roots tests are performed on all variables and based on the entire data set (Table 1). The logarithm of the real exchange rate, interest rate differential and the logarithm of the crude oil price are found to be integrated of order one. In contrast, the null hypothesis of nonstationarity for daily order flows is rejected at the 99 per cent significance level.

Insert Table 1 about here

Given the systematic bias in currency forward rates (for more on this "conditional bias," see Lyons, 2001), and their unavailability on a daily basis (the minimum contract length is 30 days), we do not test if the inclusion of a forward rate into our set of explanatory variables improves the daily predictability of the Canada/U.S. exchange rate. However, we test for bias in forward rates based on the following equation as suggested by Lyons (2001):

$$p_{t+30} - p_t = \alpha + \beta(f_{t,30} - p_t) + \varepsilon_{t+30} \tag{7}$$

where p_{t+30} denotes the spot rate realized at time t+30 (Canada/U.S.), $f_{t,30}$ denotes the 30-day forward rate of the Canadian dollar, settled at time t+30, and ε_{t+30} is a random error term. The data for this exercise were obtained from the Statistics Canada CANSIM database (data range: January 1994 – May 2002).

The regression results can be summarized as follows:

$$\hat{p}_{t+30} - \hat{p}_t = \underset{(2.937104)}{0.000525} - \underset{(-3.449215)}{0.432875}(f_{t,30} - p_t),\ R^2 = 0.010 \tag{8}$$

We report the t-values in parentheses. The estimate of β is statistically significant and negative. In other words, when the forward rate predicts the spot rate will rise, it actually falls. Additionally, the model has a very poor fit with R^2 below one per cent. This confirms the bias in the 30-day forward rate of the Canadian dollar.

In order to investigate the robustness of our ANN-generated forecasts, we focus on daily and weekly forecasting with backpropagation ANNs where we develop models of four variables (ANN model 1) and six variables (ANN model 2) using the whole data set of 2,230 observations. Two non-linear models are considered:

ANN Model 1: $\Delta rpfx_t = f(\Delta intdiff_{t-j}, \Delta oil_{t-j}, aggof_{t-j}) + \varepsilon_t;$ (9)

ANN Model 2: $\Delta rpfx_t = g(\Delta intdiff_{t-j}, \Delta oil_{t-j}, CC_{t-j}, IB_{t-j}, FD_{t-j}) + \nu_t;\ j=\{1, 7\};\ t=1,..,N.$ (10)

Only for the purpose of ANN modeling, all data were normalized to the [-1,1] interval. Each of the above non-linear models was developed based on data sets of four variables (model 1) and six variables (model 2). The model was used to forecast the daily change of the Canada/U.S. real exchange rate one day and one week into the future.

The networks trained and tested were the three-layer and four-layer backpropagation ANNs with the non-linear sigmoid and tan-sigmoid neuron activation functions in hidden layers. The number of input neurons was three for model 1 and five for model 2, while the number of hidden neurons varied between three and five for both of the models. Typically, the number of hidden layers and nodes inside the network is determined through experimentation, and this paper follows that technique. The last layer had one linear output neuron.

It is important to note that in this research we do not utilize a more complex scenario involving other ANN types and methods for determining optimal ANN structure. Our intention was to emphasize the role and usefulness of the microstructure variables in a relatively simple setting, without refining the estimation procedures. It is possible that a more complicated approach such as Gencay and Qi (2001) would be more successful.

4.2 Assessment of forecast performance

In line with the Meese and Rogoff (1983) evaluation criterion, recursive estimation (or rolling regressions) is used to evaluate the models' predictive performance. The initial estimation starts with the first 90 per cent (chronologically) of the sample N, or, for instance, *m* observations. That comprises training and validation sets for the ANN. The remaining 10 per cent is a testing (forecasting) set of initial size *k*; having estimated the model, *k* forecasts are generated. Subsequent (*k-1*) steps involve increasing the estimation sample (so that *m* increases) and shrinking the testing set (so that *k* decreases) by one period. In each subsequent step, (*k-s*) forecasts are estimated (*s*=1,...*k-1*). Finally, *k* sets of network responses (of size 1,..,*k*) can be compared to actual observations and other models.

