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TECHNICAL ANALYSIS IN FOREIGN EXCHANGE MARKETS: LINEAR VERSUS NONLINEAR TRADING RULES*

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ABSTRACT

In this paper we assess the economic significance of the nonlinear predictability of EMS exchange rates. To that end, and using daily data for nine EMS currencies covering the 1st January 1978- 31st December 1994 period, we consider nearest-neighbour nonlinear predictors, transforming their forecasts into a technical trading rule, whose profitability has been evaluated against the traditional (linear) moving average trading rules, considering both interest rates and transaction costs. Our results suggest that in most of the cases a trading rule based on a nonlinear predictor outperform the moving average, both in terms of returns and in terms of the ideal profit and the Sharpe ratio profitability indicators.

JEL classification numbers: C53, F31

KEY WORDS: Nearest-neighbour prediction methods, Technical trading rules, Exchange rates

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1. Introduction

Given that exchange rate series exhibit high volatility and an elusive data generation process [see, e. g., Baillie and McMahon (1989) and Gallant. *et al.* (1991)], predicting exchange rates poses major theoretical and empirical challenges.

The pessimism about the prediction quality of exchange rate models has become generally accepted after the publication of the influential paper by Meese and Rogoff (1983). These authors performed a large number of statistical tests, indicating that not a single structural model of exchange rate was better in predicting bilateral exchange rates during the floating-rate period than the simple random walk model.

Some approaches have been tried to improve the ability of forecasting exchange rates. One of these approaches is the nearest neighbour (NN) forecasting technique. This forecasting method relies on the premise that short-term predictions can be made based on past patterns of the time series, therefore circumventing the need to specify an explicit econometric model to represent the time series.

Meese and Rose (1990), Diebold and Nason (1990), Mizrach (1992) and Satchell and Timmermann (1995) applied NN methods to analyse exchange-rate nonlinear predictability. In contrast, Lisi and Medio (1997) concluded that the NN predictors neatly outperform the predictions derived from the random walk model, suggesting that nonlinear patterns in exchange-rate series could be exploitable for improved point prediction, while Fernández-Rodríguez and Sosvilla-Rivero (1998), using also NN methods, found empirical evidence on short-term forecastable possibilities in some currencies participating in the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS). Moreover, results in Fernández-Rodríguez *et al.* (1999) suggested that recursively computed NN predictors, when compared to both a random walk and the traditional (linear) ARIMA models, lead to important improvements in the accuracy of the point forecast, clearly outperforming both the random walk and the ARIMA directional forecasts.

On the other hand, another important line of research has evaluated the relevance of technical analysis in foreign exchange market. As is well known, technical analysis involves using charts of financial price movements to infer the likely course of future prices and therefore construct forecasts and determine trading decisions. A considerable amount of work has provided support for the view that technical trading rules are capable of producing valuable economic signals in foreign exchange markets. Dooley and Shafer (1983) presented some of the earliest evidence suggesting that technical trading rules might be detecting changes in conditional mean returns in foreign exchange rate series, generating profits in excess of the buy-and-hold strategy. Later, Sweeney (1986) also found results supportive of the profitability of similar rules, whereas Taylor (1992) documented similar evidence for even more extensive sets of rules and data series. Recently, LeBaron (1992) and Levich and Thomas (1993) followed the methodology of Brock *et al.* (1992) and used bootstrap simulations to demonstrate the statistical significance of the technical trading rules against several parametric null models of exchange rates, while Lee and Mathur (1996) showed that only in two of the six cases examined the trading rules are marginally profitable. More recently, Szakmary and Mathur (1997), Neely and Weller (1997), LeBaron (1999) and Sosvilla-Rivero *et al.* (1999a) discovered that excess returns from extrapolative

technical trading rules in foreign exchange markets are high during periods of central bank intervention. Finally, Neely and Weller (1998), using genetic programming methodology, found that *ex ante* trading rules generate significant excess returns in three of the four cases considered and Gençay (1999), using feedforward network and NN regressions, found statistically significant forecast improvements for the current returns over the random walk model of foreign exchange returns.

This empirical evidence has largely limited its attention to the moving average (MA) rule, which is easily expressed algebraically. Nevertheless, practitioners rely heavily on many other techniques, including a broad category of graphical methods ("heads and shoulders", "rounded tops and bottoms", "flags, pennants and wedges", etcetera), which are highly nonlinear and complex to be expressed algebraically. Clyde and Osler (1997) show that the nonlinear NN forecasting technique, based on the literature on complex dynamic systems, can be viewed as a generalization of these graphical methods. Based on the idea that pieces of time series sometime in the past might have a resemblance to pieces in the future, this approach falls into a general class of models known as robust regression and works by selecting geometric segments in the past of the time series similar to the last segment available before the observation we want to forecast (see, e. g., Stone, 1977, Cleveland, 1979, and Härdle and Linton, 1994). Therefore, rather than extrapolating past values into the immediate future as in MA models, NN methods select relevant prior observations based on their levels and geometric trajectories, not their location in time.

