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Journal of Empirical Finance 10 (2003) 623–640
Journal of EMPIRICAL FINANCE
www.elsevier.com/locate/econbase

Nonlinear prediction of exchange rates with monetary fundamentals

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Received 14 September 2000; accepted 30 September 2002

Abstract

This paper employs a neural network (NN) to study the nonlinear predictability of exchange rates for four currencies at the 1-, 6- and 12-month forecast horizons. We find that our neural network model with market fundamentals cannot beat the random walk (RW) in out-of-sample forecast accuracy, although it occasionally shows a limited market-timing ability. The neural network model without monetary fundamentals forecasts somewhat better for the British pound and the Canadian dollar. The model also exhibits some market-timing ability for the Deutsche mark at the 6- and 12-month horizons, and for the Canadian dollar at the 1-month horizon. In general, the model performs more poorly when it becomes more complex or when the forecast horizon lengthens. Our overall results are more on the negative side and suggest that neither nonlinearity nor market fundamentals appear to be very important in improving exchange rate forecast for the chosen horizons.

JEL classification: F31; C45; C53
Keywords: Exchange rates forecasting; Neural network; Monetary fundamentals

1. Introduction

In this paper, we employ a neural network (NN) to study the predictability of exchange rates over the short to medium forecast horizons and to investigate the

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0927-5398/03/$ - see front matter
doi:10.1016/S0927-5398(03)00008-2

usefulness of monetary fundamentals in explaining the movements of currency prices. Exchange rate forecasting is of practical as well as theoretical importance. The practical value lies in that good forecasts can provide useful information for investors in asset allocation, business firms in risk hedging, and governments in policy making. On the theoretical front, whether currency prices are predictable has important implications for the efficient market hypothesis and for theoretical modeling in international finance.

The literature shows, however, that exchange rates are largely unforecastable. In a seminal work, Meese and Rogoff (1983) estimate three linear structural models for the dollar prices of the British pound, the German mark and the Japanese yen. They find that none of these models can outperform the naive random walk (RW) model without drift in terms of out-of-sample forecast accuracy at the 1-, 6- and 12-month horizons. Furthermore, they report that neither their two time-series models nor the forward exchange rate appear to improve forecasts.

Subsequently, a number of researchers have pursued nonlinear modeling of exchange rates, with little success. For example, Engel and Hamilton (1990) and Engel (1994) show that the Markov switching model in general does not generate superior forecasts to the random walk or to the forward exchange rate. Using locally weighted regression, a nearest-neighbor nonparametric technique, Diebold and Nason (1990) report that their model is unable to provide a lower root mean square error (RMSE) out of sample than predicting form the RW with weekly data for 10 exchange rates. Their results constitute strong evidence against the existence of nonlinearities that are exploitable to improve forecasts. Using the same nonparametric approach, Meese and Rose (1991) estimate five structural models with monthly data for four currencies. They find that all five models display a general lack of ability to out-predict the RW. Mizrach (1992) demonstrates that a multivariate nearest-neighbor nonparametric model marginally improves upon the RW only for one of three exchange rates that he explores, but the improvement is not statistically significant. The results of Meese and Rose (1991) and Mizrach (1992) complement those of Diebold and Nason (1990) and further suggest that nonlinear modeling cannot improve exchange rate forecasts.

With accumulating evidence that exchange rates are essentially unforecastable over short horizons (1 year or less), recent studies have focused more on the predictability over longer horizons. Mark (1995) finds that at the 3- and 4-year horizons, a flexible-price monetary model, produces lower RMSE than the RW for three out of four currencies that he investigates, and for the Deutsche mark at the 4-year horizon, his model can beat the RW at the 5% significance level. Using data for five currencies, Chinn and Meese (1995) report that at the 3-year horizon, one of the three structural models they estimate produces a significantly lower RMSE than the RW for the Japanese yen, although results for the other four currencies remain largely negative.[1] Other studies on exchange rate unpredictability include Diebold et al. (1994), who report that incorporating the cointegration relationship among exchange rates as documented by Baillie and

[1] The robustness of long-horizon predictability results has been called into question by Kilian (1999), Berkowitz and Giorgiannni (2001), and Faust et al. (2001).

Bollerslev (1989, 1994) does not appear to improve upon the RW in out-of-sample forecast.[2]

We share the view with many researchers that standard linear models may be misspecified and hence unable to fully capture exchange rate dynamics. To this end, we deviate from the traditional approach by employing an NN technology to study the forecastability of exchange rates. One main advantage of using the NN method is that NNs are universal approximators which can approximate a large class of functions with a high degree of accuracy, while most of the commonly used nonlinear models cannot. The flexible NN mapping is data based and does not need a priori parametric restrictions that are typically needed in traditional econometric modeling. Moreover, in terms of parameterization, NNs are found to be in general more parsimonious than linear subspace methods such as polynomial, spline and trigonometric series in approximating unknown functions (Kuan and Liu, 1995). Therefore, if a nonlinear relation between exchange rates and fundamentals indeed exists, a suitably constructed NN may be able to capture it effectively. We explore the predictability of currency prices for the Japanese yen, the Deutsche mark, the British pound and the Canadian dollar at the 1-, 6- and 12-month horizons using monthly data from 1973.3 to 1997.7. We find that our NN model with monetary fundamentals does not beat the RW in out-of-sample forecast accuracy, although it occasionally shows a limited market-timing ability. The NN model without fundamentals forecasts somewhat better for the British pound and the Canadian dollar, and it exhibits some market-timing ability for the Deutsche mark at the 6- and 12-month horizons, and for the Canadian dollar at the 1-month horizon. In general, the forecasting performance deteriorates when the model becomes more complex or when the forecast horizon lengthens. Our overall results are more on the negative side and suggest that neither nonlinearity nor market fundamentals is very important in improving forecast for the chosen horizons.

The NN technologies have been increasingly employed to study financial and economic data.[3] In the study of exchange rates, Kuan and Liu (1995) report that the NNs predict daily exchange rates better than the RW in two out of five currencies they evaluate. Brooks (1997) and Gencay (1999) also document some predictability of daily exchange rates using an NN. Although the NN and nearest-neighbor regression are both nonparametric models, nearest-neighbor regression is a *local* procedure to approximate an unknown function while the NN is a *global* approximation approach. In contrast to the negative findings of Diebold and Nason (1990), these studies suggest that for high frequency data

[2] Three recent papers document the usefulness of fundamentals. Rapach and Wohar (in press) examine the relationship between exchange rates and monetary fundamentals for 14 countries over very long time spans and find substantial evidence for the importance of fundamentals. Anderson et al. (2001) find a linkage between macroeconomic news and intraday exchange rate movements. Kilian and Taylor (2001) embody smooth threshold dynamics to capture nonlinear mean reversion of exchange rates and report that exchange rates are forecastable over the long horizons (2–3 years) but not at the short horizons. On a new frontier, the market microstructure approach has been shown to cast light on the key puzzles in exchange rate economics, namely, the determination, excess volatility, and forward bias puzzles (Lyons, 2001, p. 171). The literature on exchange rate forecasting is fairly long, but we have not attempted to provide an overview here. See, for example, Frankel and Rose (1995) for a survey.