This paper considers whether the ANN model can outperform linear and random walk models in terms of root-mean squared error (RMSE), mean squared prediction error (MSPE) and the percentage of correctly predicted directions of exchange rate changes. For most of this paper, RMSE is defined as follows:

$$RMSE_{N_k} = \left[\frac{1}{N_k}\sum_{t=0}^{N_k-1}\left(\Delta \hat{rpfx}_{k+m-t} - \Delta rpfx_{k+m-t}\right)^2\right]^{\frac{1}{2}} \tag{11}$$

where N_k denotes the size of the out-of-sample testing set (N_k =*1,...,*k), $\Delta \hat{rpfx}_{k+m-t}$ is the model forecast at time (*k+m-t*), and $\Delta \mathrm{rpfx}_{\mathrm{k+m-t}}$ is the actual exchange rate change. The ratio of data allocated to training, validation, and testing was maintained at 6:3:1 throughout the recursive experiment. MSPE is defined as the square root of RMSE over the out-of-sample forecasts.

To reduce overfitting, i.e., inconsistency in calibration, which results from the network complexity (too many parameters to be estimated) and (possibly noisy) data length, one approach would be to use ANNs with hints (homogeneity, consistency, etc.). Recently, Garcia and Gencay (2000) showed that an ANN with homogeneity hint can produce a smaller out-of-sample error and a more robust estimator. Gencay and Qi (2001) found that early stopping can be as effective as the homogeneity hint in pricing options. By using early stopping in this paper we assume that response functions are estimated consistently.

In addition to RMSE, the percentage of correctly predicted signs (PERC) of the forecasted variable $\Delta rpfx_t$ is considered; this is the total number of correctly forecasted positive and negative movements, defined as:

$$PERC(N_k) = \frac{1}{N_k}\sum_{t=1}^{M} p_t \tag{12}$$

where

$$p_t = \begin{cases} 1 & if(\Delta rpfx_t \cdot \overset{\wedge}{\Delta} rpfx_t) > 0, \\ 0 & otherwise. \end{cases}$$

Sometimes, the significance of the difference in the performance of alternative models has to be tested. We use Diebold-Mariano test (Diebold and Mariano, 1995) to test the null hypothesis that there is no difference in the MSPE and PERC of two alternative models (in our case of the random walk and the ANN models).

The Diebold-Mariano test statistic for the equivalence of forecast errors is

$$S_1 = \frac{\frac{1}{M}\sum_{t=1}^{M}[d_t]}{\sqrt{\frac{2\pi f(0)}{M}}} \tag{13}$$

where M is the testing set size and f(0) is the spectral density of d_t at frequency zero. Diebold and Mariano show that S_1 is asymptotically distributed as a $\mathcal{N}(0,1)$.

As forecasts are done only one step ahead we do not have to include any of the sample autocovariances to calculate the long-run variance of d_t, $2\pi f(0)$. In this case, a consistent estimate of $2\pi f(0)$ will be the sample variance of d_t (see Diebold and Mariano, 1995).

5. Empirical Results

We investigate the robustness of the forecasting performance of ANN models in this section. The following models are considered:

Random walk model (RW):

$$rpfx_t=\alpha_0 + rpfx_{t-j} + \gamma_t,\ t=1,..,N. \tag{14}$$

Linear model (LM1):

$$\Delta \text{rpfx}_t = \gamma_0 + \gamma_1 \Delta \text{intdiff}_{-t-j} + \gamma_2 \Delta \text{oil}_{t-j} + \gamma_3 \text{IB}_{t-j} + \varepsilon_t, \ t=1,..,N. \quad (15)$$

Linear model (LM2):

$$\Delta \text{rpfx}_t = \beta_0 + \beta_1 \Delta \text{intdiff}_{t-j} + \beta_2 \Delta \text{oil}_{t-j} + \beta_3 \text{CC}_{t-j} + \beta_4 \text{IB}_{t-j} + \beta_5 \text{FD}_{t-j} + \nu_t, \ t=1,..,N. \quad (16)$$

ANN Model 1:

$$\Delta \text{rpfx}_t = f(\text{intdiff}_{t-j}, \Delta \text{oil}_{t-j}, \text{aggof}_{t-j}) + \varepsilon_t; \ t=1,..,N. \quad (17)$$

ANN Model 2:

$$\Delta \text{rpfx}_t = g(\Delta \text{intdiff}_{t-j}, \Delta \text{oil}_{t-j}, \text{CC}_{t-j}, \text{IB}_{t-j}, \text{FD}_{t-j}) + \nu_t; \ t=1,..,N. \quad (18)$$

j={1, 7}; t=1,..,N.