Since the NN approach to forecasting is closely related to technical analysis, we aim to combine these two lines of research (nonlinear forecasting and technical trading rules) to assess the economic significance of the predictability of EMS exchange rates. To that end, in contrast with the previous papers, the (nonlinear) predictions from NN forecasting methods are transformed into a simple trading strategy, whose profitability is evaluated against an alternative strategy based both on (linear) MA rules. Furthermore, unlike previous empirical evidence, when evaluating trading performance, we will consider both interest rates and transaction cost, as well as a wider set of profitability indicators than those usually examined. We have applied these investment strategies to nine currencies participating in the ERM, using daily data of exchange rates *vis-à-vis* the Deustchemark for the 1 January 1978-31 December 1994 period.

The paper is organised as follows. In Section 2 we introduce the MA technical rules, while Section 3 presents the NN predictors. The empirical results are reported in Section 4. Finally, some concluding remarks are provided in Section 5.

2. MA technical rules

Drawing from previous academic studies and the technical analysis literature, in this paper we employ the simplest and most common trading rules: moving averages. Let E_t be the daily exchange rate. Consider the moving average $m_t(n)$ when it is defined as

$$m_t(n) = \frac{1}{n} \sum_{i=0}^{n-1} E_{t-i} \quad (1)$$

where n is the length of the moving average. Very simple technical trading rules consider the signal $s_t(n_1, n_2)$ defined by

$$s_t(n_1, n_2) = m_t(n_1) - m_t(n_2) \quad (2)$$

where $n_1 < n_2$, and where n_1 and n_2 are the short and the long moving averages, respectively. When $s_t(n_1, n_2)$ exceeds zero, the short term moving average exceeds the long term moving average to a certain extent, and a "buy" signal is generated. Conversely, when $s_t(n_1, n_2)$ is negative, and a "sell" signal is given. As can be seen, the moving average rule is essentially a trend following system because when prices are rising (falling), the short-period average tends to have larger (lower) values than the long-period average, signalling a long (short) position.

We evaluate the following popular moving average rules: [1,50], [1,150], [1, 200], [5, 50], [5,150] and [5,200], where the first number in each pair indicates the days in the short period (n_1) and the second number shows the days in the long period (n_2).

3. NN and SNN predictors

The NN method works by selecting geometric segments in the past of the time series similar to the last segment available before the observation we want to forecast (see, e. g., Stone, 1977, Cleveland, 1979, and Härdle and Linton, 1994). This approach is philosophically very different from the Box-Jenkins methodology. In contrast to Box-Jenkins models, where extrapolation of past values into the immediate future is based on correlation among lagged observations and error terms, nearest neighbour methods select relevant prior observations based on their levels and geometric trajectories, not their location in time.

NN forecast can be succinctly described as follows [see Fernández-Rodríguez, *et al.* (1999) for a more detailed account]:

1. We first transform the scalar series x_t ($t=1, \dots, T$) into a series of m -dimensional vectors x_t^m , $t=1, \dots, T-m+1$:

$$x_t^m = (x_t, x_{t-1}, \dots, x_{t-m+1}) \quad (3)$$

with m referred to as the *embedding dimension*. These m -dimensional vectors are often called *m-histories*.

2. As a second step, we select k m -histories

$$x_{i_1}^m, x_{i_2}^m, x_{i_3}^m, \dots, x_{i_k}^m, \quad (4)$$

most similar to the last available vector

$$x_T^m = (x_T, x_{T-1}, x_{T-2}, \dots, x_{T-m+1}), \quad (5)$$

where $k = \lambda T$ ($0 < \lambda < 1$), and where we use the subscript " i_j " ($j=1, 2, \dots, k$) to denote each of the k chosen m -histories.

To that end, we look for the closest k vectors [expression (4)] in the phase space \mathbb{R}^m , in the sense that they maximise the function:

$$\rho(x_{i_j}^m, x_T^m) \quad (6)$$

(i. e., looking for the highest serial correlation of all m -histories, $x_{i_j}^m$, with the last one, x_T^m).

3. Finally, to obtain a predictor for x_{T+1} , we consider the following local regression model:

$$\hat{x}_{T+1} = \hat{\alpha}_0 x_T + \hat{\alpha}_1 x_{T-1} + \dots + \hat{\alpha}_{m-1} x_{T-(m-1)} + \hat{\alpha}_m \quad (7)$$

whose coefficients have been fitted by a linear regression of x_{i_j+1} on $x_{i_j}^m = (x_{i_j}, x_{i_j-1}, \dots, x_{i_j-(m-1)})$ ($r=1, \dots, k$). Therefore, the $\hat{\alpha}_i$ are the values of α_i that minimise

$$\sum_{r=1}^k (x_{i,r+1} - a_0 x_{i,r} - a_1 x_{i,r-1} - \dots - a_{m-1} x_{i,r-(m-1)} - a_m)^2.$$

Alternatively, and following by Fernández-Rodríguez *et al.* (1999), we can establish simultaneous nearest neighbours (SNNs) to x_T^m by considering the information content of other related series. To simplify notation, let us consider a set of two time series: x_t ($t=1, \dots, T$) and y_t ($t=1, \dots, T$).