[3] For a brief survey, see Qi (1996). More recent contributions include Swanson and White (1997), Garcia and Gencay (2000), Qi (1999), and Qi and Maddala (1999), among others.

the global NN approach may be superior to the local nonparametric approach. These studies, however, include no market fundamentals as explanatory variables in the forecasting equation and are therefore essentially nonlinear univariate time series analysis. An interesting and important question remains whether the global NN approach can also beat the RW at lower frequencies when fundamentals are used. Since it is important for researchers of international finance to know whether market fundamentals help predict exchange rates in a nonlinear fashion, we employ lower frequency (monthly) data to explore a possible nonlinear relation between exchange rates and fundamentals, in an attempt to address the issues of whether the unpredictability is caused by limitations of linear specifications and whether economic fundamentals are useful in explaining currency price movements. This paper thus differs from Kuan and Liu (1995), Brooks (1997), and Gencay (1999) in that our choices of explanatory variables are guided by economic theory. Our study from the global NN approach with market fundamentals complements the existing studies and, in particular, offer a direct comparison to Meese and Rose (1991), who employ a local nonparametric method using monthly data with fundamentals.

The remainder of this paper is organized as follows. Section 2 provides some theoretical background on exchange rate determination and motivates our empirical specifications. In Section 3, we introduce the NN methodology and describe various statistics to be employed to test for the forecastability of exchange rates. Section 4 describes the data, while Section 5 reports the empirical results. Concluding remarks are offered in Section 6.

2. Theoretical motivation

We employ a simple version of the monetary model of exchange rate determination, popularized by Bilson (1978) and Mussa (1978), to motivate our empirical work and to guide our choice of forecasting variables. Within this model framework, it is assumed that both the domestic and foreign countries have a transactions-type money demand function and that both countries have the same income elasticity and interest rate semi-elasticity. Combining the money-market equilibrium conditions for the two countries yields:

$$m_t - p_t = a_0 + a_1 y_t - a_2 r_t, \tag{1}$$

where m_t, p_t, and y_t are, respectively, natural logarithms of the relative money supply, relative price level and relative real income between the domestic and foreign countries; r_t is their interest rate differential; a_1 is the common income elasticity; a_2 is the common interest rate semi-elasticity; and a_0 is a constant parameter. Assuming that the purchasing power parity holds,[4] we obtain:

$$s_t = m_t - a_0 - a_1 y_t + a_2 r_t, \tag{2}$$

where s_t is the logarithm of exchange rate (domestic currency price of one unit foreign currency).

[4] For recent empirical studies supporting purchasing power parity under the current float, see Frankel and Rose (1996) and Wu (1996), among others.

Eq. (2) expresses a contemporaneous relation between the exchange rate and three fundamental variables: relative money supply, relative income and interest rate differential. Admittedly, it is derived from a fairly restricted version of the monetary model. It is, however, straightforward to adopt a more general specification by relaxing some of the assumptions. For example, if the income elasticity and interest rate semi-elasticity of the domestic country are allowed to be different from those of the foreign country, then the domestic and foreign incomes and interest rates variables will enter separately. If prices are assumed to be sticky and purchasing power parity does not hold at all times, then relative inflation rates can be added to the right hand side of Eq. (2). While these additional variables and more general specifications may offer insights about the forecast performance of the model, the direct expense is that they can rapidly increase the number of parameters and dramatically reduce the degrees of freedom,[5] apart from the increased computational burden. To remain focused and to keep the system manageable so as to obtain more precise estimates of model parameters, we adopt this relatively parsimonious specification.

It is well documented that Eq. (2) does not hold on a period-by-period basis and that deviations from this simple relation can be quite persistent due to, for example, nominal rigidities. However, over time there may exist a tendency for the exchange rate to gradually revert to its fundamental value in response to either nominal or real shocks, and hence market fundamentals may contain useful information in forecasting changes in future exchange rates. We follow Mark (1995) by postulating that the h-period ahead change in exchange rate is related to its current deviation from the fundamental value, namely:

$$s_{t+h} - s_t = b^h + c^h(m_t - a_0 - a_1 y_t + a_2 r_t - s_t) + \varepsilon_{t+h}, \tag{3}$$

where b^h and c^h are regression parameters at horizon h and ε_{t+h} is the h-period forecast error. We study three forecasting horizons ($h=1$, 6 and 12) in this paper. The above specification assumes that the exchange rate can move away from its equilibrium value in the short run, but it will converge to its fundamental value over time and the market can be expected to be efficient in the long run. How fast the market will converge towards equilibrium is an empirical issue and economic theory does not give a simple answer.

Eq. (3) thus provides some guidance for our forecasting exercise. It shows that the h-period ahead exchange rate should be related to the current level of the exchange rate, as well as three monetary variables. Notice that we do not intend to obtain the most reasonable econometric estimates of the model parameters in Eq. (3) as our purpose in this paper is not to investigate the validity of the simple monetary model per se. But rather, our focus is on examining whether market fundamentals contain any useful information in forecasting future currency prices. To this end, in the forecasting experiment below, we choose $(s_t, m_t, y_t, r_t)'$ as our parsimonious information set. We then estimate a set of flexible nonlinear NN specifications using these as explanatory variables to explain s_{t+h}. We will also estimate a simple linear regression model (LR) using these same fundamen-

[5] For example, if the domestic and foreign incomes and interest rates variables enter separately and inflation rates are included, four explanatory variables will be added to the forecasting equation, which increases the number of parameters by $4n$, where n is the number of hidden-layer units that varies from 1 to 10 in our NN model. In order to avoid under-fitting, as the number of explanatory variables rises, n needs to increase accordingly. This can further expand the total number of parameters.

tals, and compare the forecast accuracy of our NN with this benchmark model, as well as with the naive RW model and a neural network model without monetary fundamentals. The estimation strategies as well as the comparison metrics are explained in the following section.

3. Empirical methodology

We briefly explain the NN technology in Section 3.1. Section 3.2 describes the forecasting experiment, and the metrics and statistics used in the comparison of out-of-sample forecasts.