Table 2 presents linear regression estimation results for these models based on the first 2,005 observations (initial estimation set). The impact of interest rate change is more significant for lower frequency models (j=7), while the estimator of oil price change is more significant for one-day-ahead forecasting, Also, order flows are more important for higher frequency forecasting. Even though it is very small, as expected, the R^2 increased when individual order flows were taken into account.[11]

Insert Table 2 about here

Two above-specified non-linear models (ANN 1 and ANN 2) were estimated by feedforward backpropagation ANNs. Overtraining was prevented by stopping the training process when the validation set error started to increase.

Full sample estimation of 2,230 observations was used to compare the ANN and linear model's performance. After the initial estimation of the models in the first 2,005

[11] This work uses daily data over a ten-year period (as opposed to the four-month span used by Lyons and Evans, 2002); therefore, the linear "microstructure" model's R^2 is significantly lower.

observations, a set of out-of-sample forecasts was used to generate RMSEs. Each recursive re-estimation added 10 observations, so that 18 RMSEs were calculated on out-of-sample data sets ranging in size from 225 to 55 observations. This led to the selection of an ANN model 1 and ANN model 2 for one-day-ahead (j=1) and for one-week-ahead (j=7) forecasts of exchange rate changes, which were compared to linear models 1 and 2 and the random walk model.

Tables 3 (for j=1) and 4 (for j=7) list the RMSE statistics. They show that the ANN can produce promising short-run forecasts, since the RMSE for the ANN model for a given forecasting horizon is equal to or below both of the competing models.

Insert Table 3 about here

Insert Table 4 about here

The experiments show that the ANN model forecasts one-day and seven-day-ahead exchange rate changes better than the linear and random walk models. Nevertheless, the primary indicator of good forecasting power is not necessarily RMSE, but the percentage of correctly forecasted directions of real exchange rate fluctuations. In this case, the estimation involves very small values (exp 10^{-3}) that might result in small RMSEs. In turn, the presence of small RMSEs is not a guarantee that the prediction is accurate, and caution is required when interpreting the estimation results.

As noted above, the percentage of correctly forecasted exchange rate direction changes (PERC) is also considered. Recursive regression for horizons between 5 and 225 observations (step 5) reveals the superiority of the ANN model.[12] ANN model 1 (2) correctly predicted, on average, 60.14 per cent (61.81 per cent) of the direction of daily exchange rate movements, while linear model 1 (2) correctly predicted 57.18 per cent (58.75 per cent) of such changes, and the random walk model predicted 54.88 per cent. One-week-ahead forecasts yield worse results for ANN model 1 and linear model 1 against random walk for j=7, but ANN model 2 has the best results. Also, the predictive power of both non-random walk models is lower. Table 5 compares all the models used in terms of the second comparison criterion. The results clearly show that the ANN models dominate in predicting the direction of exchange rate changes one day ahead.

[12] Step 5 is used instead of step 10 to impose a more demanding setting for ANN models.

Insert Table 5 about here

Next, out-of-sample, one-step-ahead forecasts are considered. More precisely, ANN model 1 (2) is initially estimated for the first 2,006 observations. The forecast errors for the remaining 225 observations (a testing set) are calculated by extending the estimation set by one and recalculating the forecast errors until the whole testing set is exhausted. This differs from the preceding forecast experiment in that the earlier experiment did not re-estimate the model up to *t-1* to forecast the exchange rate at *t*. MSPEs and PERCs for the one-day-ahead forecasts are listed in Table 6. The striking result here is that ANN 2 correctly predicts almost 72 per cent of the directions of future exchange rate changes, while the random walk model stays at about a 55 per cent accuracy. In addition, this procedure provides statistically significant forecasts: at a 1 per cent level for the directional accuracy and at a 10 per cent with respect to the MSPE.