We are interested in making predictions of an observation of one of these series (e. g., x_T), by simultaneously considering NNs in both series. To that end:

1. We first embed both series in the same vectorial space \mathbb{R}^{2m} , paying attention to the following vector:

$$(x_T^m, y_T^m) \in \mathbb{R}^m \times \mathbb{R}^m$$

which gives us the last available m -history for each time series.

2. To establish SNNs to the last m -histories (x_T^m, y_T^m) , we can look for the closest k points that maximise the function:

$$\rho(x_i^m, x_T^m) + \rho(y_i^m, y_T^m), \quad i=m, m+1, \dots, T. \quad (8)$$

obtaining a set of k simultaneous m -histories in both series:

$$x_{i_1}^m, y_{i_1}^m$$

$$x_{i_2}^m, y_{i_2}^m$$

...

$$x_{i_k}^m, y_{i_k}^m$$

3. The predictions for x_{T+1} and y_{T+1} can be obtained from a linear autoregressive predictor with varying coefficients estimated by ordinary least squares:

$$\hat{x}_{T+1} = \hat{a}_0 x_T + \hat{a}_1 x_{T-1} + \dots + \hat{a}_{m-1} x_{T-(m-1)} + \hat{a}_m \quad (9a)$$

$$\hat{y}_{T+1} = \hat{b}_0 y_T + \hat{b}_1 y_{T-1} + \dots + \hat{b}_{m-1} y_{T-(m-1)} + \hat{b}_m \quad (9b)$$

The procedure in the time series x_t is a linear regression of $x_{i,r+1}$ on $x_{i,r}^m = (x_{i,r}, x_{i,r-1}, \dots, x_{i,r-(m-1)})$ ($r=1, \dots, k$). Therefore, the \hat{a}_i are the values of a_i that minimise

$$\sum_{r=i}^k (x_{i,r+1} - a_0 x_{i,r} - a_1 x_{i,r-1} - \dots - a_{m-1} x_{i,r-(m-1)} - a_m)^2$$

In an analogous way, the \hat{b}_i are the values of b_i that minimise

$$\sum_{r=i}^k (y_{i,r+1} - b_0 y_{i,r} - b_1 y_{i,r-1} - \dots - b_{m-1} y_{i,r-(m-1)} - b_m)^2$$

As it can be seen, the difference between this predictor and that presented in (7) is that now the NNs are established using criteria in which information on both series are used. As mentioned above, in this paper we use ERM exchange rate series. Since under the ERM, member countries agree to maintain their exchange rate *vis-à-vis* the other currencies in the system within bands around a central parity, by using SNN predictions, we attempt to incorporate structural information into the nonparametric analysis.

Finally note that our predictors depend on the values of embedding dimension m and the number of closest k points in the phase space \mathbb{R}^m . We chose them according to Casdagli's (1991) algorithm, obtaining, in our case, an embedding dimension $m=6$ and a number of SNN points equal to 2% of the sample.

4. Empirical results

In this paper, we transform the forecast from NN and SNN predictors into a simple technical trading strategy in which positive returns are executed as long positions and negative returns are executed as short positions. Such investment strategy is applied to nine currencies participating in the ERM, using daily data of exchange rates *vis-à-vis* the Deutchemark for the 1 January 1978-31 December 1994 period: the Belgian franc (BFR), the Danish crown (DKR), the Portuguese escudo (ESC), the French franc (FF), the Dutch guilder (HFL), the Irish pound (IRL), the Italian lira (LIT), the Spanish peseta (PTA) and the Pound sterling (UKL). For the six founding members (BFR, DKR, FF, HFL, IRL and LIT), the forecasting period runs from the last realignment in the EMS before the monetary turmoil (12 January 1987) to the end of the sample. Our NN and SNN predictors are used to produce forecasts one day ahead for 13th January 1987. Then, the data for this date are added to the sample, the models are re-estimated, and new forecasts are generated for all time series. This recursive process continued until forecasts are generated using 30th December 1994 data. In the case of the Spanish peseta, the pound sterling and the Portuguese escudo, we follow the same recursive process from the joining date (19th June 1989, 8th October 1990 and 9th April 1992, respectively).

In the selection of the forecasting period, we have taken into account the history of the ERM, commonly divided in three subperiods [see, e. g., Higgins (1993)]. The first subperiod extends from the inception of the ERM in March 1979 to January 1987, characterized by frequent realignments to correct for divergence in economic fundamentals of the participating nations. The second subperiod (the so-called "new ERM") lasted from 1987 to the end of 1991 and coincided with increasing confidence in the ERM, the removal of capital controls, and greater convergence in the economic fundamentals. The third subperiod covers successive crises of September 1992 and August 1993, being the German unification and the recession in Europe widely accepted as the underlying causes of such crises [see, e. g., Commission of the European Communities (1993)]. We can consider a new subperiod initiated with the broadening of the fluctuation bands to $\pm 15\%$ in August 1993 and characterized by volatility levels comparable to those prevailing before the crisis [see, e. g., Sosvilla-Rivero *et al.* (1999b)]. To allow for the learning process the agents are likely to follow in order to form their exchange-rate expectations, in the forecasting period we have only considered the experience from January 1987.