3.1. Neural networks

NNs are a class of flexible nonlinear models inspired by the way the human brain processes information. Given an appropriate number of hidden-layer units, NNs can approximate a nonlinear (or linear) function to an arbitrary degree of accuracy through the composition of a network of relatively simple functions (see Hornik et al., 1989; White, 1990, among others). There are various kinds of NNs, among which the three-layer feedforward network is most widely used and is adopted in the present study. Let f be the unknown underlying function (linear or nonlinear) through which a vector of input variables $X=(x_1, x_2, \ldots, x_k)'$ explains the output variable s, i.e., $s=f(X)$, where for simplicity superfluous time subscripts are omitted. Then f can be approximated by a three-layer NN model:

$$f(X) = \alpha_0 + \sum_{j=1}^{n} \alpha_j g\left(\sum_{i=1}^{k} \beta_{ij} x_i + \beta_{0j}\right) + \varepsilon, \tag{4}$$

where n is the number of units in the hidden layer, k is the number of input variables; g is the logistic function: $g(x)=1/(1+\exp(-x))$, a commonly used transfer function in feedforward neural networks; $\{\alpha_j, j=0,1,\ldots,n\}$ represents a vector of coefficients (weights) from the hidden-layer units to the output-layer units; $\{\beta_{ij}, i=0,1,\ldots,k, j=0,1,\ldots,n\}$ denotes a matrix of coefficients from the input-layer units to the hidden-layer units; and ε is the error term. The error term can be made arbitrarily small if n is sufficiently large. However, too large an n can cause the model to overfit in which case the in-sample errors are small but the out-of-sample errors may be large. The choice of n is data dependent and there exists no general rule for predetermining it. Thus, we perform a sensitivity analysis by exploring different values of n (from 1 to 10).

The parameters are estimated by minimizing the sum of squared errors $\Sigma\varepsilon^2$ in Eq. (4). We use the Levenberg–Marquardt algorithm for estimation because it is by far the fastest algorithm for moderate-sized (up to several hundred free parameters) feedforward NNs. The initial values of the parameters are generated with Nguyen and Widrow's (1990) method, and Bayesian regularization (MacKay, 1992) is used to prevent overfitting. Finally, to ensure that the global minimum is obtained, each network is estimated 10 times based on 10 sets of initial values, and the one with the smallest sum of square errors is retained and used to generate out-of-sample forecasts.

3.2. Out-of-sample forecast, metrics and statistics

In a sample with T observations, the out-of-sample forecasts for a given horizon h are carried out by first estimating Eq. (4) with data up through date $t_0 < T$, so that the last observation used is $(s_{t_0}, X_{t_0} - h)$. Let $(\hat{\alpha}^h_{t_0}, \hat{\beta}^h_{t_0})$ denote the coefficients estimated with these observations. The first h-period forecast is

$$\hat{s}_{t_0+h} = \hat{\alpha}^h_{0,t_0} + \sum_{j=1}^{n} \hat{\alpha}^h_{j,t_0} g\left(\sum_{i=1}^{k} \hat{\beta}^h_{ij,t_0} x_{i,t_0} + \hat{\beta}^h_{0j,t_0} \right). \tag{5}$$

This procedure is repeated for t_0+1, $t_0+2, \ldots, T-h$, thus yielding N forecast points, where $N = T - t_0 - h + 1$. Forecast accuracy is measured by the root mean square error (RMSE). We also employ the direction accuracy (DA), or the percentage of correct predictions in direction changes, as a measure of the market-timing ability of a model. We use Pesaran and Timmermann's (1992) (PT) non-parametric method to test for the statistical significance of market-timing ability of a model.

To test whether the forecasts from two competing models are equally accurate, we use the Diebold and Mariano (1995) (DM) for the significance of the difference between the squared forecast errors of the two models. Under the null hypothesis of equal forecast accuracy, the mean difference of square errors is zero, and the asymptotic distribution of the DM test statistic is standard normal. We use Newey and West's (1987) method to obtain a consistent estimate of the spectral density at frequency zero. Andrews' (1991) approximating rule is used to set the truncation lag.

An alternative method to compare forecast accuracy is to employ Wilcoxon's signed-ranks test (SR), which is distribution free. The SR test gives an observation with a larger absolute square error difference a higher weight than that with a smaller difference. Upon scaling, this statistic is asymptotically standard normal.

4. The data

All data are monthly and are obtained from IMF's *International Financial Statistics*. Our sample starts in March 1973, the same as in Meese and Rogoff (1983), and ends in July 1997 with 293 observations. We have chosen exchange rates between the U.S. dollar and the Japanese yen, the Deutsche mark, the British pound and the Canadian dollar. The first three foreign currencies along with the U.S. dollar form the core currencies in the world economy. The Canadian dollar is chosen because of Canada's close economic tie to the United States.

Exchange rates are end-of-month U.S. dollar prices of the foreign currencies. Variables chosen to proxy market fundamentals are as follows. We measure money supply by M1, and real income by industrial production in each of the countries. As for interest rates, we use Treasury-bill rates for Britain, Canada and the U.S. (line 60c). Treasury-bill rate data are not available for Japan and are available for Germany only from July 1975. Therefore, for these two countries, we use call money rates (line 60b) as an alternative measure of interest rate.

5. Empirical results

To make our study comparable to Meese and Rogoff (1983) and others, the forecast horizons, h, are chosen to be 1, 6 and 12 months. All experiments are carried out using the "rolling regression" technique, where we use data from the beginning of the sample up to the forecasting month to estimate model parameters. At each horizon, our out-of-sample forecast covers the period from January 1990 through July 1997 with 91 months.[6] For each currency, we use ex ante observations on the set of explanatory variables, X_t=(s_{t-h}, m_{t-h}, y_{t-h}, r_{t-h})′, to estimate 10 NN specifications of s_t.[7] We choose 1–10 hidden units so as to check for robustness of the results and to avoid a possible model selection bias. For comparison, we use three benchmark models: the simple RW without drift, a neural network model without monetary fundamentals (NN1), and the linear model with the same set of explanatory variables X (LR). The empirical results are organized as follows.

Table 1 reports results on the forecast performance for the Japanese yen. Similarly, Tables 2, 3 and 4 present results for the German mark, the British pound, and the Canadian dollar, respectively. To conserve space and for convenience, for the three tests, Pesaran–Timmermann (PT), Diebold–Mariano (DM) and signed-ranks (SR), we only report their p-values, defined as the significance levels at which the null hypothesis under investigation can be rejected. In calculating the DM statistic, we use two fixed lags (0 and 24) and Andrews' optimal truncation lag to estimate the spectral density at frequency zero, but only report the results obtained with Andrews' lag to economize on space.[8] In each table, Panels A, B, and C report, respectively, the results for 1-, 6-, and 12-month forecast horizons. Within each panel, Columns (1)–(4) report results for the random walk model (RW), and the NN model with monetary fundamentals (NN) at 10 levels of complexity. Columns (5)–(8) present results for the linear monetary model (LR) and the NN model without fundamentals (NN1). For each model, we report the root mean square error (RMSE) in percentage terms. For all models except the RW, a measure of market-timing ability (DA) is also shown along with the PT test for the significance of this measure. As for the RW, since it has no market-timing ability by definition and the PT test is not well defined, no DA is reported. Columns (9) and (10) compare the performance of the NN to the RW, where we use the DM and SR tests for the null hypothesis that the square forecast error using the RW is smaller than that using the NN. Organized in the same manner, Columns (11) and (12) exhibit the test results for the null hypothesis that the LR yields a smaller square forecast error than the NN; Columns (13) and (14) compare the NN1 with the NN; and Columns (15) and (16) compare the RW with the NN_1.

