**Exchange-rate forecasts with
simultaneous nearest-neighbour methods:
Evidence from the EMS***
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Abstract

In this paper we extend nearest neighbour predictors to allow for information content in a wider set of simultaneous time series. We apply these simultaneous nearest neighbour (SNN) predictors, to nine EMS currencies, using daily data for the 1st January 1978- 31st December 1994 period. When forecasting performance is measured by Theil's U statistic, the (nonlinear) SNN predictors perform marginally better than both a random walk and the traditional (linear) ARIMA predictors. Furthermore, the SNN predictors outperform the random walk and the ARIMA models when producing directional forecasts. When formally testing for forecast accuracy, in most of the cases the SNN predictor outperforms the random walk at the 1% significance level, while outperforming the ARIMA model in 3 of the 9 cases. On the other hand, our results suggest that the probability of correctly predicting the sign of change is higher for the SNN predictions than the ARIMA case.

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"...esforzaban de antemano la memoria para recordar el futuro"
Mario Vargas Llosa (La guerra del fin del mundo)

1. Introduction

Despite the paramount modelling effort registered in the last two decades, it is widely recognised that exchange rates are extremely difficult to forecast. The pessimism about the forecasting ability of exchange rate models has been generally accepted after the publication of the influential paper by Messe and Rogoff (1983). These authors performed a large number of statistical tests, indicating the superiority of the linear out-of-sample forecast of exchange obtained through a simple random walk model compared with the forecast based exchange-rate determination models that used a wider set of economic variables as regressors. This superiority is also clear when the forecast is determined *ex post* (i. e., using real historical values of the explicative variables in the regression).

It is now generally accepted that one potential reason for such poor performance could be nonlinearities in exchange-rates series. In this sense, Krugman (1991) emphasised that a target zone as the European Monetary System (EMS) will make exchange rates depend nonlinearly on fundamentals, therefore providing a theoretical foundation for the exchange rate to exhibit a nonlinear data generating process. On the other hand, Bilson (1990) argued that technical traders ("chartists") will also tend to impart nonlinearity into exchange rate movements. Furthermore, Wei (1991) shows that financial prices can exhibit nonlinearities even when there is not any news about fundamentals.

Recent advances in both analytic and computational methods have made it much easier the empirical investigation of nonlinear models and have led to a voluminous literature in this area, dramatically increasing the number of approaches to forecasting exchange rates: chaotic dynamics (e. g., De Grauwe and Vansanten, 1990), turbulent motions (e. g., Ghahghaie *et al.*, 1996) neural networks (e. g., Refenes, 1993), GARCH models (e. g., Bollerslev, Chou and Kroner, 1992), technical trading rules (e. g., Levich and Thomas, 1993), etc.

One of these approaches to forecasting is the non-parametric, nearest neighbour (NN, from now on) forecasting technique. There are several ways of computing such forecasts [see, e. g., Stone (1977), Sugihara and May (1990) and Härdle and Linton (1994)]. The basic idea behind these predictors, inspired in the literature on forecasting in nonlinear dynamical systems, is that pieces of time series sometime in the past might have a resemblance to pieces in the future. In this sense, NN predictions can be thought as a generalization of technical trading rules, which have enjoyed somewhat of a renaissance recently in the eyes of both

practitioners and the academic literature. In order to generate NN predictions, similar patterns of behaviour are located in terms of NNs. The time evolution of these NNs is exploited to yield the desired prediction. Therefore, the procedure only uses information local to the points to be predicted and does not try to fit a function to the whole time series at once [see, e. g., Bajo-Rubio Fernández-Rodríguez and Sosvilla-Rivero (1992) and Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix (1997)].¹

Meese and Rose (1990), Diebold and Nason (1990) and Mizrach (1992) apply NN methods to analyse exchange-rate nonlinear predictability. These papers find that their predictions are not better than forecasts generated by a simple random walk model, suggesting that nonlinear patterns in exchange-rate series were not exploitable for improved point prediction. Note, however, that the number of observations in those papers is relatively small, and therefore the length of the sample used to fit the NN predictors is also relatively small. This could affect negatively the performance of their NN predictions, since they do not allow for the learning process the agents are likely to follow in order to form their exchange rate expectations.