Insert Table 6 about here

To determine the percentage of correctly predicted changes that relates to positive changes, the following statistic was constructed for the initial testing sample size (k=225):

$$PERC(POS) = \frac{number\ of\ positive\ correct\ responses}{number\ of\ sample\ positive\ movements} \tag{19}$$

Similarly, for negative good hits another statistic was calculated:

$$PERC(NEG) = \frac{number\ of\ negative\ correct\ responses}{number\ of\ sample\ negative\ movements} \tag{20}$$

The term "positive changes" refers to values above the mean of estimation sample changes, while "negative changes" are values below the mean value. This corrects for the fact that there is a significantly greater number of positive changes in this sample. Taking zero as a mean value would affect the reliability of the criterion, since there were mostly positive changes in the sample.

According to Table 7, the ANN models forecast positive and negative changes roughly equally well. In comparison, failing to correct for the positive mean change would lead to the erroneous conclusion that the model predicts positive changes much better than negative changes.

Insert Table 7 about here

6. Conclusions and Further Research

In this paper, we study exchange rate models for the Canada/U.S. exchange rate. More specifically, we focus on their intra-day (high-frequency) and, subsequently, weekly forecast performances using a set of non-linear microstructure models. This paper combines two new approaches—artificial neural networks and market microstructure—to exchange rate determination to explain very short-run exchange rate fluctuations. A variable from the field of microstructure, order flow (aggregate and its components), is included in a set of macroeconomic variables (interest rate and crude oil price) to explain Canada/U.S. dollar exchange rate movements.

We find strong evidence for the microstructure effects. Our horse race for forecast performance results in a non-linear ANN model as the winner. ANN models are able to significantly improve upon a simple random walk model. Initially, two criteria are applied to evaluate model performance: RMSE and the ability to correctly predict the direction of the exchange rate movements. The ANN is consistently better in terms of RMSE than random walk and linear models for the various out-of-sample experiments. Moreover, ANN performs on average at least 3 per cent better than other models in its percentage of correctly predicted signs. This is true for both of the forecasting horizons. As expected, more accurate forecasts are generated for the shorter forecasting window, but they are still superior to the random walk model. Recursive one-step-ahead forecasts lead to considerable and statistically significant improvements (according to Diebold and Mariano, 1995 statistics) in MSPE and PERC compared to the random walk model.

The results indicate that both macroeconomic and microeconomic variables are useful to forecast high-frequency exchange rate changes. Moreover, this "hybrid model" points to the necessity of embodying (in a non-linear sense) information not only from interbank order flows, but from CC and FD transactions. Thus, the findings offer important implications for the models for exchange rate determination. Particularly, Lyons and Evans (2002) partial equilibrium model could be extended to encompass these non-linear and microstructure effects. Balancing the tension between microeconomic and microstructure variables is crucial. The question of which macroeconomic variables to use remains open for further research as only prices make sense for high-frequency models. Similarly, the panel of microstructure variables can be extended to a set of non-fundamentals which would account for the bandwagon effect, over-reaction to news, speculation, etc. However, these factors are not easy to quantify and we can only rely on different proxies for them.

The highest frequency used in this paper is a daily frequency as we try to balance the tension between macroeconomic and microstructure effects. Ideally, in order to truly understand foreign exchange markets one can attempt to follow our approach utilizing data on higher frequencies. In financial markets, the DGP is a complex network of layers where each layer corresponds to a particular frequency. We leave this complete characterization of the true DGP to further research and aggregate to daily (and subsequently weekly) information assuming the influence of random noise does not have a significant impact on our findings. Thus, the messages from this work to the mainstream paradigm of possible data generating mechanism of FX rates correspond to a particular frequency and require further investigation, once the data become available.

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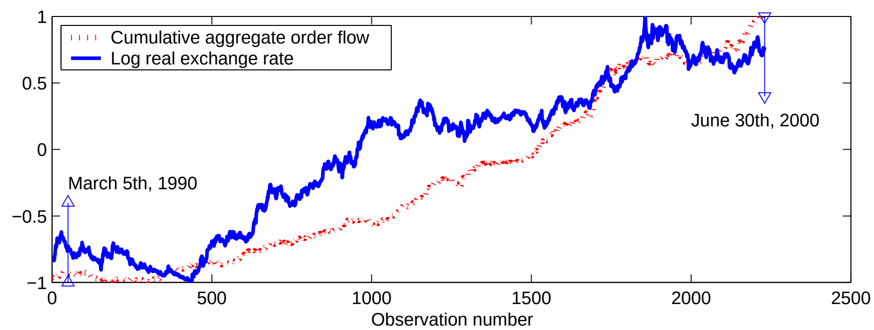
Figures

Figure 1. Above: Aggregate (cumulative) order flow and log Canada/U.S. real exchange rate. Below: IB (cumulative) order flow and log Canada/U.S. real exchange rate. Note: All values are normalized to [-1,1].