[6] Economic theory provides little guidance as how to choose an "optimal" forecasting period in a given sample. Our "rule of thumb" here is that we use roughly the first 2/3 of the sample to estimate the first rolling regression and the remaining 1/3 for out-of-sample forecasting. Too few observations used in the estimation period can render parameter estimates imprecise, especially for the NN model where a large number of parameters have to be estimated. On the other hand, a reasonable sample size is needed in the forecasting period in order to make the various test statistics for comparison reliable.

[7] According to Eq. (5), each model has a total of 1+(k+2)n parameters to estimate, where k is the number of right-hand-side variables and n is the number of hidden units.

[8] The DM test results at fixed truncation lags 0 and 24 are similar to those using Andrews' lags. They are available from the authors upon request.

We start with the Japanese yen, and discuss the full set of results at different forecast horizons in turn. We will then briefly comment on the results for the other three currencies because results across all four currencies are somewhat similar.

5.1. The Japanese yen

It is apparent that our NN model with fundamentals cannot beat the simple RW model in terms of out-of-sample forecast accuracy at any horizon. At all 10 levels of complexity, the NN produces higher RMSEs than the RW and it does so statistically significantly in most cases, as can be seen in Columns (9) and (10).[9] Furthermore, the more complex the model, the less accurate the forecast of the NN compared to the RW. Second, Columns (11) and (12) show that the NN also does not seem to improve forecasts over the LR. Third, the LR on the other hand produces a lower RMSE than the RW at the 1-, 6- and 12-month horizons, and the longer the horizon, the better the forecast by the LR compared to the RW, a pattern consistent with that documented by Mark (1995). However, this pattern does not exist for either the NN or NN1. Indeed, as the forecast horizon lengthens, the performance of both neural network models deteriorates. Four, the NN shows a limited market-timing ability at the 6- and 12-month horizons. In particular, at the 12-month horizon, when the number of hidden units is between 4 and 9, the DA measure is well above 50% and is sometimes as high as 74%. Statistically, this measure is better than pure chance at the 5 or 1% significance level. This result is in contrast with Engel (1994) who finds that at the 12-month horizon the Markov switching model produces an average DA of 52% for 13 exchange rates and this DA measure is not statistically significant. Finally, from Columns (13) and (14), compared to the NN1 with the same number of hidden layer units, the NN in general yields a higher RMSE and in many occasions performs significantly worse than the NN1.[10] In summary, the neural network model with fundamentals cannot beat the random walk, the linear structural model or the neural network model without fundaments in general (Table 1).

5.2. The Deutsche mark

These results are quite similar to those for the Japanese yen, in that neural network models with fundamentals in general produce higher forecast errors than the RW, LR, and NN1 at all horizons and at almost all complexity levels (the only exception being that the NN performs better than the LR and NN1 at 6- and 12-month horizons when $n=1$). In particular, the NN performs more poorly at longer horizons and appears to be more overfitted for larger n's. At the 6- and 12-month horizons, the NN1 has some market-timing ability, with the DA measures ranging between 53% and 55%, which are statistically significant at the 5% level (Table 2).

[9] In Columns (9) and (10), a p-value no greater than 0.05 indicates that the NN yields a lower forecast error than the RW at the 5% significance level, while a p-value no smaller than 0.95 means that the NN produces a higher forecast error at the 5% level. The same interpretation is given for the p-values reported in Columns (11)–(16).

[10] Notice that the NN and NN1 may be of different levels of complexity even with the same n because the NN uses four explanatory variables while the NN1 uses only 1 (the 1-lag value of exchange rate). Nevertheless, in the absence of more appropriate methods, we view this as a natural comparison.

Table 1
Out-of-sample performance for the Japanese yen

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Model	RMSE (%)	DA (%)	PT	Model	RMSE (%)	DA (%)	PT	RW–NN		LR–NN		NN1–NN		RW–NN1	
								DM	SR	DM	SR	DM	SR	DM	SR
Panel A: 1-month horizon															
RW	3.22	–	–	LR	3.21	56.04	0.10								
NN				NN1											
$n=1$	3.47	50.55	0.42	$n=1$	3.40	47.25	0.70	0.93	0.94	0.90	0.91	0.81	0.89	0.94	0.97
$n=2$	3.65	50.55	0.39	$n=2$	3.39	46.15	0.77	0.99	0.99	0.98	0.99	0.93	0.96	0.95	0.98
$n=3$	3.67	50.55	0.42	$n=3$	3.39	45.05	0.83	1.00	0.99	1.00	1.00	0.91	0.80	0.96	0.98
$n=4$	3.72	46.15	0.79	$n=4$	3.38	45.05	0.83	1.00	1.00	1.00	1.00	0.97	0.96	0.96	0.99
$n=5$	4.03	47.25	0.70	$n=5$	3.42	45.05	0.83	1.00	1.00	1.00	1.00	0.99	0.99	0.97	0.99
$n=6$	3.86	53.85	0.20	$n=6$	3.36	45.05	0.83	1.00	0.99	1.00	1.00	0.99	0.96	0.96	0.99
$n=7$	4.26	42.86	0.93	$n=7$	3.42	45.05	0.83	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.99
$n=8$	4.36	45.05	0.83	$n=8$	3.38	48.35	0.63	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.95
$n=9$	4.13	50.55	0.43	$n=9$	3.42	46.15	0.78	1.00	1.00	1.00	1.00	1.00	0.99	0.97	0.99
$n=10$	4.53	46.15	0.77	$n=10$	3.43	50.55	0.46	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.92
Panel B: 6-month horizon															
RW	8.93	–	–	LR	8.43	65.93	0.00								
NN				NN1											
$N=1$	9.89	49.45	0.46	$N=1$	9.84	37.36	0.99	0.77	0.98	0.84	1.00	0.53	0.88	0.96	1.00
$N=2$	12.53	42.86	0.91	$N=2$	11.02	34.07	1.00	1.00	1.00	1.00	1.00	0.98	0.99	0.96	1.00
$N=3$	11.25	54.95	0.06	$N=3$	11.11	39.56	0.98	0.97	1.00	0.98	1.00	0.54	0.50	0.98	1.00
$N=4$	14.67	59.34	0.01	$N=4$	11.18	40.66	0.97	0.99	1.00	0.99	1.00	0.94	0.99	0.98	1.00
$N=5$	15.33	50.55	0.32	$N=5$	11.19	41.76	0.95	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
$N=6$	14.59	60.44	0.01	$N=6$	11.13	41.76	0.96	1.00	1.00	1.00	1.00	0.98	0.99	0.99	1.00
$N=7$	15.31	50.55	0.34	$N=7$	11.05	48.35	0.70	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00
$N=8$	16.83	49.45	0.47	$N=8$	11.51	42.86	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$N=9$	19.82	45.05	0.79	$N=9$	11.04	43.96	0.90	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
$N=10$	21.92	38.46	0.98	$n=10$	15.57	47.25	0.75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel C: 12-month horizon															
RW	11.68	–	–	LR	11.00	72.53	0.00								
NN				NN1											
$N=1$	17.43	45.05	0.21	$N=1$	13.91	23.08	1.00	0.92	1.00	0.95	1.00	0.84	0.99	1.00	1.00
$N=2$	19.15	47.25	0.18	$N=2$	17.74	28.57	1.00	1.00	1.00	1.00	1.00	0.81	0.88	0.98	1.00
$N=3$	22.39	42.86	0.31	$N=3$	16.75	30.77	1.00	1.00	1.00	1.00	1.00	0.93	0.94	0.99	1.00
$N=4$	20.27	58.24	0.01	$N=4$	17.52	35.16	1.00	0.91	1.00	0.91	1.00	0.70	0.18	0.99	1.00
$N=5$	19.22	72.53	0.00	$N=5$	17.67	36.26	1.00	0.96	0.92	0.97	1.00	0.65	0.12	0.99	1.00
$N=6$	18.96	73.63	0.00	$N=6$	17.55	36.26	1.00	0.98	0.92	0.98	0.99	0.66	0.07	0.99	1.00
$N=7$	20.77	57.14	0.04	$N=7$	23.16	35.16	1.00	1.00	1.00	1.00	1.00	0.31	0.68	0.99	1.00
$N=8$	21.77	61.54	0.00	$N=8$	17.48	35.16	1.00	1.00	1.00	1.00	1.00	0.90	0.85	0.99	1.00
$N=9$	24.22	59.34	0.01	$N=9$	17.81	38.46	1.00	1.00	1.00	1.00	1.00	0.98	0.95	0.99	1.00
$N=10$	30.91	47.25	0.40	$n=10$	22.70	38.46	1.00	1.00	1.00	1.00	1.00	0.94	1.00	1.00	1.00