In Table 1 we report the buy and sell signals generated as percentage of the number of observations in the forecasting period ["P(Buy)" and "P(Sell)", respectively]. As can be seen, all trading rules are very active, generating every day either a sell or a buy signal. For the NN predictor, the percentage of buy signals exceeds the percentage of sell signals in the cases of DKR and HFL, while in the case of the MA trading rules this is true for BFR and HFL. Finally, note that for the SNN predictor the percentage of buy signals exceeds the percentage of sell signals in 5 out of the 9 cases considered (DKR, FF, HFL, PTA and UKL).

In order to assess the economic significance of our simple technical trading strategy, we first consider the estimated total return of such strategy:

$$R_T^i = \sum_{t=1}^n z_t r_t \quad (10)$$

where r_t is the return from a foreign currency position over the period $(t, t+1)$, z_t is a variable interpreted as the recommended position which takes either a value of -1 (for a short position) or +1 (for a long position), and n is the number of observations.

Given that trading in spot foreign exchange market requires consideration of interest rates when evaluating trading performance, we use overnight interest rates to compute r_t as follows:

$$r_t = \ln(E_{t+1}) - \ln(E_t) - \ln(1+i_t) + \ln(1+i^*) \quad (11)$$

where E represents the spot exchange rate expressed *vis-à-vis* the Deutsche mark, i is the domestic daily interest rate and i^* is the German daily interest rate.

On the other hand, assuming that transaction costs of $c\%$ are paid each time a new position (i. e., from short to long or from long to short) is established, the net return of the technical trading strategy is given by:

$$R_T^n = \sum_{t=1}^n z_t r_t + nrt \{ \ln(1-c) - \ln(1+c) \} \quad (12)$$

where nrt is the number of round-trip trades. The last term in the equation reflects the transaction costs that are assumed to be paid whenever a new position is established.

The estimated total and net returns are calculated by:

$$R_T^t = \sum_{t=1}^n \hat{z}_t r_t \quad (13)$$

and

$$R_T^n = \sum_{t=1}^n \hat{z}_t r_t + nrt \{ \ln(1-c) - \ln(1+c) \} \quad (14)$$

where \hat{z}_t is the estimated recommended position for the t th observation. The estimation of \hat{z}_t is carried out both by two nonlinear forecasting methods (NN predictors and SNN predictors) and six linear MA trading rules (1-50, 1-150, 1-200, 5-50, 5-150 and 5-200). Regarding the transaction costs, following Levich and Thomas (1993) and Osler and Chang (1995), we consider transaction costs of 0.05%.

Tables 2 and 3 report the estimated mean annual total and net return, respectively, as well as its associated t-statistics [with corrections for serial correlation and heteroskedasticity, see Hamilton (1994, Ch. 14)] as a measure of the statistical significance of the results. As can be seen in Table 2, only in 1 of the 9 cases considered (UKL) the (linear) MA trading rules outperform the trading strategy based on a nonlinear (NN or SNN) predictor. Nevertheless, the t-statistic suggests that in this case the null hypothesis that the mean annual return is equal to zero cannot be rejected. From Table 2, we can also see that in 6 out of 9 cases (BFR, DKR, ESC, HFL, LIT and PTA), the mean annual total returns from when using the SNN predictors are the highest, while for the cases of FF and IRL, it is the trading system based on the NN predictor the rule that yields the highest mean annual total returns. It should be noted that for the later cases all t -statistics reject the null hypothesis that the mean annual total returns are equal to zero. On the other hand, and as can be seen from Table 3, the mean annual net return from the nonlinear trading rule dominates that from the MA trading rules in all the cases, except for the UKL case. In 6 of such cases (BFR, DKR, ESC, HFL, LIT and PTA), the trading system based on the SNN predictor give the highest mean annual net returns, whereas in the cases of FF and IRL, the highest mean annual net return is obtained when using the NN predictors. Finally, note that in 7 of the 9 exchange rate examined (BFR, DKR, FF, HFL, IRL, LIT and UKL) the results are statistically significant (at least at the 5% level) as indicated by the t-statistics.

Besides the total and net returns, we also consider other two profitability measures: the ideal profit and the Sharpe ratio. We consider a version of the ideal profit that measures the net returns of the trading system against a perfect predictor and is calculated by:

$$R_T = \frac{\sum_{t=n+1}^{n+T+1} \hat{z}_t r_t + nrt[\ln(1-c)-\ln(1+c)]}{\sum_{t=n+1}^{n+T+1} |r_t + nrt[\ln(1-c)-\ln(1+c)]|} \quad (15)$$

According to equation (15), $R_T = 1$ if the indicator variable \hat{z}_t takes the correct trading position for all observations in the sample. If all trade positions are wrong, then the value of this measure is $R_T = -1$. An $R_T = 0$ value is considered as a benchmark to evaluate the performance of an investment strategy. Regarding the Sharpe ratio (Sharpe, 1966), it is simply the annual mean net return of the trading strategy divided by its standard deviation:

$$S_R = \frac{\mu_{\hat{R}_T}}{\sigma_{\hat{R}_T}} \quad (16)$$

According to equation (16), the higher the Sharpe ratio, the higher the mean annual net return and the lower the volatility. The results for these additional profitability measures are reported in Tables 4 and 5.