In this paper we extend local predictor presented in Farmer and Sidorowich (1987) to allow the selection of NN in a given time series using information from a wider set of simultaneous time series. In doing so, we try to explore the possible nonlinear causality relationships that could exist among those time series, when forecasting on of them. We will refer to these as simultaneous nearest neighbour (SNN) predictors.

Therefore, the purpose of this paper is to offer further evidence on the ability to forecast exchange rates using nonlinear methods. More precisely, the paper seeks to address the question about whether SNN predictors can improve out-of-sample forecasting in the EMS. In this sense, we continue further the research by Fernández-Rodríguez and Sosvilla-Rivero (1998), where a procedure, based on NN predictors, is proposed for testing the existence of nonlinear forecastable dependencies in time series, and where evidence of short-term nonlinear forecastable possibilities are found for some European currencies.

The paper is organised as follows. The SNN predictors are presented in section 2. Section 3 describes the data set and offers some preliminary results, while in Section 4 the

¹Note that the nearest neighbour approach to forecast nonlinear time series is also related to the techniques of charting (technical analysis) applied in financial markets to produce short-term forecasts (Elms, 1994).

forecast accuracy of the SNN predictors is assessed from a statistical point of view. Some concluding remarks are provided in Section 5.

2. Prediction by NN methods

Let $x_t (t=1, \dots, n)$ be a finite time series. In order to detect behavioural patterns in this series, segments of equal length are considered as vectors $x^{m, \tau}_t$ of $\underline{m}$ observations sampled from the original time series at intervals of $\tau \in \mathbb{N}$ units:

$$x^{m, \tau}_t = (x_t, x_{t-\tau}, \dots, x_{t-(m-1)\tau}), \quad t = I + \tau(m-1), \dots, n \quad (1)$$

with $\underline{m}$ referred to as the embedding dimension and τ called the delay parameter. These $\underline{m}$ -dimensional vectors are often called m-histories, while the $\underline{m}$ -dimensional space $\mathbb{R}^m$ is referred to as the phase space of time series.

The sequence of $\underline{m}$ -histories constitutes a $\underline{m}$ -dimensional object that can, for a big enough $\underline{m}$, mimic the data generation process (Takens, 1981)². In order to simplify, we shall only consider the case of $\tau = 1$ and we shall write $x^{m, 1}_t = x^m_t$.³

The proximity of two $\underline{m}$ -histories in the phase space $\mathbb{R}^m$ allows us to talk of NNs in the dynamic behaviour of two segments in the time series x_t .

To generate short-run forecasts, and as an alternative to the traditional Box-Jenkins methodology, we use the NN approach proposed by Farmer and Sidorowich (1987).

Given the data series $x_t (t=1, \dots, n)$, the local predictions are generated by analysing the historical paths of the vectors around the last available vector

$$x^m_n = (x_n, x_{n-1}, x_{n-2}, \dots, x_{n-(m-1)}). \quad (2)$$

Segments with similar dynamic behaviour are detected and used to produce the forecast. Therefore, to construct a local predictor we have considered the k $\underline{m}$ -histories

$$x^m_{i_1}, x^m_{i_2}, x^m_{i_3}, \dots, x^m_{i_k} \quad (3)$$

²Note that the use of this procedure assumes a (deterministic) data generating process of finite degrees of freedom, so that the attractor is reconstructible.

³Setting the delay equal to one implies that vectors in the $\underline{m}$ -dimensional embedding space have an alternative representation as segments of $\underline{m}$ sequential observations from the original time series.

most similar to x_n^m . The future short-term evolution of the time series will then be obtained using the information contained in the NNs found in the past.

Traditionally, to establish NNs to x_n^m , one looks for the closest k vectors (3) in the phase space $\mathbb{R}^m$, in the sense that they maximise the function:

$$\rho(x_i^m, x_n^m) \quad (4)$$

(i.e., looking for the highest serial correlation of all m -histories, x_i^m , with the last one, x_n^m).