The table reports the performance measures of alternative forecasting models and the p-values of various test statistics. Columns (1)–(4) are results for the random walk (RW), and the neural network model with monetary fundamentals (NN). Columns (5)–(8) show results for the linear monetary model (LR) and the neural network without market fundamentals (NN1). "RMSE" is the root mean square error; "DA" is direction accuracy; and "PT" shows the p-value of the Pesaran–Timmermann test. Columns (9) and (10) compare the NN and RW models with the Diebold–Mariano (DM) and the signed-rank (SR) tests. Columns (11) and (12) compare the LR and NN models. Columns (13) and (14) compare the NN1 and NN models. Columns (15) and (16) compare the NN1 and RW models.

Table 2
Out-of-sample performance for the Deutsche mark

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Model	RMSE (%)	DA (%)	PT	Model	RMSE (%)	DA (%)	PT	RW–NN		LR–NN		NN1–NN		RW–NN1	
								DM	SR	DM	SR	DM	SR	DM	SR
Panel A: 1-month horizon															
RW	3.16	–	–	LR	3.20	49.45	0.58								
NN				NN1											
$n=1$	3.43	45.05	0.80	$n=1$	3.35	45.05	0.73	0.93	1.00	0.86	0.99	0.85	0.95	0.87	0.99
$n=2$	3.60	43.96	0.82	$n=2$	3.31	45.05	0.73	0.99	1.00	0.98	1.00	0.93	0.86	0.85	0.99
$n=3$	3.67	47.25	0.69	$n=3$	3.29	46.15	0.61	1.00	1.00	1.00	1.00	0.97	0.78	0.84	0.99
$n=4$	3.67	39.56	0.97	$n=4$	3.30	48.35	0.42	1.00	1.00	1.00	1.00	0.96	0.90	0.91	0.99
$n=5$	3.66	47.25	0.61	$n=5$	3.30	48.35	0.42	0.98	0.99	0.98	1.00	0.92	0.83	0.91	0.99
$n=6$	3.72	49.45	0.50	$n=6$	3.29	48.35	0.42	1.00	0.99	1.00	0.99	0.94	0.90	0.90	0.99
$n=7$	3.72	47.25	0.69	$n=7$	3.33	47.25	0.50	0.99	0.99	0.99	0.99	0.93	0.85	0.95	1.00
$n=8$	3.58	60.44	0.02	$n=8$	3.39	42.86	0.88	0.95	0.59	0.94	0.59	0.74	0.09	0.99	1.00
$n=9$	3.80	58.24	0.06	$n=9$	3.42	45.05	0.76	0.98	0.87	0.99	0.87	0.88	0.28	0.98	1.00
$n=10$	3.95	49.45	0.56	$n=10$	3.46	46.15	0.65	1.00	0.99	1.00	0.99	0.94	0.83	0.99	1.00
Panel B: 6-month horizon															
RW	8.39	–	–	LR	9.31	49.45	0.66								
NN				NN1											
$n=1$	8.58	58.24	0.04	$n=1$	9.02	54.95	0.03	0.59	0.78	0.29	0.31	0.11	0.01	0.75	0.94
$n=2$	10.68	58.24	0.04	$n=2$	9.23	54.95	0.03	0.96	0.99	0.80	0.89	0.87	1.00	0.81	0.94
$n=3$	11.99	42.86	0.93	$n=3$	9.28	54.95	0.03	1.00	1.00	0.98	1.00	0.97	1.00	0.82	0.95
$n=4$	12.35	47.25	0.72	$n=4$	9.48	54.95	0.03	1.00	1.00	1.00	1.00	0.99	1.00	0.84	0.95
$n=5$	13.45	45.05	0.82	$n=5$	9.33	53.85	0.07	1.00	1.00	1.00	1.00	1.00	1.00	0.84	0.97
$n=6$	14.79	50.55	0.48	$n=6$	10.30	50.55	0.31	1.00	1.00	1.00	1.00	0.96	0.98	0.93	1.00
$n=7$	18.59	52.75	0.32	$n=7$	10.27	54.95	0.06	1.00	1.00	1.00	1.00	0.99	1.00	0.96	1.00
$n=8$	18.19	53.85	0.24	$n=8$	10.55	43.96	0.89	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00
$n=9$	17.51	45.05	0.85	$n=9$	11.09	47.25	0.66	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00
$n=10$	20.54	43.96	0.88	$n=10$	11.11	47.25	0.66	0.99	1.00	0.99	1.00	0.97	1.00	0.98	1.00
Panel C: 12-month horizon															
RW	10.96	–	–	LR	12.70	50.55	0.47								
NN				NN1											
$n=1$	11.26	63.74	0.00	$n=1$	13.02	52.75	0.02	0.63	0.59	0.21	0.54	0.00	0.00	0.96	1.00
$n=2$	21.18	31.87	1.00	$n=2$	13.36	52.75	0.02	0.95	1.00	0.92	1.00	0.93	1.00	0.96	1.00
$n=3$	27.42	31.87	1.00	$n=3$	13.30	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00
$n=4$	27.18	30.77	1.00	$n=4$	13.35	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00
$n=5$	30.64	26.37	1.00	$n=5$	13.44	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00
$n=6$	28.37	43.96	0.87	$n=6$	13.48	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00
$n=7$	28.25	35.16	1.00	$n=7$	13.50	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00
$n=8$	23.54	40.66	0.96	$n=8$	13.52	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00
$n=9$	26.71	38.46	0.99	$n=9$	13.55	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00
$n=10$	27.03	32.97	1.00	$n=10$	13.56	52.75	0.02	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00

The table reports the performance measures of alternative forecasting models and the p-values of various test statistics. Columns (1)–(4) are results for the random walk (RW), and the neural network model with monetary fundamentals (NN). Columns (5)–(8) show results for the linear monetary model (LR) and the neural network without market fundamentals (NN1). "RMSE" is the root mean square error; "DA" is direction accuracy; and "PT" shows the p-value of the Pesaran–Timmermann test. Columns (9) and (10) compare the NN and RW models with the Diebold–Mariano (DM) and the signed-rank (SR) tests. Columns (11) and (12) compare the LR and NN models. Columns (13) and (14) compare the NN1 and NN models. Columns (15) and (16) compare the NN1 and RW models.