As can be seen in Table 4, the MA trading rules always render negative values for the ideal profit ratio. In contrast, the trading strategy based on the nonlinear (NN or SNN) predictors renders positive values in 4 out of the 9 cases considered (DKR, FF, HFL and LIT). In all cases, except for the UKL, the use of nonlinear predictors to generate sell/buy signals produces higher values of this profitability measure than those from the MA trading rules. As for the Sharpe ratio, a similar pattern emerges from Table 5: the trading strategy based on the nonlinear predictors yields the highest Sharpe ratios in the 8 out of the 9 cases (BFR, DKR, ESC, FF, HFL, IRL, LIT and PTA), while for the UKL the highest (less negative) value is obtained from the MA trading rules.

Given that the period considered is very long and heterogeneous, we have also computed our profitability measures for different subperiods. To that end, we have divided the sample in seven parts, the breaking points being 8th January 1990 (technical realignment involved in the lira's move to narrow bands), 17th September 1992 (Pound sterling and the Italian lira suspended their participation in the ERM and the Spanish peseta was realigned), 23rd November 1992 (realignment of the Spanish peseta and the Portuguese escudo), 1st February 1993 (realignment of Irish pound), 14th May 1993 (further realignment of the Spanish peseta and the Portuguese escudo) and 2nd August 1993 (broadening of the fluctuation bands to $\pm 15\%$).

The results (not shown here, but are available from the authors upon request) indicate a significantly improve in the profitability of the trading rules based on the nonlinear predictors for those subperiods and currencies where some nonlinear forecastability was found in Fernández-Rodríguez and Sosvilla-Rivero (1998). We read this additional evidence to say that there seems to be a close relationship between the forecast performance and the credibility of the exchange-rate commitments.

5. Concluding remarks

In this paper we have assessed the economic significance of the predictability of EMS exchange rates. To that end, we have applied two nonlinear predictors (NN and SNN predictors) to nine currencies participating in the ERM of the EMS, using daily data of exchange rates *vis-à-vis* the Deutsche mark for the 1st January 1978-31st December 1994 period. The predictions from these forecasting procedures have been transformed into a technical trading rule, whose profitability has been evaluated against the traditional (linear) MA trading rules, taking into account both interest rates and transaction costs.

The main results are as follows. First, when profitability was measured using mean annual total return, in 8 of the 9 cases considered the trading strategy based on a nonlinear (NN or SNN) predictor outperform the (linear) MA trading rules, being the mean annual total returns statistically different from zero in such cases.

Secondly, when estimating mean annual net return, the trading system based on the nonlinear predictors gives the highest returns in 8 out of the 9 cases considered, being the results statistically significant in 7 of these 8 cases.

Finally, when assessing the economic value of the predictors using both the ideal profit and the Sharpe ratio, the use of nonlinear predictors as trading rules yields the highest values for both profitability measures in the 8 out of the 9 cases.

Therefore, this paper has showed the potential usefulness of nearest neighbour predictors for technical trading rules to forecast daily exchange data. To us, the results in the present paper suggest that further consideration of NN predictors for technical trading rules could be a fruitful enterprise.

Several explanations can be put forward in interpreting the observed evidence. First, as demonstrated in Neftçi (1991), technical trading rules can only be exploited usefully if the underlying process is nonlinear. Indeed, results in Fernández-Rodríguez *et al.* (1998) suggested that the data used in this paper exhibit nonlinear dependencies.

Second, Kho (1995) reports results suggesting that some proportion of the profits observed could be explained by a time-varying risk premium. However, the fact that there is not a satisfactory model of risk premium in foreign exchange markets [see Engle (1996)] means that this question cannot be answered with any degree of confidence.

Third, a number of authors [see, e. g., Shiller (1988)] have suggested that financial markets are prone to the influence of fads and fashions. Such fads provide sophisticated traders with an opportunity to profit at the expense of the crowd.

A fourth possibility is that evidence of profitable trading rules signals some form of market inefficiency, since in the finance literature the efficient market hypothesis is often interpreted as the impossibility of constructing a trade rule, based on publicly available information, which is capable of yielding consistently positive excess profits (discounted at an appropriate risk-adjusted rate) [see, e. g., Jensen (1978)]. In the foreign exchange market, if

participants are rational and risk neutral, expectations concerning future rates should be incorporated and reflected in forward exchange rates. Thus, the forward exchange rate should be an unbiased predictor of future exchange rate. However, empirical tests suggest the existence of the forward discount bias [see Engle (1996)]. Moreover, Frankel and Froot (1987) have argued that the bias can be accounted for in terms of expectational errors. If it is so, and the errors have some amount of persistence, it suggests that technical analysis may play a role in anticipating the impact of these errors on the market.

Finally, the fact that central banks frequently intervene in the foreign exchange market could provide a further explanation of the existence of profitable trading rules [see, e. g., Szakmary and Mathur (1997), Neely and Weller (1997), LeBaron (1999) and Sosvilla-Rivero *et al.* (1999)].