Once the NNs to x_n^m have been established, we consider predictors of the future evolution of x_n^m . A predictor is simply a rule for obtaining an estimate of x_{n+1} for the next observation. The prediction x_{n+1}^f of x_{n+1} can be obtained using some extrapolation of the observations

$$x_{i_1+1}, x_{i_2+1}, \dots, x_{i_k+1} \quad (5)$$

subsequent to the k NNs m -histories that have been chosen, that is to say:

$$x_{n+1}^f = F(x_{i_1+1}, x_{i_2+1}, \dots, x_{i_k+1})$$

When generating NN predictions, locally adjusted linear autoregressive predictions are usually employed:

$$x_{n+1}^f = \hat{a}_0 x_n + \hat{a}_1 x_{n-1} + \dots + \hat{a}_{m-1} x_{n-(m-1)} + \hat{a}_m \quad (6)$$

whose coefficients have been fitted by ordinary least squares, through a regression of the k NNs chosen (3) on their future evolution (5). That is to say, a linear regression of x_{i_r+1} on $x_{i_r}^m = (x_{i_r}, x_{i_r-1}, \dots, x_{i_r-(m-1)})$ ($r=1, \dots, k$) is fitted by least squares, being the $\hat{a}_i$ the values of a_i that minimise

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

Sugihara and May (1990) and Casdagli and Weigend (1994) offer a detailed exposition of this kind of predictor.

Alternatively, and following by Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix (1997), in this paper we establish SNNs to x_n^m by considering the information content of other related series. To simplify notation, let us consider a set of two time series: x_t ($t=1, \dots, n$) and y_t ($t=1, \dots, n$).

We are interested in making predictions of an observation of one of these series (e. g., x_{n+1}), by simultaneously considering NNs in both series. To that end, we embed each of these series in the vectorial space $\mathbb{R}^{2m}$, paying attention to the following vector:

$$(x_n^m, y_n^m) \in \mathbb{R}^m \times \mathbb{R}^m$$

which gives us the last available $\underline{m}$ -history for each time series.

Hence, to establish SNNs to the last $\underline{m}$ -histories (x_n^m, y_n^m) , we can look for the closest $\underline{k}$ points that maximise the function:

$$\rho(x_i^m, x_n^m) + \rho(y_i^m, y_n^m), \quad i = m, m+1, \dots, n. \quad (7)$$

In this way, we obtain a set of k simultaneous $\underline{m}$ -histories in both series:

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

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

...

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

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

$$x_{n+1}^f = \hat{a}_0 x_n + \hat{a}_1 x_{n-1} + \dots + \hat{a}_{m-1} x_{n-(m-1)} + \hat{a}_m \quad (8a)$$

$$y_{n+1}^f = \hat{b}_0 y_n + \hat{b}_1 y_{n-1} + \dots + \hat{b}_{m-1} y_{n-(m-1)} + \hat{b}_m \quad (8b)$$

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

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

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

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

As it can be seen, the difference between this predictor and that presented in (6) is that now the NNs are established using criteria in which information on both series are used.

3. Data and preliminary results

The above developed SNN predictors have been applied to daily exchange-rate data of nine currencies participating in the exchange rate mechanism (ERM) of the EMS: 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). Note that under the ERM, members countries agree to maintain their exchange rate vis-à-vis the other currencies in the system within bands around a central parity. Therefore, by using SNN predictions, we attempt to incorporate structural information into the nonparametric analysis.

Our exchange rates are expressed vis-à-vis the Deutsche mark. The database used is composed of daily (mid-market) spot rates gathered by the Bank of Spain at 13:15 (GMT). The sample period runs from 1st January 1978 to 31st December 1994 (around 4200 observations), covering in particular the EMS period, the monetary turmoil after the summer of 1992, and the new episode initiated with the broadening of the fluctuation bands to $\pm 15\%$ in August 1993. It should be noticed that multi-country analysis of financial series requires a special treatment for high-frequency (daily) data. Finally, note that the data have been purged of holidays, matching day by day the exchange-rate series and eliminating observations when there is no trading in any of the countries under study.

Before computing our local predictors, we have tested for the presence both of unit roots and nonlinear dependence in the series. Using test statistics suggested by Phillips and Perron (1988), we confirmed the existence of unit roots for all exchange rates, as expected (see, e. g., Mills, 1993)⁴. On the other hand, using the well-known BDS test statistic (see Brock, Dechert, Scheinkman and LeBaron, 1996), the null hypothesis of independently and identically distributed (iid) is rejected at the conventional levels⁵. This last result opens alternatives of nonlinear dependence as well as nonstationarity. Although nonstationarity of

⁴The computed Phillips Perron statistics are available from the authors upon requested.