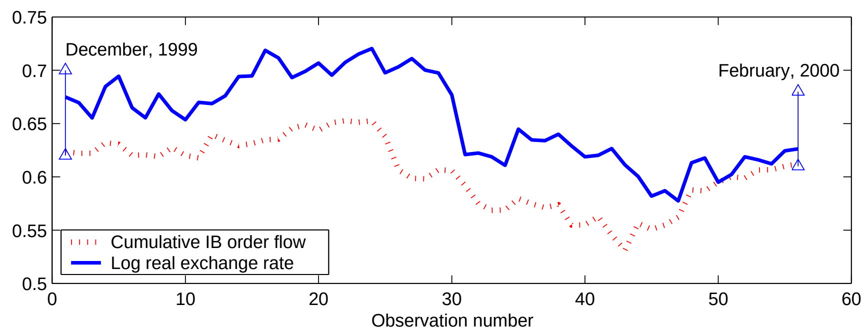


Figure Captions

Figure 1. Above: Aggregate (cumulative) order flow and log Canada/U.S. real exchange rate. Below: IB (cumulative) order flow and log Canada/U.S. real exchange rate. Note: All values are normalized to [-1,1].

Tables

Table 1. Augmented Dickey-Fuller (ADF) unit root t-tests

Variable	t-test	Lags (f)	Variable	t-test	Lags (f)
Real exchange rate	-0.84	1	Change in real exchange rate	-34.31**	1
Interest rate differential	-1.48	8	Change in interest rate differential	-19.90**	5
Crude oil price	-2.42	10	Change in crude oil price	-31.35**	2
CC	-25.31**	2			
FD	-23.43**	2			
IB	-31.12**	1			

Notes: The sample is from January 1990 to July 2000. Critical values are from Hamilton (1994): *-3.43 (1 per cent), **-2.86 (5 per cent).

Table 2. Estimation Results For Linear Models.

Estimates (standard error)	**Model**			
	Linear Model 1 (j=1)	**Linear Model 1 (j=7)**	**Linear Model 2 (j=1)**	**Linear Model 2 (j=7)**
γ_0 (exp 10^{-5})	8.09	36.53		
	(2.93e-05)	(7.08e-05)		
β_0 (exp 10^{-5})			8.72	36.35
			(2.93e-05)	(7.15e-05)
$\Delta \text{intdiff}_{t-j}$ (exp 10^{-4})	-1.13	-6.76	-1.89	-6.63
	(0.00025)	(0.00026)	(0.00025)	(0.00026)
Δoil_{t-j}	-0.0090	-0.003	-0.0087	-0.003
	(0.0065)	(0.0073)	(0.0065)	(0.0073)
aggof_{t-j} (exp 10^{-7})	-1.35	-3.74		
	(8.96e-08)	(2.16e-07)		
CC_{t-j} (exp 10^{-7})			1.33	-4.55
			(1.28e-07)	(3.11e-07)
IB_{t-j} (exp 10^{-7})			-1.015	-2.66
			(1.69e-07)	(4.07e-07)
FD_{t-j} (exp 10^{-7})			-3.86	-3.78
			(8.98e-08)	(2.16e-07)
R^2	0.0021	0.005	0.0049	0.0055

Table 3. RMSE (exp 10^{-3}) for ANN, linear, and random walk models (j=1).

Sample size	Model				
	Random Walk (j=1)	Linear Model 1 (j=1)	ANN Model 1 (j=1)	Linear Model 2 (j=1)	ANN Model 2 (j=1)
225	1.4321	1.4364	1.4270	1.4331	1.4216
215	1.4168	1.4201	1.4121	1.4155	1.4060
205	1.4232	1.4272	1.4163	1.4218	1.4119
195	1.4216	1.4240	1.4143	1.4188	1.4114
185	1.3962	1.4020	1.3871	1.3969	1.3892
175	1.3702	1.3782	1.3580	1.3717	1.3631
165	1.3482	1.3564	1.3353	1.3475	1.3428
155	1.3368	1.3442	1.3237	1.3362	1.3322
145	1.3381	1.3464	1.3238	1.3388	1.3337
135	1.3639	1.3708	1.3496	1.3622	1.3622
125	1.3696	1.3773	1.3540	1.3691	1.3671
115	1.3926	1.4026	1.3739	1.3933	1.3903
105	1.3057	1.3109	1.2963	1.3008	1.2907
95	1.3335	1.3380	1.3230	1.3256	1.3133
85	1.3652	1.3673	1.3515	1.3578	1.3508
75	1.3308	1.3353	1.3163	1.3243	1.3198
65	1.3851	1.3882	1.3738	1.3761	1.3743
55	1.4168	1.4202	1.4070	1.4156	1.4155