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Exchange rates	Non-linear trading rules						Linear trading rules											
	NN predictor		SNN predictor		[1,50]		[1,150]		[1,200]		[5,50]		[5,150]		[5,200]			
	P(Buy)	P(Sell)	P(Buy)	P(Sell)	P(Buy)	P(Sell)	P(Buy)	P(Sell)	P(Buy)	P(Sell)	P(Buy)	P(Sell)	P(Buy)	P(Sell)	P(Buy)	P(Sell)		
BFR (2) (5)	54.50	45.5	51.21	48.79	46.93	53.07	45.88	54.12	47.59	52.41	46.87	53.13	45.33	54.67	46.76	53.24		
DKR (2) (5)	48.08	51.92	43.31	56.69	51.71	48.29	53.13	46.87	54.05	45.95	50.07	49.93	52.13	47.87	52.92	47.08		
ESC (3) (6)	52.89	47.11	56.27	43.73	67.36	32.64	70.26	29.74	76.53	23.47	67.52	32.48	69.13	30.87	75.72	24.28		
FF (2) (5)	51.62	48.38	48.60	51.4	53.63	46.37	59.80	40.20	61.23	38.76	54.70	45.30	59.94	40.06	61.67	38.33		
HFL (2) (5)	46.22	53.78	47.15	52.85	43.69	56.31	40.50	59.49	39.84	60.16	40.77	59.23	37.98	62.02	37.25	62.75		
IRL (4) (5)	57.90	42.10	62.34	37.66	52.11	47.89	61.44	38.56	64.31	33.69	50.87	49.13	60.93	39.07	64.02	35.98		
LIT (3) (5)	54.69	45.31	50.22	49.78	63.03	36.97	71.74	28.26	78.92	21.08	63.91	36.09	72.91	27.09	79.06	20.94		
PTA (3) (7)	51.91	48.09	45.01	54.99	64.23	35.77	77.60	22.40	74.52	25.48	64.23	35.77	78.13	21.87	74.73	25.27		
UKL (4) (8)	50.70	49.30	48.99	51.01	56.84	43.16	61.57	38.43	61.57	38.43	56.64	43.36	61.57	38.43	61.87	38.13		

Notes: (1) P(Buy) and P(Sell) denote, respectively, the buy and sell signals generated as percentage of the number of observations in the forecasting period
(2) Time series used in establishing occurring analogues in the SNN predictor: BFR, DKR, FF and HFL.
(3) Time series used in establishing occurring analogues in the SNN predictor: ESC, LIT and PTA.
(4) Time series used in establishing occurring analogues in the SNN predictor: IRL and UKL.
(5) Forecasting period: 13-1-87 to 31-12-94.
(6) Forecasting period: 6-4-92 to 31-12-94.
(7) Forecasting period: 19-6-89 to 31-12-94.
(8) Forecasting period: 8-10-90 to 31-12-94.

TABLE.2: Mean annual total return: (1) (2)

Exchange rates	Non-linear trading rules		Linear trading rules							
	NN predictor	SNN predictor	[1,50]	[1,150]	[1,200]	[5,50]	[5,150]	[5,200]		
BFR (3) (6)	0.0631 (5.9861 ^a)	0.0670 (7.8334 ^a)	-0.0437 (-5.0054 ^a)	-0.0282 (-3.5077 ^a)	-0.0298 (-3.6200 ^a)	-0.0035 (-0.4854)	-0.0071 (-0.9706)	-0.0057 (-0.7981)		
DKR (3) (6)	0.2614 (11.7277 ^a)	0.2822 (11.5596 ^a)	-0.1734 (-6.1999 ^a)	-0.1312 (-5.0620 ^a)	-0.1367 (-5.4208 ^a)	-0.0516 (-2.7768 ^a)	-0.0323 (-2.0516 ^b)	-0.0406 (-2.5656 ^b)		
ESC (4) (7)	0.0323 (0.6578)	0.0891 (2.2230 ^a)	0.0317 (0.7455)	0.0385 (1.1145)	0.0381 (1.0782)	0.0673 (1.7961 ^c)	0.0329 (0.9258)	0.0391 (1.1333)		
FF (3) (6)	0.2448 (13.9101 ^a)	0.2427 (13.6570 ^a)	-0.1115 (-5.5922 ^a)	-0.0745 (-4.2358 ^a)	-0.0657 (-4.4343 ^a)	-0.0085 (-0.6926)	-0.0204 (-1.8477)	-0.0211 (-1.8279 ^a)		
HFL (3) (6)	0.1403 (17.6453 ^a)	0.1471 (18.1531 ^a)	-0.1131 (-11.6381 ^a)	-0.0984 (-8.8918 ^a)	-0.0845 (-8.3545)	-0.0324 (-5.9658 ^a)	-0.0237 (-4.7103 ^a)	-0.0222 (-4.6854 ^a)		
IRL (5) (6)	0.0527 (3.1079 ^a)	0.0305 (1.8536 ^c)	-0.0378 (-2.3394 ^b)	-0.0242 (-1.6387)	-0.0308 (-1.9767 ^b)	-0.0065 (-0.4002)	-0.0094 (-0.6427)	-0.0099 (-0.7225)		
LIT (4) (6)	0.2681 (6.2970 ^b)	0.3348 (9.1434 ^a)	-0.1664 (-3.5986 ^b)	-0.0449 (-1.2011)	-0.0425 (-1.1516)	-0.0332 (-0.8943)	-0.0032 (-0.0922)	-0.0008 (-0.0244)		
PTA (4) (8)	0.0405 (0.9921)	0.0677 (2.0879 ^b)	0.0626 (1.7485 ^c)	0.0193 (0.4924)	0.0473 (1.2748)	0.0483 (1.2894)	0.0368 (0.9768)	0.0349 (0.9290)		
UKL (5) (9)	-0.0663 (-1.4951)	-0.0079 (-0.2688)	0.0561 (1.4503)	0.0076 (0.1952)	0.0139 (0.3612)	0.0352 (0.9124)	0.0111 (0.2851)	0.0076 (0.1943)		