⁵These results, available from the authors upon request, are in line with those of, e. g., Hsieh (1989), Kluger and Lenz (1993) and Cecen and Erkal (1996).

the series is detected, in this paper we explore the use of nonlinear dependencies in order to forecast the series⁶.

Based on the indication of nonlinearities, we proceeded to assess the forecasting performance of our predictors for each exchange rate. Since our predictors depend on the values of embedding dimension $\underline{m}$ and the number of closest $\underline{k}$ points in the phase space $\mathbb{R}^m$, we chose them according to Casdagli's (1991) algorithm, obtaining in our case an embedding dimension $\underline{m}=6$ and a number of SNN points equal to 2% of the sample. 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 (12th January 1987) to the end of the sample. Our local predictors are used to produce forecasts one day ahead for 13rd 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 (9th June 1989, 8th October 1990 and 9th April 1992, respectively).

As it is usual in the literature, the forecasting performance was initially measured by Theil's U statistic, a summary statistic that is based on standard symmetric loss function:

$$U = \frac{\sqrt{\sum_{i=i_0}^{i_0+T} (x_i - x_i^f)^2}}{\sqrt{\sum_{i=i_0}^{i_0+T} (x_i - x_{i-1})^2}}$$

where x_i is the actual value and x_i^f the forecast value. Note that we have defined the U statistic as the ratio of the root mean square error (RMSE) of forecasts from our predictors to the RMSE of the naive random walk forecast. Therefore, a value of U less than one indicates better performance than the random walk specification.

Table 1 shows the forecasting performance of our predictors and those from the traditional ARIMA(1,1,0) models. In the former case, related exchange rate series are used for establishing SNNs. As it can be seen in Table 1, the U statistics are, for the SNN predictors, above one only in 3 of the 9 cases, suggesting that our predictors marginally outperform the random walk, although the forecasting period is very long and heterogeneous.

⁶Note also that ARCH effects could cause the rejection of the BDS, but they do not imply forecastability.

Note that our best SNN predictor presents an improvement of 18.9%. These results contrast with those previously reported in the literature. Diebold and Nason (1990) and Satchell and Timmerman (1995) applied NN predictors to weekly dollar exchange rates for the period 3 January 1973-23 September 1987 and daily dollar exchange rates for the period 1 January 1980-31 December 1992, respectively, concluding that these nonlinear predictors are outperformed by the random walk forecasts. Note, however, that the exchange rate will be, in principle, more forecastable in a target zone as the EMS than in a floating exchange rate system as the US dollar, since the presence of exchange rate band imposes restrictions on market expectations of the future behaviour of the underlying exchange rate. On the other hand, Mizrach (1992) focused on EMS exchange rates *vis-à-vis the Deutschmark* during the period 1 January 1974-31 December 1988, finding a model for the lira that outperforms the random walk in forecasting out-of-sample (with a 4.5% improvement).

Nevertheless, and as mentioned above, the number of observations in Diebold and Nason (1990) and in Mizrach (1992) is much smaller than one we used, and therefore the length of the sample used to fit the NN predictors is also much smaller. This could affect negatively the performance of their NN predictions, since they do not allow for the learning process the agents are likely to follow to form their exchange rate expectations.

From Table 1, we can also see that always, the predictors from an ARIMA(1,1,0) model always offer lower U statistics below one, the best showing an improvement of 12.2% out-of-sample. Nevertheless, in 6 out of 9 cases the SNN predictors offer lower U statistics than the ARIMA(1,1,0) model.

TABLE 1: Forecast accuracy (1)		
	SNN predictor	ARIMA(1,1,0) predictor
BFR (2) (5)	0.984	0.995
DKR (2) (5)	0.939	0.954
ESC (3) (6)	1.016	0.997
FF (2) (5)	0.908	0.952
HFL (2) (5)	0.811	0.878
IRL (4) (5)	1.014	0.997
LIT (3) (5)	0.973	0.981
PTA (3) (7)	0.995	0.999
UKL (4) (8)	1.022	0.999
Notes: (1) U statistic. (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.		