5.3. The British pound

While the NN continues to perform poorly, interestingly, the NN1 is in general able to produce a lower RMSE than both the RW and LR models. Indeed, except for $n=1$ at the 1-month horizon, the RMSE from the NN1 is lower than that of the RW for all other levels of complexity and at all horizons. In terms of statistical significance, however, we find that the NN1 beats the RW only in a few cases. In particular, using the DM test, the NN1 yields a lower RMSE at the 10% level for $n=7$ at the 6-month horizon and for $n=2$ at the 12-month horizon, and at the 5% level for $n=1$ at the 12-month horizon. Results are somewhat stronger based on the SR test. Namely, the NN1 outperforms the RW at the 10% level at the 6-month horizon for $n=4$, 5, and 7, and at the 5% level at the 12-month horizon for $n=1$ and 2 (Table 3).

5.4. The Canadian dollar

The pattern for the Canadian dollar is similar to that for the British pound. The NN1 yields a lower RMSE than the RW for n below 7 at the 1- and 12-month horizons, and for all levels of n at the 6-month horizon. None of the results are, however, statistically significant. Furthermore, at the 1-month horizon, the NN1 shows some significant market-timing ability (Table 4).

In summary, the findings on the forecastability of exchange rates using neural networks are rather negative or mixed at best. The neural network model with monetary fundamentals as explanatory variables in general underperforms the RW across all four currencies. The more complex the model specification or the longer the forecast horizon is, the more poorly the model performs compared to the RW. The model without fundamentals provides limited support for the British pound and the Canadian dollar. The neural network models have some market-timing ability in a number of cases, yet the evidence is not overwhelming.[11] While Mark (1995) reports that the forecasting ability of the linear model improves as the forecast horizon lengthens, the pattern is not discovered within the NN framework.[12] Furthermore, we find that our neural network models do not seem to be superior to the simple linear model. Our global nonparametric NN results complement the local nonparametric results of Meese and Rose (1991) and Diebold and Nason (1990) and further demonstrates the inability of nonlinear models to forecast exchange rate movements.

[11] By examining the forecasting errors over time, we do not find that the NN models perform significantly poorly at particular economic episodes relative to other periods. Interestingly, the mean forecast errors of the NN models are mostly positive for the Japanese yen and the Deutsche mark, and mostly negative for the British pound and the Canadian dollar. On another dimension, we compare the direction accuracy of the NN models with the relevant forward exchange rates, and find that the forward rates in general do a worse job in predicting the direction of future exchange rate changes than the NN models. In order to conserve space, these results are not reported but are available from the authors upon request.

[12] One possible reason why we do not find the usefulness of monetary fundamentals within the NN framework is the potential over-parameterization of the NN. To that end, we calculate the in-sample fit of the NN models (results not reported) and find that the in-sample RMSE's are much lower than the out-of-sample ones and the more complex the model, the better the in-sample fit.

Table 3
Out-of-sample performance for the British pound

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Model	RMSE (%)	DA (%)	PT	Model	RMSE (%)	DA (%)	PT	RW–NN		LR–NN		NN1–NN		RW–NN1	
								DM	SR	DM	SR	DM	SR	DM	SR
Panel A: 1-month horizon															
RW	3.20	–	–	LR	3.27	50.55	0.40								
NN				NN1											
$n=1$	3.34	50.55	0.40	$n=1$	3.22	43.96	0.88	0.94	0.92	0.99	0.99	0.90	0.92	0.91	0.95
$n=2$	3.29	46.15	0.71	$n=2$	3.18	53.85	0.28	1.00	0.99	0.61	0.85	0.99	0.98	0.25	0.40
$n=3$	3.43	48.35	0.60	$n=3$	3.19	52.75	0.36	0.96	0.93	0.95	0.61	0.95	0.84	0.30	0.48
$n=4$	3.53	42.86	0.91	$n=4$	3.19	51.65	0.43	0.99	0.98	0.99	0.93	0.98	0.97	0.36	0.48
$n=5$	3.41	46.15	0.82	$n=5$	3.19	51.65	0.43	0.98	0.99	0.97	0.88	0.97	0.98	0.38	0.51
$N=6$	3.46	45.05	0.86	$n=6$	3.19	52.75	0.35	0.97	0.99	0.93	0.69	0.97	0.99	0.37	0.50
$N=7$	3.46	43.96	0.91	$n=7$	3.19	50.55	0.48	0.98	1.00	0.96	0.85	0.98	1.00	0.37	0.66
$N=8$	3.58	40.66	0.98	$n=8$	3.19	51.65	0.40	0.95	1.00	0.92	0.78	0.94	1.00	0.39	0.37
$N=9$	3.68	45.05	0.89	$n=9$	3.20	51.65	0.41	0.99	1.00	0.98	0.78	0.98	0.99	0.51	0.63
$N=10$	3.57	45.05	0.88	$n=10$	3.19	47.25	0.72	0.99	1.00	0.98	0.86	0.99	0.99	0.40	0.83
Panel B: 6-month horizon															
RW	8.44	–	–	LR	8.71	51.65	0.29								
NN				NN1											
$N=1$	9.02	52.75	0.21	$n=1$	8.37	53.85	0.13	0.93	0.97	0.99	1.00	0.89	0.96	0.35	0.30
$N=2$	9.06	48.35	0.12	$n=2$	7.93	56.04	0.32	0.71	0.99	0.62	1.00	0.89	0.99	0.15	0.35
$N=3$	9.90	52.75	0.07	$n=3$	7.84	61.54	0.09	0.97	1.00	0.90	1.00	1.00	1.00	0.12	0.13
$N=4$	9.39	46.15	0.20	$n=4$	7.80	62.64	0.06	0.81	1.00	0.70	1.00	0.97	1.00	0.10	0.08
$N=5$	10.84	48.35	0.38	$n=5$	7.82	62.64	0.06	0.97	1.00	0.94	1.00	1.00	1.00	0.11	0.09
$N=6$	11.81	46.15	0.51	$n=6$	7.81	60.44	0.12	0.97	1.00	0.94	1.00	0.99	1.00	0.11	0.13
$N=7$	12.47	39.56	0.88	$n=7$	7.73	62.64	0.04	0.96	1.00	0.94	1.00	0.98	1.00	0.09	0.09
$N=8$	11.42	48.35	0.62	$n=8$	7.84	52.75	0.46	0.93	1.00	0.90	1.00	0.97	1.00	0.13	0.42
$N=9$	13.04	43.96	0.85	$n=9$	7.82	56.04	0.28	1.00	1.00	1.00	1.00	1.00	1.00	0.13	0.34
$N=10$	11.85	49.45	0.51	$n=10$	7.88	54.95	0.34	0.99	1.00	0.97	1.00	1.00	1.00	0.15	0.37
Panel C: 12-month horizon															
RW	10.26	–	–	LR	10.29	39.56	0.98								
NN				NN1											
$N=1$	10.76	38.46	0.99	$n=1$	9.50	62.64	0.01	0.69	1.00	0.96	1.00	0.83	1.00	0.01	0.00
$N=2$	10.45	65.93	0.00	$n=2$	9.72	58.24	0.05	0.55	0.59	0.54	0.66	0.66	0.80	0.09	0.01
$N=3$	12.62	56.04	0.14	$n=3$	9.93	49.45	0.50	0.86	0.93	0.90	0.93	0.84	0.82	0.29	0.50
$N=4$	11.88	63.74	0.00	$n=4$	9.88	54.95	0.15	0.87	0.82	0.94	0.80	0.86	0.85	0.29	0.33
$N=5$	14.63	48.35	0.59	$n=5$	9.88	54.95	0.15	0.97	1.00	0.99	1.00	0.95	1.00	0.29	0.34
$N=6$	16.33	56.04	0.14	$n=6$	9.91	53.85	0.20	0.94	1.00	0.96	1.00	0.93	1.00	0.31	0.39
$N=7$	15.37	60.44	0.02	$n=7$	9.90	54.95	0.14	0.95	0.99	0.97	1.00	0.94	0.99	0.31	0.36
$N=8$	15.16	57.14	0.09	$n=8$	9.93	56.04	0.10	0.97	0.99	0.98	0.98	0.96	0.99	0.32	0.41
$N=9$	16.44	51.65	0.40	$n=9$	9.99	53.85	0.19	0.98	1.00	0.99	1.00	0.97	1.00	0.36	0.52
$N=10$	16.85	56.04	0.13	$n=10$	10.01	52.75	0.25	0.99	1.00	0.99	0.99	0.99	0.99	0.36	0.56