Table 4. RMSE (exp 10^{-2}) for ANN, linear, and random walk models (j=7).

Sample size	**Model**				
	Random Walk (j=7)	**Linear Model 1 (j=7)**	**ANN Model 1 (j=7)**	**Linear Model 2 (j=7)**	**ANN Model 2 (j=7)**
225	0.3457	0.3461	0.3458	0.346	0.3448
215	0.3467	0.3474	0.3461	0.3473	0.3462
205	0.3504	0.3516	0.35	0.3515	0.3502
195	0.3431	0.3435	0.3427	0.3437	0.3428
185	0.3358	0.3367	0.335	0.3368	0.3358
175	0.3371	0.3381	0.3364	0.3382	0.3365
165	0.3333	0.3336	0.3328	0.3338	0.3331
155	0.3377	0.3381	0.337	0.3382	0.3373
145	0.3286	0.3308	0.3253	0.3307	0.3278
135	0.3374	0.3396	0.3338	0.3396	0.3366
125	0.3441	0.3461	0.3408	0.3462	0.3438
115	0.3554	0.3576	0.3518	0.3577	0.3553
105	0.3328	0.3351	0.33	0.3349	0.3326
95	0.3384	0.3404	0.3355	0.3404	0.3384
85	0.3523	0.3544	0.3491	0.3544	0.3521
75	0.3657	0.3682	0.3619	0.3683	0.3656
65	0.3768	0.3787	0.3743	0.3790	0.3764
55	0.3882	0.3894	0.3878	0.3895	0.3868

Table 5. The average percentages of correctly predicted signs

AVERAGE PERC (%)	Model				
	Random Walk	LM 1	ANN 1	LM 2	ANN 2
j=1	54.88	57.18	60.14	58.75	61.81
j=7	56.26	54.9	56.15	55.28	58.04

Note: This table presents the average percentages of correctly predicted signs using various models. LM1 and LM2 stand for linear models 1 and 2; ANN 1 and ANN 2 stand for ANN models 1 and 2. One-day (j=1) and one-week (j=7) forecasts are considered.

Table 6. PERC and MSPE (exp 10^{-6}) statistics for the recursive estimation

	Model		
	RW	ANN 1	ANN 2
PERC (%)	54.88	67.56	71.56
(DM)		(4.0063)*	(5.7107)*
MSPE	2.0509	2.0036	1.9566
(DM)		(-1.6841)**	(-1.7730)**

Notes: The recursive estimation is performed over the whole testing set (k=225). ANN models 1 and 2 (ANN 1 and ANN 2) and the random walk (RW) model for one-day-ahead (j=1) forecasts are considered. The Diebold-Mariano (DM) test statistics are reported in the parentheses below MSPEs and PERCs, where applicable. The critical values are +/- 1.64 and +/- 2.58 for a confidence level of 90% and 99%, respectively. (*) and (**) indicates the DM statistic is significant at 1% and 10% significance level, respectively.

Table 7. PERC (POS) and PERC (NEG)

	Model	
	ANN 1	**ANN 2**
PERC(POS) (%):		
j=1	42.98	38.02
	(89.43)	(80.49)
j=7	57.02	53.04
	(98.39)	(98.39)
PERC(NEG) (%):		
j=1	48.08	67.31
	(2.05)	(36.27)
j=7	41.44	56.36
	(0.99)	(2.97)

Note: This table presents the average percentages of correctly predicted signs using ANN models 1 and 2 (ANN 1 and ANN 2). PERC (POS) is for percentage of the positive changes and PERC (NEG) is for percentage of negative changes. One-day (j=1) and one-week (j=7) forecasts are considered (k=225). Percentages without normalization are in parentheses.