As Boothe and Glassman (1987) observe, a further test of forecasting performance relative to the forecasts of a random walk is the accuracy in predicting the direction of exchange rate movements. This is because getting the sign right in the prediction matters in markets with low transaction costs, like foreign exchange markets. To explore this possibility, we have also computed the percentage of correct predictions. Table 2 show the results, which are rather promising. In 8 out of 9 cases, our local predictors show a value higher than 50%, clearly outperforming the random walk directional forecast⁷. Note also that in all the cases, the predictors

⁷The value 0.5 is the usual benchmark. However, the results must be treated with caution, since numbers of positive changes do not necessarily coincide with the number of negative

from an ARIMA(1,1,0) model show a value greater than 50%. Finally, in 7 out of the 9 cases, our SNN predictors offer higher values than the ARIMA model.

TABLE 2: Directional forecast (1)		
	SNN predictor	ARIMA(1,1,0) predictor
BFR (2) (5)	63.23	52.19
DKR (2) (5)	67.35	63.73
ESC (3) (6)	55.95	53.86
FF (2) (5)	67.43	62.02
HFL (2) (5)	69.19	65.34
IRL (4) (5)	57.73	51.77
LIT (3) (5)	57.25	54.83
PTA (3) (7)	50.64	55.33
UKL (4) (8)	47.58	51.21
Notes: (1) Percentage of correct forecast direction. (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.		

All in all, the evidence presented in this section suggests that in predicting exchange rate time series some forecast accuracy can be gained by considering the information content of other related exchange rates through SNN predictors. The next step is to test for the statistical significance of the differences in forecast accuracy.

changes.

4. Assessing forecast accuracy of the local predictors

To assess the forecast accuracy of the SNN and ARIMA predictors we have first used the test recently proposed by Diebold and Mariano (1995). Let $\hat{x}_{1t}^f$ and $\hat{x}_{2t}^f$ denote alternative forecasts of the variable z_t , let e_{1t} and e_{2t} denote the corresponding forecast errors ($\hat{x}_{1t}^f - z_t$ and $\hat{x}_{2t}^f - z_t$, respectively), and let $d_t = |e_{1t}| - |e_{2t}|$ denotes the loss differential. The Diebold-Mariano test involves a test of the hypothesis that the mean loss differential $\bar{d}$ is zero with an appropriate correction for serial correlation in the d_t series:

$$S = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}_d(0)}{T}}}, \quad (11)$$

where $\hat{f}_d(0)$ is a consistent estimate of the spectral density of the loss differential at frequency 0, T is the number of forecasts and S is asymptotically distributed $N(0,1)$. Therefore, a significant and positive (negative) value for s would indicate a significant difference between the two forecasting errors, which would mean a better accuracy of the $\hat{x}_2^f$ ($\hat{x}_{1t}^f$) predictor.

The results are shown in Table 3. As it can be seen, we reject the null hypothesis of no difference in the loss function in 8 out of the 9 cases when assessing forecast accuracy of the random walk versus the local predictor. The results suggest that the SNN predictor outperform the random walk at the 1% significance level for the BFR, DKR, FF, HFL, IRL and LIT, while the random walk presents superior performance relative to the local predictor for the ESC and UKL at the 1% significance level.

When comparing the predictors from an ARIMA model with our SNN predictors, we reject the null hypothesis of equal absolute error in 4 of the 9 cases. The results indicate that the SNN predictor outperforms the ARIMA model at the 1% significance level for the BFR, FF and HFL, while the ARIMA model presents superior performance relative to the SNN predictor for the UKL at the 1% significance level.