The table reports the performance measures of alternative forecasting models and the p-values of various test statistics. Columns (1)–(4) are results for the random walk (RW), and the neural network model with monetary fundamentals (NN). Columns (5)–(8) show results for the linear monetary model (LR) and the neural network without market fundamentals (NN1). "RMSE" is the root mean square error; "DA" is direction accuracy; and "PT" shows the p-value of the Pesaran–Timmermann test. Columns (9) and (10) compare the NN and RW models with the Diebold–Mariano (DM) and the signed-rank (SR) tests. Columns (11) and (12) compare the LR and NN models. Columns (13) and (14) compare the NN1 and NN models. Columns (15) and (16) compare the NN1 and RW models.

Table 4
Out-of-sample performance for the Canadian dollar

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Model	RMSE (%)	DA (%)	PT	Model	RMSE (%)	DA (%)	PT	RW−NN		LR−NN		NN1−NN		RW−NN1	
								DM	SR	DM	SR	DM	SR	DM	SR
Panel A: 1-month horizon															
RW	1.22	–	–	LR	1.19	59.34	0.10								
NN				NN1											
$n=1$	1.17	59.34	0.07	$n=1$	1.20	53.85	0.25	0.07	0.14	0.04	0.15	0.19	0.18	0.11	0.36
$n=2$	1.20	52.75	0.72	$n=2$	1.20	59.34	0.06	0.34	0.57	0.53	0.59	0.46	0.83	0.21	0.20
$n=3$	1.26	49.45	0.79	$n=3$	1.20	60.44	0.04	0.80	0.81	0.92	0.92	0.88	0.87	0.21	0.21
$n=4$	1.29	49.45	0.67	$n=4$	1.20	60.44	0.04	0.93	0.92	0.98	0.97	0.96	0.93	0.26	0.25
$n=5$	1.30	47.25	0.85	$n=5$	1.20	59.34	0.05	0.94	0.97	0.99	0.99	0.97	0.96	0.22	0.23
$n=6$	1.29	49.45	0.64	$n=6$	1.20	61.54	0.02	0.88	0.87	0.95	0.94	0.92	0.86	0.21	0.22
$n=7$	1.26	52.75	0.43	$n=7$	1.22	57.14	0.12	0.78	0.76	0.89	0.83	0.77	0.85	0.49	0.49
$n=8$	1.32	56.04	0.21	$n=8$	1.26	59.34	0.04	0.92	0.85	0.97	0.93	0.74	0.68	0.83	0.56
$n=9$	1.57	51.65	0.48	$n=9$	1.30	54.95	0.17	1.00	1.00	1.00	1.00	1.00	0.99	0.95	0.81
$n=10$	1.74	56.04	0.22	$n=10$	1.29	56.04	0.09	0.97	0.99	0.97	1.00	0.94	0.92	0.91	0.67
Panel B: 6-month horizon															
RW	2.83	–	–	LR	2.75	63.74	0.00								
NN				NN1											
$n=1$	2.58	65.93	0.00	$n=1$	2.72	56.04	0.17	0.09	0.00	0.00	0.00	0.24	0.02	0.16	0.17
$n=2$	3.24	47.25	0.98	$n=2$	2.69	56.04	0.19	0.88	1.00	0.87	0.99	0.94	1.00	0.18	0.32
$n=3$	3.19	59.34	0.22	$n=3$	2.73	51.65	0.34	0.85	0.87	0.87	0.91	0.95	0.96	0.24	0.78
$n=4$	3.17	59.34	0.11	$n=4$	2.71	57.14	0.13	0.76	0.53	0.80	0.55	0.82	0.58	0.22	0.51
$n=5$	3.65	57.14	0.15	$n=5$	2.72	50.55	0.72	0.98	0.98	0.99	0.99	0.99	0.99	0.26	0.73
$n=6$	4.20	57.14	0.08	$n=6$	2.65	57.14	0.32	1.00	0.99	1.00	1.00	1.00	1.00	0.18	0.42
$n=7$	4.20	60.44	0.03	$n=7$	2.65	56.04	0.43	0.99	0.93	1.00	0.99	1.00	0.99	0.18	0.42
$n=8$	4.69	53.85	0.41	$n=8$	2.65	58.24	0.22	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.43
$n=9$	3.74	48.35	0.69	$n=9$	2.64	56.04	0.39	0.99	0.99	0.99	0.99	1.00	1.00	0.18	0.50
$n=10$	4.51	57.14	0.19	$n=10$	2.64	57.14	0.28	1.00	1.00	1.00	1.00	1.00	1.00	0.17	0.44
Panel C: 12-month horizon															
RW	4.39	–	–	LR	4.40	59.34	0.00								
NN				NN1											
$n=1$	4.28	67.03	0.00	$n=1$	4.43	52.75	0.44	0.39	0.07	0.16	0.00	0.39	0.01	0.55	0.81
$n=2$	6.51	48.35	0.53	$n=2$	4.33	53.85	0.37	0.98	1.00	0.96	1.00	0.97	1.00	0.45	0.85
$n=3$	5.04	49.45	0.71	$n=3$	4.28	48.35	0.70	0.86	0.91	0.81	0.83	0.89	0.75	0.39	0.94
$n=4$	6.72	47.25	0.76	$n=4$	4.21	50.55	0.57	1.00	1.00	0.99	1.00	1.00	1.00	0.32	0.81
$n=5$	6.81	47.25	0.73	$n=5$	4.29	42.86	0.92	1.00	1.00	1.00	1.00	1.00	1.00	0.41	0.95
$n=6$	6.91	51.65	0.33	$n=6$	4.20	42.86	0.92	1.00	1.00	1.00	1.00	1.00	1.00	0.31	0.92
$n=7$	7.98	48.35	0.60	$n=7$	4.45	45.05	0.83	1.00	1.00	1.00	1.00	1.00	1.00	0.58	0.95
$n=8$	6.90	48.35	0.64	$n=8$	4.45	45.05	0.83	0.99	1.00	0.99	1.00	0.99	1.00	0.58	0.95
$n=9$	7.69	51.65	0.40	$n=9$	4.34	45.05	0.85	0.99	1.00	0.99	1.00	0.99	1.00	0.45	0.89
$n=10$	10.85	54.95	0.25	$n=10$	4.74	42.86	0.92	0.91	1.00	0.91	1.00	0.91	1.00	0.77	0.99