Notes: (1) Returns generated by each forecasting method over the forecast sample, before transaction fees are taken into account [see equation (13) in the text].
(2) t- statistics (corrected for serial correlation and heteroskedasticity) in parenthesis: ^a, ^b, and ^c denote significance at the 1%, 5% and 10% levels, respectively.
(3) Time series used in establishing occurring analogues in the SNN predictor: BFR, DKR, FF and HFL.
(4) Time series used in establishing occurring analogues in the SNN predictor: ESC, LIT and PTA.
(5) Time series used in establishing occurring analogues in the SNN predictor: IRL and UKL.
(6) Forecasting period: 13-1-87 to 31-12-94.
(7) Forecasting period: 6-4-92 to 31-12-94.
(8) Forecasting period: 19-6-89 to 31-12-94.
(9) Forecasting period: 8-10-90 to 31-12-94.

TABLE 3: Mean annual net return (1) (2)

Exchange rates	Non-linear trading rules		Linear trading rules						
	NN predictor	SNN predictor	[1,50]	[1,150]	[1,200]	[5,50]	[5,150]	[5,200]	
BFR (3) (6)	-0.0619 (-5.8806 ^a)	-0.0580 (-6.7737 ^a)	-0.1687 (-19.3104)	-0.1532 (-19.0678 ^a)	-0.1548 (-18.8113 ^a)	-0.1285 (-17.8063 ^a)	-0.1321 (-17.9502 ^a)	-0.1307 (-18.3446 ^a)	
DKR (3) (6)	0.1364 (6.1189 ^a)	0.1572 (6.4393 ^a)	-0.2984 (-10.6697 ^a)	-0.2562 (-9.8857 ^a)	-0.2617 (-10.3778 ^a)	-0.1766 (-9.5070 ^a)	-0.1573 (-9.9967 ^a)	-0.1656 (-10.4596 ^a)	
ESC (4) (7)	-0.0927 (-1.8860 ^c)	-0.0359 (-0.8958)	-0.0934 (-2.1990 ^b)	-0.0865 (-2.5006 ^b)	-0.0869 (-2.4568 ^b)	-0.0577 (-1.5379)	-0.0921 (-2.5919 ^a)	-0.0859 (-2.4909 ^b)	
FF (3) (6)	0.1198 (6.8069 ^a)	0.1177 (6.6234 ^a)	-0.2365 (-11.8608 ^a)	-0.1995 (-11.3436 ^a)	-0.1907 (-12.8718 ^a)	-0.1335 (-10.8287 ^a)	-0.1454 (-13.1503 ^a)	-0.1461 (-12.6432 ^a)	
HFL (3) (6)	0.0153 (1.9241 ^c)	0.0221 (2.7314 ^a)	-0.2381 (-24.4976 ^a)	-0.2234 (-20.1831)	-0.2095 (-20.7122 ^a)	-0.1574 (-28.9952 ^a)	-0.1487 (-29.5279 ^a)	-0.1472 (-31.0157 ^a)	
IRL (5) (6)	-0.0723 (-4.2672 ^a)	-0.0945 (-5.7488 ^a)	-0.1628 (-10.0772 ^a)	-0.1492 (-10.0892 ^a)	-0.1558 (-9.9999 ^a)	-0.1315 (-8.1011 ^a)	-0.1344 (-9.2135 ^a)	-0.1349 (-9.8889 ^a)	
LIT (4) (6)	0.1431 (3.3608 ^a)	0.2098 (5.7296 ^a)	-0.2914 (-6.3014 ^a)	-0.1699 (-4.5449 ^a)	-0.1675 (-4.5404 ^a)	-0.1582 (-4.2609 ^a)	-0.1282 (-3.7280 ^a)	-0.1258 (-3.6508 ^a)	
PTA (4) (8)	-0.0845 (-2.0689 ^b)	-0.0573 (-1.7653 ^c)	-0.0624 (-1.7425 ^c)	-0.1057 (-2.6970 ^a)	-0.0777 (-2.0937 ^b)	-0.0777 (-2.0937 ^b)	-0.0767 (-2.0490 ^b)	-0.0901 (-2.3998 ^b)	
UKL (5) (9)	-0.1913 (-4.3125 ^a)	-0.1329 (-4.4966 ^a)	-0.0690 (-1.7841 ^c)	-0.1174 (-3.0194 ^a)	-0.1111 (-2.8958 ^a)	-0.1111 (-2.8958 ^a)	-0.0898 (-2.3284 ^b)	-0.1174 (-2.9940 ^a)	

Notes: (1) Returns generated by each forecasting method over the forecast sample, after transaction fees are taken into account [see equation (13) in the text].