TABLE 3: The Diebold-Mariano test statistic (1)		
	Random walk <i>vs.</i> SNN predictor	ARIMA <i>vs.</i> SNN predictor
BFR (2) (5)	5.11 ^a	4.16 ^a
DKR (2) (5)	12.12 ^a	0.95
ESC (3) (6)	-2.17 ^b	-0.54
FF (2) (5)	14.35 ^a	11.22 ^a
HFL (2) (5)	12.83 ^a	7.72 ^a
IRL (4) (5)	2.97 ^a	-0.21
LIT (3) (5)	3.19 ^a	1.53
PTA (3) (7)	1.14	0.38
UKL (4) (8)	-3.14 ^a	-3.16 ^a
<p>Notes: (1) ^a, ^b and ^c denote significance at the 1%, 5% and 10% levels, respectively.</p> <p>(2) Time series used in establishing occurring analogues in the SNN predictor: BFR, DKR, FF and HFL.</p> <p>(3) Time series used in establishing occurring analogues in the SNN predictor: ESC, LIT and PTA.</p> <p>(4) Time series used in establishing occurring analogues in the SNN predictor: IRL and UKL.</p> <p>(5) Forecasting period: 13-1-87 to 31-12-94.</p> <p>(6) Forecasting period: 6-4-92 to 31-12-94.</p> <p>(7) Forecasting period: 19-6-89 to 31-12-94.</p>		

Next, we further assessed the forecast accuracy of the SNN and ARIMA predictors by computing the Pesaran-Timmerman non-parametric test proportion of correctly predicted signs. Let $z_{t+k}=1$ if $(x_{t+k} x_{t+k}^f > 0)$ and $z_{t+k}=0$ otherwise. Using the same notation as Broock (1997), let $P_x = \Pr(x_{t+k} > 0)$, $P_f = \Pr(x_{t+k}^f > 0)$, and let

$$\hat{P} = \frac{1}{T} \sum_{t=0}^T z_{t+k}$$

be the percentage of correct sign predictions. Denoting the *ex ante* probability that the sign will correctly be predicted as P_* , then

$$P_* = \Pr(z_{t+k}=1) = \Pr(x_{t+k} x_{t+k}^f > 0) = P_x P_f + (1 - P_x)(1 - P_f).$$

Pesaran and Timmerman (1992) show that

$$S_k = \frac{\hat{P} - P^*}{\sqrt{(\text{var}(\hat{P}) - \text{var}(P^*))}}$$

is asymptotically distributed as a standard normal variate under the null hypothesis of independence between corresponding actual and forecast values, where $\hat{P}^*$ denotes estimated values,

$$\text{var}(\hat{P}) = \frac{1}{T} \hat{P}^*(1 - \hat{P}^*)$$

and

$$\text{var}(\hat{P}^*) = \left[\frac{1}{T} (2\hat{P}_x - 1)^2 \hat{P}_f (1 - \hat{P}_f) + \frac{1}{T} (2\hat{P}_f - 1)^2 \hat{P}_x (1 - \hat{P}_x) + \frac{1}{T^2} \hat{P}_x \hat{P}_f (1 - \hat{P}_x) (1 - \hat{P}_f) \right].$$

Note that k denotes the number of periods ahead in the prediction, being $k=1$ in our case.

As shown in Table 4, the null hypothesis of independence is rejected at the 1% significance level for 7 of the 9 cases for the SNN predictors, and for 6 of the 9 cases for ARIMA predictors. Notice that the computed values are always positive for the SNN predictors, while the ARIMA forecast of UKL is negative. Finally, it is interesting to note that the SNN predictors produce a higher value of the test than the ARIMA predictors for all cases except PTA. These results are in line with those reported in Satchell and Timmerman (1995), who take them as evidence supporting the use of nonlinear forecast procedures.

TABLE 4: The Pesaran-Timmerman test statistic (1)		
	SNN predictor	ARIMA(1,1,0) predictor
BFR (2) (5)	11.33 ^a	3.45 ^a
DKR (2) (5)	13.10 ^a	10.83 ^a
ESC (3) (6)	2.80 ^a	1.54
FF (2) (5)	13.01 ^a	9.08 ^a
HFL (2) (5)	14.97 ^a	11.89 ^a
IRL (4) (5)	6.91 ^a	3.01 ^a
LIT (3) (5)	6.31 ^a	3.79 ^a
PTA (3) (7)	0.53	1.15
UKL (4) (8)	0.18	-0.37
Notes: (1) ^a , ^b and ^c denote significance at the 1%, 5% and 10% levels, respectively. (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.		