The table reports the performance measures of alternative forecasting models and the *p*-values of various test statistics. Columns (1)–(4) are results for the random walk (RW), and the neural network model with monetary fundamentals (NN). Columns (5)–(8) show results for the linear monetary model (LR) and the neural network without market fundamentals (NN1). "RMSE" is the root mean square error; "DA" is direction accuracy; and "PT" shows the *p*-value of the Pesaran–Timmermann test. Columns (9) and (10) compare the NN and RW models with the Diebold–Mariano (DM) and the signed-rank (SR) tests. Columns (11) and (12) compare the LR and NN models. Columns (13) and (14) compare the NN1 and NN models. Columns (15) and (16) compare the NN1 and RW models.

6. Conclusion

Forecasting exchange rates has been an extremely difficult task and has long posed a challenge to academicians. Since the publication of Meese and Rogoff (1983), researchers have devoted enormous effort to formulating elegant models and developing sophisticated forecasting techniques in an attempt to beat the naive random walk model.

The goal of this paper has been to re-examine the predictability of exchange rates so as to shed some more light on the aforementioned long-standing issue. We postulate that economic fundamentals are important in driving exchange rates but the underlying relation between exchange rates and fundamentals may be inherently too complex for traditional linear models to capture adequately. Our work is motivated by several previous studies, in particular, Diebold and Nason (1990) and Meese and Rose (1991) who report negative findings using a local nonparametric method; and Kuan and Liu (1995), Brooks (1997), and Gencay (1999), who show the promise on high frequency forecasting of using the NN. We thus employ the NN—a global nonlinear procedure and choose as guided by economic theory a parsimonious set of monetary fundamentals as explanatory variables to forecast four major exchange rates. We find a general lack of ability of the NN in forecasting currency price movements. Our model with monetary fundamentals produces higher RMSE than both the random walk model and a simple linear monetary model, although it occasionally shows a limited market-timing ability. Results from the neural network model without fundamentals are only somewhat more supportive for the British pound and the Canadian dollar. The performance of the model deteriorates compared to the RW when the specification becomes more complex or when the forecast horizon lengthens. Our overall results are more on the negative side and suggest that neither nonlinearity nor market fundamentals appear to be very important in improving exchange rate forecast for the chosen horizons. Despite the demonstrated superiority of the NN compared to the local nonparametric method for high frequency data, we fail to find its relevance in lower frequency forecasting with market fundamentals. Our findings complement the local nonparametric results of Meese and Rose (1991) and Diebold and Nason (1990) and further demonstrates the inability of nonlinear models to forecast exchange rate movements. Therefore, the Meese–Rogoff results cannot be overturned even with the global nonparametric neural network models.

Several extensions are possible for future research. First, the value of the dollar appreciated dramatically in the early 1980s and abruptly dropped from late 1985, a peculiar phenomenon often called the "dollar cycle." It is unclear how this cycle affects the forecasting performance of alternative models. To avoid the possible "dollar cycle" effect, one can employ different vehicle currencies and examine the forecastability of currency prices relative to these alternative vehicle currencies.[13] Second, we have adopted a "rolling regression" strategy so as to make maximum use of sample observations in the estimation period. It will be interesting to see how a "moving regression" approach (with

[13] We have used the Deutsche mark as the vehicle currency and examine the forecastability of three exchange rates relative to the German mark. The results do not improve significantly and we obtain basically the same conclusion for the Deutsche mark-based exchange rates as the dollar-based exchange rates. These results are available upon request.

a fixed window size) performs as this latter strategy can capture possible structural changes in sample and thus may do better if structural changes did occur. Third, the forecast horizon of the NN can be extended up to 4 years to offer an interesting comparison to the long-horizon linear predictability documented in Mark (1995). Finally, it may be fruitful to compare the performance of the NN models with alternative parametric nonlinear models, such as ARCH-M, multivariate polynomial, piece-wise linear, and Markov-switching models. These as well as others are beyond the scope of this paper and are left for future research.

Acknowledgements

We would like to thank Ramazan Gencay, G.S. Maddala, Nelson Mark, Andy Naranjo, Donggyu Sul, John Wald and seminar participants at the Ohio State University, University of Windsor, Kent State University, the 1999 Computational Finance Conference at the Stern School of Business of New York University, INFORMS Cincinnati Spring 1999, and the 1999 FMA Annual Meeting for helpful conversations and comments. We are indebted to Richard Baillie (the editor) and the anonymous referees whose comments have led to an improvement of the paper. We are also grateful to Suwanna Chanyawongsak for research assistance and Diane Williams for proofreading. Min Qi acknowledges with thanks the financial support from Kent State University's Research Council and College of Business Administration. Yangru Wu thanks Rutgers University's Research Council and Rutgers University's Faculty of Management for financial support. The usual disclaimer applies. Part of this work was completed while Yangru Wu was visiting the Hong Kong Institute for Monetary Research. He thanks the Institute for its hospitality. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Hong Kong Institute for Monetary Research, its Council of Advisors, or Board of Directors.

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