(2) t-statistics (corrected for serial correlation and heteroskedasticity) in parenthesis: ^a, ^b, and ^c denote significance at the 1%, 5% and 10% levels, respectively.

(3) Time series used in establishing occurring analogues in the SNN predictor: BFR, DKR, FF and HFL.

(4) Time series used in establishing occurring analogues in the SNN predictor: ESC, LIT and PTA.

(5) Time series used in establishing occurring analogues in the SNN predictor: IRL and UKL.

(6) Forecasting period: 13-1-87 to 31-12-94.

(7) Forecasting period: 6-4-92 to 31-12-94.

(8) Forecasting period: 19-6-89 to 31-12-94.

(9) Forecasting period: 8-10-90 to 31-12-94.

TABLE 4: Ideal profit ratio (1)

Exchange rates	Non-linear trading rules		Linear trading rules					
	NN predictor	SNN predictor	[1,50]	[1,150]	[1,200]	[5,50]	[5,150]	[5,200]
BFR (2) (5)	-0.5479	-0.5127	-1.4925	-1.3548	-1.3691	-1.1366	-1.1688	-1.1559
DKR (2) (5)	0.2388	0.2753	-0.5225	-0.4486	-0.4582	-0.3092	-0.2754	-0.2900
ESC (3) (6)	-0.1793	-0.0695	-0.1807	-0.1673	-0.1681	-0.1116	-0.1782	-0.1663
FF (2) (5)	0.2599	0.2554	-0.5132	-0.4328	-0.4137	-0.2897	-0.3155	-0.3170
HFL (2) (5)	0.1356	0.1963	-2.1112	-1.9809	-1.8574	-1.3953	-1.3186	-1.3054
IRL (4) (5)	-0.2839	-0.3710	-0.6389	-0.5858	-0.6115	-0.5161	-0.5274	-0.5293
LIT (3) (5)	0.1538	0.2255	-0.3133	-0.1827	-0.1801	-0.1701	-0.1378	-0.1353
PTA (3) (7)	-0.1359	-0.0921	-0.1004	-0.1701	-0.125	-0.1234	-0.142	-0.1450
UKL (4) (8)	-0.2932	-0.2037	-0.1057	-0.1799	-0.1703	-0.1376	-0.1746	-0.1799

Notes: (1) The ideal profit measures the returns of the trading system against a perfect predictor [see equation (15) in the text].

(2) Time series used in establishing occurring analogues in the SNN predictor: BFR, DKR, FF and HFL.

(3) Time series used in establishing occurring analogues in the SNN predictor: ESC, LIT and PTA.

(4) Time series used in establishing occurring analogues in the SNN predictor: IRL and UKL.

(5) Forecasting period: 13-1-87 to 31-12-94.

(6) Forecasting period: 6-4-92 to 31-12-94.

(7) Forecasting period: 19-6-89 to 31-12-94.

(8) Forecasting period: 8-10-90 to 31-12-94.

TABLE 5: Sharpe ratio (1)

Exchange rates	Non-linear trading rules		Linear trading rules					
	NN predictor	SNN predictor	[1,50]	[1,150]	[1,200]	[5,50]	[5,150]	[5,200]
BFR (2) (5)	-0.1583	-0.1484	-0.4285	-0.3875	-0.3917	-0.3243	-0.3335	-0.3298
DKR (2) (5)	0.1635	0.1900	-0.3483	-0.2964	-0.3031	-0.2023	-0.1800	-0.1897
ESC (3) (6)	-0.0880	-0.0342	-0.0886	-0.0821	-0.0825	-0.0548	-0.0874	-0.0816
FF (2) (5)	0.1835	0.1801	-0.3437	-0.2878	-0.2748	-0.1916	-0.2087	-0.2097
HFL (2) (5)	0.0555	0.0814	-0.8277	-0.7685	-0.7046	-0.5119	-0.4825	-0.4775
IRL (4) (5)	-0.1045	-0.1363	-0.2349	-0.2152	-0.2247	-0.1895	-0.1936	-0.1943
LIT (3) (5)	0.0941	0.1392	-0.1898	-0.1101	-0.1085	-0.1025	-0.0830	-0.0815
PTA (3) (7)	-0.0732	-0.0497	-0.0541	-0.0916	-0.0673	-0.0665	-0.0765	-0.0781
UKL (4) (8)	-0.1646	-0.1142	-0.0593	-0.1008	-0.0955	-0.0772	-0.0979	-0.1008

Notes: (1) The Sharpe ratio is obtained dividing the mean return of the trading system by its standard deviation [see equation (16) in the text].
(2) Time series used in establishing occurring analogues in the SNN predictor: BFR, DKR, FF and HFL.
(3) Time series used in establishing occurring analogues in the SNN predictor: ESC, LIT and PTA.
(4) Time series used in establishing occurring analogues in the SNN predictor: IRL and UKL.
(5) Forecasting period: 13-1-87 to 31-12-94.
(6) Forecasting period: 6-4-92 to 31-12-94.
(7) Forecasting period: 19-6-89 to 31-12-94.
(8) Forecasting period: 8-10-90 to 31-12-94.