Given that the period considered is very long and heterogeneous, we have also computed our predictors 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 $\pm 15\%$). To save space we have not reported the results here (they are available from the authors).

upon request). They suggest that the forecasting performance of the SNN predictors is in general better before September 1992 than those for the whole period for all currencies. After September 1992, only in the cases of the Belgian franc, the Dutch guilder and the Danish krone, there is some evidence of an improvement in the forecast performance of the SNN predictors. These results reflect the turbulences registered in the currency market, coinciding with the increasing uncertainty about the future of monetary union in Europe⁸. On the other hand, there seems to be a correlation between better forecast performance and the credibility of the exchange-rate commitments, as documented in Fernández-Rodríguez, Sosvilla-Rivero and Martín-González (1997).

4. Concluding remarks

The purpose of our paper has been to contribute to the debate on the relevance of nonlinear forecasts of high-frequency data in financial markets. To that end, we have extended the local predictor presented in Farmer and Sidorowich (1987) to allow the selection of nearest neighbour in a given time series using information from a wider set of simultaneous time series. We have applied these simultaneous nearest neighbour (SNN) predictors to nine currencies participating in the exchange rate mechanism (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 main results are as follows. First, when evaluating the forecasting performance for the whole sample using Theil's U statistic, the (nonlinear) SNN predictors performed marginally better than both a random walk and the traditional (linear) ARIMA predictors. Furthermore, the SNN predictors outperformed the random walk and the ARIMA models when producing directional forecasts.

Secondly, we considered two tests of forecast accuracy. The Diebold-Mariano test suggested that most of the cases the SNN predictor outperforms the random walk at the 1% significance level, while outperforming the ARIMA model in 3 of the 9 cases. On the other hand, the Pesaran-Timmerman test shows that the probability of correctly predicting the sign of change is higher for the SNN predictions than the ARIMA case.

Taken together, the evidence presented here confirm the results of recent research which has emphasized the importance of predictable components in exchange rate [see, e. g. Levich and Thomas (1993) and Fernández-Rodríguez and Sosvilla-Rivero (1998)]. Further work is needed

⁸See Commission of the European Communities (1993) and European Commission (1994) for a detailed description of the developments within the ERM during this period.

in order to understand the causes and structure of this predictability in exchange markets, since this issue is important both for understanding the forces driving exchange movements, but also for both exchange-rate dealers.

References:

- Bajo-Rubio, O., Fernández-Rodríguez, F. and S. Sosvilla-Rivero, 1992, Chaotic behaviour in exchange-rate series: First results for the peseta-US dollar case, *Economics Letters*, 39, 207-211.
- Bilson, J., 1990, 'Technical' currency trading, in: L. Thomas, ed., *The currency-hedging debate* (IFR Publishing, London, UK).
- Bollerslev, T., Chou, R. Y. and K. F. Kroner, 1992, ARCH modeling in finance: A review of the theory and empirical evidence, *Journal of Econometrics*, 52, 5-59.
- Boothe, P. and D. Glassman, 1987, Comparing exchange rate forecasting models: Accuracy versus profitability, *International Journal of Forecasting*, 3, 65-79.
- Brock, W., Dechert, W., Scheinkman, J. and B. LeBaron, 1996, A test for independence based on the correlation dimension, *Econometric Reviews*, 15, 197-235.
- Brooks, C., 1997, Linear and non-linear (non-)forecastability of high-frequency exchange rates, *Journal of Forecasting*, 16, 125-145.
- Casdagli, M., 1991, Nonlinear forecasting, chaos and statistics, Working Paper 91-05-022, Santa Fe Institute.
- Casdagli, M. and A. S. Weigend, 1994, Exploring the continuum between deterministic and stochastic modelling, in: A. S. Weigend and N. A. Gershenfeld, eds., *Time series prediction: Forecasting the future and understanding the past* (Addison Wesley, Reading, MA.).
- Cecen, A. A. and C. Erkal, 1996, Distinguishing between stochastic and deterministic behaviour in foreign exchange rate returns: Further evidence, *Economics Letters*, 51, 323-329.
- De Grauwe, P. and K. Vansanten, 1990, Deterministic chaos in the foreign exchange market, CEPR Discussion Paper 370, London.
- Diebold, F. and J. Nason, 1990, Nonparametric exchange rate prediction?, *Journal of International Economics*, 28, 315-335.

- Diebold, F. X. and R. S. Mariano, 1995, Comparing predictive accuracy, *Journal of Business and Economic Statistics*, 13, 253-263.
- Elms, D., 1994, Forecasting in financial markets, in: J. Creedy and V. L. Martin, eds., *Chaos and non-linear models in economics* (Edward Elgar, Aldershot, UK).
- Farmer, D. and J. Sidorowich, 1987, Predicting chaotic time series, *Physical Review Letters*, 59, 845-848.
- Fernández-Rodríguez, F. and Sosvilla-Rivero, S., 1998, Testing Nonlinear Forecastability in Time Series: Theory and Evidence from the EMS, *Economics Letters*, 59, 49-63.
- Fernández-Rodríguez, F., Sosvilla-Rivero, S. and J. Andrada-Félix, 1997, Combining information in exchange rate forecasting: Evidence from the EMS, *Applied Economics Letters*, 4, 441-444.
- Fernández-Rodríguez, F., Sosvilla-Rivero, S. and J. Martín-González, 1997, Credibility in the EMS: New evidence using nonlinear forecastability tests, Working paper 97-14, FEDEA.
- Ghahghaie, S., Breynabb, W., Peinke, J., Talkner, P. and Y. Dodge, 1996, Turbulent cascades in foreign exchange markets, *Nature*, 281, 767-770.
- Härdle, W. and O. Linton, 1994, Applied nonparametric methods, in: R. F. Engle and D. MacFadden, eds., *Handbook of Econometrics*, 4 (Elsevier, Amsterdam, The Netherlands).
- Hsieh, D. A., 1989, Testing for nonlinear dependence in daily foreign exchange rates, *Journal of Business*, 62, 339-368.
- Kluger, P. and C. Lenz, 1993, Chaos, ARCH and the foreign exchange market: Empirical results from weekly data, *Rivista Internazionale di Scienze Economiche e Commerciali*, 40, 127-140.
- Krugman, P., 1991, Target zones and exchange rate dynamics, *Quarterly Journal of Economics*, 106, 669-682.
- Levich, R. and Thomas, L., 1993, The significance of technical trading rule profits in the foreign exchange market: A bootstrap approach, *Journal of International Money and Finance*, 12, 451-474.

- Messe, R. A. and K. Rogoff, 1983, Empirical exchange rate models for the seventies: Do they fit out of sample?, *Journal of International Economics*, 14, 3-24.
- Meese, R. A. and A. K. Rose, 1990, Nonlinear, nonparametric, nonessential exchange rate estimation, *American Economic Review Papers and Proceedings*, 80, 603-619.
- Mills, T. C., 1993, *The econometric modelling of financial time series* (Cambridge University Press, Cambridge, UK).
- Mizrach, B., 1992, Multivariate nearest-neighbour forecasts of the EMS exchange rates, *Journal of Applied Econometrics*, 7, S151-S163.
- Pesaran, M. H. and A. Timmermann, 1992, A simple nonparametric test of predictive performance, *Journal of Business and Economic Statistics*, 10, 461-465.
- Phillips, P. C. B. and P. Perron, 1988, Testing for unit root in time series regression, *Biometrika*, 75, 335-346.
- Refenes, A., 1993, Constructive learning and its application to currency exchange rate forecasting, in: R. Trippi and E. Turban, eds., *Neural networks in finance and investing* (Probus, Chicago).
- Satchell, S. and A. Timmermann, 1995, An assessment of the economic value of non-linear foreign exchange rate forecasts, *Journal of Forecasting*, 14, 477-497.
- Stone, C. J., 1977, Consistent nonparametric regression, *Annals of Statistics*, 5, 595-620.
- Sugihara, G. and R. M. May, 1990, Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series, *Nature*, 344, 734-741.
- Takens, F., 1981, Detecting strange attractors in turbulence, in: D. Rand and L. Young, eds., *Dynamical systems and turbulence* (Springer-Verlag, Berlin).
- Wei, S., 1991, Price volatility without news about fundamentals, *Economics Letters*, 37, 453-458.

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